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affiliée à l'Université de Montréal

**Water quality management in chlorinated distribution systems under
changing climate and demand patterns**

FAEZEH ABSALANDOGAHEH

Département de génies civil, géologique et des mines

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

Génie Civil

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POLYTECHNIQUE MONTRÉAL

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Cette thèse intitulée:

Water quality management in chlorinated distribution systems under changing climate and demand patterns

présentée par **Faezeh ABSALANDOGAHEH**

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

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DEDICATION

پرده بگردان و بزن ساز نو
 همین که رسید از فلک آواز نو
 تازه و خندان نشود گوش و هوش
 تا ز خرد در نرسد راز نو

Translated to:

Draw the curtain, and strike a new melody

For a fresh celestial tune has arrived

Let not the ear and mind remain stale

Until new secrets from wisdom unveil

-Rumi-

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RÉSUMÉ

Cette étude porte sur l'impact des changements climatiques et des activités humaines sur la qualité de l'eau potable en milieu urbain en mettant l'accent sur le réseau de distribution. Il souligne la nécessité pour les services publics des eaux de se préparer aux perturbations potentielles de la qualité de l'eau et de la santé publique dues à des facteurs tels que le réchauffement climatique, les événements météorologiques extrêmes, les économies d'eau et l'urbanisation. Ces changements affectent des paramètres cruciaux tels que la température, la teneur en carbone organique dissous (COD) et l'âge de l'eau, qui influencent considérablement les niveaux de chlore libre et de trihalométhanes (THM) dans l'eau. La gestion du chlore et des THM dans les réseaux de distribution (RD) est essentielle pour garantir la qualité de l'eau et la conformité réglementaire.

Les études précédentes ont exploré séparément les effets des événements climatiques sur la qualité de l'eau potable à la source, mais il existe un manque de connaissances sur l'impact combiné de la matière organique, des variations de température et de la réduction de la demande en eau dans les RD. De plus, malgré l'augmentation des températures du sol, on dispose de peu de connaissances sur la manière dont les îlots de chaleur urbains (ICU) et les vagues de chaleur estivales affectent la température de l'eau potable dans les RD, en particulier pendant les périodes de chaleur. Il est essentiel de comprendre si les espaces verts en ville peuvent atténuer les effets de cette hausse de température. Cette question est cruciale compte tenu de la profondeur à laquelle les canalisations des réseaux de distribution sont enfouies au Canada (au minimum 1,8 mètre), ce qui pourrait minimiser l'impact des conditions de surface sur la température de l'eau. Aborder ces questions pourrait améliorer notre compréhension de la gestion de l'eau en milieu urbain pour mieux faire face aux défis d'origine climatique ou humaine.

Pour atteindre l'objectif principal de cette étude, nous avons subdivisé notre travail en plusieurs objectifs spécifiques. Le premier objectif est de développer une méthode de prédiction du chlore et des THM dans les RD à grande échelle, en abordant spécifiquement les défis liés à l'eau à forte teneur en ammoniac et aux variations de dosage et de rechloration dans les RD. Le deuxième objectif se concentre sur l'examen approfondi des effets combinés de la COD, des fluctuations de température et de la réduction de la demande en eau sur les variations de chlore et de THM dans les RD à grande échelle. Le dernier objectif consiste à étudier l'impact des îlots de chaleur urbains sur la température de l'eau potable en ville et à déterminer si les canalisations profondément

enfouies au Canada sont affectées par les vagues de chaleur et les îlots de chaleur urbains pendant les périodes de forte chaleur. Nous avons comparé les températures de l'eau mesurées dans les zones de surfaces imperméables ayant tendance à devenir plus chaudes en raison de leur capacité à absorber et retenir la chaleur à celles avec de végétation abondante. Nous cherchons à déterminer si les espaces verts jouent un rôle dans la réduction de la température de l'eau potable en milieu urbain.

Pour accomplir ces objectifs, nous avons mis en œuvre une approche multidisciplinaire faisant appel à divers outils et méthodologies. Nous avons prélevé des échantillons d'eau à l'usine de traitement de l'eau et dans les RD de ville du Québec (Canada). En laboratoire, nous avons effectué des tests de chloration pour adapter et calibrer les modèles de prédiction du chlore et des THM, en utilisant MATLAB pour l'étalonnage des modèles. Nous avons simulé différents scénarios de température et de COD dans l'eau traitée à travers des tests en laboratoire. En utilisant le logiciel de simulation de la qualité de l'eau EPANET, nous avons prédit le chlore et les THM dans les RD à l'aide d'un modèle à taux variable. Pour évaluer la température de l'eau à Montréal, nous avons utilisé des images satellite dans QGIS pour sélectionner des zones affectées par les îlots de chaleur et des zones avec une végétation abondante. Au cours d'une campagne de surveillance sur le terrain de 2,5 mois, nous avons installé des sondes de température à divers emplacements. Pour modéliser la température de l'eau dans les RD de Montréal, nous avons combiné MATLAB avec le modèle de simulation de la qualité de l'eau WaterGEMS.

Concernant le premier objectif, nos résultats de validation, basés sur des mesures en laboratoire et sur le terrain, ont montré une prédiction adéquate du chlore et des THM dans l'eau avec des concentrations élevées et faibles en ammoniac tout au long des saisons. Notamment, lors de la validation des prédictions de THM avec des mesures sur le terrain en utilisant le modèle à taux variable, nous avons obtenu des résultats précis pour 20 des 22 points, avec une erreur de moins de 5 µg/L. Cette recherche représente la première utilisation à grande échelle du modèle à taux de réaction variable pour anticiper les niveaux de chlore et de THM. Cette approche adaptable présente l'avantage de rationaliser le processus, pouvant s'ajuster aux changements de dosage, aux conditions de rechloration et aux concentrations élevées en ammoniac sans nécessiter une recalibration. Dans le deuxième objectif, nos résultats ont révélé que l'influence de la COD et de la température sur les THM était plus importante que celle de la demande en eau. Pour le chlore, tous les facteurs étudiés étaient significatifs. L'examen de la fiabilité du réseau dans divers scénarios de

qualité de l'eau a mis en évidence l'importance critique de niveaux de COD dépassant 2,2 mg/L et de températures dépassant 25°C. Un dépassement de ces seuils pourrait conduire à une non-conformité des normes relatives au chlore et aux THM dans le réseau, accroissant ainsi le risque de prolifération microbienne, d'exposition accrue aux THM et de préoccupations au niveau des consommateurs. Pour le troisième objectif, nos résultats ont montré que même dans les climats froids, la température de l'eau des canalisations profondément enfouies peut être influencée par les températures de l'air et de la surface du sol. Les zones urbaines avec des températures de surface élevées ont connu des températures élevées de l'eau distribuée, avec une augmentation allant jusqu'à 8°C entre l'usine de traitement et les bâtiments des consommateurs. De manière surprenante, les zones avec plus de verdure avaient des températures de l'eau plus basses, avec un effet rafraîchissant allant jusqu'à 8°C. La relation entre la température de l'air et celle de l'eau dans les RD ne révélait pas une forte corrélation entre ces variables. Cependant, il existait une forte corrélation entre les températures du sol modélisées et les températures de l'eau, indiquant que la température du sol est un indicateur fiable des variations de température de l'eau. Notre modèle de température de l'eau concordait de manière précise avec les mesures réalisées avec des erreurs quadratiques moyennes de 0,39 à 2,55°C dans les zones végétalisées et une valeur P moyenne de 2,6E-03, et des erreurs quadratiques moyennes de 0,23 à 2,82°C dans les zones affectées par les îlots de chaleur urbains, avec une valeur P moyenne de 6,12E-04. Ces tests statistiques soulignent la signification et la précision de nos prévisions.

Cette thèse aborde des défis critiques et offre des perspectives pour améliorer la gestion de l'eau potable en milieu urbain face aux changements mondiaux et climatiques mondiaux. La réalisation du premier objectif nous a permis d'aborder efficacement le défi de la prédiction du chlore et des THM dans les eaux riches en ammoniac et nous avons réussi à prédire les THM dans un RD à grande échelle. Le deuxième objectif nous a permis de déterminer que la qualité de l'eau post-traitement est principalement influencée par la formation des THM, tandis que la qualité du traitement et les conditions du RD étaient également cruciales pour le chlore. Cela est particulièrement important pour les politiques d'économie d'eau au Québec, car la diminution de la demande en eau exige une attention accrue pour maintenir des niveaux de chlore suffisants dans le RD. Nos résultats ont également révélé que les emplacements vulnérables pour le chlore et les THM pouvaient différer, incitant à une réévaluation des points de surveillance réglementaires partagés. Le troisième objectif a souligné l'importance de surveiller la température de l'eau dans les

zones urbaines sensibles, même à proximité de l'usine de traitement de l'eau. Cette constatation remet en question la sélection traditionnelle des sites de surveillance, qui repose principalement sur l'âge de l'eau et la distance par rapport à l'usine de traitement. Pour atteindre le troisième objectif, nous avons introduit une approche innovante utilisant des images satellite pour la modélisation de la température du sol spécifique à chaque site dans les zones urbaines. Cette approche permet aux services publics, en particulier ceux disposant de ressources limitées, de modéliser les températures spécifiques à chaque site en fonction des conditions climatiques locales et des températures de la surface du sol. Une telle modélisation est un outil précieux pour la surveillance de la qualité de l'eau en milieu urbain et pour le placement stratégique de capteurs de qualité de l'eau, en mettant l'accent sur les zones sensibles.

ABSTRACT

This study comprehensively examines the impact of climate change and human activities on urban drinking water quality. It emphasizes the need for water utilities to prepare for potential disruptions to water safety and public health due to factors like global warming, extreme weather events, water-saving policies, and urbanization. These changes affect crucial parameters like temperature, dissolved organic carbon (DOC), and water age, which significantly influence the levels of free chlorine and trihalomethanes (THMs) in water. Managing chlorine and THMs in distribution systems (DS) is vital for ensuring water safety and regulatory compliance.

Previous studies have separately explored the effects of climatic events on downstream drinking water quality, but a knowledge gap exists regarding the combined impact of organic matter, temperature variations, and reduced water demand within DS. Furthermore, despite reports of increasing soil temperatures, there's limited knowledge about how urban heat islands (UHI) and summer heatwaves affect drinking water temperature in DS, especially during hot periods. It's unclear whether green spaces in cities can mitigate this temperature rise. This issue is crucial given that Canadian distribution network pipes are buried deep (minimum 1.8 meters), potentially minimizing the impact of surface conditions on water temperature. Addressing these questions enhances our understanding of urban water management in the face of natural and human-induced challenges.

To achieve the overarching goal of this study, we have subdivided our work into several specific objectives. The first objective is to develop a method for predicting chlorine and THMs in full-scale DS, specifically addressing challenges in high-ammonia water and varying dosage and rechlorination in the DS. The second objective focuses on the comprehensive examination of the combined effects of DOC, temperature fluctuations, and water demand reduction on of chlorine and THMs variations in a full-scale DS. The final objective is to investigate the impact of UHIs on drinking water temperature in cities and determine whether deeply buried pipes in Canada are affected by heatwaves and UHIs during hot periods. By comparing measured water temperatures in areas with impervious surfaces to those with abundant vegetation, we seek to ascertain whether green spaces play a role in reducing drinking water temperatures in urban settings.

To accomplish these objectives, we implemented a multidisciplinary approach that involved the use of various tools and methodologies. We collected water samples from the water treatment plant

and the DS of cities in Quebec. In the lab, we conducted chlorination tests to adapt and calibrate chlorine and THM prediction models, using MATLAB for model calibration. We simulated different temperature and DOC scenarios in treated water through lab tests. Using the EPANET water quality simulation software, we predicted chlorine and THMs within the DS with a variable rate model. For monitoring water temperature in Montreal, we used satellite imagery in QGIS to select areas affected by heat islands and areas with abundant vegetation. During a 2.5-month field monitoring campaign, we installed temperature loggers at various locations. To model water temperature within Montreal's DS, we combined MATLAB with the WaterGEMS water quality simulation model.

In the first objective, our validation results, based on both lab and field measurements, showed successful prediction of chlorine and THMs in water with high and low ammonia concentrations across varying seasons. Notably, when validating THM predictions with field measurements using the variable rate model, we achieved accurate results in 20 out of 22 points, with an error of less than 5 µg/L. This study marks the first application of the variable reaction rate model for real-scale chlorine and THM prediction, offering a time-saving and adaptable approach that accommodates changing dosages, rechlorination conditions, and high ammonia concentrations without recalibration. In the second objective, our results revealed that the influence of DOC and temperature on THMs was more substantial than water demand. For chlorine, all studied factors were critical. Assessing network reliability in various water quality scenarios revealed that DOC levels above 2.2 mg/L and temperatures over 25°C were pivotal. Exceeding these levels could result in network-wide violation of chlorine and THMs standards, raising the risk of microbial regrowth, elevated THM exposure, and customer concerns. In the third objective, our findings showed that even in cold climates, deeply buried pipe water temperature can be affected by air and soil surface temperatures. Areas with high land surface temperatures in cities experienced elevated water temperatures, with up to an 8°C increase from the treatment plant to customers' buildings. Surprisingly, areas with more greenery had lower water temperatures, with up to an 8°C cooling effect. The relationship between air temperature and water temperature in the DS lacked a clear correlation. However, a strong correlation existed between modeled soil temperatures and water temperatures, indicating soil temperature as a reliable indicator of water temperature changes. Our water temperature modeling closely matched measured temperatures, with root mean square errors (RMSE) ranging from 0.39 to 2.55°C in vegetated areas and an average P-value of 2.6E-03, and

RMSE ranging from 0.23 to 2.82°C in UHI-affected areas with an average P-value of 6.12E-04. These statistical tests underscore the significance and accuracy of our predictions.

Our study tackles critical challenges and offers insights for improving urban water management amid global and climate changes. In the first objective, we effectively addressed the challenge of predicting chlorine and THMs in high-ammonia waters and successfully predicted THMs within a full-scale DS. In the second objective, post-treatment water quality primarily influenced THM formation, while both treatment quality and DS conditions were equally crucial for chlorine. This is particularly relevant for Quebec's water-saving policies, as declining water demand requires increased attention to maintaining sufficient chlorine levels within the DS. Importantly, our findings revealed that vulnerable locations for chlorine and THMs may differ, prompting a reconsideration of shared regulatory monitoring points for both chlorine and THMs. The third objective highlighted the importance of monitoring water temperature in urban hotspots, even at locations close to the water treatment plant. This finding challenges the traditional monitoring site selection which relies mainly on water age and distance from the treatment plant. To achieve the third objective, we introduced an innovative approach using satellite imagery for site-specific soil temperature modeling in urban areas. This approach empowers utilities, especially those with limited resources, to model site-specific water temperatures based on local climate conditions and land surface temperatures. Such modeling is a valuable tool for monitoring urban water quality and strategically placing water quality sensors, prioritizing hotspots.

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LIST OF SYMBOLS AND ABBREVIATIONS

ANN	Artificial Neural Network
Br	Bromide
CV	Coefficient of Variance
DS	Distribution System
DOC	Dissolved Organic Carbon
D1-H	High Demand Scenario
D2-R	Reference Demand Scenario
D3-L	Low Demand Scenario
D4-VL	Very Low Demand Scenario
DBPs	Disinfection By-products
F _G	Global Factor
HAAs	Haloacetic Acids
LCD	Liters per Capita per Day
LD	Legionnaire's Disease
Lp	Legionella pneumophila
LST	Land Surface Temperature
MR	Multivariate Regression
NOM	Natural Organic Matter
PFAS	Polyfluoroalkyl Substances
R	Reliability Index
RT	Residence Time
R _{Cl₂}	Chlorine Reliability

R_{THM}	THM reliability
%R100	Percentage of Nodes Containing a Reliability equal to 100
RMSE	Root Mean Square Error
R^2	R-squared
r	Correlation Coefficient
Sc	Scenario
SDS	Simulated Distribution System
Sc	Scenario
TOC	Total Organic Carbon
THMs	Trihalomethanes
TTHMs	Total Trihalomethanes
THMFP	THMs formation potential
UHIs	Urban Heat Islands
VRRC	Variable Reaction Rate Constant
WTP	Water Treatment Plant

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CHAPTER 1 INTRODUCTION

The term "global change" resonates with everyone, signifying a world in a perpetual state of transformation. While change in the global climate is an inherent and inevitable facet of nature, the rate of this change is increasing, and it is becoming a growing concern. While some of these shifts are natural, human activities are accelerating them and intensifying their impact on our lives. Increasing global temperatures, heightened climatic events like wildfires and extreme precipitation, and the rapid urbanization rate are all impacting natural and human-made systems. One such system directly influencing human health and well-being is the human-water system. The quality of drinking water plays a crucial role in public health, significantly affecting individual and community safety and well-being. Access to safe and clean drinking water is a fundamental human right, and compromised water quality can lead to various health issues, from acute gastrointestinal illnesses to long-term concerns such as cancer and developmental disorders (Reynolds et al., 2008). Global climate variability is anticipated to result in more frequent and severe extreme weather events, including extreme precipitations, floods, heatwaves, and wildfires (Khan et al., 2015). These events can jeopardize drinking water quality by compromising the integrity of water catchments, reservoirs, treatment processes, and drinking water distribution systems (Danilenko et al., 2010). Ensuring drinking water safety necessitates careful water resource management, efficient treatment and disinfection processes, and efficient monitoring throughout the DS.

Since the beginning of the 20th century, disinfection has been the main way of ensuring water safety and preventing waterborne disease and death (Ohar and Ostfeld, 2014). The efficacy of chlorine as a disinfectant is supported by its broad range of antimicrobial activity, cost-effectiveness, and ease of use (Hua et al., 2015). Inadequate chlorine residual in the DS network poses a water safety threat due to the potential for pathogen regrowth, notably in case of pathogen intrusion (Hatam et al., 2020; Tryby et al., 1999; Zhang and Lu, 2021). Drinking water regulations across various jurisdictions usually mandate a minimum residual chlorine concentration at the entry point and/or throughout the DS (Code of Federal Regulations (CFR), 2010; Walski, 2019a). However, one of the adverse consequences of chlorination is the reaction of chlorine with organic compounds (e.g., humic and fulvic acids) or inorganic compounds (e.g., bromide (Br⁻)) present in water, resulting in the formation of Disinfection Byproducts (DBPs) (Simard et al., 2011a). To date, more than 600

DBPs have been identified, with THMs and Haloacetic acids (HAAs) being the most rigorously regulated in many countries due to their reported health implications (Wang et al., 2007). Balancing the need to retain an adequate level of free chlorine for ensuring water safety while simultaneously minimizing the formation of THMs presents a critical challenge for water utilities.

The rate of chlorine decay and THM formation depends on the water characteristics as well as the conditions prevailing in the DS (Kali et al., 2021). Regarding the water characteristics, elevated ammonia concentrations (Hua et al., 2015), elevated temperature (Uyak et al., 2007; Valdivia-Garcia et al., 2019; Xu et al., 2022) and higher concentration of DOC (Clark et al., 2001; Ferretto et al., 2021; Liu et al., 2022b) are some of the most influencing parameters increasing the rate of chlorine decay or THM formation reported in several studies. Concerning the network and operating conditions, water demand, pipe wall conditions, suspended/sedimented solids, mixing, and biofilms formation play the most important roles (Baribeau et al., 2001; Hallam et al., 2002; Zhang et al., 2017). Chlorine decay and THM formation start in the water treatment plant and continue during the water travel time in the DS. Extended water travel times or stagnation in the DS exacerbates the negative impacts of all the aforementioned factors and further decrease chlorine availability and increase THM concentrations within the DS (Simard et al., 2011a).

Numerous aspects of global change are impacting the quality of drinking water. Global climate change is raising Earth's surface and surface water temperatures worldwide (Czernecki and Ptak, 2018). Higher temperatures result in drier vegetation and altered weather patterns, fostering conditions conducive to more intense wildfires (Crandall et al., 2021; Olefeldt et al., 2013). Extreme weather events, particularly following wildfires, can elevate sediment flux and turbidity levels in downstream water sources (Chow et al., 2019a; Wei et al., 2021). The ramifications of these factors include reduced infrastructure lifespan, increased treatment costs, and elevated levels of contaminants and natural organic matter in water.

Human responses to global change add another layer of complexity to the problem. To achieve the United Nations' Sustainable Development Goal 6, clean water and sanitation for all, water demand management is a vital strategy for sustainable water resource use (Cf, 2015). Water demand reduction leads to prolonged water residence times in the DS (Hatam et al., 2021). Moreover, the development of cities and increasing rates of urbanization worldwide has replaced the natural soil

surfaces with minerals and introduced materials such as concrete and asphalt into urban systems (Zhu et al. (2021)). This increase in impervious surfaces has led to higher Land Surface Temperature (LST) and soil subsurface temperature in cities compared to suburban areas (Estrada-Calderon and Becerra-Santacruz, 2022). The gradual heat release from these hotspots with elevated heat capacity contributes to the UHIs effect. Elevated temperatures in the soil surrounding buried water pipes can induce a warming effect in drinking water (Blokkeer and Pieterse-Quirijns, 2013). Thus, hotspots in urban areas may face higher water temperatures during warm periods.

This research aims to provide a holistic perspective, painting a comprehensive picture bridging the knowledge gaps and addressing implications of the changes on drinking water quality in chlorinated distribution networks through a multidimensional approach. Our study begins by tackling a critical challenge faced by utilities, which is predicting chlorine and THM levels under high ammonia concentrations, changing dosages, and rechlorination conditions. We will then delve into the combined effects of climatic events and water demand reduction on chlorine and THM availability within the distribution system, an area with limited prior research. Furthermore, we will explore the relative significance of each factor in influencing chlorine and THM concentrations within the distribution system. Finally, we assess the unknown effects of urbanization and the loss of green spaces on drinking water temperature in the distribution systems and investigate whether the creation of UHIs in cities can lead to water temperature disparities. We also aim to understand whether greener spaces in the distribution network of cities contain lower drinking water temperatures. In light of the new knowledge gained from this research, we will reassess the efficacy of existing urban water management strategies, determining whether they remain effective in the context of climate change adaptation. The research is performed on three full-scale DS in the province of Quebec, Canada. The findings of this research will be useful for utilities in Quebec and all over the world.

This Ph.D. thesis is composed of 8 chapters. The second chapter is a critical literature review highlighting all the factors discussed and addressed during this research. Chapter 3 will summarize the methodology and the objectives of the work and questions to be addressed. Chapters 4 to 6 are the three articles published or submitted to scientific journals. Chapter 7 provides a general discussion and addresses the limitations and challenges encountered during this research. The 8th chapter provides a conclusion and offers recommendations for future research.

CHAPTER 2 CRITICAL LITERATURE REVIEW

In this chapter, we delve into a comprehensive exploration of key stressors stemming from both climatic and anthropogenic changes that impact drinking water quality and safety in the distribution networks. We will examine their potential implications for chlorine availability, THMs concentrations, and temperature variations within the distribution networks. The chapter is divided into several sections, each focusing on distinct stressors and the importance of addressing them. First, we address the effects of climatic changes, including surface water warming, wildfires followed by intense precipitations, and surface water browning. Then, we discuss the implications of anthropogenic changes, with a particular focus on water-saving strategies and urbanization. Following these discussions, we emphasize the critical importance of predicting water temperature and quality in the context of climate change adaptation. Lastly, we identify and address the knowledge gaps related to the impacts of changing conditions on drinking water quality and management. This chapter aims to provide a thorough understanding of the multifaceted challenges that influence the quality and safety of drinking water in chlorinated distribution systems.

2.1 Drinking water quality under global change

The study of the impacts of global change on drinking water quality is crucial due to the potential adverse consequences on public health and well-being. Global change can compromise water quality through the introduction of pollutants, the disruption of treatment processes, and changes in the DS conditions. These changes can in turn result in disinfectant decay and formation of DBPs in chlorinated network and compromising microbial safety in chlorinated or unchlorinated networks. Chlorine is a commonly employed disinfectant worldwide, functioning by destroying or inactivating pathogenic microorganisms such as *Salmonella*, *Campylobacter*, *norovirus*, and opportunistic bacteria like *Legionella pneumophila* (CDC, 2020; Galal-Gorchev, 1996). Chlorine can be introduced at various stages of the water treatment process, including pre-chlorination, post-chlorination, or as a secondary disinfectant to sustain microbial safety within DS (Ohar and Ostfeld, 2014). Lower chlorine residuals often indicate higher DBP concentrations in the system (Hua et al., 2015). Exposure to DBPs such as THMs and HAAs can happen through ingestion, inhalation, and skin absorption. For volatile DBPs like THMs, ingestion, and skin absorption has the highest association with high THMs levels in the blood (Nieuwenhuijsen et al., 2009; WHO, 2005). In

non-volatile DBPs like HAAs, ingestion is the main route of exposure while it is slightly absorbed through the skin as well (Nieuwenhuijsen et al., 2009). Short-term exposure to THMs and HAAs is not likely to cause health effects while early epidemiological studies revealed that long-term exposure with THMs and HAAs can lead to an increased health risk especially among men (Villanueva et al., 2015). Table 2.1 lists the different compounds included in THM4 and HAA5 classification with their health impacts and main routes of exposure.

Table 2.1 Classes of THMs and HAAs, their exposure routes and their health impacts

Class of DBPs	Exposure routes and health issues
THM4: Chloroform (highest carcinogenicity) Bromodichloromethane Chlorodibromomethane Bromoform (lowest carcinogenicity)	<u>Chloroform</u> : Inhalation is the major way of exposure (WHO, 2005). Brominated THMs: In boiled water the inhalation (especially during showering) is the major contamination route (Nieuwenhuijsen et al., 2009). For non-boiled water, oral ingestion is the major contamination route (Wang et al., 2007). Results show that males are more vulnerable to inhalation risk and women are more vulnerable to ingestion risk (WHO, 2005). Health issues: Bladder cancer for non-smoker men is 40% higher among the patients exposed to THMs greater than 1956 ($\mu\text{g/L}$) (WHO, 2005). Colon, rectal, pancreatic, and brain cancer and reproductive disorders have a non-significant association (WHO, 2005).
HAA5: Monochloroacetic acid Dichloroacetic acid Trichloroacetic acid Monobromoacetic acid Dibromoacetic acid	Skin absorption and oral ingestion are the main routes of exposure (Villanueva et al., 2015). Health issues: High concentrations of HAA5 in animals body have shown to impact liver, pancreas, brain and nervous system but no meaningful relationship was found for human (Sadiq and Rodriguez, 2004). Also, dichloroacetic acid has been used in medications for the treatment of some metabolic disorders in concentrations 10,000 times higher than the levels human can be exposed to by drinking water. Side effects includes drowsiness, low cholesterol and fasting glucose and mild impacts on the nervous system (Sadiq and Rodriguez, 2004). Studies haven't yet proved any relationship between HAA5 exposure and reproductive issues (Sadiq and Rodriguez, 2004).

The importance of drinking water quality cannot be overstated, and it is essential that efforts for improving water quality remain a priority for governments to ensure public health and environmental protection. Therefore, it is essential to address the impacts of climate change and

anthropogenic activities on urban water systems. These impacts can be highly interrelated, and they may challenge water supply system in more than one way. A thorough assessment of these stressors will help in developing effective strategies to ensure the provision of safe and reliable water services to consumers. Such strategies may include investing in climate-resilient infrastructure, improving water treatment processes, or improving the current regulations in accordance with the new conditions prevailing in our systems.

2.1.1 Global warming of surface waters

Surface water warming is a global concern primarily driven by the warming of the Earth's climate (Czernecki and Ptak, 2018), increased rainfalls and surface runoffs into rivers and lakes, and land use changes which can reduce the shading effect of vegetation and increase heat absorption by the Earth's surface (Murdoch et al., 2000). The summer surface temperature in the lakes around the world has increased at an average pace of $0.34^{\circ}\text{C}/\text{decade}$ between 1985 and 2009 while the ice-covered lakes are warming faster than their ambient air temperature (O'Reilly et al., 2015). Surface water warming has several implications for climatic events, including changes in precipitation patterns and intensities, and increased frequency and severity of extreme weather events such as heat waves, droughts, and floods (Ren et al., 2023; Schindler, 2001; Trenberth et al., 2014). Surface water warming can have significant impacts on the quality of drinking water as well. As the water temperature increases, it can lead to a higher rate of bacterial growth (Leveque et al., 2021), which can in turn lead to an increased disinfectant demand such as chlorine or chloramine (Bondank et al., 2018). However, warmer water can also reduce the effectiveness of chlorine as a secondary disinfectant, resulting in an increased risk of microbial contamination and the potential for waterborne diseases in the DS (Lai and Dzombak, 2021). Furthermore, the increased use of disinfectants in response to higher temperature can lead to the increased formation of chlorinated DBPs notably THMs and HAAs (Valdivia-Garcia et al., 2019).

2.1.2 Increasing wildfires frequency and severity

In recent decades, wildfires have become increasingly frequent in many parts of the world (Crandall et al., 2021). In Canada, there has been a decrease in the number of wildfires, decreasing from 73,130 between 2000 and 2009 to 60,262 between 2010 and 2019, thanks to improved fire

prevention and a reduced number of human-caused fires. However, the severity of lightning-induced fires has risen significantly, and the burnt areas have expanded from 17.4 million hectares in the 2000-2009 period to 29.1 million hectares from 2010 to 2019 (Canadian Interagency Forest Fire Centre (CIFFC), 2023; CBC News, 2023). In 2023, the total burnt area from wildfires in Canada exceeded 18 million hectares, impacting Alberta, British Columbia, the Northwest Territories, Nova Scotia, Ontario, and Quebec. This historic disaster broke the wildfires records in both Canada and North America (Canadian Interagency Forest Fire Centre (CIFFC), 2023).

Wildfires can significantly degrade water quality, impacting both water supply and drinking water treatment. Increased sediment loads can decrease reservoir lifespan, impair treatment processes, and hinder detection of bacteria and viruses (Bladon et al., 2014; Smith et al., 2011). Water supplies without adequate treatment facilities are particularly vulnerable to prolonged disruption from post-fire sediment flux (Khan et al., 2015). Treatment problems can arise at high levels of turbidity, necessitating increased disinfection and oxidation of metals and organics with chlorine or ozone which can lead to the formation of DBPs (Smith et al., 2011). Firefighters' use of brominated flame retardants can have adverse health effects by increasing the Br load in the source water (Smith et al., 2011). When chlorine or chloramine oxidizes Br, it produces bromine species (HOBr/OBr^-) that increase the formation of brominated DBPs, causing higher health risks than their chlorinated counterparts (Smith et al., 2011). Moreover, due to the reduced molecular weight of the dissolved organic matter and loss of their side chains during the burning process, alum (aluminum sulfate) coagulation is less efficient in removing DBP precursors from ash leachates (Hohner et al., 2019; Smith et al., 2011).

The discharge of burnt vegetation and soil nutrients into downstream water bodies can significantly impact total organic carbon (TOC) concentrations in the downstream lakes and rivers (Chow et al., 2019a; Hohner et al., 2017). Numerous studies have investigated the impact of wildfires on downstream water bodies, with results demonstrating that the effect can vary considerably depending on the severity of the fire, size of the watershed, the intensity of precipitation or snowmelt, type of burnt vegetation in fire, and the primary mechanisms governing the carbon transport within the watershed (Chow et al., 2019a; Leveque et al., 2020; Olefeldt et al., 2013; Wei et al., 2021). After the 2011 Slave Lake fire in Alberta, Olefeldt et al. (2013) found no detectable increase in DOC in the downstream lake water and suggested that the dominant source for carbon

transport to this lake was deeper peat layers that were unburnt. Hohner et al. (2019) found reduced DOC in simulated burnt watersheds with a lower coagulation efficiency in the burnt samples indicating higher required alum dosages for treatment. The Lost Creek wildfire in 2003 in Alberta caused an increase in DOC in the downstream watersheds from 1-2 mg/L to 3-5 mg/L (Sham et al., 2013). Crandall et al. (2021) also report a 2.1-fold increase in DOC concentrations in burned watersheds after a megafire in Utah, USA in 2018.

The TOC and UV254 of the source water have the highest correlation (amongst TOC, UV254, pH, alkalinity, Calcium hardness, total hardness, turbidity, Br, and NH₃-N) with the treated water TOC (Li et al., 2014). Therefore, water supply systems impacted by wildfires are under the risk of higher DOC (the dissolved fraction of TOC) and hence decreased chlorine and increased THM concentrations. Moreover, by transporting and discharging substantial amounts of ash sediments by post-fire runoffs, the pH of the water bodies will increase, which augments THM formation potential and alters THM composition to higher chloroform percentages (Hung et al., 2017; Sham et al., 2013). According to Chow et al. (2019a), THM formation in water treatment plants supplied from the burnt catchments after the Hayman fire in Denver (2002) was nearly double compared to the unburnt catchments (203 ± 26 µg/L vs. 114 ± 17 µg/L). Revchuk and Suffet (2014) also found that a 71% increase in source water DOC can lead to up to 49% increase in the THM formation potential, i.e., from 170 µg/L pre-fire to 253 µg/L post-fire. The ramifications of wildfire on various water uses downstream are becoming a growing concern, specifically regarding the provision of potable water (Bladon et al., 2014). This may necessitate supplementary treatment infrastructure and raise operations and maintenance costs in the affected downstream communities.

2.1.3 Surface water browning

During the 1980s and 1990s, the issue of atmospheric acid deposition prompted the implementation of national and international regulations aimed at limiting emissions of sulfur and nitrogen oxides. As a result of these measures, regions in both North America and Europe have exhibited substantial reductions in SO_x emissions, leading to a corresponding decrease in sulphate deposition (Anderson et al., 2023). The elevated pH and alkalinity of the natural waters led to increased DOC and color in inland and coastal waters across multiple regions, including Northeastern North America and Northern Europe, which is also known as the 'browning' of aquatic ecosystems (Stetler et al., 2021).

This phenomenon was historically initiated by reduced acid deposition but today has several other drivers, including land-use change (Kritzberg et al., 2014), shifting to warmer and wetter climates (De Wit et al., 2016), and revegetation of the landscapes (Meyer-Jacob et al., 2020).

Water supply systems in many communities use surface water as a source for drinking water. In the US, 61% of public water supply withdrawals were from surface water in 2015, while in Canada, surface water provided 89% of drinking water in 2011 (Anderson et al., 2023). Therefore, understanding changes in surface water quality is crucial for designing sustainable water treatment solutions, as most infrastructures were designed based on historical water quality. A study on the Sudbury lakes in Ontario, Canada reveals that the DOC levels in acid-sensitive lakes have increased twofold since 1981, with a mean rise of +1.6 mg/L, whereas in buffered reference lakes, the mean DOC levels have increased only by 0.8 mg/L (Meyer-Jacob et al., 2020). In the absence of more rigorous treatments under higher DOC levels, the DOC in treated water can increase. Due to the higher abundance of organic matter to react with disinfectants, this can increase the formation of DBPs and raise the risk of DBPs non-compliance if the problem persists for a long time (Anderson et al., 2023). The issue of surface water browning on DBPs formation is a concern for water treatment plants, as DBPs are strictly regulated in water supply systems. Therefore, it is important to consider the level of DOC in the source water when designing drinking water treatment processes and selecting disinfectant dosage, to minimize the formation of DBPs.

2.1.4 Urban development and its potential implications for drinking water temperature

Urbanization refers to the change in land cover as a result of industrialization, immigration, economic developments, and lifestyle change (Abdullah and Barua, 2022; Kafy et al., 2020). According to the world urbanization prospect by the United Nations (2018 revision), despite urban areas comprising only 0.1% of the total land on Earth, approximately 55% of the world's population resides in urban areas, which is predicted to increase to 68% by 2050 (United Nations, 2018). By increasing the use of asphalt and concrete used in buildings, roads, and parking lots, the percentage of impervious surfaces in rural areas has increased (Abdullah and Barua, 2022). Impervious surfaces have a higher heat capacity resulting in absorbing and retaining the heat more effectively while vegetation and soil surface will decrease the heat capacity of the surface through transpiration

and evaporation (Ranagalage et al., 2019). The land surface temperature directly influences the thermal conditions of the underlying soil layers. When LSTs are high, such as during periods of heatwaves, the heat is transmitted into the soil leading to an increased soil temperature at various depths. The intensity of this warming effect is influenced by factors like soil composition, moisture content, vegetation cover, wind speed and direction, and building height (Alexander, 2021; Blokker and Pieterse-Quirijns, 2013). Several studies in the literature emphasize the important role that vegetation, particularly trees, shrubs, grass, and other herbaceous vegetation play in mitigating heat and regulating LST in cities. Edmondson et al. (2016) observed an increase of 0.6°C in mean daily soil surface temperature when moving 5 km from the city peripheries towards the central areas. Also, among different kinds of vegetation, areas covered with shrubs and trees exhibited a mean maximum daily soil temperature 5.7°C higher than areas dominated by herbaceous vegetation due to their higher heat capacity (Edmondson et al., 2016). Another research by Zhou et al. (2017) revealed that the percentage of tree coverage played a significant role in regulating soil surface temperature. They found that as the tree coverage increased, there was a substantial decrease in soil surface temperature, demonstrating the cooling effect provided by greater tree coverage on the surrounding environment. In another study conducted by Alexander (2021), it was demonstrated that increasing vegetation cover from 0-5% to 95-100% had a profound impact on LST. Specifically, the median LST had a substantial decrease of 4.2°C. This finding highlights the substantial cooling potential associated with a significant increase in vegetation cover.

Currently, urban settings are confronted with the growing need of designing climate-resilient infrastructures that can withstand the impacts of climate change and population growth, all while adhering to sustainable management principles. Increasing the percentage of green spaces offers the advantage of significantly reducing soil surface temperatures. Table 2.2 provides a summary of the documented effects of changes in land use and urban greening on LST in urban environments. This table presents an overview of how rapid urbanization and the loss of vegetation have influenced LST patterns in several fast-growing cities around the world.

In summary, studies in various urban areas have shown that the reduction in vegetation cover due to urbanization is correlated with substantial LST increases, sometimes reaching 11°C, as seen in Cumilla, Bangladesh (Kafy et al., 2022). Conversely, increasing vegetation coverage induces a cooling effect on LST. A study on seven cities in the United States showed that there is a

quantifiable correlation between greening and LST where a 1% increase in tree coverage resulted in an average cooling of 0.09°C, and a 1% increase in grass coverage led to an average cooling of 0.02°C (Smith et al., 2023).

Table 2.2 Summary of the impact of land use and land coverage on land surface temperature in Various Countries

Reference	Reported impact on land surface temperature	Country/city
Zhu et al. (2021)	Urban parks' LST is on average 3.6°C lower than its surrounding. The most significant temperature difference between green spaces and hot spots in the city was 7.8°C, which was observed during summer days.	Jinan, China
Kafy et al. (2022)	Using remote sensing, a notable correlation was discovered between the reduction in vegetation cover and the increase in LST. Over the course of 25 years, the city witnessed a 9% decline in its vegetation cover due to urbanization, resulting in an 11-°C rise in its average LST.	Cumilla, Bangladesh
Edan et al. (2021)	A study on land use and land cover changes between 2000 and 2020 using remote sensing methods revealed that an 8.7% expansion of urban areas and a 25.8% reduction in green cover resulted in an average increase of 3.8°C in maximum LST during the summer and 3.16°C during the winter.	Al Kut, Iraq
Smith et al. (2023)	A study on the impact of city greening on LST showed that, on average, there is a cooling of 0.187°C for every 1% increase in albedo. Additionally, for each 1% increase in tree coverage, there is an average cooling of 0.09°C, and for each 1% increase in grass coverage, an average cooling of 0.02°C occurs.	Seven cities, US
Menberg et al. (2013)	A study on groundwater temperature in shallow subsurface areas revealed regional differences ranging from 3°C to 7°C between urban and rural areas.	Six cities, Germany
(Edmonds on et al., 2016)	By moving 5 km from the peripheries to the city center, the mean daily LST increased by 0.6°C.	UK
(Alexanderson, 2021)	Increasing the vegetation cover from 0-5% to 95-100% decreased the median LST by 4.2°C.	Four cities, Denmark

Higher soil surface and subsurface temperature could potentially increase the drinking water temperature in the pipes underground (Blokker and Pieterse-Quirijns, 2013). As mentioned previously, water temperature within the DS significantly impacts a range of physical, chemical, and biological processes. Elevated water temperature accelerates the reaction rate between chlorine and organic/inorganic constituents in water, resulting in a reduction of free chlorine residual

concentration, an increase in the formation of DBPs, and higher risk of bacterial regrowth (Lai and Dzombak, 2021). The World Health Organization advises to keep water temperatures outside the 20-50°C range to suppress the growth of potentially harmful organisms (World Health Organization, 2022). Predicting water temperatures, especially during hot seasons, is crucial for understanding temperature dynamics within the distribution network. In chlorinated networks, this would allow us to detect areas potentially at risk of low disinfection residual and higher risk of microbial growth. In some countries, such as the Netherlands (with non-chlorinated networks) and the Czech Republic, regulatory thresholds for water temperature below 25°C are in place (Agudelo-Vera et al., 2020). Minimizing water temperature helps ensure the safety and quality of drinking water within both chlorinated and unchlorinated distribution networks. Blokker and Pieterse-Quirijns (2013) used a micrometeorology model and incorporated anthropogenic heat elements into it to predict surface and subsurface soil temperature in urban settings. They later used the subsurface soil temperature to predict water temperature within the water distribution systems, which enabled them to model and monitor variations in water temperature within a DS. This model can be considered as a great tool for predicting areas at risk of extreme water warming especially during hot seasons.

2.1.5 Water demand management strategies

2.1.5.1 The importance of water demand management

Water demand management is an important approach to sustainable water resources which can be achieved through public education (Neale et al., 2007), pricing (Boland, 1997), and the adoption of water-saving technologies (Waller and Scott, 1998). Aside from the benefits for the preservation of natural resources, it can significantly benefit water utilities facing challenges during periods of high water demand. These challenges include the risk of supply shortages (Brown et al., 2019), more frequent nuisances due to more frequent breakdowns (Sauvé, 2011), the need for expensive infrastructure investments to meet peak demand (Maas, 2003; Morton, 2011), and the potential for higher water costs in communities where water is priced per volume. In addition, high water demand can lead to increased energy consumption and greenhouse gas emissions associated with water treatment and distribution (Stillwell et al., 2011). To address these challenges, water utilities

must prioritize water conservation, invest in infrastructure to improve system efficiency, and develop strategies for managing peak demand.

2.1.5.2 Water demand management by the government of Quebec

Canada is among the highest water consumers globally with 7% of the world's renewable freshwater (Adamowski et al., 2012). In Quebec, the urban water demand has decreased by over 25% in the last two decades as part of the Quebec water saving strategy (SQEEP, 2019-2025). However, per capita demand in Quebec still exceeds the national average per capita consumption. The new 2019-2025 strategy aims to further reduce demand by 20% compared to 2015 (SQEEP, 2019-2025). While urban water demand reduction has become an essential strategy for managing water resources and ensuring long-term water sustainability, it is important to consider the implications of water demand reduction for drinking water quality.

2.1.5.3 Implications of lower water demand for water utilities

One of the primary consequences of reducing urban water demand for water supply systems is the potential for changes in water age and disinfectant residual levels (Blokke et al., 2008b). The relationship between water demand and water age depends on various factors, such as the size and complexity of the distribution network, as well as the hydraulic conditions within the network (Kourbasis et al., 2020). Higher water age can increase the risk of microbial growth and compromise water's microbial safety (Dias et al., 2019; Hua et al., 2015). Additionally, prolonged water stagnation in the piped network can result in lower levels of disinfectant residuals, such as free chlorine or chloramines, which are essential for controlling microbial growth and ensuring drinking water safety in chlorinated networks (Baribeau et al., 2001). The reduction in chlorine residual can occur due to various factors, such as chlorine decay, dilution, and adsorption to pipe surfaces (Simard et al., 2011b).

Low-pressure areas and areas with stagnant water due to low water demand are particularly susceptible to biofilm formation, as the extended water residence time provides an ideal environment for the growth of microorganisms (Fish et al., 2016). The accumulation of biofilm on the interior surface of pipes and other infrastructure in the distribution system can lead to the release

of harmful contaminants into the water supply, such as bacteria, fungi, and other microorganisms (Liu et al., 2016).

Additionally, low pressure can result in backflow events, where contaminated water is drawn back into the distribution system, potentially compromising the microbial safety of the water (Hatam et al., 2018). The flushing of the network is also compromised during low pressure events, which can lead to the buildup of stagnant water, sediments, and contaminants (Sunny et al., 2020). The accumulation of sediments in low-pressure areas can lead to aesthetic issues such as discoloration and turbidity which can be aesthetically unappealing and can cause concerns and potentially complaints among consumers about the safety of their drinking water (Fish et al., 2017).

The prolonged contact time between chlorine and the dissolved organic matter existing in water can lead to the higher formation of DBPs, such as THMs, which are known to have deleterious impacts on human health (Dion-Fortier et al., 2009). THMs are formed through the reaction of chlorine with organic matter in the water. The formation of THMs is dependent on several factors, including the concentration of organic matter, the pH of the water, and the reaction time (Dias et al., 2019). As such, it is crucial for water utilities to monitor THM levels and take measures to minimize their formation. Treatment processes, such as activated carbon filtration and advanced oxidation, have been found to be effective in reducing THM levels in the water supply (Cool et al., 2019; Valdivia-Garcia et al., 2019).

Overall, urban water demand reduction is critical for managing water resources in urban areas. However, the implications for drinking water quality must be carefully considered to ensure that public health is not compromised. Effective management strategies, such as careful monitoring, appropriate treatment processes, and infrastructure improvements, can help maintain high water quality standards while reducing water demand (Cool et al., 2019).

2.1.6 A summary of the impacts of global change on water supply systems

Figure 2.1 summarizes the negative impacts of global change on drinking water quality in different levels of water supply, treatment, and distribution.

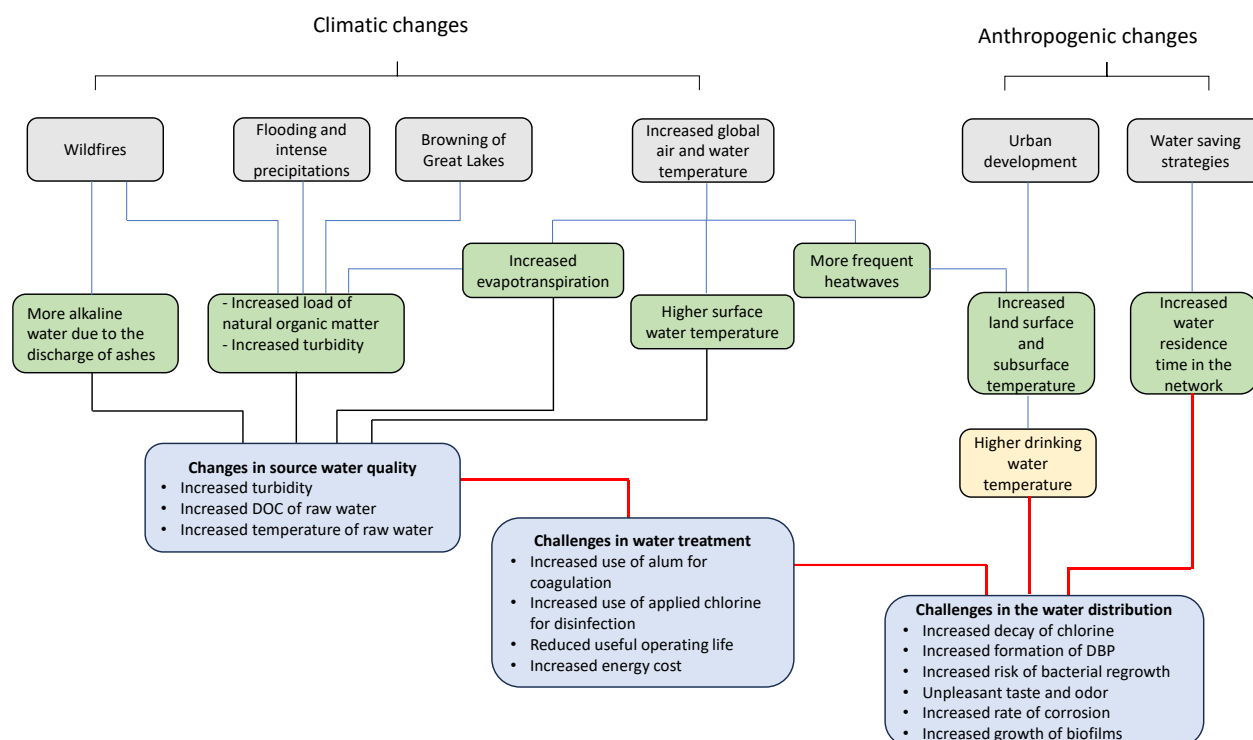


Figure 2.1 The impacts of climatic and anthropogenic changes on drinking water quality: impacts on source water quality, water treatment, and distribution network

2.2 Water quality prediction under changing conditions

Water quality modeling is an effective tool for utilities to identify potential sources of contamination, determine thresholds leading to water quality non-compliance, evaluate treatment options, and prioritize areas for improvement. Water quality modeling can help utilities determine the impact of source water quality on the distribution network and the effectiveness of treatment processes in removing contaminants. Modeling enables utilities to identify the most effective and cost-efficient solutions to improve water quality, optimize chlorine availability, minimize THM formation, and prioritize investment in areas of the network that require improvement.

2.2.1 The importance of chlorine and DBP prediction in the network

The prediction of chlorine and DBP levels in drinking water distribution systems is of utmost importance to ensure water safety and adherence to regulatory standards. The availability of

chlorine at appropriate levels is essential for preventing the spread of waterborne diseases. THMs are a worldwide regulatory and public health concern due to their potential carcinogenic and mutagenic effects. Therefore, it is important to monitor and control THMs in the distribution system to ensure that the water supplied to consumers is safe. Several factors such as temperature, DOC, and demand play a crucial role in predicting chlorine and DBP levels. However, under global change, these factors are rapidly changing, making it challenging to predict future levels of these compounds accurately. For instance, a recent study conducted on Quebec municipalities showed a 23% probability of THM non-compliance until 2050 (Cool et al., 2019). To address this issue, a chlorine and THM prediction model must be developed to predict future changes in chlorine and THMs in DS under changing conditions.

2.2.2 Previous models and their limitations

2.2.2.1 Free chlorine prediction

Free chlorine prediction models have been developed to estimate the amount of chlorine required at the water treatment plant to achieve a target residual disinfectant concentration in DS (Monteiro et al., 2014). These models typically use variables such as flow rate, chlorine dose, and contact time to predict the concentration of free chlorine in the treated water and in the DS (Gibbs et al., 2006). However, the accuracy of these models in real-scale applications is limited by several factors. For instance, the models are often developed based on laboratory experiments with idealized conditions, which may not fully represent the complex and dynamic water quality variations that occur in real systems. Additionally, the accuracy of the models is often affected by the variability in water quality parameters, such as temperature, pH, DOC, and the presence of other chemicals, especially ammonia, that can react with chlorine and change the expected behavior of chlorine (Wang et al., 2010).

The 1st-order kinetic model and its modified versions, such as parallel 1st-order or limited 1st-order models, have been widely used by researchers and water utilities to predict chlorine decay in water treatment systems (Al Heboos and Licskó, 2017; García-Ávila et al., 2021a; Hallam et al., 2002; Meng et al., 2013). Despite their usefulness in lab-scale applications, these models have limitations in real-scale applications. Firstly, the parameters estimated by these models are dependent on the

applied dosage of chlorine, which may vary constantly in real scale. Secondly, these models use a constant rate for chlorine decay prediction, which may not accurately reflect the complex and dynamic water quality variations that occur in real systems (Fisher et al., 2017; Hua et al., 2015). The constant reaction rate may overestimate or underestimate the rate of chlorine decay in some water treatment systems. To address these limitations, a variable reaction rate constant (VRRC) model has been developed by (Hua et al., 2015). Some of this model advantages are:

1. Model coefficients are independent of the applied chlorine dosage which occurs constantly in water utilities.
2. Model coefficients do not change under rechlorination in the DS, which is a common practice in operation of the water supply systems to ensure sufficient chlorine residual system wide.
3. Model rate constant can change with temperature following an Arrhenius equation.
4. Model calibration does not require extensive measurements in the field or the lab.

This model will be discussed in length in chapter 4.

2.2.2.2 THM prediction

THMs are widely used as a DBP representative in water quality standards. Many municipalities in the world propose no specific regulation for HAAs, but only for THMs, which could be due to the facts that: 1) THMs may be more well-known and more extensively studied, 2) the water supply in a particular region may be more prone to THM formation than HAA formation, making THMs a greater concern for regulators in that area, and 3) THM measurement is faster, easier, and less costly compared to HAA measurement (Sérodès et al., 2003; Wang et al., 2007). After the discovery of chloroform and its harmful effects in 1974, considerable efforts have been put in developing models that can predict the THM formation potential in drinking water (Sadiq and Rodriguez, 2004). THM prediction models in the literature can fit to certain categories such as multivariate regression models, artificial neural network models, parallel models, or logistic regression models. A summary containing the features of each category with their limitations is presented in Table 2.3. Most of the previously established models in the literature require several input variables such as pH, temperature, Br concentration, TOC, and applied chlorine dosage (Clark et al., 2001; Sadiq and Rodriguez, 2004). As a result, the model will need recalibration under

changing operating conditions, like rechlorination via chlorine booster stations or temperature variations (Hua et al., 2015). To meet the THM regulations under global change, a robust prediction model is needed to work under changing operating conditions. Modeling THMs in the water distribution network can have two main benefits. First, it can be a useful management tool to adjust the chlorine dosage while avoiding high concentrations of THMs, 2) it can be a metric to evaluate the efficiency of treatment as high THMs can be a sign of high organic matters in water. Based on the concept of variable chlorine decay rate, Hua (2016) developed a variable rate model for THMs formation. This variable reaction rate THM model which will be discussed in length in chapter 4, also works under variable applied chlorine dosage, rechlorination, and in the presence of ammonia in water. Several models have been developed to predict chlorine and THMs, but they have limitations, such as complexity and limited applicability. Having a less complex model that is more applicable will enable utilities to predict chlorine and THMs in the DS with less complexity, allowing them to identify vulnerable locations in the network for corrective actions. Table 2.3 provides a summary of some of the most common THM prediction models in the literature with their limitations and features.

Table 2.3 A summary of some of the most utilized THM prediction models, their features, and limitations

Model features and limitations	Reference
Multivariate regression (MR) models: 1st-order: $TTHM = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots \beta_n X_n$ Nth-order: $TTHM = \alpha X_1^{\beta_1} X_2^{\beta_2} X_3^{\beta_3} \dots X_n^{\beta_n}$ Scale: field/lab scale measurements. Features: They are the most widely used models in literature. The model follows a linear or nonlinear relationship between the independent variables (temperature, pH, Bromide concentration, TOC, etc.) and the dependent variable (TTHM). This model prediction can have R² values up to 0.92. Limitation: There is no proof of adaptation of the model to new operating conditions such as mixing or rechlorination. They also often require extensive measurements for calibration.	(Sérodes et al., 2003) (Sadiq and Rodriguez, 2004) (Morrow and Minear, 1987) (Ibarluzea et al., 1994) (Golfinopoulos and Arhonditsis, 2002) (Clark et al., 2001)
Artificial neural network (ANN) models: Scale: Lab/Field Features: In these models, a set of data (including Br concentration, temperature, pH, DOC content, chlorine dosage, etc.) will be used as the input signals for training the model and one or more hidden layers will be created for processing information and creating neurons relating the input signals to the output layer (response). Finally, like every other predictive model, a set of data is used for validation of the model. A comparison between the MR and ANN models showed that ANN can predict better in conditions that lead to high concentrations of THMs like in higher temperatures, higher chlorine dosage, higher load of organic carbon or longer residence times. However, the MR models will have a better prediction in situations where THM concentration are lower (Milot et al., 2002). Limitation: ANN models are often complex and require several input parameters, meaning requiring extensive data from utilities, for model development. This information is not always available or easily accessible. Moreover, they fail to adapt themselves under changing operating conditions such as temperature change, rechlorination or mixing of two streams of water.	(Milot et al., 2002) (Kulkarni and Chellam, 2010) (Rodriguez and Sérodes, 2004)

Table 2.3 A summary of some of the most utilized THM prediction models, their features, and limitations (cont'd)

Model features and limitations	Reference
Parallel first order models: $TTHM = \alpha D \{1 - f e^{(-k_r t)} - (1 - f) e^{(-k_s t)}\}$ Scale: Lab scale measurements. Features: A parallel first order model which comprises the 1st-order rate constant for rapid k_r and slow k_s reaction rate constants. This model requires D (chlorine dosage) and α (known as the THM yield coefficient) as the input parameters. Limitations: This model needs recalibration under different temperatures and there is no evidence for the validity of model under rechlorination or mixing.	(Gang et al., 2003; Milot et al., 2002)
Logistic regression models for predicting probability of violation: $P = \frac{e^{A(treatment)+B(region)+C(season)+D(source)+f}}{1 + e^{A(treatment)+B(region)+C(season)+D(source)+f}}$ Scale: field/lab scale measurements. Features: A model for Measuring the probability of exceeding the established THM regulations. This model uses binary coded variables for treatment, region, season and source (expressed in 0 or 1) and empirical coefficients (A, B, C, D) that vary based on each water source and treatment method. Limitation: While the model is able to predict the susceptibility of drinking water to form high concentrations of THMs, it fails to measure the concentration of THMs and cannot be used in monitoring water quality throughout the distribution network.	(Gang et al., 2003; Milot et al., 2000)

2.3 Knowledge gaps

2.3.1 Water quality prediction in full-scale systems under changing operating conditions

Despite advancements in water quality modeling, several knowledge gaps remain in predicting water quality in full-scale systems under changing operating conditions. One of the key challenges is the presence of ammonia in surface water sources, which can significantly impact chlorine decay

and reduce the precision of the conventional models. Furthermore, changing operating conditions in DS such as changes in dosage and re-chlorination can render conventional models inefficient and require recalibration. The increased complexity and time required for predicting chlorine and THMs under changing conditions further limits the ability of utilities to use these models in real-scale applications. Therefore, there is a pressing need for an applicable model that can address the current needs of utilities, particularly those using surface water sources with ammonia and those facing changing operating conditions due to seasonal and abrupt changes in water quality.

To address these knowledge gaps, the first objective of this Ph.D. project is to predict chlorine and THMs considering the impact of ammonia and the changes in operating conditions in a full-scale water supply system. The study will fill critical knowledge gaps and provide valuable insights for water utilities to improve their monitoring and management of water quality in full-scale systems.

2.3.2 Predicting the combined effect of climatic change and water demand management on drinking water quality

With global warming and heatwaves on the rise, the average and seasonal temperatures of water bodies are increasing. This is also changing the historical patterns in the frequency and intensity of climatic events such as wildfires and floods. As a result, the physico-chemical characteristics of source water are changing, leading to changes in the quality of treated water. On the other hand, the global water crisis calls for more careful management of the water resources, which has led to significant reductions in urban water demand in many countries including Canada with a continuing trend. Since the water distribution networks were designed based on the historical water demands in the past, demand reduction will prolong water residence times in the network, which threatens the microbial safety of water. The shifts in the source water quality as well as the distribution network conditions calls for more careful management of water supply systems and rethinking the current approaches that are mainly based on the historical water quality records.

Water supply systems are complex systems with interrelated elements. For a successful prediction of water quality evolutions under global change, one needs to study all the impacting elements together. These elements will impact drinking water quality in our networks both individually and synergistically resulting in unforeseen outcomes that would not have been identifiable if they were

studied separately. To fill this gap, the second objective of this Ph.D. is dedicated to studying the combined effect of climatic and anthropogenic (especially water demand) change on drinking water quality in cities. The approach and the results of this work will enable utilities to identify weak points and areas for improvement in current systems. Vulnerable areas in the network could be identified and quality monitoring and corrective actions could be emphasized in these zones to ensure uniformly safe drinking water quality all over the water distribution network.

2.3.3 Understanding the impact of urban heat islands and green spaces on drinking water temperature in cities

While numerous studies have explored the effects of Urban Heat Islands and green spaces on surface and subsurface soil temperatures, their influence on drinking water temperature within distribution networks remains relatively undocumented. Comparing the results of soil temperature modeling to actual drinking water temperature measurements within a Dutch DS, it was observed that the drinking water temperature, at an average depth of 1 meter, aligns closely with the surrounding soil temperature. Furthermore, it was reported that in a relatively warm year, the drinking water temperature exceeded its regulatory threshold of 25°C at several sampling points (Blokker and Pieterse-Quirijns, 2013). With the ongoing global increase in air temperatures, it is anticipated that this trend will become more pronounced in the future.

In cold climate regions like Canada, water pipes are buried at depths of at least 1.8 meters to prevent freezing. While it might be assumed that the UHI effect would have minimal impact on water temperature, the extent to which the surrounding soil affects the water temperature in these deeply buried pipes during hot periods in summer remains a mystery. Furthermore, the potential impact of city greening on moderating LST has been documented but its effectiveness for moderating the drinking water temperature within cities distribution networks is yet to be discovered.

The results from this study will provide valuable insights into whether UHIs can lead to disparities in drinking water temperature across the distribution network. They will also shed light on the effectiveness of green spaces in urban areas as a water temperature management strategy. Understanding the dynamics between UHIs, vegetation, soil temperature, and drinking water temperature in the water distribution networks is essential for effective urban water management.

By investigating the influence of land surface cover on drinking water temperature, valuable information can be obtained to guide water quality management practices. The findings will assist in informed decisions regarding sustainable urban planning and management of drinking water resources.

CHAPTER 3 RESEARCH OBJECTIVES, HYPOTHESIS AND METHODOLOGY

The overarching objective of this project is to model and predict drinking water quality dynamics under the pressures of climate change and human activities in cities. To reach this goal, three sub-objectives were defined. Below, each of the three objectives, their corresponding hypothesis, originality, and the questions they address will be discussed.

Objective 1: to model and predict free chlorine and THM concentrations in a full-scale water distribution network using a variable rate model.

The specific objectives are as follows:

1. Predict free chlorine residual and THMs in ammonia-containing waters without recalibrating the model;
2. Predict free chlorine and THMs in a full-scale water distribution network in a city in Quebec;
3. Validate predictions with direct field measurements in different points in the distribution network;
4. Compare the goodness of prediction of the VRRC model with the first-order model for chlorine and THMs prediction;

Hypothesis related to objective 1:

5. Transitioning from the rapid to the slow reaction phase in ammonia-containing waters necessitates recalibration of the conventional chlorine prediction models. Using a variable reaction rate constant model would allow us to reach this goal without recalibration.
6. Precision of chlorine and THMs prediction will improve by 10% compared to the first-order prediction model in both no-ammonia or ammonia-containing waters.

Novelty:

Although the VRRC model developed by Hua et al. (2015) has been tested in lab-scale experiments involving low-ammonia waters ($<0.05 \text{ mg N-NH}_3/\text{L}$), its applicability to ammonia-containing waters and its validation in a real-scale DS remain unexplored. Moreover, this study aims to utilize

the VRRC model to predict THMs in the drinking water networks, using a full-scale DS in a city in Quebec as the case study. To our knowledge, this is the first attempt to use the VRRC model to predict and validate chlorine/THMs in a full-scale network.

Achieving these objectives will answer the following questions:

- What is the accuracy of predicting free chlorine residual and THMs in ammonia-containing waters using a variable rate model compared to the 1st-order and parallel 1st-order model?
- How well can free chlorine and THMs be predicted compared to the direct field measurements in a full-scale water distribution network?

Chapter 4 is dedicated to a detailed background, methodology, results, and discussion about this objective in form of an article.

Objective 2: to model and predict the combined effects of climatic events and water demand reduction on chlorine and THMs in the distribution networks.

The specific objectives are as follows:

7. Model the combined impact of water warming and DOC increase on chlorine and THM behavior in the DS;
8. Model and predict the combined effect of demand reduction with DOC/temperature increase on chlorine and THMs in a water distribution system;
9. Use a reliability index to measure the overall network performance with a quantifiable metric, in terms of maintaining sufficient free chlorine levels and minimizing THMs under various climate or demand scenarios;
10. Identify vulnerable zones in the water distribution networks with insufficient free chlorine, at risk of microbial regrowth, or excessive THM formation, potentially leading to regulatory non-compliance;

Hypothesis related to objective 2:

11. The impact of lower water demand on chlorine and THM concentrations in the DS will be more significant than the impact of climatic events or water warming on chlorine and THM concentrations.

Novelty:

This study aims to evaluate how water warming, DOC increase, and demand reduction collectively impact chlorine and THM concentrations in a drinking water distribution system. The study employs a reliability index to describe the system's performance with a quantitative measure, with regards to recommended standards for chlorine and regulatory requirement for THMs. To the best of our knowledge, no previous study has investigated the combined effects of water warming, climatic events, and demand reduction on THMs and free chlorine in a full-scale water system. Additionally, there is a lack of research examining the relative significance of these factors within the network using a reliability index.

Attaining the above-mentioned goals will address the following questions:

- What is the impact of water warming and DOC increase on the rates of chlorine decay and THM formation in the drinking water distribution systems?
- How does the combined effect of demand reduction, DOC/temperature impact the levels of chlorine and THMs in the DS and is there a synergistic effect between them?
- Which zones within the DS are more vulnerable to insufficient chlorine or high THM formation?
- Are current approaches for water quality monitoring in the DS sufficient to ensure microbial safety and adherence to regulatory standards?

A detailed background, methodology, results, and discussion about this objective is provided in form of an article in chapter 5.

Objective 3: to monitor and model drinking water temperature during summer heatwaves and understand the impact of urban heat islands and city greening on water temperature in the city of Montreal.

The specific objectives are as follows:

12. Monitor drinking water temperature in the DS in two contrasting neighborhoods in Montreal, one with abundant green coverage and the other with less green coverage and more UHIs;

13. Compare the warming effect of heat islands with the cooling effect of green spaces on drinking water temperature at pipe depth of 1.8 m;
14. Model local soil temperatures using the meteorological information combined with the local soil conditions and satellite imagery for soil classification;
15. Model drinking water temperature in the distribution network using the local soil temperatures and validate the results with the measured data;

Hypothesis related to objective 3:

16. The deeper burial of pipes in cold regions will dampen the effect of heatwaves on drinking water quality and the drinking water temperature will not be affected by radiation and heatwaves.
17. The existence of green spaces (vegetation) will induce a cooling effect on soil surface and subsurface temperature. This will have a cooling effect on drinking water temperature in the deeply buried pipes.

Novelty:

This study is focused on monitoring and modeling drinking water quality in deeply buried pipes in cold climates during summer heatwaves. It also evaluates if the UHI will affect drinking water temperature in these deeply buried pipes and whether having green spaces in the cities will counter this heating effect. To the best of our knowledge, no study has ever studied the impacts of heatwaves on drinking water quality in the DS in northern regions nor any study has ever evaluated the heating effect of UHIs versus the cooling effect of green spaces on drinking water temperature within the water distribution networks.

The following questions will be answered after accomplishing the above goals:

- Are water pipes at 1.8 meters depth affected by heatwaves during summer?
- Does creation of UHIs in cold climates induce warming effects in piped water that threaten water safety for its consumers?
- Does city greening have the potential to reduce piped water temperature?
- How well can the model predict drinking water temperature in the DS, and how does it compare to the measured data?

- Are current standards for designing water distribution systems adapted to future climate under constant and continuous global warming or they should change?

Chapter 6 is dedicated to this objective where detailed background, methodology, results, and discussion are provided in the form of an article.

3.1 Methodology

This chapter organizes the methodology into specific categories corresponding to the nature of the work, including sampling, laboratory testing, modeling, validation, and more. Each section provides a concise explanation of the methods used. The objectives of this study have led to the creation of three articles. Chapters 4, 5, and 6 are dedicated to these articles, each containing a detailed methodology specific to its objective. To offer a comprehensive overview of the sequential methodology employed in each article, Figure 3.1, Figure 3.2, and Figure 3.3 provide a concise presentation of the stepwise processes for each.

Article 1: Predicting chlorine and trihalomethanes in a full-scale water distribution system under changing operating conditions

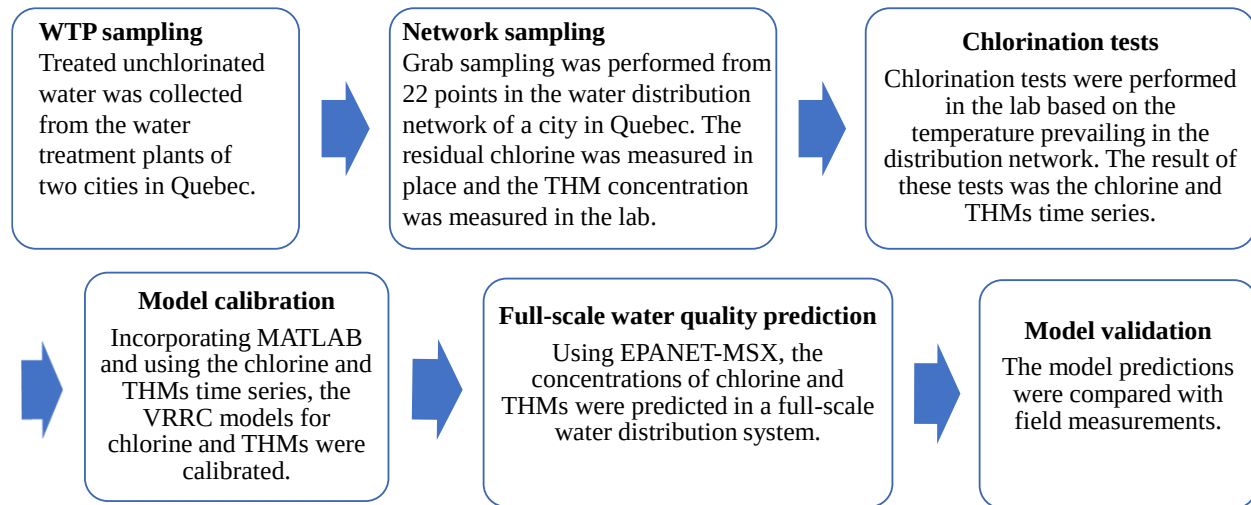


Figure 3.1 Sequential methodology for achieving objective 1.

Article 2: Climate change and future water demand: implications for chlorine and trihalomethanes management in water distribution systems

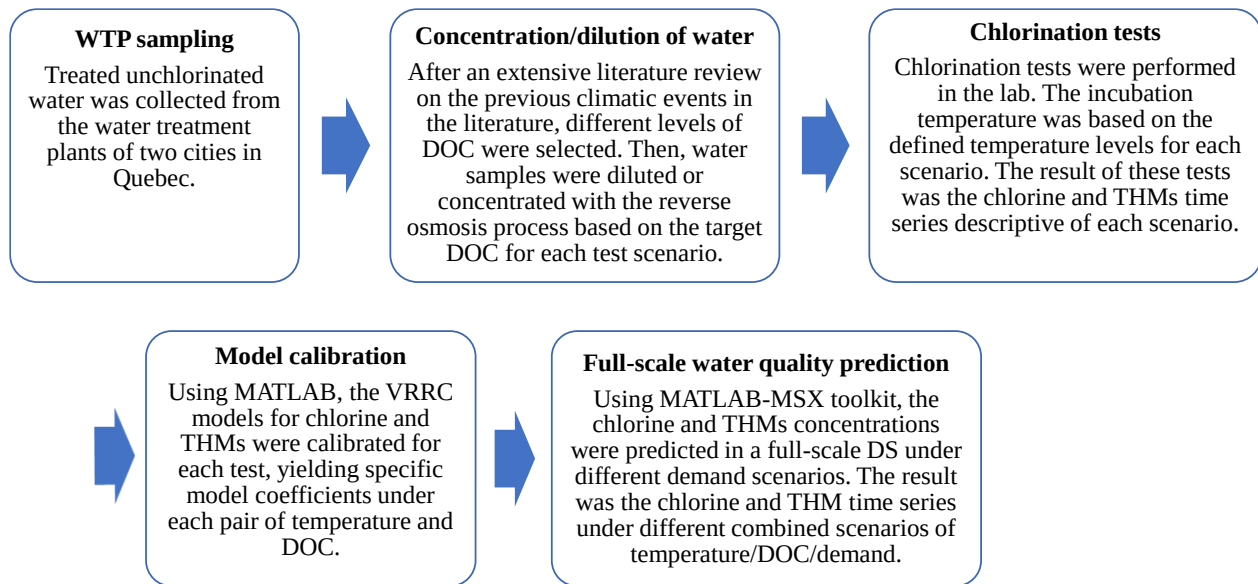


Figure 3.2 Sequential methodology for achieving objective 2.

Article 3: Heat islands vs. City greening: real-time monitoring and modeling of drinking water temperature in a Canadian city

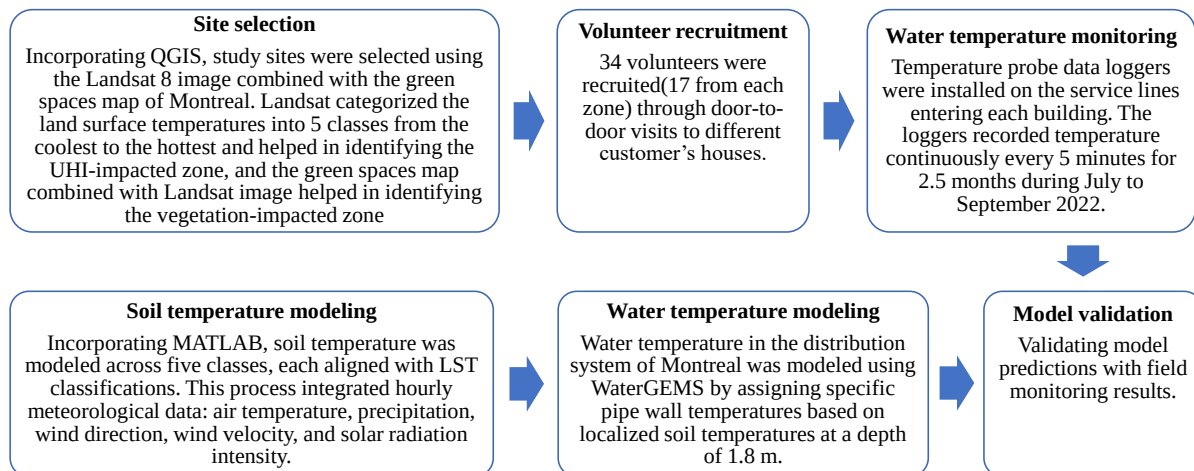


Figure 3.3 Sequential methodology for achieving objective 3.

3.1.1 Sampling campaigns

3.1.1.1 Water treatment plant sampling (objectives 1 &2)

For chlorination tests, treated unchlorinated water was collected from water treatment plants in two cities in Quebec, referred to as city A and city B. Sampling from city A WTP was performed in October 2020 and sampling from city B was performed in March 2021 and October 2021. The water would be collected with prewashed buckets (as illustrated in Figure 3.4) and stored in the fridge before tests.



Figure 3.4 sampling treated unchlorinated water from the water treatment plant.

3.1.1.2 Network sampling (objective 1)

A sampling was conducted in the DS of city B to validate chlorine and THMs predictions with real field measurements. The sampling took place in March 2021 and October 2021. A total of 22 regulatory sampling points were identified in commercial areas, including supermarkets, auto shops, and gas stations. The locations of the 22 sampling points are illustrated in Figure 3.5. Samples were collected from indoor taps. One of the taps is shown in Figure 3.6.A. Each tap was sterilized using alcohol before sampling, and water ran for two minutes before collecting each sample. Free chlorine measurements were performed on-site using the Hach Pocket Colorimeter TM II, USA, with a precision of ± 0.05 mg/L. A picture of the on-site chlorine measurement is

shown in Figure 3.6.B. For THM measurement, each sample was collected in two 45 ml airtight amber vials with Teflon caps. Prior to use, these vials were thoroughly washed with chlorine solution and three times with Milli-Q water. Subsequently, the filled vials were sent to the laboratory for THM measurement using gas chromatography, a method that will be discussed in detail in chapter 4 section 4.2.3.1.



Figure 3.5 Location of the 22 sampling points in the city marked with red triangles and the water treatment plant marked with a star

(A)



(B)



Figure 3.6 A) The indoor tap used for sampling in one of the sampling points; B) free chlorine measurement with the pocket colorimeter.

3.1.2 Chlorination tests (objective 1 and 2)

Chlorination tests were conducted in accordance with the simulated distribution system (SDS) test. The SDS test is a standardized test for simulating the chlorine decay and DBPs formation originating from the bulk decay in water (American Public Health Association (APHA) et al., 2012). After injecting the required chlorine dosage, samples were kept in the incubator under the test temperature. The dosage and temperature of each chlorination test would vary according to the applied chlorine dosage and temperature prevailing in the water treatment plant on the sampling time. For THM measurement, chlorinated water was poured into 45-ml airtight amber vials (in duplicate) right after chlorine injection and kept in the incubator. For each THM measurement, ammonium sulfate was added to the 45-ml samples to stop the chlorine reaction with natural organic matter and other compounds in water. Then, the quenched samples were kept in the fridge (temperature approximately 5°C) for a maximum duration of two weeks before THM measurement. Free chlorine and THMs were measured at several timesteps during the experiment (4 h, 8 h, 24 h, 32 h, 48 h, 56 h, 72 h, 80 h, 96 h, 120 h). Free chlorine was measured with the colorimetric method with a Hach UV-Visible spectrophotometer (DR-5000) according to the method 4500-Cl G of standard method for the examination of water and wastewater (American Public Health Association (APHA) et al., 2012). THM concentrations were measured with gas chromatography (Agilent Technologies 7890B gas chromatograph, USA) with a precision between 5-7.6 µg/L depending on the type of THMs. THM measurement was performed according to method EPA 524.2 (measurement of purgeable organic compounds in water by capillary column gas chromatography/mass spectrometry) (United States Environmental Protection Agency (USEPA), 1992). All the analyses for chlorine and THMs were done in duplicates, and the coefficient of variance (CV) was calculated.

3.1.2.1 Concentration with reverse osmosis membrane (objective 2)

To assess the influence of higher concentrations of DOC on chlorine and THMs within the distribution network, water samples underwent a concentration process using a reverse osmosis membrane (DOW-FILMTEC, USA: membrane BW30-4040, surface area: 7.2 m²). To ensure the membrane's purity and prevent any potential impact on the test water's DOC, a clean-in-place procedure was carried out. Initially, the membrane underwent a 5-hour wash with a 1N NaOH

solution in 30 liters of Milli-Q water, followed by rinsing with demineralized water until the DOC concentration in the concentrate stream matched that of the demineralized water in the feed tank. Subsequently, after cleaning the membrane, the feed water was introduced into a tank and pumped onto the membrane using a diaphragm Hydra-Cell pump (D10 series, Laval, Canada), with the concentrate stream being recirculated into the feed tank. This process continued until the desired DOC level was achieved in the feed tank.

3.1.3 Modelling and predicting drinking water quality (objectives 1 and 2)

3.1.3.1 Model calibration

The calibration of the VRRC model for chlorine and THMs was performed using MATLAB R2019b. The chlorine and THM time-series obtained in the lab were fitted to the model using nonlinear differential equation curve fitting. Then, the goodness of fit was calculated with MATLAB curve fitting toolbox (cftool 3.5.10).

3.1.3.2 Full-scale prediction

We used EPANET-MSX version 2.00.12 to model chlorine residual and THMs in the DS. The DS was previously modeled with EPANET 2.0, and the daily water production pattern from the water treatment plant (WTP) served as the demand pattern for all network nodes. Extending the simulation time to five days for water quality model stabilization, the results on the fifth day were reported. To compare predictions with observations, the sampling time for each node was matched with the simulation results. For instance, if the field observations occurred at 10 AM, the simulation results at 10 AM on the fifth day would be used for validation. Finally, we compared predictions of VRRC model with the 1st-order model prediction to evaluate the improvement in prediction.

3.1.4 Water temperature monitoring campaign (objective 3)

Two contrasting study sites were chosen based on LST and green coverage. QGIS 3.26.2 software was employed to assess the city's heat islands and green spaces. Landsat 8 satellite imagery, categorizing soil temperature into five classes from coolest to hottest, was utilized. To ensure the consistency of the chosen area, Landsat 8 maps from 2013, 2016, and 2019 were examined. Additionally, the Montreal green space map was consulted to identify areas rich in vegetation,

encompassing trees, parks, and grass. Both selected zones needed to be in close proximity to the same WTP for convenient water temperature comparisons and share similar meteorological conditions, such as air temperature, wind speed, and direction. Figure 3.7 shows the two selected study areas. This figure contains the 2019 Landsat 8 image including five temperature classifications from the coolest, shown with green, to the hottest, shown with red. Additionally, the figure depicts water distribution system pipes, the water treatment plant location, and temperature monitoring points marked with thermometers. This intricate and time-intensive selection process was made feasible with valuable input and expertise from the City of Montreal regarding the drinking water distribution system sectors. This effort resulted in selecting two contrasting zones called the UHI impacted zone and the vegetation impacted zone.

With authorization from the City of Montreal, a comprehensive drinking water temperature monitoring campaign was carried out. The first step involved obtaining residents' permission to install temperature loggers in their buildings, which lasted three weeks with multiple visits to different areas in each sector. It resulted in recruiting 34 volunteers—17 from each designated zone. In the UHI-impacted zone, 12 commercial and 5 residential buildings were monitored, while in the vegetation-impacted zone, 10 residential and 7 commercial buildings were monitored. Next, temperature loggers (EasyLog temperature probe data logger) with $\pm 0.5^{\circ}\text{C}$ accuracy were installed on service lines connecting distribution pipes to each building. the picture of the logger is shown in Figure 3.8.A. Typically, the visible portion of the service lines was in basements, garages, or occasionally on the ground floor. Installation involved attaching the copper element to the exterior pipe wall under insulation. A sample of the installation is shown in Figure 3.8.B.

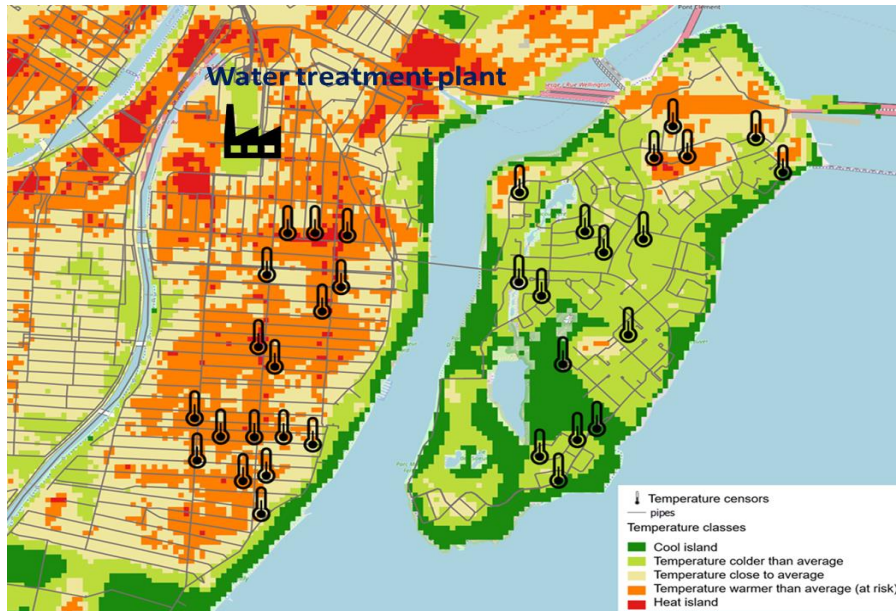


Figure 3.7 The study area showing the UHI-impacted zone on the left and the vegetation impacted zone on the right. The image shows the distribution systems pipes, the water treatment plant location, and the location of the 34 monitoring points.

(A)



(B)



Figure 3.8 A) The temperature probe data logger B) installation of the temperature probe on a pipe with insulation

3.1.5 Soil and water temperature modeling (objective 3)

To model soil temperature, we obtained hourly meteorological data, including air temperature, wind speed, wind direction, precipitation, and solar radiation, from the Environment and Climate Change department of the Government of Canada. This meteorological data was then integrated

into the soil temperature model, allowing us to calculate hourly soil temperature at a depth of 1.8 meters underground during the study period. Subsequently, the obtained soil temperature values were utilized as boundary conditions in the water temperature model and as the outer pipe wall temperature.

For water temperature modeling, we used the hydraulic model of the City of Montreal, developed using WaterGEMS. The water temperature modeling itself was conducted using the multispecies extension of EPANET (EPANET-MSX) with the WaterGEMS user interface. Each day of prediction necessitated a separate simulation.

CHAPTER 4 ARTICLE 1 – PREDICTING CHLORINE AND TRIHALOMETHANES IN A FULL-SCALE WATER DISTRIBUTION SYSTEM UNDER CHANGING OPERATING CONDITIONS

In this chapter, we introduce the adaptation and application of a variable reaction rate model for the prediction of chlorine and THMs in full-scale applications. This work effectively addresses critical challenges encountered by utilities when predicting chlorine and THMs in full-scale networks. Traditional chlorine and THM prediction models often struggle to provide accurate predictions under high concentrations of ammonia due to the rapid change in reaction rates, requiring frequent recalibration. This recalibration process demands additional time, effort, and poses challenges for real-scale applications. Moreover, when dealing with variable chlorine dosages or recalibration conditions within the DS, recalibration becomes a necessity. This work offers a straightforward solution to these issues while enhancing prediction precision. Furthermore, it achieves highly precise THM predictions within a full-scale DS using only simple, lab-based experiments, eliminating the need for recalibration in the network. The results of this research have been published on November 15th, 2022 in the “Water” journal. The supplementary materials are provided in Appendix A.

PREDICTING CHLORINE AND TRIHALOMETHANES IN A FULL-SCALE WATER DISTRIBUTION SYSTEM UNDER CHANGING OPERATING CONDITIONS

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Abstract

Predicting free chlorine residual and Trihalomethanes (THMs) in water distribution systems (DS) is challenging, given the variability and imprecise description of the chlorination conditions prevailing in full-scale systems. In this work, we used the variable reaction rate constant (VRRC) model, which offers the advantage of describing variable applied dosage and rechlorination

conditions without the need for model recalibration. The VRRC model successfully predicted chlorine decay and THMs formation in ammonia-containing water at the lab scale. Comparing the goodness of fit results showed a better fit by the VRRC model than the 1st-order and an equally good fit compared to the parallel 1st-order model. However, the independence of the VRRC coefficients upon chlorine dosage made it a better choice for full-scale implementation than the parallel 1st-order model. Chlorine and THMs predictions in the DS were performed in 22 locations from a full-scale DS in southern Quebec (Canada). Chlorine predictions by VRRC were conducted in the spring and fall of 2021 under changing water quality conditions (temperature, DOC, dosage). With a prediction target of 0.1 mg/L absolute error, the VRRC model met this target in 77% of the points in the spring and 73% in the fall. While the predictions were comparable and slightly better than those of the 1st-order model, the main advantage of the VRRC was its applicability under variable dosage and rechlorination conditions (e.g., booster chlorination). THMs predictions in the DS were successfully performed in fall 2021. While 91% of the nodes had less than 5 µg/L of absolute prediction error with the VRRC model, the 1st-order model only met this target in 1 out of 22 points. In addition to its high precision, the VRRC can predict THMs using only the lab scale experiments for model parametrization. This enables small utilities with limited resources to predict the possibility of THMs non-compliances under changing water quality conditions with simple lab-based experiments. Changing climatic conditions can deteriorate drinking water quality, raise regulatory concerns for chlorine and THMs, and threaten public health. Water utilities can use the simple approach proposed in this work to assess the possibility of non-compliance under changing conditions. Moreover, the efficiency of different interventions or mitigation strategies to resolve or avoid non-compliance can be evaluated with this approach.

KEYWORDS: Global change; THMs prediction; chlorine prediction; water distribution network

4.1 Introduction

4.1.1 The Importance and Challenges of Predicting Free Chlorine Residual and THMs in Drinking Water Distribution Systems

Chlorine is the most common water disinfecting agent used worldwide due to its high efficiency for virus and bacteria inactivation, affordability, and persistence in water as a secondary disinfectant (Jonkergouw et al., 2009; Méité et al., 2015). In many drinking water regulations

across jurisdictions, a minimal residual chlorine concentration is required at the distribution system's inlet and/or extremities. According to the code of federal regulation (40 CFR part 141.72), for treated water originating from surface water, chlorine residual in the DS "cannot be undetected in more than 5% of the samples each month" for any two consecutive months (Code of Federal Regulations (CFR), 2010). Some other regulations require maintaining a specific level of minimum chlorine residual (e.g., 0.1 mg/L or 0.2 mg/L) all over the network (Walski, 2019a). The reaction of chlorine with organic and inorganic constituents in water may produce disinfection by-products (DBPs) (Rossman et al., 2001). Among the many DBPs identified up to now, THMs are the most commonly regulated DBPs worldwide (Chhipi-Shrestha et al., 2018; Sérodes et al., 2003; Simard et al., 2011a). THMs result from the reaction of chlorine with natural organic matter (NOM) and bromide ions in water. According to the United States Environmental Protection Agency, the maximum total THMs concentration in the DS should not exceed 80 µg/L (EPA, 2010; United States Environmental Protection Agency (USEPA), 2010), based on the locational annual running average.

Predicting free chlorine and THMs concentrations in a DS is crucial to ensure both the control of microbial regrowth and compliance with DBPs regulations (Tryby et al., 1999). However, several factors complicate this prediction and make most prediction models inefficient. Some of the critical factors are (1) presence of ammonia in water, (2) changes in the applied dosage and rechlorination in the DS, which happens frequently, (3) seasonal or extreme climatic events that change the water quality parameters (such as pH, NOM, temperature), and (4) the chlorine demand exerted by the deposits found on internal pipe walls.

4.1.2 Chlorine Prediction Models

According to Hua et al. (2015) and Fisher et al. (2011), an ideal model for chlorine prediction should meet five criteria: (1) accuracy, (2) simplicity in calibration, (3) performing under rechlorination, (4) independence upon applied dosage, and (5) constant parameters over the entire water travel time. The 1st-order kinetic model and its modified forms (parallel 1st-order or limited 1st-order) have been the most commonly used by researchers and water utilities (Al Heboos and Licskó, 2017; García-Ávila et al., 2021a; Hallam et al., 2002; Meng et al., 2013). While these models can perform reasonably well under certain conditions, their limitations have also been documented. First, the fitted parameters are dependent on the applied dosage. Second, these models

use a constant rate for chlorine decay prediction, which has proved to be erroneous (Fisher et al., 2017; Hua et al., 2015). A Variable Reaction Rate Constant (VRRC) model for predicting chlorine decay has been developed by Hua et al. (2015) with the advantages of independence upon the applied dosage and re-chlorination in the DS. While this model has been previously tested in lab-scale experiments on low-ammonia waters (<0.05 mg N-NH₃/L), it has not been tested on ammonia-containing waters nor validated in a real-scale DS.

4.1.3 THMs Prediction Models

Based on a hypothesis by Clark (1998), THMs formation is proportional to chlorine consumption with a linear relationship. Boccelli et al. (2003) have used this hypothesis to estimate THMs formation using a 2nd-order chlorine decay model, and Gang et al. (2003) used it to estimate THMs concentrations using the parallel 1st-order model. However, the relationship between chlorine consumption and THMs formation is not entirely linear since not all the chlorine consumption results in THMs formation (Deborde and Von Gunten, 2008). Additionally, different NOM sizes (Gang et al., 2003) and structures (Yang et al., 2008) have different reactivities with regard to THMs formation. As a result, assuming a linear relationship between chlorine decay and THMs formation will increase the prediction error. Therefore, a surrogate for the THMs formation potential is needed to represent better the THMs precursors in water (Gallard and von Gunten, 2002; Zhang et al., 2013). Hua (2016) developed a VRRC model to predict THMs formation with a variable rate. Like the VRRC model for chlorine, this VRRC-THMs model has not yet been tested in high ammonia concentrations, and a full-scale DS.

4.1.4 Study Objectives and Approach

This study aims to evaluate the VRCC model's performance in predicting chlorine decay and THMs formation in the presence of ammonia, and in a full-scale DS. The predictions will be compared to the 1st-order and parallel 1st-order model's predictions. Finally, full-scale network predictions will be validated with field observations in 22 points and compared to the 1st-order model prediction for chlorine and THMs.

4.2 Materials and Methods

4.2.1 Chlorine and THMs Prediction in the DS: Overall Approach

The procedure for predicting chlorine and THMs in the DS is divided into two main steps. Step one involves sampling at the WTP, performing simulated distribution system (SDS) tests in the lab, and using the lab results to estimate the model parameters. Step two consists of applying the calibrated model to predict chlorine and THMs concentrations in the DS with EPANET-MSX (Shang et al., 2011) and comparing predictions with field measurements. The lab experiments in step one were performed using waters from two WTP/DS, one with moderate concentration of ammonia (city A) and the other with low ammonia (city B). Step two was only conducted in city B due to the higher number of available regulatory points ($n = 22$) for model validation. This allowed us to evaluate the model performance in different pipe diameters, water residence times, and flow conditions. The different steps for prediction in the DS are described below.

4.2.2 Step One: Parameter Estimation and Model Preparation

4.2.2.1 Sampling at WTP

Water samples were collected from the WTPs (A and B). A different river water supplies each WTP. Three sampling campaigns were carried out in October 2020, March 2021, and October 2021. Therefore, filtered waters from each WTP exhibited different characteristics in terms of DOC, pH, temperature, and ammonia concentration. The treatment trains of each WTP are presented in Figure 4.1, and the red stars indicate the sampling locations for the chlorination experiments.

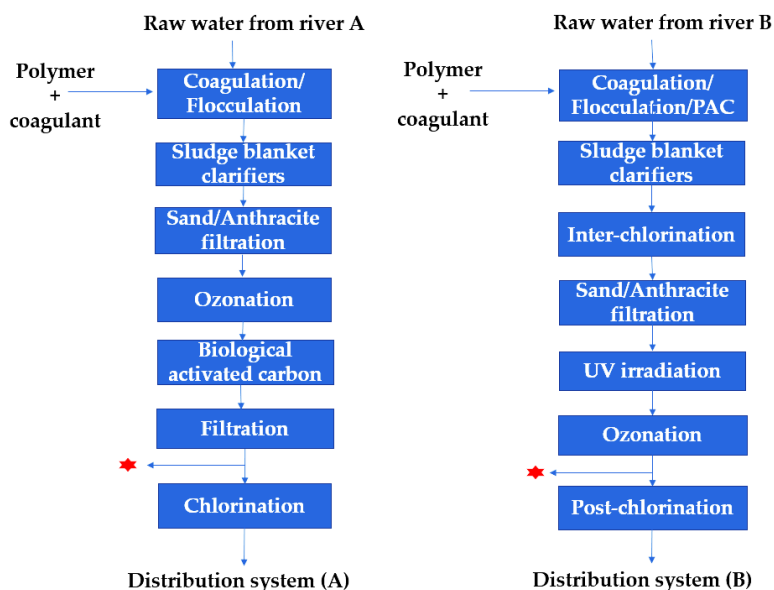


Figure 4.1 Schematic of the treatment chains for WTPs of City A and City B. The stars indicate the location of the sampling point in each plant.

4.2.2.2 Simulated Distribution Systems (SDS) Assays

The SDS test is a standardized assay to simulate the chlorine demand originating from the bulk decay and formation of DBPs (American Public Health Association (APHA) et al., 2012). After chlorine injection, samples were transferred to 45-mL amber vials and incubated under the same temperature prevailing in the DS on the sampling day. Free chlorine residual was measured at multiple contact times (4 h, 8 h, 24 h, 32 h, 48 h, 56 h, 72 h, 80 h, 96 h, 120 h) based on the method 4500-Cl G of standard method for the examination of water and wastewater (American Public Health Association (APHA) et al., 2012). After each measurement, two 45 mL vials were quenched with ammonium sulfate, and the corresponding THMs concentrations were measured according to method EPA 524.2 (measurement of purgeable organic compounds in water by capillary column gas chromatography/mass spectrometry) (United States Environmental Protection Agency (USEPA), 1992). All the analyses for chlorine and THMs were done in duplicates, and the coefficient of variance (CV) was calculated.

4.2.2.3 VRRC Model Parameters Estimation

The parameter estimation for chlorine and THMs models was performed using MATLAB R2019b (nonlinear differential equation curve fitting). The goodness of fit, including R-squared (R^2), root

mean square error (RMSE), and probability value (*p*-value), was calculated using the curve fitting toolbox of MATLAB (cftool 3.5.10).

- VRRC-chlorine model

Equation (4.1) presents the VRRC model for free chlorine prediction.

$$\frac{dCl_2}{dt} = -\alpha e^{-\beta \left(\frac{\Delta Cl_2(t)}{\Delta Cl_{2max}} \right)} \cdot Cl_2(t) \cdot [\Delta Cl_{2max} - \Delta Cl_2(t)] \quad (4.1)$$

In this model, $Cl_2(t)$, expressed in mg/L, is the free chlorine concentration and $\Delta Cl_2(t)$ is the chlorine demand in mg/L and is expressed as applied dosage $-Cl_2(t)$. ΔCl_{2max} , the maximum chlorine demand (mg/L), is obtained based on the standard method (American Public Health Association (APHA) et al., 2012) under specific conditions ($pH = 8 \pm 0.2$, temperature = 25 ± 2 °C, and a free chlorine residual 3–5 mg/L after 7 days). Finally, α (Lmg⁻¹h⁻¹) and β (unitless) are model parameters and are specific to physicochemical characteristics of water, mainly the NOM (Hua et al., 2015). After finding the optimum parameters, the goodness of fit was compared to the 1st-order model (Vasconcelos et al., 1997), and the parallel 1st-order model (Powell et al., 2000).

- VRRC-THMs model

The VRRC-THMs model by Hua (2016) needs a multi-step process for parameter estimation by first calibrating the model parameters based on trichloromethane formation, and then using a bromide substitution factor to estimate the total THMs formation. To reduce the model's complexity and predict total THMs in one step, the original model was modified, and the final model is presented in equation (4.2).

$$\frac{dTHM}{dt} = M \cdot e^{N \times \left(\frac{-\Delta THM(t)}{\Delta THM_{max}} \right)} \cdot Cl_2(t) \cdot (\Delta THM_{max} - \Delta THM(t)) \quad (4.2)$$

In this equation, M and N are model parameters describing the THMs formation rate, where M is expressed in (mg Cl₂/L)⁻¹hr⁻¹ and N is unitless. These parameters remain constant during the water travel time in the network. $Cl_2(t)$ is the concentration of free chlorine at each time, and $\Delta THM(t)$ is the formed THMs at each time (µg/L), which equals $THM(t) - THM(0)$. Finally, ΔTHM_{max} represents the maximum total THMs formation potential (µg/L) corresponding to the maximum chlorine demand obtained in the previous step. After estimating the model parameters,

the model fit was compared to the 1st-order THMs model's prediction by Clark (1998). The 1st-order THMs model is presented in equation (A.1) in the Supplementary Material, and Figure A.1 shows the relationship between 1st-order chlorine and THMs concentrations for the estimation of THMs yield coefficient.

4.2.3 Step Two: Model Prediction and Validation

4.2.3.1 Sampling in Full-Scale DS

City B has an average annual production rate of 28,800 m³/day, and its EPANET network model includes approximately 2000 pipes and 1500 nodes. The average operating pressure of the network is 500 kPa. The pipe diameters range from 150 mm in secondary pipes to 600 mm in distribution mains. The pipe materials range from stainless steel for the pipes leaving the WTP, concrete for the distribution mains, cast iron for the secondary pipes, and PVC for most smaller diameter pipes. There are in total 22 regulatory control points in the network. The sampling points are in commercial areas, e.g., gas stations and commercial buildings. All samples were taken from the indoor consumer taps. The taps were left open for two minutes before collecting the samples. The precision of the chlorine measurement (Hach pocket colorimeterTM II, Saint-Laurent, Canada) was ± 0.05 mg/L and for THMs, the quantification limit of the gas chromatography (Agilent Technologies 7890B gas chromatograph, Saint-Laurent, Canada) was between 5 – 7.6 μ g/L depending on the type of THMs. Therefore, to evaluate the goodness of our predictions, a target of ± 0.1 mg/L prediction error for chlorine and ± 5 μ g/L prediction error for the THMs was considered acceptable. A segment of the overall layout of the city's DS and the sampling points are presented in Figure 4.2. Predictions of free chlorine concentrations were carried out in two seasons, Spring (March) when the water temperature was 4°C and Autumn (October) when the water temperature was 17°C.

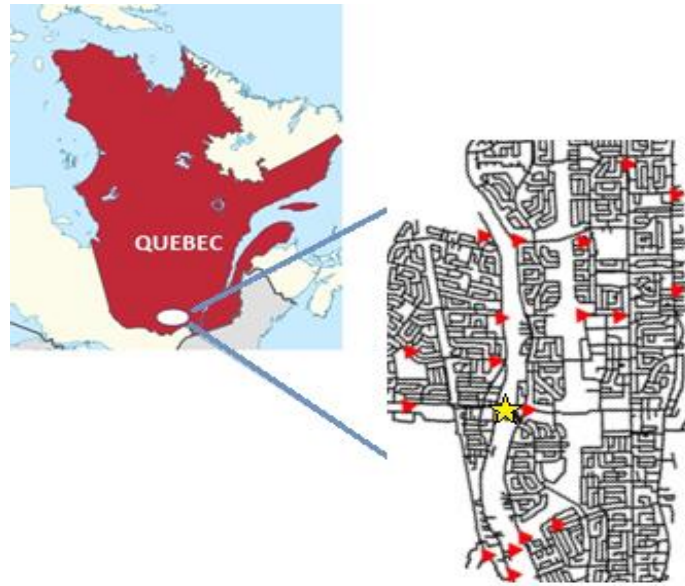


Figure 4.2 Layout of the DS of city B in southern Quebec (the image is neither showing the whole network nor all the 22 sampling points for model validation). The locations of the sampling points are indicated with red triangles, and the WTP is marked with a yellow star.

4.2.3.2 VRRC Model Prediction and Comparison with Field Observations

Chlorine consumption in a DS originates from the bulk decay and wall decay (Fisher et al., 2017; Shang and Uber, 2007). The VRRC model predicts bulk decay only, and to use the model in a real-scale DS, a 1st-order wall decay model by Rossman et al. (1994) was used in conjunction with the VRRC model. The supplementary material explains the wall decay model in equations (A.2) and (A.3). The overall chlorine decay equation composed of the bulk decay and the wall decay equation is presented in equation (4.3).

$$\left(\frac{dCl_2}{dt}\right)_{\text{total}} = -\alpha e^{-\beta\left(\frac{\Delta Cl_2(t)}{\Delta Cl_{2\max}}\right)} \cdot Cl_2(t) \cdot [\Delta Cl_{2\max} - \Delta Cl_2(t)] - \frac{2k_w k_f}{R(k_w + k_f)} \cdot Cl_2(t) \quad (4.3)$$

In this equation, k_w is the constant wall reaction rate with a unit of length per time and k_f is the mass transfer coefficient (length/time), R is the pipe radius (length) and $Cl_2(t)$ is the concentration of chlorine in the pipes (mg/L) (Rossman, 2000). The k_w was estimated using 6 out of 22 data points with the aim of minimizing the RMSE between the predicted and the observed chlorine residuals. Then, the estimated k_w was used for prediction of the 16 remaining points in the network. More details about estimation of k_w and k_f are provided in the Supplementary Material (part B).

Modeling chlorine residual and THMs in the DS was conducted with the EPANET-MSX version 1.1.00. The DS of the city had been previously modeled with EPANET 2.0 and the daily water production pattern of the WTP was used as the water demand pattern of all the network nodes (the pattern is provided in Figure A.2 in the Supplementary Material). The demand patterns of ± 3 days before and after the sampling were checked to ensure there were no anomalies around the sampling day that could impact our results, and no anomalies were found. The hourly head pattern of the plant was also applied to EPANET. The simulation time was extended to five days to stabilize the water quality model (Shang et al., 2011), and the results on the fifth day of the simulation were reported.

To compare predictions and observations, the sampling time for each node was identified first. For example, if the field observation was done at 10 AM, the simulation results at 10 AM of the fifth day of simulation was identified. Finally, the predictions were compared to the 1st-order model for chlorine and THMs. The overall methodological approach of the study is summarized in Figure 4.3.

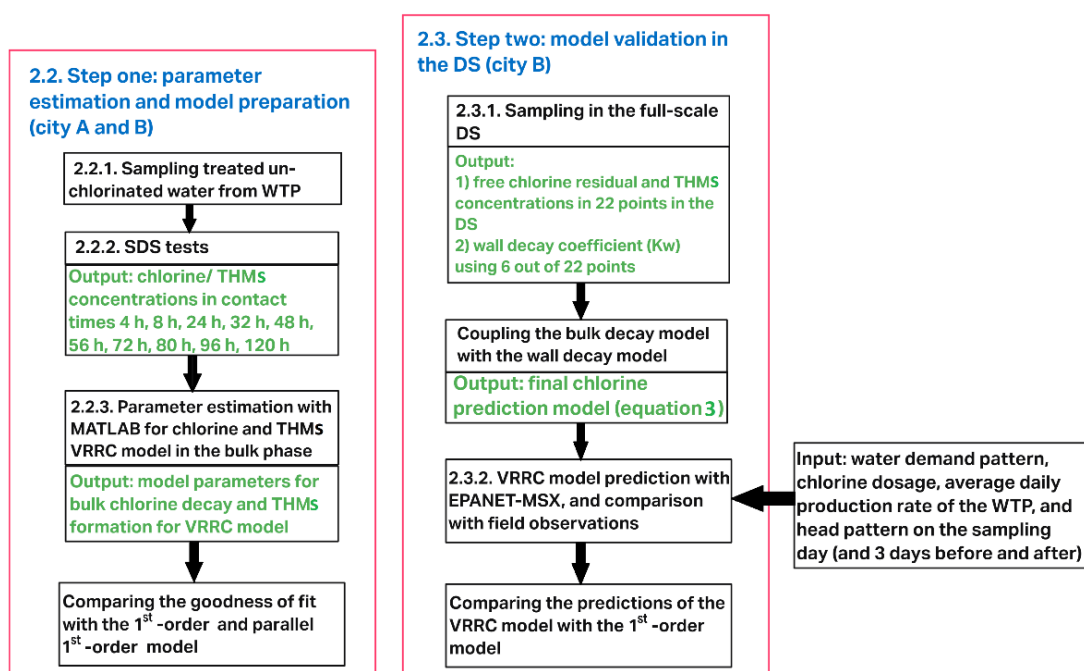


Figure 4.3 Overall methodological approach for parameter estimation and model validation in the DS.

4.3 Results and Discussion

4.3.1 Parameter Estimation for the VRCC Model

Table 4.1 shows the characteristics of each water sample including DOC, ammonia concentration, pH, applied dosage in the lab, and the standard deviations for each parameter. Sampling from the plant of city A was carried out in late October 2020 when the water temperature was 10°C. At this period of the year, only partial nitrification was achieved in the biological filters (Liu et al., 2020), which explains the presence of ammonia in water.

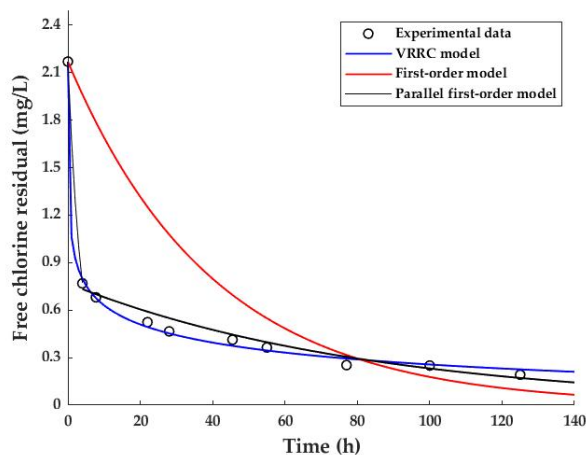
Table 4.1 Characteristics of the water samples (average $\pm$ standard deviation) taken from cities A and B.

Water source	DS Temperature (°C)	Ammonia Concentration (µg/L)	DOC (mg C/L)	pH	Applied Dosage in the Lab (mg Cl ₂ /L)
City A WTP (October 2020) 1 sample tested	10 $\pm$ 1.5	91 $\pm$ 5	2.1 $\pm$ 0.03	7.1 $\pm$ 0.03	2.17 $\pm$ 0.03
City B WTP (March 2021) 2 samples tested	4 $\pm$ 1.5	<5	1.52 $\pm$ 0.04	7.84 $\pm$ 0.03	1.12 $\pm$ 0.009
City B WTP (October 2021) 3 samples tested	17 $\pm$ 2.05	<5	1.68 $\pm$ 0.04	7.82 $\pm$ 0.02	2.0 $\pm$ 0

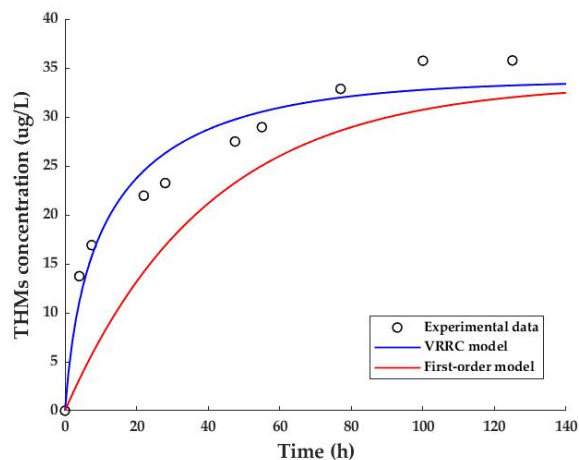
The predictions of the VRRC model for bulk chlorine decay and THMs formation were estimated with a CV less than 4% for Chlorine and CV less than 4.5% for THMs measurements. The results, including the curve fitting and the goodness of fit (R^2 , RMSE, and p -value) for each test, are presented in Figure 4.4.

Plant of city A—October 2020

(A)

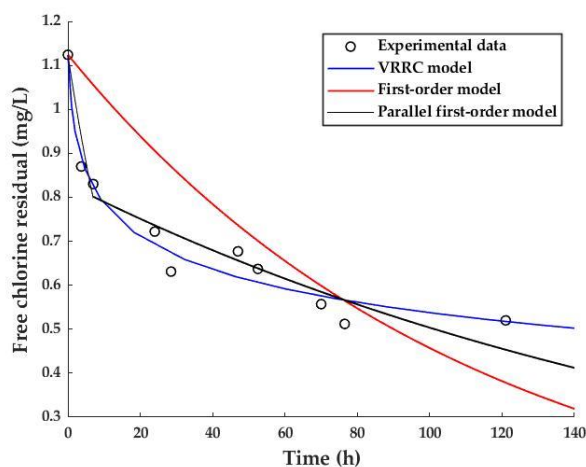
VRRC: $R^2 = 0.99$, RMSE = 0.03, p -value < 0.0011st-order: $R^2 = 0.602$, RMSE = 0.61, p -value < 0.001Parallel 1st-order: $R^2 = 0.99$, RMSE = 0.04, p -value < 0.001

(D)

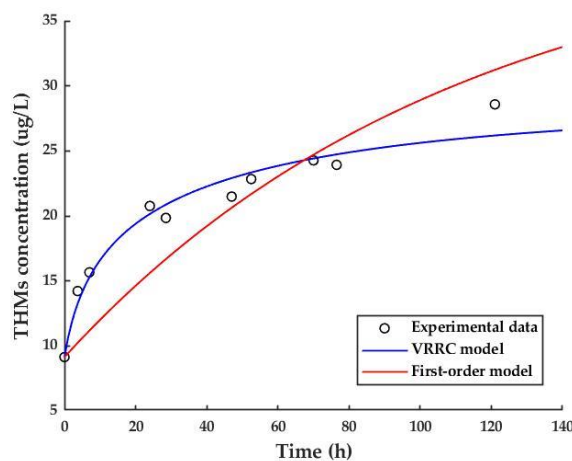
VRRC: $R^2 = 0.96$, RMSE = 2.42, p -value < 0.0011st-order: $R^2 = 0.92$, RMSE = 3.58, p -value < 0.001

Plant of city B—March 2021

(B)

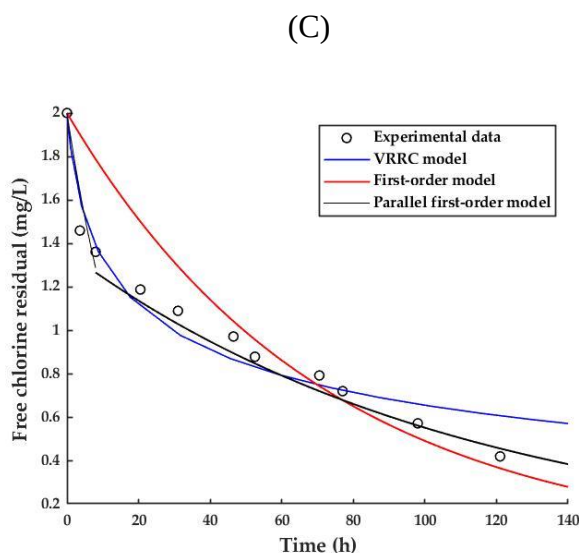
VRRC: $R^2 = 0.97$, RMSE = 0.03, p -value < 0.0011st-order: $R^2 = 0.78$, RMSE = 0.15, p -value < 0.001

I

VRRC: $R^2 = 0.96$, RMSE = 1.06, p -value < 0.0011st-order: $R^2 = 0.89$, RMSE = 2.92, p -value < 0.001

Parallel 1st-order: $R^2 = 0.94$, RMSE = 0.05, p -value < 0.001

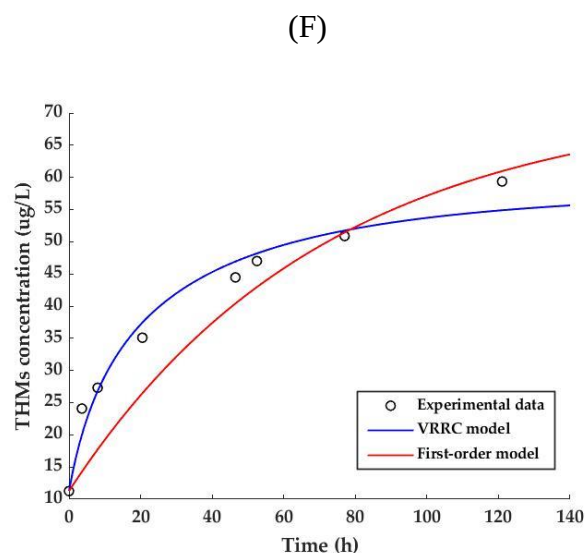
Plant of city B—October 2021



VRRC: $R^2 = 0.95$, RMSE = 0.1, p -value < 0.001

1st-order: $R^2 = 0.91$, RMSE = 0.23, p -value < 0.001

Parallel 1st-order: $R^2 = 0.97$, RMSE = 0.08, p -value < 0.001



VRRC: $R^2 = 0.97$, RMSE = 2.52, p -value < 0.001

1st-order: $R^2 = 0.95$, RMSE = 6.11, p -value < 0.001

Figure 4.4 Curve fitting results and goodness of fit for chlorine and THMs; comparison with the 1st-order and the parallel 1st-order model.

As it can be seen in Figure 4.4.A, the initial chlorine demand in the first few hours of the experiment was very high. This was due to the rapid reaction of free chlorine with ammonia. In this test, 69% of chlorine was consumed in the first 7.5 h of the experiment, reaching 91% after 125 h. Because of this significant decay rate in the initial stages of the reaction, the 1st-order model provided a poor fit to the experimental data. While the parallel 1st-order model fit was comparable to that of VRRC, it required finding the proper contact time for separating the slow reaction phase from the fast phase. Then, the model had to be recalibrated at the end of the slow phase, and the coefficient would change. In contrast to the parallel 1st-order model, VRRC model could predict chlorine decay with only one set of parameters for the whole test duration without recalibration. Moreover, VRRC coefficients are independent of the applied dosage. This means that under variable dosage of the treatment plant, we can still use the same parameters, whereas the parallel 1st-order model would need recalibration.

Regarding plant of city B (Figure 4.4, parts B and C), the chlorine decay rate was more stable as compared to city A due to (1) negligible concentration of ammonia in water, (2) lower DOC concentration (1.68 mg C/L in city B compared to 2.1 mg C/L in city A), and (3) the intermediate chlorination performed before the filtration process that reduced the initial chlorine demand. The VRRC-chlorine model provided a better fit than the 1st-order model, and the parallel 1st-order model fit was equally good. The goodness of fit statistics also showed better fit by VRRC compared to the 1st-order model, and comparable to the parallel 1st-order model.

THMs prediction results are presented in Figure 4.4 (sections D, E, and F). In presence of ammonia (city A plant), VRRC showed a better fit compared to the 1st-order THMs model. As opposed to the chlorine decay rate, which had a drastic decline in the first few hours, the THMs formation rate was steadier given that the ammonia-Cl₂ reaction does not lead to the formation of THMs. In WTP of city B, where the ammonia concentration was low, VRRC provided a better fit than the 1st-order model. The goodness of fit statistics provided below each figure show that VRRC yielded a higher R² and a lower RMSE in all three waters, indicating that the fit was improved compared to the 1st-order THMs model.

4.3.2 Predicting Free Chlorine and THMs in the DS

4.3.2.1 Free Chlorine Prediction

Figure 4.5 presents the predicted free chlorine versus the observed values in both seasons. The optimized k_w for the studied network was 0.04 m/day for March (DS water temperature=4°C) and 0.12 m/day for October (DS water temperature=17°C). The faster kinetics and higher k_w in higher temperatures have been previously reported in the literature (Kahil, 2016; McGrath et al., 2021; McNeill and Edwards, 2002; Volk et al., 2000). Prediction of free chlorine in city B met our target accuracy in both Spring and Fall in most of the sampling points. This figure also shows the goodness of fit statistics for both VRRC and the 1st-order models (R², RMSE, and p -value). Table A.1 in the supplementary materials presents the sampling points' diameters, observed nodal residual chlorine, and VRRC prediction results in both seasons.

In Spring, the target precision of ± 0.1 mg/L was met in 77 % of the sampling points (17 out of 22) with both VRRC and the 1st-order model. The prediction errors were higher than ± 0.1 mg/L in points N4, N11, N13, N20, and N22. All these nodes were located on small diameter pipes (150–

250 mm). In smaller diameters, the ratio of surface to volume increases, which in turn increases the interaction of pipe walls and biofilm material with water. This high interaction increases the pipe wall decay coefficient locally. Fisher et al. (2017) have previously shown that using a single k_w value for the whole network will generally lead to better predictions in larger pipes and higher errors in smaller pipes. Based on our results, using two different k_w values, one for the transport mains (larger pipes) and one for the distribution lines (smaller pipes), could improve the prediction results. Another error source was that Nodes N13, and N20 were on network dead ends, and N4 was on the extremities and very close to a dead end. The hydraulics of these points are usually poorly described in hydraulic models like EPANET, and the water stagnation is usually higher than the calculations of EPANET which leads to increased prediction error (Rossman et al., 1994).

Prediction of free chlorine in October met the precision target at 73% of the points (16 out of 22 points) with the VRRC model and 68% of the points (15 out of 22) with the 1st-order model. Points N7, N12, N13, N16, N21, and N22, had prediction errors higher than ± 0.1 mg/L. The diameters of pipes in all these points were between 150–200 mm, which led to a higher prediction error because of the wall decay effect. In addition to having a small diameter, Node N13 was at a dead end, which increased the prediction error.

In addition to the above reasons for the prediction error, the samples were collected from non-residential buildings during the COVID pandemic. This situation may have modified the water demand allocation in the DS, which was not well described in the hydraulic simulation. Finally, the RMSE in both seasons was 0.12, close to our precision target of maximum ± 0.1 mg/L error. The overall prediction was deemed acceptable considering five dead ends and the pandemic contextual factors.

To improve prediction, we can allocate specific demand patterns to the nodes on the distribution pipes. Blokker et al. (2008a) found that using a stochastic demand with a smaller hydraulic timestep (one minute instead of one hour used in this work) will reduce the prediction error. A bottom-up approach with a small timestep can describe the household demand variations more realistically. This will lead to a more realistic calculation of RT at each node and lower prediction errors.

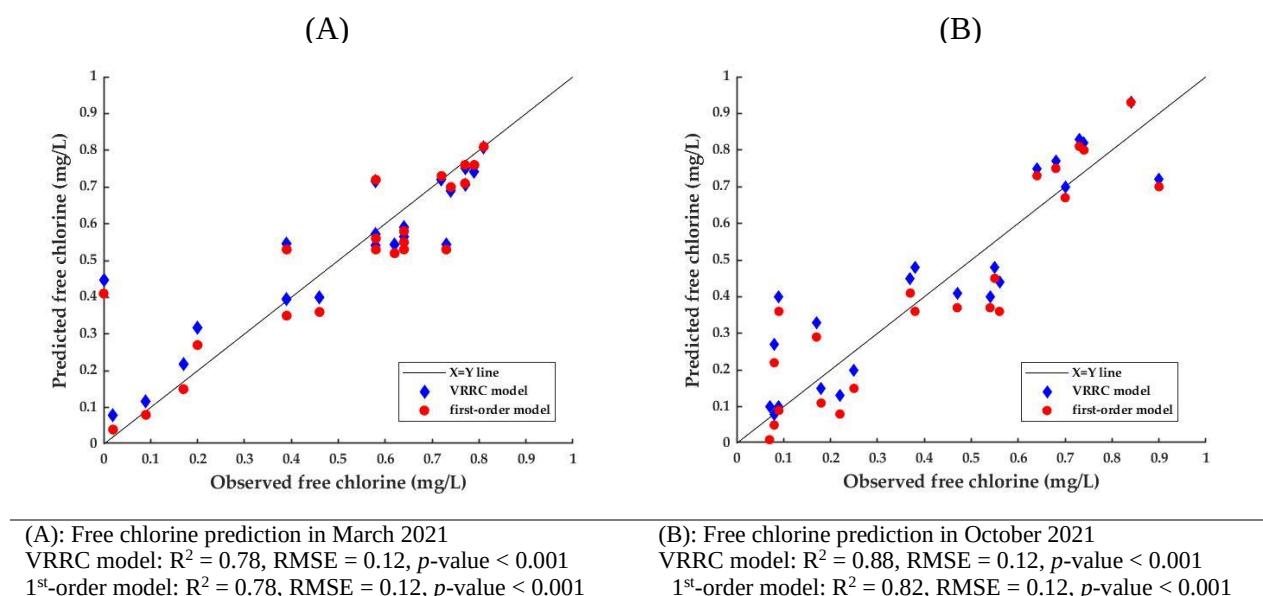


Figure 4.5 Free chlorine prediction results in the DS of city B using the VRRC model compared to the 1st-order model.

4.3.2.2 THMs Prediction

The prediction results for the VRRC and the 1st-order models and the goodness of fit statistics are presented in Figure 4.6 THMs prediction in the DS was performed in two ways: (1) considering the bulk chlorine decay only, and (2) considering both bulk and wall decay. For the VRRC model, predicting with the bulk decay met the target precision of $\pm 5 \mu\text{g/L}$ in 91% (20 out of 22) of the locations with an RMSE = $3.7 \mu\text{g/L}$. However, considering both bulk and wall decay reduced the performance as our target was met in 73% (16 out of 22) of the locations with an RMSE = $5.3 \mu\text{g/L}$. This result suggests that the organic matter adsorbed on pipe walls and deposits did not act as a significant source of DBPs precursors. Koch et al. (1991) have also found that THM-SDS values obtained in the lab correlate perfectly with field measurements. Since THMs formation is influenced by free chlorine reconcentration, a conclusion from this result in the studied network could be that the dominant source of chlorine prediction error (especially in the smaller diameter pipes) is not the wall decay effect but rather due to the lack of specific demand patterns (which lead to RT calculation errors). The fact that most of the smaller diameter pipes in this DS are made of PVC (have lower k_w) supports this assumption. THMs predictions with the 1st-order model considering the bulk decay met the target precision only in 1 out of 22 locations (Figure 4.6.B). Considering both wall and bulk decay did not help meeting our target as the prediction error

increased substantially. The lack of fit of the 1st-order model is due to an overestimation of THMs given that not all chlorine decay led to the formation of THMs. Table A.2 presents the nodal THMs concentrations measured in the field, their corresponding pipe diameter, THMs prediction with VRRC using bulk decay, and their absolute prediction errors.

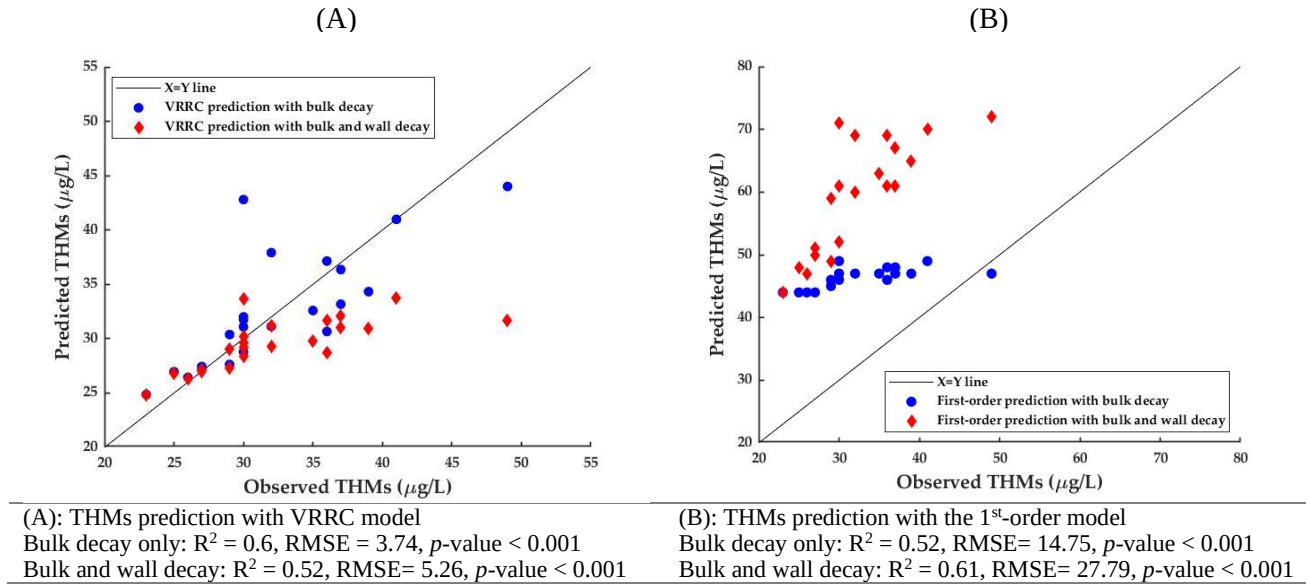


Figure 4.6 THMs prediction results and goodness of prediction in the DS; comparison between the VRRC and the 1st-order models.

4.4 Conclusions

The VRRC model was an effective tool for predicting chlorine and THMs in the lab and in a full-scale DS. Free chlorine prediction in the presence of ammonia is challenging for most models, given the significant change in chlorine decay rate. VRRC successfully predicted chlorine and THMs in the presence of ammonia without recalibration or the need to change the parameters as opposed to the 1st-order and the parallel 1st-order model. Prediction of free chlorine in the DS was performed in two seasons to test the model applicability under seasonal changes in water quality (temperature, DOC, dosage, k_w). The free chlorine predictions with VRRC (in low-ammonia concentrations) were comparable and slightly better than the 1st-order model's prediction. Accurate prediction of chlorine in the full-scale DS is essential in meeting the minimum set points set by several jurisdictions. Another advantage of using the VRRC in full-scale applications is its constant model coefficients under variable dosage and rechlorination.

THMs prediction in the DS was successfully achieved with the VRRC, while the 1st-order model predictions did not meet our prediction target ($\pm 5 \mu\text{g/L}$). An advantage of this approach was that a precise THMs prediction was achieved using only lab-scale results without calibration of the model in the network. This ability especially becomes important to utilities under global change in drinking water quality. Under abrupt or seasonal changes in source water quality, the risk of THMs non-compliance in the DS may increase. Meeting DBPs regulatory standards is one of the utilities' most important concerns, especially under changing climatic conditions. A simple tool to predict the possibility of THMs non-compliance, especially in the extremities and riskier locations, can be an asset to utilities. Predicting THMs non-compliance from the treatment plant will also enable utilities to test the efficiency of different strategies for reducing THMs in the DS.

The chlorine and THMs predictions with VRRC were validated in various DS locations with different physical and hydraulic conditions, from the treatment plant to the DS extremities. As a result, this model can be used to predict chlorine/THMs in the entire DS of the city. The simplicity of our approach makes it easily accessible to small utilities with limited resources. Under changing conditions, our system can be used to assess the risk of chlorine/THMs non-compliance under different climatic scenarios. The results can be the starting point for decision-making on mitigation strategies to avoid the negative consequences of adverse climatic events on public health.

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CHAPTER 5 ARTICLE 2 – CLIMATE CHANGE AND FUTURE WATER DEMAND: IMPLICATIONS FOR CHLORINE AND TRIHALOMETHANES MANAGEMENT IN WATER DISTRIBUTION SYSTEMS

In this chapter, we model and predict the combined impacts of climatic events, water warming, and reductions in water demand on the variations in chlorine and THMs within a full-scale water distribution network. This article addresses a crucial question, particularly in the context of Quebec's water conservation strategy: how does reducing water demand in cities affect water quality? It also introduces a reliability index that simplifies the assessment of nodal and overall network performance under various combined scenarios, offering a quantitative measure for network performance evaluation. Furthermore, by mapping nodal reliabilities within the distribution network of the city, we identify vulnerable zones that may experience deviations from recommended or regulatory standards for chlorine and THMs. Additionally, we assess the effectiveness of increasing chlorine dosage as a corrective measure, revealing that it could exacerbate the situation by leading to excessive THM concentrations and an elevated risk of high THM exposure among consumers. This article was submitted in August 3rd, 2023 to the Journal of Environmental Management. The supplementary materials are provided in Appendix B.

CLIMATE CHANGE AND FUTURE WATER DEMAND: IMPLICATIONS FOR CHLORINE AND TRIHALOMETHANES MANAGEMENT IN WATER DISTRIBUTION SYSTEMS

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Abstract

The global change in surface water quality calls for increased preparedness of drinking water utilities. The increasing frequency of extreme climatic events combined with global warming can

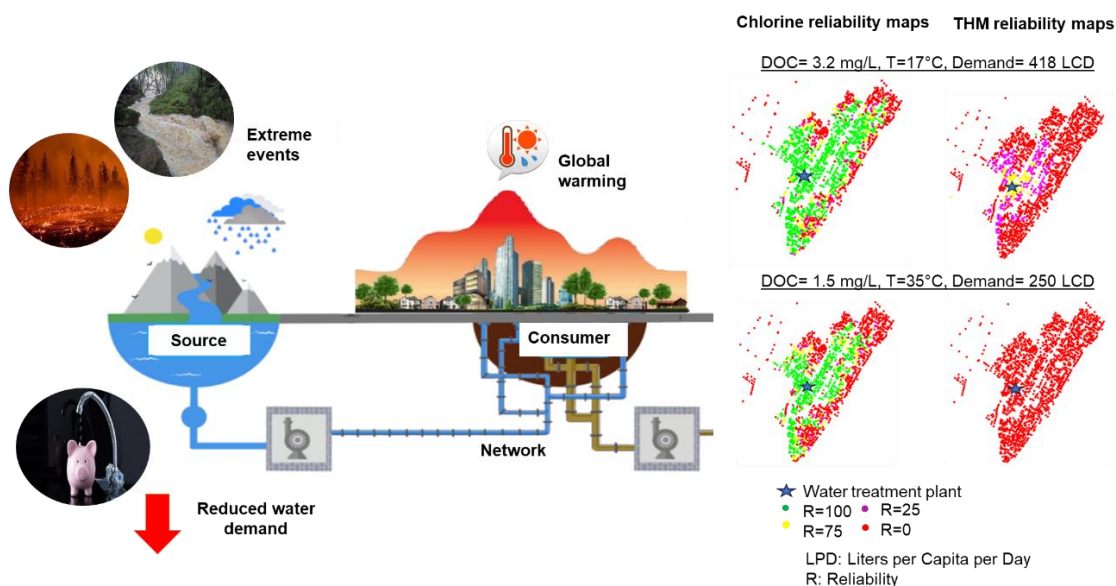
impact source and treated water characteristics such as temperature and natural organic matter. On the other hand, water saving policies in response to water and energy crisis in some countries can aggravate the situation by increasing the water residence time in the drinking water distribution system (DS). This study investigates the individual and combined effect of increased dissolved organic carbon (DOC), increased temperature, and reduced water demand on fate and transport of chlorine and trihalomethanes (THMs) within a full-scale DS in Canada. Chlorine and THM prediction models were calibrated with laboratory experiments and implemented in EPANET-MATLAB toolkit for prediction in the DS under different combinations of DOC, temperature, and demand. The duration of low chlorine residuals (<0.2 mg/L) and high THM (>80 μ g/L) periods within a day in each scenario was reported using a reliability index. Low reliability zones prone to microbial regrowth or high THM exposure were then delineated geographically. Results revealed that water demand reduction primarily affects chlorine availability, with less concern for THM formation. The reduction in nodal chlorine reliability was gradual with rising temperature and DOC of the treated water and reducing water demand. Nodal THM reliability remained unchanged until certain thresholds were reached, i.e., temperature $>25^{\circ}\text{C}$ for waters with DOC <1.52 mg/L, and DOC >2.2 mg/L for waters with temperature $=17^{\circ}\text{C}$. At these critical thresholds, an abrupt network wide THM exceedance of 80 μ g/L occurred. Under higher DOC and temperature levels in future, employing the proposed approach revealed that increasing the applied chlorine dosage (which is a conventional method used to ensure sufficient chlorine coverage) results in elevated exposure to THMs and is not recommended. This approach aids water utilities to assess the effectiveness of different intervention measures solve water quality problems, identify site-specific thresholds leading to major decreases in system reliability, and integrate climate adaptation into water safety management.

KEYWORDS: *Water distribution network, climatic events, water conservation, water quality modeling, disinfection by-product, water quality management*

Highlights

- Water demand reduction is more concerning for microbial safety than for THM formation.
- Global warming, increased NOM and reduced water demand concurrently threaten water safety.
- THM precursors and temperature have a more critical impact on network THMs than water residence time.

Graphical abstract



5.1 Introduction

Global change has jeopardized water quality by increasing the temperature of water resources and introducing contaminants into waterbodies, thereby affecting the operating conditions in water supply systems (Leveque et al., 2021; Tanaka et al., 2006). Increased temperature and excess nutrients in water can lead to the growth and proliferation of pathogenic organisms such as parasites, bacteria, and viruses, consequently increasing the risk of human exposure and waterborne diseases (Cissé, 2019; Semenza, 2020). Disinfection is an effective tool to ensure microbial safety in many water supply systems worldwide, and chlorine is a commonly used disinfectant due to its high efficiency, low cost, and flexibility in application (Basupi and Nono, 2019; Hua et al., 2015). Enforcing a minimum free chlorine residual at the point of entry or throughout the DS is regulated in various jurisdictions (United States Environmental Protection Agency (USEPA), 2010). Free chlorine residuals greater than 0.2 mg/L have been proven to substantially suppress the prevalence of opportunistic bacteria *Legionella pneumophila* in DS, emphasizing the pivotal role of chlorine in safeguarding human health (Donohue, 2021). One of the negative side effects of chlorination is the formation of disinfection by-products (DBPs), which pose chronic health risks to water consumers (Khan et al., 2021; United States Environmental Protection Agency (USEPA), 2010). Ensuring microbial safety while minimizing DBPs, especially THMs, has always been a challenge for water utilities. Chlorine decay and THM formation are affected by water characteristics and

network operating conditions, with temperature (Uyak et al., 2007; Valdivia-Garcia et al., 2019; Xu et al., 2022) and the concentration of natural organic matter (NOM) (Clark et al., 2001; Ferretto et al., 2021; Liu et al., 2022b) being two of the most critical factors. As the temperature and NOM of source water are subject to change under varying climatic conditions, it is crucial to recognize the potential impacts on the fate of chlorine and DBPs in water distribution networks.

The rise in air temperature has also had a trickling impact on the temperature of surface and drinking water and consequently water safety, as bacterial growth and rapid disinfectant decay are predominant at higher water temperatures (Agudelo-Vera et al., 2020; Lai and Dzombak, 2021). Higher temperatures will increase the formation rate of DBPs, particularly THMs, as reported in other studies (Albanakis et al., 2021; Valdivia-Garcia et al., 2019). In a previous study, THM formation in samples collected from a DS in the summer and fall (higher temperature periods) were on average five times higher than those collected in the winter (Rodriguez et al., 2004). Another study investigated the probability of THM noncompliance in reference to the US EPA regulations for future climate scenarios using a multilevel regression model, with temperature, precipitation, and treatment type as variables. Historical THM records from 13 utilities in Canada were used to predict a probability of noncompliance of at least 23% until 2050 .

Global warming and anthropogenic activities have caused more frequent occurrence of extreme events such as wildfires (Olefeldt et al., 2013) and floods (Mian et al., 2023) over the past few decades. Following a post-fire discharge or snowmelt, burnt vegetation and soil nutrients are mobilized and discharged into downstream waterbodies, potentially increasing the NOM concentration (Chow et al., 2019b; Hohner et al., 2017). The interconnection between the terrestrial and aquatic carbon cycle following a post-fire runoff depends on many factors such as the severity of the fire (Chow et al., 2019b; Wei et al., 2021), watershed size (Chow et al., 2019b; Olefeldt et al., 2013), precipitation or snowmelt intensity (Senhorst and Zwolsman, 2005), type of vegetation (Leveque et al., 2021), and the primary mechanism and source of organic carbon transport in the watershed (Jensen et al., 2017). Different studies on the impact of post-fire discharge events on DOC concentration in source water have shown varying results with increased levels (Crandall et al., 2021; Sham et al., 2013), decreased levels (Hohner et al., 2019), or no change in the downstream DOC concentration (Olefeldt et al., 2013). Higher concentrations of DOC in treated waters may decrease the effectiveness of chlorine disinfection and increase the formation of DBPs. In 2002, after the Hayman fire in Denver (USA), the THM formation potential in water treatment plants

(WTPs) intake from burnt catchments was observed to be nearly double that from unburnt catchments ($203 \pm 26 \mu\text{g/L}$ vs $114 \pm 17 \mu\text{g/L}$) (Chow et al., 2019b). After wildfires in California in 2007 and 2009, a 71% increase in source water DOC led to a 49% increase in the THM formation potential (Revchuk and Suffet, 2014).

Global warming has also induced lake browning in northern regions including several great lakes in Canada. The primary causes of browning are increased DOC in the waterbodies caused by higher temperature and precipitation (De Wit et al., 2016), change in land use (Kritzberg et al., 2014), and lower sulphur and chloride deposition (Keucken et al., 2017; Monteith et al., 2007). A study on 15 boreal lakes in Canada has revealed a significant increase in lake DOC input over the last 40 years (Couturier et al., 2022), which could correspond to higher DOC in the WTP intake downstream (Anderson et al., 2017). While there is limited information about the long-term impacts of browning on THMs, the increased DOC of source waters would most likely increase the THM formation potential in the affected water supply systems.

Governments worldwide are adopting water-saving measures as part of a global movement towards integrated management strategies to conserve water resources (Cf, 2015). Canada has 7% of the world's renewable freshwater and is among the highest water consumers globally (Adamowski et al., 2012). In 2019, the average per-capita drinking water consumption in Canada (including residential, industrial, commercial, and other applications) was 411 liters per day, which was 15% lower compared to the per-capita demand in 2011 (Statistics Canada, 2021). The Quebec government has set a target to further reduce its total water demand by 20% by 2025, compared to the reported demand in 2015 (Ministère du Développement durable, 2018). One of the main implications of lower water demand for water supply systems is the increased water age, which typically induces reduced disinfectant residual concentrations in the network, which in turn can lead to compromised microbial safety (Agudelo-Vera et al., 2016). In addition, the prolonged contact time between free chlorine and the organic and inorganic compounds in water can lead to higher concentrations of THMs in the DS (Dias et al., 2019; Dion-Fortier et al., 2009). One study on the consequences of water conservation in a Canadian DS estimated that a 47% reduction in the total network demand can result in an increment of 23% in the population exposed to low chlorine ($<0.2 \text{ mg/L}$) and an increment of $5 \mu\text{g/L}$ (1 mg/L applied dosage) in the simulated median THMs in the network (Hatam et al., 2021).

Temperature, DOC, and water age are three factors that influence drinking water quality in distribution networks, and many studies have employed modeling or laboratory analysis to report the individual impacts of these factors on chlorine decay and THM formation. Water supply systems are complex and consist of interrelated elements. In full-scale networks, variations in temperature, DOC, and water demand happen simultaneously with likely synergistic effects. To the best of our knowledge, no study has yet analyzed the combined effect of these variables on water quality in a water distribution network using experimental results. In this study, chlorine and THM concentrations were modeled in a full-scale Canadian DS supplied by surface water. Chlorine and THM models were calibrated using chlorination experimental results. A reliability index (Hatam et al., 2021) was then employed to quantify and compare the performance of the modeled system under different scenarios, with respect to relevant thresholds enforced in the Quebec jurisdiction. Finally, the geographical representation of nodal reliability allowed identifying vulnerable zones at risk of longer periods of chlorine deficiency and THM exceedance from the threshold. No prior study has focused on the relative importance of temperature, DOC, and water demand in a DS while providing visual representation of vulnerable zones. This type of presentation can support the identification of the most suitable remedial measures under conditions of low reliability, ensuring the maintenance of sufficient chlorine levels and avoiding high THM concentrations.

5.2 Methodology

The case study is based on a full-scale network of a municipality located in the province of Quebec, Canada. Source water from a river is treated and fed into the network, serving a population of under 100,000 people. Treated water samples were collected from the WTP before final chlorination in October 2021. The DOC concentration and temperature of the treated water were 1.52 mg/L and 17°C, respectively, at the time of sampling, which was considered representative of the operating conditions of the plant. The overall methodology of this study encompasses six main steps. A brief illustration of the procedure for each step is presented in Figure 5.1, and in-depth explanations of each step can be found in the corresponding sub-section.

5.2.1 Selection of test variable values (T, DOC, demand)

Temperature, DOC, and water demand were selected as test variables for this study. The impact of intense climatic events on DOC levels in treated water cannot be predicted with certainty and can be different for each event, resulting in either no change, a decrease, or an increase. However, it is important to predict the negative impact of “increased” DOC levels on chlorine and THMs in the DS. While the DOC composition may change after a sudden event or under gradual shifts in source water quality, DOC concentration has a more significant effect on THM formation potential (THMFP) than its composition. Seasonal changes in DOC composition in a certain source water were shown to have no impact on THM formation per mg DOC (Valdivia-Garcia et al., 2019). Another study suggested that NOM fractionation provided little benefit in determining THMFP, indicating that DOC concentration, UVA₂₅₄ absorbance, and hydrophobic NOM fraction are strong indicators of correlation with THMFP (Golea et al., 2017). Four DOC levels - a very low DOC of 0.72 mg C/L, the operating DOC for the treated water in the WTP of 1.52 mg C/L, an intermediate DOC of 2.22 mg C/L, and the highest DOC concentration of 3.20 mg C/L (2.1 times the operating DOC) - were selected. These DOC values were selected based on findings that reported a 2.1-fold increase in DOC in burnt watersheds after a megafire in the US (Crandall et al., 2021) and Canadian post-wildfire increases in DOC from 1-2 mg/L to 3-5 mg/L (Sham et al., 2013).

Water temperature variation was monitored throughout the DS over the course of a year, in 2021, and the maximum seasonal temperature values were selected for this study, i.e., 5°C (winter), 25°C (summer), and 17°C (fall). In addition, a higher value of 35°C was used to represent conditions of extreme heat. Such extreme temperature has been reported occasionally in near-by networks in summer and could occur more in future climate. To study the effect of water demand, four daily per-capita demand values were chosen (see Table 5.1): the 2020 annual average demand of 302 liters per capita per day (LCD) in the studied network, a 37% higher demand (418 LCD), and two reduced water demand values corresponding to the 20% reduction target in Quebec (250 LCD) and to a more drastic water conservation target reducing demand by 50% (153 LCD) (Agudelo-Vera et al., 2016). Selected temperature and DOC values determine the chlorine and THM concentrations for the laboratory experiments, while water demand values impact chlorine and THM behavior in the water distribution network by increasing or decreasing the water residence time in the network. Four chlorination tests were conducted under constant

DOC (1.52 mg/L) and variable temperatures (5°C, 17°C, 25°C, and 35°C), and three additional tests were performed under constant temperature (17°C) and variable DOC (0.7 mg/L, 2.2 mg/L, and 3.2 mg/L). Each chlorination test generated distinct coefficients for the chlorine and THM prediction models. After calibrating these models for 7 water conditions, water quality simulations were performed in the water distribution network under the four selected demand scenarios. In total, 28 simulations were conducted to represent the combination of seven water quality conditions and four demand scenarios.

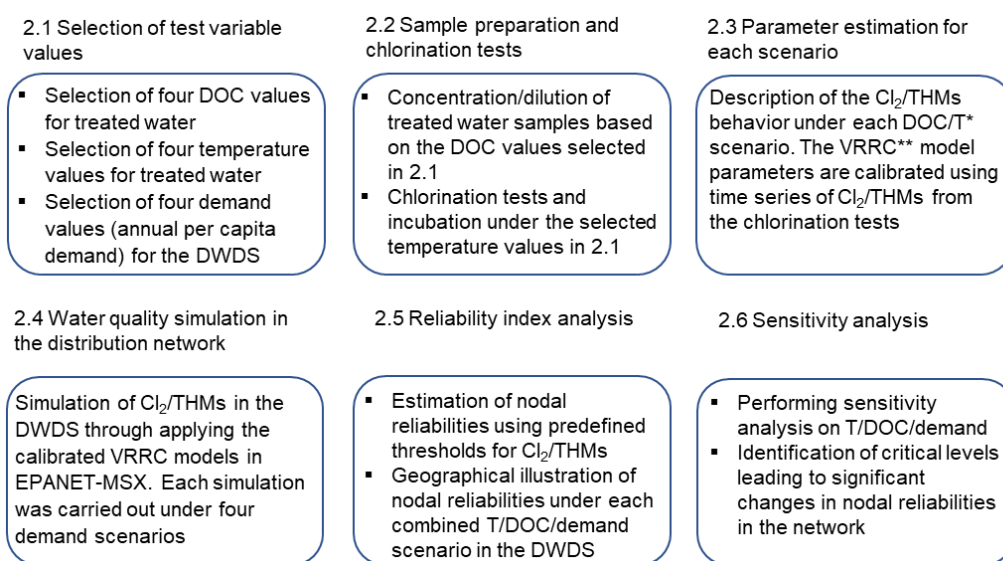


Figure 5.1 Methodological framework for water quality analysis in the distribution network under temperature/DOC/demand scenarios. * T: temperature. ** VRRC: a model with a Variable Reaction Rate Constant

5.2.2 Sample preparation and chlorination tests

Treated water samples were collected from the WTP of the municipality before final chlorination. The treatment chain consists of conventional treatment followed by post-ozonation and chlorination before distribution. Water samples with the four selected DOC levels (Section 5.2.1) were prepared. The lower DOC level was achieved by diluting the collected water samples with Milli-Q water (DOC=20-40 $\mu\text{g C/L}$), while the higher DOC levels were attained by concentrating the samples with a reverse osmosis membrane process (DOW-FILMTEC, USA: membrane BW30-4040, surface: 7.2 m^2).

To ensure that the membrane was free from impurities that could impact the test water DOC, a clean-in-place procedure was performed. First, the membrane was washed for 5 hours with a solution of NaOH (1N) in 30 liters of Milli-Q water, followed by rinsing with demineralized water until the DOC in the concentrate stream matched that of the demineralized water in the feed tank. After cleaning the membrane, feed water was poured into a tank and pumped onto the membrane using a diaphragm Hydra-Cell pump (D10 series, Laval, Canada), and the concentrate stream was recirculated into the feed tank. The process continued until the desired DOC was achieved in the feed tank.

To confirm that there was no DOC loss through the permeate stream and that the DOC matrix of the feed and the concentrate were identical, the permeate, feed, and the concentrate were analyzed with the uniform formation condition test (Summers et al., 1996). This analysis involved diluting the concentrated feed sample (DOC=3.2 mg/L) with Milli-Q water to achieve the same DOC level as the feed sample (DOC=1.52 mg/L). All three samples, including the permeate, feed, and diluted concentrate, were then treated with 3.17 mg/L of chlorine and allowed to rest for 24 hours at a pH of 7.5 and a temperature of 22°C. Finally, the free chlorine demand and the THM formation in both samples were measured and compared. DOC was measured with a Sievers M5310 C online total organic carbon (TOC) analyzer (Boulder, USA).

Chlorine and THM time series were determined through the simulated distribution system test for a duration of 7 days (Rice et al., 2012). For each of the 7 chlorination tests, three different chlorine doses, ranging from 1.5 mg/L to 3.5 mg/L, were applied (resulting in a total of 21 tests) Table B.1 in the Supplementary Material enumerates DOC concentrations, temperature values, and the applied chlorine dosages for each test. Free chlorine concentration was measured with the diethyl-p-phenylene diamine colorimetric method, and THM concentration was measured using gas chromatography (Agilent Technologies 7890B gas chromatograph, Saint-Laurent, QC, Canada). The maximum chlorine demand and THMFP for each tested water sample was also measured under specific conditions described in the standard method (pH= 8 ± 0.2 , temperature= $25\pm2^{\circ}\text{C}$, and a free chlorine residual = 3-5 mg/L after 7 days) (Rice et al., 2012). The results of these tests were then used to calibrate the chlorine/THM prediction models.

5.2.3 Parameter estimation for each scenario

A variable reaction rate constant (VRRC) model for predicting chlorine and THMs has been previously tested and validated in a full-scale network in two seasons (Absalan et al., 2022). The VRCC model was first proposed based on lab-scale experiments to account for the heterogeneity of natural organic matter reactivity with chlorine (Hua et al., 2015). The advantage of this model over other alternative kinetic models (such as 1st-order, parallel 1st-order, and 2nd-order) is the independence of its parameters on chlorine dosage variations and re-chlorination in the DS. Additionally, this model can predict Cl₂/THMs in water containing ammonia precisely without the need for recalibration during the fast and slow reacting phases.

The VRRC model was previously tested and validated with field measurements under seasonal variations in DOC and temperature, with up to 77% precision for chlorine and 91% for THMs (Absalan et al., 2022). The chlorine and THM laboratory assay time series were utilized to calibrate VRRC models for chlorine and THMs specific to each water sample. Parameter estimation involved nonlinear differential equation curve fitting using MATLAB R2019b. More information regarding the fitting and network prediction procedure is provided in Absalan et al. (2022).

5.2.4 Water quality simulation in the distribution network

The EPANET model of the city network includes 1891 junctions and 2500 pipes. The water demand pattern used in the EPANET input file was the hourly production pattern of the WTP (Absalan et al., 2022). Table 5.1 describes each demand scenario, the basis for each scenario, and their corresponding F_G . Water quality simulations were conducted using the EPANET-MATLAB toolkit (Eliades et al., 2016). To run each simulation, an extended period simulation for a duration of 17 days, a hydraulic time step of 1 hour, and a water quality timestep of 5 minutes were employed, and the concentrations of the free chlorine and THMs on the 17th day were reported.

The selection of 17 days was to ensure the stability of water quality conditions in the extremities and dead ends under the lowest demand scenarios. To evaluate all the scenarios with the same criteria, a minimum required residual of 0.2 mg/L was chosen (Walski, 2019b). In practice, there is no minimum regulatory requirement for chlorine residual in the studied network. Regarding THMs, a maximum threshold of 80 µg/L was chosen based on the US EPA surface water treatment

rule (United States Environmental Protection Agency (USEPA), 2010). While this threshold is originally based on the locational annual running average, in this work, it is used as an indication of the maximum allowable THM concentration in the system for individual predictions at all nodes in the DS.

Table 5.1 Demand scenarios for water quality simulations

Demand scenario	Global factor for each scenario	Reference
D1-H H: high	37% higher demand compared to the 2020 daily average ($F_G = 1.37$). Total water demand*: 418 LCD	Municipality's annual average report in 1989
D2-R R: reference	Average day of 2020 ($F_G = 1$). Total water demand: 306 LCD	Municipality's annual report in 2020
D3-L L: low	20% reduction in water demand by the installation of water meters in industrial, commercial, and institutional sectors ($F_G = 0.8$). Total water demand: 250 LCD	Quebec water conservation plan (Horizon 2019-2025) (Ministère du Développement durable, 2018)
D4-VL VL: very low	50% reduction in total water demand based on the Dutch average daily water demand ($F_G = 0.5$). Total water demand: 153 LCD	Dutch average daily water demand (Agudelo-Vera et al., 2016)

* Total water demand is the sum of residential and non-residential demands divided by population.

5.2.5 Reliability index

The nodal reliability index (R) of all network nodes (with nonzero demand) was calculated for all the 28 combined temperature/DOC/demand scenarios. This index has been previously applied by (Hatam et al., 2021) and represents the fraction of time in a day (number of hours out of 24 hours) during which chlorine residual is above 0.2 mg/L and THMs are below 80 µg/L. The value of R ranges from 0 to 100, where 0 signifies that the criterion is not met at any time during the day, and 100 indicates that the criterion is met during the entire 24 hours. An average nodal reliability of 75 means that 75% of the time during the day (18 hours), free chlorine concentration is above 0.2 mg/L, or THM concentration is below 80 µg/L. The geographical distribution of nodal reliability for chlorine and THMs was then plotted using MATLAB.

$$R_{Cl_2} = \begin{cases} 0: Cl_2 < 0.2 \text{ mg/L all day} \\ 100: Cl_2 > 0.2 \text{ mg/L all day} \end{cases} \quad R_{THM} = \begin{cases} 0: THMs > 80 \text{ } \mu\text{g/L all day} \\ 100: THMs < 80 \text{ } \mu\text{g/L all day} \end{cases}$$

5.3 Results and discussion

5.3.1 The combined effect of increase in DOC and reduction in water demand under constant temperature

Figure 5.2 presents the combined effect of the reduction in water demand and the increase in DOC on free chlorine (A) and THMs (B) under a constant temperature of 17°C in all the network nodes with nonzero demand (1799 nodes). The applied chlorine dosage under all simulated scenarios was 2.0 mg/L, which is representative of the average applied dosage in the WTP at the time of the study. In Figure 5.2.A, free chlorine residual was observed to decline in the DS. Under the highest and lowest demand scenarios (D1-H and D4-VL), a 2.5 mg/L increase in DOC (comparing DOC = 3.2 mg/L to DOC = 0.7 mg/L) led to a 70% and 86% decline in the median free chlorine residual in the system, respectively. In Figure 5.2.B, THM concentrations show an increasing trend in the DS. Under the highest and lowest demand scenarios (D1-H and D4-VL), a 2.5-mg/L increase in DOC led to a 298% and 271% increase in the median THM concentration, respectively. THM formation was limited at many nodes as chlorine residuals dropped to zero midway across the DS; otherwise, the THM median concentration would have been expected to increase by more than 271%. This implies that the individual effect of DOC increase on median free chlorine residuals and THMs across the system is intensified under lower water demand. Under constant water demand, increments in DOC resulted in up to 298% increase in THs concentrations whereas under constant DOC, variable water demand led to a 31% increase in median THM concentration across the network. These results suggest that a 63% reduction in water demand (comparing D1-H to D4-VL) is less concerning for THMs in the network than a 2.5 mg/L increase in the DOC concentration of treated water. Regarding free chlorine residuals (Figure 5.2.A), calculated percentage declines did not vary significantly (55-86%) between scenarios of fixed and variable water demand. Hence, both demand reduction and DOC increase are of concern for maintaining safe levels of free chlorine residual concentration in the DS.

The observed difference in the impact of water demand and DOC on THMs compared to chlorine residuals indicates that THM formation is primarily influenced by source water quality factors

(temperature and DOC) rather than the water residence time (RT) in the network. Longer RTs amplify the pipe wall effect and based on the findings, would not significantly affect THM formation within the DS, suggesting that THMs are predominantly dependent on water quality factors. To validate this hypothesis, the chlorine/THM concentrations measured in the simulated distribution system tests in the laboratory (where only bulk effects were considered) were compared to the simulated chlorine/THMs in the DS (where both bulk and wall effects were considered). Under the reference water demand scenario (D2-R), the nodal RTs in the network ranged from 16 h to 169 h, with 96% of the nodes having $RT \leq 50$ h. At $RT = 50$ h, the bulk chlorine demand determined in the laboratory was 1.12 mg/L, whereas the average daily nodal chlorine demand in the network for nodes with $RT \cong 50$ h was between 1.8-1.9 mg/L. This showed that the pipe wall effect in the network was responsible for up to 39% of the total chlorine decay in the system. The THM concentration under the bulk decay effect measured in the laboratory was 47 $\mu\text{g/L}$ at $RT = 50$ h, and the average daily nodal THMs in the DS were between 50-52 $\mu\text{g/L}$ for the nodes with $RT \cong 50$ h. This suggests that the network wall effect increased the THM formation by only 7.5%. A similar result has been reported where THM concentrations in the field were successfully predicted using laboratory-based experiments and bulk decay effects, thus highlighting the limited effect of pipe walls on THM formation (Absalan et al., 2022).

Under the 20% water demand reduction scenario (D3-L) and at $\text{DOC} = 2.2$ mg/L (Figure 5.2.B), some of the nodal THMs began to exceed the 80 $\mu\text{g/L}$ reference threshold. Depending on how long this condition persists, it could potentially lead to regulatory non-compliance for THMs. A further increase in DOC or a further decreasing demand would increase the number of these nodes and the extent of THM exceedance from the threshold. At $\text{DOC} = 3.2$ mg/L, the THM reference threshold was exceeded under all water demand scenarios, suggesting the need for additional DOC removal before chlorination, especially under lower water demand conditions.

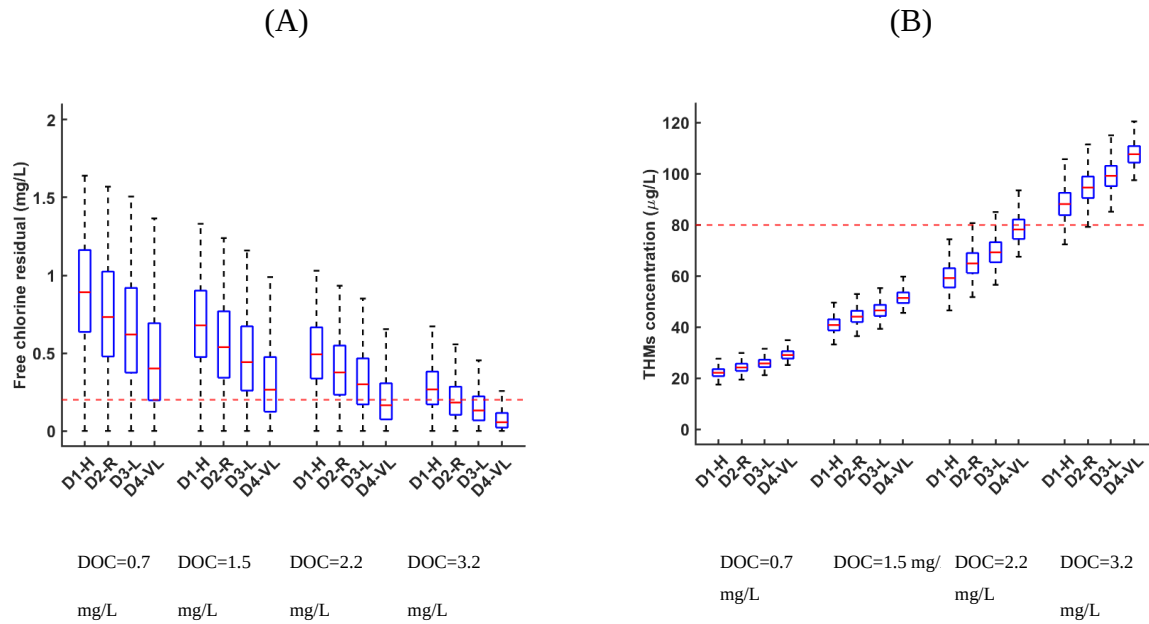


Figure 5.2 Combined effect of DOC and water demand reduction on nodal free chlorine residuals (A) and THM concentrations (B) in the DS under constant temperature (17°C). D1-H represents $F_G=1.37$; D2-R represents $F_G=1$ (reference scenario); D3-L represents $F_G=0.8$ (low demand); and D4-VL represents $F_G=0.5$ (very low demand). The applied dosage was 2 mg/L in all tested scenarios. Boxplots represent the free chlorine and THM concentrations in all the nodes for 24 hours. Whiskers represent the minimum and maximum chlorine/THM concentrations in the DS. Boxes represent the 25% percentile, median, and 75% percentile.

5.3.2 The combined effect of water warming and reduction in water demand under constant DOC

Under constant DOC (1.5 mg/L), the combined effect of water warming and water demand reduction on free chlorine residual and THMs in all the nodes with nonzero demand (1799 nodes) is presented in Figure 5.3 (A and B). Under the highest water demand scenario (D1-H), increasing the temperature from 5°C to 35°C caused a 56% decrease in the median free chlorine residual and a 194% increase in the median THM concentration in the system. Under the lowest water demand scenario (D4-VL), the same increase in temperature led to a 65% reduction in the median free chlorine residual and a 204% increase in median THM concentration in the system. At the lowest temperature scenario (5°C), a 62% decrease in median free chlorine residual and a 14% increase in median THMs in the system were observed after a 63% water demand reduction from D1-H to

D4-VL. At the extreme warming scenario (35°C), the same reduction in water demand led to a 71% decrease in median free chlorine residual and a 17% increase in median THMs in the system. These observations reveal that: (1) the impact of warming on chlorine/THMs is intensified under lower water demand scenarios, and the impact of reduction in water demand on chlorine/THMs becomes more severe at higher temperatures; (2) reduction in water demand exhibits a more intense impact on nodal chlorine than nodal THMs; (3) warming impacts nodal THMs (maximum 204% increase under lowest water demand level) more severely than nodal chlorine residuals (maximum 65% decrease under lowest water demand level). At the average operating DOC of the tested water (1.5 mg/L), up to 25°C warming did not cause THM concentrations to go above 80 µg/L, even at the lowest water demand scenario. Water-saving plans would thrive at the operating DOC level since THM concentrations exceedance remain below the threshold even at the highest summer temperature. However, under the extreme warming scenario (water temperature=35°C), THM concentrations were above the reference threshold of 80 µg/L under all water demand scenarios.

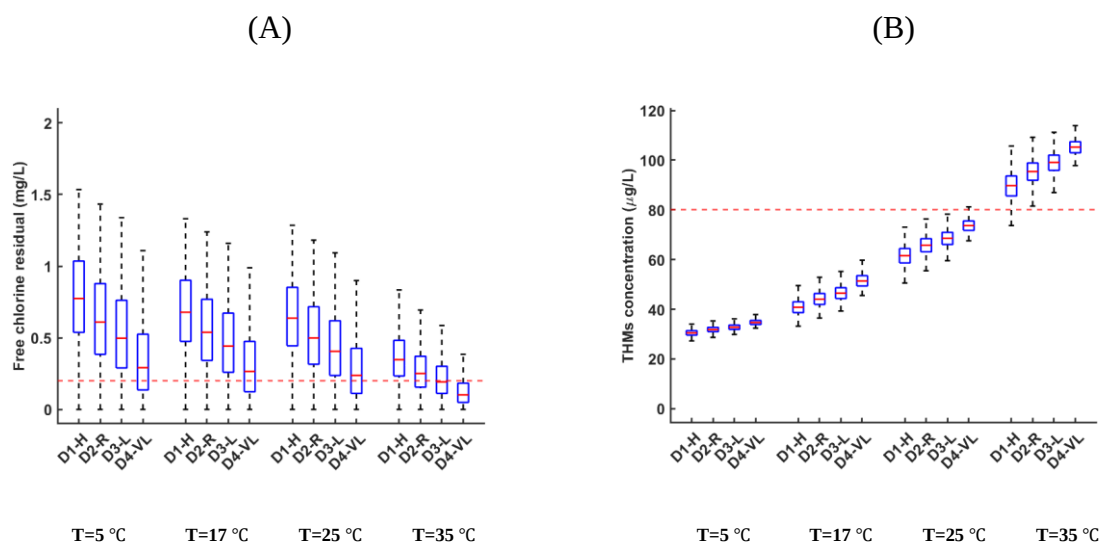


Figure 5.3 Combined effect of water warming and water demand reduction on nodal free chlorine residuals (A) and THM concentrations (B) in the DS under constant DOC=1.5 mg/L. D1-H represents $F_G=1.37$; D2-R represents $F_G=1$ (reference scenario); D3-L represents $F_G=0.8$ (low demand); and D4-VL represents $F_G=0.5$ (very low demand). The applied dosage was 2 mg/L in all tested scenarios. Boxplots represent the free chlorine and THM concentrations in all the nodes for 24 hours. The whiskers represent the minimum and maximum values, and the boxes represent the 25% percentile, median, and 75% percentile.

5.3.3 Reliability index

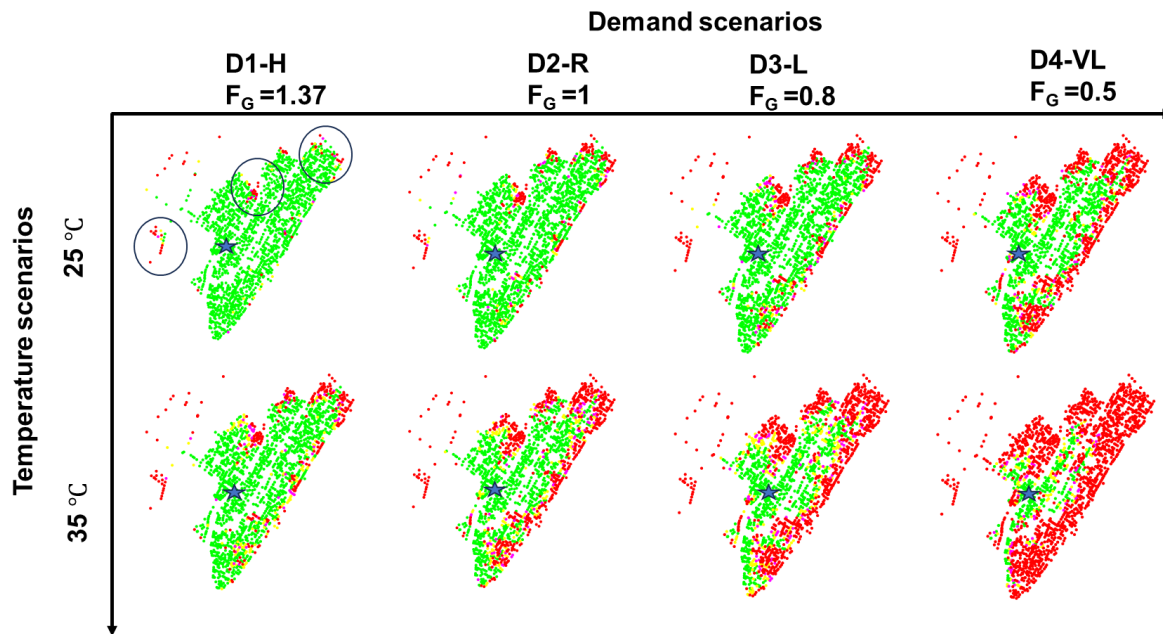
Figure 5.4 depicts the combined effect of the reduction in water demand and water warming on nodal reliability index R for free chlorine residuals (R_{Cl_2} , Figure 5.4.A) and THMs (R_{THM} , Figure 5.4.B) under constant $DOC=1.52$ mg/L. Only results at 25°C and 35°C are presented, and the results at 5°C and 17°C are presented in the Supplementary Material (Figure B.1).

The nodal R_{Cl_2} gradually decreased with increasing temperature, starting from the extremities and dead ends (with the highest residence time) to the water treatment plant (with the lowest residence time). Under the highest demand scenario (D1-H), the percentage of nodes with $R_{Cl_2}=100$ decreased from 96% at $T=5^\circ\text{C}$ to 75% at $T=35^\circ\text{C}$. Under the warmest scenario (temperature= 35°C), reducing the demand from the D1-H to D4-VL reduced the percentage of nodes with $R_{Cl_2}=100$ from 75% to 16%. R_{THM} was 100 under all demand scenarios at 5°C and 17°C across the network. At $T=25^\circ\text{C}$, R_{THM} decreased to 0 in a few nodes at the extremities, while most of the nodes still had $R_{THM}=100$. At $T=25^\circ\text{C}$, $R_{THM}=100$ was still reported for 98.5% of the network nodes even under the lowest water demand scenario (D4-VL). At $T=35^\circ\text{C}$, the nodal R_{THM} decreased dramatically, and the percentage of the nodes with $R_{THM}=100$ was computed as 0.1%, suggesting potential widespread exceedance of the 80 $\mu\text{g/L}$ reference value across the network. This was also true under the 2020 average annual water demand in the municipality (D2-R).

Figure 5.5 shows the combined effect of an increase in DOC and a reduction in water demand on nodal R_{Cl_2} (A) and R_{THM} (B) under constant temperature (17°C). Only results at $DOC=2.2$ mg/L and 3.2 mg/L are presented, and the results at $DOC=0.7$ mg/L and 1.5 mg/L are presented in the Supplementary Material (Figure B.2). Under the highest demand scenario (D1-H, $FG=1.37$), by increasing the DOC from 0.7 mg/L to 3.2 mg/L, the percentage of the nodes with $R_{Cl_2}=100$ decreased from 98% to 57%. At the highest tested DOC (3.2 mg/L), decreasing the water demand from $FG=1.37$ to $FG=0.5$ (D1-H to D4-VL) led to a decline in the percentage of the nodes with $R_{Cl_2}=100$ to 4.2%. The nodal R_{THM} was 100 under all water demand scenarios at $DOC=0.7$ mg/L and 1.52 mg/L. At $DOC=3.2$ mg/L and across the water demand scenarios, the percentage of the nodes with $R_{THM}=100$ decreased to 0.1% ($\sim 0\%$), indicating widespread nonreliability and greater than 80 $\mu\text{g/L}$ THM concentrations across the entire network.

Overall, the shift in the nodal R_{THM} was more abrupt compared to that of R_{Cl_2} . At the highest tested temperature (35°C), reference demand (D2-R, $F_G=1$), and DOC (1.52 mg/L), while the R_{THM} was 0 in the entire network, R_{Cl_2} remained at 100 in 54% of the network nodes. At the highest tested DOC (3.2 mg/L), reference demand (D2-R, $F_G=1$), and temperature=17°C, while the R_{THM} was 0 across the network, R_{Cl_2} remained at 100 in 36% of the network nodes. The geographical illustration of nodal reliabilities serves several purposes, including the: (1) identification of more vulnerable areas in the system to help target corrective actions;(2) identification of the most strategic sites for re-chlorination stations to ensure sufficient chlorine coverage; (3) improvement of site selection for regulatory THM monitoring at critical locations; (4) knowledge of the scope of water quality issues based on the R-index value and the number of nodes with low R-index under different scenarios.

A: chlorine reliability



B: THM reliability

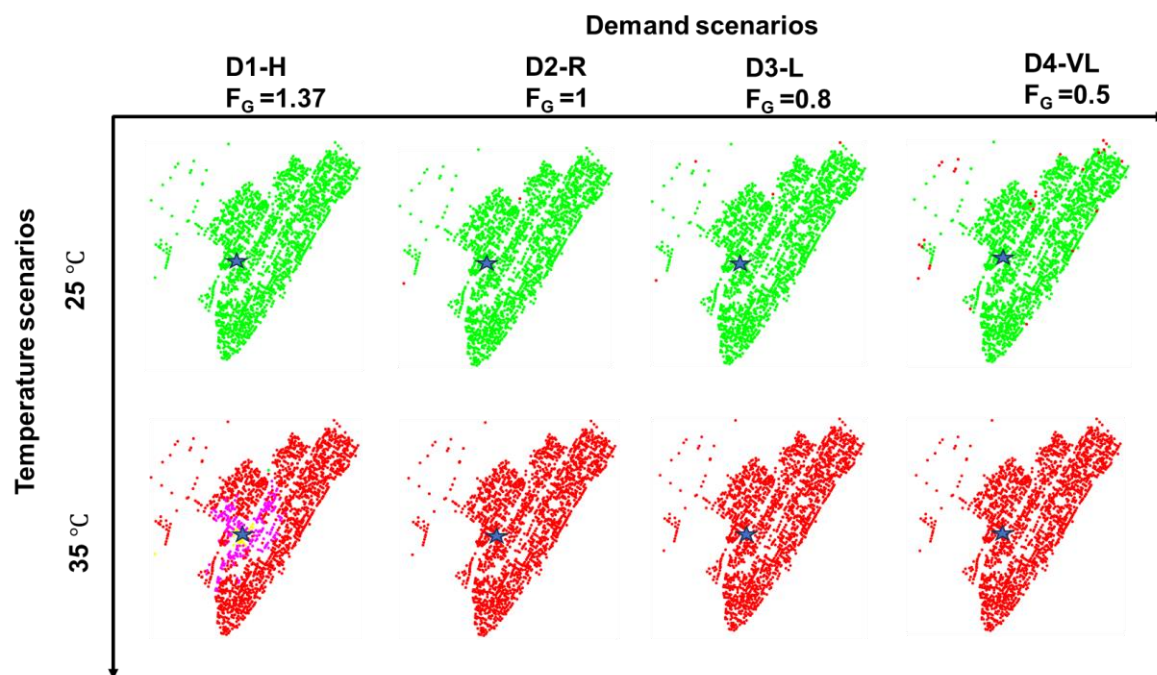
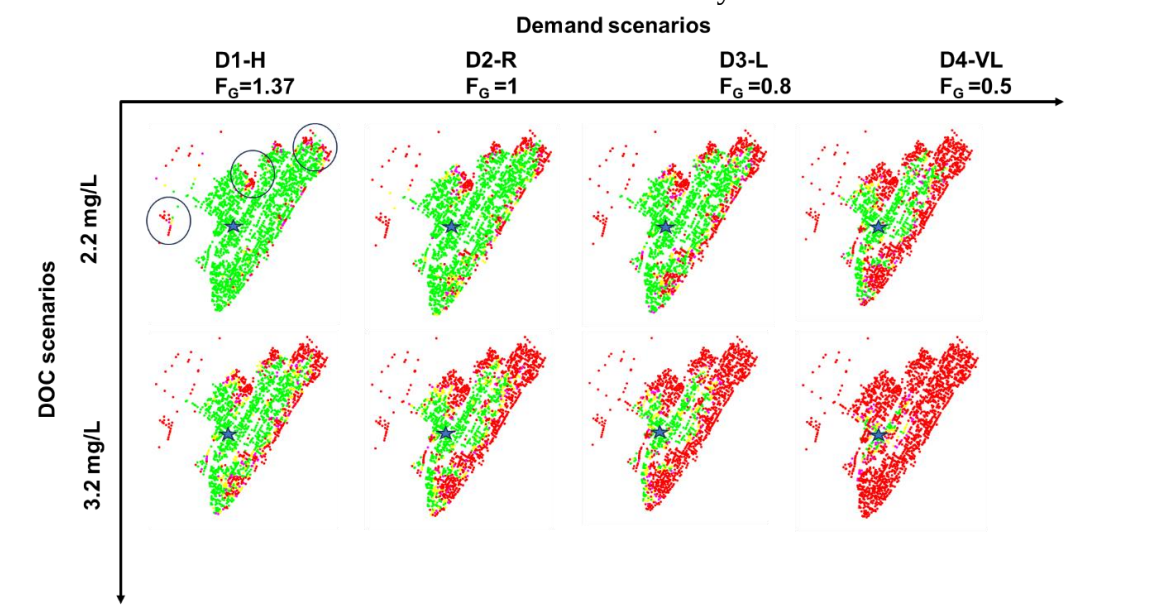


Figure 5.4 The combined effect of water warming and reduction in water demand on (A) chlorine and (B) THM reliability in the network under constant DOC (1.5 mg/L). Green nodes, R=100; yellow, R=75; purple, R=25; and red, R=0. The WTP is indicated with a star on all the maps. A sample of extremities and dead ends in the DS is also demonstrated in the upper left map in part A.

A: chlorine reliability



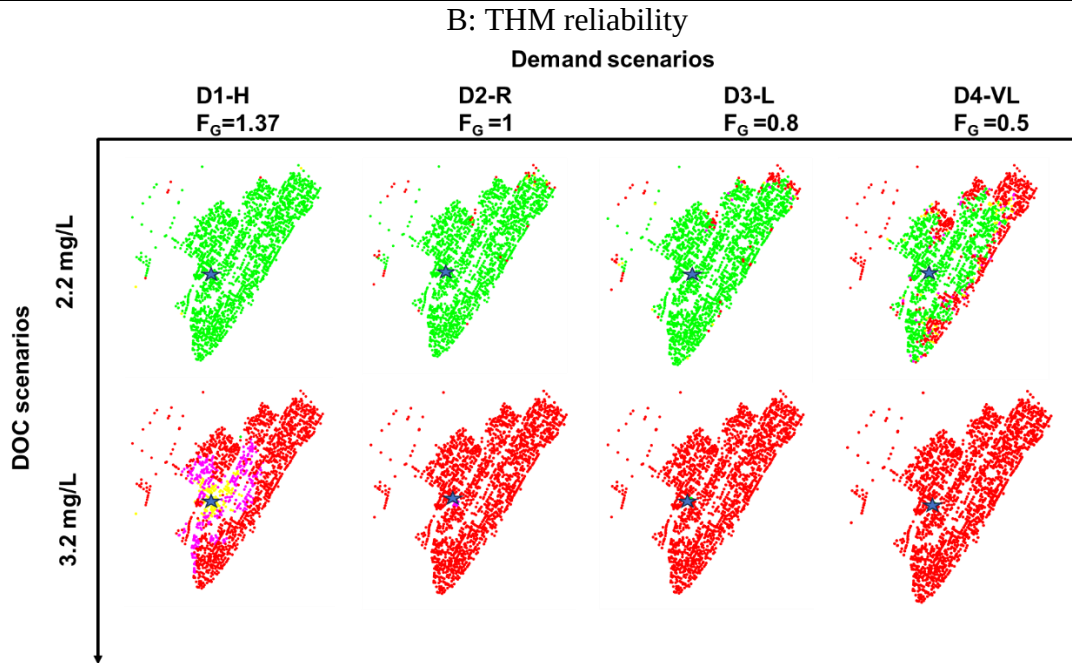


Figure 5.5 The combined effect of increased DOC and reduction in water demand on (A) chlorine A) and (B) THM reliability in the network under constant temperature (17°C). Green nodes, $R=100$; yellow, $R=75$; purple, $R=25$; and red, $R=0$. The WTP is indicated with a star on all the maps. A sample of extremities and dead ends in the DS is also demonstrated in the upper left map in part A.

5.3.4 Sensitivity analysis

A sensitivity analysis was performed to evaluate the impact of each variable (temperature, DOC, demand) on the overall performance of the network (Figure 5.6). The overall performance is presented as a percentage of the nodes with $R=100$ (%R100). The baseline scenario used in this analysis was the normal operating conditions at the WTP at the time of study (temperature=17°C, DOC=1.52 mg/L, and $F_G=1$). To evaluate the individual impact of each variable, one variable was modified, while the two others were held constant. Under constant DOC and water demand, increasing the water temperature from 5°C to 35°C causes a 36% reduction in %R100 for chlorine and a 100% reduction in %R100 for THMs. Under constant water temperature and water demand, a 2.5 mg/L increase in DOC led to a 58% and 100% reduction in %R100 for chlorine and THMs, respectively. Under constant water temperature and DOC, a 63% reduction in the water demand caused a 40% decline in %R100 for chlorine but no reduction in THMs. Overall, water warming,

reduction in water demand, and increased DOC all have a significant impact on R_{Cl_2} , while R_{THM} is more pronouncedly influenced by DOC and water temperature than by water demand.

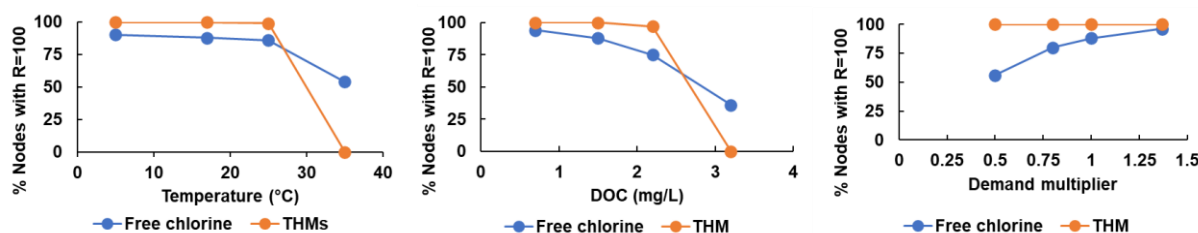


Figure 5.6 Sensitivity analysis for three independent variables (temperature, DOC, and water demand) to determine the percentage of the nodes with reliability (R)=100.

Consequence of increasing the chlorine dosage

One of the solutions to prolong chlorine availability in the DS is to increase the applied chlorine dosage in the WTP. While this measure can resolve the issue of low chlorine residual in the system, it increases the THM concentration. To demonstrate this, an applied chlorine dosage of 3 mg/L was tested in some of the most critical scenarios described in Sections 3.1 - 3.3. These scenarios reported the lowest chlorine and THM reliabilities at an applied chlorine dosage of 2 mg/L.

The impact of increased chlorine dosage on the percentage of nodes with $R=100$ (%R100) are reported in Table 5.2. Under the highest annual summer temperature (25°C), DOC (1.52 mg/L), average annual water demand ($D2-R$, $F_G = 1$), and an applied chlorine dosage of 2 mg/L, 86% of the nodes met the reliability criterion 100% of the time (24h/day) for chlorine and 99% of the nodes met the R100 criterion for THMs. Increasing the dosage from 2 to 3 mg/L under the same conditions would increase the %R100 for chlorine by 8%; however, for THMs, it would cause a 62% decline in %R100.

%R100 for chlorine showed 44-82% improvement across all other tested scenarios when the chlorine dosage was increased to 3 mg/L. THM reliability is not listed for all but one scenario in the table, as for all the other reported conditions, the %R100 for THMs were zero at an applied chlorine dosage of 2 mg/L. It is realistically expected that increasing the chlorine dosage will only worsen the THM reliability. These findings call into question the efficacy of increasing initial

chlorine dosage to respond to probable future operating conditions and preserve water quality in the distribution network.

Table 5.2 Impact of increased applied chlorine dosage from 2 mg/L to 3 mg/L on %R100 (percentage of nodes with reliability=100).

T (°C)	DOC (mg/L)	F _G	Species	Dose=2 mg/L	Dose=3 mg/L
%R100					
25	1.52	1	Chlorine	86	94
25	1.52	1	THMs	99	37
35	1.52	1	Chlorine	54	99
35	1.52	0.8	Chlorine	38	99
35	1.52	0.5	Chlorine	16	98
17	3.20	1	Chlorine	36	85
17	3.20	0.8	Chlorine	22	74
17	3.20	0.5	Chlorine	4	48

5.4 Relevance to the water industry

Chlorine stability and THM formation are strongly impacted by water temperature, DBP precursors (like DOC), and water demand, all of which can potentially worsen due to either climatic change (resulting in higher water temperatures and increased NOM) and/or initiatives to conserve water (increasing water age). This study revealed that the correlation between the studied variables (water temperature, DOC, and water demand) and chlorine and THM concentrations was highly nonlinear and led to abrupt spatial changes within the DS. The network reliability results showed that there is a site-specific threshold for DOC and temperature, which leads to a significant system-wide reduction in reliability, especially for THMs. Therefore, it would be useful for each water supply system to identify such thresholds under a range of scenarios to prepare for the trickling effects of climate change. Furthermore, water conservation plays a significant role in aggravating the impact of increased DOC and temperature on the DS, especially in terms of chlorine stability. Testing potential water management strategies (including demand management and modifications to the network) using the proposed approach in this research seems critical to support the necessary decisions to be made at the municipal level towards climate adaptation.

The US EPA Climate Change Adaptation Resource Center has recommended a set of alternative actions to assist communities increase their climate resilience (United States Environmental

Protection Agency (USEPA), 2023). These recommendations include, but are not limited to, diversifying water sources, modifying industrial and agricultural demand, and reducing residential water demand, all of which will likely decrease urban water demand and could ultimately lead to insufficient disinfectant residual in the DS (United States Environmental Protection Agency (USEPA), 2023). One of the major concerns regarding insufficient free chlorine residual is the resulting growth and proliferation of opportunistic pathogens in the network and in premise plumbing inside buildings (Donohue, 2021). The trade-off between maintaining sufficient chlorine residual for microbial safety and avoiding the formation of DBPs requires an optimal minimization of chlorine dosage (Zhang and Lu, 2021). This could however become more challenging under future scenarios of higher DOC and temperature levels. As tested in this study, conditions of extreme heat (e.g., leading to water temperature up to 35°C in the network) and other intense climatic events (like forest fires or intense precipitation) raising DOC levels in source water up to 3.2 mg/L (or more) could occur simultaneously, especially during the summer period, and cause a widespread chlorine deficiency below 0.2 mg/L and THM concentrations greater than 80 µg/L. This would not necessarily lead to noncompliance for THMs, as compliance is based on a yearly moving average in Canada and the United States. In cold climate regions (like the case study site), low levels of THMs, typically measured throughout the winter months, can lead to relatively low annual average values despite the high potential THM values that could be expected during the summer months. Further investigation would be helpful to better understand the potential impact of such high (seasonal) THM values at a given location on the aesthetic quality of water, which could lead to customer complaints, as well as the potential health risks associated with THM exposure (Hrudey, 2009). One possible solution would be to control the drinking water temperature which could be indirectly accomplished by increasing vegetation coverage in cities (reducing impervious surfaces). Plant transpiration and evaporation are known to induce a cooling effect on the soil surface and subsurface temperatures (Alexander, 2021; Zhou et al., 2017). Hence, urban greening could potentially be considered as a remedial action towards mitigating the rise in drinking water temperature in the DS under a warming climate. More research is necessary to confirm the effectiveness of urban greening on the improvement of drinking water quality.

Currently, the most prominent strategies to maintain disinfectant residual and control DBPs in chlorinated DS is to employ monochloramine or apply a stricter treatment to control the DOC levels in treated water (Vikesland et al., 2001). While there are no enforceable maximum contaminant

levels for TOC in drinking water across jurisdictions, the USEPA Surface Water Treatment Rules requires water facilities with source water TOC greater than 2 mg/L to explore several treatment options to reduce their TOC concentrations (United States Environmental Protection Agency (USEPA), 1999). The required TOC removal percentage varies based on the source water TOC and alkalinity levels (United States Environmental Protection Agency (USEPA), 1999). In the context of the challenge posed by highly persistent per- and polyfluoroalkyl substances (PFAS) in water supplies (which has recently urged many governments to consider developing PFAS regulations), advanced treatment processes such as granular activated carbon (Belkouteb et al., 2020), nanofiltration/reverse osmosis (Liu et al., 2022a), or ion-exchange resins (Zhang et al., 2019) are expected to be increasingly included in WTPs to control PFAS, with the side benefit to achieve greater DOC removal and reduce THMFP.

In addressing the water crisis under global change, water demand reduction is necessary, notably under the current conditions of high-water consumption rates reported in North America (as compared to elsewhere) (Adamowski et al., 2012). Yet such water conservation measures are shown to have a significant impact on free chlorine residuals, particularly under higher water temperature scenarios. The predictive analytic tool proposed in this article can assist water managers to identify vulnerable areas in their network, which can then be subjected to surveillance and corrective actions such as real-time monitoring of water pressure and flow, pressure regulation to avoid stagnation, flushing programs to reject stagnant water and induce circulation (Avvedimento et al., 2020), optimal placement for re-chlorination stations in the network, and development of more strategic water quality monitoring programs, especially during warm seasons. Finally, in some cases, it may be possible to redesign existing DSs to incorporate self-cleaning features (Agudelo-Vera et al., 2016). However, the feasibility and cost-effectiveness of this strategy depends on various factors (for example, age, size, design features, and system constraints) as well as the potential benefits and costs of the proposed changes.

5.5 Conclusion

Predicting the evolution of drinking water quality under global change is essential for climate adaptation in water supply systems. For the studied variables in this study, an increase in temperature, DOC and residence time in the network (due to demand reduction), which could all potentially occur simultaneously in future scenarios, will have an exacerbated impact on chlorine

and THM deviances from acceptable thresholds, as compared to the individual impact of each variable. For THMs, changes in drinking water quality (namely, temperature and DOC) are more critical compared to the changes in water residence time in the network. For free chlorine residuals, both changes in water quality and water demand had significant impacts. Therefore, for a more realistic prediction of future water quality challenges and given the projected lower water demands, it is recommendable to investigate the synergetic effects of different potential combinations of these variables for a given DS. In addition, disinfectant monitoring in the distribution network should be emphasized in water quality management strategies under changing operating conditions.

The proposed analytical approach in this study can be beneficial to drinking water utilities in the identification of critical site-specific thresholds. These thresholds can help in determining possible action levels to prevent or mitigate microbial safety issues or regulatory noncompliance and can improve preparedness and response time under adverse situations. To enhance microbial safety and reduce DBP precursors, preventive actions could be taken at different levels, from source to tap. At the source level, source protection plans should be put in place to control the introduction of microbial contaminants and DBP precursors into the system; yet the scope of such preventing actions is often beyond the power of utilities alone and requires coordination among several actors. At the treatment level, employing advanced treatment processes could reduce DBP precursors and increase disinfectant availability. At the distribution level, reliability maps showed that the distribution of low reliability nodes for chlorine and THMs are not the same and in some scenarios where chlorine nodal reliability was 100, THM reliability was 0, and conversely. Therefore, the use of reliability maps can assist in identifying the optimized location of chlorine boosting stations and improving the selection of regulatory monitoring points, particularly for THMs.

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Conflict of interest declaration

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

CHAPTER 6 ARTICLE 3 – IMPACT OF HEAT ISLANDS VS. CITY GREENING: REAL-TIME MONITORING AND MODELING OF DRINKING WATER TEMPERATURE IN THE CITY OF MONTREAL IN CANADA

This chapter delves into a crucial and often poorly understood question: Does the presence of urban heat islands impact water temperature in our water distribution networks? And if so, can this issue be mitigated by increasing green spaces within the city? To tackle these significant inquiries, we conducted water temperature monitoring in the city of Montreal, specifically in two distinct areas: the heat island-affected zone and the vegetation-impacted zone. For the first time, we introduced an innovative approach to model and predict local drinking water temperature in urban settings, utilizing meteorological data in combination with satellite imagery. The results of this research shed light on a pivotal issue: water temperature disparities. Our findings reveal that urbanization and the formation of heat islands can indeed influence drinking water temperatures, even within deeply buried pipes in Canada, reaching depths of at least 1.8 meters. The excessive heating, with recorded temperatures soaring up to 32°C, carries potential implications for water quality management within the distribution system, necessitating further investigation. Fortunately, our results also demonstrate that this issue can be addressed by increasing the presence of trees, shrubs, and green spaces within urban environments. This article was submitted to the Journal of Water Research on November 14th, 2023. The supplementary materials are provided in Appendix C.

IMPACT OF HEAT ISLANDS VS. CITY GREENING: REAL-TIME MONITORING AND MODELING OF DRINKING WATER TEMPERATURE IN THE CITY OF MONTREAL IN CANADA

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Abstract

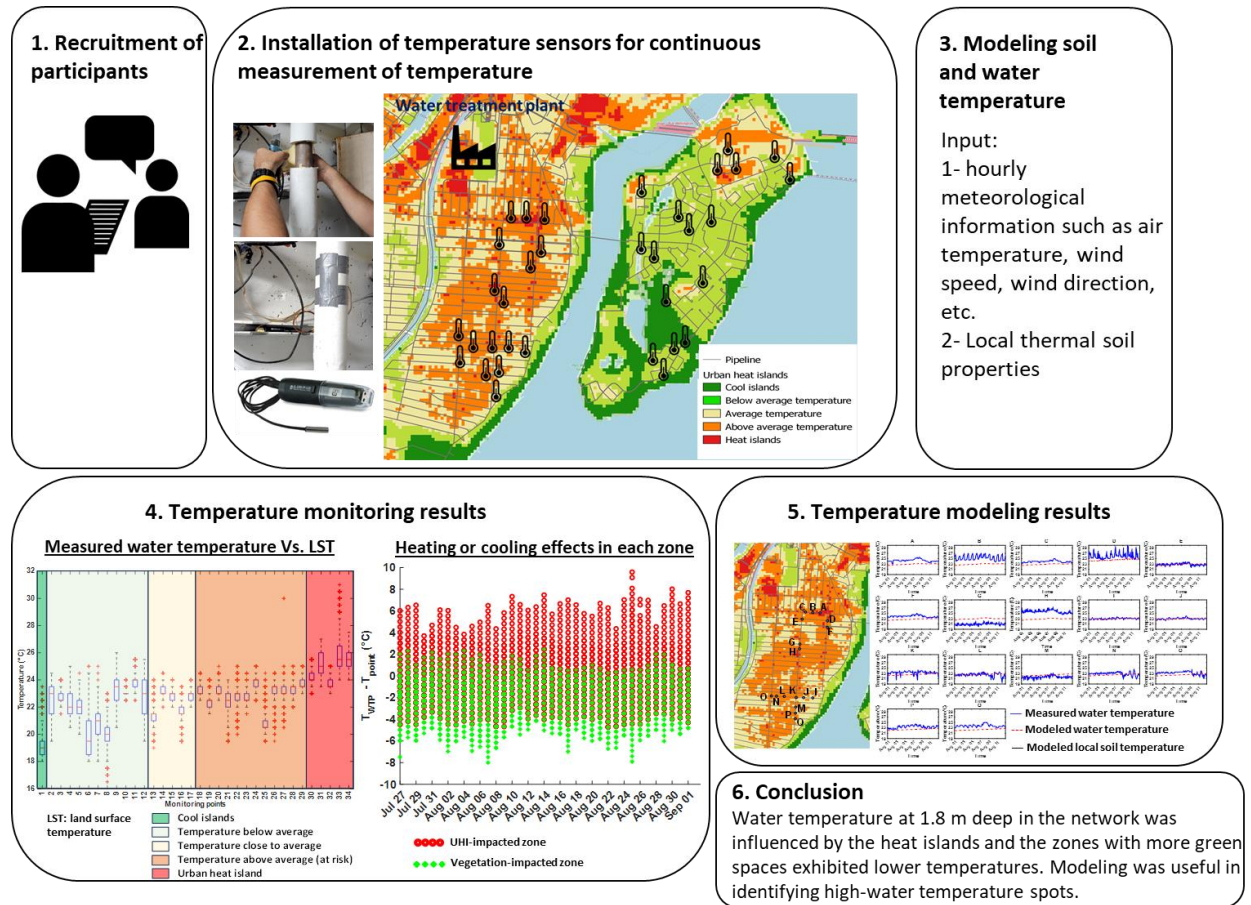
Urbanization increases the land surface temperature through surface mineralization, adversely affecting vegetation and enhancing the urban heat island (UHI) effect. Global climate change has intensified this warming effect with more frequent and intense heatwaves during hot seasons. While these transformations influence soil temperature, their consequences on drinking water temperature within the drinking water distribution system (DWDS) remains poorly understood. Literature proposes to increase pipe burial depths to mitigate drinking water heating during summer. In this study, we monitored drinking water temperatures in a DWDS in Montreal, Canada with deeply buried pipes (average 1.8 m) during the summer of 2022, focusing on two contrasting zones in terms of UHI and green coverage. Monitoring revealed an 8°C heating effect compared to the water treatment plant, attributed to low green coverage and anthropogenic heat. Conversely, the greener zone exhibited cooler drinking water temperatures, reaching a maximum cooling effect of 8°C as compared to the temperature at the exit of the water treatment plant. Utilizing a soil and water temperature model, we predicted drinking water temperatures within the DWDS with acceptable accuracy. Soil temperature modeling results aligned well with measured water temperatures, highlighting DWDS water temperature approaching its surrounding soil temperature fairly quickly. Despite heatwaves, no immediate correlation emerged between air temperature records and measured water temperatures, emphasizing soil temperature as a superior indicator. An increase in water age displayed no correlation with an increase in measured water temperature, underscoring the dominant influence of UHI and green coverage on water temperature. These findings highlight the cooling advantages of green spaces during summer, providing valuable insights for sustainable urban planning.

KEYWORDS: *Global warming, urban heat island, urban greening, drinking water temperature, temperature modeling, water distribution network*

Highlights

- UHIs increase drinking water temperature, even in deeply buried pipes (depth:1.8 m).
- City greening can moderate drinking water temperature during hot periods.
- Up to 8°C heating in UHIs and 8°C cooling in green areas were observed.
- Soil (rather than air) temperature can be used as an indicator of temperature in DWDS.
- Increased water age does not provoke increased temperature in the DWDS.

Graphical abstract



6.1 Introduction

Urbanization is replacing natural land coverage with impervious surfaces, causing reduced evapotranspiration, increased heat capacity of the land surface and increased land surface temperature (LST) (Ranagalage et al., 2019; Wang et al., 2022). Elevated LSTs in cities due to natural global warming, urbanization, vegetation loss, and anthropogenic heat cause irregularities in urban energy balance and leads to creation of UHIs, increasing the local air, soil surface, and soil subsurface temperature (Estrada-Calderon and Becerra-Santacruz, 2022; Menberg et al., 2013). Alexander (2021) found that increasing the building heights and decreasing the vegetation height can increase the LST in cities. Zhu et al. (2021) studied the cooling effect of urban parks in Jinan, China, using Landsat 8 images and showed that the urban parks' LST is on average 3.6°C lower than its surrounding, with the most significant cooling effect of 7.8°C during summer days.

Kafy et al. (2022) found a significant correlation between the vegetation loss and LST in the fast-growing city of Cumilla in Bangladesh. In 25 years, the city lost 9% of its vegetation cover due to urbanization, leading to a 11-°C increase in its average LST. Edan et al. (2021) studied the impact of land use/land cover change on LST from 2000 to 2020 in Al Kut, Iraq, using remote sensing techniques: they found that a 8.7% increase in urban areas and 25.8% decrease in green cover led to an average increment in the maximum LST by 3.79°C and 3.16°C in summer and winter, respectively. Smith et al. (2023) studied the effectiveness of albedo manipulation and urban greening on LST in seven cities in the United States. They found on average 0.18°C cooling per % albedo increase, 0.09°C cooling per % tree coverage, and 0.02°C cooling effect per % grass cover. Menberg et al. (2013) monitored groundwater temperature in shallow subsurface areas in six German cities and found 3-7°C regional differences between the urban and rural areas. In the province of Quebec, Canada like many other regions in the world, the climate trends are showing increased number of hot days ($T > 30^{\circ}\text{C}$) and an increase in the number and duration of heatwaves (Leveque et al., 2021). This will in turn increase the soil surface and subsurface temperature during summer. Since some of the city's infrastructure, notably the DWDS, is buried underground, creation of UHIs could potentially affect the drinking water temperature in the pipes.

Physical, chemical, and biological processes in the DWDS are greatly impacted by water temperature. (Kimbrough, 2019) studied the impact of the increasing air temperature on drinking water (supplied from surface waters) temperature and quality in four DWDS in Pasadena, United States, from 2001 to 2016. They found that a 1.6-°C increase in median nighttime temperature led to a 0.8 to 1.4-°C increase in median drinking water temperature, a significant decrease in disinfectant (chloramine) residual and a significant increase in nitrite concentrations (due to ammonia-oxidizing bacteria activity). Increased temperature also increases the rate of chlorine decay and disinfection by-products formation (Lai and Dzombak, 2021). While many countries such as Canada, United States, France, and UK monitor water temperature during their regulatory water quality monitoring programs, the Netherlands and Czech Republic have regulated drinking water temperature in the DWDS (Agudelo-Vera et al., 2020). (Blokker and Pieterse-Quirijns, 2013) used a micrometeorology model, and (Agudelo-Vera et al., 2015) incorporated anthropogenic heat sources into the model, to predict soil temperature using meteorological information. Comparing the soil temperature modeling results with drinking water temperature measurements in a Dutch DWDS revealed that drinking water temperature at the average depth of 1 meter reaches its

surrounding soil temperature. They reported that the drinking water temperature in several sampling points exceeded its regulatory threshold of 25°C in a relatively warm year. Considering the increasing trends in global air temperature, they expected this trend to be amplified in the future (Blokkeer and Pieterse-Quirijns, 2013).

While several studies have reported the impacts of UHI and green spaces on soil surface and subsurface temperature, their impact on drinking water temperature within the DWDS is not well understood. In a cold climate region such as Canada with water pipes buried at least 1.8 meters deep (to avoid freezing), it could be expected that the water temperature would not be impacted by the UHI effect. In this work, for the first time, we use a combined data-driven and model-driven approach to assess the impact of UHI and vegetation on drinking water temperature in a full scale DWDS. The case study is the city of Montreal (Quebec, Canada), with deeply buried pipes, and the study is carried out during summer (heatwaves) 2022. We continuously monitor water temperature in two full-scale sectors in Montreal DWDS – namely the ‘vegetation-impacted zone’ and the ‘UHI-impacted zone’– for 2.5 months. The water temperatures in these two contrasting zones will be compared to investigate the impact of UHI on deeply buried pipes and will shed light on the effectiveness of city greening (vegetation increase) for moderating water temperature in DWDS during hot periods. It also evaluates the effectiveness of deeper pipe burial as a mitigative measure to solve the problem of water warming. Finally, we adapt and evaluate the water temperature model by Blokkeer and Pieterse-Quirijns (2013) to our case study.

6.2 Methodology

The study consists of four main steps, namely: (i) the site selection for field data collection, (ii) temperature monitoring in the DWDS, (iii) soil temperature modeling, and (iv) drinking water temperature modeling including validation.

6.2.1 Study site selection for field data collection

For the temperature monitoring campaign, two study sites with contrasting land surface temperature and green coverage were selected. To select these two zones, the Landsat 8 images, classifying soil temperature into five distinct classes, were studied in combination with the green spaces map of Montreal using the QGIS 3.26.2 software. To ensure consistency in our results, we compared three Landsat 8 maps from the years 2013, 2016, and 2019, all with a resolution of 30m

x 30m. Our objective was to confirm that there were no significant differences among these maps that could influence the choice of the study area (Donneesquebec, 2019). Finally, the 2019 map which was captured on June 9th, 2019, between 15:30 and 16:30 was selected (shown in Figure 1.A). In this figure, the soil surface temperature is classified into five distinct classes. Class 1 is the cool islands, class 2 is the below average temperature zones, class 3 is the average temperature zones, class 4 is the above average zones, and class 5 is the heat islands. The zone on the left, the UHI-impacted zone, has a higher density of buildings and concrete/paved surfaces and a higher LST according to the Landsat image. The zone in the vicinity on the right, the vegetation-impacted zone, contains greener spaces such as parks, trees, bushes and more shaded areas and has a lower LST. The two selected zones had to be ideally connected to the same water treatment plant (WTP) to facilitate the water temperature comparison. Moreover, the two studied zones had to be close to one another to share the same meteorological conditions such as air temperature, wind speed, and direction.

6.2.2 Water temperature monitoring

With prior authorization from the City of Montreal, a comprehensive water temperature monitoring campaign was undertaken. This campaign involved door-to-door interactions with residents to request their permission to install temperature loggers in their building. This process which took several weeks and several visits to different parts of each sector resulted in the recruitment of 34 volunteers – 17 from each designated zone. In the UHI-impacted zone, 12 commercial buildings (restaurant, fire station, supermarket) and 5 residential buildings were monitored. In the vegetation-impacted zone, 10 residential buildings and 7 commercial buildings (supermarket, public pool, commercial center) were monitored. The next step was the installation of temperature loggers for water temperature measurement. The temperature loggers (EasyLog temperature probe data logger purchased in Montreal, Quebec with an accuracy of $\pm 0.5^{\circ}\text{C}$), shown in Figure 6.1.B, was installed on the service lines connecting the distribution pipes to each building. The visible part of the service lines was usually found in the basement, garage, or in some cases on the ground floor. The installation involved taping the copper element to the pipe exterior wall under insulation. A sample of one of the installations is shown in Figure 6.1.C. Both the pipe material and the temperature probe material composed of copper, providing high conductivity and sufficiently accurate temperature measurement of the water within the pipes. The loggers measured and recorded

temperature continuously every 5 minutes during the period of July to September 2022. This campaign resulted in an extensive database of the water temperature variations with more than 21,000 data points from each building. The placement of the monitoring points in the UHI-impacted zone and vegetation-impacted zone is displayed in Figure 6.1.A, with the monitoring points marked with letters A to Q in each zone.

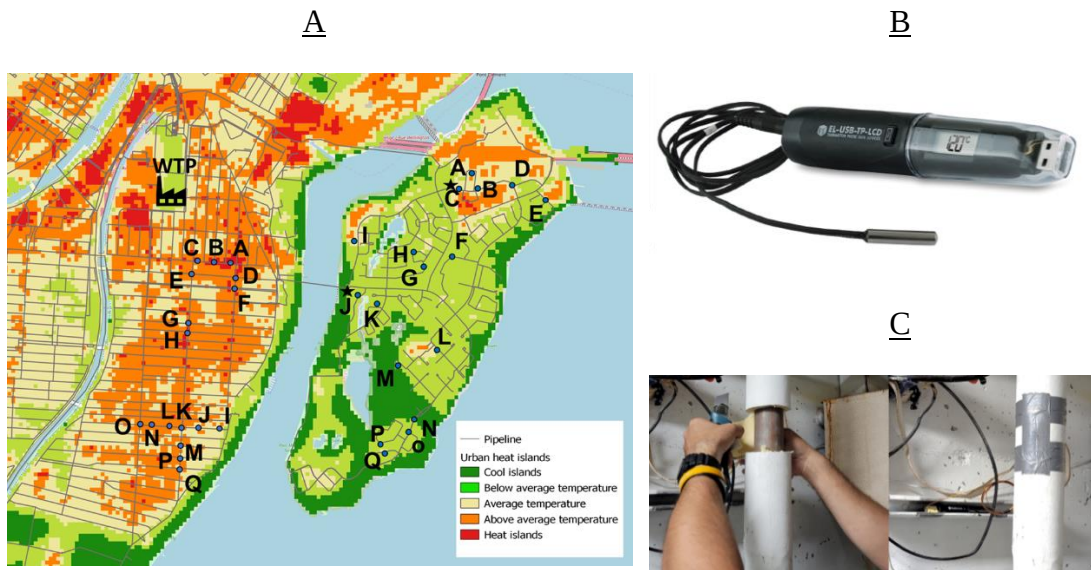


Figure 6.1 A: Two monitoring zones – vegetation-impacted zone on the right and the UHI-impacted zone on the left, the WTP feeding both zones, and the placement of the temperature loggers indicated with letters, B: temperature probe data logger, and C: Installation of a temperature logger on the service line. Point C* is the north entrance and point J* is the east entrance connecting the UHI-impacted zone to the vegetation-impacted zone.

6.2.3 Modeling soil temperature

The soil temperature model by Blokker and Pieterse-Quirijns (2013) incorporating the data from the anthropogenic heat sources by (Agudelo-Vera et al., 2017) is presented in Equation (6.1).

$$\begin{aligned} \rho_{soil} C_{p,soil} \frac{\partial T_{soil}}{\partial t} &= \lambda_s \frac{\partial^2 T_{soil}}{\partial Z_s^2} + \frac{1}{\Delta Z} (R_{net} + Q_F - \Delta Q_s - L_v E - \rho_{soil} C_{p,soil} (T_{ss} \\ &\quad - T_{RL}) / R_g) \end{aligned} \quad (6.4)$$

In this equation, ρ_{soil} (kg.m^{-3}) and $C_{p, soil}$ ($\text{J.kg}^{-1}.\text{K}^{-1}$) are the density and heat capacity of the soil. T_{soil} is the soil temperature, t is the time (h), z is the depth (m), and λ_s ($\text{W.m}^{-1}.\text{K}^{-1}$) is the thermal conductivity of the soil. R_{net} (W.m^{-2}) is the net radiation and Q_F (W.m^{-2}) represents the anthropogenic heat from the surface. T_{ss} is the soil surface temperature (K), T_{RL} is the roughness layer temperature (K), and R_g (W.m^{-2}) is the global radiation. ΔQ_s (W.m^{-2}) is the net surface and subsurface heat storage flux (uptake and release) which can also be written with Equation (6.2) (Agudelo-Vera et al., 2017). In this equation, a_1 (unitless), a_2 (W.m^{-2}), and a_3 (W.m^{-2}) are empirical coefficients for different surface types.

$$\Delta Q_s = a_1 R_{net} + a_2 \frac{\partial R_{net}}{\partial t} + a_3 \quad (6.5)$$

Equation 1 and Equation 2 were used to model soil temperature in five distinct soil scenarios corresponding to the five LST classes obtained from the satellite images. The average soil density (2710 kg.m^{-3}), specific heat capacity ($10^3 \text{ J.kg}^{-1}.\text{K}^{-1}$), and heat conductivity ($1.6 \text{ W.m}^{-1}.\text{K}^{-1}$ for class 1 to 4) were taken from a local study conducted by Tarnawski et al. (2015) on average thermal properties of soils in Montreal. The heat conductivity for class 5 or the heat islands was set to $2.6 \text{ W.m}^{-1}.\text{K}^{-1}$ based on the study of Agudelo-Vera et al. (2017). The specific coefficients corresponding to each of the five soil coverage classifications (local climate zones) are based on a study conducted by Stewart and Oke (2012) and presented in Table C.1 in the supplementary material. The average albedo of Montreal (0.19) was also taken from a study conducted by Frie et al. (2022) reporting the average albedo of Montreal. Albedo is a measure of surface reflectivity which quantifies what fraction of solar radiation is reflected and not absorbed by the soil (Frie et al., 2022). Hourly meteorological data of air temperature ($^{\circ}\text{C}$), wind speed (m/s), Wind direction (degree), solar radiation (J/cm^2), and Precipitation (mm) from the McTavish weather station was obtained from the Environment and Climate Change Department of the Government of Canada. The duration of the data was from 2016 to 2022 and the selected weather station was the closest to the study sites. The data was then incorporated in the soil temperature model via MATLAB R 2021b and soil temperature was predicted at different depths underground for all the five scenarios (Agudelo-Vera et al., 2017).

6.2.4 Modeling and validating water temperature

The water temperature model is presented in Equation (6.3), Equation (6.4), and Equation (6.5) (Blokkeer and Pieterse-Quirijns, 2013).

$$\frac{dT_{water}}{dt} = k (T_{outer\ wall} - T_{water}) \quad (6.6)$$

$$k = \frac{4 \cdot \alpha_{water}}{D_1^2 \left(\frac{1}{Nu} + \frac{\lambda_{water} \cdot \ln\left(\frac{D_2}{D_1}\right)}{2 \cdot \lambda_{pipe}} \right)} \quad (6.7)$$

$$D_2 = D_1 + 2 \cdot pipewall_ratio \cdot D_1 \quad (6.8)$$

$T_{outer\ wall}$ is the soil temperatures surrounding the pipe which is used as the pipe boundary condition. α_{water} is the thermal conductivity of water ($1.36e^{-7} \text{ m}^2 \cdot \text{S}^{-1}$) and λ_{water} is the specific conductivity of water ($0.57 \text{ W} \cdot \text{m}^{-1} \cdot \text{K}^{-1}$). λ_{pipe} is $15 \text{ W} \cdot \text{m}^{-1} \cdot \text{K}^{-1}$ for stainless steel, $60 \text{ W} \cdot \text{m}^{-1} \cdot \text{K}^{-1}$ for cast iron, $0.43 \text{ W} \cdot \text{m}^{-1} \cdot \text{K}^{-1}$ for asbestos cement, and $0.16 \text{ W} \cdot \text{m}^{-1} \cdot \text{K}^{-1}$ for PVC pipes. Nu is the Nusselt number equal to $0.027 \cdot Pr^{0.33} \cdot Re^{0.8}$ assuming turbulent flow. D_1 is the pipe inside diameter (mm), and D_2 is the outer pipe diameter (mm) with the assumption of $pipewall_ratio$ equal to 0.07. The boundary condition for the underground pipes – used as the pipe outer wall temperature in the model – was determined by using the resulting soil temperature at a depth of 1.8 m from the previous step. The soil temperature variations were studied for 24 hours each day to see whether we can use one single soil temperature for the whole day in the equation. After verifying that the soil temperature variation was 0.5°C on average, one single soil temperature – the soil temperature at midday – was used as the $T_{outer\ wall}$ and integrated into (6.6).

Overlaying the LST maps from Landsat imagery from step 1 onto the hydraulic model of the city helped categorizing pipes into five distinct temperature classes. Subsequently, based on the temperature classification, a distinct pipe wall temperature was assigned to $T_{outer\ wall}$ in the soil temperature model, allowing the accurate prediction of water temperature variations within every single pipe based on the local soil temperature surrounding each pipe. The hydraulic network of the city was modeled in WaterGEMS (10.04.00.108). The water temperature modeling was carried

out with the Multi-species Analysis, based on the EPANET-MSX model with WaterGEMS user interface.

Due to the absence of water meters in buildings, specific water demand per household couldn't be measured. To address this limitation, the average daily water demand pattern in the city of Montreal in summer (Figure C.1 in the supplementary material) was applied to the hydraulic model. After stabilizing the network hydraulics, a 7-day water quality simulation ensued to allow for system-wide stabilization. Each day involved a new soil temperature ($T_{outer\ wall}$) in the model, and the stabilized water temperature variations were compared to field measurements. Model validation employed statistical tests in MATLAB R2021b.

6.3 Results

6.3.1 Temperature monitoring results

After recovering all the temperature loggers, the temperature data were extracted for analysis. Figure 6.2 shows the correlation between monitored temperatures and the LST classifications based on satellite image. Each boxplots present the continuous (every 5 minutes) water temperatures in one monitoring point during the period of July 27th and August 12th, resulting in 34 box plots. It is worth noting that one participant withdrew from the study after August 12th. To ensure a fair and uniform comparison among all monitoring points, we limited the data presentation on this figure to this period. Table 6.3 presents the average values for minimum, median, and maximum water temperatures for each LST classification. A distinct warming trend is observed as soil temperature classifications increase from 1 to 5. The median recorded temperature difference between class 1 and class 5 reaches a maximum of 6.5°C, with an average difference of 5.7°C, indicating a significant warming effect on water temperatures when transitioning from low LST zones to high LST zones. Notably, classes 3 and 4 exhibit minimal temperature differences, primarily due to their proximity, where water passes through class 4 soils (warmer areas) to reach class 3 soils. In contrast, Class 5, the heat islands, shows temperatures 1.6-1.8°C higher in minimum and median, and 2.8°C higher in maximum compared to class 4.

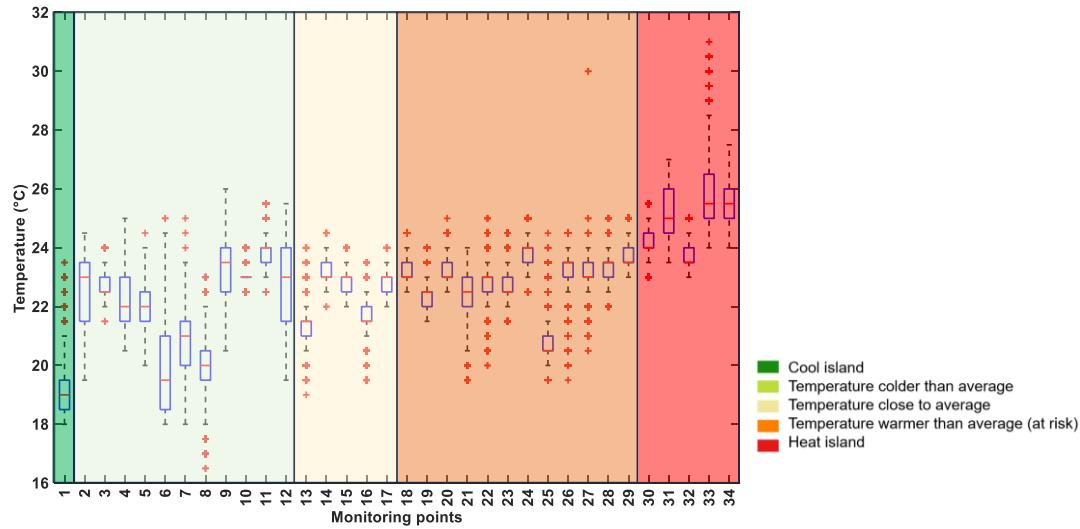


Figure 6.2 Monitoring results in the 34 sampling points in UHI-impacted zone and vegetation-impacted zone during the period of July 27th to August 12th. The boxes present, 25th percentile, median, and 75th percentile. The whiskers present the minimum and maximum and the outliers are presented with red plus signs.

Table 6.3 The minimum, median, and maximum recorded temperatures from the temperature loggers with regards to their LST classification based on the satellite image

LST classification based on Landsat image		Class 1	Class 2	Class 3	Class 4	Class 5
Monitored water temperature (°C)	Average minimum (°C)	18	20.18	21.6	22.04	23.6
	Average median (°C)	19	22.11	22.4	22.88	24.7
	Average maximum (°C)	21	24.18	23.1	23.71	26.5

Figure 6.3 illustrates the water temperature monitoring results plotted against the average water age at each monitoring point. Notably, our findings reveal no discernible correlation between temperature variations and average water age at each monitored point. Previous studies by Agudelo-Vera et al. (2020) on a Dutch DWDS suggested that longer water residence times (greater than 12 hours) in the network led to elevated temperatures. They also noted a trend of increasing temperatures further downstream from the WTP. Similarly, Machell and Boxall (2014) conducted a study in the UK, investigating the relationship between measured water temperatures and water age. Their findings showed a rising trend in temperature for samples taken from unperturbed pipes

with longer water ages. It is important to note that in both previous cases, the source water temperature was considerably lower than the surrounding soil temperature. For example, in the Dutch case study (Blokkeer and Pieterse-Quirijns, 2013), the source water originated from underground sources with an average temperature of 10°C, while a constant soil temperature of 25°C was used for modeling water temperature in the DWDS. In contrast, our case study utilizes surface water from a river, which exhibits higher temperatures during the summer (ranging from 22-25°C). In this scenario, the water temperature can be influenced by various soil coverages and, consequently, different soil temperatures along its journey to the customer's building. This can either lead to a cooling or heating effect based on the surrounding soil temperature.

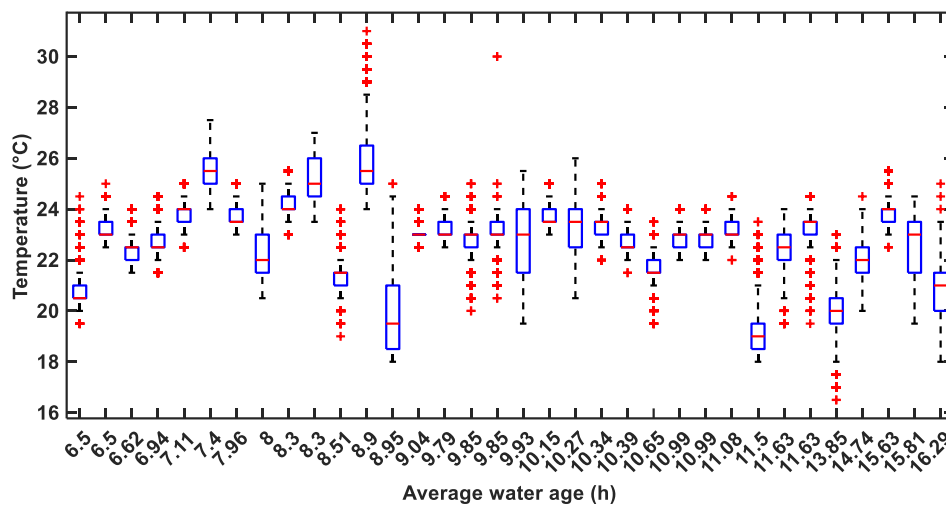


Figure 6.3 Correlation between the monitoring temperature results and the average water age in the model at each sampling point between July 27th and August 12th.

To study the correlation between water temperature and air temperatures, Figure 6.4.A shows the average hourly monitored water temperatures along with the hourly air temperature plotted together for the period of July 27th to September 1st. In the UHI-impacted zone, the average hourly water temperature ranged between 19.9°C and 30.9°C, with an average temperature of 23.7°C over the entire period. In contrast, the vegetation-impacted zone exhibited water temperatures between 16.6°C and 26°C, with an average temperature of 22.3°C throughout the period. The recorded air temperatures ranged from a maximum of 31.6°C on August 6th to a minimum of 12.3°C on September 1st. Comparing the peak dates for water temperature (August 10th, 16th, 25th, 30th) with the peak dates for air temperature (August 6th, 7th, 20th, and 29th) do not confirm any immediate

influence of air temperature on measured water temperature. Based on our observations, the peaks in air temperature are followed by peaks in water temperature with a few days lag (between 1 to 9 days). To investigate the potential correlation between hourly air temperatures and water temperatures in all monitoring points, we calculated the correlation coefficient r . This coefficient quantifies both the direction and strength of the linear relationship between air and water temperature variations. In the UHI-impacted zone, r values ranged from -0.44 to 0.6, with an average r of 0.07. Conversely, in the vegetation-impacted zone, r values fell within the range of -0.4 to 0.31, with an average r of -0.05. The results suggest that no definitive correlation exists between hourly air and water within the DWDS.

To estimate the cooling or warming effects in each zone, we calculated the difference between the hourly temperatures at each point and the temperature at WTP exit for the period of August 27th to September 1st. The results are presented in Figure 6.4.B. Our findings reveal that in the UHI-impacted zone, the maximum warming observed was 8°C on August 25th, while in the vegetation-impacted zone, the maximum warming reached 2.5°C on August 14th. In the vegetation-impacted zone, the maximum cooling was 8°C on August 7th and August 25th and the maximum cooling in the UHI-impacted zone was 4.7°C on August 9th. On average, the cooling effect in the vegetation-impacted zone was 1.6°C, while the UHI-impacted zone showed an average cooling of 0.2°C. It's worth noting that water is transferred to the vegetation-impacted zone via two connecting pipes that pass under the river. The northern connecting pipe is a 20-inch diameter with a water travel time of 1.7 hours, while the eastern connecting pipe is 30 inches in diameter with the same travel time. In the northern region, the hourly average temperature difference between the WTP and point C, the north entrance, in the vegetation-impacted zone ranged from 0 to 2.5°C, with an average of 1.4°C throughout the study period. In the east, the hourly average temperature difference between point F in the UHI-impacted zone and point J, the east entrance, in the vegetation-impacted zone varied from -0.5°C to 3°C, averaging 1.5°C. A plot showing the monitored temperatures in the vegetation-impacted zone with regards to the two entrance temperatures is provided in Figure C.2 in the supplementary material. Comparing the monitored temperatures at the two entrance points with the rest of the points showed that the two entrance nodes can be considered the warmest points in the vegetation-impacted zone, while the rest of the monitored points generally exhibit lower temperatures. This indicates that the cooling effect in the vegetation-impacted zone is influenced

not only by the river but also by the passage of water through the zone, which has a lower soil temperature.

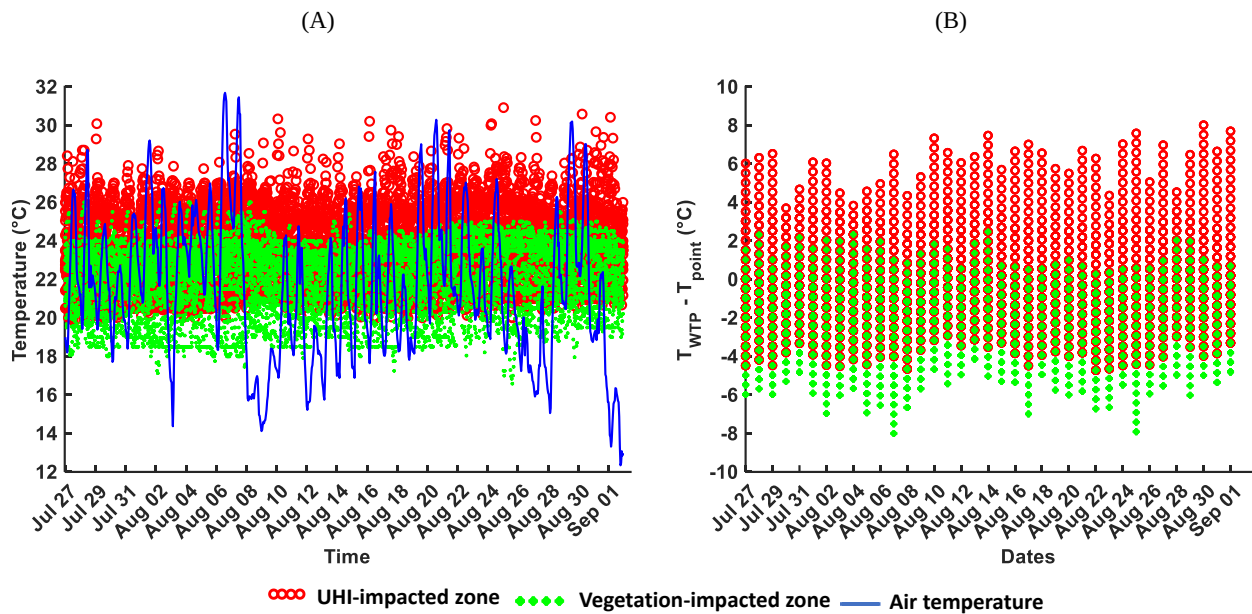


Figure 6.4 A: Average hourly temperatures in all 34 monitored points and the average hourly air temperature during the period of July 27th and September 1st, B: temperature differences between the WTP average daily temperature (T_{WTP}) and the recorded hourly temperatures at each location (T_{point}) during the period of July 27th to September 1st.

6.3.2 Soil temperature modeling results

Figure 6.5 shows the hourly soil temperature modeling results at the depth of 1.8 m across five soil scenarios between July 27th and August 12th. During this period, the average soil temperature for class 1 was 18.5°C. Moving from class 1 to 5, the average soil temperatures increased by 6.2°C. As previously shown in Figure 6.2, the maximum difference between median water temperature measurements for class 1 and 5 is 6.5°C, which aligns closely with the difference between the average modeled soil temperatures between these two classes. Figure 6.5 also contains the minimum, average, and maximum daily water temperatures from the monitoring campaign during the same period to show the alignment between modeled soil temperatures and measured water temperatures. According to Figure 6.5, the maximum daily water temperatures do not exceed the values associated with class 5 soil temperature, except in three locations within the UHI-impacted

zone, where the maximum water temperature reached up to 30.9°C but the maximum soil temperature did not exceed 26°C. On the other hand, the minimum daily water temperatures do not fall below the minimum soil temperatures, except at two points within the vegetation-impacted zone, where minimum daily water temperature reached down to 16.6°C, whereas soil temperature did not go below 18°C.

To investigate the effect of deeper pipe burial on soil temperature, the modeled soil temperature at two different depth of 1 m (as in the Dutch case study by Blokker and Pieterse-Quirijns (2013)) and 1.8 meter used in the Canadian DWDS were compared. At 1 m depth, the soil is on average 3.98°C cooler than the surface and at 1.8 m depth, the soil is on average 6.91°C cooler than the surface. So, increasing the burial depth from 1 m to 1.8 m in the studied area leads to a 2.9°C cooling effect on average soil temperature surrounding pipes. This value could vary in each case study based on their soil conductive properties.

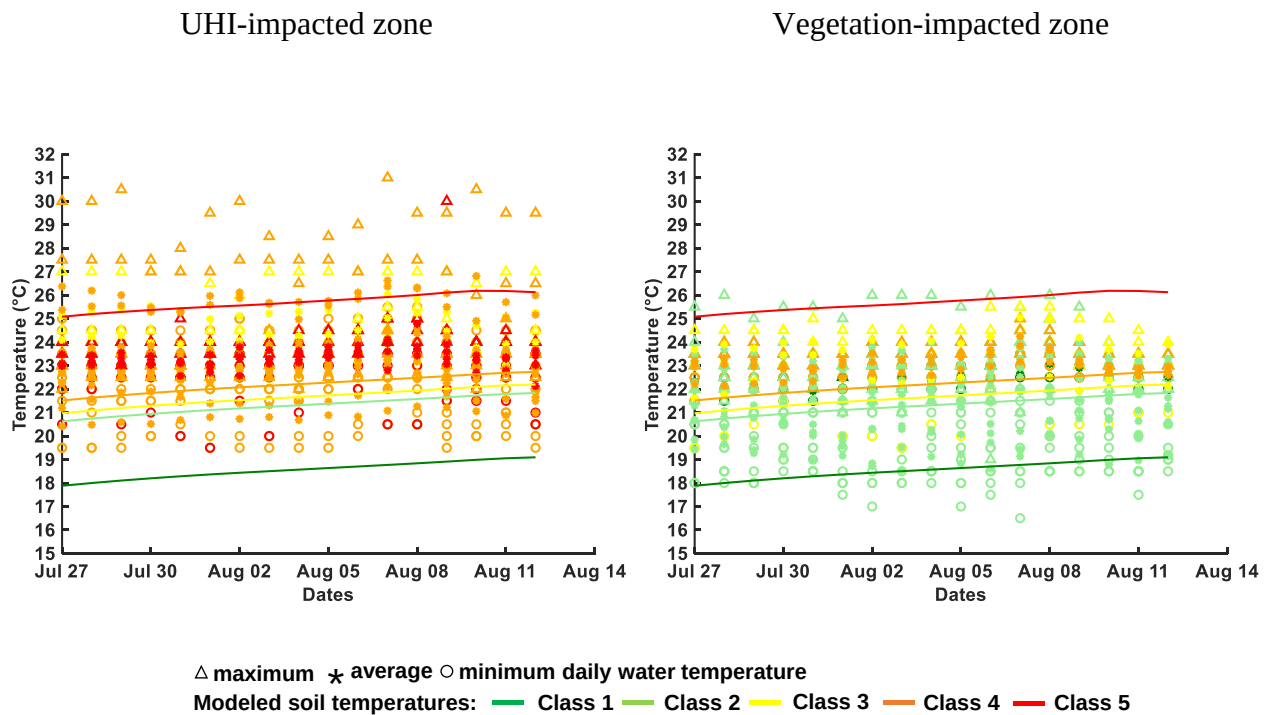


Figure 6.5 Modeled soil temperatures in five classes plotted along the minimum, average, and maximum daily measured water temperatures in all the 17 monitoring points from July 27th to August 12th. The water temperature records from each point is color-coded based on the placement of each point with regards to the soil classification.

6.3.3 Water temperature modeling results

The water temperature modeling results during the period of August 1st to August 12th are presented in Figure 6.6 along with the soil temperature modeling results and water temperature measurements. As seen in the figure, the variations in the measured water temperature are much greater than the modeled water temperature variations. These variations are due to different water consumption habits (time, duration, and intensity of using bathroom, shower, cooking, garden watering, etc.), type of building (residential, commercial), and the number of residents present in each building. For example, in the vegetation impacted zone, the participants in points L and N were on vacation during the period of August 9th to 12th and the participants in point I were on vacation from August 5 to 8. As a result, the water temperature stabilizes in these points as shown in Figure 6.6, which reflects water stagnation in the service lines during these periods. Due to the absence of demand variations in each household and using a similar demand pattern in the WaterGEMS corresponding the daily average demand pattern in the city for August, comparing the hourly results were not possible. Consequently, the daily average modeled and measured temperatures were compared to discuss the goodness of prediction.

It's important to emphasize that the soil temperature data in Figure 6.6 pertains to the local soil temperature in the immediate vicinity each monitoring points. In contrast, water temperature modeling reflects the composite influence of water passing through various pipes, each with different soil and hence, $T_{outer\ wall}$ temperatures, impacting the overall water temperature. In Figure 6.6.A for the UHI-impacted zone, although points A, B, C, D, and H are situated in soil class 5, the modeled water temperature in these locations is lower than the modeled soil temperature. This discrepancy arises from the fact that the pipes connected to these points originate from areas with lower soil temperature classes 4 and 3. The modeled water temperature reflects the entire journey of water within the DWDS, hence appearing lower than the local soil temperature. In the rest of the points, where the local soil temperature aligns more closely with the average pipe temperature that water flows through, the soil/water temperature difference are minimized. Similarly, in Figure 6.6.B for the vegetation-impacted zone, water arriving from the warmer UHI-impacted zone initially maintains a higher temperature at points F, G, and H, remaining under the influence of the upstream soil temperature. However, as it traverses through cooler pipes within the vegetation-impacted zone, the soil/water temperature differential declines. Subsequently, at point M, where

the water passes through class 3 pipes, the modeled water temperature surpasses the local soil temperature.

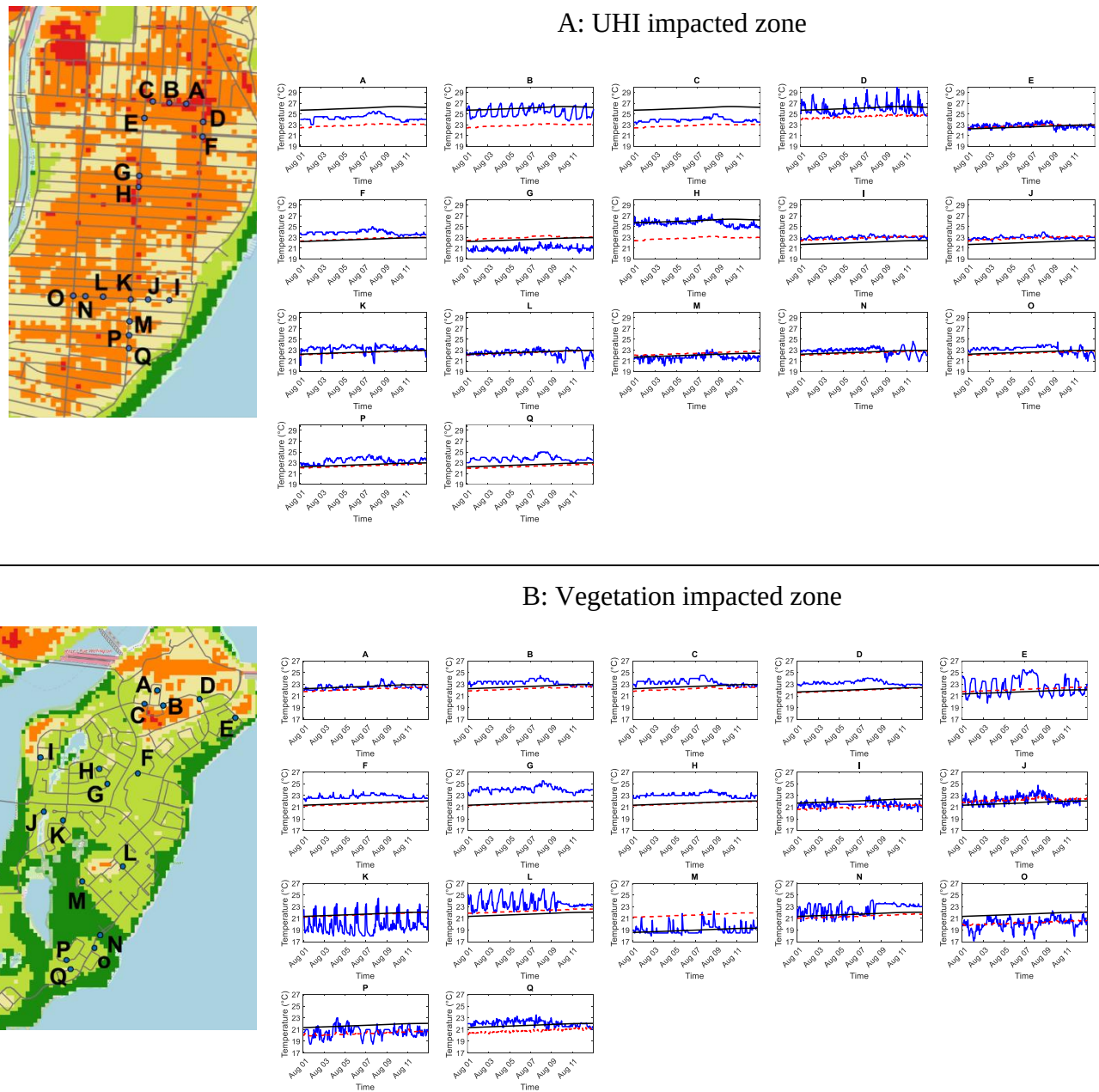


Figure 6.6 Water temperature modeling and monitoring results and soil temperature modeling results in all the 17 monitored points in the UHI-impacted zone (6A) and vegetation-impacted zones (6B) between August 1st and 12th. Each figure corresponds to one monitoring point in the network with their corresponding location indicated on the map with letters. Legend: — measured water temperature, - - - modeled water temperature, — modeled local soil temperature

To illustrate the impact of soil temperature on modeled water temperatures, the water temperature variations during August 1st to 12th were plotted in Figure 6.7 with boxplots in an ascending order based on the average water age of each point in the DWDS. The point codes are specified under each boxplot and the average water travel time is specified above each boxplot. Figure 6.7.A shows the results in the UHI-impacted zone. Some points were in vicinity and had similar water travel times, so only the points with different water travel times are reported. Points M and J, belonging to LST class 3 with an average modeled soil temperature of 21.8°C, exhibit water temperatures higher than their respective local soil temperatures. These two class-3 points are in proximity to class 4 soil temperatures, with an average soil temperature of 22.4°C, and water sourced from class 4 soils with higher average temperatures reaches them. This underscores the influence of upstream soil temperature on water temperatures, highlighting that soil temperature affects water temperature not only at the pipe location but also during the water trajectory. Figure 6.7.B presents results for the vegetation-impacted zone. Given the presence of two entrances and water mixing, we focused on water sourced exclusively from the east entrance (or point J in the vegetation-impacted zone). A trace analysis in WaterGEMS determined the percentage of water sourced from the north and east entrances, enabling us to isolate nodes receiving 100% of their supply from the east entrance. All the points in the plot belong to soil class 2, with an average soil temperature of 21.5°C. It is evident that lower soil temperature results in lower water temperature, aligning with the model's predictions. Furthermore, increased water travel time within the vegetation-impacted zone leads to decreased modeled water temperatures, highlighting the impact of soil temperature on water temperature variations and the coherence between soil and water temperature models. Notably, points Q and P are located near soil class 1, and the pipes serving them pass through cooler soils with an average temperature of 18.7°C.

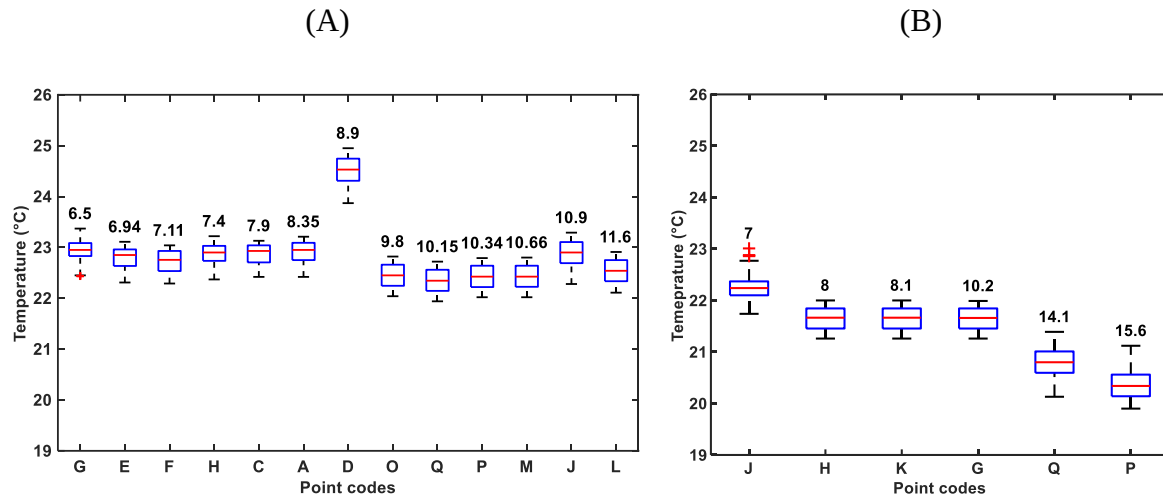


Figure 6.7 Modeled water temperatures during water travel time from August 1st to 12th in A: the UHI-impacted zone and B: vegetation-impacted zone from east entrance exclusively.

The goodness of prediction statistics between measured and predicted daily water temperatures is presented in Table 6.2. This table contains the minimum/average/maximum prediction error, the root means square error (RMSE), and the P-value for the daily average predicted temperatures. In the UHI-impacted zone, the minimum prediction error is between 0°C and 1.98°C, the average prediction error is between 0.2°C and 2.78°C, and the maximum prediction error is between 0.33°C and 3.26°C across all 17 points. In the vegetation impacted zone, the minimum prediction error is between 0.01°C and 1.66°C, the average prediction error is between 0.32°C and 2.53°C, and the maximum prediction error is between 0.75°C and 3.19°C across all 17 points. The RMSE in the vegetation impacted zone is between 0.39°C and 2.55°C and the average P-value is 2.6E-03. The RMSE in the UHI impacted zone ranges between 0.23°C and 2.82°C and the average P-value is 6.12E-04. These results highlight the significance of the prediction results. To examine the correlation between the predicted and measured temperature timeseries and the temporal alignment of the predicted results with the measured data, a cross correlation analysis was performed, and the results are presented in Figure C.3 at supplementary materials. A cross-correlation equal to 1 at lag 0 at all points suggests that the predictive model is performing well for all points, replicating the variations and trends in the measured temperature time series.

Table 6.2. Goodness of prediction statistics in the UHI-impacted and vegetation-impacted zones (period: August 1st to August 12th)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	
Vegetation-impacted zone	Minimum Error (°C)	0.17	0.28	0.31	0.56	0.01	0.64	1.53	0.58	0.24	0.10	1.06	0.57	1.66	0.51	0.07	0.05	0.53
	Average Error (°C)	0.45	1.11	1.19	1.33	0.75	1.25	2.42	1.45	0.55	0.34	1.75	1.38	2.52	1.24	0.42	0.34	1.36
	Maximum Error (°C)	0.76	1.62	1.93	1.83	2.87	1.55	3.19	1.82	0.82	0.75	2.57	1.91	3.04	1.98	1.09	1.34	1.81
	RMSE (°C)	0.48	1.18	1.27	1.38	1.14	1.28	2.45	1.49	0.59	0.39	1.81	1.43	2.55	1.33	0.53	0.53	1.43
	P-Value	8.33E-06	4.11E-06	7.61E-06	4.68E-07	2.06E-02	3.35E-08	5.16E-09	1.11E-07	4.85E-06	2.39E-04	3.83E-07	4.05E-07	3.06E-09	6.57E-06	2.00E-03	2.14E-02	1.99E-06
UHI-impacted zone	Minimum Error (°C)	0.74	1.68	0.64	0.62	0.10	0.47	1.67	1.98	0.00	0.12	0.14	0.03	0.11	0.01	0.46	0.70	
	Average Error (°C)	1.41	2.42	1.05	1.47	0.26	1.14	2.02	2.78	0.20	0.27	0.73	0.35	0.78	0.64	0.80	0.95	1.42
	Maximum Error (°C)	2.06	2.95	1.52	2.04	0.41	1.65	2.18	3.26	0.33	0.41	1.21	1.39	1.17	0.91	1.26	1.51	2.33
	RMSE	1.46	2.45	1.08	1.54	0.27	1.21	2.02	2.82	0.23	0.28	0.80	0.51	0.84	0.69	0.90	1.02	1.48
	P-Value	1.09E-07	1.23E-10	3.32E-08	1.88E-07	1.12E-06	1.13E-06	2.93E-14	4.62E-10	1.52E-04	9.88E-08	1.70E-05	1.02E-02	3.03E-06	6.21E-06	4.48E-05	3.49E-06	2.61E-07

6.4 Discussion

The drinking water temperature monitoring results showed that water at 1.8 m underground pipes can still be under the influence of heatwaves and UHIs during summer. The modeling results showed that the average soil temperature at 1.8 m depth is on average 2.93°C cooler than the soil temperature at 1 m, suggesting that pipe burial could be an effective measure for dampening the water warming effect during hot periods. However, in our case, deeper pipe burial did not eradicate the issue of water warming and the water temperature in the studied network would still go as high as 32°C (hourly average of 30.9°C) during summer days.

Our hypothesis suggests that service lines reflect DWDS water temperature during high-demand hours. During low-demand and stagnation periods, service line temperature may vary from DWDS, influenced by surrounding soil temperature. In UHI-impacted zones, prolonged stagnation could elevate temperatures due to extended contact with the warm environment, while in vegetation-impacted areas, temperatures might decrease due to prolonged contact with the cooler environment. The lack of water meters and information about stagnation periods in buildings prevented verification of this hypothesis. Nevertheless, stagnation occurred in both zones, but significantly elevated temperatures were only observed in the UHI-impacted zone. Consequently, whether stagnation occurred or not, the UHI-impacted zone consistently exhibited higher temperature readings.

Comparing the heating and cooling effect in the two contrasting zones showed that the maximum heating effect in the UHI-impacted zone was 5.5°C higher than the maximum heating in the vegetation-impacted zone. Moreover, the maximum cooling effect in the vegetation impacted zone was 3.3°C higher than the maximum cooling in the UHI-impacted zone (Figure 6.4.B). The influence of local climate zones on drinking water temperature hasn't been explored in prior studies. Our findings align with existing research, indicating increased LST in urban areas with impervious surfaces and lower LST in green spaces with parks and shadows (Alexander, 2021; Edan et al., 2021; Kafy et al., 2022; Smith et al., 2023; Zhu et al., 2021).

The peak air temperatures did not coincide with peak water temperatures, indicating that the temperature of drinking water in pipelines is more influenced by the surrounding soil environment than air temperature. This aligns with the findings of Blokker and Pieterse-Quirijns (2013), who demonstrated that drinking water temperature in DWDS reflects the surrounding soil temperature. Throughout the study, raw water temperature at the WTP inlet ranged from 21°C to 24°C, and treated water temperature varied between 23°C and 25°C. There was no discernible relationship between source water temperature and drinking water temperature at monitoring points. This is consistent with the observations of Agudelo-Vera et al. (2015), who found no correlation between source water temperature and tap water temperature in Dutch distribution networks, affirming the influence of surrounding soil temperature on water temperature.

Discrepancies between modeled and measured water temperatures stem from uncertainties in the soil and water temperature model. The soil temperature model lacks calibration with field measurements, relying on an average soil conductivity value for Montreal Island from Tarnawski et al. (2015), which may not accurately represent local conditions due to variations in pipe fillings, soil coverage, and heat conductivities. The parameter 'Q' in the soil temperature model, representing anthropogenic heat sources, is adapted from Stewart and Oke (2012) for different urban settings. Achieving a more realistic prediction requires detailed knowledge of underground heat sources like subway tunnels, geothermal systems, district heating systems, power plants, landfills, and buildings, as well as local thermal and hydraulic properties of soils in each zone (Kreitmair et al., 2020; Menberg et al., 2013). For instance, in UHI-impacted zones, where water temperatures exceeded the maximum soil temperature, proximity to a subway station emitting excess heat from tunnels was observed. In the absence of such extensive data, remote sensing techniques using LST maps offer a viable alternative. The uncertainties in water temperature model

arise from: a) applying a uniform consumption pattern to all network nodes, which doesn't accurately reflect real consumption variations, b) unexpected factors during the monitoring period (e.g., unknown vacation periods, flushing/firefighting water demand, connections to temporary networks, or regular maintenance activities). These uncertainties may have influenced water trajectory and demand, impacting the modeled drinking water temperature.

Studying monitored water temperature variations with regards to average water age within the DWDS showed no correlation, suggesting that the soil subsurface temperature during the water travel time and the contact time between water and each specific soil (or pipe wall) temperature is more important than the overall time the water has spent in the network.

The observed discrepancies in water temperature in this study could potentially have implications for water quality management practices in the DWDS. Firstly, in chlorinated networks such as this case study, it is commonly reported that the extremities of the network are more prone to microbial risks due to longer water travel times and therefore, depletion of chlorine. As a result, network extremities are chosen for regulatory water quality monitoring or for adjusting the applied chlorine dosage at the WTP to ensure sufficient chlorine coverage across network. The present work showed that the points in the UHI-impacted zone with a lower residence time exhibited the highest recorded temperatures up to 32°C, which could potentially lead to higher rates of chlorine decay and lower residual chlorine in these zones. Secondly, the hotspots in the networks are not considered in the choice of sampling points for regulatory monitoring. These hot zones could be prone to insufficient chlorine residual or elevated disinfection by-product levels. This matter requires further investigation to assess the potential risks of hot zones on chemical and microbial drinking water quality in DWDS. Finally, the potential risks of such extreme temperatures for pathogen regrowth within the DWDS requires more attention. For example, *Legionella pneumophila* (*Lp*), an opportunistic pathogens responsible for the potentially fatal Legionnaire's disease, is monitored mainly in cooling towers and buildings, assuming minimal *Lp* growth in the DWDS, largely associating it with water stagnation and heating within buildings (National Academies of Sciences, 2019). Although there are no specific regulations for *Lp* in the DS, the "Guidelines on Drinking Water Distribution Systems Best Practices" for Quebec municipalities (Quebec Government, 2023) suggests maintaining a minimum free chlorine of 0.1 mg/L in the DWDS to prevent microbial regrowth. Chlorine monitoring sites are typically situated at the peripheries and dead-end points. Consequently, the impact of the UHIs within the city on chlorine levels remains unexplored, and

the potential effects of temperature variations on *Lp* growth in the DWDS are not taken into account.

The results of this study were a proof of the effectiveness of greening as a solution to dampen the extreme heatwaves and UHI effect on DWDS, during summer, and can reduce the level of exposure of urban communities to heat. However, for the greening to be effective, it should be done in a certain pipe length and not only on a particular pipe. Tracing the water temperature variations along the water trajectory in the DWDS underscore the influence of water traveling from cooler areas and the significance of soil temperatures surrounding the pipes, extending beyond just local soil temperature. This interplay between soil temperature, water trajectory, and local water temperature provides valuable insights into the dynamics of the water temperature in the DWDS. To evaluate the effectiveness of greening in moderating water temperature, the proposed modeling approach offers great potential.

The proposed approach for water temperature modeling combined with satellite imagery across diverse types of soil coverage holds great potential to enhance strategic greening initiatives and supplement decision-making processes. Furthermore, our approach can aid in the optimal placement of water quality sensors within DWDS, considering hot zones impact. In the context of climate change adaptation, addressing disparities in drinking water temperature within cities becomes imperative. Investigating the implications of the observed disparities for water quality and public health is a critical next step.

6.5 Discussion

The drinking water temperature monitoring results showed that water at 1.8 m underground pipes can still be under the influence of heatwaves and UHIs during summer. The modeling results showed that the average soil temperature at 1.8 m depth is on average 2.93°C cooler than the soil temperature at 1 m, suggesting that pipe burial could be an effective measure for dampening the water warming effect during hot periods. However, in our case, deeper pipe burial did not eradicate the issue of water warming and the water temperature in the studied network would still go as high as 32°C in the service lines during summer days. It is hypothesized that during high-demand hours, service lines are representative of the DS water temperature, and during low demand hours and stagnation periods, the temperature in the service line can be higher or lower than the DS temperature depending on the soil temperature surrounding pipes. In the UHI-impacted zones, it is

expected that longer water stagnation will lead to higher temperatures due to longer contact of water with its surrounding hot environment. In contrast, in the vegetation-impacted zone, this could lead to lower temperatures because of the longer contact time between water and its cool environment. Because of the lack of water-meters in the buildings, this hypothesis could not be verified.

Comparing the heating and cooling effect in the two contrasting zones showed that the maximum heating effect in the UHI-impacted zone was 5.5°C higher than the maximum heating in the vegetation-impacted zone. Moreover, the maximum cooling effect in the vegetation impacted zone was 3.3°C higher than the maximum cooling in the UHI-impacted zone.

The dates of peak air temperatures did not align with those of peak water temperatures, suggesting that drinking water temperature in the pipelines is more under the influence of its surrounding soil environment than the air temperature. This was previously suggested by Blokker and Pieterse-Quirijns (2013) when the modeling results showed that drinking water temperature in the DS reaches its surrounding soil temperature. During the study period, the raw water temperature measured at the inlet of the WTP varied between 21°C and 24°C and the treated water temperature varied between 23°C and 25°C. Comparing the variations in source water temperature with the drinking water temperature variations at each monitoring point showed no association between these two variables, due to the relatively stable source water temperature during this period with a limited impact on the drinking water temperature in the DS. This was previously seen by Agudelo-Vera et al. (2015) when the source water temperature from two pumping stations – one using surface water and the other using groundwater – had no correlation with the tap water temperature measurements in two Dutch distribution networks, confirming that water temperature is under the impact of its surrounding soil temperature.

Discrepancies between the modeled and measured water temperature come from uncertainties in the soil and water temperature model. The lack of soil temperature model calibration with field measurements led to using average soil conductivity value for Montreal Island from a study by Tarnawski et al. (2015). This may not accurately reflect the local conditions in the studied area due to variations in pipe fillings, soil coverage, and their heat conductivities. Additionally, the parameter 'Q' in the soil temperature model, which represents anthropogenic heat sources, was adopted from the study of Stewart and Oke (2012) for different urban settings. To have a more

realistic prediction of subsurface soil temperature, one needs extensive knowledge of the underground heat sources such as subway tunnels, geothermal systems, district heating systems, power plants, landfills, and buildings as well as local thermal and hydraulic properties of the soils in each zone (Kreitmair et al., 2020; Menberg et al., 2013). For example, the points in the UHI-impacted zone whose temperatures exceeded the maximum soil temperature were close to a subway station, which can emit excess heat from subway tunnels. In the absence of such extensive and resource-intensive data, remote sensing techniques using the LST maps proved to be a good alternative. The uncertainties in the water temperature modeling process includes a) using a similar pattern for all the network nodes which is not a realistic description of the real consumption patterns, b) unpredicted factors during the monitoring period such as unknown vacation periods in each household, 3) flushing or firefighting water demand, 4) connections to the temporary network, or 5) regular maintenance activities. All these uncertainties in the water temperature modeling process could have altered the water trajectory in the pipelines or change the demand both of which would affect the modeled drinking water temperature.

Studying water temperature variations with regards to water age within the DS showed no significant correlation, suggesting that the soil subsurface temperature during the water travel time and the contact time between water and each specific soil (or pipe wall) temperature is more important than the overall time the water has spent in the network. In chlorinated networks such as this case study, it is commonly reported that the extremities of the network are more prone to microbial risks due to longer water travel times and the depletion of chlorine. As a result, network extremities are chosen for regulatory water quality monitoring or for adjusting the applied chlorine dosage at the WTP to ensure sufficient chlorine coverage across network. The present work showed that the points in the UHI-impacted zone with a lower residence time exhibited the highest recorded temperatures up to 32°C, which could potentially lead to higher rates of chlorine decay and lower residual chlorine in these zones. This matter requires further investigation to assess the potential risks of hot zones on chemical and microbial drinking water quality in DS. This is particularly important for water utilities for strategic planning of regulatory water quality monitoring.

The results of this study were a proof of the effectiveness of greening as a solution to dampen the extreme heatwaves and UHI effect on DS, during summer, and can reduce the level of exposure of urban communities to heat. However, for the greening to be effective, it should be done in a certain pipe length and not only on a particular pipe. Tracing the water temperature variations along the

water trajectory in the DS underscore the influence of water traveling from cooler areas and the significance of soil temperatures surrounding the pipes, extending beyond just local soil temperature. This interplay between soil temperature, water trajectory, and local water temperature provides valuable insights into the dynamics of the water temperature in the DS. To evaluate the effectiveness of greening in moderating water temperature, the proposed modeling approach offers great potential.

The proposed approach for water temperature modeling combined with satellite imagery across diverse types of soil coverage holds great potential to enhance strategic greening initiatives and supplement decision-making processes. Our study demonstrates a newfound advantage, expanding the scope and applications of urban green infrastructure. By mitigating the heat island effect on drinking water temperature, this approach contributes to reducing human exposure to the associated heat-related risks. Furthermore, our approach can aid in the optimal placement of water quality sensors within DS, enhancing decision-making in monitoring and regulation. The extensive water temperature monitoring conducted during the summer also presents opportunities to optimize regulatory monitoring points. This advocates for an increase in the number of monitoring locations within high-temperature regions of DS. In the context of climate change adaptation, addressing disparities in drinking water temperature within cities becomes imperative. Investigating the implications of temperature disparities in urban settings for water quality and public health is a critical next step.

6.6 Conclusion

The study's outcomes reveal key insights into the impact of heat islands and vegetation on drinking water temperature:

- Even in cold climates, deeply buried pipes at 1.8 m can be susceptible to the influence of heat islands during summer. In areas characterized by extensive UHI impact and limited vegetation, an important warming of up to 8°C was observed from the WTP to the service lines connected to consumer buildings. Conversely, zones with higher vegetation cover exhibited remarkable cooling, of up to 8°C.

- Soil temperature was found to be a superior indicator of water temperature variations compared to the local air temperature. This finding supports the utility of such modeling tool to improve water management in cities.
- Prolonged water residence times in the DWDS did not lead to higher water temperatures. This can be attributed to the overriding influence of local soil coverage in the studied zones on water temperature, surpassing the impact of water residence time.
- Although deeper pipe burial could partially reduce the water temperature in the pipes, it is not necessarily a comprehensive solution to eradicate the water warming problem completely during hot periods. This is especially the case in systems with high mineralized surfaces and systems depending on surface water sources as these sources have inherently higher source temperatures compared to underground sources during hot periods.
- The efficacy of urban greening in moderating drinking water temperature was noteworthy. It should be noted that greening should be done in a certain pipe length to be effective.

Water temperature modeling is a powerful decision-making tool for monitoring water temperature variations within cities. Notably in the absence of extensive data and resources for direct water temperature monitoring, water utilities can benefit from the proposed approach for improved water quality management. Looking forward, it is recommended to assess the repercussions of the observed temperature disparities on microbial and chemical water quality within the DWDS.

Acknowledgement

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CHAPTER 7 GENERAL DISCUSSION

In this chapter, we will engage in a comprehensive discussion of the findings of this research project, aiming to integrate and synthesize these insights effectively. We will delve into the important aspects of each finding while also highlighting their interconnections and mutual implications. Furthermore, we will explore the broader significance of these findings within the context of climate change and drinking water quality management.

The overarching goal of this research project was to develop a comprehensive framework for the assessment of drinking water quality in chlorinated distribution systems under changing climatic and demand conditions. The project thoroughly examines the multifaceted impacts of climatic events, global warming, water-saving policies, and urban development on drinking water quality and disparities in the distribution system. Our aim was to comprehensively investigate some of the pivotal factors that directly influence drinking water quality, either at its source or within the DS. The initial step was the adaptation of a robust model for predicting chlorine residual and THMs concentrations within full-scale DS and its validation using field data. This model then played a pivotal role in our second objective, serving as a strong tool to evaluate the influence of climatic events, water warming, and water saving policies on chlorine and THMs concentrations within the DS. The studied factors encompassed temperature, DOC, and water demand. Our investigations yielded invaluable insights into the relative significance of each of these factors concerning chlorine and THMs concentrations, while also highlighting critical threshold levels that, when exceeded, would result in significant violations of recommended or regulatory standard for chlorine and THMs. Moreover, we identified vulnerable zones within the network where these violations were more likely to occur and assessed the efficacy of increased dosage as a potential solution in such instances. In our third objective, we assessed the impact of urban development on local drinking water temperature within distribution networks, which in turn could affect its overall quality. This aspect of the project uncovered the unknown influence of the UHIs effect on water temperature within cities and provided valuable insights into how green spaces can serve as regulators of water temperature within the DS. To achieve this, we developed a multidisciplinary approach that integrated satellite imagery with the water distribution network map of the city and meteorological data to monitor and model local water temperature fluctuations within the DS.

In Figure 7.1, we present a visual representation of the overarching objective of this work, along with the three specific objectives and the milestones achieved within each of them. This graphical representation encapsulates the essence of this research journey. In the following sections of this chapter, we will delve deeper into the findings, elucidating their implications, and their collective contribution to the broader field of water quality management in the context of climate change adaptation.

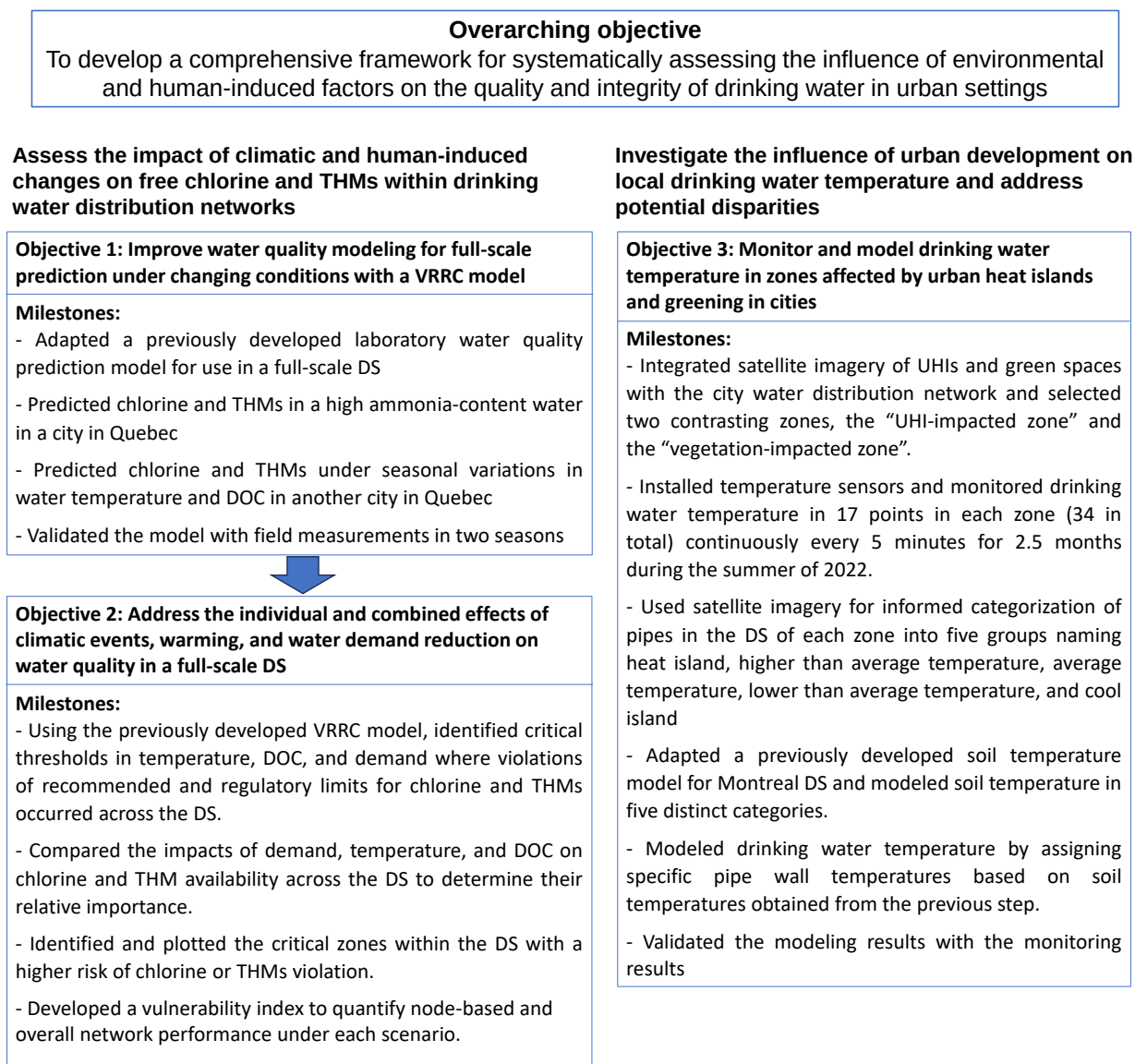


Figure 7.1 Overarching objective, specific objectives, and the milestones achieved in each step of the work

7.1 What should we expect from water quality prediction models and how they can improve the operation and resilience of our systems?

Water quality prediction models offer valuable insights and benefits for water utilities across several critical aspects. Firstly, they provide a means of assessing the effectiveness of water treatment processes. In chlorinated networks, chlorine plays a vital role in ensuring the safety of drinking water for consumers. To monitor the microbial quality of water, free chlorine levels are regularly checked in water distribution networks. THMs, which are chlorination byproducts, are also strictly regulated due to their potential carcinogenic properties. A robust model that successfully predicts variations in chlorine and THMs within a DS can help utilities ensure that the quality of treated water aligns with established standards. These models also play a crucial role in assessing how changing operational conditions, such as fluctuations in water demand due to seasonal changes or water-saving policies, affect variations in water quality. Moreover, a robust model enables a comprehensive examination of how evolving water quality, influenced by factors like climatic events and warming, impacts the entire network. This holistic perspective can assist utilities in making informed decisions about their systems. Furthermore, these models facilitate the evaluation of measures designed to enhance water quality within the DS, ensuring that end-users receive safe and clean drinking water.

To achieve these goals effectively, water quality prediction models should demonstrate flexibility in adapting to fluctuations in water quality parameters, such as temperature and DOC, which are fundamental in determining source water quality. Additionally, these models should be capable of accommodating common changes in operational parameters, including adjustments in dosages and re-chlorination practices across the distribution network. Finally, a specific challenge arises when ammonia is present in utilities relying on surface water sources. The rapid reaction of ammonia with natural organic matter during the first few hours of the chlorination process significantly impacts the decay rate of chlorine. Constant-rate models such as the 1st-order model, commonly employed for water quality prediction, prove ineffective in the presence of high ammonia concentrations and the parallel 1st-order model requires recalibration for shifting from the fast phase to the slow reaction phase. In this project, an alternative model known as the Variable Reaction Rate Constant (VRRC) model was used which addressed these challenges with a simple

calibration process with minimal required inputs for chlorine and THMs prediction in a full-scale DS. This model was previously used in lab-based experiments and for low-ammonia waters. In this work, we adapted this model to predict chlorine and THMs in a WTP in Quebec with ammonia during cold seasons. We then combined the VRRC model with a 1st-order wall decay model to predict chlorine residual and THMs in the full-scale DS and the predictions were validated with direct field measurements in 22 points in two seasons. The chlorine prediction results demonstrated its potential in enhancing water quality prediction. The VRRC-chlorine model demonstrated an exceptional fit in high ammonia concentrations, with an R-squared (R^2) of fit of 0.99 and a Root Mean Square Error (RMSE) of 0.03 mg/L. In contrast, the 1st-order model had a weak fit due to the rapid initial chlorine decay rate, achieving an R^2 of 0.602 and an RMSE of 0.61 mg/L. VRRC-THMs model successfully predicted THMs concentrations with a prediction error of less than 5 $\mu\text{g/L}$ in 20 out of 22 validation points with an R^2 of 0.6 and an RMSE of 3.74. In contrast to VRRC, the 1st-order THM model only predicted 1 out of 22 points with 5 $\mu\text{g/L}$ precision with an R^2 equal to 0.52 and an RMSE of 14.75. The 1st-order THMs model failed to predict THMs concentrations in the DS because of the overestimation of the THMs prediction.

The 1st-order THM model, as described in Article 1 and Appendix A, attempted to correlate chlorine decay to the formation of THMs with a linear correlation, using a THM yield coefficient. However, this approach is unrealistic because it neglects a significant factor in chlorine decay within a water distribution system—the pipe wall effect. In reality, a substantial portion of chlorine decay occurs due to the reaction of free chlorine with pipe wall materials and the biofilm that accumulates inside the pipes. To explore the impact of network conditions, including the pipe wall effect, on chlorine concentrations, we conducted a comparative analysis. This analysis involved comparing the laboratory-based chlorine measurements, influenced only by water quality, with the field chlorine measurements that accounted for both water quality and network conditions. The results from our sampling in March 2021 revealed that the pipe wall effect contributed to up to 45% of the total chlorine decay. In October 2021, our findings showed that network conditions were responsible for up to 17.5% of the total chlorine decay, underscoring the significant influence of network conditions on chlorine decay. However, when we examined laboratory results and network measurements for THMs variations, it became evident that THMs are primarily driven by source water quality, with network conditions having a minimal impact. This finding aligns with the research conducted by Koch et al. (1991), which demonstrated a strong correlation between

lab-based THM tests and field measurements. In their study, pipe wall effects were found to have little influence on THM concentrations within the distribution system.

Field testing of the VRRC model in a full-scale network across two seasons validated its effectiveness under varying temperatures, DOC, ammonia, and pH in source water as well as changes in applied dosage in the treatment process. Ensuring accurate water quality prediction is essential for delivering safe drinking water. By employing the VRRC model, utilities can maintain compliance with regulatory standards in the face of changing climate conditions and evolving water quality challenges. Our approach serves as a valuable tool for utilities to evaluate strategies for reducing THMs in the distribution system, a critical aspect of safeguarding public health. One of the key strengths of this work is its accessibility. Its simplicity in calibration makes it a valuable tool for utilities of all sizes, including those with limited resources. This accessibility provides small utilities with an opportunity to benefit from advanced predictive capabilities. The proposed approach and model set a precedent for more accurate and resilient water quality predictions in the face of evolving challenges, such as climate change and shifts in water sources. This, in turn, enhances the operational efficiency and resilience of water systems, ultimately benefiting water utilities and the communities they serve.

7.2 Climatic events and water saving measures impacting water quality management in the distribution system

The primary objective of Article 2 was to assess the individual and combined impacts of increased DOC, elevated temperature, and reductions in water demand on chlorine and THMs concentrations in a full-scale DS. This investigation aimed to provide insights into the relative importance of each factor in relation to the other two. Table 7.1 presents a summary of the isolated effects of each factor, while keeping the other two constant, on the mean free chlorine and THMs concentrations across the DS. To provide context, we assessed the compliance with recommended chlorine levels (0.2 mg/L) and regulatory limits for THMs (maximum 80 µg/L) by calculating the percentage of nodes where violations occurred. The violation of THMs regulatory limit was based on the daily average THMs values. The results revealed that a 63% reduction in water demand resulted in a 53.3% decrease in the mean chlorine residual, causing a 42% increase in the percentage of nodes with daily chlorine concentrations falling below 0.2 mg/L throughout the DS. Concerning THMs, a reduction in water demand led to a 26.1% increase in the mean THMs concentration across the

DS, although this increase did not breach the regulatory threshold of 80 µg/L for THMs. Water demand reduction translates to increased residence times within the DS and increases the contact time of water with the pipe walls and increases the impact of network on chlorine decay and THMs formation. The observations in article 1 about the high impact of network conditions on chlorine and its lower impact on THMs also aligns well with these results. This observation highlights the critical importance of governmental water conservation strategies in maintaining adequate chlorine levels within the network. A shortage of chlorine may increase the risk of bacterial regrowth within the system. However, it does not significantly impact THMs and does not lead to regulatory non-compliance.

Table 7.1 Effects of water demand, temperature, and doc changes on chlorine and THMs in the distribution system

Constant	Variable	Free chlorine residual		THMs concentration	
		% decrease in mean Cl ₂ across DS nodes	% increase in nodes with mean daily Cl ₂ <0.2 mg/L	% increase in mean THMs across DS nodes	% increase in nodes with mean daily THMs>80 µg/L
Temperature= 17°C DOC=1.5 mg/L	Demand decreases by 63%	53.3%	42%	26.1%	0
Demand= 305 LCD* DOC=1.5 mg/L	Temperature increases from 5°C to 35°C	57.7%	40%	199.4%	100%
Demand= 305 LCD Temperature= 17°C	DOC increases from 0.7 mg/L to 3.2 mg/L	73.4%	62%	289%	100%

* LCD: litres per capita per day

Shifting the focus to the impact of DOC and temperature variations on free chlorine availability, it becomes apparent that their effects are comparable to the effect of demand reduction, with DOC being slightly more influential. For instance, increasing water temperature from 5°C to 35°C results in a 40% increase in the percentage of nodes within the DS where free chlorine residual falls below 0.2 mg/L. On the other hand, elevating DOC levels from 0.7 mg/L to 3.2 mg/L causes a substantial

62% increase in the percentage of nodes with free chlorine residual below 0.2 mg/L. However, when considering the effects of DOC and temperature variations on THMs concentrations, these factors play a significantly influential role. An increase in DOC levels in treated water above 2.2 mg/L leads to a network-wide violation with the violation of the 80 µg/L regulatory threshold for THMs in 100% of the nodes. The significance of maintaining DOC levels below 2.2 mg/L remains essential, regardless of variations in demand or temperatures. Exceeding this threshold can lead to network-wide THM violations and it should be avoided by implementing measures to reduce DOC through treatment processes.

While accurately predicting the influence of climatic events on DOC levels in downstream water bodies remains challenging and uncertain, existing literature presents varied findings, including reports of no change, increased DOC, and decreased DOC following climatic events. However, certain studies have detected elevated DOC concentrations in downstream watersheds. Consequently, it is of utmost importance to assess the potential impact of heightened DOC levels on chlorine and THMs availability within our systems and identify threshold levels that could trigger regulatory violations.

The reliability index, ranging from 0 to 100, signified compliance with chlorine or THM standards. A value of 0 indicated that the standards were never met, while 100 implied consistent adherence to regulations throughout the day. The reliability maps generated using MATLAB, in conjunction with the coordinates of all network nodes, served as a valuable tool for pinpointing the origins of issues related to insufficient free chlorine or excessive THMs within the network. The changes in nodal reliabilities revealed distinct patterns. For chlorine, the decline in reliability initiated at the network's extremities and dead ends. With decreasing water demand, areas with lower chlorine levels gradually shifted from these peripheral regions towards the central areas and the WTP. Conversely, for THMs, alterations in nodal reliability exhibited more abrupt variations, and demand reduction had minimal impact on THM reliability within the distribution system. Notably, under conditions where DOC surpassed 2.2 mg/L or when the temperature exceeded 25°C, a system-wide decline in THM reliability occurred. Interestingly, this breach began under the highest demand scenarios at the WTP, rather than originating from the network's dead ends or extremities.

7.3 Urban heat islands vs. green spaces: how do they affect drinking water temperature

7.3.1 Water temperature disparities in the distribution network

It is commonly believed that ensuring safe water quality is primarily contingent on the quality of treatment and maintenance of the water distribution network. However, there's often little awareness of the potential disparities within a water distribution network stemming from anthropogenic heat sources on the surface or subsurface. In our third article, we explored how urbanization and the creation of UHIs impact drinking water quality. UHIs can create local climate zones where the local air temperature is significantly higher than in the surrounding areas, leading to elevated soil surface temperatures. Typically, soil temperature decreases with depth. In Quebec, the design standard for pipes in the water DS requires a minimum burial depth of 1.8 meters to prevent freezing during winter. Consequently, there was a prevailing belief that the influence of heatwaves and UHIs would not be noticeable at such depths.

In our study, we examined two closely situated zones, the 'vegetation-impacted zone' and the 'UHI-impacted zone'. Both zones were connected to the same WTP and shared similar initial conditions regarding water temperature variations from the source. They also experienced nearly identical meteorological conditions, which meant that factors such as heatwaves, wind conditions, and precipitation changes affected both zones concurrently. This ensured a fair comparison where all conditions were similar, with the main difference being the land surface coverage during the water travel time through each zone. The UHI-impacted zone predominantly consisted of pavement and concrete with limited tree cover and parks. In contrast, the vegetation-impacted zone boasted an abundance of trees, bushes, and grass.

Table 7.2 summarizes the minimum, average, median, and maximum monitored water temperatures as well as the cooling or heating effects observed at all 34 monitoring points for the period of July 27th to September 1st in both zones. This cooling or heating effect is calculated by subtracting the monitored temperatures at each monitored point from the treated water temperature at the WTP. A negative sign denotes that the water temperature had decreased from the WTP to the monitoring point, while a positive sign signifies an increase in water temperature from the treatment plant to each point.

The results revealed that water temperatures in the UHI-impacted zone were consistently higher compared to the vegetation-impacted zone. The most notable differences between these two zones are observed in the minimum and maximum temperature records, rather than the averages. The lowest recorded water temperature in the vegetation-impacted zone was 16.5°C, which is 3°C lower than the minimum recorded temperature in the UHI-impacted zone. On the other hand, the highest recorded temperature in the UHI-impacted zone reached 32°C, which was 6°C higher than the maximum recorded temperature in the vegetation-impacted zone. Comparing the cooling and heating effects in each zone, the UHI-impacted zone displayed a maximum water heating of 8°C, which was 5.5°C higher than the maximum heating in the vegetation-impacted zone. Concerning cooling, the maximum cooling effect occurred in the vegetation-impacted zone, reached 8°C which was 3.7°C higher than the maximum cooling in the UHI-impacted zone.

Table 7.2 Summary of the water temperature monitoring results during the period of July 27th to September 1st as well as the temperature difference between each monitored point and the WTP temperature shown with the $T_{\text{monitored}} - T_{\text{WTP}}$. The positive values mean water was heated from the WTP to the customer's building and the negative values mean that cooling took place from the WTP to the customer's house.

	Monitored temperature (°C)				$T_{\text{monitored}} - T_{\text{WTP}}$ (°C)			
	Minimum	Average	Median	Maximum	Minimum	Average	Median	Maximum
Vegetation-impacted zone	16.5	22.3	22.5	26.0	-8.0	-1.6	-1.1	2.5
UHI-impacted zone	19.5	23.7	23.5	32.0	-4.7	-0.2	-0.2	8.0

7.3.2 Soil and water temperature modeling results

The soil temperature modeling results demonstrate a strong correlation with LST classification. For example, during the period of July 27th to August 12th, the average soil temperatures increased by 6.22°C as LST class shifted from 1 to 5. Notably, the difference between the median water temperature measurements in the same LST classes during the same period was 6.5°C which closely mirrored the average soil temperature differences. This correspondence underscores the validity of the soil temperature model's results. The water temperature modeling results show that daily water temperature variations are more pronounced than the modeled temperature variations.

These fluctuations in monitored water temperature are attributed to factors such as different water consumption habits, building types (residential or non-residential), and occupancy levels. Using a similar demand pattern for all the nodes caused a similar temperature variation pattern in the modeling results. Comparing the goodness of prediction statistics between measured and predicted daily drinking water temperatures emphasizes the accuracy of the predictive model. The minimal prediction errors and low root mean square errors (RMSE) highlight the model's effectiveness. Overall, the results suggest that LST classification, soil temperature, and modeling inputs such as the water consumption patterns and the hydraulic calibration of the model play crucial roles in predicting water temperature in distribution systems. These findings have significant implications for water distribution system design and management, especially in areas affected by UHIs with higher soil temperatures.

7.3.3 Impact of local environmental factors on drinking water temperature

7.3.3.1 Impact of land surface temperature

The results of the water temperature monitoring demonstrate a notable correlation between water temperatures and LST classifications derived from satellite imagery. The collected data distinctly reveal a warming effect corresponding to increasing LST. The relationship between water temperature and LST classifications indicates the potential use of satellite imagery for preliminary identification of zones susceptible to extreme warming during the summer. This is especially important for utilities with lack of data and resources to monitor and model drinking water temperature in the DS. This, in turn, can assist utilities in selecting water quality monitoring points and in conducting more in-depth soil and water temperature modeling within these zones to better understand water temperature variations during hot periods.

7.3.3.2 Impact of source water temperature

Values and variations in source water temperature did not display a significant correlation with fluctuations in drinking water temperature within the DS. The source water for the city under study, originating from a river, exhibited temperature variations ranging from 22°C to 25°C throughout the monitoring period. Although variations in source water quality were relatively modest, drinking water temperature within the DS exhibited considerable fluctuations during the day. This observation which is consistent with the previous findings of Agudelo-Vera et al. (2015) reinforces

the notion that drinking water temperature is predominantly influenced by the surrounding soil temperature.

7.3.3.3 Impact of air temperature

Analyzing the trends in both air temperature and water temperature throughout the monitoring period does not reveal any conclusive correlation between fluctuations in air temperature and corresponding variations in drinking water temperature within the DS. When we compare the dates of peak water temperature with those of peak air temperature, no immediate influence of air temperature on measured water temperature becomes evident. Rather, the alignment between the measured water temperatures and the modeled soil temperatures suggests that drinking water temperature within the pipelines is primarily influenced by the temperature of its surrounding soil environment, rather than by changes in air temperature. Furthermore, when we compare the variations in modeled soil temperatures with recorded air temperature data over the study period, it becomes apparent that soil temperature variations tend to lag behind air temperature variations by a few weeks. Although this lag cannot be directly quantified, a visual analysis of the data confirms its presence. This observation highlights the complex relationship between air and soil temperatures and their combined effect on drinking water temperature in the DS.

7.3.4 Impact of water travel time in the distribution network on water temperature

The results of the monitoring campaign revealed that there is no correlation between variations in water temperature at different points within the DS and their respective average water residence times. Points located in the vegetation-impacted zone generally exhibited higher water ages (ranging from 6.2 hours to 17.6 hours) compared to points in the UHI-impacted zone (ranging from 5.6 hours to 13 hours). However, interestingly, the vegetation-impacted zone points had lower temperatures. This finding is in contrast with previous studies by Agudelo-Vera et al. (2020) which indicated that extended water travel times (exceeding 12 hours) were associated with elevated temperatures, and Machell and Boxall (2014) who observed an upward trend in temperature for samples collected from pipes with longer water residence times. The differences between our study and these two studies can be attributed to two main factors. First, in both previous studies, the source water temperature was significantly lower than the temperature of the surrounding soil

(10°C versus 25°C), while in our case, the source water temperature ranged from 22°C to 25°C, resulting in a continuous rise in water temperature from the WTP to each zone. Second, the previous studies assumed a uniform soil coverage throughout the entire distribution system. In our study, we encountered contrasting soil coverages in different zones. These varying soil coverages within the studied zones, along with distinct land surface temperatures, led to fluctuating soil subsurface temperatures across the network. Comparing the measurement of water temperature with soil temperature modeling results revealed that, as water traveled from the treatment plant to each house, the water temperature approached the temperature of the soil surrounding it. This phenomenon caused the water temperature to be either higher or lower than its initial temperature at the WTP at different points within the distribution system.

7.3.5 The significance of local warming for water quality management

The creation of UHIs has resulted in disparities in water temperature. Traditionally, our focus has been on water warming at the source and its potential impact on chlorine and THMs within the DS. In Objective 2, our aim was to study the impact of global warming on water temperature. To do so, we analyzed historical water temperature data from the WTP. This analysis revealed that 25°C represented the highest recorded temperature during summer. We chose this temperature as the maximum summer water temperature within the water distribution network, also considering a more extreme scenario of 35°C, which seemed unlikely at the time. However, as we delved into Objective 3, we discovered that while water temperature within the plant cannot exceed 25°C on the hottest days, it can reach as high as 32°C at certain points within the water distribution network. This finding challenged the notion of a uniform temperature assumption throughout the network for modeling water temperature, which we now realize is not realistic. Assuming a constant temperature for water within the ds results in an underestimation of chlorine decay and THM formation at some zones. While chlorine residuals and THMs may meet standards at 25°C, they do not maintain these levels at 32°C.

Elevated temperatures within the distribution system can harm water quality, both chemically and microbially. Higher temperatures accelerate the decay of chlorine residuals and increase the formation of carcinogenic disinfection by-products, as noted by (Kimbrough, 2019). Of particular concern is the growth of pathogenic bacteria such as *Legionella pneumophila* (Lp), which thrives in heated water systems and buildings, causing the fatal Legionnaire's disease (LD) and a milder

illness known as Pontiac Fever (National Academies of Sciences, 2019). In 2014, LD incurred \$402 million in medical costs in the United States, ranking it among the costliest and deadliest waterborne diseases (National Academies of Sciences, 2019). LD cases exhibit seasonality, with most occurring during hot periods, suggesting that elevated water temperatures in urban settings could lead to an increase in LD cases in the future. Notably, the optimal temperature range for *Lp* growth is 25-43°C (National Academies of Sciences, 2019), a range observed multiple times during the monitoring period. Although there are no specific regulations governing *Lp* within the distribution system, the "Guide de bonnes pratiques d'exploitation des installations de distribution d'eau potable" (Quebec Government, 2023) recommends maintaining a minimum free chlorine concentration of 0.1 mg/L in the distribution system to prevent microbial regrowth. Additionally, Donohue (2021) reported that free chlorine residuals greater than 0.2 mg/L significantly suppress the prevalence of opportunistic bacteria, including *Lp*, in drinking water distribution systems. Based on the results of our second article on a distribution network in Quebec, temperatures above 25°C were associated with 45% of the nodes in the network exhibiting an average daily chlorine residual below 0.2 mg/L and 100% of the nodes exceeding the THMs limit of 80 µg/L. These findings suggest a potential chlorine deficiency in heat islands, which, coupled with the exceptionally high temperatures, could pose a serious concern for *Legionella* and other pathogens. This highlights the need for further investigation into its implications for water microbial quality within the distribution system, particularly for vulnerable individuals and marginalized communities. These conditions have the potential to lead to disparities in water quality.

In practice, the adjustment of the applied chlorine dosage at the WTP is based on water quality indicators with water temperature being one of the important factors. Therefore, dosage adjustments are made during warmer seasons based on treatment plant water temperature. However, this practice solely considers the water temperature at the WTP and not within the DS. This underscores that relying solely on water temperature at the treatment plant to determine chlorine dosage underestimates the true chlorine decay and the THM formation occurring within the DS. Consequently, certain zones in the network may experience insufficient chlorine levels or excessive THM formation. These findings emphasize the importance of considering local water temperatures in water quality management within distribution systems.

7.4 Recommendations for utilities under changing conditions

7.4.1 Reducing the THM precursors

In Section 7.3, it was observed that the breach of THMs occurs when certain conditions are met, namely when the temperature exceeds 25°C and the DOC level surpasses 2.2 mg/L. Importantly, this breach originates not at the distribution system's extremities but, rather, at the WTP. This finding highlights the significance of addressing THM formation at its source by reducing the THM precursors. The mitigation of DBPs in drinking water treatment typically revolves around two primary strategies: alternative disinfection methods and the removal of DBP precursors before chlorination.

Switching from chlorine to chloramine has been widely acknowledged as an effective means of minimizing the formation of regulated DBPs (Bond et al., 2014; Seidel et al., 2005). While this transition may seem promising for treatment plants, it can have significant implications for lead (Pb) release. In cases where the secondary disinfectant changes from chlorine to monochloramine, reductive dissolution of lead dioxide (PbO₂) can lead to elevated Pb levels at the tap water (Lin and Valentine, 2008). A famous example of this phenomenon is the lead crisis in Washington D.C. during 2001 to 2004 (Anderson et al., 2023). Consequently, controlling DBPs by removing their precursors represents a more viable approach.

7.4.2 Increasing the applied chlorine dosage

One of the solutions to prolong chlorine availability in the DS is to increase the applied chlorine dosage in the WTP. While this measure can resolve the issue of low chlorine residual in the system, it increases the THM concentration. In high temperatures and DOC levels, the percentage of chlorine residual breaching the minimum 0.2 mg/L threshold is significant. Normally, the first solution is to increase the applied chlorine dosage to ensure the coverage within the DS. To see if increasing the dosage can be a suitable corrective action in high DOC or temperature scenarios, the effectiveness of increasing the dosage from 2 mg/L to 3 mg/L on the chlorine and THMs coverage was assessed in article 2. Some of the most critical scenarios were studied with a DOC of 1.52 mg/L and 3.2 mg/L, a temperature of 17°C, 25°C, and 35°C, and an average demand of 305 LCD, 250 LCD, and 153 LCD. For example, at temperature of 25°C and DOC of 1.52 mg/L and under 305 LCD annual demand and 2 mg/L of applied chlorine dosage, 86% of the network nodes had

an R_{Cl_2} of 100 and 99% of the nodes had an R_{THM} of 100. By increasing the dosage from 2 mg/L to 3 mg/L the percentage of nodes with $R_{Cl_2}=100$ increased by 8% but the percentage of nodes with $R_{THM}=100$ decreased by 62%. Among all scenarios, we witnessed between 44-82% improvement in percentage of nodes with $R_{Cl_2}=100$ when the chlorine dosage was increased to 3 mg/L.

THM reliability in all the other scenarios was zero across all network nodes, even when an applied chlorine dosage of 2 mg/L was maintained. consequently, increasing the applied dosage will only worsen the THM reliability. These results suggest that, under conditions of elevated DOC and temperature in treated water, increasing the applied chlorine dosage can be counterproductive rather than corrective.

7.4.3 Controlling water temperature

7.4.3.1 Deeper pipe burial

In Article 3, the soil temperature modeling results were compared at the depth of 1 meter (common in the Netherlands and similar regions without freezing issues) and at 1.8 meters depth in Quebec to evaluate the effectiveness of deeper pipe burial for water temperature moderation. The results revealed that increasing the burial depth results in an average reduction of 2.9°C when transitioning from a 1-meter depth to 1.8 meters. This average value was obtained from five different soil scenarios in our case study and may vary in other regions due to local soil properties. Since the soil temperature modeling results closely matched the water temperature monitoring results, we can confidently assert that deeper pipe burial can serve as a viable corrective action for mitigating extreme heat in the distribution system. However, it's essential to consider the costs associated with implementing this solution, as well as the potential disruptions in service, CO₂ emissions, and inconvenience to customers during the process. Furthermore, the effectiveness of this solution should be assessed within the context of the specific area under study. For instance, in Montreal, despite achieving an average cooling effect of 2.9°C, we still observed exceptionally high water temperature records, reaching up to 32°C in the red zone.

7.4.3.2 Increasing Green Spaces

An alternative strategy, which is not only more sustainable but also offers a range of additional benefits, is the strategic planting of trees and other types of vegetation and green infrastructure for

the expansion of shaded areas. Increasing green space coverage not only contributes to water temperature regulation but also enhances the overall health and well-being of communities. To ensure that all residents have access to green spaces and trees and can benefit from the advantages they offer, Konijnendijk (2021) introduced the 3-30-300 guiding principle for urban forest programs. This principle suggests that every resident should have visibility of at least three decent-sized trees from their home, each neighborhood should maintain a minimum canopy cover of 30%, and every resident should reside within 300 meters of a high-quality park or green space (Konijnendijk, 2021). Ling (2022) conducted an evaluation of 180 residences in the cities of Toronto and Mississauga and found that only 12% of them met the requirements of this principle. Intriguingly, their study revealed a statistically significant correlation between the elements of this principle and property listing prices. The top third of the highest-priced residences had a higher proportion of trees and green spaces (Ling, 2022). The uneven access to green spaces, combined with the apparent benefits of green spaces for water temperature regulation, implies that lower-income and marginalized communities may have access to water with lower chemical and microbial quality. This hypothesis requires further investigation and carries significant implications for underserved communities.

7.4.4 Changing the old way things are done

7.4.4.1 Evolving water quality monitoring strategies

Currently, *Lp* monitoring in Quebec primarily focuses on cooling towers in the buildings, assuming that *Lp* growth is minimal within the DS and mainly attributed to water stagnation and heating systems within buildings (National Academies of Sciences, 2019). Chlorine monitoring sites are also typically situated at the peripheries and dead ends of the network. Peripheries are chosen due to higher water age, increasing the chances of chlorine depletion and THM formation caused by extended chlorine reaction times. Dead ends are selected because of water stagnation, where the risk of chlorine depletion and the formation of THMs is higher. However, our findings from objective 3 have shown that some of the hottest temperature records were reported in zones very close to the WTP. The existing management protocols may overlook these hot zones due to their proximity to the WTP. As a result, the impact of UHIs within the city on chlorine levels and THM formation remains unexamined, and the potential effects of local warming on *Lp* within the DS will be overlooked. It is recommended to consider these zones for regulatory monitoring – at least

during hot periods – as they may be at risk of low chlorine residuals and high THM concentrations and potentially increased risk of *Lp* growth.

7.4.4.2 Embracing Multidisciplinary Approaches

Our research demonstrates that employing a combination of tools can provide a deeper insight into the ways climate change affects our systems. Given that global changes impact our systems in multiple ways, it is essential to employ a variety of tools to comprehend and predict the implications of climate change effectively. In objective 1, we combined sampling from the WTP and field, laboratory tests, MATLAB programming, and water quality simulation to predict chlorine and THMs within the DS. In objective 2, we leveraged laboratory tests, MATLAB programming, water quality simulation, and spatial mapping techniques to predict drinking water quality under different scenarios and map reliabilities within the DS. In objective 3, we utilized geospatial information systems, satellite imagery, hydraulic and water quality modeling tools, and MATLAB programming in harmony with field water temperature monitoring to realize the impact of UHI and green spaces on water temperature. This multidisciplinary approach allowed us to describe the dynamics of water temperature and quality within the DS more realistically, facilitating a more comprehensive understanding of the complex relationships within the water distribution system in the context of global change and urbanization.

7.5 limitations and challenges

Despite the successful execution of this project, we encountered several noteworthy challenges and limitations. Our multifaceted approach, encompassing modeling, simulation, sampling, and monitoring, revealed various aspects of water quality dynamics. In Table 7.3, we present and discuss the primary limitations and challenges that influenced our methodologies and how they were handled.

Table 7.3 Project challenges, limitations, impact, and handling

Objective	Limitation/challenge	Discussion and mitigation
Objective 1	Lack of specific demand patterns	Due to the absence of specific demand patterns for the residential and non-residential buildings in the studied city, we employed a uniform hourly demand pattern based on the WTP's production rate for water quality prediction. Having more specific demand patterns which reflect the water consumption intensity and duration more realistically would enhance the precision of prediction. Despite this limitation, the chlorine prediction was successful in 73% (in Autumn) to 77% (in spring) of the validation points with less than 0.1 mg/L prediction error and THM prediction was successful in 91% of the validation points with less than 5 µg/L prediction error.
	Lack of continuous chlorine and THM measurement in the distribution system	Online sensors for chlorine residual measurement over an extended duration could improve model calibration for better daily predictions in the distribution system. However, the measurement of THMs poses challenges due to time constraints and specialized instrumentation required. Our research successfully addressed many aspects of water quality prediction, despite these constraints.
Objective 2	Lack of information about the impact of wildfire events in Quebec	To study the impact of post-fire rainfall events on chlorine and THMs in the DS, we conducted an extensive literature review on previous wildfire events and their impacts on downstream water utilities' DOC in Canada and US. The DOC values selected for our work were based on the actual DOC levels in the water utilities in Alberta (Canada) and Utah (US) post-wildfire. Though knowledge of the specific effects on DOC concentration in Quebec would provide more realistic results, our approach and findings are a significant step in assessing the implications of intense climatic events on decay and THM behavior in drinking water distribution systems.

Table 7.3 Project challenges, limitations, impact, and handling (cont'd)

Objective	Limitation/challenge	Discussion and mitigation
Objective 3	The Engagement Challenge: Earning Trust and Cooperation	A pivotal phase of our research entailed direct engagement with local citizens in the two study sites, where we tried to convey the significance of our study and secure their cooperation. This endeavor extended over several weeks, requiring numerous hours and multiple visits to households, and face to face interaction with the citizens. What made this campaign particularly demanding was the necessity to persuade individuals who lacked prior knowledge or expertise about our research and were under no obligation to participate, rendering this outreach a truly unique and intricate experience. Furthermore, earning their trust to allow the installation of an "unfamiliar device" within their homes, responsible for monitoring water temperature over an extensive 2.5-month period, proved to be a formidable task. This phase of our research exemplifies the commitment and perseverance required to overcome challenges and emphasizes the significant role of community involvement in advancing scientific understanding.
	Lack of water meters in residential buildings	Having specific demand data for each building would provide us with the means to explore the relationship between water demand fluctuations and variations in water temperature. This information could also aid in investigating correlations with the highest and lowest recorded temperatures and demand levels. Furthermore, it would enable a comprehensive analysis of the influence of water consumption habits, which are influenced by factors such as the number of occupants in each household and the intensity and duration of water use per individual. Crucially, this data would facilitate a more precise examination of the impact of stagnation on water temperature. It is hypothesized that stagnation amplifies the influence of the surrounding soil on water temperature. Consequently, we anticipate that in the UHI-affected zone, stagnation may lead to extreme warming, while in the vegetation-affected zone, stagnation may result in cooler temperature records. Nevertheless, further investigation is necessary to substantiate these hypotheses and provide a more detailed understanding of these effects.

Table 7.3 Project challenges, limitations, impact, and handling (cont'd)

Objective	Limitation/challenge	Discussion and mitigation
	Lack of information about local soil characteristics	Precise information regarding soil conductivity within the five distinct soil classifications mentioned in objective 3 would improve the calibration of the soil temperature model. In our study, an average soil conductivity value for Montreal was used for soils in classes 1 to 4. For soils in class 5, the UHI class, we used values from a Dutch case study describing soil conductivity in hotspot urban areas with concrete and pavements which was similar to our studied site. Nevertheless, the limited number of pipes in class 5 is unlikely to significantly impact our results. Moreover, the soil and water temperature results were close to the measurements and were successful in overall.
	Lack of soil temperature measurements	Incorporating soil temperature measurements within the distribution system would enhance the calibration of the soil temperature model.
	Lack of knowledge about the surface and underground heat sources	Improved knowledge of underground heat sources, such as district heating systems, heat from metro tunnels, and building heat emissions, could refine the model's anthropogenic heat source (Q) value. Our model incorporated values from relevant literature to address this limitation.

CHAPTER 8 CONCLUSIONS AND RECOMMENDATIONS

In this research, we aimed to address the impacts of global change on drinking water quality in cities. We studied the impact of different factors that could impact drinking water quality at different levels such as: 1) at the WTP level by changing the source and treated water quality under climatic events and global warming, 2) at the operating level by decreasing the water demand due to governmental water saving strategies, and 3) at the DS level by creating the UHIs and creating water temperature disparities. In this chapter, the conclusions of the research will be formulated in a way that would answer the research questions proposed in the beginning. Then, the potential of this research for future works will be discussed.

8.1 Conclusion

The first objective aimed to enhance water quality modeling in full-scale DS to predict chlorine and THM variations under high ammonia concentrations and seasonal changes in water quality. The questions asked were:

1. What is the accuracy of predicting free chlorine residual and THMs in ammonia-containing waters using a variable rate model compared to the 1st-order and parallel 1st-order model?
2. How well can free chlorine and THMs be predicted compared to the direct field measurements in a full-scale water distribution network?

The conclusions after realizing this objective are:

- The VRRC model could successfully predict chlorine variations in high-ammonia content waters with an R^2 of 0.99 and RMSE of 0.03 whereas the 1st-order model had a R^2 of 0.6 and an RMSE of 0.61. In low-ammonia containing waters, VRRC chlorine still had a superior prediction ($R^2=0.95-0.97$ & $RMSE=0.03-0.1$) compared to the 1st-order model ($R^2=0.78-0.91$ & $RMSE=0.15-0.23$). Considering the precision target set at the beginning which was ± 0.1 mg/L, VRRC had a superior prediction over the 1st-order model.
- THM prediction in high ammonia waters with VRRC had an R^2 of 0.96 and RMSE of 2.42 whereas the 1st-order model had an R^2 of 0.92 and an RMSE of 3.58. In low-ammonia containing waters, VRRC still had a superior precision ($R^2=0.96-0.97$ & $RMSE=1.06-2.52$) compared to the 1st-order THM model ($R^2=0.89-0.95$ & $RMSE=2.92-6.11$).

- The chlorine validation results in the DS showed that VRRC model predicted chlorine in 16-17 out of 22 total validation points with ± 0.1 mg/L precision. The 1st-order model predicted chlorine in 15-17 out of 22 of the validation points with ± 0.1 mg/L precision. THM validation results showed that VRRC achieved the target precision of ± 5 μ g/L in 20 out of 22 points, whereas the 1st-order model met this target in 1 out of 22 points.
- Prediction of THMs in a full-scale DS with VRRC model had a high precision only using lab-based results without calibration with the field THM values, showing that the model can be used in full-scale applications.

The second objective was to address the individual and combined effects of climatic events, warming, and water demand reduction on chlorine and THMs in a full-scale DS and the questions to answer were:

1. What is the impact of water warming and DOC increase on the rates of chlorine decay and THMs formation in the drinking water distribution systems?
2. How does the combined effect of demand reduction, DOC/temperature impact the levels of chlorine and THMs in the DS and is there a synergistic effect between them?
3. Which zones within the DS are more vulnerable to insufficient chlorine or high THMs formation?
4. Are current approaches for water quality monitoring in the DS adapted to future climate under constant and continuous global warming or they should change?

The conclusions after realizing this objective are:

- The combination of temperature increase, elevated DOC levels, and reduced water demand significantly exacerbates chlorine and THM violation from recommended and regulatory standards.
- Temperature and DOC change have a more concerning impact on THM formation than increased water residence time within the DS.
- For maintaining sufficient free chlorine residuals, both water quality conditions (temperature and DOC) and water demand reduction have significant effects, emphasizing the need for a comprehensive understanding of these interacting variables.

- The reliability maps revealed discrepancies in the distribution of low-reliability nodes for chlorine and THMs, indicating that nodes with high THM levels could be in different locations from those with low chlorine levels. This variation in node locations should be considered during water quality monitoring and corrective measures.

- Under higher DOC levels, chlorine residual becomes scarce, starting from the extremities of the DS. adjusting the applied chlorine dosage at the WTP based on the chlorine residual at the extremities is a common practice by the WTP operators. Under higher DOC and/or temperature levels, this method may cause elevated levels of THMs and, if the conditions persist long enough, may potentially cause noncompliance in the DS.

Apart from the questions addressed, our study uncovered other noteworthy findings:

- A substantial percentage of the total THM formation in the DS is formed in the WTP prior to distribution. Under higher DOC levels, WTPs should closely monitor their proximity to THM formation potential to avoid breaching the regulatory levels.

- Comparing utilities treatment performance based on the percentage of THM formation potential they produce at the WTP exit could be used as a valuable metric. Higher applied chlorine dosage can lead to closer proximity to the THMFP at the WTP exit. This metric has the potential to improve THM and chlorine management strategies.

The third objective was to monitor and model drinking water temperature in the city of Montreal, Quebec under variations in land surface coverage to address the effects of UHIs and green spaces on water temperature variations within the DS. The questions asked were:

1. Are water pipes at 1.8 meters depth affected by heatwaves during summer?
2. Does creation of UHIs in cold climates induce warming and threaten water safety for its consumers?
3. Does city greening have the potential to reduce water temperature?
4. How well can the model predict drinking water temperature in the DS, and how does it compare to the measured data?
5. Are current standards for designing water distribution systems reassuring under constant and continuous global warming or they should change?

The conclusions regarding this objective are:

- Comparing water temperature at 1.8 m with those at 1 m showed that deeper pipe burial can in fact reduce the drinking water temperature, but its effectiveness depends on the significance of the heating taking place. For example, in the case of Montreal, water temperature in the pipes was still under the influence of UHIs, increasing up to 32°C at some points.
- Comparing the water temperature records with the initial temperature at the WTP revealed water passing by the zones with elevated soil temperatures can cause up to 8°C heating in water temperature. Nevertheless, the extent of heating could vary based on the case study conditions.
- City greening was shown to be effective for reducing water temperature as travelling in the vegetation-impacted zone led to up to 8°C cooling compared to the WTP initial temperature.
- Current water quality management measures, which primarily focus on monitoring chlorine and THMs in the distribution system based on water age, may not effectively address areas with low chlorine levels and elevated THMs due to UHI effects with lower water age.
- Water temperature modeling using the meteorological data and local land surface characteristics showed to be able to closely predict changes in the water temperature in the DS.
- Modeling water temperature in the absence of extensive resources available for field monitoring can be a great tool for identification of hot water temperature zones in urban areas and can help water quality management.
- The weak alignment between the WTP and DS water temperature compared to the strong alignment between the soil and DS water temperatures shows that soil temperature is a stronger indicator of water temperature variations.
- The alignment of the LST classifications with the water temperatures in the DS shows that LST satellite images can be a great tool for preselection of local high water temperature zones.

8.2 Recommendations for future research

To advance our understanding of the implications of changing conditions for drinking water quality, some recommendations for future work is listed below:

1- Investigate the impact of household demand variations on drinking water temperature:

Study the impact of water demand variations in households on drinking water temperature. This research will facilitate a deeper understanding of the dynamic relationship between water temperature and household demand. It will also provide insight into predicting the impact of water-saving strategies on water temperature variations in the DS.

2- Enhance water quality monitoring during hot seasons:

Implementing the proposed method for water temperature modeling to develop recommendations for chlorine and THM monitoring sites during hot seasons. This will enhance the water quality monitoring strategies, potentially improving water quality management during hot periods.

3- Create an integrated map of hot zones in Quebec and Canada:

Utilize the proposed method for water temperature monitoring and modeling to create an integrated map that identifies areas at risk of extreme water warming during hot season. Such a map will aid in proactive measures to address water quality issues in regions experiencing temperature-related challenges.

4- Investigate the relationship between UHI intensity and microbial water quality:

Utilize the water temperature monitoring results to assess microbial water quality, including indicators such as *E. coli* and fecal coliform, in hot zones. This investigation aims to uncover potential correlations between the UHI intensity (i.e., the degree of warming compared to the average temperature in the DS) and microbial water quality. If a positive correlation is established, it could lead to the development of targeted strategies for improving water safety in UHI-impacted areas.

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APPENDICES

APPENDIX A SUPPLEMENTARY INFORMATION FOR ARTICLE 1

Journal: Water (published on 2022-11-15)

Title: Predicting chlorine and trihalomethanes in a full-scale water distribution system under changing operating conditions

Authors: Faezeh Absalan, Fatemeh Hatam, Benoit Barbeau, Michèle Prévost and Françoise Bichai

A.1 1st-order THMs model

The 1st-order THMs model is presented in equation (A.1). In this equation, T is the THMs yield coefficient (expressed in $\mu\text{g THMs/mg Cl}_2$) and M is the initial THMs concentration in water ($\mu\text{g/L}$). $\text{Cl}_2(0)$ is the applied chlorine dosage, and $\text{Cl}_2(t)$ is the free chlorine residual concentration at each time.

$$THM(t) = T(\text{Cl}_2(0) - \text{Cl}_2(t)) + M \quad (\text{A.1})$$

The value of M in our experiments was $11.26 \mu\text{g/L}$. The value of T was $32.25 \mu\text{g THMs/mg Cl}_2$ which was calculated based on the linear correlation between THMs and 1st-order chlorine decay ($R^2=0.95$). This correlation is presented in Figure A.1.

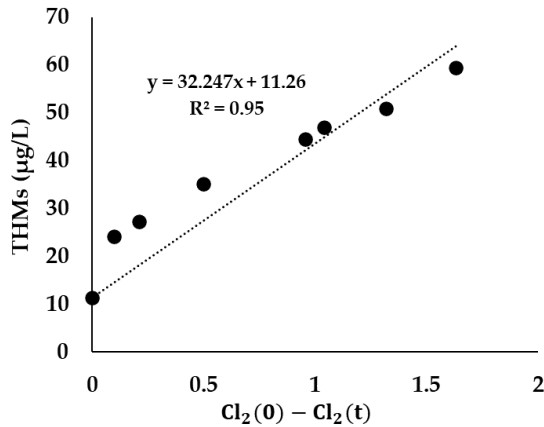


Figure A.1 Correlation between THMs and 1st-order chlorine decay for estimating the THMs yield coefficient.

A.2 Wall chlorine decay prediction

For the wall decay, a 1st order model by Rossman et al. (1994) was chosen which is presented in equation (A.1).

$$\left(\frac{dCl_2}{dt}\right)_{wall} = -\frac{2k_w k_f}{R(k_w + k_f)} \cdot Cl_2(t) \quad (A.1)$$

k_f , the mass transfer coefficient, can also be written as in equation (A.3)

$$k_f = Sh \cdot \frac{D}{d} \quad (A.2)$$

Sh is the Sherwood number, D is the molecular diffusivity of chlorine in water (units of length²/time) and d is the pipe diameter (length unit). The Sherwood number was calculated with $0.0149 * Re^{0.88} * Sc^{0.33} * D/d$ equation chosen based on the recommendations of the EPANET user manual for turbulent flow (Rossman, 2000). The value of k_w depends on the characteristics of the DS, such as the pipe material, roughness, age, diameter, and temperature (García-Ávila et al., 2021b). Calculating k_w in a full-scale DS is impossible in the lab as it needs extensive field measurements, and it can result in a different k_w for each pipe. In turn, we can usually assume a constant value for k_w using a portion of the nodes to estimate the optimum k_w that will minimize the prediction's root mean square error (RMSE). While the impact of pipe material is not considered in this model, the impact of pipe diameter and flow conditions will be reflected in Re and k_f . As a result, each pipe will reflect a different chlorine decay rate specific to the hydraulics

of the DS. In this work, 6 out of 22 points were used for k_w estimation. These points covered a range of different diameters (200 mm to 500 mm), residual free chlorines (0.09 mg/L to 0.77 mg/L), and water residence times (0.5 h to 55 h). The optimum k_w was 0.04 m/day in the spring and 0.12 m/day in the fall. In the end, the estimated k_w was used for all the 22 points, and they still minimized the RMSE of the whole 22 points.

A.3 Demand pattern used for the water quality simulation with EPANET

For simulation of the chlorine and THMs in the distribution system, a water demand pattern was applied to all the nodes. This demand pattern was based on the production pattern of the water treatment plant on the sampling day. Figure A.2 demonstrates the demand patterns for March 2021 (A) and October 2021 (B) for city B.

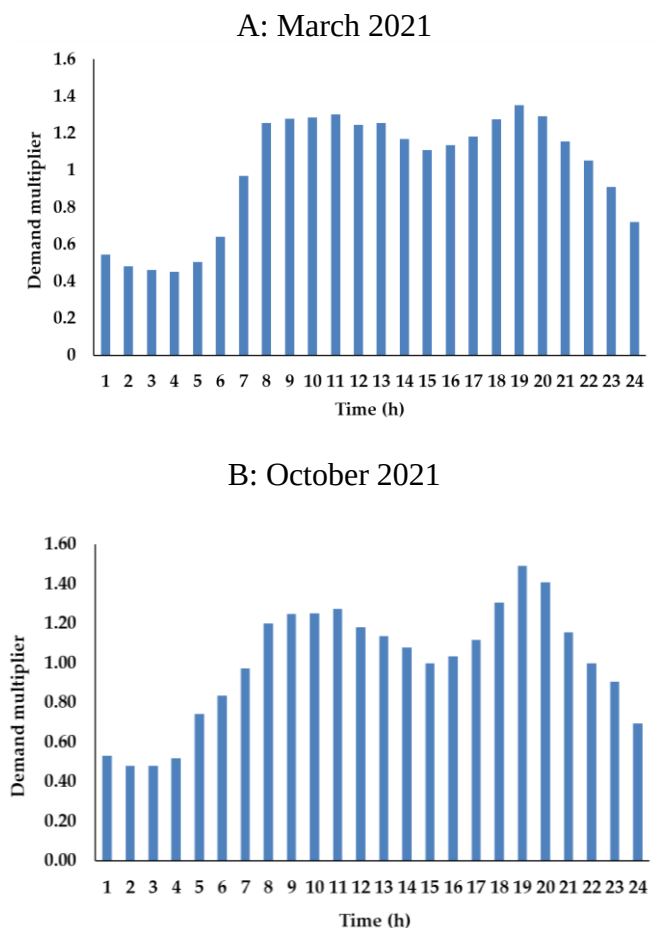


Figure A.2 Hourly water demand patterns for March and October 2021 in city B

A.4 VRRC model prediction results in the distribution system

Table A.1 presents the details of the chlorine prediction in March and October 2021 in city B. This table contains the pipe diameter corresponding to each sampling point as well as the observed chlorine residual measured in the field, the predicted chlorine residual with the VRRC model, and the absolute prediction error.

Table A.1 Free chlorine prediction results in the field including the pipe diameter, free chlorine residual (observed and predicted), and absolute prediction error

Point	Diameter (mm)	March 2021			October 2021		
		Observed free chlorine (mg/L)	VRRC prediction (mg/L)	Absolute prediction error (mg/L)	Observed free chlorine (mg/L)	VRRC prediction (mg/L)	Absolute prediction error (mg/L)
N1	500	0.79	0.74	0.05	0.74	0.82	0.08
N2	300	0.74	0.69	0.05	0.7	0.70	0.00
N3*	250	0.64	0.56	0.08	0.37	0.45	0.08
N4	150	0.2	0.32	0.12	0.09	0.10	0.01
N5	150	0.17	0.22	0.05	0.08	0.08	0.00
N6	200	0.39	0.39	0.00	0.18	0.15	0.04
N7	150	0.64	0.55	0.09	0.56	0.44	0.13
N8	300	0.62	0.54	0.08	0.38	0.48	0.10
N9	250	0.46	0.40	0.06	0.25	0.20	0.05
N10*	250	0.02	0.08	0.06	0.22	0.13	0.10
N11	200	0.58	0.72	0.14	0.64	0.75	0.10
N12	200	0.58	0.54	0.04	0.54	0.40	0.14
N13*	200	0	0.45	0.45	0.08	0.27	0.19
N14	200	0.64	0.59	0.05	0.55	0.48	0.07
N15	600	0.81	0.81	0.00	0.84	0.93	0.09
N16	250	0.58	0.57	0.01	0.17	0.33	0.16
N17	150	0.09	0.12	0.03	0.07	0.10	0.03
N18	400	0.77	0.75	0.02	0.73	0.83	0.10
N19*	500	0.72	0.72	0.00	0.68	0.77	0.09
N20*	250	0.73	0.54	0.19	0.47	0.41	0.06
N21	250	0.77	0.71	0.06	0.9	0.72	0.18
N22	150	0.39	0.55	0.16	0.09	0.40	0.31

*: Dead ends

Table A.2 contains the THMs prediction results in the distribution system of city B (considering the bulk decay only). This table contains the pipe diameters, observed THMs concentration, predicted THMs concentration, and the absolute prediction errors.

Table A.2 THMs prediction results in the DS including the pipe diameter, THMs concentrations (observed and predicted), and absolute prediction error

Sampling points	Diameter (mm)	Observed THMs ($\mu\text{g/L}$)	Predicted THMs ($\mu\text{g/L}$)	Absolute prediction error ($\mu\text{g/L}$)
N1	500	25.08	26.96	1.88
N2	300	30.05	28.79	1.26
N3*	250	32.45	31.14	1.31
N4	150	29.92	37.92	5.47
N5	150	30.02	42.80	12.78
N6	200	36.46	37.14	0.68
N7	150	29.74	32.01	2.28
N8	300	36.52	33.17	3.35
N9	250	37.34	36.36	0.97
N10*	250	40.73	40.98	0.24
N11	200	26.88	27.44	0.56
N12	200	30.01	31.09	1.08
N13*	200	39.31	34.33	4.98
N14	200	29.13	30.38	1.25
N15	600	23.08	24.86	1.78
N16	250	34.78	32.59	2.18
N17	150	48.92	44.01	4.91
N18	400	26.49	26.44	0.05
N19*	500	29.31	27.63	1.68
N20*	250	30.00	31.75	1.74
N21	250	27.48	27.26	0.23
N22	150	35.56	30.66	4.90

*: Dead ends

APPENDIX B SUPPLEMENTARY INFORMATION FOR ARTICLE 2

Journal: Journal of Environmental Management (submitted on 2023-08-03)

Title: Climate change and future water demand: implications for chlorine and trihalomethanes management in water distribution systems

Authors: Faezeh Absalan, Fatemeh Hatam, Michèle Prévost, Benoit Barbeau, Françoise Bichai

Table B.1 presents the temperature, DOC, and the applied chlorine dosages for all the tests.

Table B.1 Temperature, DOC, and applied chlorine dosage levels for each test

Test #	Temperature (°C) $\pm$ standard deviation	DOC (mg/L) $\pm$ standard deviation	Applied chlorine dosages (mg/L)
1	5 $\pm$ 1.5: Maximum temperature from January to March 2021	1.52 $\pm$ 0.04: Operating DOC in treated water in October 2021	1.5, 2, 2.63
2	17 $\pm$ 2.05: maximum temperature from October to December 2021	1.52 $\pm$ 0.04	1.5, 2, 2.63
3	25 $\pm$ 0.7: maximum temperature from July to September 2021	1.52 $\pm$ 0.04	2, 3, 3.5
4	35 $\pm$ 0.7: extreme temperature increase	1.52 $\pm$ 0.04	1.5, 2, 3
5	17 $\pm$ 2.05	0.72 $\pm$ 0.06	1.7, 2, 2.5
6	17 $\pm$ 2.05	2.22 $\pm$ 0.05	2, 3, 3.5
7	17 $\pm$ 2.05	3.2 $\pm$ 0.02	2, 3, 3.5

Figure B.1 presents the combined effects of warming and demand reduction chlorine (A) and THMs (B) reliabilities at constant DOC of 1.5 mg/L. Figure B.2 presents the combined effects of

DOC increase and demand reduction chlorine (A) and THMs (B) reliabilities at constant temperature of 17°C.

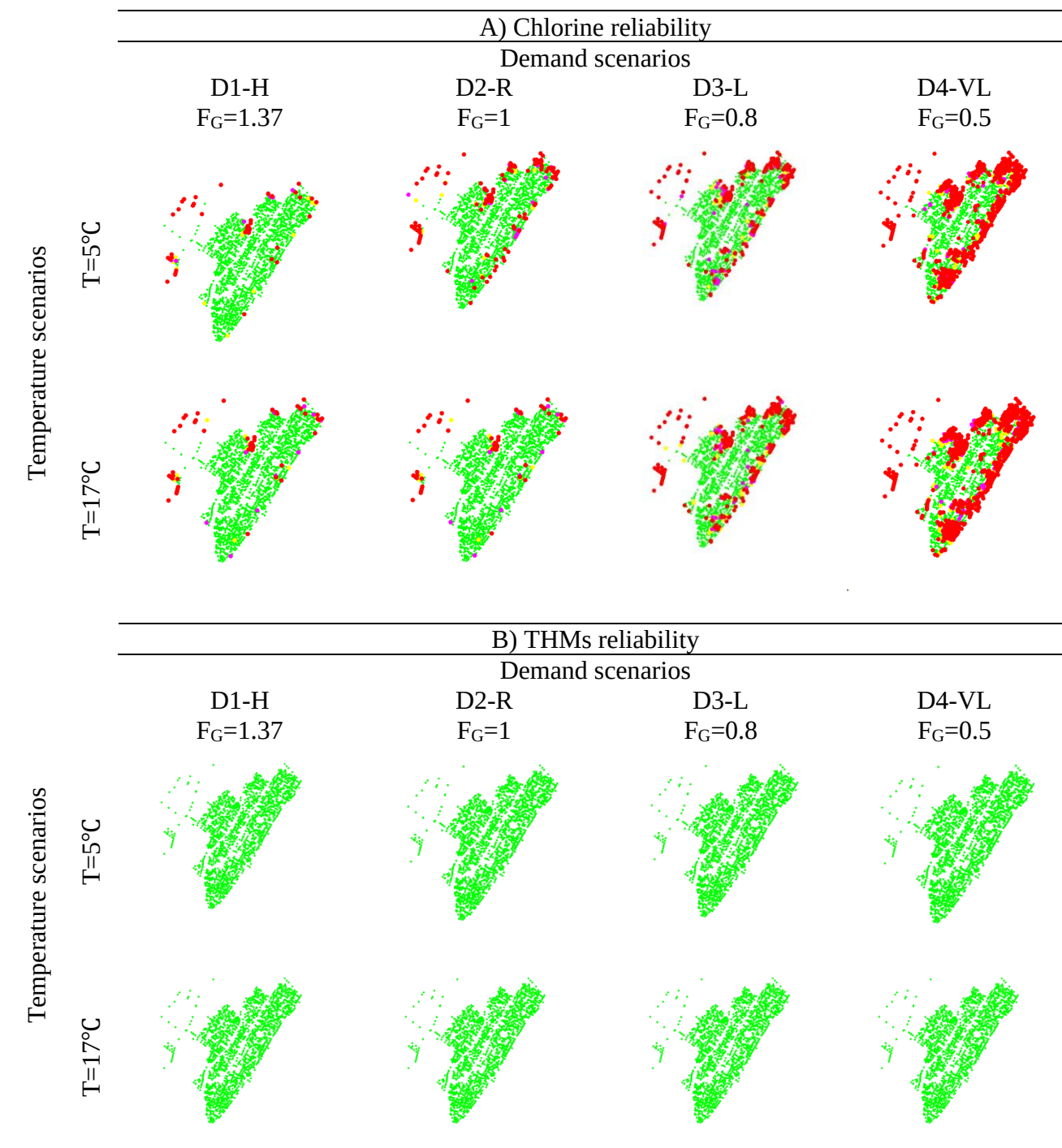


Figure B.1 The combined effect of warming and demand reduction under constant DOC= 1.5 mg/L on chlorine (A) and THMs (B) reliability in the network. In this figure, green indicates R=100, yellow indicates R=75, Purple indicates R=25, and red indicates R=0

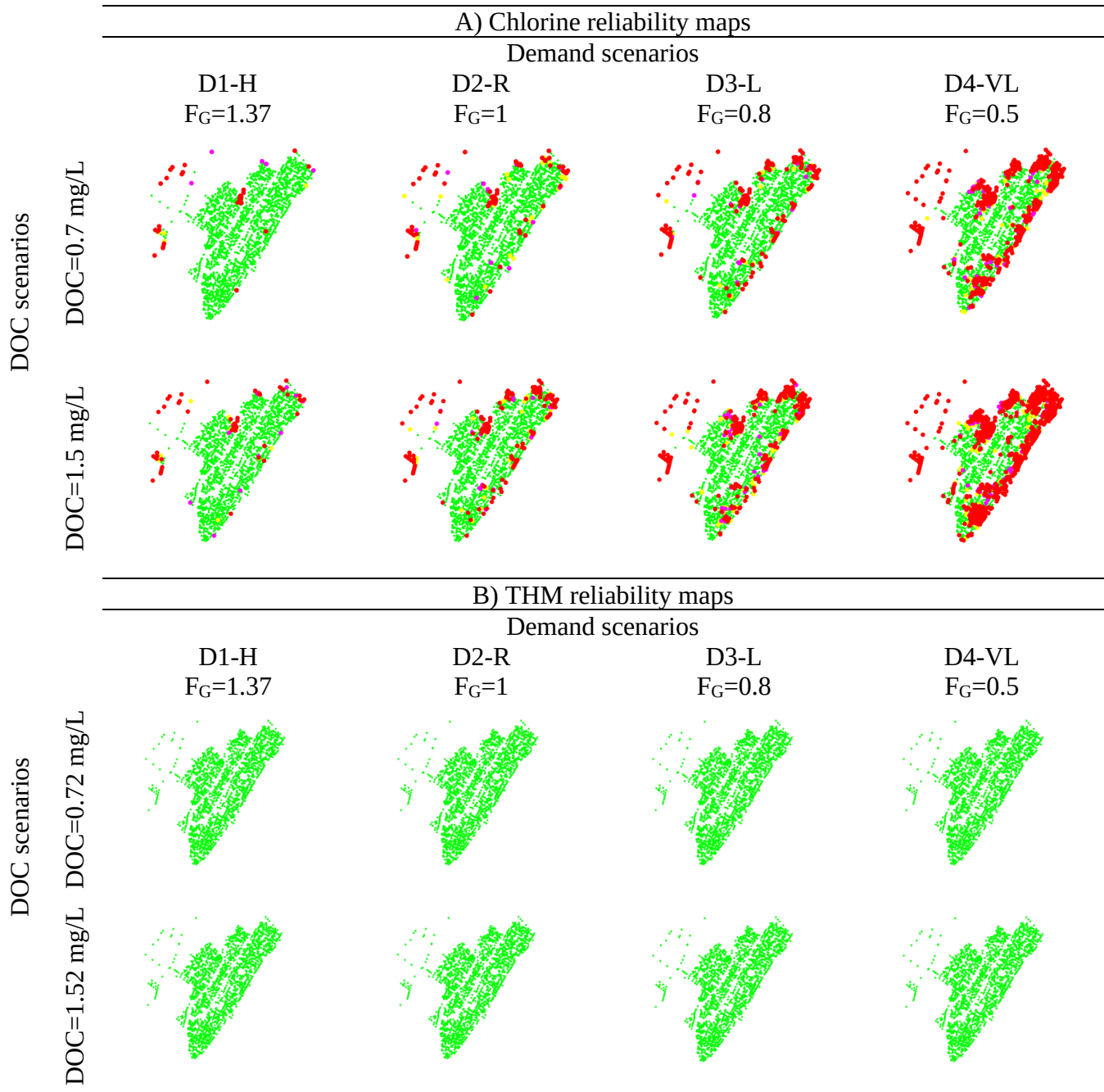


Figure B.2 The combined effect of DOC increase and demand reduction under constant temperature ($T=17^{\circ}\text{C}$) on chlorine (A) and THMs (B) reliability in the network. In this figure, green indicates $R=100$, yellow indicates $R=75$, Purple indicates $R=25$, and red indicates $R=0$

APPENDIX C SUPPLEMENTARY INFORMATION FOR ARTICLE 3

Journal: Water Research (submitted on 2023-11-14)

Title: Impact of heat islands vs. city greening: real-time monitoring and modeling of drinking water temperature in the city of Montreal in Canada

Authors: Faezeh Absalan, Fatemeh Hatam, Mirjam Blokker, Marie-Claude Besner, Michèle Prévost, Françoise Bichai

Table C.1 presents the coefficients used in the soil temperature model for different soil scenarios that was used in this work.

Table C.1 Coefficients used in the soil temperature model for different soil scenarios

Soil surface classification	Q_f	Grass	Shadow	a_1^*	a_2^*	a_3^*	Albedo
1	50	Yes	Yes	1	30	-50	0.19
2	100	Yes	Yes	1	30	-100	0.19
3	100	No	Yes	0.8	30	-100	0.19
4	100	No	No	0.8	30	-100	0.19
5	150	No	No	0.8	30	-120	0.19

The hourly demand pattern applied to the hydraulic model for water quality modeling is provided in Figure C.1.

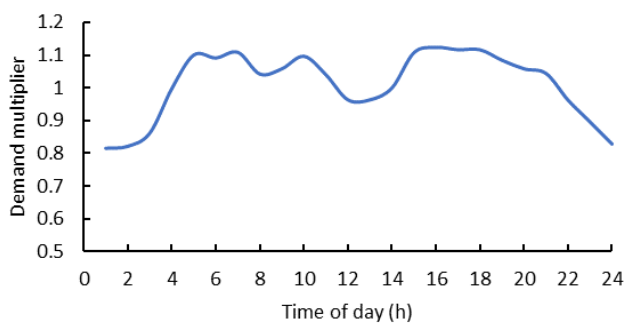


Figure C.1 Water demand pattern used in the hydraulic model of the two zones under study

The temperature variations in the vegetation-impacted zone with regards to the two entrance nodes feeding this zone is presented in figure C.2.

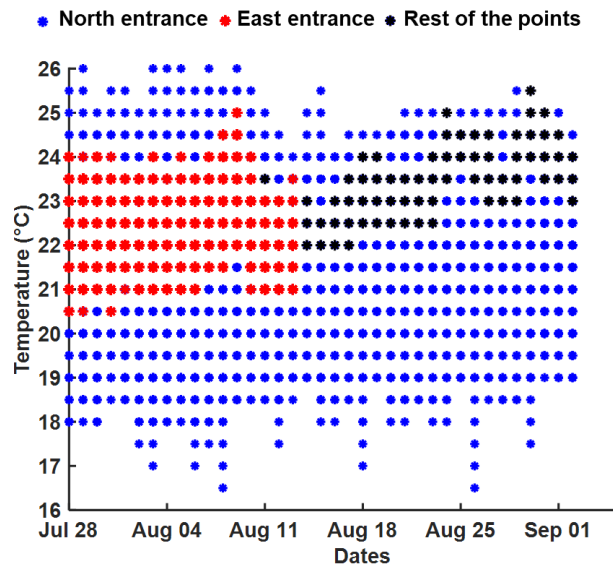


Figure C.2 Temperature records in the vegetation impacted zone with regards to the two entrance nodes. The north entrance is indicated with red and the east entrance is indicated with black. The temperature records of the east entrance were available only until August 12th.

The cross-correlation results of validating water temperature models with the field measurements is provided in Figure C.3.

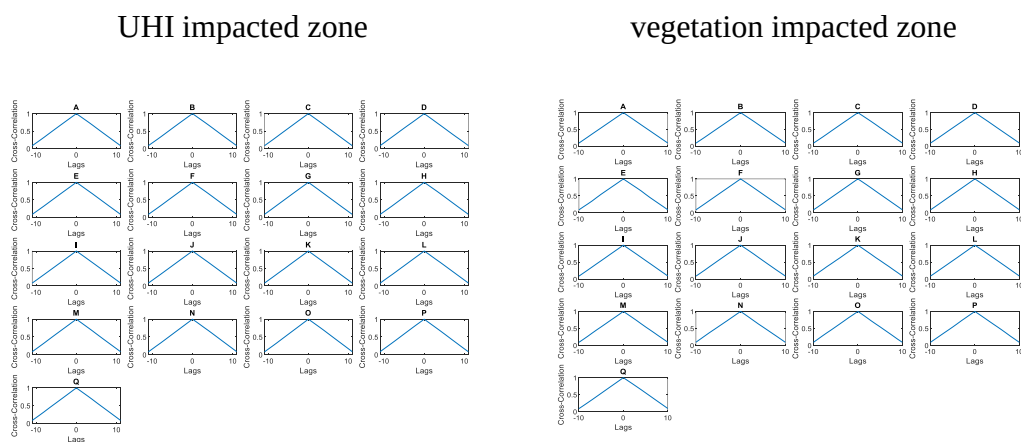


Figure C.3 Cross-correlation analysis results between the measured and predicted temperatures across all 17 points in the UHI and vegetation impacted zones (period: 1-12 August).