Evaluation and improvement of robustness in drinking water treatment systems to manage turbidity- and natural organic matter (NOM)-related water quality upsets during extreme weather events

by

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This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

Kirti S. Nemani was the sole authors of chapters 1, 2A and 6 which were written under the supervision of co-supervisors Drs. Peter Huck and Sigrid Peldszus and were not written for publication. Chapters 2B, 3, 4 and 5 were written with the intent to publish, with chapter 5 currently submitted to a journal and containing contributions by co-authors, as outlined below. Chapter 3 is a published manuscript. Chapter 2B and 4 will be later converted to manuscripts.

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Exceptions to sole authorship of this thesis are as follows:

- Chapter 3: This work was published in ACS Environmental Science and Technology (ES&T) Water (2023). The research presented in this study was conducted by Kirti S. Nemani at University of Waterloo under the supervision of Dr. Peter Huck and Dr. Sigrid Peldszus. Kirti prepared the first manuscript draft and executed subsequent revisions. Dr. Huck and Dr. Peldszus contributed to the review and revision of the manuscript.

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Abstract

Climate change poses significant challenges for drinking water treatment plants (DWTPs), with extreme weather events increasingly impacting water quality. While various aspects of climate adaptation, such as source water protection and demand management, are crucial, managing water quality is paramount for consumer safety. Understanding the effects of climate-driven water quality exacerbations on DWTPs is essential, including identifying watershed risk factors and their impact on treatment processes. Quantifying and substantiating a treatment system's capability and vulnerability to different raw water quality scenarios, especially for turbidity and Natural Organic Matter (NOM) is crucial for performance assessment and preparing for future extreme weather events. In this context, enhancing robustness, which is the ability of a DWTP to maintain desired drinking water quality even during raw water quality disturbances, is key to safeguarding treatment processes against sudden and long-term changes in surface water quality. However, existing tools for assessing vulnerabilities and improving resilience in critical infrastructure lack a focus on water quality management and specifically on evaluating and enhancing treatment process robustness. A comprehensive framework is needed to guide utilities in determining the robustness of their systems and devising strategies to address deficiencies. There is also a need for robustness metrics specifically addressing NOM reduction/removal which is still an unexplored area.

This thesis contributes to understanding climate impacts on drinking water treatment processes, focusing on two critical water quality parameters (WQPs) - turbidity and NOM. It explores the implications of turbidity and NOM variations on treatment processes within the context of watershed changes due to climate change. Additionally, this thesis examines the robustness of DWTPs as a vital climate adaptation strategy, synthesizing related concepts like resilience, reliability, risk, and vulnerability to present a comprehensive understanding within the context of DWTPs.

The most significant contribution of this research is the development and introduction of three robustness frameworks tailored to DWTPs. The general framework outlines systematic steps for assessing and improving overall robustness, while the parameter-specific framework applies this methodology to specific water quality parameters (WQPs). A plant-specific framework then

tailors the parameter-specific approach to individual DWTPs. The thesis proposes a parameter-specific framework for turbidity, utilizing the turbidity robustness index (TRI) for evaluation of individual treatment processes and the overall robustness index (ORI) for the overall assessment of the plant. This framework is applied to two full-scale DWTPs, Plants A and B in Ontario, Canada, using historical plant data and bench-scale experimental data simulating extreme high-turbidity scenarios. The application identifies less robust processes vulnerable to climate extremes, operational responses for short-term robustness, and critical WQP thresholds necessitating capital improvements. This framework serves as a valuable tool for assessing and enhancing the robustness of DWTPs, offering insights into their current state, and aiding in climate adaptation planning.

Another notable contribution of this research lies in the comparative analysis of outcomes from four DWTPs where the turbidity robustness framework was implemented. This comparison not only underscores the versatility of the framework, but also offers valuable insights into the performance of four distinct plants using standardized metrics. It also introduces a decision-tree for charting out the next steps for utilities based on the robustness assessment and shows examples tailored to each plant, enhancing the practical applicability of the framework.

This thesis also addresses the lack of NOM-related robustness metrics and introduces a novel index, Organic Matter Robustness Index (OMRI) to quantify the robustness of critical treatment processes. This index aims to incorporate the complexity of NOM in natural waters and the variety of surrogate parameters used for measurement at DWTPs in the NOM robustness quantification. Apart from the OMRI, this research also proposes another quantitative method for evaluating NOM robustness by extending the use of TRI to appropriate NOM surrogate parameters. This index was incorporated in the NOM robustness framework, which was applied to plant B, with a focus on historical plant data as well as experimental data simulating extremely high NOM scenarios. Short-term adaptation options in the form of operational changes were identified to improve the removal of NOM in such adverse source water situations. The results from this study show the applicability and ease of use of the OMRI to a full-scale DWTP and offer insights into the current operational robustness with respect to NOM of plant B.

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Dedication

This dissertation is dedicated to:

My Mother, who is the reason behind every good thing in my life.

My Nanamma (grandmother), who always aspired for me to pursue higher education.

My Tatagaru (grandfather), who loved reading my stories and always said I would write something very meaningful in my life.

Table of Contents

Examining Committee Membership ..... **ii**

Author's Declaration ..... **iv**

Statement of Contributions ..... **v**

Abstract ..... **vii**

Acknowledgements ..... **ix**

Dedication ..... **xi**

List of Figures ..... **xvi**

List of Tables ..... **xviii**

List of Abbreviations ..... **xx**

1. Chapter 1: Introduction **1**

1.1. Problem statement 1

1.2. Research objectives 2

1.3. Thesis organization 3

2. Chapter 2: Background & Literature Review **5**

2A.1. Climate change and extreme weather events 6

2A.1.1. Linking anthropogenic climate change to enhancements in the hydrological cycle 6

2A.1.2. Changes in precipitation patterns and extreme weather due to climate change 7

2A.2. Impact of extreme weather events on surface water quality 9

2A.2.1. Turbidity 9

2A.2.2. Natural Organic Matter 11

2A.3. Impact of changes in turbidity and NOM on drinking water treatment operations 13

2A.3.1. Turbidity 15

2A.3.2. NOM 16
2B.1. Introduction 20
2B.2. Robustness and related concepts 21
2B.2.1. Robustness 23
2B.2.2. Resilience 26
2B.2.3. Reliability 28
2B.2.4. Risk and vulnerability 30
2B.3. Differences and similarities between robustness, resilience, reliability, risk, and vulnerability from a drinking water treatment perspective 32
2B.4. Conclusions and recommendations for future work 36

3. Chapter 3: Practical Framework for Evaluation and Improvement of Drinking Water Treatment Robustness in Preparation for Extreme-Weather-Related Adverse Water Quality Events 38
3.1. Introduction 39
3.2. Approach and Methodology 40
3.2.1. Conceptual framework development 40
3.2.2. Full-scale data collection and analysis (Plant framework, Step 4: Evaluation, scenarios 1 and 2) 41
3.2.3. Extremely high turbidity bench-scale jar tests simulating CFS (Plant framework, Step 4: Evaluation, scenario 3) 42
3.2.4. Factorial design bench-scale experiment for adaptation (Plant framework, Step 6: Adaptation) 42
3.3. Results and Discussion 42
3.3.1. Section 1: Development of Robustness Frameworks 42
3.3.2. Section 2: Application of the turbidity robustness framework to Plant A (plant-specific framework) 52
3.3.3. Discussion of the turbidity robustness framework and its application to plant A 56
3.4. Conclusions and why is this important for the water treatment industry? 57

4. Chapter 4: Assessing Turbidity Robustness in DWTPs : Comparative Analysis of Evaluation Outcomes and Decision Tree Guidance for Climate Change Adaptation 59
4.1. Introduction 59
4.2. Approach and Methodology 60
4.2.1. Overview of the turbidity robustness framework 60

4.2.2. Full scale DWTP data collection and analysis for Plant B 61
4.2.3. Extremely high turbidity bench-scale jar tests simulating CFS for Plants A and B 62
4.2.4. Factorial design bench scale experiment for adaptation of plant B 62
4.3. Results and discussion 63
4.3.1. Turbidity robustness framework application to full-scale DWTPs 63
4.3.2. Comparing the turbidity robustness assessments of four DWTPs 70
4.4. Answering 'what next?': incorporating outcomes of the framework into a decision-tree for water planners (835 words) 74
4.5. Conclusions (250 words) 81

5. Chapter 5: Assessing Drinking Water Treatment Robustness: Development and Application of an Organic Matter Robustness Index 83
5.1. Introduction 83
5.2. Approach and methodology 85
5.2.1. Organic matter robustness index development 85
5.2.2. TRI sensitivity analysis to assess impact of input dataset size on TRI results 86
5.2.3. Development of the NOM robustness framework 86
5.2.4. Development of the NOM plant framework and application to Plant B 87
5.3. Results 89
5.3.1. Development of quantitative robustness evaluation methods for NOM 89
5.3.2. NOM parameter framework 94
5.3.2.1. Step 1: Selection - rational for selecting NOM 95
5.3.2.2. Step 2: Identification of critical and vulnerable treatment processes 96
5.3.2.3. Step 3: Criteria- Setting goal values for each critical treatment process 98
5.3.2.4. Step 4: Evaluation - quantifying NOM robustness for each critical treatment process 98
5.3.2.5. Step 5: Assessment- determining overall plant robustness 99
5.3.2.6. Step 6: Adaptation- exploring options to improve plant robustness 99
5.3.3. Application of the NOM robustness framework to a full-scale DWTP 100
5.4. Discussion 103

6. Chapter 6: Conclusions 105
6.1. Summary of findings 105
6.2. Impact and limitations 109

6.3. Future directions and implications for the water treatment industry 111
6.4. Publications and presentations 113

References 115

Appendices……. 128

A. Appendix A 128

B. Appendix B 141

C. Appendix C 168

List of Figures

Figure 2.1: Typical treatment train for a conventional surface water treatment plant 14

Figure 2.2: Link between robustness, reliability, resilience, risk, and vulnerability 34

Figure 2.3: Possible responses of a DWTP to extreme water quality event and interpretation of its state 35

Figure 3.1: General Robustness Framework..... 43

Figure 3.2: Detailed methodology for steps 1 and 4 of general robustness framework 44

Figure 3.3: TRI evaluation of critical treatment steps at Plant A..... 54

Figure 4.1: Overview of the turbidity robustness framework. 61

Figure 4.2: Robustness evaluation outcomes of step 4, Plant B 66

Figure 4.3: Initial bench scale simulation of high raw water turbidities and effectiveness of Plant B coagulation regime. 68

Figure 4.4: Process flow diagrams, data collection points and number of treatment units of Plants A, B, C and D..... 71

Figure 4.5: ORI results of the four DWTPs. 73

Figure 4.6: Proposed decision tree to incorporate outcomes of turbidity robustness framework into climate adaptation projects. 76

Figure 4.7: Example of decision tree for Plant A..... 78

Figure 4.8: Example of decision tree for Plant B..... 79

Figure 4.9: Example of decision tree for Plant C..... 80

Figure 4.10: Example of decision tree for Plant D 81

Figure 5.1: Summary of the NOM parameter framework 95

Figure 5.2: OMRI evaluation of collected data 102

Figure A.1: Plant A treatment scheme..... 131

Figure A.2: Daily % removal vs. raw water turbidity (2019-2020)..... 133

Figure A.3 Jar test results with spiked raw water turbidities ranging from 50-1000 NTU at settling times 16 mins and 30 mins. 134

Figure B.1: TRI evaluation results (scenario 1 and 2) for Plant A critical treatment processes (intake, CFS, filtration) 147

Figure B.2: Scenario 3 bench-scale turbidity simulation test with reservoir sediment for Plant A 149

Figure B.3: TRI assessment of remaining filters at Plant B..... 158

Figure B.4: Initial jar test experiment to check the effectiveness of polymer addition 166
Figure C.1: General Robustness framework. 168
Figure C.2: Plant B process flow chart and sample collection points 169
Figure C.3: DOC weekly trends at Plant B 169
Figure C.4: Weekly UV absorbance at 254 nm at Plant B 170
Figure C.5: Weekly THMFP at Plant B 170
Figure C.6: Initial jar test results to identify limitation of plant coagulation regime 173

List of Tables

Table 2.1: Sources of particulate matter in surface waters 10

Table 2.2: Effect of turbidity on various drinking water treatment steps 16

Table 2.3: Effects of NOM on drinking water treatment steps 19

Table 2.4: Summary of key DWTP studies on robustness and related concepts 21

Table 2.5: Summary of definitions of robustness and related concepts from a drinking water treatment context during a water quality disturbance 37

Table 3.1: Guidance list for identifying critical and vulnerable drinking water treatment steps with respect to turbidity. 48

Table 3.2: Demonstration of the proposed RC assignment to a robustness metric. 50

Table 3.3: Critical steps and possible operational adaptation options 51

Table 4.1: Details of Plants A, B, C and D 71

Table 5.1: Examples of OMRI sub-indices and their associate objectives/terms 92

Table 5.2: OMRI rating scale, details and corresponding robustness categories (RC) for use in the NOM framework 94

Table 5.3**:** Identification of critical and vulnerable treatment processes for NOM 97

Table 5.4: Critical treatment processes and potential operational responses relating to NOM reduction/removal 100

Table A.1: Decision process for selecting weights A1 and A2 129

Table A.2: Classification of system operation for interpretation of TRI 129

Table A.3: Daily average turbidities for week 14 and 21 133

Table A.4: Jar test procedure for flow of 400-500 L/s as specified by Plant A operations 133

Table A.5: Relative importance and weights assigned to critical treatment steps 134

Table A.6: Overall Robustness Index (ORI) calculation data for Case 1 (equal weights for all critical processes) 135

Table A.7: Overall Robustness Index (ORI) calculation data for Case 2 (low weight for intake, high weight for filtration) 136

Table A.8: Overall Robustness Index (ORI) calculation data for Case 3 (high weight for intake, high weight for filtration) 137

Table A.9: Overall Robustness Index (ORI) calculation data for Case 4 (combination of high and low weights based on raw water turbidity) 138

Table A.10: Levels and values of factors for factorial design experiment 140

Table A.11: Factorial design experiment results 140
Table B.1: Factorial design experiment factors and levels for plant B 143
Table B.2: Plant A CFS operational data for weeks with ‘severely upset’ ORI s 145
Table B.3: Combination weighting ORI approach for Plant A weeks 27-105 149
Table B.4: Seasonal medians and median thresholds for two methodologies 155
Table B.5: Weeks corresponding to scenario 2 for methods 1 and 2 155
Table B.6: ORI Scenario 1- Equal weights for CFS and filtration 158
Table B.7: ORI Scenario 2- CFS high weight (0.8) and filtration low weight (0.2)..... 160
Table B.8: ORI Scenario 3- CFS low weight (0.2) and filtration high weight (0.8)..... 163
Table B.9: ANOVA results of the factorial design experiment 166
Table C.1: Results of TRI sensitivity analysis with two data sets and two averaging methods. 168
Table C.2: Plant B surrogate parameters and correlations for different sample locations data .. 170
Table C.3: Plant B raw water surrogate parameter data and OMRI for 4 weighting scenarios .. 171
Table C.4: Plant B CFS surrogate parameter data and OMRI for 4 weighting scenarios..... 171
Table C.5: Plant B filtration surrogate parameter data and OMRI for 4 weighting scenarios.... 172
Table C.6: Significance of operational factors on water quality parameters determined using ANOVA..... 173
Table C.7: OMRI results of factorial design experiment with coded factors 174

List of Abbreviations

ANOVA: Analysis Of Variance
AWWA: American Water Works Association
CFS: Coagulation-Flocculation-Sedimentation
COD: Chemical Oxygen Demand
CREAT: Climate Resilience Evaluation and Awareness Tool
CRWU: Climate Ready Water Utilities
DBPs: Disinfection By-Products
DOC: Dissolved Organic Carbon
DWTPs: Drinking Water Treatment Plants
GAC: Granular Activated Carbon
HACCP: Hazard Analysis and Critical Control Point
IHSS: International Humic Substances Society
IPCC: Intergovernmental Panel on Climate Change
MTBF: Mean Time Between Failures
NOM: Natural Organic Matter
NTU: Nephelometric Turbidity Units
OMRI: Organic Matter Robustness Index
ORI: Overall Robustness Index
PAC: Powdered Activated Carbon
PFAS: Per- And Poly-Fluoroalkyl Substances
PIEVC: Public Infrastructure Engineering Vulnerability Committee
QMRA: Quantitative Microbial Risk Assessment
RCs: Robustness Categories
SOPs: Standard Operating Procedures
SRNOM: Suwannee River NOM
SUVA: Specific Ultraviolet Absorbance
THMFP: Trihalomethane Formation Potential
THMs: Trihalomethanes
TOC: Total Organic Carbon
TRI: Turbidity Robustness Index
UV: Ultraviolet

UVA: UV Absorbance

UVT: UV Transmittance

VSAT: Vulnerability Self-Assessment Tool

WHO: World Health Organization

WQIs: Water Quality Indices

WQPs: Water Quality Parameters

“न चोरहार्यं न च राजहार्यं न भ्रातृभाज्यं न च भारकारि।

व्यये कृते वर्धते एव नित्यं विद्याधनं सर्वधनप्रधानम्॥“

Transliteration: na caurahāryaṁ na ca rājahāryaṁ na bhrāṭr̥bhājyaṁ na ca bhārakārī।
vyaye kr̥te vardhate eva nityaṁ vidyādhanaṁ sarvadhana pradhānam ॥

Translation: It cannot be stolen by thieves, nor can it be taken away by kings. It cannot be divided among brothers, nor does it cause any burden on your shoulders. If spent, it will always keep growing— the wealth of knowledge is the most superior wealth of all.

1. Chapter 1: Introduction

1.1. Problem statement

Surface water (i.e. water collected on the earth's surface in streams, rivers, lakes, and wetlands) is an important source of freshwater and accounts for 88% of the total volume of drinking water produced by drinking water treatment plants (DWTPs) in Canada (Statistics Canada, 2021). Since the DWTP design and operation is heavily reliant on the surface water quality, any sudden water quality upset poses a challenge to maintain a steady production of safe drinking water at DWTPs. Extreme weather events, which are currently enhanced by anthropogenic climate change, can cause unprecedented changes in surface water quality parameters such as turbidity and Natural Organic Matter (NOM) (Ahmadi & Moradkhani, 2019; Bates, 2008). Both these parameters are important, not only for meeting treatment goals and drinking water regulations, but also for smooth operations of a DWTP (Crittenden, 2012).

Therefore, any disturbance in the concentration or composition of turbidity and/or NOM can pose a challenge for the drinking water treatment process. Current drinking water treatment operations are dependent on the operators' tacit knowledge and may not be optimized for adverse water quality conditions that are becoming common due to climate change impacts (Thorne & Fenner, 2011) . When faced with extremely high values of turbidity and organic matter that go beyond levels experienced in the past, plant shutdowns may occur. This is because utilities may not be prepared to face such unprecedented water quality levels, which may even go beyond the design limit of the treatment processes (Levine et al., 2016).

One way to ensure the continuous operation and the desired level of finished water quality even during water quality upsets is by improving the robustness of drinking water treatment processes (Hartshorn et al., 2015; Huck & Coffey, 2004). A robust treatment system is insensitive to source water quality changes and continues to achieve the desired water quality even during raw water quality disturbance by adapting the plant operations to the source water quality (Huck & Coffey, 2004). To improve the robustness of a system, it is first necessary to assess the current limits of treatment under three water quality scenarios: normal range, extreme values experienced in the past and extremely high values that may occur in the future due to extreme weather. Knowing the

current status of a treatment plant is essential to develop targeted improvements and implement strategic measures, ensuring the system can effectively handle a spectrum of water quality challenges and maintain optimal performance even in adverse conditions. Additionally, it is crucial to evaluate the treatment thresholds of a DWTP in relation to extreme weather water quality conditions. Beyond these limits, mere short-term operational adjustments may prove insufficient to attain the desired treatment levels, necessitating upgrades or strategic capital planning. To achieve this, it is helpful to quantify robustness of treatment processes. In addition, it is also useful to have a framework that can guide utilities to do this assessment and implement the results for improving robustness in a systematic way.

Prior work in this area has been limited to quantification of robustness with respect to turbidity using a Turbidity Robustness Index (TRI) that assessed primarily the filtration process, and to some extent the clarification process (Hartshorn et al., 2015; Huck & Coffey, 2004; Hurst et al., 2004; Li & Huck, 2008; Zorić et al., 2020). A methodology for robustness assessment of an entire DWTP was proposed by Zhang et al. (2012), but was limited in its application to full scale DWTP data. Moreover, these studies are based on historic water quality levels and do not consider extreme turbidity scenarios that are gaining attention due to impacts of anthropogenic climate change. The existing literature also lacks a comprehensive examination of the robustness of NOM removal in DWTPs. Currently, there is a notable absence of a quantitative evaluation methodology specifically designed to gauge the robustness of DWTPs in removing NOM. This highlights the need for quantitative metrics that can comprehensively address NOM, while considering its multifaceted impacts on drinking water treatment. Further research is also required to establish a general procedure assessing and improving robustness of a DWTP. This evaluation is important for both turbidity and NOM under different source water quality scenarios, in order to identify short term operational responses to ensure continuous operations during water quality upsets, and finally, find the treatment boundaries of a DWTP, beyond which capital upgrade may be needed.

1.2. Research objectives

The main objective of this research is to develop a robustness framework to guide water treatment utilities during short-term surface water quality disturbances caused by extreme

weather events, the frequency and intensity of which is expected to increase due to climate change. The framework would be used to evaluate and improve the short-term robustness of a DWTP by incorporating feasible operational measures. The framework is intended to be generally applicable and can be tailored to any utility. It would serve as a proactive planning tool that can help in developing new standard operating procedures (SOPs) for addressing challenging water quality conditions and can be included in a utility's climate adaptation plans.

The detailed objectives of this research are:

1. To understand the impacts of extreme weather events on levels of turbidity and NOM in surface waters and the subsequent repercussions on DWTP operations
2. To explore robustness and related concepts such as resilience, reliability, risk, and vulnerability in the context of drinking water treatment
3. To develop a general robustness assessment framework which can be tailored to any water quality parameter and DWTP
4. To develop and apply a turbidity framework that provides specific quantitative tools for robustness evaluation and comprehensively explores robustness assessment and improvement
5. To compare the turbidity framework application outcomes of four full-scale DWTPs and develop a decision support framework that incorporates the results of the framework into an action roadmap with both short-term operational strategies and long-term adaptation options.
6. To develop robustness evaluation methodology for NOM including a new quantitative robustness index
7. To develop and apply an NOM framework which incorporates the new robustness index

1.3. Thesis organization

This dissertation is comprised of 6 chapters, along with a list of references and appendices.

Chapter 2 presents the literature review and addresses objectives 1 and 2. Section 2a addresses objective 1 and provides a general overview of the impacts of extreme weather events on turbidity and NOM and then further delves into the specific impacts of water quality disturbances on various DWTP processes and their operations. Section 2b provides an overview of general definitions and applications of robustness and related concepts such as resilience, reliability, risk, and vulnerability, and explores related studies in drinking water treatment. It also articulates

definitions for all the terms by consolidating the existing understanding and elucidating their context within the framework of drinking water treatment.

Chapter 3 introduces the general robustness framework and the turbidity-specific framework (objectives 3 and 4). It further demonstrates the application of the turbidity framework to a full-scale DWTP (plant A) over a period of 6-months. Appendix A provides the supporting information for chapter 3.

Chapter 4 shows the application of the turbidity framework to 2 DWTPs (plant A and B) over a period of 2 years (objective 4). It further extends this application by comparing the framework assessment outcomes among 4 DWTPs (plants A, B, C and D) and finally proposes a decision-support framework that can help a utility translate the results of this assessment into practical action plans, which can either be short-term or long-term (objective 5). Appendix B provides the supporting information for chapter 4.

Chapter 5 introduces a robustness index for the quantitative robustness evaluation of treatment processes for NOM removal (objective 6). It also shows the development and application of an NOM-specific framework to a full-scale DWTP, plant B (objective 7). Appendix C provides the supporting information for chapter 5.

Chapter 6 summarizes the conclusions of this thesis and the primary contributions of this research, synthesizing the key findings and establishing connections between all chapters. It also highlights the limitations of the current work and scope for future research.

2. Chapter 2: Background & Literature Review

This literature review is divided into two sections. Section 2A details the impact of extreme weather-related surface water quality disturbances on drinking water treatment operations. This section takes a top-down approach starting with a discussion of anthropogenic climate change and how it is linked to the recent changes in the hydrological cycle causing a subsequent increase in intensity and frequency of extreme weather events. Next, impacts of such events on surface water quality is discussed, especially from the lens of changes in turbidity and NOM which are two of the most crucial water quality parameters (WQP) for drinking water treatment operations. Finally, the implications of turbidity and NOM variations on specific drinking water treatment processes are presented. The primary objective of this section is to comprehensively understand the challenges encountered by DWTPs stemming from the variability in surface water quality. This understanding extends beyond an isolated examination of just the DWTP and, instead, integrates these challenges into the broader context of watershed changes due to climate change.

Section 2B delves into robustness of DWTPs, which is an effective climate adaptation strategy addressing water quality challenges. A robust treatment process ensures availability of good water quality even during expected and unexpected raw water quality perturbations, thereby safeguarding the health of the human population it serves. However, since there are several other concepts interrelated to robustness such as resilience, reliability, risk, and vulnerability, it was pertinent to discuss them as well. This section undertakes a critical review of the definitions and applications of each of these concepts within the domain of drinking water treatment. Furthermore, Section 2B endeavors to synthesize this information and presents a comprehensive conceptual figure that interconnects these crucial ideas within the context of DWTPs, especially from a water quality management perspective.

2A: Impacts of Extreme Weather on Drinking Water Treatment With Surface Water Sources

2A.1. Climate change and extreme weather events

Anthropogenic climate change has caused various changes in the hydrological cycle, some of which include an increase in atmospheric water vapor, changes in the intensity and extremity of precipitation patterns, the melting of ice, and changes in soil moisture and runoff (e.g. Bates et al., 2008). One of the noticeable impacts of climate change is the increase in occurrence and severity of extreme weather events. Several meteorological phenomena such as hurricanes, cyclones, floods, natural annual and decadal climatic variations (monsoons, El Niño Southern Oscillations, etc.) cause extreme weather, anthropogenic climate change plays a major role in intensifying these mechanisms in the hydrological cycle.

The importance of the hydrological cycle in facilitating such extreme weather becomes evident looking at the main events generally perceived as extreme occurrences, all of which are associated with changes in precipitation patterns. Stephenson (2008) classified extreme weather in six categories: (a) tropical cyclones and hurricanes, (b) extratropical cyclones, (c) convective phenomena, (d) mesoscale phenomena, (e) floods, and (f) droughts. While these phenomena cause extreme behavior in more than one climatic variable e.g., wind speed and temperature, precipitation is a common and underlying mechanism in all of them. Therefore, the focus of this literature review is limited to extreme precipitation events, but other extreme weather associated with wildfires, heat waves, or cold waves is not included in the scope of this review.

2A.1.1. Linking anthropogenic climate change to enhancements in the hydrological cycle

The generation and transport of water vapor along with temperature drives the physical processes associated with the hydrological cycle such as evaporation, transport of water vapor by general circulation in the atmosphere, condensation, precipitation, and runoff (Oliver & Oliver, 1995). The relationship between temperature and water vapor is given by the Clausius-Clapeyron relationship, which implies an exponential increase in the water vapor with an increase in temperature, which amounts to a 7% change for every 1°C change in temperature (Alduchov & Eskridge, 1996).

Therefore, raised surface temperatures that we associate with anthropogenic climate change have enhanced the hydrological cycle by increasing the water vapor content in the atmosphere (Trenberth, 2011). The Clausius-Clapeyron relationship becomes especially important over the

oceans where more water is available for converting to water vapor. This also enhances the general circulation in the atmosphere, which is the main mechanism for the redistribution of solar radiation as latent heat over latitudes (Dingman, 2015). An increase in moisture also increases the latent heat, resulting in circulations being achieved at lower wind speeds.

Consequently**,** the convergence of moisture in stormy areas, which is a precursor to intense rainfall and other extreme events, becomes more common due to climate change (Trenberth, 2011). Under the current wind patterns, more moisture is transported from the subtropics to convergence zones at higher altitudes where the weather systems naturally favor storms. Since all extreme precipitation events feed on moisture availability, there is a chance of increased heavy rainfall events from different meteorological phenomena (Dore, 2005; Kiehl & Trenberth, 1997; Trenberth 2011).

Interestingly, while the relationship between the total water vapor and sea-surface temperature strongly follows the Clausius-Clapeyron relationship in tropical and sub-tropical regions, it weakens at the extra-tropical areas. This indicates the complexity of precipitation predictions and the spatial and temporal variability of rainfall patterns (Trenberth, 2011). There have been conflicting results over the change of rainfall regionally and globally due to climate change. Despite this, several patterns linking precipitation changes to climate change have emerged, which are discussed in the next section (Bates et al., 2008; Trenberth 2011).

2A.1.2. Changes in precipitation patterns and extreme weather due to climate change

Different mechanisms of extreme precipitation are dominant in different regions of the world. While extratropical cyclones contribute to most of the extreme precipitation in the mid latitude and high latitude regions, Eastern Africa is mostly dominated by extreme precipitation driven by convective and orographic mechanisms. Some regions in the low and mid latitudes of Asia and Central America receive extreme precipitation due to a combination of all these weather systems (Utsumi et al., 2016). There is still a gap in understanding the cumulative effects of these mechanisms, knowing which may inform future climate adaptation efforts (Dowdy & Catto, 2017).

Most studies have reported change in rainfall patterns regionally and globally (Bates et al., 2008; Easterling et al., 2000a; Trenberth 2011). While precipitation has increased in the mid and high

latitudes, it has decreased in the tropical regions (Bates et al., 2008; Easterling, 2000b; Trenberth 2011). These changes are quite evident especially for Southern Asia, Africa and the Mediterranean. Apart from the volume of precipitation, the nature of precipitation is also undergoing changes. In the Northern latitudes, there has been a shift from snowfall to rainfall coupled with an earlier onset of spring. Over the last three decades, most places have observed that the mean precipitation has not increased, but the amount of heavy rainfall has (Dore, 2005; Easterling, 2000b; Trenberth, 2011). Because of such changes, an increase in the likelihood of heavy rains and floods, especially in the northern latitudes, are reported by future scenarios (Bates et al., 2008).

It is interesting to note here that an increase in dry periods in a region does not imply a decrease in the risk of intense rainfall and floods in the same region. There is a high likelihood of having intense rain, and an overall decreased rainfall frequency mixed with long dry periods. This likelihood is increased due to decreases in mean precipitation that will be seen especially in the tropical and sub-tropical regions (Bates et al., 2008).

Due to the spatial and temporal variability of precipitation, interpreting the effect of greenhouse gas emissions on the hydrological cycle, and establishing trends for future climate, remain complex. Attributing long term trends based on observations made over short durations was one of the early concerns raised over conclusions derived about hydrological enhancement (Easterling et al., 2000b). However, despite some gaps, there is increasing evidence that “the observed historical trends of increasing heavy precipitation are linked to global warming” (Groisman et al., 2005). The 2014 and 2023 Intergovernmental Panel on Climate Change (IPCC) reports also concur, reporting that the observational and modelling studies agree it is likely that heavy rainfall has increased over the twentieth century, and that this trend is due to global warming (Bates et al., 2008, IPCC 2021, IPCC 2023). The IPCC special report on climate extremes also concludes that the overall increase in extreme precipitation due to anthropogenic climate change has been confirmed with the additional evidence from regional climate data (Seneviratne et al., 2012). For Canada, it was ascertained that the climate has warmed and will continue warming due to anthropogenic influence, while also causing an overall increase in the precipitation pattern and intensification of weather extremes in some regions (Warren & Lulham, 2021)

2A.2. Impact of extreme weather events on surface water quality

Surface water quality depends on biological, chemical and anthropogenic influences, and on the flow and velocity of water (Ahmadi & Moradkhani, 2019). Extreme weather events that cause intense rainfall or droughts impact these factors and, therefore, the quality of water. The exacerbation of poor water quality can be due to an increase in particulate matter, organics, nutrients, pathogens and other water contaminants, such as toxic chemicals (Bates et al., 2008). This change in water quality has repercussions on freshwater ecosystems and on human health. Since surface water is an important drinking water source all over the world, it is important to consider the implications of extreme weather events on water quality, especially the water quality parameters that are important for DWTP design and operation.

Gathering information about the quality of the source waters is the first step towards designing a water treatment system (Crittenden, 2012). Depending on the source water quality and the treatment goals, the treatment process is decided. The treatment goals are set to attain the desired value of some water quality parameters such as pathogens, turbidity, inorganic and organic constituents, and specific contaminants, the limits of which are regulated. There are several parameters that affect the treatability of water such as turbidity, color, natural organic matter and pathogens (Crittenden, 2012). These parameters are, therefore, crucial for process optimizations that ensure smooth operations of drinking water treatment systems. The primary focus of this research is turbidity and NOM, both of which are essential water quality parameters for the design and operation of drinking water treatment systems and are discussed in more detail in the following sections.

2A.2.1. Turbidity

Turbidity is the measure of the ability of a liquid to pass light, making it an optical property of water. It is most commonly used to indicate the presence of suspended solids and particulates in water and is generally expressed in Nephelometric Turbidity Units (NTU). A clear liquid would transmit the light without any change in the direction of the light whereas a liquid with suspended particles would scatter and absorb the light instead. An increase in turbidity measurement is an indicator of more scattering, implying that there are more particulates in the water. Turbidity measurements are also dependent on the size, shape, and the refractive index of

the particles (Crittenden, 2012; Mukundan et al., 2013). Turbidity in surface waters depends on a range of factors and is one of the most variable parameters.

The main sources of turbidity in surface waters can be classified into two categories: weathering process, where water encounters rocks, minerals and soils; and biological activity. Presence of decomposed organic matter can also introduce suspended solids into the water, making turbidity an indicator of particulate NOM as well (Hartshorn et al., 2015). Particles can also be introduced from anthropogenic sources such as industrial and agricultural effluents and residues. The sources of particulate matter have been summarized in Table 2.1 (Crittenden, 2012). Transport of these particulates can be through direct erosion and runoff from land, atmospheric deposition during rain, or through biological activity in the waters (Crittenden, 2012). Turbidity in surface water can vary over a large range of values. Turbidity in reservoirs and lakes is generally stable and often falls within the range of 1-20 NTU, although high turbidity events, often localized, can occur. In streams and rivers, turbidity typically ranges between 10-4000 NTU or even higher, and is more variable due to extreme weather or changes in the flow rates of water (Crittenden, 2012).

Table 2.1: Sources of particulate matter in surface waters (Adapted from Crittenden, 2012)

Source	**Particulate matter**	
	Colloidal	Suspended
Weathering	Clay, silica, ferric oxide, aluminium oxide, magnesium oxide	Clay, silt, sand, inorganic soils
Biological Activity	Organic Polymers	Cell fragments

An increase in the concentration of particulate matter in surface water is of great concern for drinking water production. Particulates can serve as good adsorption sites for microorganisms and provide nutrients for their growth, making them crucial pathogen risk factors. Increase in turbidity has been found to be correlated with an increase in pathogens such as *Giardia* and *Cryptosporidium* (Huck & Coffey, 2004; Whitehead et al., 2009; Bertone et al., 2016). High turbidity has a negative impact on disinfection efficiency of chlorination, ozonation, and Ultraviolet (UV) radiation. Particles can either physically shield pathogens that adsorb onto the

particle surface or reduce disinfection efficiency by scattering UV light or reacting with ozone (Bertone et al., 2016; Crittenden, 2012; Health Canada, 2012). Due to these reasons, turbidity in the finished water is regulated.

2A.2.1.1. Changes in turbidity during extreme weather events

In general, during heavy rainfalls and floods, there is an increase in the turbidity of surface water (Bates et al., 2008; Bertone et al., 2016; Crittenden, 2012; Khan et al., 2015; Mukundan, et al., 2018; Whitehead et al., 2009). This occurs due to increased runoff from terrestrial sources that washes off fluvial soils into water bodies, increasing the particulate matter over a short period of time and causing turbidity spikes (Bates et al., 2008; Bertone et al., 2016; Khan et al., 2015; Whitehead et al., 2009). The mixing of water due to high flows can cause resuspension of settled particles during heavy rainfall and floods. This can be especially significant for stratified storage reservoirs that draw water from the upper layer or epilimnion that might become more turbid during these times (Bertone et al., 2016).

There is a general decrease in turbidity of rivers and streams during droughts due to reduced flow velocities and greater sedimentation (Mosley, 2015). In some cases, an increase in river water turbidity was attributed to point sources in the catchment such as wastewater discharge, construction sites, and acid mine drainage sites (Anderson & Faust, 1972; Mosley, 2015). In shallow lakes and reservoirs, turbidity can increase due to the resuspension of sediments and the increase in the concentration of colloids. There is also a risk of turbidity spikes in conditions where a drought event is followed by heavy rainfall, leading to remobilizations of sediments in the water body (Ahmadi & Moradkhani, 2019).

2A.2.2. Natural Organic Matter

NOM is a complex mixture of organic compounds with different molecular weights and chemical characteristics (Crittenden, 2012; Health Canada, 2019). The most common NOM fractions are biopolymers, humic acids, fulvic acids, low molecular weight acids, bases and neutral compounds (Huber et al., 2011). NOM is most commonly characterized as hydrophobic or hydrophilic based on the polar nature of the constituents. Generally, lower molecular weight fractions contribute to the hydrophilicity, whereas higher molecular weight fractions are mostly hydrophobic in nature (Health Canada, 2020).

Since carbon is the key constituent of NOM, water quality parameters such as total organic carbon (TOC) and dissolved organic carbon (DOC) concentrations are used to quantify and represent the NOM in water. TOC and DOC are also the parameters used to quantify NOM when required for water treatment design and operation. Initially, NOM was a concern due to the yellowish colour, taste, and odour it imparts on water, compromising its aesthetic quality. Over time, NOM was found to be a precursor for disinfection by-products (DBPs), which can be toxic and carcinogenic, leading to drinking water regulations (Au, Alpert, & Pernitsky, 2011; Crittenden, 2012; Parsons et al., 2014).

NOM in surface water can originate from two sources: biological activity within the water (autochthonous or aquagenic) and the terrestrial ecosystem (allochthonous or pedogenic). The biological activity includes the decomposition and secretion of aquatic organisms within the water body; while the terrestrial activity includes the secretion and decay of plants, animals and human waste on the land (Crittenden, 2012). NOM from the land is mobilized by rainfall that percolates into the organic topsoil and moves further downward to the mineral soil. 88% of allochthonous NOM is originated from the organic soil layer; therefore, runoff from organic soils is a concern for surface water quality (Health Canada, 2019). As for autochthonous NOM, algal blooms are one of its biggest contributors, especially for lake systems. Allochthonous NOM is generally dominantly hydrophobic in nature whereas autochthonous NOM is more hydrophilic. There are anthropogenic sources of organic matter as well, coming from wastewater treatment effluents and stormwater discharges. This is mainly hydrophilic in nature (Health Canada, 2020).

2A.2.2.1. Changes in NOM characteristics and quantity during extreme weather events

Studies have reported an increase in NOM in surface waters due to extreme precipitation and increased runoff from snowmelts (Hurst et al., 2004; James et al., 2016), which may cause a four to five times increase in DOC concentrations (Saraceno et al., 2009). During extreme rainfall/floods, the mobility and transport of water is responsible for the change in the nature and concentration of NOM. In general, there is an increased flushing of topsoil during heavy rainfalls and floods, which is usually rich in organic matter. Due to the high flow and velocity of water, this topsoil can bypass all adsorption sites on its path and reach the surface waters (Ritson et al., 2014). Heavy rainfall also causes vertical mixing in a surface water body, and this may cause an increase in the organic carbon content that gets dissolved in the water (Khan et.al, 2015). The

residence time of flowing water also reduces which results in a shorter period of NOM decomposition. As a result, organic compounds with higher aromaticity or hydrophobicity reach the surface waters (Bertone et al., 2019; Hurst et al., 2004; Khan et al., 2015; Ritson et al., 2014).

During droughts, for rivers and streams, some studies reported an increase in the NOM concentrations which might be due to an increase in the aquatic biomass productions (Mosley, 2015). Some studies also reported a decrease in NOM, but the mechanisms of this trend are not very well explained (Mosley, 2015). Most studies report an increase in NOM concentrations in lakes and reservoirs during droughts due to increased productivity rates induced by lower volumes and higher temperatures (Mosley, 2015).

In general, the mechanism seems to be that droughts change the accumulation rate of sediments from catchments and increase biological productivity rates. These sediments can get mobilized through rainfall after the drought. This would explain the initial decrease in organic carbon followed by a sudden flush if there is a rainfall event (Khan et al., 2015). This explanation is further supported by instances of decreased color during the drought followed by an increase in color, which has been linked to the humic and fulvic acids that are washed out post drought. In terms of the change in nature of NOM due to droughts, most studies reported an increase in the hydrophilic nature of NOM (Khan et al., 2015; Ritson et al., 2014; Wright et al., 2014).

2A.3. Impact of changes in turbidity and NOM on drinking water treatment operations

The main objective of drinking water treatment is to provide safe and aesthetically pleasing water which is achieved by targeted removal of particles and pathogens, and control of other relevant water quality parameters. The turbidity and NOM of raw water play an important role in determining the treatment required to accomplish these goals. Turbidity reduction is a direct indicator of particle removal, making it a measure of treatment effectiveness. The presence of NOM indirectly affects the particle removal process, as it will be seen in this chapter. Both turbidity and organic carbon affect the pathogen removal process, as well as other processes, e.g., adsorption of contaminants in the case of organic carbon.

The two main categories of surface water treatment are conventional and membrane treatment processes. Conventional treatment is used for treating moderate to high raw water turbidities (> 20 NTU) and moderate to high TOC (>4 mg C/L). It involves coagulation, flocculation, sedimentation, filtration, and disinfection. Direct filtration, which omits the sedimentation step, is often used for low turbidity waters. Filtration in conventional treatment is achieved by using granular media filters such as rapid sand gravity filters or dual media filters. A typical treatment train for conventional treatment is shown in Fig. 2.1. The main benefits of using the conventional treatment include operational flexibility and hydraulic stability (Crittenden, 2012).

Membrane treatment uses low pressure membranes such as microfiltration and ultrafiltration membranes for water treatment. The pre-treatment and disinfection in membrane systems typically comprise the same processes as in conventional plants. The membranes themselves can remove turbidities of <10 NTU, but in combination with other steps of a conventional water treatment, they can be used to treat any quality of water (Crittenden, 2012). This is one of the main advantages of membrane treatment, in addition to its modular design and easy automation.

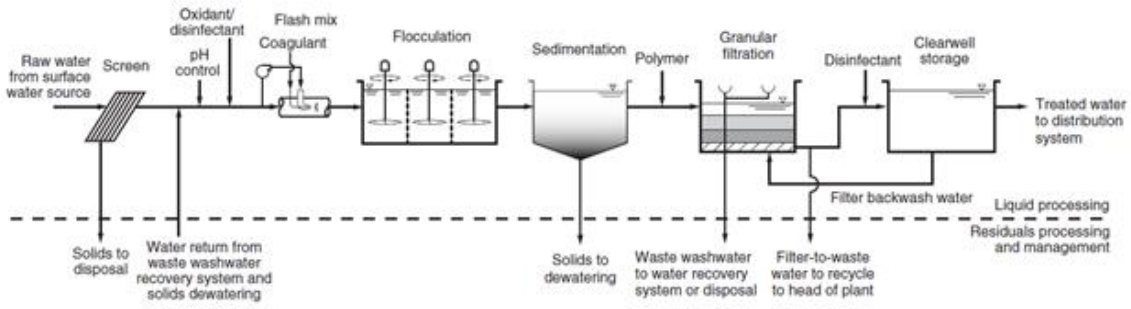


Figure 2.1: Typical treatment train for a conventional surface water treatment plant (Crittenden, 2012)

Conventional treatment is the most widely used process for surface water treatment. About 60% of treated water in Canada was obtained from conventional and direct filtration methods, serving 66% of the population, while only 8% of the population was served by membrane filtration plants (Statistics Canada, 2011). Given this reliance on the conventional water treatment process, it is essential to consider what a changing climate and changes in water quality means for the water treatment process. The following sections discuss the impacts of changes in turbidity and NOM on drinking water treatment processes.

2A.3.1. Turbidity

The physico-chemical removal of turbidity is done through coagulation, flocculation, sedimentation, and filtration steps. An increase in source water turbidity and duration of the turbidity spike during heavy rainfall and floods impacts all the treatment steps directly or indirectly. There have been instances of DWTPs facing turbidity spikes of 3750 NTU (Bow River watershed, Alberta, 2013) and 3000 NTU (Red Deer river, Alberta, 2005) due to extreme rainfall, floods, and freeze-thaw events (Yarahmadi, 2019). There have also been instances of plant shutdowns due to extreme turbidity values that overwhelmed the treatment system and caused filter water effluent turbidity to go above the regulated limits (Qiu et al., 2019; Lake Huron WTP, 2009). With increases in the intensity and extremity of extreme weather events, such turbidity incidents are prone to becoming more common and widespread, and likely more severe.

Apart from the raw water turbidity, achieving turbidity targets also depends on tangible elements such as coagulant usage, type of coagulant, plant size and age; and intangible elements such as operator skill and attention. If the pre-treatment i.e., coagulation-flocculation-sedimentation (CFS) fails to sufficiently decrease a turbidity spike, it is likely that the filters are overwhelmed, reducing filter run times and increasing the need for more frequent backwashes.

Apart from the coagulation, flocculation, sedimentation, and filtration steps, which are the steps directly responsible for removing turbidity, steps like disinfection and distribution of treated water are also impacted. During high turbidity events, if the filtered water quality is >0.5 NTU (in jurisdictions that allow this value) even for short intervals, particles can enter the distribution system and may facilitate microbiological growth within the pipes and lead to violation of the water quality standards (Gauthier et al., 2003). The possible effects of increased turbidity on the various treatment steps are shown in Table 2.2 (Adapted from Health Canada, 2012, p. 12).

Table 2.2: Effect of turbidity on various drinking water treatment steps

Parameter/Process	Possible Effect of Turbidity
Color	Cloudy/turbid appearance
Coagulation & flocculation	Raise/lower pH Raise/lower alkalinity Affects zeta potential Increased coagulant demand Increase in pH adjustment chemicals Change in floc characteristics Increase in floc growth time (Qui et al., 2019)
Sedimentation	Increased settling time Increased residues
Filtration	Reduces filter run times Plugs filters Increases backwash frequency
Disinfection	Increase in disinfection demand Harbors pathogens Physically blocks UV light Potential to form DBPs
Distribution	Particulate matter deposition Microbiological growth and transport

2A.3.2. NOM

Changes in the concentration and character of NOM can impact several conventional treatment steps such as coagulation, filtration, and disinfection. Since most treatment plants monitor NOM by measurement of DOC or other surrogate parameters, it is important to note that while a change in the concentration of NOM is reflected in the DOC value, change in the NOM composition may not be associated with a change in DOC (Goss & Gorczyca, 2013; Montreuil, 2011).

Effect of the NOM is most commonly seen on the coagulation, adsorption, and disinfection steps in drinking water treatment. The coagulation process converts a portion of the dissolved organics into the solid phase either by precipitation or adsorption on the coagulant molecules, which are subsequently removed by flocculation, sedimentation, and filtration (Edzwald, 1993). During coagulation, NOM can act as a ligand and forms a complex with the coagulant, hence, an increase in NOM concentrations increases the coagulant demand (Edzwald, 1993). While both particulate matter and NOM constituents carry a negative charge, NOM has about 10-100 times greater negative charge which makes destabilization of NOM crucial during coagulation (Edzwald, 1993).

Therefore, for some surface waters, coagulant doses are controlled by NOM concentration rather than turbidity even when the target is particulate removal (Au et al., 2011; Ritson et al., 2014). Anderson et al. (2017) reported a four-fold increase in alum demand over a period of 25 years due to an increase in NOM levels. The nature of NOM present in water also plays an important role in coagulation. It was found that almost double the coagulant was required to coagulate fulvic acids, which are more hydrophilic, than an equal mass concentration of humic acids (Edzwald, 1993). While hydrophobic NOM can be removed by coagulation, removal of hydrophilic NOM by coagulation is very poor (Au et al., 2011; Edzwald, 1993; Parsons et al., 2014). If the nature of NOM is a mixture of both hydrophobic and hydrophilic parts, and includes compounds of both lower and higher molecular weights, then, coagulation can achieve potentially 40-60% DOC removal (Edzwald & Tobiason, 1999). Specific UltraViolet Absorbance (SUVA) is used as a surrogate parameter for NOM as it is an indicator of NOM character and concentration (in limited capacity) and can be used for adjusting coagulant dosages in DWTPs (Edzwald, 1993; Parsons et al., 2004).

The increase in the hydrophilic nature of NOM, as seen during droughts, can make NOM removal by coagulation difficult (Au et al., 2011; Ritson et al., 2014). On the other hand, the increase in the hydrophobic nature and high molecular weights of NOM, as seen during floods and heavy rainfalls, makes it easier to remove NOM by coagulation (Au et al., 2011; Ritson et al., 2014). However, this increases the coagulant demand of the treatment process. Also, the hydrophobic nature can remain elevated for a long time in the surface waters, which is a cause for concern (Ritson et al., 2014).

Processes such as enhanced coagulation directly target NOM removal through CFS which involves coagulation done with higher coagulant doses and lower pH. This however can increase both the coagulant dose and pH adjustment chemicals like lime. This is corroborated by Anderson et al. (2017), who reported a 1.75-fold increase in lime consumption.

During an extreme weather event, the connection between turbidity and NOM changes also plays a major role in the treatment performance. While there might not always be a clear correlation in their concentration changes, NOM can increase along with turbidity during a turbidity spike and the elevated NOM levels can persist even after the turbidity comes down to pre-spike levels (Hurst et al., 2004; James et al., 2016). In treatment plants, where coagulant dosage is optimized for NOM removal instead of turbidity, sub-optimal coagulation can be avoided (Hurst et al., 2004; James et al., 2016; Qui et al., 2019). Sub-optimal coagulation is also a concern for the log-reduction of pathogens (Health Canada, 2020).

One of the biggest concerns with NOM in water is its potential to react with chlorine and to form DBPs (Anderson et al., 2017; Crittenden, 2012; Delpla et al., 2009; Ritson et al., 2014). Certain groups of DBPs such as trihalomethanes (THMs) are carcinogenic in nature, which has resulted in the regulation of their concentration in the distribution system (Crittenden, 2012). An increase in the organic precursors leads to increased production of DBPs (Crittenden, 2012). DBP formation has been strongly associated with the hydrophobic fraction of NOM in surface waters (Ritson et al., 2014). Therefore, an increase in the hydrophobic fraction during extreme rainfall, floods and droughts can be problematic for water treatment.

Apart from coagulation and disinfection, NOM can also hinder contaminant removal and affect other treatment steps. NOM can form complexes with organic and inorganic contaminants such as pesticides and metals, making them more soluble and therefore harder to remove by treatment. It can decrease the adsorption capacity of activated carbon by blocking or occupying the adsorption sites available for contaminants (Crittenden, 2012). Certain NOM fractions can also cause fouling in membrane systems (Peldszus et al., 2011). The effects of NOM on drinking water treatment processes are summarized in Table 2.3.

Table 2.3: Effects of NOM on drinking water treatment steps (Adapted from Crittenden, 2012, p. 54)

Process/Parameter	**Effect of NOM**
Color	Yellow/brownish appearance
Coagulation	Increased coagulant demand Increase of pH adjustment chemicals
Rapid gravity media filtration/ biological filtration	Decrease in filter run time
Membrane filtration	Adsorption on filter media/membranes Fouling of membrane filters Plugging of filters
Disinfection	DBP formation Increase in disinfection demand Decrease in disinfection efficiency
Adsorption	Formation of soluble complexes with inorganic metals and pesticides Decreases adsorption capacity of activated carbon

2B: Robustness and related concepts in drinking water treatment systems

Scope of review:

The purpose of this section is to review existing literature of robustness and related concepts from a drinking water treatment context and highlight the gaps and opportunities for advancement in this field. This review will only focus on the application of robustness and other related concepts in the field of drinking water treatment. It will also highlight the similarities and differences between the different concepts. Since these concepts have found application in the broader field of water resources engineering, it was pertinent to mention their definitions for a holistic analysis, however, it is not within the scope of this review to discuss these works in detail.

2B.1. Introduction

Evaluating the performance of DWTPs, especially from the context of changing climate and challenging water quality is a complex task. DWTPs consist of interdependent processes influenced by a multitude of variables. Assessing their performance can take two main forms: analyzing each process separately or evaluating the entire system. Service providers tend to focus on individual stages, while regulators look at the DWTP as a whole to ensure compliance (Oliveira et al., 2014).

In this context, the concept of robustness emerges as a cornerstone for evaluating DWTP performance under a variety of raw water scenarios. However, the interrelationships between robustness and other related concepts such as resilience, reliability, risk, and vulnerability remain intricate and multifaceted. To identify the needs of a DWTP for performance evaluation and improvement, it is important to understand these concepts and the associated evaluation procedures. This section of the literature review is driven by a twofold objective: to comprehensively examine how robustness and related concepts are approached in the context of drinking water treatment, and to identify key studies that directly apply these concepts to Drinking Water Treatment Plants (DWTPs). This section addresses several key questions: what

does robustness mean within the framework of drinking water treatment? How have robustness and related concepts been applied in assessing the performance of DWTPs based on existing literature? What relationships exist between robustness and its counterparts in this context?

2B.2. Robustness and related concepts

In this section, a concise overview of the general definitions of robustness, resilience, reliability, risk, and vulnerability in the broader context of water resources is provided for contextual understanding. Subsequently, the focus narrows down to these concepts within the specific domain of drinking water treatment. The section also investigates quantitative metrics associated with these concepts, particularly their application in the evaluation of drinking water treatment systems. Table 2.4. shows a summary of key studies from the literature, which have applied these concepts to DWTPs.

Table 2.4: Summary of key DWTP studies on robustness and related concepts

Source	Concepts covered	Scope of assessment	Methods used
Huck & Coffey (2002)	Robustness	Filters at 1 DWTP	Turbidity Robustness Index (TRI)
Hurst et al. (2003)	Robustness	CFS at 1 DWTP	TRI
Li & Huck (2008)	Robustness	Filters at 3 DWTPs	TRI
Hartshorn et al. (2015)	Robustness	Filters at 5 DWTPs	TRI
Upton et al. (2017)	Robustness, reliability,	Filters at 1 DWTP	TRI, Mean Time Between Failures

	resilience		
Oliveira et al., 2014)	Reliability	Finished water from 1 direct filtration DWTP	Coefficient of reliability from Niku et al. (1979)
Melo et al. (2016)	Reliability	Finished water from 5 direct filtration DWTPs	Coefficient of reliability from Niku et al. (1979)
de Oliveira et al. (2021)	Reliability	Finished water from 20 conventional DWTPs	Coefficient of reliability from Niku et al. (1979)
Melo et al. (2021)	Reliability	Raw water and finished water from 6 DWTPs	Coefficient of reliability from Niku et al. (1979)
Summerscale & McBean (2011)	Risk	5 DWTPs	Different risk assessment frameworks
Zhang et al. (2012)	Robustness, reliability, risk	CFS, filtration, disinfection (limited application to full-scale DWTP)	TRI, other metrics for reliability and risk
Szpak & Tchórzewska-Cieślak (2017)	Reliability, availability	1 DWTP	Availability index
Cyna (1997)	Reliability, availability	3 DWTPs (equipment)	Reliability and availability metrics

2B.2.1. Robustness

Definitions

In the context of water resources management, one of the early definitions of robustness was stated as the flexibility of project designs and operating policies that enable adaptation to a wide range of possible demand conditions at little additional cost (Hashimoto et al., 1982a). This definition focuses on the overall system sensitivity to cost rather than the design. It also considers the opportunity cost by comparing the actual costs of a project to the least cost project design (Hashimoto et al., 1982a). Additionally, robust optimization is a framework that incorporates risk aversion into optimization models, allowing decision-makers to evaluate trade-offs among different goals or objectives, variation in factors pertaining to the different objectives, and the risk of violating constraints or missing targets (Watkins et al., 1997). In more recent studies, in addition to the overall economic perspective, robustness in water resource systems often pertains to the ability of system designs to remain insensitive to fluctuations and exhibit satisfactory performance across a wide range of inputs (Borgomeo et al., 2018; Herman et al., 2015; Moody & Brown, 2013; Whateley et al., 2014). This includes the evaluation of the system's performance under a wide range of future scenarios and rewards strategies that perform well under various future conditions(Maier et al., 2016).

The evaluation of robustness in water resource systems has been approached through two main methods: the top-down approach and the bottom-up approach. The top-down approach focuses on considering future climate scenarios and their potential impacts on the system. It involves using climate model outputs to assess the system's sensitivity and vulnerability to climate change. On the other hand, the bottom-up approach takes a more problem-driven perspective. It begins by understanding the system and identifying specific problems or vulnerabilities. Then, it characterizes the sensitivity and vulnerability of the system to climate change and assesses its robustness accordingly. This approach allows decision-makers to have a more comprehensive understanding of their system, its dynamics, and its specific vulnerabilities.

The top-down approach is valuable for considering broad climate scenarios and potential impacts, providing a high-level overview. However, this approach has limitations due to the high variability and uncertainty associated with climate model outputs, which can influence the

accuracy of the results. Additionally, the top-down approach may not provide the detailed information necessary for decision-makers to understand their system and identify appropriate adaptation measures(Moody & Brown, 2013). The bottom-up approach offers a more detailed and context-specific analysis that focuses on the specific system characteristics, vulnerabilities, and adaptation needs (Di Francesco et al., 2020; Maier et al., 2016; Watkins et al., 1997). Both approaches have their strengths and limitations, and a combination of both can provide a more comprehensive evaluation of robustness in a specific water resource system. By incorporating both top-down and bottom-up perspectives, decision-makers can obtain a better understanding of the potential impacts of climate change, while also considering the system's specific characteristics and vulnerabilities, enabling them to make more informed and effective decisions.

Within the field of drinking water treatment, considering future conditions and uncertainty, a robust water supply system is one that functions very well under normal circumstances and deviates minimally from this when challenged (Huck & Coffey, 2004). Robustness in drinking water treatment is approached from a multi-barrier perspective (Huck, 2015). A robust water supply system encompasses the robustness of all five elements: source, treatment (design and operation), distribution, monitoring, and response. It emphasizes the importance of technical, institutional, and human factors for robustness.

The key difference between water resource management and drinking water treatment lies in their scope. Water resource management encompasses the broader aspects of managing water resources, including supply, demand, and overall system optimization. It focuses on the flexibility of project designs, cost considerations, optimization under uncertainty, and the evaluation of system performance in meeting goals. On the other hand, drinking water treatment specifically addresses the treatment process and the multi-barrier approach to ensure safe drinking water. It emphasizes the robustness of all five elements involved in the water supply system: source, treatment, distribution, monitoring, and response.

Despite their differences, there are notable similarities between the two fields. Both water resource management and drinking water treatment recognize the importance of adaptability and resilience to a wide range of conditions and inputs. They both consider the influence of future uncertainty, albeit with varying approaches, and the need to evaluate system performance under

different scenarios. Additionally, both fields acknowledge the significance of technical, institutional, and human factors in achieving robustness.

Quantitative application in drinking water treatment

While indices quantifying robustness exist in the broader field of water resource management, their application to drinking water treatment plants has been limited (Moody & Brown, 2013; Whateley et al., 2014). In the context of drinking water treatment, quantitative robustness assessment using an index has predominantly been utilized to evaluate the effectiveness of treatment processes in achieving desired turbidity goals and ensuring the removal of pathogens.

Turbidity, a measure of the cloudiness or haziness of water, is a critical parameter in drinking water treatment. Robustness indices such as the TRI have been developed to assess the stability and performance of granular media filtration systems specifically in terms of turbidity (Huck & Coffey, 2002; Li & Huck, 2008). The TRI incorporates factors like filter performance goals, average performance, and deviation from the average to quantify the system's robustness in meeting turbidity targets. This metric allows for the identification of unstable filter operations and enables comparisons of performance under various conditions and pre-treatment schemes (Hartshorn et al., 2015; Huck et al., 2002; Hurst et al., 2004; Li & Huck, 2008; Stein et al., 2017; Templeton et al., 2007; Upton et al., 2017; Zhang et al., 2012; Zorić et al., 2020). Table 2.4. showcases the key studies that have implemented a quantitative robustness assessment of DWTPs.

Additionally, the removal of pathogens is a paramount concern in drinking water treatment. Robustness assessments have also been carried out to assess the efficiency and reliability of treatment processes in pathogen removal. These evaluations often rely on methodologies such as Quantitative Microbial Risk Assessment (QMRA) which is primarily a risk assessment framework used by regulatory bodies to assess and measure the potential health hazards associated with microorganisms in drinking water (Health Canada, 2019). Several studies have utilized this risk assessment framework in a scenario-based approach to evaluate treatment robustness under different conditions, including scenarios like treatment failure and source water challenges (Hamouda et al., 2016; Zhang et al., 2012).

2B.2.2. Resilience

Definitions

The widely accepted and frequently reiterated definition of resilience in water systems pertains to the duration it takes for a system to recover to a satisfactory state following a period of failure (Hashimoto et al., 1982b). One of the foremost introductions of resilience as a performance metric for water resource systems was by Hashimoto et al. (1982b) who also introduced the quantitative analysis of resilience. Other fundamental works widely cited include Fiering (1982), Moy et al. (1986), and Srinivasan et al. (1999). While all these works address system resilience, there was a difference in their approaches. While Hashimoto et al. (1982b) focusses on the speed with which the system returns to its original state after failure, Moy et al. (1986) focusses more on the duration of the failure period. Fiering (1982) on the other hand proposed resilience measured as the resilience against crossing a desirable performance threshold.

Over time, the definitions of resilience shifted from a sole focus on the time element to a more holistic approach that includes the whole span of a system's response to a disturbance. Broadly, previous resilience assessments have predominantly employed three primary methodologies: a) evaluating resilience against the breach of a performance threshold, b) measuring resilience in terms of response and recovery post a system failure, and c) assessing resilience in the context of adaptive capacity (i.e. a system's ability to adapt to the disturbance) and effective system management (Wang et al., 2009). Resilience metrics have also been categorized as duration-based, frequency-based, magnitude-based, and volume-based metrics and while these have been historically applied in isolation, there is growing recognition of the benefits associated with integrating these diverse metrics (Roach et al., 2018).

Based on a review of the water resource system resilience metrics, Wang et al. (2009) suggests that resilience is 'not a single thing' but rather a 'family of ideas'. This idea of resilience being a collection of diverse conceptualizations agrees with other definitions of resilience for critical infrastructure such as water supply systems. All the definitions underscore that resilience is a multifaceted concept that cannot be comprehensively defined by a single parameter. Instead, it can encompass a range of interrelated factors, including the speed of recovery, robustness, redundancy, resourcefulness, and the capacity for adaptation (Quitana et al., 2020). Resilience is

also frequently associated with a system's ability to adapt to changing conditions and disturbances. This capacity for adaptation is recognized as a critical aspect of resilience that enables systems to thrive in dynamic environments (Blackmore et al., 2008). From an action-oriented perspective, resilience is often depicted as a combination of proactive and reactive strategies. Definitions frequently highlight that resilience is achieved through a blend of preventative actions taken proactively to enhance preparedness and corrective actions implemented reactively in response to disturbances (Pamidimukkala et al., 2021). From a drinking water treatment perspective, all the aspects of resilience such as adaptive capacity, point of failure, time of recovery are applicable (Quitana et al., 2020). Based on the desired focus of a DWTP, one or more aspects of resilience can be evaluated.

Quantitative application in drinking water treatment

From a comprehensive review done for resilience assessment frameworks for critical infrastructure (Guo et al., 2021), it was seen that only three directly addressed water supply systems, and with limited evaluations of full-scale DWTPs. The American Water Works Association (AWWA) M19 manual calculates resilience as a product of service outage, vulnerability, and threat (AWWA 2018). Upton et al. (2017) defines resilience as the mean time to recover and apply this metric to evaluate the resilience of rapid gravity filters at a DWTP. Zhang et. al (2012) on the other hand, concluded that it is difficult to propose a general quantitative metric for resilience as it is highly dependent on various factors such as location, size and personnel at a DWTP, and excluded resilience from their study.

Several other studies have proposed quantitative metrics to evaluate drinking water system resilience and details of these methods can be found in a review done by Quitana et al. (2020). Examples of such metrics include calculation of resilience factors that incorporate the duration and severity of failure. This approach defines resilience as a sum of normative (level of failure defined by the regulatory body), accepted (level of failure accepted by the end user) and critical (level of failure beyond system recovery) resiliencies (Cubillo & Martínez-Codina, 2019). One key highlight of this review was the focus of these studies on technical aspect of resilience, i.e. quantification of the time of recovery. However, it is important to integrate other dimensions of

resilience such as the environmental, organizational, social, and economic dimensions to get a complete assessment of DWTP resilience.

In addition to academic sources, there are several tools and frameworks in grey literature (publications, reports, or documents that are produced outside of academic publishing channels) which can be applied to DWTPs to assess their resilience to extreme weather conditions. U.S. EPA has a dedicated section for drinking water and wastewater resilience which is further divided into tools for assessment, planning, training, response, recovery, and surveillance. One tool that unifies all these steps and gives a roadmap for building resilience against extreme weather events is the Route to Resilience tool (U.S. EPA, 2020). It is a step-by-step guide for utilities with short educational videos and, based on the area of interest, the generated reports would further outline specific products, guides, tools for the first five steps of resilience.

Other useful tools such as the Climate Resilience Evaluation and Awareness Tool (CREAT), which was developed under US EPA's Climate Ready Water Utilities (CRWU) initiative, and the Vulnerability Self-Assessment Tool (VSAT) also tie into the steps of the Route to Resilience framework (U.S. EPA, 2016; U.S. EPA, 2019). The main objectives of CREAT are to include creating an awareness about potential impacts of climate change on water operations, and guide utilities in identifying risks from climate change and corresponding adaptation options and comparing the costs of the adaptation options with the losses that could be incurred due to climate change related threats. Another similar framework is Water Research Foundation's utility resilience practical framework which can help water, wastewater and stormwater utilities set specific resilience goals and find practical tools available to reach those goals (WRF, 2023).

2B.2.3. Reliability

Definitions

In civil and environmental engineering, reliability is defined as the probability of non-failure of a project either with respect to the performance or the structure. It is seen as a complementary to risk, which is the probability of failure (Hashimoto et al., 1982b; Singh et al., 2007). Reliability analysis serves two distinct purposes: it is employed during the design phase of a new system to ensure non-failure, and it is also utilized during the review of an existing system to evaluate its

ongoing performance and reliability. There are two main approaches to reliability analysis: traditional and probabilistic. The traditional or deterministic approach assumes the worst-case scenario and adds safety margins to the design to cover unknowns. While this has been a successful approach in the past, the safety factors added to the design are not necessarily based on true knowledge of the system, leading to possible overdesigning and does not say much about the reliability of the system. The probabilistic approach on the other hand, is the assessment of the system performance in all possible conditions by accounting for uncertainty in the relevant system parameters.

The reliability metrics available for quantifying the reliability for water resource systems are typically based on the probabilistic approach. Different mathematical techniques that can be used to solve the probability density function have been discussed in detail in Singh (2007). These metrics typically consider the dynamic nature of the water resource systems, meaning the dependence of reliability on time, interpreting it as number of days a system was in a satisfactory state over a given duration (Asefa et al., 2014; Maier et al., 2016).

Reliability for drinking water treatment plants primarily emphasizes compliance with water quality standards rather than structural reliability. 'Failure' of an existing drinking water treatment plant refers to the probability of a DWTP not meeting its water quality targets, which are regulated and can have serious health implications if not followed strictly. When approaching from a drinking water design perspective, reliability can mean incorporating uncertainty in process parameters and imposing constraints on different operational and performance factors such as hydraulic residence time, filter loading rates, effluent particulate concentration, and filter run times (Boccelli et al., 2007). Factoring uncertainty and a target reliability into the drinking water treatment design can ensure a robust design while also avoiding under-design or over-design of the different processes (Singh, 2007).

Quantitative application in drinking water treatment

In the literature, the assessment of drinking water treatment reliability has involved several metrics, often rooted in the mathematical techniques mentioned in the previous section. Some studies have taken a holistic approach, evaluating the reliability of the entire DWTP, while others have focused on specific treatment processes. In some cases, general engineering reliability

metrics, such as mean time between failures (MTBF), have been applied to the field of drinking water treatment (Upton et al, 2017; Zhang et al., 2012). For instance, Upton et al. (2017) utilized MTBF to determine the reliability of rapid gravity filters, defining 'failure' in terms of a turbidity spike. Alternatively, Zhang et al. (2012) introduced a methodology for calculating the reliability of individual treatment processes within a DWTP. This approach involved defining relevant performance functions for each process and calculating the total reliability as a product of the individual process reliabilities.

Another approach for evaluating DWTP reliability includes the application of a coefficient of reliability developed by Niku et al. (1979), which was originally developed to assess waste water treatment reliability. This metric assesses process reliability in meeting a specific water quality goal. Several studies have extended the use of this metric to DWTPs, however, it could only be used to assess reliability with respect to turbidity and had limited use for other parameters such as color and pH (de Oliveira, Melo et al. (2021); Melo et al. (2016); Oliveira et al., 2014)

A few studies have quantitatively analyzed the complementary concept of availability of a DWTP rather than reliability (Cyna (1997); Szpak & Tchórzewska-Cieślak (2017)). Availability pertains to the probability of a system being operational at any given time, accounting for the operation-failure-repair cycle, while reliability primarily focuses on the operation-failure cycle (Cyna, 1997). As DWTPs are inherently repairable systems, these studies opted to explore availability. For instance, Cyna (1997) proposed a methodology for such an assessment and applied it to new projects at three DWTPs. This methodology centered on calculating availability based on the reliability of individual equipment components within the plant, such as pumps, tanks, and filters. A similar approach of calculating an availability index on individual components of the DWTP and combining them for the entire plant was used by Szpak & Tchórzewska-Cieślak (2017).

2B.2.4. Risk and vulnerability

Definitions

The simplest definition of risk is that it's the probability of the failure of a system (Hashimoto et al., 1982b). However, risk to any system is much broader in scope and includes three

overarching questions: what the harmful event is, what is the probability of the event occurring, and what are the consequences of the event (Singh et al., 2007; Lindhe et al., 2009). Risk characterization can be done based on the severity and likelihood of the harmful scenario. Vulnerability is a measure of the magnitude of repercussions that can happen from a potential failure (Hashimoto, 1982b). This concept encapsulates the extent to which a system is susceptible to adverse outcomes when faced with unforeseen challenges or disruptions (Asefa et al., 2014). It is an intrinsic quality of a system that reflects the degree of fragility or exposure to harm within a given context. Vulnerability is inherently tied into the concept of risk, as risk assessment also includes identifying system vulnerabilities to a certain threat and estimating how significant the consequences are. There are several techniques, both qualitative and quantitative, for risk assessment of water resources systems in the literature. As this is already a well researched area, details of such techniques can be found elsewhere (Lindhe et al., 2009).

Quantitative application in drinking water treatment

In drinking water treatment, risk assessment takes various forms, tailored to the specific priorities that a utility aims to address in its decision-making processes. This can be focussed on treatment and distribution operations, with assessments of compliance risk and reliability (i.e., probability of success). It can also be more planning and strategy focussed with vulnerability assessments and asset management (Pollard & Stephenson, 2016). Water safety plans developed by World Health Organization (WHO) (2008) provides a risk-based approach of managing drinking water systems. Another similar approach of risk assessment is the hazard analysis and critical control point (HACCP) system which identifies specific risks in a DWTP and the control points for mitigating those risks (Lindhe, 2010). The concept of ‘critical’ points and ‘controls’ in this approach allows for a quantitative monitoring of risks in a DWTP (Hamilton et al, 2006).

There are several other similar quantitative interpretations of risk for DWTPs in the literature. Zhang et al. (2012) defined risk as the product of probability of the occurrence of an adverse event and its consequence. AWWA Manual M19 defines it as a product of consequence, vulnerability, and threat. There have been other studies that investigate DWTP risk assessment using modelling approaches such as fault tree analysis and QMRA, however it is not within the

scope of this paper to discuss all the studies in this area (Lindhe, 2010; Rosén et al., 2008; Summerscales & McBean, 2011)

2B.3. Differences and similarities between robustness, resilience, reliability, risk, and vulnerability from a drinking water treatment perspective

It is evident from the definitions of these concepts that while there is no fixed definition for each and definite overlap among several, there are some underlying fundamental features for each term, which can help in coming to a common understanding of them.

While previous studies have proposed and applied different quantitative metrics to evaluate these concepts, it is difficult to pitch a 'one size fits all' mathematical definition and there needs to be customization for each system (Hashimoto et al., 1982b), and possible evaluation of multiple metrics to get a bird's eye view of the system performance. This section explores the interrelationships between robustness, resilience, reliability, risk, and vulnerability and finally presents a conceptual figure linking them in the context of drinking water treatment.

Resilience and robustness have a close relationship, with these two terms often being used interchangeably in literature and in common dialogue. However, it is suitable to say that resilience, especially in the context of critical infrastructures such as DWTPs, is an integration of robustness (ability to withstand), redundancy (existence of alternate systems), resourcefulness (ability to identify priorities and mobilize resources), and rapidity (ability to act in a timely manner) (Quitana et al., 2020). Therefore, while robustness is built into the concept of resilience, there is an aspect of recovery or 'bouncing back' attached to resilience which distinguishes the two.

When examining from the perspective of system capacities, as emphasized by Balaei et al. (2018) and Quitana et al. (2020), robustness can be envisioned as a combination of the absorptive and adaptive capacity of a DWTP. Absorptive capacity denotes the extent to which ongoing operations can effectively withstand disturbances. This capacity endures until a threshold is reached, beyond which adjustments in operations become necessary, transitioning the system into its adaptive state. On the other hand, resilience embodies a broader spectrum of capacities including not only absorptive and adaptive capacities but also the restorative capacity.

In essence, resilience reflects the system's ability not only to absorb and adapt to disruptions but also to efficiently restore its functionality after such events have occurred. Resilience is also closely linked to vulnerability, with some studies finding an inverse relationship between the two, meaning that systems with high resilience had low vulnerability and vice-versa (Hashimoto et al., 1982b; Kjeldsen & Rosbjerg, 2004).

Reliability and robustness share a close association, potentially even closer than that of robustness and resilience. A robust system inherently embodies reliability, signifying that a system designed to handle a wide array of conditions and disturbances is dependable in its standard operations. Therefore, a fully robust system has 0% failure and hence, is 100% reliable. A system's reliability can also be seen as a function of its robustness and redundancy in design and operations (Quitana et al., 2020). However, a system's reliability under routine circumstances does not guarantee robustness in the face of significantly deviating scenarios. These scenarios can be categorized into past events, based on historical trends, and potential future events, especially under extreme conditions like severe weather (Maeir et al., 2016). For a DWTP, this distinction is crucial. While a DWTP may exhibit a high reliability in routine and even slightly deviated scenarios, its robustness may be compromised if it has not been engineered to ensure the desired level of reliability for entirely unforeseen water quality ranges, such as those resulting from extreme weather events.

To distinguish DWTP performance across various scenarios, it is essential to incorporate risk assessment, identifying vulnerabilities both in design and operations. Risk and reliability are interconnected concepts, with risk representing the likelihood of failure and reliability denoting the likelihood of success. On the other hand, there exists a trade-off between reliability and vulnerability, as it's impractical to achieve the highest reliability and lowest vulnerability simultaneously across all risk scenarios (Hashimoto et al., 1982b). In an ideal scenario, a DWTP strives for 100% reliability under both normal and stress-inducing conditions. This stringent aim is justified by the significant consequences of DWTP failures, which would not only impose substantial costs on utilities, but also pose substantial risks to society, if the DWTP is not shut down. In addition, DWTP shutdowns also pose significant risk to the society, causing water shortages, especially if there are no alternative sources of drinking water available to the community.

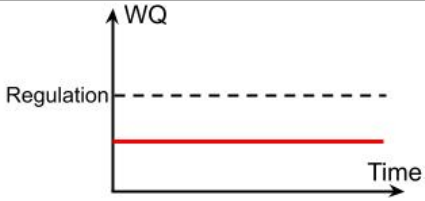
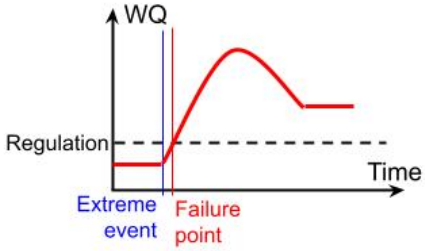
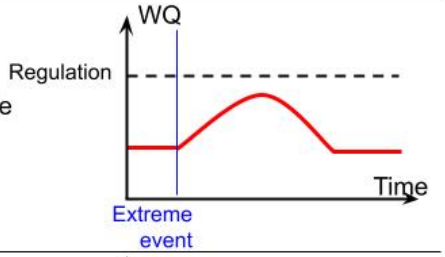
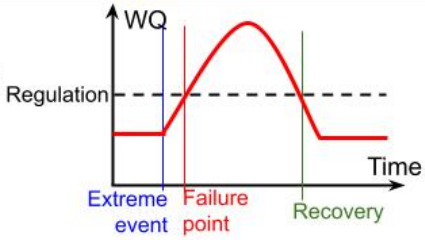
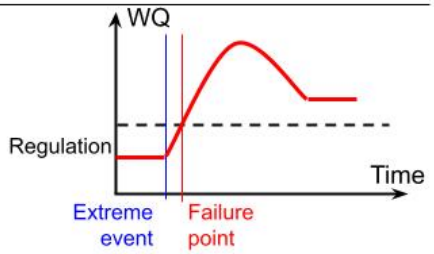
Source Water Quality (WQ) Scenario	System Vulnerability	Risk	State
a. Normal	Low	Low	• Reliable 
b. Normal	High	High	• Unreliable • Not robust • Not resilient 
c. Extreme	Low	Low/ Medium	• 100% Reliable • Robust 
d. Extreme	Low	High	• 60% (Medium) Reliability • Resilient 
e. Extreme	High	High	• Unreliable • Not robust • Not resilient 

Figure 2.2: Link between robustness, reliability, resilience, risk, and vulnerability

Figure 2.2. shows the interconnectedness of these concepts and the source water quality condition, system vulnerability, level of risk and system state in response to the scenario. This attempts to tie in the different concepts discussed so far. Two different vulnerability modes, low

and high, are considered. This refers to the inherent DWTP vulnerability, either by design, age of infrastructure or operations. Two water quality scenarios, normal and extreme, are considered and the resulting risk from the combination of the scenario and system vulnerability is mentioned. The final column in the figure shows the state of the DWTP in response to each scenario and how it can be characterized in terms of reliability, robustness, and resilience. The baseline performance (Fig 2.2.a.) is reliable under normal WQ, low vulnerability and low risk. When there is extreme WQ, depending on the vulnerability of the system, the risk will either be moderate or high and the subsequent state of the DWTP will switch to the adaptive mode, Fig 2.2.c., (robust) or go through a period of failure and switch to the recovery mode, Fig 2.2.d (resilient). The other two cases (Fig. 2.2.b and Fig 2.2.e) show DWTPs with high inherent vulnerabilities, in which case, failure to meet compliance standards will be likely. Figure 2.3 presents a complementary illustration depicting the characteristic of a water quality extreme during an extreme event and offers insights into the potential outcomes of the final drinking water based on the response and state of the DWTP.

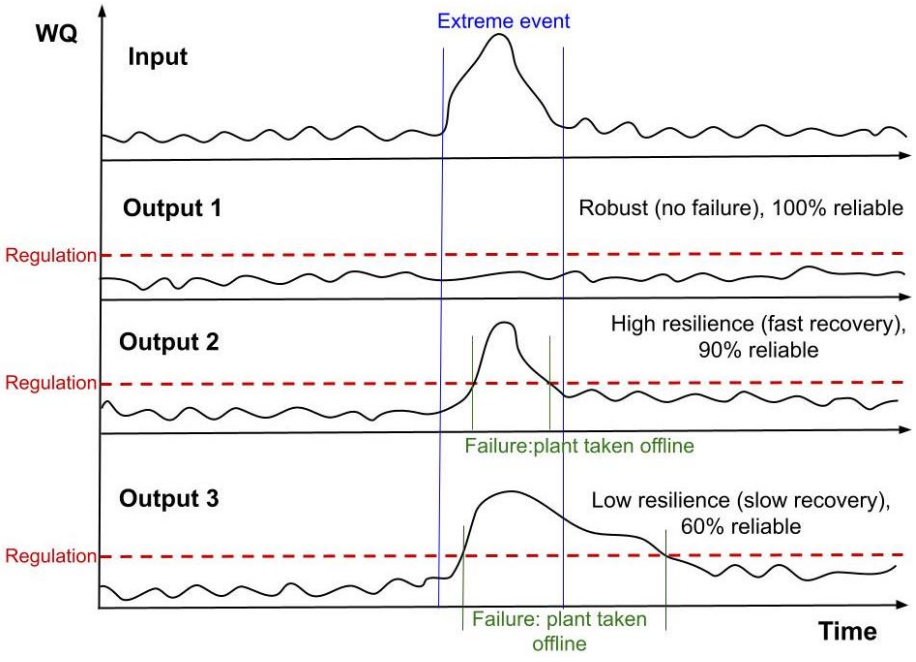


Figure 2.3: Possible responses of a DWTP to extreme water quality event and interpretation of its state

2B.4. Conclusions and recommendations for future work

It is evident from the discussion above that robustness is at the core of several interconnected concepts and can be viewed as a central pillar in understanding and enhancing system reliability, resilience, risk management, and vulnerability assessment. Robustness, as the ability of a system to adapt and perform well: i.e., always achieving a pre-set performance goal under various conditions and disturbances, forms the basis for resilience. Resilience encompasses not only the capacity to withstand disruptions but also the ability to recover swiftly from adverse events. A robust system will always be within the desired performance range, preventing any instances of failure and the need for transition into the recovery stage.

Reliability also shares a close bond with robustness. A highly reliable system is one that consistently operates as expected, even in the face of minor deviations from normal conditions. This reliability is an outcome of the system's robustness in accommodating expected variations. Risk, in contrast, is complementary to reliability. It represents the probability of failure, where higher risk indicates a greater likelihood of system failure. Risk management strategies often involve improving reliability and robustness to mitigate adverse outcomes. Vulnerability, closely linked with resilience, signifies a system's susceptibility to harm or damage when faced with adverse conditions. By enhancing robustness, a DWTP can reduce its vulnerability, as a more robust system is better equipped to withstand and recover from disturbances, thereby lowering the potential for harm. The definitions of these concepts from a drinking water treatment context are shown in Table 2.5.

In essence, robustness serves as the cornerstone, providing the groundwork for comprehending and enhancing the performance of DWTPs in terms of reliability, resilience, risk management, and vulnerability reduction. Also, understanding the intricate connections between these concepts is critical for developing strategies to ensure the uninterrupted delivery of safe drinking water to communities, especially during periods of adverse raw water quality caused by extreme weather events.

Table 2.5: Summary of definitions of robustness and related concepts from a drinking water treatment context during a raw water quality disturbance

Term	**Definition for a DWTP**
Reliability	Measure of performance above the minimum performance goal i.e. likelihood of success
Robustness	Ability to stay above minimum performance goal even during input disturbances
Resilience	Ability to achieve at least the minimum performance goal (robustness) and the ability to recover from failure (high resilience=quick recovery)
Risk	Measure of performance below the minimum performance goal i.e. likelihood of failure.
Vulnerability	Measure of susceptibility to input disturbances and severity of possible system failure

While there have been frameworks to improve climate adaptation of DWTPs and enhance one or more of the concepts discussed in this paper (Zhang et al., 2012; Levine et al., 2016), their application to full-scale treatment plants, especially from a perspective of extreme water quality management, has been limited. There is therefore a need to assess the entire treatment process as a whole and identify the current limitations and failure points of the treatment system. Once the current limits are known, the possible short-term adaptation options can be tested to extend the treatment capability. While previous studies have proposed operational changes to sustain treatment performance, there is a need to test these experimentally under different scenarios of the water quality parameters of interest.

3. Chapter 3: Practical Framework for Evaluation and Improvement of Drinking Water Treatment Robustness in Preparation for Extreme-Weather-Related Adverse Water Quality Events

This chapter is a published manuscript: Nemani, Kirti S., Peldszus, Sigrid, Huck, Peter M. (2023) Practical Framework for Evaluation and Improvement of Drinking Water Treatment Robustness in Preparation for Extreme-Weather-Related Adverse Water Quality Events. ACS ES&T Water, 3, 5, 1305–1313. https://doi.org/10.1021/acsestwater.2c00627

Abstract

Robustness is the ability of a drinking water treatment plant (DWTP) to achieve the desired finished water quality even during adverse raw water quality events. Increasing the robustness of a DWTP is beneficial for regular operations and especially for extreme weather adaptation. This paper proposes three robustness frameworks: a) a general framework outlining the main steps and methodology for systematic assessment and improvement of the robustness of a DWTP; b) a parameter-specific framework applying the general framework to a water quality parameter (WQP); and c) a plant-specific framework applying the parameter-specific framework to a DWTP. A parameter-specific framework for turbidity is presented using Turbidity Robustness Index (TRI) for evaluation, and applied to a full-scale DWTP in Ontario, Canada. This evaluation was conducted with historical plant data, as well as bench-scale experimental data simulating extremely high turbidity scenarios. The framework application is capable of identifying: (i) less robust processes which are likely to be vulnerable during climate extremes; (ii) operational responses to increase short-term robustness, and (iii) a critical WQP threshold beyond which capital improvements are necessary. The proposed framework provides insights into the current state of robustness of a DWTP and serves as a tool for climate adaptation planning.

3.1. Introduction

A robust drinking water treatment system can be defined as one that "provides excellent performance under normal conditions and deviates minimally during periods of upset or challenge" (Huck & Coffey, 2004). Increases in extreme weather events due to climate change (IPCC, 2021; Seneviratne et al., 2012) can cause unprecedented changes in surface water quality parameters (WQP) such as turbidity (Bates et al., 2008; Crittenden, 2012; Khan et al., 2015; Mukundan et al., 2018; Whitehead et al., 2009; Yarahmadi, 2019) and pose operational challenges to DWTPs (Ma et al., 2022). Increasing short-term robustness of DWTPs by changing operational conditions can be a viable adaptation option during a sudden event such as a turbidity spike. However, most DWTP designs only consider historical peaks, but not WQP extremes made more likely by the effects of climate change, and the plants may have aging infrastructure (Levine et al., 2016; Qiu et al., 2019). Therefore, it is important to understand the operational treatment limits by assessing robustness quantitatively, and to increase robustness by improving treatment through a systematic change in operational conditions.

One metric that quantifies robustness is the TRI (Huck Coffey, 2004; Huck et al., 2002; Li & Huck, 2008), which assesses the robustness of clarification and filtration processes at full scale DWTPs (Hartshorn et al., 2015; Hurst et al., 2004; Templeton et al., 2007; Zorić et al., 2020). These studies, however, have been limited to individual treatment steps rather than an entire DWTP, have only focussed on historical data, without considering possible turbidity extremes, and were limited to relatively short time frames. Limited research studies have developed climate adaptation frameworks for entire DWTPs, but were generally not able to quantitatively assess full scale DWTPs (Jalili et al., 2022; Zhang et al., 2012). In the grey literature there are frameworks for improving the resilience of DWTPs during extreme weather events, which are only qualitative in nature and are targeted more towards re-starting a DWTP after failure than on continuing operations to avoid a failure (U.S. EPA, 2016; U.S. EPA, 2019; U.S. EPA, 2020), as is the focus of robustness.

The current study focuses on the robustness of DWTPs and proposes a framework to systematically evaluate individual treatment processes, assess the entire DWTP, and improve its robustness. The framework is then demonstrated on a full-scale DWTP to provide a proof-of-concept. The general robustness framework developed in this study can be applied to any WQP,

and the current paper demonstrates it for turbidity, which is a regulated parameter in 80 countries and is of utmost importance for drinking water treatment operations (WHO, 2018). Increases in raw water turbidity directly impact several treatment processes and the ability of a DWTP to produce safe drinking water. An increase in raw water turbidity has been correlated with an increase in pathogens such as *Giardia* and *Cryptosporidium* (Bertone et al., 2016; Huck & Coffey, 2004; Whitehead et al., 2009) and has a negative impact on the disinfection efficiency of chlorination, ozonation and UV radiation (Bertone et al., 2016; Crittenden, 2012; Health Canada, 2012). The turbidity framework provides steps and tools to identify critical treatment steps and performs a quantitative evaluation of the robustness of these critical steps and the overall plant. This evaluation typically uses historical on-line data and also simulates extremely high turbidity scenarios at bench-scale. The next step of the framework is the optimization of critical treatment steps for such high turbidity scenarios, which is not usually carried out at DWTPs. Finally, the developed turbidity framework was applied to a full-scale DWTP in southern Ontario, Canada.

3.2. Approach and Methodology

3.2.1. Conceptual framework development

A good conceptual framework is flexible, has capacity for modification, and provides an understanding of the phenomenon being studied (Jabareen, 2009). The approach followed for constructing the robustness frameworks in this study had two goals: 1. to provide a generally applicable sequence of steps, which can be expanded to any WQP following the proposed methodology, and 2. to provide a specific and detailed expansion of these steps to one WQP that can be readily applied to a full scale DWTP.

To develop the current framework, both the academic and grey literature were surveyed for previous examples of robustness and resilience frameworks with a focus on drinking water treatment. There was little or no direct application of existing resilience models in the development of the current framework, but the general idea about conceptual frameworks for water was taken from the various EPA resilience models and other resources (Moncrieff-Gould et al., 2018; U.S. EPA, 2016; U.S. EPA, 2019; U.S. EPA, 2020).

3.2.2. Full-scale data collection and analysis (Plant framework, Step 4: Evaluation, scenarios 1 and 2)

Full scale plant data from Plant A were collected for 6 months (weeks 1-24 of 2019) from different process locations (Figure A.1) for train 1 (coagulation-flocculation-sedimentation (CFS) unit 1 and filters 1 and 2). It should be noted that while Plant A has the flexibility to operate trains 1 and 2 separately, water is typically blended after CFS and then distributed to the 4 filters. Filters 1 and 2 were chosen to represent roughly 50% of the water treatment along with CFS unit 1 for demonstrating the framework application. This included online turbidity and flowrate data in 5-minute intervals. Since the online data set was large, MATLAB® by MathWorks® was used for processing and computations. Before analyzing the data, data as described below were identified and removed after consultation with plant personnel, so that the data set only reflected the readings when the processes were fully operational for water production. This was done for all three critical treatment steps, using turbidity and corresponding flow rates. For the intake, the influent and effluent data below a flowrate threshold of 1 L/s were removed as this indicated that the intake was shut off. For CFS, the following criteria were adopted:

1. Turbidity values above 8 NTU were removed as these values were deemed unreliable by Plant A staff because they were approaching the upper bound of reliable quantification of the turbidimeter setting which was 10 NTU
2. Turbidity values corresponding to flow rates less than 100 L/s were removed as flows below this threshold indicate that the blenders were taken off-line for cleaning or other operational interventions
3. Sudden jumps were removed using the ‘hampel’ function in MATLAB® for both flowrate and turbidity data in 30 min time windows (10 data points). These sudden jumps were either due to instrumentation still stabilizing or general instrumentation errors.

For filtration, effluent turbidity data during backwash were removed by setting a flowrate threshold of 1 L/s. MATLAB® codes for identifying valid data and TRI calculations based on the index in (Li & Huck, 2008) are provided in the Appendix A, section 2.2.1.

3.2.3. Extremely high turbidity bench-scale jar tests simulating CFS (Plant framework, Step 4: Evaluation, scenario 3)

Raw water entering Plant A was used to generate water of extremely high turbidity ranging from 50-1000 NTU by adding kaolin (K1512, Sigma Aldrich) in amounts ranging from 0.07-0.65 g/L. Coagulant (STERN PAC (Kemira), 40% strength) and polymer i.e. coagulant aid (Magnafloc® LT22s, 0.2% strength) stock solutions were obtained from plant A. The coagulant was dosed at 30 mg/L and the polymer at 0.3 mg/L.

A standard jar test apparatus (Phipps & Bird) was used and the test procedure for a 400-500 L/s flow scenario developed by plant A personnel was adopted (Table A.4). This lower flow scenario was chosen to account for a possible flow reduction the plant might employ during an elevated turbidity event.

3.2.4. Factorial design bench-scale experiment for adaptation (Plant framework, Step 6: Adaptation)

A 2^3 full factorial design with two center-point replicates was chosen as the experimental design to study the effect of three optimization factors i.e., coagulant dose, polymer (coagulant aid) dose, and settling time. The levels of the three factors and corresponding dosages can be found in Table A.10. The reagent preparation and jar test procedure used for this experiment are the same as in 3.3.

3.3. Results and Discussion

3.3.1. Section 1: Development of Robustness Frameworks

Three frameworks were developed for DWTP robustness evaluation, overall assessment, and improvement:

1. General: outlines the main steps and defines the methodology for developing parameter-specific details
2. Parameter-specific: general framework tailored to a specific WQP of importance.
3. Plant-specific framework: parameter-specific framework tailored to the processes and surface water quality of a specific DWTP.

3.3.1.1. General framework

There are six main steps in the general framework, as outlined in Fig. 3.1.:

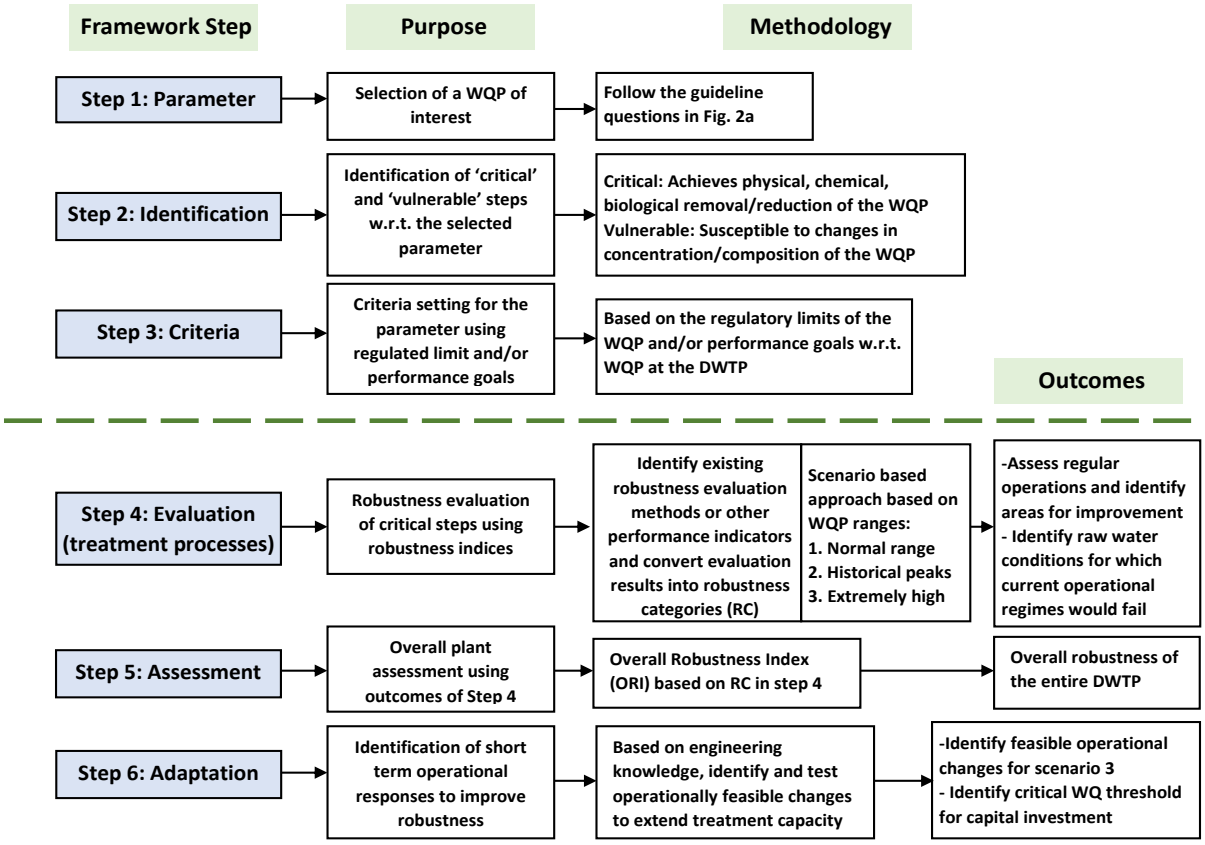


Figure 3.1: General Robustness Framework

Step 1: Parameter- This step involves the selection of a WQP which is impacted by extreme weather and is of operational importance to a DWTP. This WQP will be the basis of the robustness evaluation. Figure 3.2a provides a guideline for this process. It is important to note here that equal importance is given to WQPs that are regulated and WQPs which are not regulated but can impact other regulated parameters and other treatment processes. An example of such a WQP is background organic matter (Natural Organic Matter - NOM) as it can impact the levels of other regulated parameters such as disinfection-by-products (DBP), and the performance of treatment steps such as coagulation, filtration, disinfection, and adsorption.

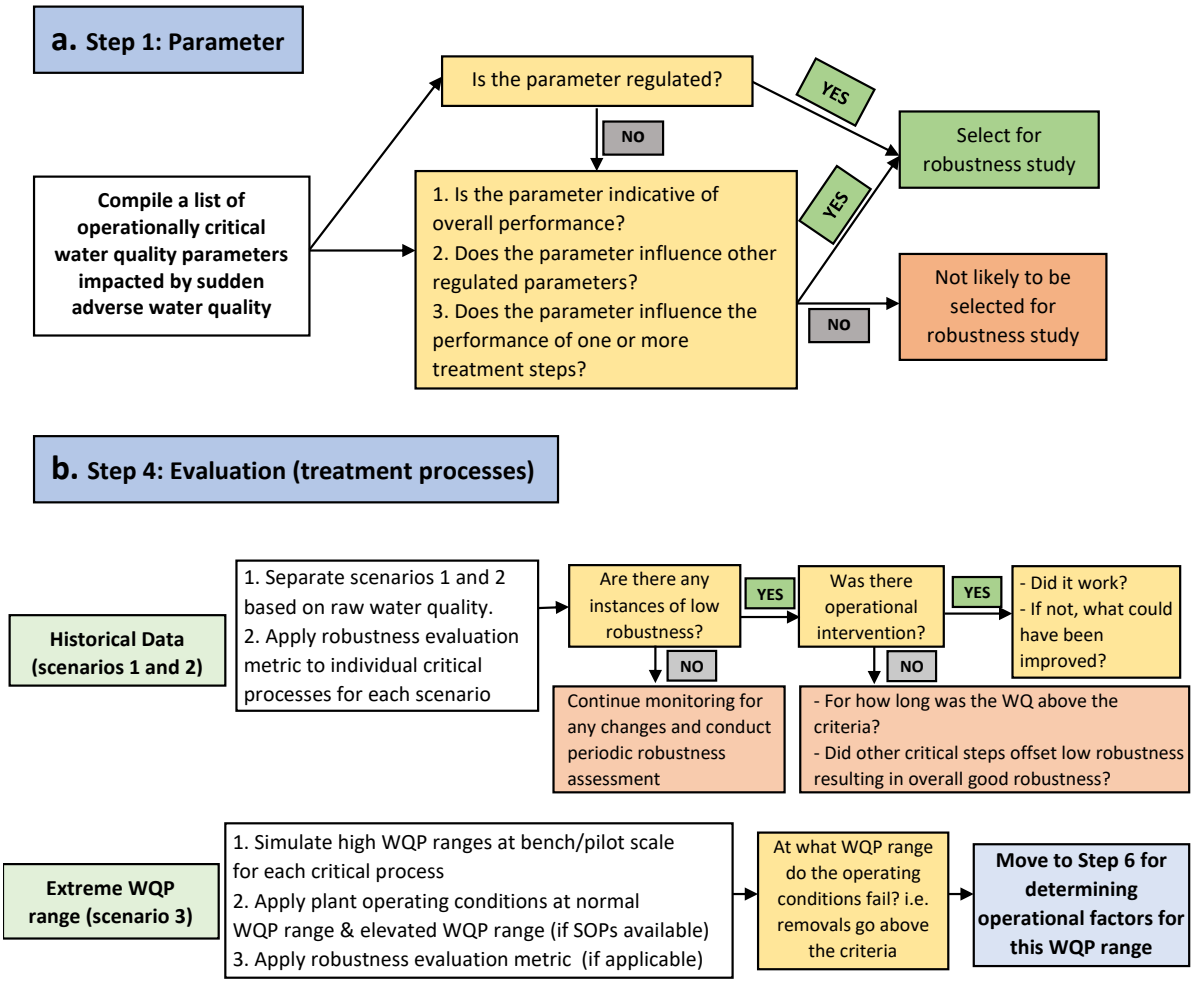


Figure 3.2: Detailed methodology for steps 1 and 4 of general robustness framework a) presents a guideline for selection of a WQP for robustness framework application b) shows the steps for robustness evaluation of critical treatment processes for three scenarios. The questions provided here serve as a guideline, so that each DWTP can tailor its investigation based on the evaluation results.

Step 2: Identification- This step involves the classification of treatment processes at a DWTP as critical and/or vulnerable. Critical processes are defined as steps achieving physical, chemical, and/or biological reduction (removal) of the chosen WQP. Vulnerable processes are defined as steps that are susceptible to an increase in the concentration or a change in the nature of the WQP. The robustness evaluation in the next steps of the framework is done for the critical treatment processes, whereas the identification of vulnerable processes highlights the impact sudden WQP perturbations may have on DWTP operations.

Step 3: Criteria- In this step, a criterion for the selected WQP is set for each critical step based on the regulated values and/or treatment performance goals associated with the parameter at the selected DWTP. This step sets a treatment goal as a threshold beyond which the robustness of a step would decrease and potentially cause operational challenges.

Step 4: Evaluation (individual treatment processes)- The goal of this step is to conduct a quantitative robustness evaluation of each critical process for the selected WQP. For this, any existing robustness methodology applicable to the WQP will be identified. If there are none, other existing evaluation method may be used or tailored. In some cases, new methods will need to be developed. This evaluation will be conducted for 3 raw water scenarios of the WQP:

- Scenario 1: normal range
- Scenario 2: historical peaks
- Scenario 3: extreme values not yet experienced but that may be encountered during future extreme weather events.

Quantification of treatment robustness in scenarios 1 and 2 allows an assessment of historical performance of the DWTP and can serve as a diagnostic tool to narrow down patterns of low robustness, possible causes, and whether any operational adjustments were made to overcome periods of low robustness. This retroactive assessment could also be potentially included in a water quality management plan alongside other periodic assessments such as filter run time and filter index analysis.

Scenario 3 evaluation focusses on identification of raw water conditions at which climate adaptation measures for critical treatment processes become necessary for treatment to remain robust. In a way, this is to give an early indication of the ‘failure point’ or threshold of a treatment process beyond which operational intervention (short-term measures) or capital investment (long-term measures) become inevitable.

The first two scenarios can be evaluated based on the historical data available at the plant over a certain duration. The third scenario can be evaluated using water samples and simulating, for example, extremely high turbidities in bench-scale set-ups. The detailed steps for evaluation are shown in Figure 3.2b.

Table 3.2 shows the proposed robustness categories (RC) to be assigned to each critical treatment process based on the evaluation outcomes. The goal is to link the robustness metric to the effluent WQP from that step and convert the results into six categories of system robustness (adapted from Li, 2004). An example of how this was done for the turbidity robustness metric i.e. the TRI, is shown in Table 3.2. This conversion to RCs will make evaluation results consistent across different WQPs and treatment processes, and their evaluation methodologies.

Step 5: Assessment (overall plant)- Based on the evaluation outcomes of individual critical treatment processes from Step 4, an overall assessment of the selected DWTP will be done using an Overall Robustness Index (ORI) (equation 1). This overall assessment will be conducted for each scenario where possible.

Equation 1:

$$\text{ORI} = \frac{W_1 \times RC_1 + \cdots + W_n \times RC_n}{\sum_1^n W_i}$$

ORI: Overall Robustness Index

W_1: Weight of critical process 1

RC_1: Robustness Category of critical process 1

W_{n}: Weight of critical process n

RC_{n}: Robustness Category of critical process n

$\sum_1^n W_i$: Sum of weights

The ORI is based on a weighted average approach incorporating the evaluation results for all individual critical processes. This approach is similar to the simple additive robustness concept presented in (Huck, 2015) which defines the overall robustness of a water supply systems as the sum of robustness of its individual elements (source, treatment, distribution, monitoring and response) and indicates that, because lower robustness of one element can be compensated for by greater robustness of one or more other elements, the concept of a ‘chain being only as strong as its weakest link’ does not apply.

General guidelines for assigning weights are given below:

Step 1: Rank the treatment processes in order of their importance.

Step 2: Assign higher weight (0.5 and above) to the more or most important process. For example, filtration or the final treatment process would be ranked highest for the turbidity framework since filtered or finished water turbidity is regulated. The sum of all the weights is equal to 1.

Step 3: Conduct a sensitivity analysis of the index with different weights to evaluate how the weighting scenarios influence the outcome of the ORI and the overall plant assessment.

The actual value of the weights will be determined together with the utility carrying out the robustness framework assessment, based on the experiential knowledge specific to their DWTP. This step is intended as a self-assessment of the DWTP.

Once the weights for each critical treatment step are determined, the ORI can be calculated using Equation 1. The naming of the ORI categories follows the naming convention of the RCs (as will be seen in Table 3.2).

Step 6: Adaptation- The goal of this step is to identify and apply short-term operational responses to improve the robustness of the system beyond the initial failure point identified during evaluation of scenario 3 (extremely high WQP range) in Step 4. This step includes testing of short-term responses, initially at bench-scale and maybe later at pilot-scale, to determine their feasibility and effectiveness. This step may result in identifying: a) a successful operational regime for Scenario 3 resulting in extreme weather Standard Operating Procedures (SOPs), and b) the critical threshold beyond which capital investments may be required.

3.3.1.2. Parameter-specific framework for turbidity

Steps 1 and 2 (Parameter and Identification): Turbidity was chosen for this study as turbidity is a regulated parameter and is of utmost importance for DWTP operations, impacting treatment effectiveness of several processes. Commonly used drinking water treatment processes were categorized as ‘critical’ and/or ‘vulnerable’ w.r.t. turbidity based on engineering knowledge (Table 3.1). In addition, the nature of control on the turbidity removal process was also identified for the critical treatment processes. This is meant to guide a DWTP in choosing the critical treatment processes for their robustness assessment w.r.t. turbidity.

Table 3.1: Guidance list for identifying critical and vulnerable drinking water treatment steps with respect to turbidity.

Process	Critical		Vulnerable
	Yes/No	**Nature of control on turbidity removal process**	**Yes/No**
Intake (including any storage units)	Varies	Natural, maybe operational	Yes
Coagulation	Yes	Operational	Yes
Flocculation	Yes	Operational	Yes
Sedimentation	Yes	Design, operational	Yes
Dissolved Air Flotation	Yes	Operational	Yes
Filtration	Yes	Operational, design	Yes
Rapid granular media filtration			
Membrane filtration			
Biological filtration			
Adsorption	No	-	Varies
Powdered Activated Carbon			Depends on point of usage
Granular Activated Carbon			Yes
Ozonation	No	-	Yes
Disinfection	No	-	Yes
Distribution system	No	-	Yes

The criticality of an intake system for turbidity would vary depending on its design, and placement in the source water. As such, intakes are not designed for turbidity removal apart from

screening larger debris, but there may be some particulate reduction due to intake design such as a raw water reservoir or variable depth intake systems.

As CFS are designed primarily for turbidity removal, they were categorized as critical processes. Operational parameters for coagulation and flocculation such as coagulant type and dosage, coagulant aid use, pH and mixing speed, can be adjusted whereas operational control of sedimentation can only be achieved through an overall change in flow rate, which would affect residence time.

Filter performance is mostly dependent on the efficacy of pre-treatment achieved by CFS, which is normally included, although direct filtration may involve only coagulant addition and no flocculation-sedimentation steps. Operational control in the filtration step includes changing the hydraulic loading rates, filter run length, backwash duration, backwash rate, and air scouring conditions. Other factors such as filter media and bed depth are part of the filter design and cannot be controlled operationally.

While all critical steps would be inherently vulnerable, all vulnerable steps may or may not be critical, i.e., contribute to the removal/reduction of the WQP. For example, disinfection is not a critical step for turbidity, but it is a vulnerable step, because increased turbidity can increase pathogen loading, thereby increasing the disinfectant demand for chlorine and ozone, and also interfere with the actual disinfection/inactivation. Similarly, distribution systems are also vulnerable to turbidity changes, which can contribute both to particulate matter deposition and to potential microbiological growth and transport.

Step 3 (Criteria): The criterion for finished water quality was set as 0.3 NTU as per drinking water regulations in the province of Ontario, Canada (O.Reg. 170/3). In addition, performance goals for turbidity at the selected DWTP for different treatment steps were considered and will be discussed in more detail in section 3.3.2.

Step 4 (Evaluation): For evaluating scenarios 1 (normal range) and 2 (historical peaks) from historical data, the TRI was identified as a suitable robustness metric (Huck Coffey, 2004; Huck et al., 2002; Li & Huck, 2008). While the TRI has been previously used only for evaluating filtration performance and for limited durations (e.g., a few filter-run cycles), it was determined that the index can be expanded to any critical process with online turbidity data acquisition and

for any desirable length of time. This expansion is an innovative contribution of the present research. Scenario 2 should be evaluated separately from scenario 1 by distinguishing the two cases based on the raw water turbidity. For scenario 2, it is also important to review any high turbidity SOPs at the DWTP and review the operational response of the plant during a previous turbidity event.

Scenario 3 (extremely high turbidities) evaluation can be carried out by simulating high turbidity raw water using synthetic clay such as kaolin, or by collecting raw water during a storm event and concentrating the particulate matter. The typical plant operational parameters can then be applied in bench/pilot scale experiments to determine the performance of the treatment steps for the simulated water quality. As a first step, jar tests are recommended for CFS, and bench-scale filters for the filtration step evaluation. If a plant has a SOP for high turbidity events, it should be used in scenario 3 testing. If not, typical plant operational parameters should be employed. It should be noted that TRI is only applicable to scenarios 1 and 2, and scenario 3 is evaluated by whether a treatment process is able to reduce elevated turbidities below the set criterion.

Step 5 (Assessment): Since the robustness categories originally defined for TRI (Table A.2) correspond to the RC proposed in Table 3.2, the ORI proposed in section 3.3.1.1. can be easily applied to a turbidity-specific overall assessment for scenarios 1 and 2. The assessment of historical data as TRIs for individual treatment processes can be interpreted for the overall plant with ORI for scenarios 1 and 2. This in conjunction with the insights derived from the bench-scale experiments for scenario 3 gives a complete assessment of the DWTP robustness.

Table 3.2: Demonstration of the proposed RC assignment to a robustness metric. TRI values reflect the effluent turbidity ranges and have originally been assigned to six robustness categories. The description of these categories has also been used to describe the RC and ORI categories for overall treatment assessment.

TRI Value	**Effluent WQP range corresponding to TRI**	**Category Description**	**RC/ORI Number**
<60	0.1-0.5 x criterion	Very Stable	1
60-100	0.6-0.8 x criterion	Stable	2
100-130	0.9-1.2 x criterion	Slightly disturbed	3

130-160	1.3-1.5 x criterion	Moderately disturbed	4
160-200	1.6-1.8 x criterion	Upset	5
>200	>2 x criterion	Severely upset	6

Step 6 (Adaptation): Based on the robustness assessment outcomes, once it is determined which critical treatment steps at a DWTP are low in robustness, short-term adaptation options (Table 3.3) can be tested at bench-scale or pilot scale (if available) to obtain at least an initial assessment of their effectiveness and feasibility. A factorial experimental design is recommended to determine the most significant factors.

Table 3.3: Critical steps and possible operational adaptation options

Critical step	Potential operational responses
Intake	• Intake can be shut off beyond a certain raw water turbidity level • Intake depth can be changed for variable depth systems
Coagulation	• Coagulant dose • Coagulant type • pH adjustment • Additional chemicals such as coagulant aid • Zeta potential can be used as a tool to monitor and control coagulant dosage
Flocculation	• Mixing speed, G • Mixing duration, t
Sedimentation	Surface loading rate of the system
Filtration	• Hydraulic loading rate • Filter run time • Backwash duration • Modified backwash techniques • Addition of filter aid polymers

3.3.2. Section 2: Application of the turbidity robustness framework to Plant A (plant-specific framework)

3.3.2.1. Steps 1-3 (Selection, Identification, Criteria)

To demonstrate the application of the turbidity framework, a full-scale DWTP in Southern Ontario, Canada (referred to as Plant A) was chosen (Figure A.1). One of the unique features of Plant A is its raw water storage reservoir with 4 cells in series at the intake, with about 48 hours of residence time. This reservoir was included in the robustness evaluation as some turbidity removal by natural settling occurs (Figure A.2).

Following the steps of the parameter-specific framework for turbidity, the critical treatment steps were identified as the intake (reservoir), CFS and filtration (Figure A.1). Next, the criteria for robustness evaluation were set for each critical step as: 25 NTU for intake (reservoir), 2 NTU for CFS and 0.1 NTU for filtration, which is below the regulatory limit of 0.3 NTU (32). This was done after discussions with Plant A personnel about the expected performance goals with respect to turbidity.

3.3.2.2. Step 4: Evaluation

Evaluation of critical process 1: Intake (reservoir) for historical data (scenarios 1 and 2)

Scenarios 1 and 2 for Plant A could not be evaluated separately due to the intake-shut off protocol which was set at 50 NTU. Hence, higher turbidity values, which would classify as historical peaks, were never experienced by the plant over the duration of this study. The TRI values for the intake (reservoir) show robust performance, with most of the values falling in the 'very stable' category and only two values falling in the 'stable' category (Figure 3.3a). The effluent turbidity was always below 17 NTU even for raw water turbidities higher than 30 NTU. In addition, higher raw water turbidities (>20 NTU) corresponded to higher percentage removals in the reservoir due to natural settling (Figure A.2).

Evaluation of critical process 2: CFS for historical data (scenarios 1 and 2)

Figure 3.3b shows that most of the TRI values lie in the 'very stable' and 'stable' category. However, the exceptions were week 14 (TRI 143, 'moderately disturbed') and week 21 (TRI 178, 'upset'). In both weeks, the daily average effluent turbidities were higher than T_{goal} (2 NTU) with values as high as 3.7 NTU for week 14 and 3.1 NTU for week 21 (Table A.3). In addition,

the TRI for week 21 is higher than for week 14 even though week 14 had higher daily average effluent turbidities. One possible reason is that the TRI incorporates not only the average performance, but also the variability of the performance (1^{st} term in SI equation 1). Week 21 has less uniformity, meaning a higher range of turbidity values, which resulted in a higher weighting on the 1^{st} term, therefore leading to a higher TRI. The lower CFS robustness in those two weeks was noted by plant staff, as the corresponding higher effluent turbidities were tagged in the monitoring data. However, there was operational intervention only for week 21 where the polymer dosage increased from 0.26 mg/L to 0.31 mg/L. While this was a larger change than usual, the dosage was well within the operational ranges (Plant A staff., personal communication, November 9, 2022).

Evaluation of critical step 2: Filtration for historical data (scenarios 1 and 2)

TRI was calculated for train 1, i.e., filters 1 and 2. For the duration of the study these filters were very robust, with most of the values in the 'very stable' range and a few values in the 'stable' range (Figure 3.3c, 3.3d). The effluent turbidities for both filters were close to 0.05 NTU, i.e. half the T_{goal}. The low robustness of the CFS process in week 14 and 21 was offset by the robust filtration, indicating that filters at Plant A may be able to handle turbidities higher than 2 NTU during a high turbidity event.

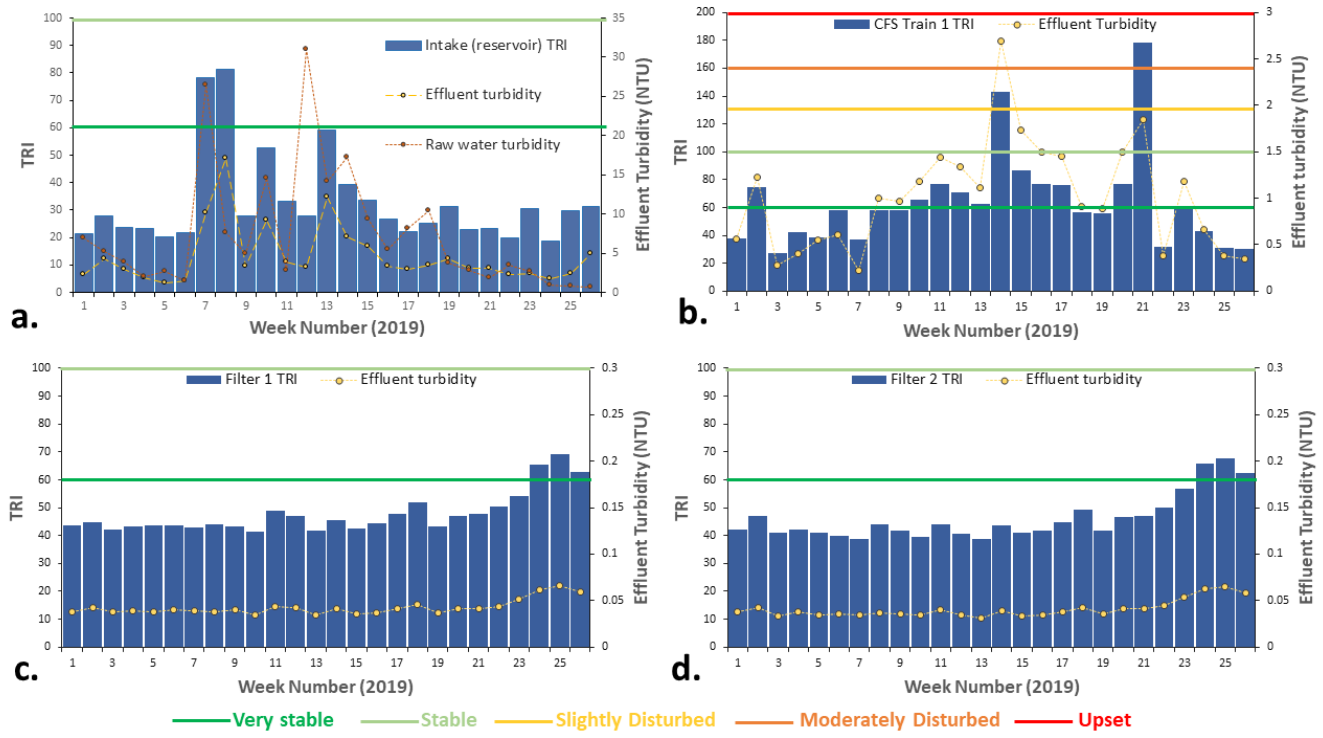


Figure 3.3: TRI evaluation of critical treatment steps at Plant A

a. Intake (reservoir) TRI values with raw water and effluent turbidities at T_{goal}= 25 NTU b. CFS train 1 TRI values and effluent turbidities at T_{goal}=2 NTU c. Train 1 filter 1 TRI values and effluent turbidities at T_{goal}=0.1 NTU d. Train 1 filter 2 TRI values and effluent turbidities at T_{goal}= 0.1 NTU

Evaluation of critical process 2: CFS for scenario 3 (extremely high turbidity values)

Since Plant A did not have any specific SOPs for high turbidity events, typical plant dosages for coagulant (30 mg/L) and coagulant-aid (0.3 mg/L) were used for Scenario 3 evaluation. Jar tests for spiked raw water turbidities of 50-1000 NTU showed that the plant chemical dosages were able to achieve high removals well below T_{goal} (2 NTU), even for extremely high raw water turbidities for settling times of 16 and 30 min (Figure A.3). This suggests, within the limitations of bench-scale results, that current plant dosages may work very well even for high raw water turbidities.

3.3.2.3. Step 5: Assessment

To calculate the ORI for historical data (scenarios 1 and 2), where TRI categories correspond to RCs, four weighting approaches were applied to measure the sensitivity of the index:

i. Case 1: equal weight of 0.33 for all processes
ii. Case 2: low weight for intake (0.1), high weight for filtration (0.5)
iii. Case 3: high weight for intake (0.25), high weight for filtration (0.5)
iv. Case 4: combination weight based on raw water turbidity range. High weight (0.25) for intake for raw water turbidity >25 NTU, low weight (0.1) for raw water turbidity <25 NTU, constant high weight (0.5) for filtration.

Filtration was given higher importance as filter effluent is regulated, and weights for the intake were changed due to observed higher percentage removals for higher raw water turbidities (Figure A.2). Regardless of the weighting approach, the overall robustness of Plant A lies in the 'stable' or 'very stable' categories for the assessment period, with only one instance of 'slightly disturbed' for week 21 based on the weighting cases 2 and 4 (Figure A.4). The four weighting approaches are shown to demonstrate the application of the ORI by considering several factors (Appendix A, section 2.2.4, Tables A.6-9). The decision of which weights to assign is based on the judgment of the DWTP applying the framework.

For extremely high turbidities (scenario 3), since the current CFS operational regime is quite robust, i.e., it performed very well in bench-scale tests even for extremely high turbidity scenarios, the current CFS dosages may serve plant A well during sudden turbidity spikes. Ideally, this could be confirmed by pilot testing.

3.3.2.4. Step 6: Adaptation

Testing of operational adaptation options builds on the results of the evaluation (section 4.2.2.) and is applied to critical treatment processes identified as having a low robustness, most likely in scenario 3. Plant A operational parameters for CFS were robust even for extremely high turbidity ranges. However, since this study intends to demonstrate a complete application of the proposed framework, bench-scale jar tests using simulated 700 NTU raw water and a full factorial design were used to test three short-term operational responses- change in coagulant and polymer dose and change in settling time. While there was a slight lowering of final turbidity with increased

settling time, there were not any significant factors upon performing ANOVA with the data (α = 0.05) (Table A.11). This may be because the original chemical dosages were sufficient to treat the high turbidity and did not require higher dosages. However, this method demonstrates how a utility can perform bench-scale tests to provide an initial assessment of short-term responses in case of low robustness of a treatment process.

3.3.3. Discussion of the turbidity robustness framework and its application to plant A

The turbidity robustness framework demonstrates how the general framework can be tailored to a specific WQP. The quantitative robustness evaluation of individual critical treatment steps using the TRI is a key feature of the turbidity framework. This study also extended the application of the TRI to treatment processes other than filtration and to a prolonged period, which has not been done in previous studies.

Based on the evaluation of the historical data (scenario 1 and 2), the plant A intake reservoir functions as a natural sedimentation basin, which significantly reduced higher raw water turbidities, presumably providing a natural cushion for future extreme turbidity events. CFS was found to be low in robustness for two out of 26 weeks, but this was offset by operational intervention and robust filter performance as even when the water quality after CFS was not within the expected range i.e. <2 NTU, the filters were producing finished water of <0.1 NTU turbidity. The consistent overall performance of Plant A is further evidenced by the ORI, which remained ‘stable’ and ‘very stable’ throughout the assessment period except in week 21 which was ‘slightly disturbed’ based on the weighting approach.

A concern raised by the plant personnel was the reliability of turbidimeter data for CFS which emphasizes not only the need for robust treatment and operations, but also for robust instrumentation to aid in monitoring and response. For scenario 3 (extreme future weather events), current CFS operational parameters seem to be robust based on the high turbidity experiment, but this is limited by the applicability of bench-scale results and the use of synthetic clay, Kaolin, which may not represent the particle characteristics entering the system during extreme weather. Further investigation for scenario 3 is recommended not only for CFS, but also for filtration. These additional investigations may identify a critical turbidity threshold beyond

which operational interventions will not be successful and capital improvements to the plant will become necessary. Going forward, the assessment demonstrated here could be incorporated in a water quality management plan thereby documenting past plant performance quantitively and highlighting process scenarios where interventions are needed and can be planned for in the future. Though plant A performance could not be evaluated separately for normal raw water turbidity (scenario 1) and past turbidity peaks (scenario 2), other plants may wish to do so, thus giving them a better indication of plant performances during turbidity spikes.

The TRI concept may be extended to other WQP, which are monitored online, but it may have limited application to parameters less frequently monitored. Though the latter may hinder the evaluation step of the general robustness framework for other WQP, it provides an incentive for developing robustness metrics for other WQP of importance and for increased water quality monitoring at DWTPs.

3.4. Conclusions and why is this important for the water treatment industry?

This study proposes a framework that provides steps for a systematic robustness evaluation of individual treatment processes as well as the overall DWTP and demonstrates its application to a full-scale DWTP. The framework can be used to develop evaluation and adaptation methodologies for any WQP. This is useful not only for evaluating regular operations and performance during past water quality disturbances, but also for more extreme weather situations that may impact the raw water quality and threaten DWTP operations in the future, making this a potential climate adaptation tool.

One of the important features of this framework is the quantitative evaluation of treatment performance during extreme water quality events for which plant operations may not be prepared. While recognizing the limitations of bench scale experiments, by performing such simple experiments simulating extreme raw water qualities, an initial indication of the robustness of the critical treatment processes can be obtained, and the raw water conditions at which current treatment procedures might fail can be provisionally assessed. Beyond this point, operational changes can be tested for effectiveness as short-term adaptation options. It takes planning and effort to implement such changes, therefore, having a sense of whether such a measure is useful in advance helps in climate preparedness. Another crucial feature of the framework is the interaction with the plant personnel to understand the nuances of plant operation during normal

and extreme weather events. This helped in developing the framework as a practical tool rather than a desktop exercise.

Application of the robustness framework can help a DWTP in developing SOPs for an extreme weather event, which can guide operators in making operational changes in a systematic manner. This can potentially be incorporated into drinking water safety plans which are periodically assessed in Canadian provinces like Alberta (Alberta Ministry of Environment and Protected Areas Drinking water safety plan). If it is identified that none of the short-term operational changes are successful in treating the WQP to acceptable values, a DWTP may consider long-term options as a part of climate adaptation planning such as infrastructure modifications to increase its treatment robustness.

Supporting information: Additional details about the framework application, experiment, TRI theory and calculation, ORI calculation, including figures and tables (Appendix A).

Disclaimer

In several instances in this study, commercial products and/or trade names were mentioned. The use of commercial names does not constitute endorsement or recommendation of these products and/or instruments by the authors.

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4. Chapter 4: Assessing Turbidity Robustness in DWTPs : Comparative Analysis of Evaluation Outcomes and Decision Tree Guidance for Climate Change Adaptation

4.1. Introduction

Robustness, denoting a drinking water treatment plant's (DWTP) capacity to sustain desired water quality standards even in challenging raw water conditions, holds paramount importance in maintaining a consistent supply of safe and high-quality drinking water. With the increasing variability in raw water quality, there is a risk to DWTP operations and their ability to provide drinking water of desired quality. Changes in turbidity, which is one such critical, regulated WQP showing variable trends due to climate extremes, can cause impacts on plant operations, and associated chemical and maintenance costs (Price & Heberling, 2018). This underlines the importance of having a structured and quantitative assessment of treatment robustness to enhance plant operations and climate preparedness. Such an assessment identifies less robust treatment processes vulnerable during water quality events, prompting further investigation and actions to enhance short-term and/or long-term DWTP robustness.

Nemani et al. (2023) addressed this need and introduced three distinct robustness frameworks, including a general methodology, a parameter-specific adaptation, and a plant-specific implementation along with a proof-of-concept turbidity robustness framework. That study focussed on identifying tools for quantitative robustness measurement using the turbidity robustness index (TRI) and used historical plant data, as well as controlled experiments to simulate treatment performance in extreme turbidity scenarios. This approach, introduced by Nemani et al. (2023), can identify vulnerable processes, suggests strategies for short-term robustness enhancement, and determines critical thresholds that prompt necessary capital interventions. Additionally, the framework can also support a DWTP’s climate adaptation planning.

The main objectives of the present study are to a) demonstrate the in-depth application of the turbidity robustness framework to full scale DWTPs over a period of 2 years, b) provide insights by comparing the results of the framework application to 4 DWTPs with different source waters,

treatment processes and operational regimes, and c) provide guidance in the form of a novel decision tree for the next steps. This decision tree includes potential pathways a utility can take following the outcomes of the robustness evaluation and includes both short-term and long-term planning options. This presents one of the most comprehensive quantitative robustness evaluations, while also showcasing the ease of application of the turbidity robustness framework to different DWTPs, and the insights it offers that can be compared across 4 different DWTPs. The two DWTPs chosen for a) are situated in Southern Ontario, Canada, each drawing water from distinct sources: one from a lake and the other from a river. Reza (2022) conducted a comprehensive robustness analysis following the framework presented in Nemani et al. (2023) on two additional full-scale treatment plants chosen for objective b). The present study presents a detailed four-way comparison of these DWTPs. This comparative analysis spans the same 2-year period, shedding light on the robustness of each facility and highlighting the insights drawn from the quantitative robustness assessment of individual treatment processes and the overall plant. Finally, the current work proposes a decision support tree to achieve objective c) which translates the turbidity robustness framework outcomes into both immediate operational tactics and long-term capital strategies. This connection between assessment and action equips DWTPs with a comprehensive decision tool to effectively translate robustness evaluations into climate adaptation projects.

4.2. Approach and Methodology

4.2.1. Overview of the turbidity robustness framework

The general robustness framework developed in Nemani et al. (2023) is a practical tool to enhance treatment robustness during challenging raw water quality scenarios. The framework introduces a series of six steps, following which a DWTP can evaluate the current state of robustness of the treatment processes as well as identify potential adaptation options for extreme water qualities. This was further expanded as a turbidity robustness framework, which outlines specific tools for robustness evaluation for turbidity reduction/removal (Fig. 4.1, adapted from Figure 3.1.).

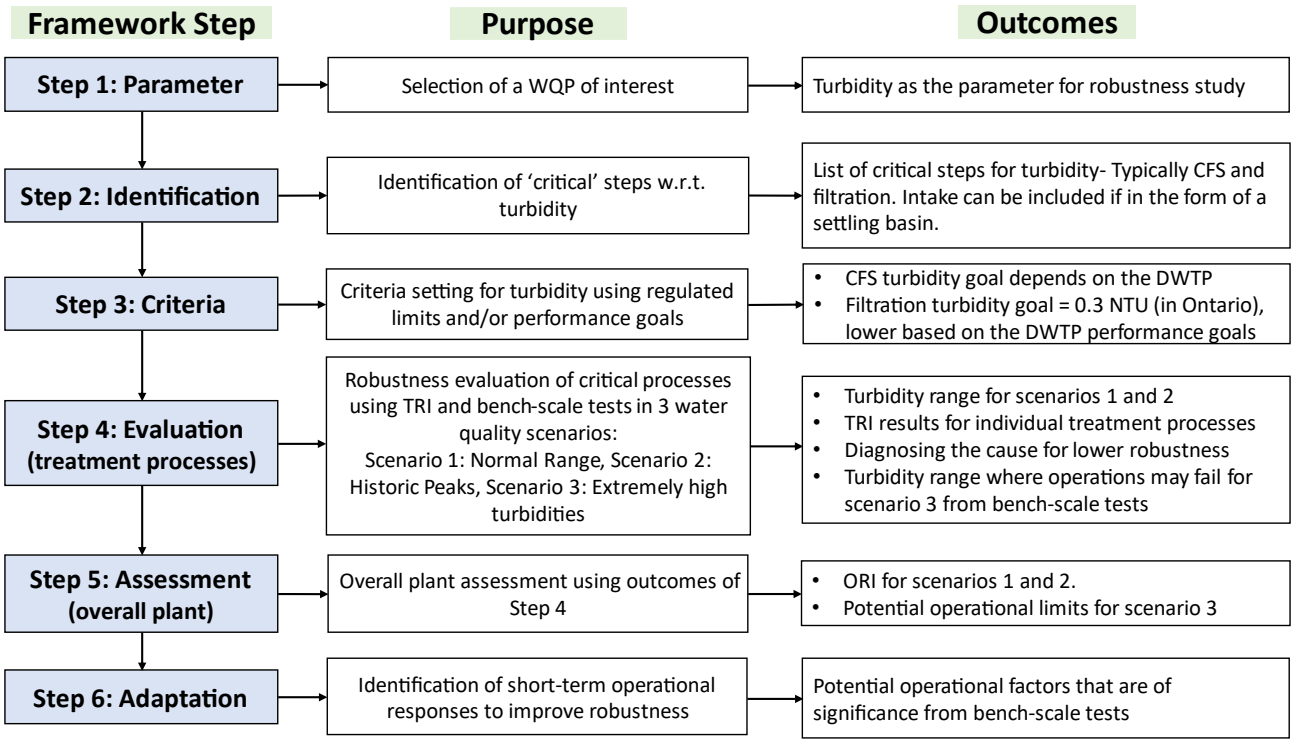


Figure 4.1: Overview of the turbidity robustness framework. Scenario 1 refers to normal turbidity ranges, scenario 2 refers to historical events and scenario 3 refers to extremely high turbidity ranges.

4.2.2. Full scale DWTP data collection and analysis for Plant B

Full scale plant turbidity data was collected for Plant B over a 2-year period (2019-2020) from different process locations (Figure 4.4B) from Train 1 (coagulation-flocculation-sedimentation (CFS) unit 1 and filters 1-6) and Train 2 (CFS unit 2 and filters 7-12). Online hourly turbidity data for raw water were used to determine the scenario 1 and scenario 2 events for the robustness evaluation. Scenario 2 (historical turbidity) peaks were identified using the two methodologies developed by Reza (2022). Methodology 1 calculated a weather event as seasonal median turbidity + seasonal median turbidity*50%, for at least 1 hour and methodology 2 calculated a weather event as seasonal median turbidity + seasonal median turbidity*100% + 5 NTU, for at least 1 hour (Reza, 2022). All calculations for scenario 2 development were done using Microsoft Excel™.

Online turbidity and flow data at 5-minute intervals were collected for the TRI analysis for the individual treatment steps. MATLAB® by MathWorks® was used for mathematical computations. After consultation with Plant B personnel, data non-representative of active operation (such as filter backwash periods, periods of CFS and filter shutdowns) were identified and removed. For both CFS and filtration, the flow threshold was set to 1 L/s as anything below this flowrate indicates either backwash or shutdown. All turbidities corresponding to this flowrate were removed. In addition, for filtration, HAMPEL function in MATLAB® was used to remove any sudden jumps in the data exceeding 50-minute time windows (10 data points) which are typically representative of the stabilization time during filter start-up or shutdown. All MATLAB® codes are presented in Appendix B, section 1.1.

4.2.3. Extremely high turbidity bench-scale jar tests simulating CFS for Plants A and B

For Plant B, unchlorinated raw water was collected from Plant B intake. Coagulant (Clar Ion A7, Chemtrade) stock solution (49% strength) and polymer (Polyfloc AP 1100P, Suez/Lenntech) powder was obtained from the plant. After discussion with Plant B personnel, a turbidity regime for different raw water turbidity ranges was identified. The plant coagulant dose for the normal turbidity range up to 10 NTU is between 15-25 mg/L of alum and for the elevated turbidity range (>10 NTU) is between 25-35 mg/L of alum. Following this protocol, turbidities above 10 NTU were dosed at 35 mg/L of alum for the bench scale jar tests. Doses of both 15 and 25 mg/L were tested at 10 NTU. Polymer was dosed between (0.1-0.6 mg/L) for the initial test. A standard jar test apparatus (Phipps & Bird) was used for the jar tests with 30 seconds rapid mixing at 100 rpm, followed by flocculation mixing at 70 rpm for 5 minutes and 40 rpm for 5 minutes. Settling times of 5 minutes and 10 minutes were tested. Zeta potential (ZP) values before and after CFS were also measured.

4.2.4. Factorial design bench scale experiment for adaptation of plant B

A 2^3 full factorial design with two center-point replicates was chosen as the experimental design to study the effect of three optimization factors i.e., coagulant dose, addition of polymer as a coagulant aid, and settling time. Raw water turbidity of 700 NTU was simulated using kaolin (K1512, Sigma Aldrich). The levels of the three factors and corresponding dosages can be found

in Table B.1. The reagent preparation and jar test procedure used for this experiment are the same as in 2.2. Data analysis was done using Analysis of Variance (ANOVA). The mid-point replicates were used to determine the effects and significance of factors on turbidity. Calculations were done using Microsoft Excel.

4.3. Results and discussion

4.3.1. Turbidity robustness framework application to full-scale DWTPs

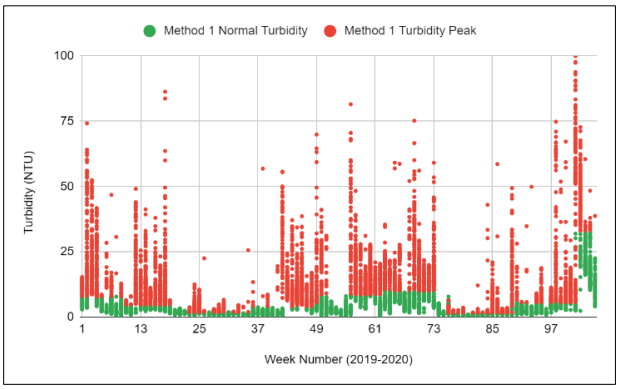
The turbidity robustness framework was applied to plants A and B over a two-year period (2019-2020) in this study. Application of the turbidity robustness framework was demonstrated on Plant A for a 6-month period in Nemani et al. (2023) as a proof of concept, which in this chapter has been extended to two years as shown in appendix B, section 2. Plant B takes its raw water from Lake Huron, one of the Great Lakes in Southern Ontario, Canada whereas plant A river based DWTP. Plant B follows a conventional treatment scheme: coagulation, followed by flocculation, sedimentation, and rapid media filtration. Chlorination is done at the intake for mussel control and after filtration for disinfection. The filtered water is stored in a clear-well before discharge to the distribution system (and pH adjustment), which also aids in getting the required CT value for disinfection. The primary chemical used for CFS is alum as the coagulant; in addition, polymer is dosed as a filter aid to the settled water during periods of high turbidity.

The Incoming turbidity at the facility typically remains low, measuring less than 10 NTU. However, there are instances of elevated turbidity, reaching up to 100 NTU, particularly during intense precipitation and storm events. This increase is sometimes also attributed to blending of water and sediment from an upstream creek feeding into the lake as well as wind action redistributing the sediment at the shallow intake. The plant also faces challenges in treating low turbidities during winter months with the particulate matter resisting settling out in the CFS process.

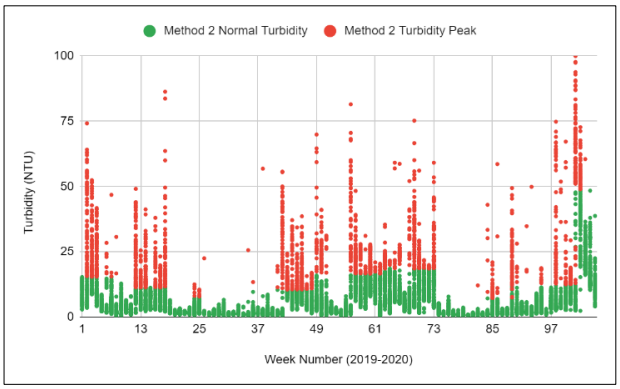
The critical treatment processes for Plant B for turbidity removal were identified as CFS and filtration (Step 2: Identification). The performance goal or T_{goal} for settled water turbidity was set at 2 NTU, and at 0.1 NTU for filtered turbidity, which is below the provincial regulation of 0.3 NTU (Step 3: Criteria). These goals were decided based on discussions with plant staff. The subsequent steps of the framework are discussed in detail in the following sections.

4.3.1.1. Plant B, Step 4, Evaluation: Normal range (scenario 1) and historical peaks (scenario 2)

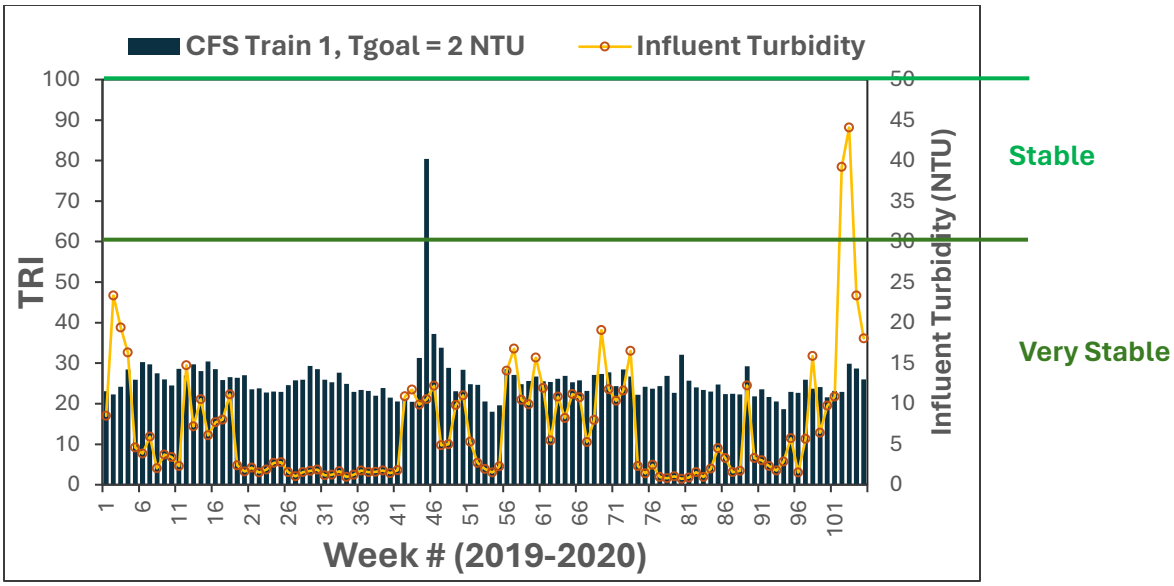
One of the features of the turbidity robustness framework is the robustness evaluation based on three turbidity scenarios, i.e., normal range (scenario 1), historic peaks or past turbidity events (scenario 2), and extreme values (scenario 3). To distinguish between normal range and past turbidity events, Reza (2022) developed two methodologies, which identify turbidity thresholds based on seasonal medians. The current study applied both methods to the Plant B raw water dataset to identify the most suitable method for plant B. The seasonal medians and thresholds, as outlined in Table B.4, revealed that method 1 had a notably low turbidity threshold, leading to 90 out of 105 weeks being categorized as turbidity event weeks. By comparison, the method 2 turbidity threshold, which was adjusted such that the baseline turbidity was 10 NTU or lower, which is considered 'normal' for Plant B, resulted in 62 of 105 weeks as turbidity events (Table B.5) Based on these results method 2 was deemed more appropriate for Plant B raw water conditions, which are similar to Plant D (which is labelled as Plant B in Reza (2022)). Scenarios 1 (normal turbidity range) and 2 (historic peak) as identified by the two methods are shown in Figure 4.2A and 4.2B.



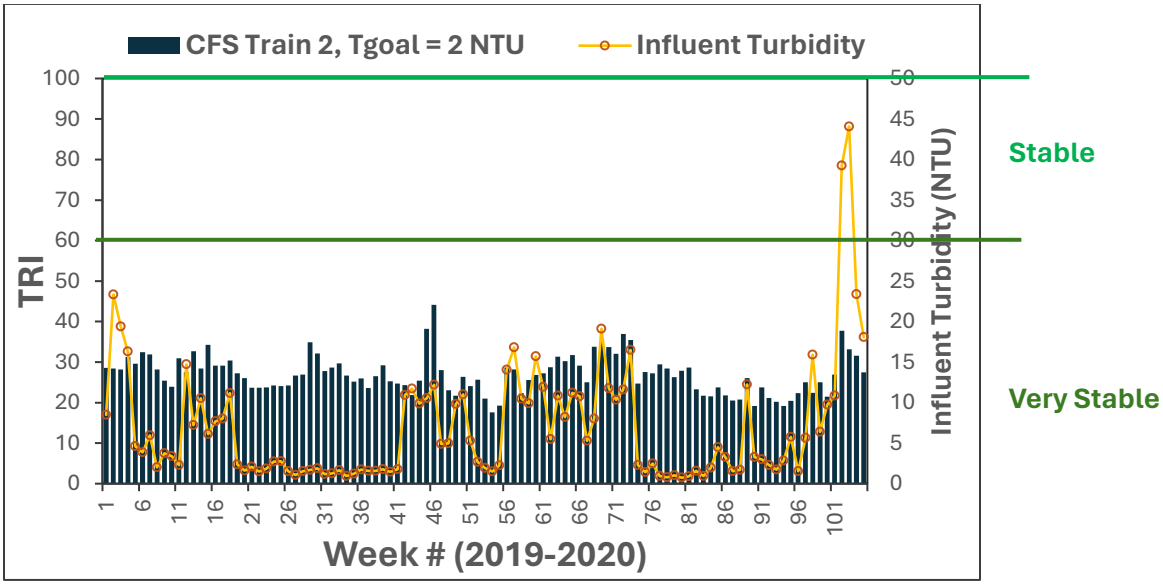
A



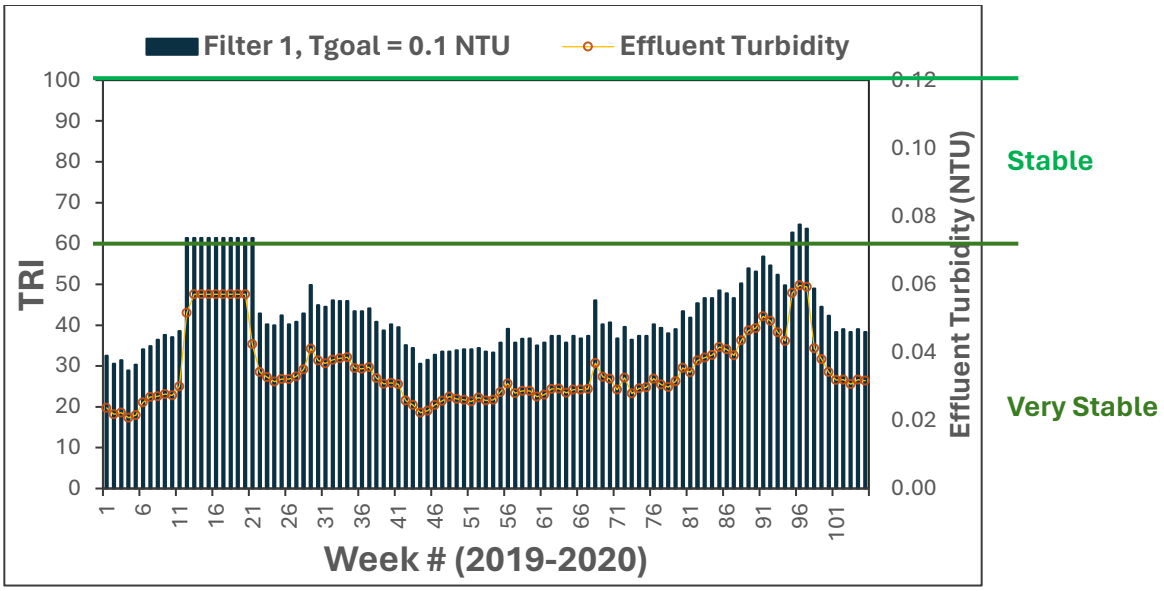
B


CFS Train 1, Tgoal = 2 NTU
Influent Turbidity
TRI
Influent Turbidity (NTU)
Week # (2019-2020)
Stable
Very Stable

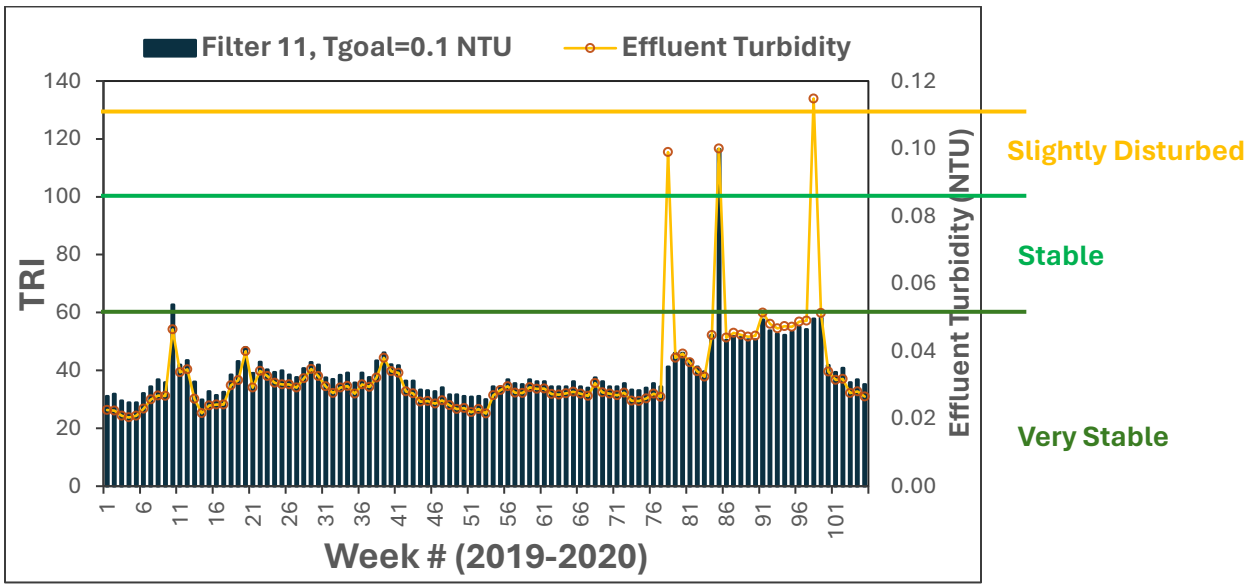
C


CFS Train 2, Tgoal = 2 NTU
Influent Turbidity
TRI
Influent Turbidity (NTU)
Week # (2019-2020)
Stable
Very Stable

D



E



F

Figure 4.2: A, B: Methods 1 and 2 (adopted from Reza (2022)) respectively for identifying turbidity scenarios 1 and 2 for Plant B; C, D: TRI evaluation results (scenarios 1 and 2) for Plant B CFS trains 1 and 2; E, F: TRI evaluation results (scenarios 1 and 2) for Plant B filtration process, filters 1 (best) and filter 11 (worst due to one instance of 'slightly disturbed' robustness).

Results of Step 4 (Evaluation) for CFS (Scenarios 1 and 2).

CFS TRIs for Plant B were mostly in the 'very stable' category for both trains 1 and 2, except for week 46 which fell in the 'stable category' (Figure 4.2C, 4.2D). The settled water turbidities were much lower than the performance goal of 2 NTU, close to 0.5 NTU which is 25% of the goal value, which explains the excellent TRI values. The performance of the two CFS units was excellent for both scenario 1 and 2 weeks, indicating that the CFS performance continued to be robust even during higher raw water turbidities.

Results of Step 4 (Evaluation) for Filtration (Scenarios 1 and 2).

Similar to CFS, the 12 filters at Plant B exhibited robust performance through 2019-2020 with only two instances of slightly disturbed TRIs (filter 11, week 85, TRI=116 and filter 12, week 10, TRI=108). Week 85 represents a week with a turbidity event, while week 10 corresponded to a normal turbidity range. However, in both cases the CFS TRIs and settled water turbidities were very low, therefore, it is unlikely that the higher filtration TRIs were due to a raw water disturbance. Moreover, since these values are only slightly above the 'stable' limit and still lie at the filtration T_{goal}, they were treated as one-off events. Filters 5, 6, 9, and 12 were intermittently taken offline, leading to the gaps in the TRI values (Fig B.3.)

4.3.1.2. Plant B, Step 4, Evaluation: Extremely high turbidities (Scenario 3)

High turbidities from 10-1000 NTU were generated at bench-scale using kaolin to evaluate the CFS operational robustness for scenario 3. Following the framework, the objective of the first bench-scale simulation was to identify the turbidity threshold beyond which Plant B CFS operational regime would be unable to meet the CFS T_{goal} of 2 NTU.

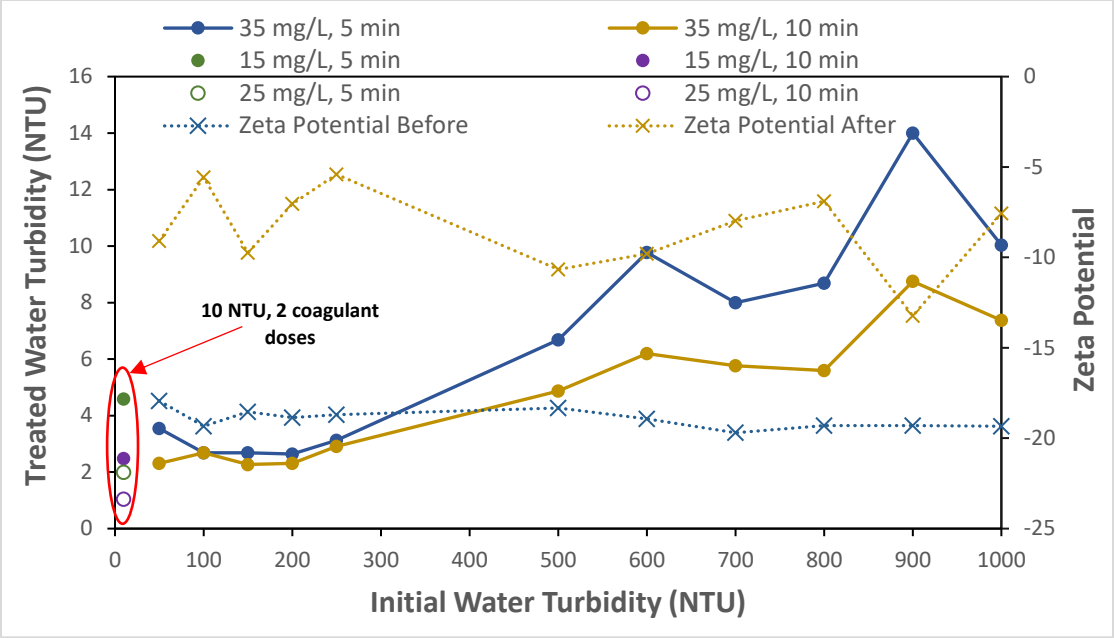


Figure 4.3: Initial bench scale simulation of high raw water turbidities and effectiveness of Plant B coagulation regime. Figure shows turbidities at settling times of 5 minutes and 10 minutes and the corresponding zeta potentials before and after jar tests. It also shows the coagulant dosage used for the jar tests.

Fig. 4.3. shows that the Tgoal (2 NTU) is breached from 100 NTU upwards, but there is a marked jump from 500 NTU upwards, giving an initial indication of the turbidity threshold at which the current CFS regime for high turbidities may start to fail. It was also seen that lower settling turbidities were achieved for a higher settling time of 10 minutes starting at 500 NTU and higher. None of the coagulant dosages were able to reach the optimal charge neutralization ZP range of -5 to +5 mV.

4.3.1.3. Plant B, Step 5, Overall Assessment : normal ranges and historic peaks (scenarios 1 and 2)

The individual TRIs for the two critical treatment processes calculated in section 4.3.1. were converted to robustness categories (RCs) as demonstrated by Nemani et al. (2023) and the Overall Robustness Index (ORI) for scenarios 1 and 2 were calculated. Similar to Plant A, three weighting scenarios were selected: 1) equal weighting for both critical processes, 2) high (0.8) weight for CFS and low weight (0.2) for filtration, and 3) low (0.2) weight for CFS and high (0.8) weight for filtration. In all three scenarios, the Plant B ORI was 1 or 'very stable' for the

entire duration of the study period. Even the two instances of higher filter TRIs noted in section 4.3.3.1. were compensated by the overall robust filtration performance over 12 filters and robust CFS performance even when calculating the ORI using the higher weight (0.8) for CFS. The ORI calculations are shown in Tables B.6-8.

For scenario 3 (extreme turbidities), since it was found that the CFS operational regime might potentially fail at turbidities higher than 500 NTU (Fig. 4.3), the next step in the framework (step 6: adaptation) was investigated as described in section 4.3.1.4.

4.3.1.4. Plant B, Step 6: Adaptation

Following the initial bench-scale simulation performed in section 4.3.1.3., a high scenario 3 turbidity of 700 NTU was chosen for the factorial design experiments to identify the potential short-term adaptation options to improve CFS robustness during extremely high turbidity events. The value 700 NTU was also chosen to be consistent with the adaptation jar tests done for plant A in Nemani et al. (2023). Three factors were chosen as potential short-term adaptation options: increasing coagulant dose, increasing settling time and addition of polymer as a coagulant aid. Currently, Plant B utilizes the polymer as a filter aid during high turbidity events and it is manually added to the settled water (before entering the filters) on an as-needed basis, typically twice a year.

To check the effectiveness of polymer addition earlier in the treatment train as a coagulant aid rather than a filter aid, initial jar tests were performed at a turbidity of 500 NTU with no polymer, and 0.1, 0.3 and 0.6 mg/L polymer doses (Fig. B.4). These dosages correspond to those used by Plant B and are also within the 1 mg/L maximum limit prescribed by NSF (NSF product and service listings). Settled water turbidity notably improved upon the introduction of the polymer, which was supported by the visual observation of the formation of larger and denser flocs. ANOVA results for the subsequent bench-scale factorial design experiment further corroborated the initial findings, in which all three factors, coagulant dose, polymer dose and settling time were found to be statistically significant at $\alpha=0.05$ (Table B.9). The two-factor and three-factor interactions were also found to be significant. The LOF error was also found to be significant, indicating curvature in the regression model. It is to be noted that since the objective

of the experiment was to determine the significant operational factors and not to present a dosing model, regression analysis and model-fitting were not performed.

4.3.2. Comparing the turbidity robustness assessments of four DWTPs

Plants A and B from the current study, alongside two additional DWTPs (C and D) assessed by Reza (2022), were systematically compared. This comparative analysis aimed to draw conclusions regarding the insights obtained from the turbidity robustness framework evaluations of these plants, evaluate ease of applicability, and identify key factors influencing their performance, ultimately providing valuable insights for optimizing turbidity control strategies at the plant. Plants A and C draw their water from the Grand River watershed, which is the largest watershed in Southern Ontario (Veale & Cooke, 2016). Plant A is located upstream and plant C is downstream within within the watershed. Plant B sources its water from Lake Huron, while Plant D draws water from Lake Ontario, both of which are part of the Great Lakes. Each of the four plants features distinct process schemes, in addition to having different source waters. Plants B and D employ conventional treatment schemes, while Plants A and C incorporate more advanced treatment processes, including biofiltration, UV disinfection, and Actiflo® (Fig. 4.4). The critical treatment processes across all four plants with respect to turbidity consist of CFS and filtration except for Plant A, for which the intake is also included. For this study it is defined to include a reservoir that provides natural sedimentation especially during high raw water turbidities (Nemani et al., 2023). Each of the four DWTPs encounters elevated turbidity events: the Grand River, categorized as a medium-highly impacted river, experiences turbidity fluctuations attributed to intense precipitation and runoff events, while areas of the intakes in the two Great Lakes witness turbidity variations due to heavy precipitation, as well as the mixing and resuspension of particles caused by winds. Table 4.1 shows the maximum turbidity experienced by the four DWTPs during calendar years 2019 and 2020. For TRI calculation (step 4: evaluation), CFS T_{goal} was 2 NTU for plants A and B and 1 NTU for plants C and D. Filtration T_{goal} was 0.1 NTU for all four DWTPs.

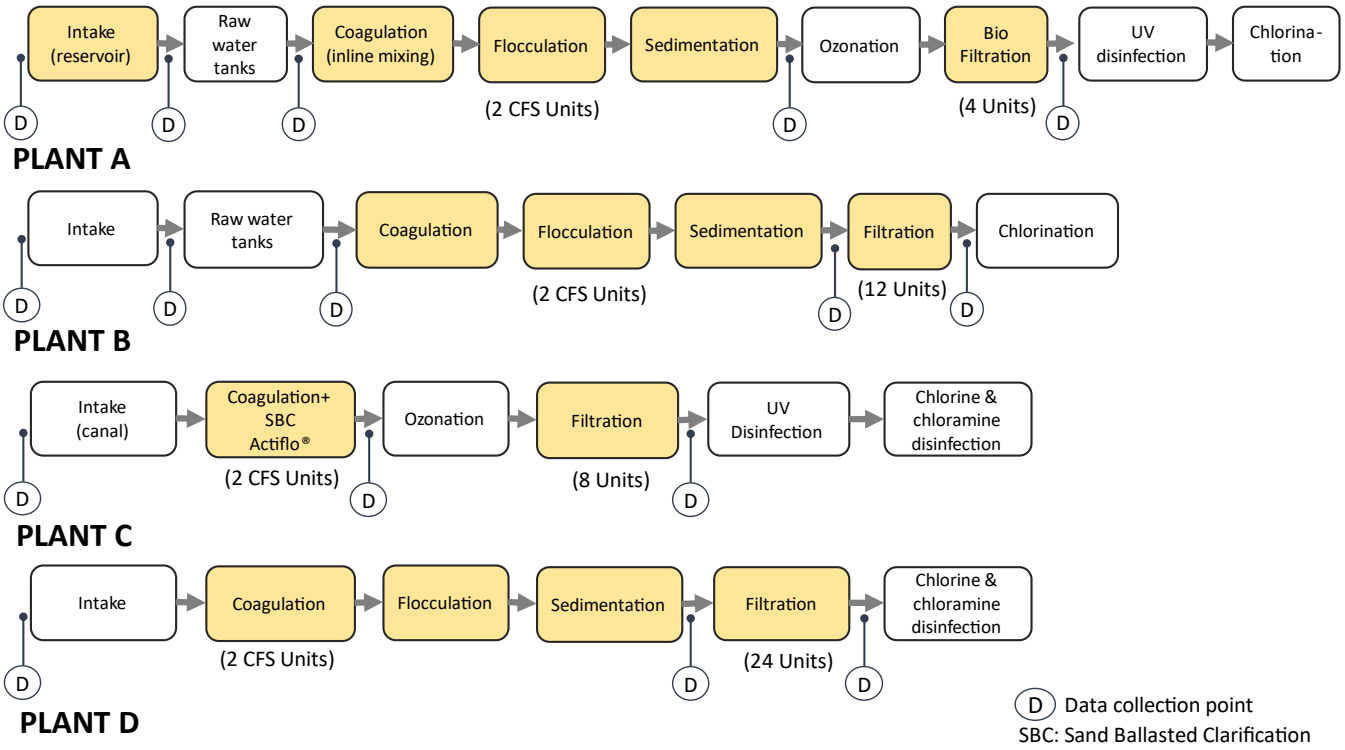


Figure 4.4: Process flow diagrams, data collection points and number of treatment units of Plants A, B, C and D. Critical treatment processes with respect to turbidity are highlighted in yellow.

Table 4.1: Details of Plants A, B, C and D

Plant ID	Source Water	Treatment capacity (L/s)	No. of trains	No. of CFS units	No. of filters	Max raw water turbidity in 2019-2020
A	Grand River	840	2	2	4	50
B	Lake Huron	3935	2	2	12	100
C	Grand River	1376	2	2	8	160
D	Lake Ontario	2719	2	2	24	180

4.3.2.1. Comparison of overall plant robustness (step 5) for normal turbidity range and historic peaks (scenarios 1 and 2)

To compare the robustness evaluations of the four DWTPs across scenarios 1 and 2, the final ORIs as well as the methodology used for distinguishing between the scenarios was considered.

For plant A, scenario 1 or normal turbidity range was set to values below 50 NTU as any values above that are considered as ‘high’ turbidities by the plant operators (scenario 2). Scenario 2, however, could not be separately evaluated for Plant A due to the intake shutdown policy for raw water turbidities above 50 NTU. Scenarios for Plants B and D were assessed using method 2 developed by Reza (2022), while Plant C underwent evaluation using method 1, as outlined by Reza (2022). Identification of valid data points for the critical processes in all four DWTPs was carried out in consultation with plant operators.

For comparing overall plant robustness of the four DWTPs, two ORI weighting approaches were examined: the first employing a more conservative stance for each plant determined by the weights resulting in the worst ORIs (combination weight for Plant A- this was based on raw water turbidity range. High weight (0.25) for intake for raw water turbidity >25 NTU, low weight (0.1) for raw water turbidity <25 NTU, and constant high weight (0.5) for filtration and CFS-heavy weight for Plants C and D), and the second utilizing an equal weighting approach. Minor differences from the two ORI weighting approaches were observed, notably affecting Plants A, C, and D, where the conservative approach resulted in more instances of 'slightly disturbed' process robustness. Conversely, no change in ORIs for Plant B was noted with alterations in weights.

Among the plants with the same source water i.e. the Grand River, Plant A was more robust with more weeks in ‘very stable’ and ‘stable’ categories and only 6-8 weeks of ‘slightly disturbed’ robustness, depending on the weighting approach. In contrast, Plant C exhibited a higher frequency of weeks categorized as 'slightly disturbed' (Fig. 4.5). Several factors may have contributed to this, including the more stringent CFS T_{goal} of 1 NTU at Plant C. Another factor is the intake shut-off policy at plant A, which prevents turbidities exceeding 50 NTU from entering the plant and is therefore limiting the maximum incoming raw water turbidity. Plant B fed by Lake Huron exhibits no instances of disturbed robustness, as all weeks consistently fall within the 'very stable' category. In contrast, Plant D fed by Lake Ontario experienced more occurrences of 'slightly disturbed' weeks along with a few instances of 'moderately disturbed' weeks. It is crucial to note that Plant D adheres to a much stricter CFS T_{goal} (half of that of Plant B), which should be considered in such comparisons. Overall, Plant B demonstrates the best performance, consistently maintaining 'very stable' robustness throughout all weeks.

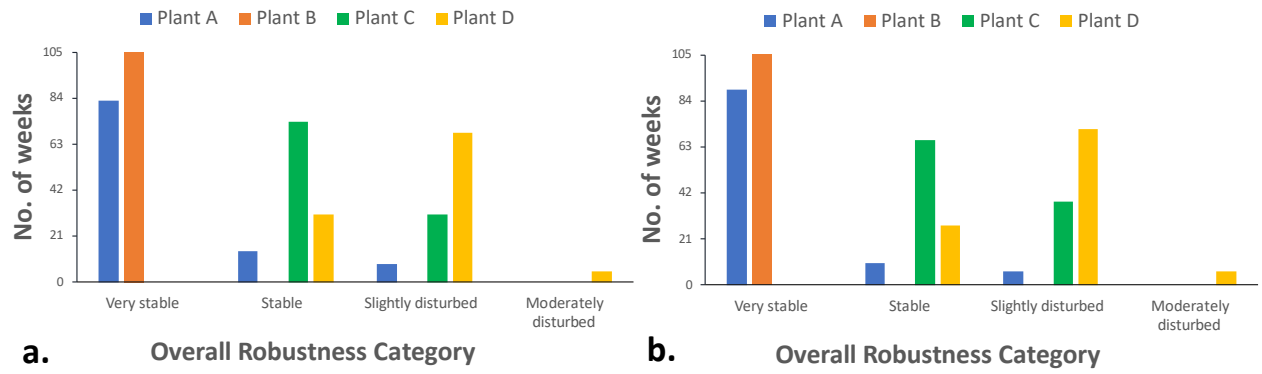


Figure 4.5: ORI results of the four DWTPs. with a. representing conservative weighting approach and b. representing equal weights for the critical treatment processes

The root cause of the diminished robustness in Plants A, C and D was attributed to the performance of the CFS process. Interestingly, the filters across all four DWTPs consistently exhibited robust performance and compliance with drinking water regulations and stricter performance goal of 0.1 NTU. This observation sheds light on several crucial aspects of treatment robustness. Typically, CFS serves as the primary barrier in most conventional treatment plants, acting as the 'first line of defense' against influent turbidity fluctuations. Additionally, CFS encounters higher variability in influent water quality compared to other later treatment stages, emphasizing its critical role in the overall treatment process. Moreover, since settled water turbidity is not regulated, DWTPs have more flexibility in managing higher CFS effluent turbidity or lower CFS robustness instead of resorting to steps such as plant shutdowns. This also highlights that treatment robustness is not a case of ‘a chain only being as strong as the weakest link’ (Huck, 2015). In fact, low CFS robustness was compensated by consistently robust filter performance for plants A, C and D. Hence, while robustness outcomes can vary significantly depending on factors such as source water quality, treatment scheme, operational protocol, and internal plant goals, there were also noteworthy similarities, particularly in the context of robust filter performance observed across all four DWTPs. This also showcases utilities' commendable commitment to maintaining the robustness of their filter systems, preventing plant shutdowns, and ensuring their capability to consistently provide safe drinking water to the communities they serve.

4.3.2.2. Comparison of CFS robustness (step 4, evaluation and step 6, adaptation) for extremely high turbidities (scenario 3)

The evaluation of scenario 3 was investigated for Plants A, B, and D, with the simulation of high turbidity raw water using kaolin for all three plants. Furthermore, to simulate elevated turbidity levels using an alternative method, sediment from the intake basin of Plant A (Appendix B, section 2.2) and stormwater samples were employed for Plants A and D, respectively. Plant A the CFS operational regime for extremely high turbidities was found to be sufficient, indicating well optimized dosages for different turbidity ranges. For plant B and C, the CFS goal value was exceeded for raw water turbidities at 250 NTU and 400 NTU respectively. Various operational changes for CFS, including adjustments to coagulant dose, polymer dose, microsand dose (in the case of Plant C), and settling time, were examined. None of these factors were found to be significant for Plant A (α=0.05) (Nemani et al., 2023). In contrast, all factors, including coagulant and polymer dose, as well as settling time, were found significant for Plant B. For Plant C, statistical significance was observed only in relation to coagulant and microsand dosages. This information forms the basis for further steps as illustrated in the next section.

4.4. Answering 'what next?': incorporating outcomes of the framework into a decision-tree for water planners (835 words)

The outcomes of the turbidity robustness framework, when applied to a DWTP, can be incorporated into a decision-making paradigm, aiding water managers in climate adaptation planning. This work explores introducing a decision tree which integrates the results of Steps 4 (Evaluation), 5 (Assessment), and 6 (adaptation), and which draws a roadmap for further actions a DWTP can take. To achieve this, the methodology behind Decision Support Systems (DSS) was studied and implemented. In general, there are some common components in environmental decision making (Raseman et al., 2017), which are also applicable for the formulation and implementation of the proposed decision-tree:

1. Identification of the stakeholders: Stakeholders for a DWTP will be the operators, water managers, personnel at the concerned municipality, consultants (if hired for future projects), and water consumers (potentially).
2. Problem formulation: There are several elements that must be considered by a DWTP while implementing the decision tree-

a) Decision variables- these are the parameters that can be considered by the decision maker. For example, implementation of new or revised operational responses for extreme water quality events, introduction of a new treatment process, or expansion of an existing process are all potential decisions a DWTP can make. These can be broadly divided into short-term and long-term decisions based on the turn-around time, cost, and impact. Step 6 of the robustness framework showcased the factors effective for high turbidity removals next steps that a DWTP can consider as next steps in the decision-making process.

b) Objectives- The three main objectives of a DWTP planning for climate adaptation would be: increasing robustness, decreasing cost, and decreasing the time of a chosen project (longer project durations are associated with more costs, therefore, optimizing the time of a project is always desirable).

c) Identifying constraints- Some common constraints pertaining to DWTP operation would be drinking water regulations, licenses associated with the DWTP processes or plant operation contractors and desired reliability of the DWTP when experiencing extreme water quality events. As such, a DWTP always aims for 100% reliability under normal conditions to meet the safety and water demand of the targeted population. However, while planning for water quality extremes and deciding between different climate adaptation options, the DWTP may choose an option with a lower reliability as there may be a tradeoff between the three objectives discussed in b) (for e.g., 90% reliability constraint indicates that the DWTP will be reliable (i.e. not fail or not be shut down) 90 out of 100 times there is a water quality event). This ultimately refers to the decision to choose the tolerance of a DWTP towards plant-shutdowns during an adverse event such as floods, storms, or wildfires.

3. Collecting and analyzing information obtained from applying the turbidity framework.
4. Apply the decision tree to arrive at the desired outcome.

A decision tree that can be incorporated after application of the turbidity robustness framework is proposed in Fig. 4.6.

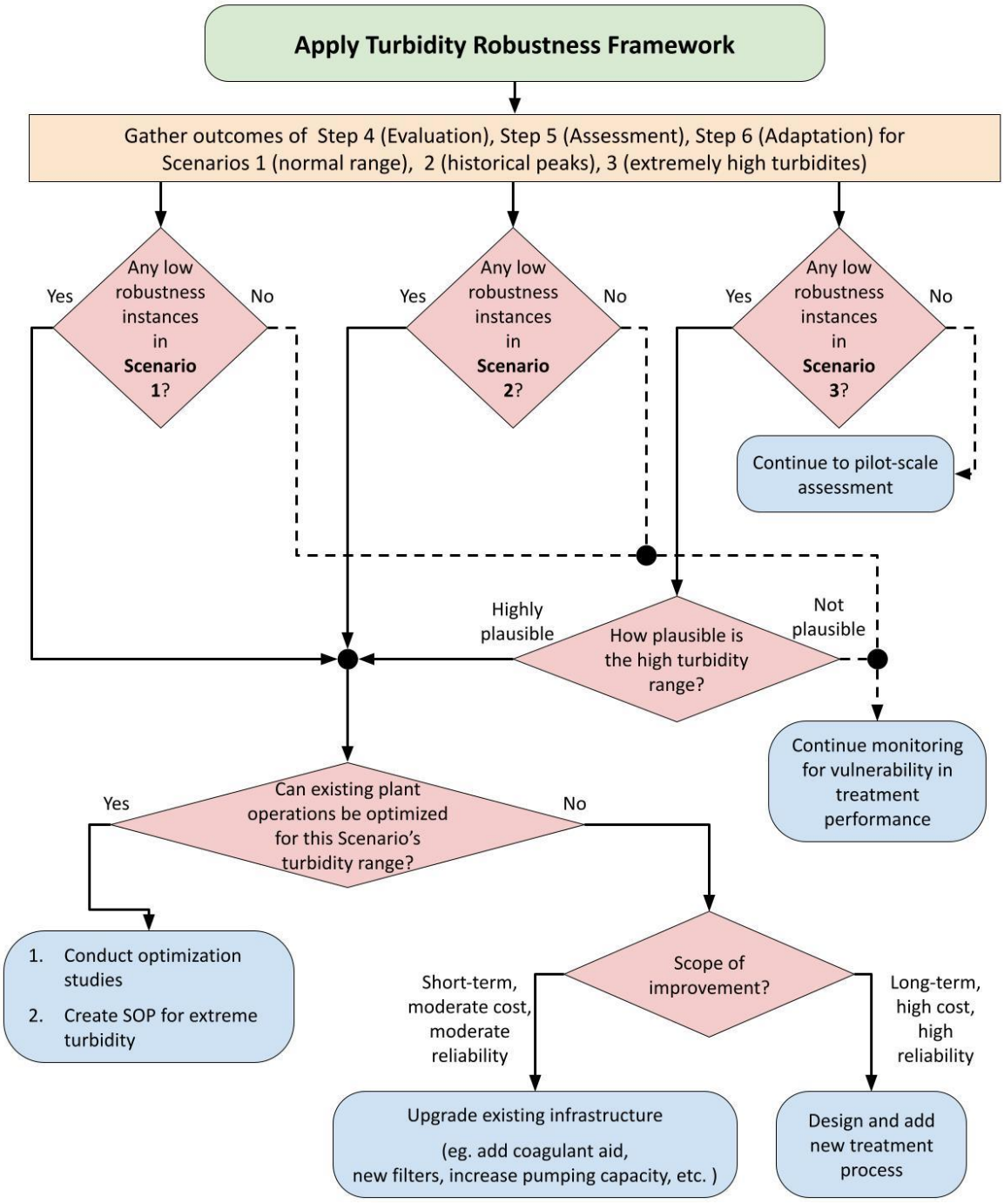


Figure 4.6: Proposed decision tree to incorporate outcomes of turbidity robustness framework into climate adaptation projects.

Following this decision tree, a DWTP can explore various options to enhance their treatment robustness and formulate a climate adaptation plan. This plan can involve augmenting existing

strategies or using it as a foundational framework to integrate into their planning. If a DWTP does not see any instances of low robustness in any of the three scenarios, the utility can opt for furthering the scenario 3 experiments from bench-scale to pilot-scale, while continuing to periodically re-assess treatment robustness using TRI and ORI. If a plant experiences instances of lower robustness in scenarios 1 and 2, the utility can consider further optimization studies to improve treatment operations.

In case a plant experiences low robustness in Scenario 3, the utility must plan for the level of adverse turbidity that is expected in the future due to increased extreme weather events which the plant might want to plan for. The current turbidity framework recommends finding the effectiveness of the operational regime over a wide range of scenario 3 turbidities, which may be of varying concern for the plant. For example, a two-fold increase from historical turbidity peak can be a more likely scenario than a ten-fold increase from the historical turbidity peak. These considerations must be made while answering the question 'how likely is the turbidity threshold' for Scenario 3. Depending on the level of extreme turbidity a DWTP would like to plan for, the DWTP can choose between immediate optimization studies, short-term projects such as addition of operational factors or upgrades and long-term projects such as addition of a new treatment process. It should be noted that these options are not mutually exclusive of one-another, and it is recommended for the plant to conduct cost-benefit analyses of all the available options before deciding.

Figs. 4.7, 4.8, 4.9 and 4.10 illustrate decision tree examples for the four DWTPs based on robustness evaluation outcomes. Plant A presents a distinctive scenario where, despite some instances of low robustness in scenario 1, the CFS regime demonstrated robustness for scenario 3 turbidity. In such cases, confirmation can be obtained through a pilot-scale assessment of scenario 3 turbidity, while also optimizing the coagulation regime within the normal turbidity range of 1-50 NTU (Fig. 4.7).

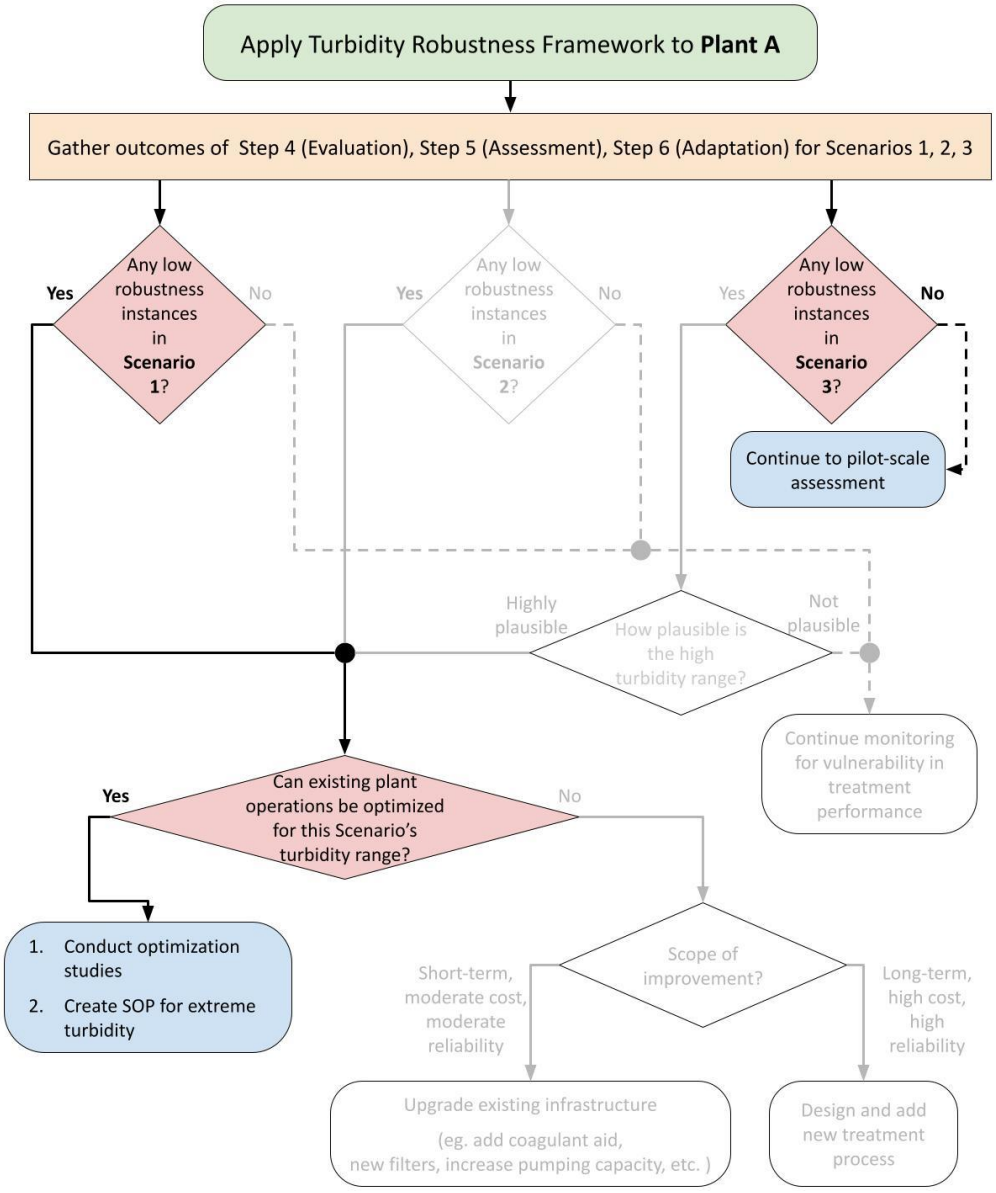


Figure 4.7: Example of decision tree for Plant A. The steps that are not valid are shown in grey.

Plant B, exhibiting robust performance in scenarios 1 and 2, but lower robustness in scenario 3, may initiate improvement by increasing the coagulant dose (Fig. 4.8). For optimizing dosages under turbidities exceeding 500 NTU, additional jar tests across varied seasonal turbidity conditions are essential, which were not within the scope of this study. Given the higher raw water turbidities during storm conditions, and with routine stormwater sampling in place, optimization studies using stormwater can provide a more accurate representation of particles entering the plant compared to kaolin. Furthermore, for long-term enhancement, since initial

bench-tests indicate that addition of polymer can improve settled water turbidity in both normal and elevated turbidity regimes, it might be of interest for Plant B to further confirm these findings at a pilot-scale test and plan for addition of coagulant aid as an additional operational step. Since the current infrastructure of the plant does not have a polymer dosing system, this would involve significant infrastructural changes and capital investment and would be a short-term, moderate cost adaptation option.

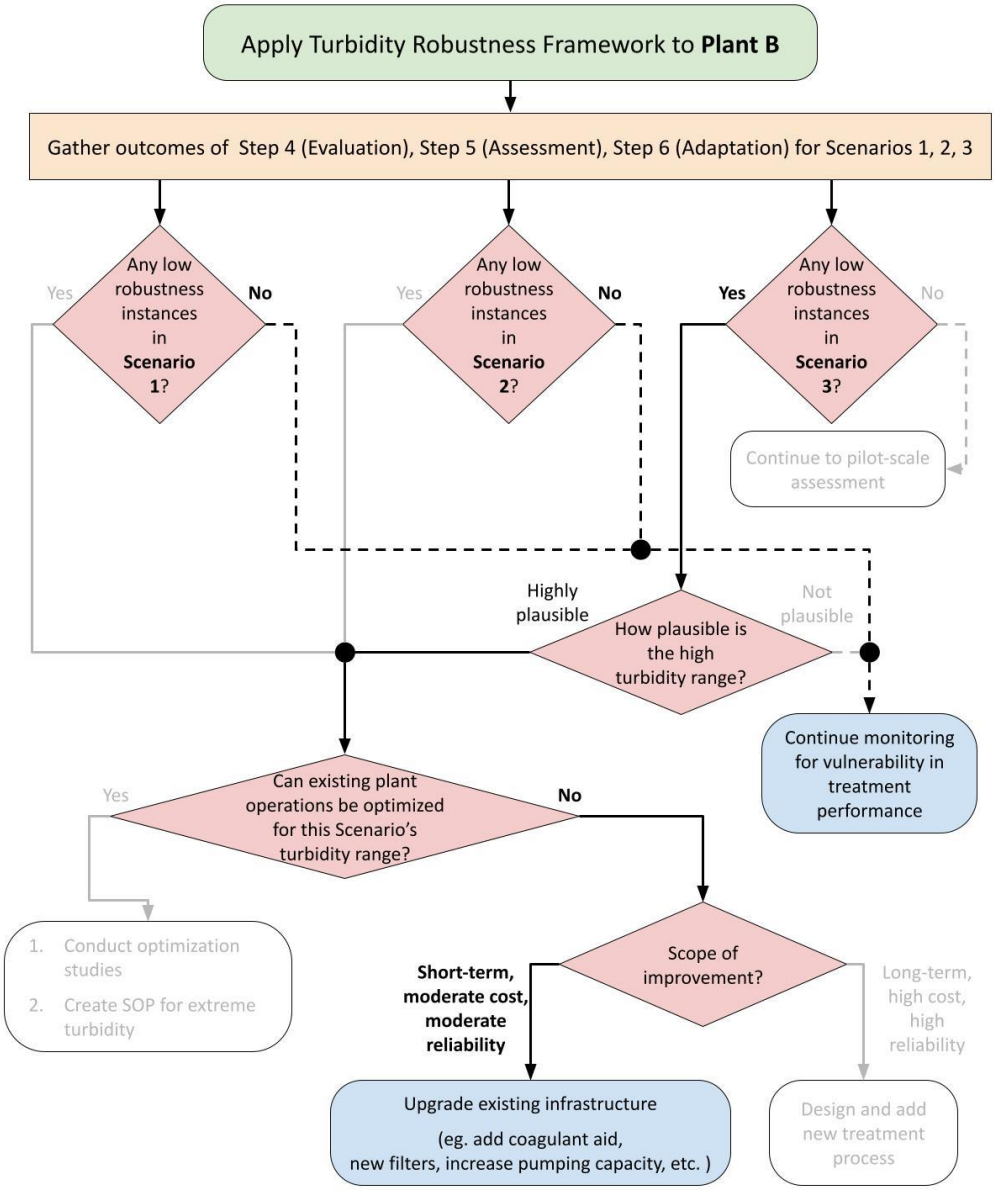


Figure 4.8: Example of decision tree for Plant B. The steps that are not valid are shown in grey.

For Plants C and D, it is advisable to conduct optimization studies to enhance CFS performance under turbidity scenarios 1 and 2 (Fig. 4.9, 4.10). Additionally, developing standard operating procedures (SOPs) tailored for various turbidity ranges would facilitate effective operational adjustments at the plants. Considering that scenario 3 was not evaluated for Plant D, it should be the next step in advancing robustness evaluations.

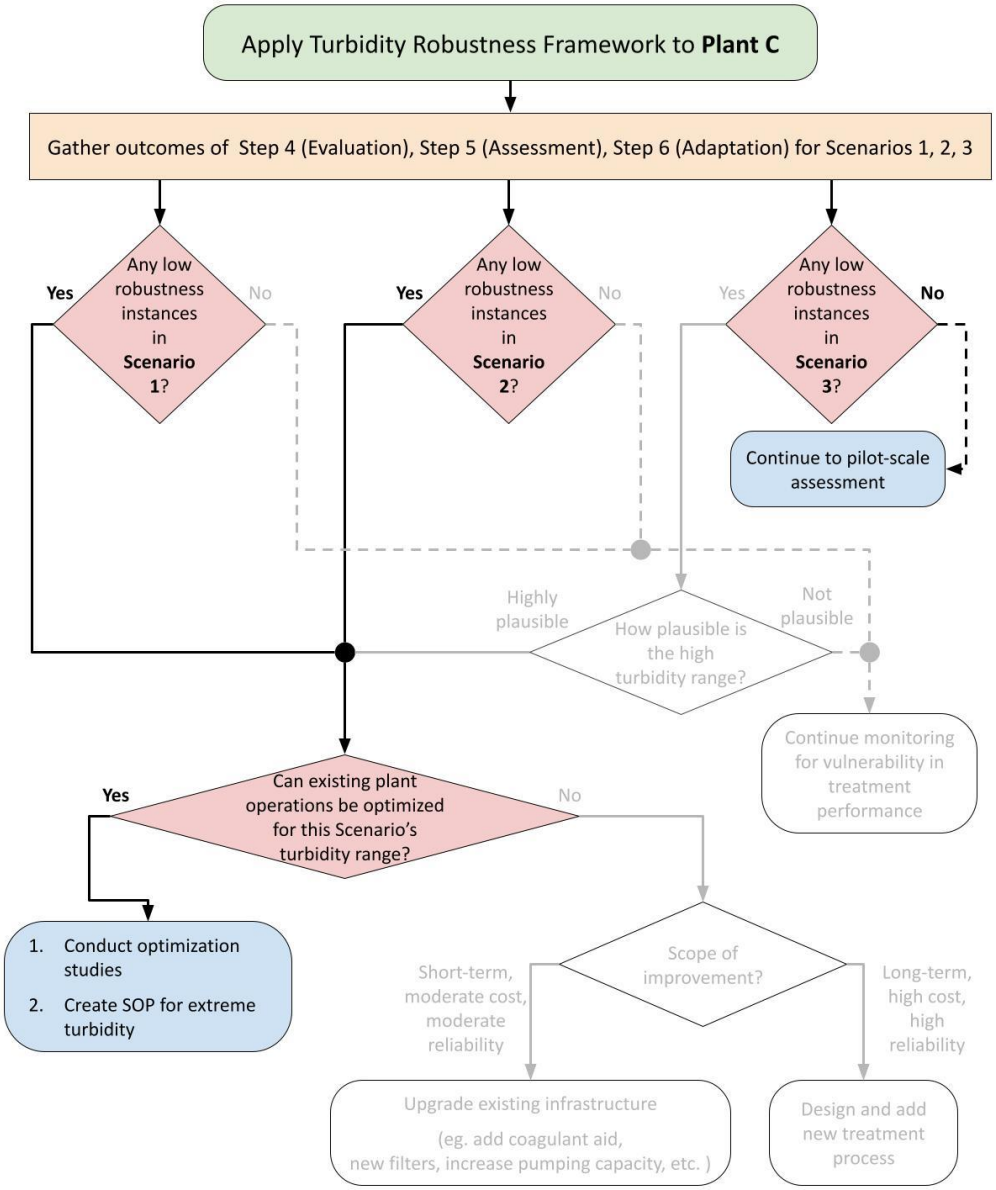


Figure 4.9: Example of decision tree for Plant C. The steps that are not valid are shown in grey.

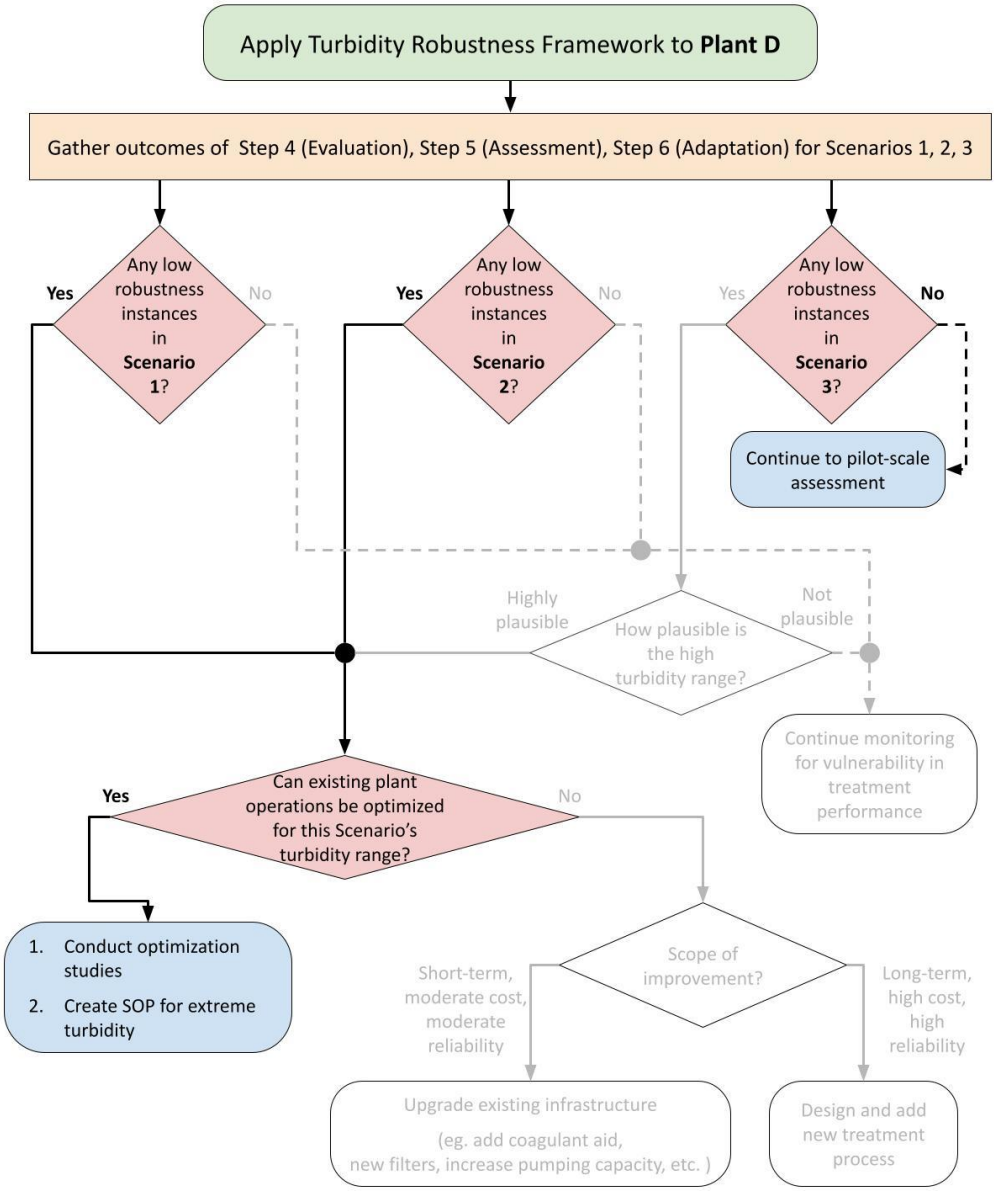


Figure 4.10: Example of decision tree for Plant D. The steps that are not valid are shown in grey.

4.5. Conclusions

This study demonstrates an in-depth application of the turbidity robustness framework to two full-scale DWTPs over a period of two years. It also compares the robustness of four different DWTPs, and provides guidance for next steps. The similarities and differences in source waters, treatment schemes and operational procedures of the four DWTPs provide an insight into what does and does not work for a specific DWTP. Quantitative robustness outcomes from the current

work provide a DWTP with the ability to diagnose the causes of low robustness, identify the limiting turbidity range for the treatment processes, and identify feasible operational changes. The turbidity robustness framework serves as a robust foundation for conducting quantitative analyses of DWTPs, offering valuable insights into both current treatment performance and prospective scenarios. The comparative assessment of the framework across four diverse DWTPs not only demonstrates its ease of application, but also highlights its ability to compare distinctly different plants, revealing varying outcomes for each.

This research also addresses ‘what’s next?’ after a DWTP successfully applied the turbidity robustness framework and wants to incorporate the outcomes into its decision-making process for climate adaptation projects for the next several years. Building and maintaining resilient infrastructure is one of the visions of Canada’s first national adaptation strategy (ECC Canada, 2022) and especially in the current scenario of increasing extreme weather events, there will be a push towards ensuring DWTPs can continue functioning in the face of climate change. The decision tree presented provides utilities with a tool to choose strategies that can increase short-term and long-term robustness of their treatment processes and disseminate relevant information for planning for such projects.

5. Chapter 5: Assessing Drinking Water Treatment Robustness: Development and Application of an Organic Matter Robustness Index

This chapter is a submitted manuscript: Nemani, Kirti S., Peldszus, Sigrid, Huck, Peter M. Assessing Drinking Water Treatment Robustness: Development and Application of an Organic Matter Robustness Index, Manuscript ID: ew-2024-00218s. Submitted to ACS ES&T Water.

Abstract

Natural organic matter (NOM) significantly impacts drinking water treatment processes, potentially creating operational challenges during extreme weather events. This underscores the importance of treatment process robustness for ensuring consistently safe drinking water production despite variations in raw water quality. To improve robustness, it is crucial to quantitatively evaluate treatment process robustness in different raw water NOM scenarios. To address the lack of NOM-specific robustness methods, the Organic Matter Robustness Index (OMRI) was developed. It is comprised of three key components- the first term quantifies NOM reduction/removal during treatment, the second focuses on treatment processes specifically vulnerable to NOM changes, and the third aligns the index with regulations. This quantitative robustness method was then incorporated into the development and application of an NOM robustness framework to a full-scale drinking water treatment plant (DWTP), assessing historical and future extremely high NOM scenarios. Short-term operational responses to high NOM scenarios, including increased coagulant dose, polymer addition as a coagulant aid and extended settling time were examined at bench scale. The results highlight the OMRI's practicality, ease of use and adaptability to full-scale DWTPs, thereby assessing DWTPs' operational NOM robustness. This comprehensive approach can guide decision-making in DWTPs, informing future extreme weather adaptation efforts.

5.1. Introduction

NOM (here meant to include algal organic matter and effluent organic matter) is a complex mixture of organic compounds with different molecular weights and chemical characteristics that

affects the quality and safety of drinking water treated in drinking water treatment plants DWTPs (Crittenden, 2012; Heath Canada, 2020). Extreme weather events such as heavy precipitation and snowmelt runoffs, can significantly elevate NOM levels, at times leading to 4-5 times increase in DOC concentrations (Saraceno et al., 2009; Hurst et al., 2004; James et al., 2016). The specific nature of extreme weather conditions also dictates NOM characteristics in source waters (Anderson et al., 2023; Bertone et al., 2019; Khan et al., 2015; Ritson et al., 2014; Wright et al., 2014). These substantial fluctuations in NOM concentration and characteristics can impact several processes in DWTPs, such as coagulation, filtration, disinfection, and adsorption, presenting operational challenges.

To ensure consistent drinking water quality during challenging raw water conditions, a viable strategy involves enhancing the robustness of treatment processes. Robustness refers to a DWTP's capacity to sustain a desired water quality, even when faced with fluctuations in input conditions (Huck & Coffey, 2004). It is important to quantitatively evaluate the current state of robustness of treatment processes to identify vulnerabilities within a DWTP and direct climate adaptation efforts in the right places in the form of operational changes or upgrades (Nemani et al., 2023). While this has been demonstrated for turbidity by developing a robustness framework (Nemani et al., 2023), little attention has been given to NOM, which not only affects treatment processes, but also operational factors, such as coagulant dose (Ritson et al., 2014; Anderson et al., Au et al., 2011), and regulated parameters, such as disinfection by-products (DBPs) (Sillanpää, 2015). It is, therefore, crucial to examine the robustness of treatment processes concerning NOM, by developing a robustness framework for NOM which focusses on obtaining quantitative results when investigating adverse raw water quality scenarios.

A quantitative method evaluating robustness of individual treatment processes for NOM is at the core of such a framework, which is still an unexplored area. The most used quantitative metrics in drinking water treatment practise are filter indices. While these are good indicators of filtration performance, they do not give an indication of how robust a filter is with respect to a WQP over time and cannot be applied to any other processes except filtration. Other metrics such as the surface water quality indices (WQIs) (Uddin et al., 2021) only evaluate the raw water quality, taking several WQPs into consideration, but do not present any information about process robustness. The only index that directly quantifies the robustness of a treatment process is the

TRI and its different modifications over the years (Huck & Coffey, 2004; Hartshorn et al., 2015; Li & Huck, 2008). TRI is basically a statistical tool, which is not specific to turbidity, meaning it can potentially be applied to other water quality parameters such as NOM. However, TRI calculations typically involve large data sets and its application to smaller data sets has not been explored. Although TRI holds potential as a statistical tool to quantitatively assess NOM treatment robustness, its implementation may be limited due to the small datasets typically associated with NOM surrogate parameters, as these are not regulated in most countries.

The objectives of the current study are to: a) develop a quantitative evaluation methodology for assessing robustness of drinking water treatment processes with respect to NOM reduction/removal, b) develop an NOM robustness framework incorporating the quantitative methods from a), and c) apply the framework to a DWTP. Regarding a quantitative robustness method, the potential TRI application to NOM data was investigated. Furthermore, a new quantitative method the OMRI was developed to capture the different facets of NOM impacts on DWTP processes and to address cases of limited NOM data availability for robustness evaluation. These quantitative robustness evaluation approaches were integrated into the parameter-specific framework designed to assess and enhance DWTP robustness in terms of NOM reduction/removal. Finally, the developed NOM robustness framework was applied to a full-scale DWTP in southern Ontario, Canada.

5.2. Approach and methodology

5.2.1. Organic matter robustness index development

The relevant literature was reviewed with the goal of understanding the suitability, applicability, and approaches of existing quantitative methods/indices relating to water quality. These metrics were categorized in three main categories:

a. Indices used in drinking water treatment practise
b. Robustness-specific indices in drinking water treatment
c. Other WQIs

From a review of these categories of indices, the main phases of index formulation were identified (Uddin et al., 2021), which were then followed for the development of the OMRI:

Phase 1: Selection of relevant WQPs i.e. NOM surrogates

Phase 2: Creation of sub-indices which convert the WQP values into a dimensionless term

Phase 3: Aggregation of the sub-indices using a mathematical function which may or may not include the weighting of individual sub-indices

Phase 4: Calculation of the final index, which compresses the subindices into a single value, and creation of a rating scale to categorize the final value of the index into one of several qualitative water quality ranges (e.g. poor, very poor, excellent etc.)

5.2.2. TRI sensitivity analysis to assess impact of input dataset size on TRI results

Two distinct datasets were employed in the sensitivity analysis. Data set 1 is comprised of 1700 filter effluent turbidity data points from Plant B, chosen from a random filter run (excluding filter backwash). Data set 2 contains 2000 randomly generated numbers between 1-100, obtained from the 'RANDBETWEEN' function in Microsoft Excel™. The size of this dataset was chosen to represent the typical number of data points in a filter run and the values represent the typical raw water turbidity range at Plant B. TRI was computed across various subsets of datasets 1 and 2, including the entire dataset, 1/10th (comprising 170 and 200 data points), and 1/100th of each dataset (comprising 17 and 20 data points). Two distinct methods were applied to condense the data for generating the two subsets in each dataset: in the first method, the representative point for the first 10 data points was determined by averaging them, whereas in the second method, the 10th or the last data point itself was considered as the representative point.

5.2.3. Development of the NOM robustness framework

The main steps for robustness framework development were followed: selection (of a WQP, NOM in this case), identification (of treatment processes capable of removing/reducing NOM), criteria (NOM treatment goals for said processes), evaluation (individual treatment processes), assessment (overall plant) and adaptation (exploring operational changes to improve NOM robustness) (Nemani et al., 2023). The general framework is shown in Fig. C.1.

5.2.4. Development of the NOM plant framework and application to Plant B

5.2.4.1. Sampling and water quality analysis

Plant B draws its raw water from Lake Huron in southern Ontario, Canada, and follows a conventional treatment scheme: coagulation (using alum), flocculation, sedimentation (CFS), and rapid media filtration. Chlorination is employed at the intake for mussel control and after filtration. Polymer is dosed as a filter aid to the settled water a few times a year during periods of high turbidity. The finished water is stored in a clear-well and then pH-adjusted before being discharged to the distribution system.

Due to limited availability of NOM surrogate parameter data at Plant B, a routine sampling regime was established to collect water quality data and establish a baseline for occurrence and reduction/removal. Weekly samples were collected at six process locations: raw water (unchlorinated), post sedimentation train 1 and 2, post filtration train 1 and 2 and treated water (Fig. C.2). The samples were analysed for TOC, DOC, UV transmittance (UVT) and absorbance (UVA) at 254 nm, and trihalomethane formation potential (THMFP). TOC/DOC analysis was conducted using Shimadzu TOC-L CSH analyser (standard method 5310B (APHA, 2023). UV_{254} was measured using Agilent Technologies Cary 100 UV-Vis Spectrophotometer (standard method 5910B (APHA, 2023)) THMFP was analyzed using a HP 5890 series II gas chromatograph and HP 7673 autosampler (standard method 5710B (APHA, 2023)). The TOC, DOC and UV_{254} data were collected for 43 weeks (4 Aug 2022 - 27 Jul 2023) and THMFP data for 24 weeks (2 Feb 2023 - 27 Jul 2023).

5.2.4.2. Application of NOM framework to Plant B: Bench scale experiments for step 4 (evaluation) and step 6 (adaptation)

Simulation of water with high NOM concentrations

Unchlorinated raw water was collected from the Plant B intake (2.0 mgC/L DOC, 1.2 NTU turbidity). High NOM concentrations were simulated using Suwannee River NOM (SRNOM) (International Humic Substances Society (IHSS), 2R101N), which was made into a stock solution of 176 mg C/L (King, 2020). Appropriate volumes were added to the unchlorinated raw

water to make solutions with final DOC concentrations of 2, 4, 8, 16 and 32 mgC/L for the bench-scale experiments.

Plant Framework Step 4, Evaluation: Jar test for scenario 3 evaluation (extreme raw water NOM)

An initial jar test to check the effectiveness of the current Plant B coagulation regime on high NOM waters was conducted using the water prepared in above section. A standard jar test apparatus (Phipps & Bird) was used with 30 seconds rapid mixing at 100 rpm, followed by flocculation mixing at 70 rpm for 5 minutes and then 40 rpm for 5 minutes. Settling times of 5 minutes and 10 minutes were tested. The coagulant (Clar Ion A7, Chemtrade) stock solution (49% strength) and polymer (Polyfloc AP 1100P, Suez/Lenntech) powder were obtained from Plant B. The coagulant was dosed at 35 mg/L during this initial jar test, representing the maximum coagulation dosage employed at the plant based on the raw water conditions. No polymer was added during the initial jar test as polymer is not used as a coagulant aid at the plant.

Plant Framework Step 6, Adaptation: factorial design experiment

A 2^3 full factorial design with two mid-point replicates was used to study the effect of three optimization factors i.e., coagulant dose, addition of polymer as a coagulant aid, and settling time. The high and low levels were: coagulant dose at 35 and 70 mg/L, polymer dose at 0 and 0.6 mg/L, and settling time at 5 and 15 minutes. Additionally, two mid-point replicates were conducted (Coagulant 52.5 mg/L, polymer 0.3 mg/L, and settling time 10 minutes). Unchlorinated raw water from Plant B was spiked with SRNOM to obtain an initial DOC of 8.2 mg C/L, which corresponded to 47% initial UVT and 167.8 µg/L initial THMFP and pH 6.8. Post coagulation pH was between 5.7-5.9. Coagulant and polymer solutions were made using the Plant B stock solution as described in the previous section. TOC, DOC, UV_{254} and THMFP were analyzed for all samples after coagulation. Data analysis was done using Analysis of Variance (ANOVA) in Microsoft Excel™. The mid-point replicates were used to determine the pure error and significance of the effects.

5.3. Results

5.3.1. Development of quantitative robustness evaluation methods for NOM

The lack of quantitative methods for assessing the robustness of treatment processes with respect to NOM poses a challenge, necessitating their development. As NOM and its surrogates are not normally regulated, many plants only collect limited organics data. NOM treatment goals are also highly variable, largely depending on source water characteristics and regulations for NOM-related parameters such as DBPs, leading to some DWTPS having e.g. DOC treatment goals while others do not. Furthermore, NOM itself cannot be quantified. Instead, surrogate parameters have to be selected, which have to be consistent with the NOM treatment goals and be suitable for any developed quantitative NOM evaluation method. Considering these limitations, approaches to surrogate parameter selection are discussed before introducing two quantitative approaches developed for robustness evaluation of NOM:

5.3.1.1. Selection of suitable NOM surrogate parameters for robustness evaluation

NOM in drinking water is commonly indicated by TOC, DOC, UV_{254}, chemical oxygen demand (COD) and color (Matilainen, 2011). Among these, bulk parameters such as TOC and DOC are commonly used as the main NOM surrogate parameter. In cases where TOC/DOC data are limited, correlation studies between alternative surrogate parameters and TOC/DOC are needed to select the most suitable parameter for NOM representation. For example, UV_{254} may be used as a surrogate for DOC as it is easier to measure and can be monitored online. However, the relationship between DOC and UV_{254} depends on source water, climatic events, and watershed influences on NOM, making it not universally applicable to all DWTPs (Minor et al., 2014).

5.3.1.2. Evaluation approach 1: Application of the TRI formula to available organics data

TRI has traditionally been used on large turbidity datasets. In addition, TRI is calculated over a specific time frame (e.g. a filter run or a week) as it uses percentiles in its formula. Considering these, application of the TRI method to a different WQP other than turbidity would be suitable for scenarios where NOM surrogate parameters are measured online or monitored with a higher frequency. For scenarios with a limited organics dataset, sensitivity analysis of the TRI was done to check the number of data points required to arrive at a meaningful final value. Previous studies (Huck & Coffey, 2004; Li & Huck, 2008) have only discussed the application of TRI to

turbidity data but have not commented on the number of data points required to reach a meaningful TRI result.

The results from the TRI sensitivity analysis showed that for data set 1, TRI values remained the same for all 3 subsets and the two averaging approaches (Table C.1). For data set 2, TRI values remained the same for the second method, where the condensed subset was derived by using the last data point as the representative data point. For the first method, the TRI values were 63 for 2000 data points, 58 for 200 data points and 56 for 20 data points. The standard deviation among these TRI values was 3.54. Therefore, the TRI formula can be used reasonably well with smaller data sets, however, since the formula includes a percentile function, it is recommended to have at least 3, and ideally 10 or more data points for calculating one TRI value over a specific time frame e.g. a week. This approach of evaluating process robustness using the TRI formula can be applicable for NOM surrogate parameters that are measured daily, or at least a few times a week.

5.3.1.3. Evaluation approach 2: Development of OMRI

The main goal of the OMRI is to quantify the robustness of different drinking water treatment processes with respect to different aspects of organic matter removal/reduction. The multifaceted nature of NOM, and its varied impacts on treatment processes can make it challenging to comprehensively assess NOM treatment robustness using a single surrogate parameter. To address this issue, the OMRI gives the option to use several NOM surrogates associated with different NOM treatment goals. The overall OMRI development approach is outlined in the current section. Note that while this methodology was taken from WQI development literature, the main goal of WQI, which is to determine an overall water quality based on several WQPs, is different from the proposed robustness method.

- **Phase 1: Selection of relevant terms for the OMRI**

NOM is a complex mixture that can be quantified by a number of surrogate parameters drawing on different properties of the NOM. These surrogates are interrelated with no fixed relationships as they vary for different source waters. Due to the complexity of NOM, its impact on drinking water treatment processes can be direct or indirect based on which aspect is considered. Keeping this in mind the proposed OMRI has the following terms:

1. **Overall NOM reduction/removal term:** This term gives an indication of the overall NOM reduction/removal of the treatment process being evaluated. This would incorporate a surrogate WQP, which directly measures the NOM and can be reasonably used to estimate NOM. This term can also be a combination of two or more terms based on the surrogates used to monitor NOM at the utility.

2. **Treatment specific term:** This term specifically addresses vulnerable treatment steps at a DWTP i.e. steps that can be adversely impacted by NOM but do not remove/reduce NOM. Treatment goals for NOM surrogates are typically established for earlier treatment steps, which reduce/remove NOM and therefore mitigate adverse impacts on vulnerable processes such as UV disinfection and membrane filtration. Overall, this term assesses how well the vulnerability to changes in NOM is controlled by earlier treatment steps and the overall treatment process.

3. **Regulation specific term:** this term focusses on the regulations associated with NOM levels in the finished water quality. DBPs would fall under this category. Any changes in raw water NOM and decrease in its reduction/removal would lead to an increase of DBPs in the finished water, possibly leading to non-compliance, as DBPs are regulated in drinking water. In response to regulated surrogate parameters, this term may be modified for a specific utility based on the region's regulatory policies.

Therefore, the proposed index is a function of these three terms:

$$\boldsymbol{OMRI = f(overall\ OM\ indicating\ term, treatment\ specific\ term, regulation\ specific\ term)}$$

Based on the specific aspects of NOM that a DWTP is most concerned with and the corresponding NOM treatment goals, the plant can select which terms to include in the OMRI. Note that not all three terms have to be used. It is optional. Once the suitable terms are chosen, the appropriate surrogate parameters for each term must be selected. The different terms and the associated surrogate parameters are discussed further in phase 2.

- **Phase 2: Creation of sub-indices for different terms**

In a sub-index each term compares the WQP against the performance goal and/or regulation associated with the WQP, thus making the result dimensionless. Table 5.1 provides a list of possible sub-indices applicable to DWTPs. This is not an exhaustive list, and a utility may

include terms specific to their treatment processes. Additionally, some of the suggested sub-indices can be used for more than one objective/term as per the DWTP's requirements.

Table 5.1: Examples of OMRI sub-indices and their associate objectives/terms

Sub-index	Suggested objective
$\frac{\text{DOC}}{\text{Goal DOC}}$	Overall OM concentration
$\frac{\text{UV abs (at 254 nm)}}{\text{Goal UV (abs at 254 nm)}}$ Or $\frac{100-\text{UVT (at 254 nm)}}{100-\text{Goal UVT (at 254 nm)}}$	Overall OM concentration; treatment specific goal/ licensing requirement, especially for UV disinfection
$\frac{\text{Color (TCU)}}{\text{Goal Color (TCU)}}$	Overall OM concentration; treatment specific goal to meet aesthetic objective
$\frac{\text{THM}}{\text{Goal THM}}$ or $\frac{\text{THMFP}}{\text{Goal THMFP}}$	Regulatory requirement for THM for finished water quality. THMFP maybe more suitable for other process locations.
$\frac{\text{Haloacetic acids (HAA)}}{\text{Goal HAA}}$	Regulatory requirement
$\frac{\text{Specific UV absorbance (SUVA)}}{\text{Goal SUVA}}$	Treatment specific or plant specific goal for DBP control
$\frac{\text{Biopolymer fraction}}{\text{Goal biopolymer fraction}}$	Treatment-specific goal for membrane filters

- **Phase 3: Aggregation and weighting of the sub-indices**

A simple additive aggregating approach is proposed for the subindices. This approach best reflects robustness in drinking water treatment and supply, which has been described as the sum of the robustness of its individual elements (Huck, 2015). An additive approach is also a common approach used in WQIs, where 5 of the 7 main WQI models used an additive function for aggregating subindices (Abrahão et al., 2007; Brown et al., 1970; Gazzaz et al., 2012; Lumb et al., 2011; Uddin et al., 2021). This approach is also utilized when deciding on the risk of a certain group of compounds in drinking water, where the total risk is the sum of those of individual compounds. One notable example is the U.S EPA hazard index for per- and poly-

fluoroalkyl substances (PFAS) (U.S. EPA, 2021). The final OMRI is proposed as a weighted average of the individual terms, where the terms are assigned relative weights based on which term has more importance from the utility's perspective (Equation 1). Equal weighting of each term can be a starting point for an initial evaluation using the OMRI.

Equation 1:

$$\boldsymbol{OMRI} = \frac{(w_1 * \boldsymbol{overall\ treatment\ term} + w_2 * \boldsymbol{treatment\ specific\ term} + w_3 * \boldsymbol{regulation\ specific\ term})}{w_1 + w_2 + w_3}$$

- **Phase 4: Final index and rating scale**

The rating scale for OMRI ranges from 0.5 to 2, inclusive of both end points. These values correspond to six robustness categories ranging from 'very stable' to 'severely upset' (Table 5.2). This follows the same six categories as the TRI and the overall robustness index (ORI) of the turbidity and general robustness frameworks (Fig. C.1). The values corresponding to each robustness category represent the sum of the ratios of the WQP in each term of the OMRI divided by its goal value. For example, the 'very stable' category represents OMRI values of ≤ 0.5 meaning that the measured WQP(s) in the OMRI are normally ≤0.5 times the goal value set for that WQP. Similarly, the 'severely upset' category represents OMRI values of ≥2, indicating that the measured WQP(s) in the OMRI are always greater than twice the goal value, therefore, failing to meet the performance goal or regulation for the entire duration of the evaluation. Robustness categories (RC) from 1-6 are assigned to the OMRI categories for the calculation of ORI in Step 5, of the framework, the overall plant assessment. The OMRI range stays the same for any number of terms in the final index, as the values of the final range were derived by varying the ratios of each term.

Table 5.2: OMRI rating scale, details and corresponding robustness categories (RC) for use in the NOM framework

OMRI Range	Category Description	Meaning	Robustness Category
≤0.5	Very Stable	Measured values are <=0.5 times the goal value	1
>0.5 to ≤0.8	Stable	Measured values 0.5-0.8 times the goal value	2
>0.8 to ≤1.1	Slightly disturbed	Measured values 0.8-1.1 times the goal value	3
>1.1 to ≤1.7	Moderately disturbed	Measured values 1.1-1.7 times the goal value	4
>1.7 to ≤2.0	Upset	Measured values 1.7-2 times the goal value	5
>2.0	Severely upset	Measure values are >2 times the goal value	6

5.3.2. NOM parameter framework

The NOM robustness framework was developed using the general robustness framework (Nemani et al., 2023), see Fig. C.1, as a guideline. It gives a detailed outline for robustness evaluation, overall plant assessment and short-term adaptation options at DWTPs, with respect to NOM (Fig. 5.1). The modified TRI or the OMRI were incorporated in the NOM framework as essential tools for quantifying the NOM robustness of individual treatment processes in the robustness evaluation step of the NOM framework. Following is a description of each step of the NOM robustness framework.

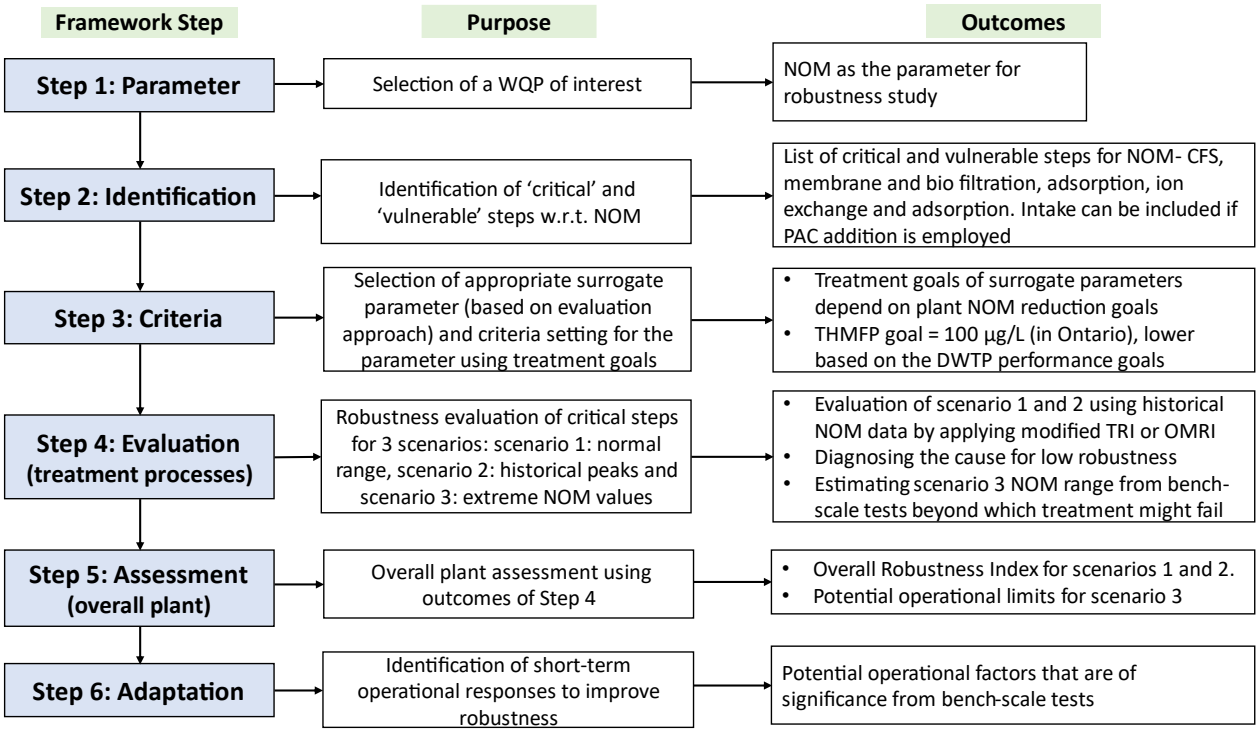


Figure 5.1: Summary of the NOM parameter framework

5.3.2.1. Step 1: Selection - rational for selecting NOM

The first step of the framework is the selection of the WQP. NOM was selected for robustness assessment as it is not only impacted by extreme weather events but is also an important operational factor that determines treatment effectiveness and impacts other treatment processes and WQPs. The effect of NOM is felt on all processes in a DWTP, especially on coagulation, adsorption, and disinfection. Increases in NOM concentrations can increase the coagulant demand due to a higher negative charge and NOM complexation with the coagulant, which makes destabilization of NOM crucial during coagulation (Edzwald, 1993). Therefore, for some surface waters, coagulant doses are controlled by NOM concentration rather than turbidity (Au et al., 2011; Ritson et al., 2014). The nature of NOM also plays an important role in coagulation, preferably removing hydrophobic NOM over hydrophilic NOM (Au et al., 2011; Edzwald, 1993; Parsons et al., 2014).

A major concern with NOM is its potential to react with chlorine and to form DBPs such as THMs, which are regulated (Crittenden, 2012; Ritson et al., 2014; Anderson et al., 2017; Delpla et al., 2009). An increase in the organic precursors will lead to increased production of DBPs

(Crittenden, 2012). Apart from coagulation and disinfection, NOM changes can impact direct filtration (Sillanpää, 2015) and membrane filtration performance (Peldszus et al., 2011). NOM also hinders contaminant removal by forming complexes with organic and inorganic contaminants such as pesticides and metals (Crittenden, 2012). It can decrease the adsorption capacity of activated carbon by blocking the adsorption sites available for contaminants (Crittenden, 2012). Similar mechanism can also hinder the effectiveness of oxidants and ion exchange resins used for contaminant removal in DWTPs (Sillanpää, 2015). Distribution systems are also vulnerable to NOM increases as portions of the NOM can enhance bacterial regrowth in the distribution system (Levine et al., 2016).

5.3.2.2. Step 2: Identification of critical and vulnerable treatment processes

Critical treatment steps are defined here as the processes that aid in physical, chemical, or biological reduction/removal of NOM, while vulnerable steps refer to treatment processes inherently sensitive to any alterations in source water NOM concentration/composition. The critical and vulnerable steps, as well as the nature of control of the critical steps on NOM reduction/removal are shown in Table 5.3. The rationale for treatment processes being vulnerable to NOM changes was discussed in Section 5.3.2.1, this section will focus on the critical treatment processes.

For NOM, intakes may be a suitable location to add powdered activated carbon (PAC) for seasonal control of organics (Crittenden, 2012), making it a critical step for plants that have this provision. Apart from removal of suspended and colloidal matter, CFS steps can also remove NOM. While the particulate fraction of the NOM is destabilized like turbidity, the dissolved fraction, DOC, can be removed up to 30% by coagulation. Higher reduction/removal of up to 80% can be achieved when aided with a higher coagulant dose and a reduction in pH (Crittenden, 2012), which is known as enhanced coagulation. Since CFS can aid in NOM reduction/removal, they were classified as critical steps.

The criticality of the filtration step for NOM reduction/removal varies depending on the nature of organics and the type of filters used. Some particulate and colloidal organic matter may be removed during granular media filtration, but the dissolved organic fraction is not. Membrane filtration can remove NOM fractions based on the pore size of the membranes used [14].

Biological filtration can remove at least some of the biodegradable portion of the NOM and reduce the DBP formation potential of surface water (Servais et al., 2005).

Adsorption is both a critical and vulnerable step for NOM reduction/removal. PAC and granular activated carbon (GAC) can facilitate organics removal, but this will reduce the adsorption efficiency for micropollutants. Ion exchange is also effective for NOM reduction/removal, especially since the advent of magnetic ion exchange resins (Levchuk et al., 2018). Oxidation can reduce the impact of NOM by transforming its nature (Świetlik et al., 2004). However, some oxidants may increase the potential to form certain DBPs, and also reduce the biological stability of the finished water (Bond et al., 2011).

Table 5.3**:** Identification of critical (can remove/reduce the concentration of NOM) and vulnerable (susceptible to changes in NOM) treatment processes for NOM

Process	**Criticality**		**Vulnerability**
	Yes/No	Nature of control over NOM reduction/removal process	Yes/No
Intake	Varies	PAC addition may be done for waters with high NOM	Yes
Coagulation	Yes	Operational	Yes
Enhanced coagulation	Yes	Operational	Yes
Flocculation	Yes	Operational	Yes
Sedimentation	Yes	Design	Yes
Filtration	Varies	Operational	Yes
Granular media filtration	No	-	Yes
Membranes	Yes	Operational, design	Yes
Biofiltration	Yes	Operational, design	Yes
Adsorption	Yes	Operational	Yes
Ion exchange	Yes	Design	Yes
Oxidation	Yes	Operational, design	Yes
Disinfection	No	-	Yes
Distribution system	No	-	Yes

5.3.2.3. Step 3: Criteria- Setting goal values for each critical treatment process

In step 3 of the framework treatment objectives are established for each treatment process, marking a point where the robustness of a treatment process might diminish, leading to potential operational difficulties. Criteria are typically established for all critical treatment processes based on performance goals and regulations, and they form the basis for step 4 (Evaluation). For NOM, as there are multiple surrogate WQPs, criteria would be determined by the DWTP based on the chosen surrogate parameter(s). This decision is also dependent on the robustness evaluation approach (see Section 5.3.1). If the DWTP opts for the TRI, the surrogate parameter has to be suitable for TRI calculation, requiring a minimum number of data points. When using OMRI, surrogate parameters suitable for each term of the OMRI will be chosen. It is to be noted only a single measured data point is required per term of the OMRI.

After selecting surrogate parameters, criteria are established based on treatment guidelines, regulatory limits, and internal goals. For DBP control, recommended water quality targets for DOC removal include <2 mg C/L for high DBP-yield systems and <4 mg C/L for low yield (Health Canada, 2020; U.S. EPA, 1999). Aesthetic color goals are <15 TCU (Health Canada, 2022), and UV disinfection licensing typically requires adherence to a UVT limit. There are regulatory requirements for DBPs in drinking water such as THMs and haloacetic acids (HAAs).

It should be noted that for source waters with low NOM levels, the treatment scheme may not target NOM reduction. The biggest driver for NOM reduction is usually DBP formation, hence for waters that have high DBP formation potential, NOM reduction/removal may be a goal at the DWTP. Different DWTPs may also choose different surrogate parameters of NOM such as UV_{254} or SUVA for monitoring. They may or may not have specific treatment goals for the measured parameters, although the monitoring may be done for other operational reasons such as changing the coagulant dose. The NOM criteria should be decided following discussions with DWTP personnel during application of the NOM robustness framework to a specific plant.

5.3.2.4. Step 4: Evaluation - quantifying NOM robustness for each critical treatment process

This step involves a quantitative robustness evaluation of the critical treatment processes for three NOM concentration ranges in the source water: normal range (scenario 1), historical peaks

(scenario 2) and extreme NOM values, which may be experienced in the future due to climate change (scenario 3). Scenarios 1 and 2 focus on the historical plant data, whereas scenario 3 can be initially evaluated by simulating extreme NOM ranges at bench scale. The robustness evaluation approaches described in Section 5.0 (TRI or OMRI) can be applied to evaluate scenarios 1 and 2. DWTPs can select the approach most suitable for their needs based on data availability, and the goal for conducting the robustness assessment. The extreme NOM values in scenario 3 can be approximately simulated by spiking raw water with NOM isolated from the raw water using reverse osmosis (Green et al., 2015). Since this is a complicated process and may not be accessible to all DWTPs, an NOM substitute such as synthetic lab grade humic and fulvic acids, or SRNOM can also be used. For DWTPs that experience frequent storm water conditions with high organic content, such raw water may also be suitable for the extreme NOM experiments.

5.3.2.5. Step 5: Assessment- determining overall plant robustness

In step 5 the ORI is calculated, which reflects the overall robustness of a DWTP and is based on the robustness evaluation of individual treatment processes. It is a weighted average of the RCs assigned to the OMRI/TRI values of the critical treatment processes obtained in step 4. The weighting of the RCs will be determined by the utility based on the relative importance of the treatment processes for NOM reduction/removal.

5.3.2.6. Step 6: Adaptation- exploring options to improve plant robustness

The adaptation step identifies potential short-term operational responses a utility can make to increase robustness of treatment processes to meet the utility's NOM treatment objectives (Table 5.4).

Table 5.4: Critical treatment processes and potential operational responses relating to NOM reduction/removal

Critical step	Potential operational responses
Intake	• Addition of PAC
Coagulation	• Coagulant dose • Coagulant type • pH adjustment for enhanced coagulation • Additional chemicals such as coagulant aid • Addition of PAC post CFS, before filtration
Biological filtration	• Use of filter aid • Decrease in filtration rate • Increase in backwash frequency
Membrane filtration	• Change in permeate flux • Change in transmembrane pressure
Oxidation	• Change in oxidant dose and type
Ion exchange	• Increase in regeneration frequency
Adsorption	• Increase in contact time (decrease in flowrate) • Increase in regeneration frequency

5.3.3. Application of the NOM robustness framework to a full-scale DWTP

5.3.3.1. Steps 1-3: Selection, Identification, Criteria

To demonstrate the application of the organic matter robustness framework, Plant B on Lake Huron, Ontario, Canada was chosen. Plant B source water typically has a low DOC (<2 mg C/L). A few times per year, storm events with higher turbidities (>10 NTU) are experienced, which are operationally challenging and even resulted in a plant shutdown in 2009. Since then, Plant B has been conducting routine storm water sampling and analysis to understand raw water changes and challenging operational conditions. While DOC during these storm events has been below 3 mg C/L, elevated color levels (up to 1400 TCU) and low UVT (as low as 40%) have been reported,

which may cause operational challenges in the future (Plant B storm water sampling data, 2010-2020).

NOM was identified as a WQP of interest for robustness assessment as the plant was interested in exploring challenging future raw water conditions due to increased storms. CFS was identified as the critical process. Plant B does not have any specific treatment goals for DOC, UV or any other NOM surrogate parameter, as finished water DOC is typically very low. Both DOC and UVT were chosen as surrogate parameters for the assessment. Criteria were set at 2 mgC/L for DOC and 90% for UVT based on Health Canada (2020) guidelines (Health Canada, 2020). THMs were monitored to comply with the regulatory standard of 100 µg/L (O. Reg. 169/03).

5.3.3.2. Step 4: Evaluation

Of the processes in plant B, only CFS could potentially removing NOM and was therefore evaluated. However, influent raw water and post filtration water were also considered to gauge the sensitivity of the OMRI index and assess any changes after each treatment process. TRI could not be used to quantify DOC removal robustness, as DOC data were too limited for TRI calculations, and UV_{254}, which could have provided sufficient data, was not correlated to DOC, and therefore not a suitable surrogate for DOC (Figs. C.3, C.4, C.5, Table C.2). As a result, only OMRI was selected for quantifying NOM robustness of treatment processes, since it requires a lot less data and gauges several aspects of NOM removal simultaneously.

The three terms chosen for OMRI evaluation at plant B were DOC for overall performance, UVT for impact on disinfection and THMFP for the regulatory term. While UV disinfection is currently not employed, it was selected to represent its potential use in the future and to demonstrate the OMRI application with all three terms. Therefore, equation 1 was modified to:

$$\boldsymbol{OMRI} = \frac{\left(w_1 \frac{\boldsymbol{DOC}}{\boldsymbol{Goal\ DOC}} + w_2 \frac{\boldsymbol{100 - UVT\ at\ 254\ nm}}{\boldsymbol{100 - Goal\ UVT\ at\ 254\ nm}} + w_3 \frac{\boldsymbol{THMFP}}{\boldsymbol{Goal\ THMFP}}\right)}{w_1 + w_2 + w_3}$$

Due to the lack of historical peaks in the collected data, scenarios 1 (normal range) and 2 (historical peaks) could not be evaluated separately. Four weighting cases were considered for the OMRI to gauge index sensitivity and to demonstrate potential variations of the weighting approach. For all four cases, the OMRI of the critical process CFS was found to be in the ‘very

stable' and 'stable' categories (Fig. 5.2). The filtration OMRI was found to be essentially the same as the CFS OMRI, since organics removal is not expected in rapid filtration (Table C.4, SI5). The raw water OMRI changed not only over time (Fig. 5.2a, Table C.3) but also based on the weighting criteria, with case 3 and case 4 being the worst and best OMRI cases, respectively (Fig. 5.2b). This could be because UVT of the raw water was quite low for certain weeks, leading to a higher OMRI when UVT was weighted higher (case 3). However, the THMFP was still below the regulated value, leading to a lower OMRI, when THMFP was weighted higher (case 4) (Fig. 5.2b).

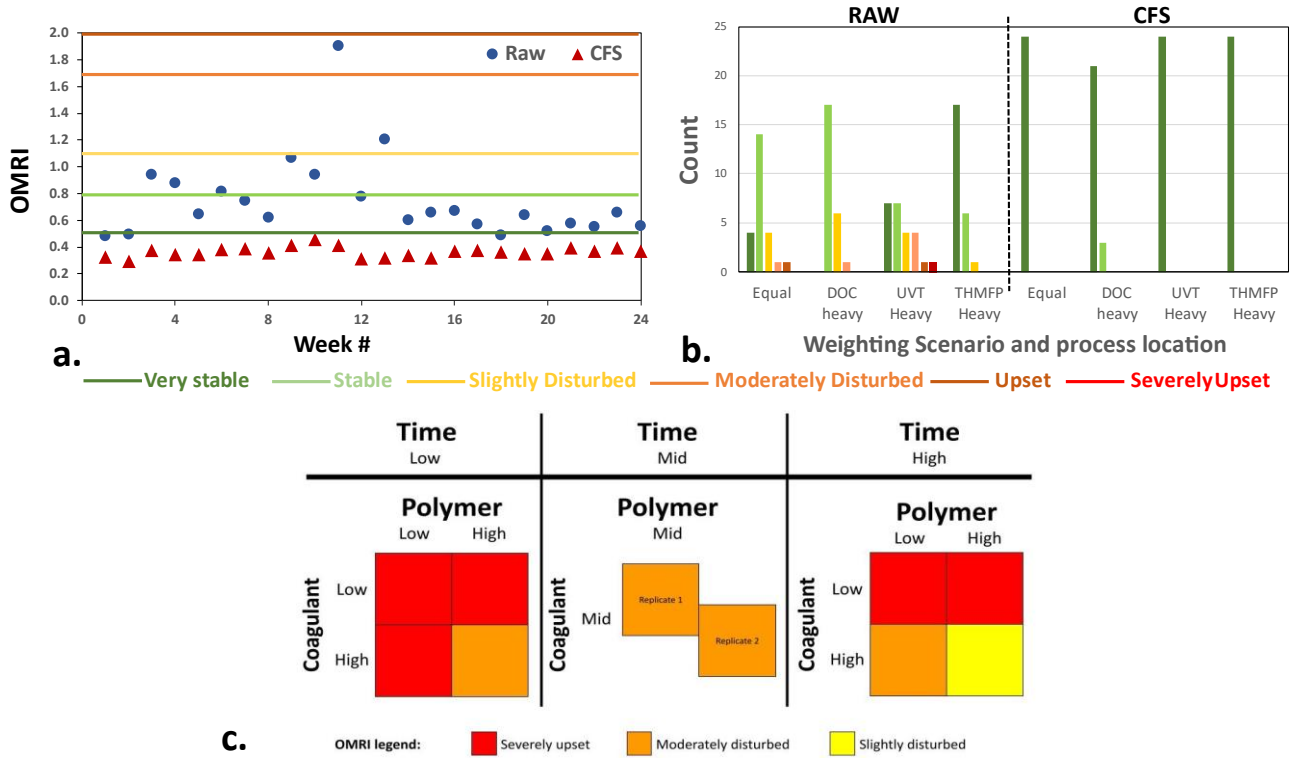


Figure 5.2: OMRI evaluation of collected data (scenarios 1 and 2) of raw water and the CFS process with a) equal term weighting; b) comparison of four different weighting approaches: case 1 with equal weighting for all three parameters, case 2 with 5x relative weight for DOC term, case 3 with 5x relative weight for UVT term, and case 4 with 5x relative weight for THMFP term; c) OMRI values (equal weighting of the terms) for factorial design experiments assessing three factors at two levels: coagulant dose (35 and 70 mg/L), polymer dose (0 and 0.6

mg/L), settling time (5 and 15 minutes) and two mid-point replicates (coagulant 52.5 mg/L, polymer 0.3 mg/L, and settling time 10 minutes)

The initial evaluation of extremely high NOM values (scenario 3), testing plant B's current CFS regime in bench-scale jar tests showed that a raw water DOC of 8 mgC/L was the threshold beyond which all three WQP criteria were exceeded, resulting in OMRI values of 3.8 and higher. Accordingly, the initial raw water DOC for the step 6 (adaptation) experiment was set to 8 mgC/L (Fig. C.6).

5.3.3.3. Steps 5-6: Assessment and adaptation

The overall robustness of plant B is the same as the CFS robustness (OMRI), as CFS is the sole critical process. For the adaptation step, three potential operational changes i.e., increase in coagulant dose, addition of polymer and increase in settling time were evaluated in bench-scale jar tests using a two-level factorial design with a replicated midpoint. Enhanced floc formation was evident when polymer was introduced. The ANOVA analysis for the three response variables (DOC, UVT, and THMFP) indicated significant effects of coagulant dose, polymer dose, and settling time on UVT (α=0.05). For DOC, the coagulant and polymer doses demonstrated significance, while none of the factors were significant for THMFP (Table C.6). This was further confirmed by the OMRI values of the different combinations of the three factors (Fig. 5.2c, Table C.7). While most of the OMRIs lie in the 'upset' and 'severely upset' categories, the case with high coagulant dose and high polymer dose shows improvement, and for high values of all three factors it moves to 'slightly disturbed'.

5.4. Discussion

This study for the first time explores TRI application to WQPs other than turbidity, showcasing the potential use of the statistical metric for NOM surrogates and by extension for other WQPs relevant for robustness estimations. Since TRI calculations incorporating percentiles span over a certain time-period, a sufficiently large dataset is required to generate one TRI value and subsequently enough values to estimate process robustness. The newly developed OMRI is a comprehensive tool to quantitatively assess NOM robustness of treatment processes, while addressing the complexity of NOM and its effects on treatment. OMRI can be calculated for

single data points in time, overcoming the constraint with TRI when applied to smaller datasets. Additionally, it can also be used to evaluate extreme NOM (scenario 3), which was not possible with TRI. TRI and OMRI are both key tools within the NOM robustness framework with either of them being suitable for robustness evaluations. The choice of the method depends on data availability at a DWTP and the scope of the NOM-related treatment goals.

The overall robustness framework introduced previously (Nemani et al., 2023) was tailored to NOM with relative ease, showing the flexibility of the framework. When applying the NOM framework to a DWTP, TRI was assessed as a possible tool to quantify DOC removal robustness of treatment processes but could not be used due to lack of data. Instead, the OMRI introduced in this research was tailored to a utility's needs and was shown to capture changes in NOM-related WQPs. Overall, Plant B's CFS operational regime is robust for typical NOM ranges, but might fail during higher incoming DOC values. While increasing the coagulant dose and addition of polymer as a coagulant aid were shown to increase treatment robustness during simulated extreme NOM conditions in bench-scale tests, detailed process optimization is required to ascertain the requisite dosage and feasibility of these adaptation options, as would be the case in any treatment plant. Even though the OMRI application within the NOM robustness framework was done with only a 6-month data set and a single DWTP, it shows potential as a quantitative method that can effectively encompass the different impacts of NOM on water treatment.

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6. Chapter 6

6.1. Summary of findings

The main goal of this research was the development of a robustness assessment framework to help DWTPs in the evaluation and improvement of their treatment process robustness in preparation for adverse source water quality changes. Specifically, the study centered on two critical WQPs — turbidity and natural organic matter (NOM), showcasing the development and application of robustness frameworks that can evaluate robustness quantitatively and provide avenues for targeted improvement of treatment processes.

This research contributes significantly to filling several key research gaps identified in Chapter 2, enhancing the understanding and practical application of robustness in drinking water treatment. Firstly, it introduces a comprehensive robustness framework that specifically targets managing water quality during extreme weather events, a dimension overlooked in prior resilience frameworks. Additionally, it emphasizes the use of quantitative metrics for assessing robustness, a feature lacking in previous frameworks. These metrics allow for a more objective comparison of four treatment plants, establishing a common baseline for evaluation. Secondly, the research expands the scope of the previously developed robustness metric, TRI, to encompass all relevant treatment processes involved in turbidity removal, including CFS, intake reservoirs, and filtration, as well as over a longer evaluation period of two years. Previously, TRI had primarily been applied to filtration processes and spanned over short periods.

Thirdly, this thesis broadens the evaluation of robustness beyond turbidity to include NOM, another critical water quality parameter for DWTP operation. By extending the robustness evaluation to NOM, this research addresses a significant gap in the literature. Lastly, the research tackles the absence of quantitative robustness metrics for NOM evaluation by introducing OMRI and proposing an alternative evaluation approach using TRI. This not only enhances the comprehensiveness of robustness assessment for NOM but also provides a more holistic understanding of the challenges and solutions in drinking water treatment.

A detailed summary of findings corresponding to the research objectives is given below:

1. Anthropogenic climate change is a driver for intensified extreme weather events and for disruptions in the hydrological cycle. These alterations manifest as deteriorating water quality characterized by sudden and substantial fluctuations in turbidity and NOM levels in surface waters. Given the pivotal roles of turbidity and NOM in DWTP operations, their adverse effects extend across various treatment processes, influencing overall drinking water quality. Effectively managing turbidity and NOM during extreme weather conditions emerges as a critically important task for utilities to safeguard the integrity of their water treatment processes, as has been detailed in chapter 2A. (Objective 1: To understand the impacts of extreme weather events on turbidity and NOM in surface waters and its subsequent repercussions on DWTP operations).

2. Robustness is at the core of enhancing performance and furthering climate adaptation efforts of DWTPs, and is closely related to resilience, reliability, risk, and vulnerability. The improved understanding of robustness and related terms from a drinking water treatment context outlined in chapter 2B can help utilities aim for a holistic approach to extreme weather adaptation. This becomes particularly pertinent in current times in both North America and worldwide, where the impacts of extreme weather events are increasingly affecting DWTPs. (Objective 2: To explore robustness and related concepts such as resilience, reliability, risk, and vulnerability in the context of drinking water treatment).

3. The newly developed robustness framework presents a practical and systematic approach to evaluate robustness of individual treatment processes and the overall plant robustness with respect to a WQP for several raw water quality scenarios. Conducting a quantitative evaluation of the current plant's robustness offers valuable insights into vulnerabilities and critical points within the treatment process. These insights, in turn, serve as a valuable foundation for targeted improvements and strategic process modifications. The framework exhibits flexibility and adaptability, accommodating various WQPs, including those not specifically explored. It can seamlessly be tailored to suit the specific needs and characteristics of any DWTP. (Objective 3: To develop a general robustness assessment framework which can be tailored to any water quality parameter and DWTP)

4. The turbidity robustness framework provides a systematic approach with stepwise instructions for evaluating individual treatment robustness using turbidity robustness index

(TRI) and the overall plant robustness using the ORI. While the individual process TRIs provide detailed analyses of process robustness and pinpoint specific durations of low robustness, the ORI can be used to provide a bird-eye's view when drawing conclusions about a plant's overall robustness, and be used for further planning. This methodology can be applied to critical treatment processes relevant for turbidity reduction/removal and can be extended seamlessly over any chosen duration, allowing DWTPs the flexibility to apply it across multiple years of data. In addition, the methodologies presented for simulation of extreme turbidities at bench scale also provide DWTPs with the avenue of exploring treatment effectiveness at extremely high turbidities, which may be encountered during extreme weather events. (Objective 4: To develop and apply a turbidity framework which provides specific quantitative tools for robustness evaluation and comprehensively explores robustness assessment and improvement).

5. The turbidity robustness framework also serves as an excellent foundation for comparing DWTPs at different locations, with different source waters and different treatment schemes, as illustrated by the comparison of the robustness assessment of 4 DWTPs. The decision tree further provides useful tools to transform information into action, enabling the implementation of insights gained from the robustness assessment. (Objective 5: To compare the turbidity framework application outcomes of four full-scale DWTPs and develop a decision support framework that incorporates the results of the framework into an action roadmap with both short-term operational strategies and long-term adaptation options).

6. Two distinct approaches for quantitatively evaluating NOM robustness were introduced: the first involved extending TRI usage to NOM surrogate parameters, while the second introduced the newly developed index, organic matter robustness index (OMRI). The application of TRI to WQPs other than turbidity is a novel exploration, displaying promising potential for DWTPs with routine monitoring data of NOM surrogate parameters. OMRI, on the other hand, overcomes limitations posed by limited data sets, offering a more comprehensive treatment of NOM's complexity and its impact on various treatment processes. The three components of OMRI can be customized to align with a plant's specific treatment scheme, NOM data availability, and NOM related treatment objectives. Additionally, OMRI is shown to be adaptable for assessing extreme NOM scenarios

simulated at bench-scale. (Objective 6: To develop a robustness evaluation methodology for NOM, including a new quantitative robustness index).

7. The NOM-specific framework incorporating the two robustness evaluation approaches rounds up all the steps in the framework for a complete robustness evaluation and assessment of a DWTP. It also demonstrates the extreme NOM evaluation for CFS at bench-scale and potential short-term adaptation options such as increasing coagulant dose, settling time and introduction of a polymer. (Objective 7: To develop and apply a NOM framework which incorporates the new robustness metrics).

Some general findings and conclusions from the research are:

- Quantitative robustness metrics like TRI, ORI, and OMRI provide a comprehensive understanding of a DWTP's current robustness status, offering detailed insights into both specific treatment processes and overall plant performance. While routine metrics such as filter indices and percentage removals, commonly monitored by plants, offer valuable information about treatment performance, an assessment using these robustness indices allows a plant to contextualize its performance across various raw water quality scenarios, seasons, and source water conditions, potentially over multiple years. This data mining process and comprehensive assessment using robustness metrics yield valuable insights into the performance of different processes, particularly under challenging raw water quality scenarios. Integrating this information with operational data paints a clear picture of the plant's robustness across diverse raw water quality scenarios.

- Evaluating extreme raw water qualities at bench-scale and testing the effectiveness of plant operational regimes, as demonstrated in scenario 3, presents a unique approach. This method offers a valuable tool for a DWTP to plan for various "what-if" scenarios. Despite the limitations of bench-scale tests, these straightforward approaches can help establish protocols for addressing such scenarios if they materialize. For instance, the research outcomes for Plant B revealed improved settled water quality with the introduction of a polymer as a coagulant aid, sparking interest among plant personnel for future planning and optimization studies. It is also advisable for plants with pilot testing capabilities to consider conducting similar experiments at the pilot scale as the next step.

- In evaluating all DWTPs in this study, filters demonstrated high robustness concerning both turbidity and NOM, as evidenced by historical data in scenarios 1 and 2. The regulated turbidity in filtered water contributes to this robust performance, and although NOM lacks regulation, its control, especially for membrane filters, is prioritized. Instances of low overall robustness were attributed to CFS, underscoring the importance of the process, which serves as the first line of defense in most treatment plants with conventional as well as advanced treatment. There is also more flexibility in changing CFS operations and controlling the settled water turbidity and NOM such that the filters can continue functioning optimally even during extreme raw water qualities. Therefore, planning and establishing protocols for changing CFS operations during extreme weather events can prove to be very useful for climate change adaptation plans.
- Collaborating with plant operators during the development or implementation of any robustness framework is essential for customizing its application to a specific DWTP. Plant personnel possess inherent and profound knowledge of their drinking water treatment system, often intuitively understanding potential vulnerabilities that may result in operational challenges, particularly during adverse raw water quality conditions. It is crucial to leverage this system knowledge and validate subjective insights with objective information from the robustness assessments to ensure that appropriate actions can be effectively mobilized.

6.2. Impact and limitations

The impact of this research on studies beyond this thesis are described below:

1. The turbidity robustness framework developed in chapter 3 has since been applied to two other full-scale DWTPs by Reza (2022) in her master's thesis.
2. The turbidity and NOM frameworks are currently being applied to two full-scale DWTPs in Alberta, Canada. Both DWTPs have historically faced extreme turbidity and NOM (measured as color) during spring run-off, extreme rainfall and floods, and currently want to evaluate and improve their treatment robustness. This work is being done in collaboration with the author and supervisors Dr. Huck and Dr. Peldszus.

As with any scientific research, the research presented in this thesis are not without limitations, some of which are highlighted below:

- The final adaptation step (step 6: adaptation) was only applied to one critical treatment process, CFS, for both turbidity and NOM frameworks due to time constraints and scope of the current research. Designing bench-scale and pilot scale experiments for other critical treatment steps such as filtration in addition to CFS will help in further understanding operational limitations of the treatment processes at both plants A and B, and any other plants evaluated in the future.

- Simulation of extreme turbidity was done primarily using a surrogate such as kaolin. Similarly, for NOM simulations, Suwannee River NOM, which, while being a natural product, does not accurately represent the exact NOM profile of the raw water of the DWTP evaluated in this study. While both these methods were sufficient for demonstrating the adaptation step of the turbidity and NOM frameworks, other more representative methods such as sediment (as shown for Plant A) or actual storm water could be more beneficial.

- Conclusions about scenario 3, extremely high turbidity and NOM in raw water, are discussed within the limitations of bench-scale experiments. While there is value and need for such experiments to get an initial understanding of the treatment limits, exact optimization of dosages for high raw water quality ranges requires further bench-scale testing and potentially pilot scale experiments.

- The ORI is a simple index representing overall plant robustness, incorporating individual process robustness scores. However, the weights assigned to each critical process for the ORI calculation is dependent on the decision made by the utility conducting the assessment and can change the overall plant robustness assessment. These weights, therefore, must be chosen carefully, preferably after a sensitivity analysis to make sure that the weight assignment is not arbitrary and does not bias the overall outcomes.

- Application of TRI to suitable NOM surrogates, while illustrated conceptually, could not be applied to actual full-scale DWTP data due to limitations of the data set at Plant B (chapter 5). To fully demonstrate this methodology, additional research is warranted at a different plant, where comprehensive NOM surrogate data is available.

- The OMRI and NOM framework was only applied to one DWTP with data collected over a six-month period. Continuing water quality monitoring to extend these results as well as application to other DWTPs, especially ones that have a historic record of challenging raw water NOM, would enhance comprehensiveness of these findings and emphasize the index's applicability.

6.3. Future directions and implications for the water treatment industry

The robustness frameworks introduced in this study are anticipated to make substantial contributions to understanding current levels of treatment robustness and preparing DWTPs for the impacts of future climate change. Ongoing refinement of the turbidity and NOM frameworks, coupled with their expanded application to additional DWTPs, holds the potential to persuade a growing number of utilities to apply robustness assessments to their treatment systems. Several avenues for future research in this domain are described below:

- The general robustness framework and the two parameter-specific frameworks for turbidity and NOM can be easily implemented to DWTPs not just in Canada, but to any DWTP in the world. Both turbidity and NOM frameworks were seen to be flexible and adaptable to DWTPs of different sizes, source waters and treatment schemes, highlighting their potential to be adopted across different countries.

- Employing the procedures and methodologies developed in this research, it is feasible to formulate parameter-specific robustness frameworks for WPQs such as microbiological indicators, cyanotoxins and other pollutants such as microplastics. This extends the application of robustness assessments beyond those directly influenced by extreme weather events, encompassing broader WQPs of general concern.

- Looking ahead, exploring new robustness metrics for assessing the robustness of drinking water treatment processes to different WQPs or refining the existing indices introduced in this research is on the horizon. It is worth noting that the robustness indices used in this thesis and any new indices developed in future are designed for DWTPs as the primary end-users.

Therefore, keeping the indices and their application straightforward will be pivotal for broader application of robustness evaluations in future.

- The robustness frameworks outlined in this thesis hold the potential to evolve into user-friendly software packages, facilitating convenient download and presenting information in a format suitable for tabletop exercises. This mode of accessibility is envisioned to be more user-friendly for DWTPs compared to traditional academic journal articles.

- Numerous utilities have established water quality management plans and regularly perform performance tests, including capacity/stress testing. Integrating the robustness assessment frameworks into these existing plans can seamlessly enhance the utility's routine performance assessments. By becoming an integral component of the ongoing evaluation processes, these frameworks offer a valuable tool for utilities to improve their robustness and readiness to address climate-related challenges, aligning with the broader objectives of proactive water quality management.

- An essential avenue for advancing this research lies in the integration of the robustness assessment framework into policy guidance documents. Notably, the past five years have witnessed significant growth in this domain, with federal and provincial governments introducing new policies geared towards enhancing the resilience of critical infrastructure. One notable example is the American Water Infrastructure Act of 2018 (AWIA), which underscores the importance of developing resilience of critical water infrastructure (such as DWTPs) for natural disasters, emergencies, and climate change. It requires DWTPs to conduct risk assessments and prepare emergency response plans as part of enhancing resiliency. Other examples include Canada’s National Adaptation Strategy, climate adaptation plans developed by individual provinces and the Public Infrastructure Engineering Vulnerability Committee (PIEVC) protocol developed by Engineers Canada and Natural Resources Canada. The tools recommended by entities like the U.S. EPA and the PIEVC protocol primarily focus on risk and vulnerability assessments and resilience enhancement of infrastructure, often overlooking specific aspects related to extreme weather raw water quality management. The robustness frameworks proposed in this research can fill this gap, serving as a valuable addition to existing frameworks. By seamlessly integrating the frameworks developed in this research into established approaches, such as those outlined by

the U.S. EPA and PIEVC, a more comprehensive and holistic climate change adaptation strategy can be achieved.

- There is also potential for extending the applicability of the six steps and the methodology of the general robustness framework to fields beyond drinking water treatment, including wastewater treatment, resource recovery, environmental remediation, and various other sectors, where the robustness and performance of critical infrastructure systems are of paramount importance.

6.4. Publications and presentations

- Peer-reviewed publication:

Chapter 3: Nemani, K. S., Peldszus, S., & Huck, P. M. (2023). *Practical Framework for Evaluation and Improvement of Drinking Water Treatment Robustness in Preparation for Extreme-Weather-Related Adverse Water Quality Events.* ACS ES&T Water, 3(5), 1305–1313. https://doi.org/10.1021/acsestwater.2c00627

Chapter 5: Nemani, K. S., Peldszus, S., & Huck, P. M. *Assessing Drinking Water Treatment Robustness: Development and Application of an Organic Matter Robustness Index*. Submitted to ACS ES&T Water (2024). Manuscript ID: ew-2024-00218s.

- Conference presentations:

Nemani, K.S., Peldszus, S., Self, J., Bryans, B., Huck, P. M. (Nov 5-9, 2023). *Navigating Natural Organic Matter (NOM) Treatment During Extreme Weather: Building Robustness.* AWWA Water Quality Technology Conference (WQTC), Dallas, Texas, USA.

Nemani, K.S., Peldszus, S., Huck, P. M. (Jun 1-3, 2023). *Extreme weather adaptation of drinking water treatment plants: A framework to evaluate and improve operational robustness.* IWA Young Water Professional Conference, Vancouver, British Columbia, Canada.

Nemani, K.S., Peldszus, S., Huck, P. M. (Jun 6-9, 2022). *A framework for evaluating and improving robustness of drinking water treatment plants during extreme weather-related turbidity spikes.* Canadian Water Resource Association National Conference, Canmore, Alberta, Canada.

Nemani, K.S., S. Peldszus, and Huck, P. M. (May 2-4, 2022). *Robustness in Drinking Water Treatment Systems to Manage Turbidity Related Water Quality Upsets During Extreme Weather.* Ontario's Water Conference & Trade Show, Niagara Falls, Canada.

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Appendices

A. Appendix A

Supporting Information for Chapter 3

1. Turbidity Robustness Index (TRI) theory

The TRI equation consists of two terms: the first is a measure of the uniformity of turbidity performance over a specific duration (single filter run or a time specific period), while the second term indicates the overall filter performance. An ideal TRI value for the originally developed index (1) would be equal to 1, indicating that a filter is always able to meet its turbidity goal and with minimal deviation. TRI values >1 indicate unstable filter operation or low robustness. The TRI can be used for different percentiles of turbidity in the filter effluent such as 90, 95 and 99 percentiles.

This index was further improved by (2) by developing a system to assign weights to the two terms in the TRI equation (Eq. SI1) which was used in the turbidity robustness calculations. This is done by an initial robustness assessment, W, of the filter effluent turbidity data for a filter run for turbidity values above the 50th percentile and a comparison with a reference value, N= 50 (Eq. SI2). Based on the results of this assessment, weights A1 and A2 for the two TRI terms were assigned using the decision process shown in Table A.1. The higher and lower values were chosen as 0.9 and 0.1 respectively for A1 and A2. The modification also included multiplying the index by 100 to give a value that could be more easily related to.

Equation SI1:
$$TRI_{90} = \left[A_1 \frac{T_{90}}{T_{50}} + A_2 \frac{T_{50}}{T_{goal}}\right]$$

TRI_{90} = Turbidity Robustness Index for 90th percentile turbidity

T_{50} = Median filter effluent turbidity

T_{90} = 90th percentile filter effluent turbidity

T_{goal} = Turbidity performance goal

Equation SI2: $$W = \left[\frac{T_{50}}{T_{goal}} + \frac{T_{60}}{T_{goal}} + \frac{T_{70}}{T_{goal}} + \frac{T_{80}}{T_{goal}} + \frac{T_{90}}{T_{goal}}\right] \times 10$$

Table A.1: Decision process for selecting weights A1 and A2

Case	System Designation	Comparison of N and W	If	Then
1	robust	W is lower than or equal to N	$\frac{T_{90}}{T_{50}} \leq \frac{T_{50}}{T_{goal}}$	$A_1 > A_2$
2			$\frac{T_{90}}{T_{50}} > \frac{T_{50}}{T_{goal}}$	$A_1 < A_2$
3	less robust	W is higher than N	$\frac{T_{90}}{T_{50}} \leq \frac{T_{50}}{T_{goal}}$	$A_1 < A_2$
4			$\frac{T_{90}}{T_{50}} > \frac{T_{50}}{T_{goal}}$	$A_1 > A_2$

The classification of system operation with respect to robustness based on the TRI values is shown in Table SI2 (2). The classification categories were developed based on a statistical analysis of the TRI ranges by relating them to effluent turbidity ranges (3). For example, a TRI < 60 ('very stable' category) indicates that the upper turbidity percentile (T_{50} – T_{90}) of the effluent turbidity was almost half of the T_{goal} for the entire duration of the assessment. On the other hand, a TRI > 200 will only be obtained when T_{50} – T_{90} is more than double the $T_{goal,}$ indicating that the system never produces water of desirable quality for the entire duration of the analysis.

Table A.2: Classification of system operation for interpretation of TRI

Class of system operation quality	**Robustness index value**
Very Stable	<60
Stable	60-100
Slightly disturbed	100-130
Moderately disturbed	130-160
Upset	160-200
Severely upset	>200

1.2. Sample TRI calculation

The following shows a sample calculation for a random filter run taken from Plant B data.

Based on the filter data, the following values were obtained:

Tgoal	0.1
N	50
W	13
T90/T50	1.1
T50/Tgoal	0.2
A1	0.1
A2	0.9
TRI90	33

Based on the TRI theory discussed above, the following steps are followed to calculate TRI:

Step 1: Calculate W, which is 13 in this case.

Step 2: Compare with N=50. We find that N>W, representing case 1 or 2 from table A.1.

Step 3: Compare T90/T50 and T50/Tgoal. In this case, T90/T50 is greater than T50/Tgoal, thereby representing case 2 in table A.1.

Step 4: Decide A1 and A2. Since A1 is less than A2 as per table A.1, A1=0.1 and A2=0.9, and the final TRI value obtained was 33.

2. Plant-specific framework: plant A additional information

2.1. Plant A treatment scheme, critical processes, data collection points

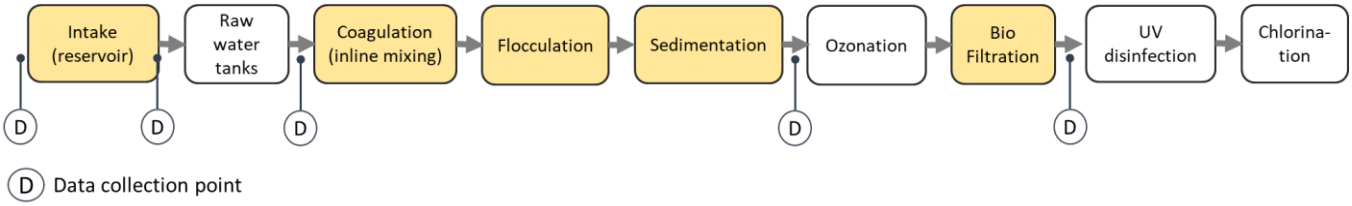


Figure A.1: Plant A treatment scheme with critical processes highlighted in yellow and data collection points represented with ‘D’

2.2. Plant A data analysis information

2.2.1. MATLAB® codes for identifying invalid data points and analysis

- Function for TRI calculation

```
function tri = TRI(turb)
    tgoal = 0.1;
    term1 = prctile (turb,90)/prctile (turb, 50);
    term2 = prctile (turb, 50)/tgoal;
    N = 50;
    W = ((prctile(turb,90)+prctile (turb, 80)+ prctile (turb, 70) + prctile (turb,
60) + prctile (turb, 50))/tgoal)*10;
    if(W<=N)
        if (term1<= term2)
            A1=0.9;
            A2=0.1;
        else
            A1=0.1;
            A2=0.9;
        end
    else
        if (term1<= term2)
            A1=0.1;
            A2=0.9;
        else
            A1=0.9;
            A2=0.1;
        end
    end
    tri = (A1*term1 + A2*term2)*100;
end
```

- Function for weekly TRI calculation

```
%weekly TRIs calculation
function [startDates, tris, avgturb] = WeeklyTri(dateList, turb)
    startDates = [];
    tris = [];
    avgturb = [];
    rowFrom=1;
    f = waitbar(0, 'Starting');
for i=1:length(turb)
        waitbar(i/length(turb), f, sprintf('Progress: %d %%',
floor(i/length(turb)*100)));
            if (weeknum (dateList(i)) ~= weeknum (dateList(rowFrom)) )
                startDates = [startDates string(datestr(dateList(i, :), "YYYY mm
DD"))];
                a= TRI (turb(rowFrom:(i-1)));
```

```
                avgturb= [avgturb, mean(turb(rowFrom:(i-1))),];
                tris = [tris, a,];
                rowFrom = i;
            end

end
```

- Function for identifying invalid data points in intake and filtration data

```
%Cleaning for intake and filtration

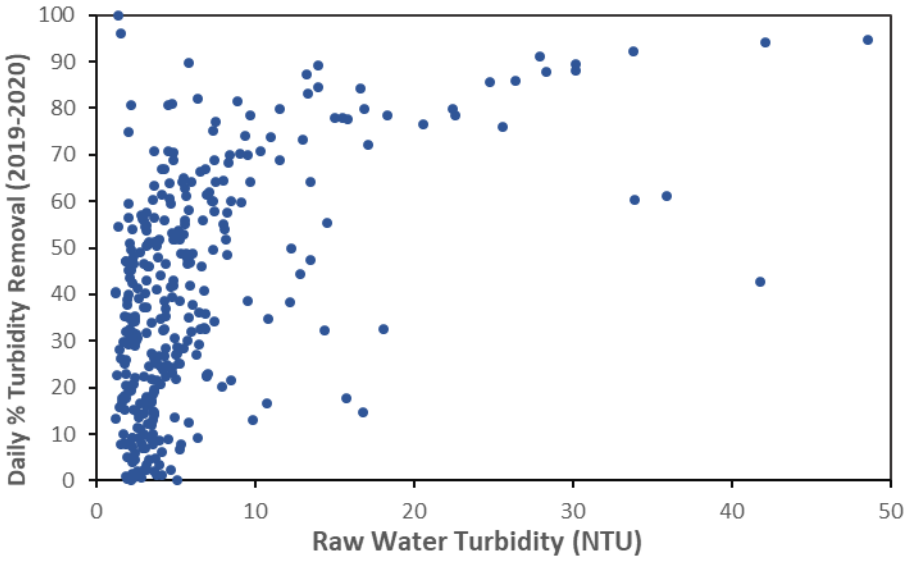
function [startDates,t] = Clean1 (dateList, flowRate, turb)
flowRateThresh = 1;
startDates = [];
t = [];
for i=1:length(turb)
        if(flowRate(i)>flowRateThresh)
        startDates = [startDates string(datestr(dateList(i, :), "YYYY mm DD"))];
        a= turb(i);
        t = [t, a,];
        end
end
```

- Function for identifying invalid data points in CFS data

```
%Cleaning for Coag-floc-sed

function [startDates,t] = Clean2 (dateList, flowRate, turb)
flowRateThresh = 100;
startDates = [];
t = [];
%turbidity sudden outlier removal
[~, outlierIndexTurb] = hampel (turb,10);
turb = turb(~outlierIndexTurb);
dateList = dateList(~outlierIndexTurb);
flowRate = flowRate (~outlierIndexTurb);
%flowrate outlier removal
[~,outlierIndexFlow] = hampel (flowRate, 10);
turb = turb(~outlierIndexFlow);
dateList = dateList(~outlierIndexFlow);
flowRate = flowRate (~outlierIndexFlow);
for i=1:length(turb)
        if((flowRate(i)>flowRateThresh) && (turb(i)<8))
        startDates = [startDates string(datestr(dateList(i, :), "YYYY mm DD"))];
        a = turb(i);
        t = [t, a,];
        end
end
end
```

2.2.2. Scenarios 1 and 2 evaluations (historical data)



- Figure A.2: Daily % removal vs. raw water turbidity for two-year historical data (2019-2020) at the intake (reservoir). Higher %removals were seen for the higher raw water turbidity range (>20 NTU)

- Table A.3: Daily average turbidities for week 14 and 21

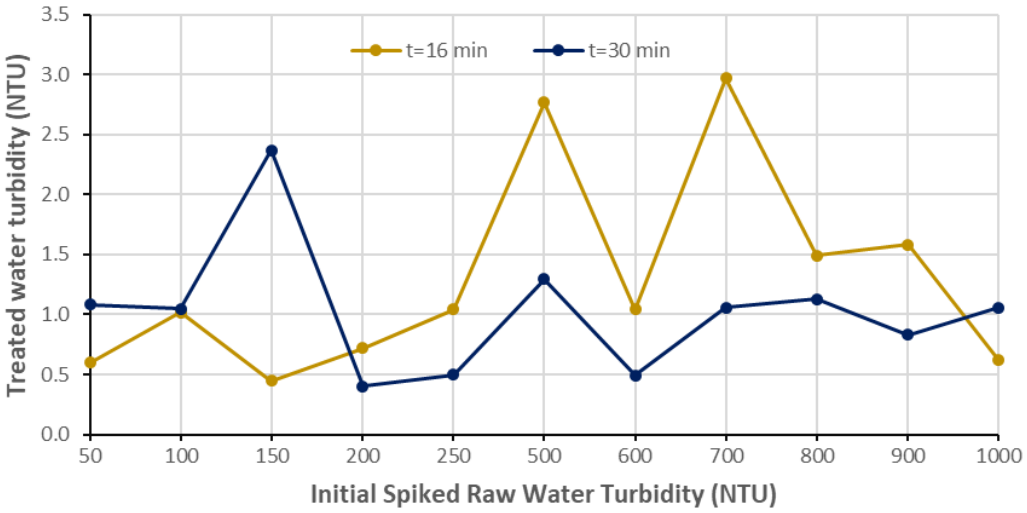
Day #	Week 14 daily avg effluent turbidity (NTU)	Week 21 daily avg effluent turbidity (NTU)
1	3.2	3.0
2	3.2	2.5
3	3.7	3.1
4	2.9	2.3
5	2.2	0.5
6	2.1	0.4
7	1.6	0.3

2.2.3. Scenario 3 evaluation (extremely high turbidity)

- Table A.4: Jar test procedure for flow of 400-500 L/s as specified by Plant A operations

Mixing	RPM	Time (min)

Coagulation:	300	0.5
Flocculation:	70	2
	50	5
Polymer	50	2
	25	8
Settling:	0	16
		Total = 33



- Figure A.3 Jar test results with spiked raw water turbidities ranging from 50-1000 NTU at settling times 16 mins and 30 mins.

2.2.4. Scenario 1 & 2 overall plant assessment

- Table A.5: Relative importance and weights assigned to critical treatment steps

Critical treatment step	**Case 1 weights**	**Case 2 weights**	**Case 3 weights**	**Case 4 weights**	
				Raw water turbidity <25 NTU	**Raw water turbidity >25 NTU**
Intake reservoir	0.33	0.1	0.25	0.1	0.25
CFS	0.33	0.4	0.25	0.4	0.25

Filtration	0.33	0.5	0.5	0.5	0.5
Total Sum	1	1	1	1	1

- Table A.6: Overall Robustness Index (ORI) calculation data for Case 1 (equal weights for all critical processes)

Week Number	**Intake TRI**	**RC**	**CFS TRI**	**RC**	**Filtration TRI**	**RC**	**ORI**	**Overall system robustness**
1	21	1	38	1	45	1	1	Very stable
2	28	1	75	2	46	1	1	Very stable
3	24	1	28	1	43	1	1	Very stable
4	23	1	43	1	44	1	1	Very stable
5	20	1	39	1	44	1	1	Very stable
6	22	1	58	1	44	1	1	Very stable
7	78	2	37	1	43	1	1	Very stable
8	81	2	58	1	47	1	1	Very stable
9	28	1	58	1	45	1	1	Very stable
10	53	1	66	2	43	1	1	Very stable
11	33	1	77	2	46	1	1	Very stable
12	28	1	71	2	47	1	1	Very stable
13	59	1	62	2	44	1	1	Very stable
14	39	1	143	4	47	1	2	Stable
15	34	1	87	2	45	1	1	Very stable
16	27	1	77	2	46	1	1	Very stable
17	22	1	76	2	49	1	1	Very stable
18	25	1	57	1	54	1	1	Very stable
19	31	1	56	1	45	1	1	Very stable
20	23	1	77	2	50	1	1	Very stable
21	23	1	178	5	51	1	2	Stable

22	20	1	32	1	56	1	1	Very stable
23	31	1	59	1	64	2	1	Very stable
24	19	1	43	1	61	2	1	Very stable
25	30	1	31	1	64	2	1	Very stable
26	31	1	31	1	60	2	1	Very stable

- Table A.7: Overall Robustness Index (ORI) calculation data for Case 2 (low weight for intake, high weight for filtration)

Week Number	**Intake TRI**	**RC**	**CFS TRI**	**RC**	**Filtration TRI**	**RC**	**ORI**	**Overall system robustness**
1	21	1	38	1	45	1	1	Very stable
2	28	1	75	2	46	1	1	Very stable
3	24	1	28	1	43	1	1	Very stable
4	23	1	43	1	44	1	1	Very stable
5	20	1	39	1	44	1	1	Very stable
6	22	1	58	1	44	1	1	Very stable
7	78	2	37	1	43	1	1	Very stable
8	81	2	58	1	47	1	1	Very stable
9	28	1	58	1	45	1	1	Very stable
10	53	1	66	2	43	1	1	Very stable
11	33	1	77	2	46	1	1	Very stable
12	28	1	71	2	47	1	1	Very stable
13	59	1	62	2	44	1	1	Very stable
14	39	1	143	4	47	1	2	Stable
15	34	1	87	2	45	1	1	Very stable
16	27	1	77	2	46	1	1	Very stable
17	22	1	76	2	49	1	1	Very stable
18	25	1	57	1	54	1	1	Very stable

19	31	1	56	1	45	1	1	Very stable
20	23	1	77	2	50	1	1	Very stable
21	23	1	178	5	51	1	3	Slightly disturbed
22	20	1	32	1	56	1	1	Very stable
23	31	1	59	1	64	2	2	Stable
24	19	1	43	1	61	2	2	Stable
25	30	1	31	1	64	2	2	Stable
26	31	1	31	1	60	2	2	Stable

- Table A.8: Overall Robustness Index (ORI) calculation data for Case 3 (high weight for intake, high weight for filtration)

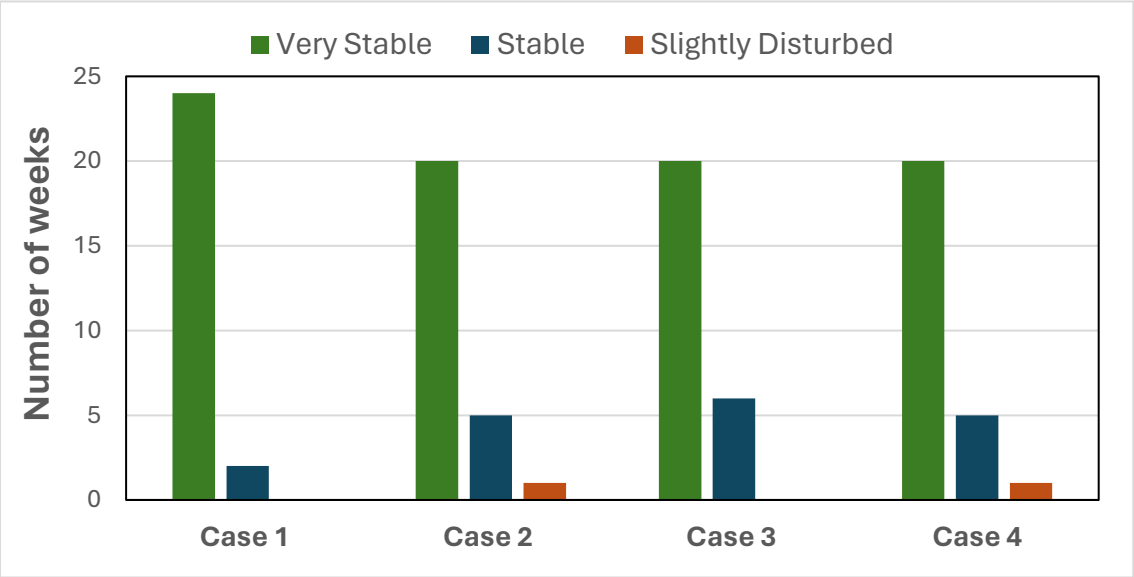
Week Number	**Intake TRI**	**RC**	**CFS TRI**	**RC**	**Filtration TRI**	**RC**	**ORI**	**Overall system robustness**
1	21	1	38	1	45	1	1	Very stable
2	28	1	75	2	46	1	1	Very stable
3	24	1	28	1	43	1	1	Very stable
4	23	1	43	1	44	1	1	Very stable
5	20	1	39	1	44	1	1	Very stable
6	22	1	58	1	44	1	1	Very stable
7	78	2	37	1	43	1	1	Very stable
8	81	2	58	1	47	1	1	Very stable
9	28	1	58	1	45	1	1	Very stable
10	53	1	66	2	43	1	1	Very stable
11	33	1	77	2	46	1	1	Very stable
12	28	1	71	2	47	1	1	Very stable
13	59	1	62	2	44	1	1	Very stable
14	39	1	143	4	47	1	2	Stable

15	34	1	87	2	45	1	1	Very stable
16	27	1	77	2	46	1	1	Very stable
17	22	1	76	2	49	1	1	Very stable
18	25	1	57	1	54	1	1	Very stable
19	31	1	56	1	45	1	1	Very stable
20	23	1	77	2	50	1	1	Very stable
21	23	1	178	5	51	1	2	Stable
22	20	1	32	1	56	1	1	Very stable
23	31	1	59	1	64	2	2	Stable
24	19	1	43	1	61	2	2	Stable
25	30	1	31	1	64	2	2	Stable
26	31	1	31	1	60	2	2	Stable

- Table A.9: Overall Robustness Index (ORI) calculation data for Case 4 (combination of high and low weights based on raw water turbidity)

Week Number	**Raw water turbidity (NTU)**	**Intake TRI**	**RC**	**CFS TRI**	**RC**	**Filtration TRI**	**RC**	**ORI**	**Overall system robustness**
1	7	21	1	38	1	45	1	1	Very stable
2	5	28	1	75	2	46	1	1	Very stable
3	4	24	1	28	1	43	1	1	Very stable
4	2	23	1	43	1	44	1	1	Very stable
5	3	20	1	39	1	44	1	1	Very stable
6	1	22	1	58	1	44	1	1	Very stable
7	26	78	2	37	1	43	1	1	Very stable
8	8	81	2	58	1	47	1	1	Very stable
9	5	28	1	58	1	45	1	1	Very stable
10	15	53	1	66	2	43	1	1	Very stable
11	3	33	1	77	2	46	1	1	Very stable

12	31	28	1	71	2	47	1	1	Very stable
13	14	59	1	62	2	44	1	1	Very stable
14	17	39	1	143	4	47	1	2	Stable
15	9	34	1	87	2	45	1	1	Very stable
16	6	27	1	77	2	46	1	1	Very stable
17	8	22	1	76	2	49	1	1	Very stable
18	10	25	1	57	1	54	1	1	Very stable
19	4	31	1	56	1	45	1	1	Very stable
20	3	23	1	77	2	50	1	1	Very stable
21	2	23	1	178	5	51	1	3	Slightly disturbed
22	3	20	1	32	1	56	1	1	Very stable
23	3	31	1	59	1	64	2	2	Stable
24	1	19	1	43	1	61	2	2	Stable
25	1	30	1	31	1	64	2	2	Stable
26	1	31	1	31	1	60	2	2	Stable



- Figure A.4: Sensitivity analysis of four weightage approach cases for Plant A ORI assessment. Case 1 weights: Intake=0.3, CFS= 0.3, Filtration= 0.3; Case 2 weights: Intake=0.1, CFS= 0.4, Filtration= 0.5; Case 3 weights: Intake=0.25, CFS= 0.25, Filtration=

0.5; Case 4 weights: same as case 2 for raw water turbidity <25 NTU and same as case 3 for raw water turbidity >25 NTU

2.2.5. Scenario 3 adaptation (extremely high turbidity)

- Table A.10: Levels and values of factors for factorial design experiment

Level	**Coagulant dose (mg/L)**	**Polymer dose (mg/L)**	**Settling time (min)**
-	30	0.3	16
0	45	0.45	23
+	60	0.6	30

- Table A.11: Factorial design experiment results

Factorial combination	**Final turbidity (NTU) t=16 min**	**Final turbidity (NTU) t=30 min**
(- -)	2.08	0.62
(+ -)	0.71	0.36
(- +)	0.96	0.58
(+ +)	0.53	0.63
Centre point (0 0)	0.81	
Centre point replicate (0 0)	1.13	

B. Appendix B

Supporting Information for Chapter 4

1. Plant B methodology additional details

1.1. MATLAB codes used for identifying valid data points from coagulation-flocculation-sedimentation (CFS) and filtration turbidity data

- Function for removing non-representative CFS data

```
function [startDates,turb] = CleanCFS (dateList, flowRate, turb)
%Cleaning for CFS_Plant B
flowRateThresh = 1;
flowRateThreshIndex = flowRate > flowRateThresh;
turb = turb(flowRateThreshIndex);
dateList = dateList(flowRateThreshIndex, :);
% flowRate = flowRate (flowRateThreshIndex);
startDates = [];
for i=1:length(dateList)
        startDates = [startDates; string(datestr(dateList(i, :), "YYYY mm DD"))];
end
```

- Function for removing filter backwash data

```
function [startDates,turb] = Clean1 (dateList, flowRate, turb)
%Cleaning for filtration_Plant B
flowRateThresh = 1;
%flowrate outlier removal
[~,outlierIndexFlow] = hampel (flowRate, 10, 2);
turb = turb(~outlierIndexFlow);
dateList = dateList(~outlierIndexFlow, :);
flowRate = flowRate (~outlierIndexFlow);
%flowrate threshold
```

```
flowRateThreshIndex = flowRate > flowRateThresh;

turb = turb(flowRateThreshIndex);

dateList = dateList(flowRateThreshIndex, :);

% flowRate = flowRate (flowRateThreshIndex);

startDates = [];

for i=1:length(dateList)

        startDates = [startDates; string(datestr(dateList(i, :), "YYYY mm DD"))];

end
```

- Function for Turbidity Robustness Index (TRI) calculation

```
function tri = TRI(turb)

%change tgoal according to the process and corresponding goal value

    tgoal = 0.1;

    term1 = prctile (turb,90)/prctile (turb, 50);

    term2 = prctile (turb, 50)/tgoal;

    N = 50;

    W = ((prctile(turb,90)+prctile (turb, 80)+ prctile (turb, 70) + prctile (turb,
60) + prctile (turb, 50))/tgoal)*10;

    if(W<=N)

        if (term1<= term2)

            A1=0.9;

            A2=0.1;

        else

            A1=0.1;

            A2=0.9;

        end

    else

        if (term1<= term2)

            A1=0.1;

            A2=0.9;

        else

            A1=0.9;

            A2=0.1;
```

```
        end
    end
    tri = (A1*term1 + A2*term2)*100;
end
```

- Function for calculating weekly TRIs

```
function [startDates, tris, avgturb] = WeeklyTri(dateList, turb)
    startDates = [];
    tris = [];
    avgturb = [];
    rowFrom=1;
    f = waitbar(0, 'Starting');
for i=1:length(turb)
        waitbar(i/length(turb), f, sprintf('Progress: %d %%',
floor(i/length(turb)*100)));
            if (weeknum (dateList(i)) ~= weeknum (dateList(rowFrom)) )
                startDates = [startDates string(datestr(dateList(i, :), "YYYY mm
DD"))];
                a= TRI (turb(rowFrom:(i-1)));
                avgturb= [avgturb, mean(turb(rowFrom:(i-1))),];
                tris = [tris, a,];
                rowFrom = i;
            end

end
```

1.2. Factorial design experiment details

Table B.1: Factorial design experiment factors and levels for plant B

Factors	**Low (-)**	**Mid-point (0)**	**High (+)**
Coagulant, C (mg/L)	35	52.5	70
Polymer, P (mg/L)	0	0.3	0.6
Settling time, T (min)	5	10	15

2. Plant A turbidity robustness framework application

The current study extends the previous application of the turbidity robustness framework to Plant A to a two-year period (2019-2020) and to both the treatment trains. This was done to get a more comprehensive understanding of the plant's robustness and to establish whether plant performance deviated from the previously evaluated 6 months time frame. The critical treatment processes at Plant A are the intake (reservoir), CFS and filtration (Step 2: Identification). T_{goals} were set at 25 NTU for intake, 2 NTU for CFS and 0.1 NTU for filtration (Step 3: Criteria). Scenarios 1 and 2 could not be separated for Plant A due to their intake shut off policy as explained in detail in Nemani et al. (2023).

2.1. Plant A, Step 4: Evaluation: Normal range (scenario 1) and historical peaks (scenario 2)

The intake showed robust performance, with most TRIs falling in the 'very stable' and few in the 'stable category' (Fig B.1A). The few instances with higher raw water turbidities (>25 NTU) had much lower effluent turbidities indicating possible removal of turbidity from natural settling as was hypothesized in Nemani et al. (2023).

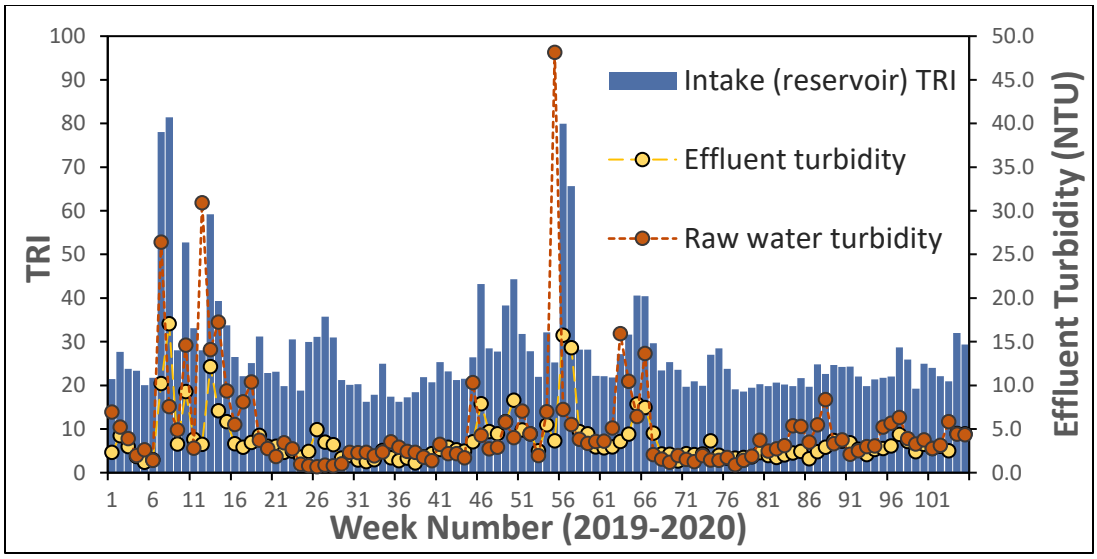
The CFS robustness for both trains 1 and 2 showed more variation (Fig. B.1B-C), with 16 out of 105 weeks not categorized in the 'stable' or 'very stable' categories. Of these 16 average CFS TRIs, 4 fell in the 'slightly disturbed' category, 4 in the 'moderately disturbed category', 1 in the 'upset' category and 7 in the 'severely upset' category. The effluent turbidities for these weeks and the corresponding coagulant and polymer doses were investigated. It was seen that the settled water turbidities for these weeks were below the Tgoal of 2 NTU, but the 90^{th} percentile was quite high (certain days of the week exhibiting elevated turbidities), with some values 3-4 times Tgoal, resulting in the 'severely upset' category. It was also seen that some of these weeks had increased coagulant and polymer doses, going as high as 120 mg/L coagulant and 1.0 mg/L. While these data points could be valid, it's worth noting that some may reflect periods when the CFS was undergoing maintenance or shutdown. This suspicion arises from their alignment with maxed out peak dosing pump flow rates which were flagged in red within the SCADA system. Some of these dosages are also higher than typical dosing range (30-50 mg/L coagulant and 0.3-0.5 mg/L polymer). None of these weeks however, corresponded to higher raw water turbidities; in fact, the raw water turbidities were found to be on the lower end, ranging between 0.8-6.3

NTU with 10 of 16 weeks falling in the fall and winter months. It could be possible that the lower turbidities coupled with colder temperatures resulted in lower removals due to improper formation of flocs. The settled water turbidities and corresponding coagulant and polymer doses are given in Table B.2.

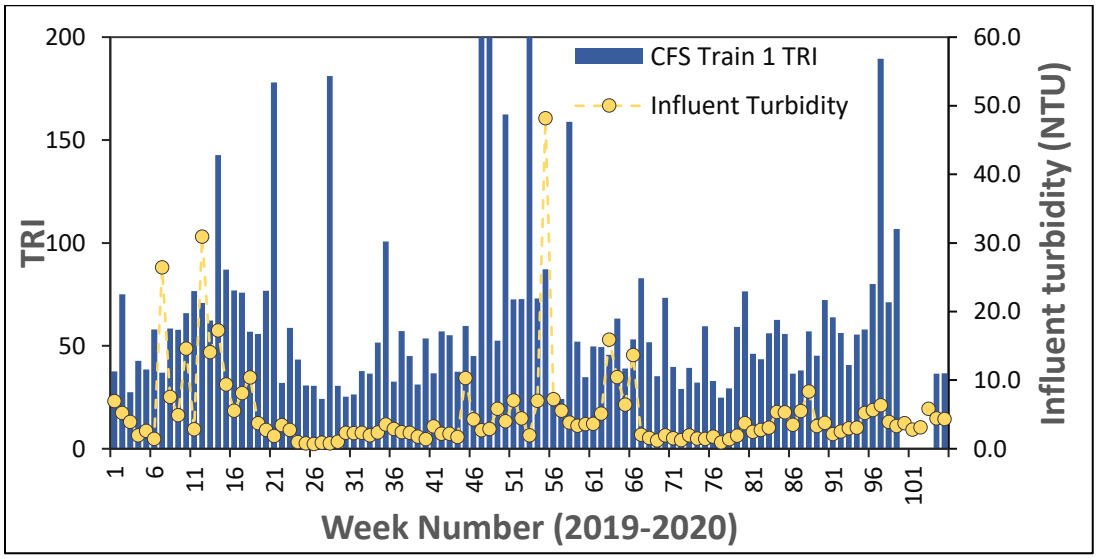
Table B.2: Plant A CFS operational data for weeks with 'severely upset' ORI s

Week #	33	48	53	98	99	103
Average TRI value	218	303	230	338	1190	397
Source	Train 2	Train 1	Train 1	Train 2	Train 2	Train 2
Source Train TRI	399	538	392	604	2274	397
Daily settled water turbidities of source train	0.9	4.7	7.6	0.7	6.1	3.0
	1.0	0.7	-	2.5	1.8	7.9
	1.1	0.4	-	6.6	0.3	6.5
	1.7	0.5	-	0.3	0.1	0.6
	2.6	0.7	4.9	1.4	0.1	0.2
	4.8	0.7	0.7	3.4	0.3	0.1
	8.0	0.3	0.8	7.1	0.4	0.1
Coagulant dose (mg/L)	25-48	29-50	33-56	49-86	46-120	40.1-120
Polymer dose (mg/L)	0.16-0.25	0.6-0.9	0.67-1.0	0.20-0.68	0.2-1.0	0.36-1

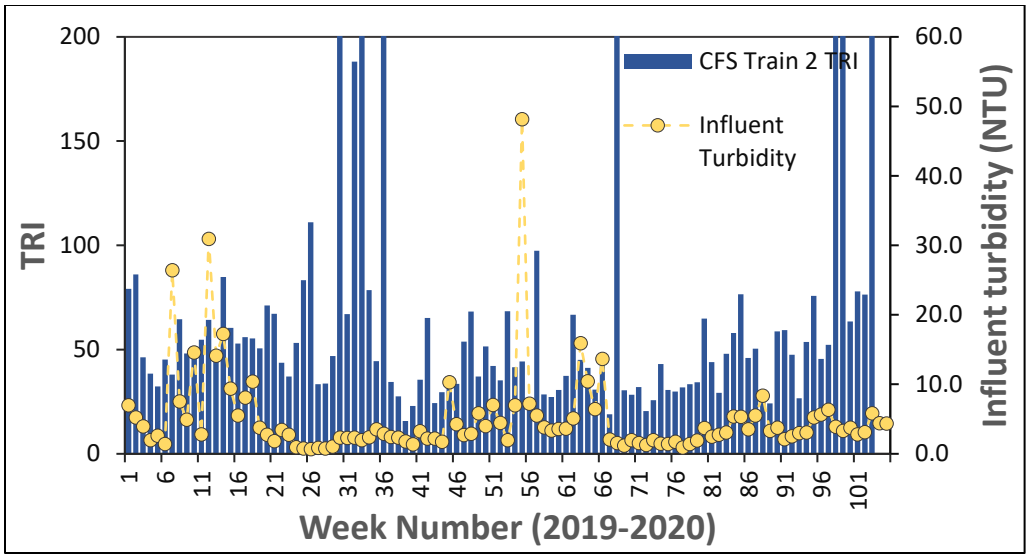
Filters 1-4 (Fig B.1D-G) exhibited robust performance throughout the two-year period, with most values falling in the 'very stable' and 'stable' categories for all the filters. The filter effluent turbidity remained at almost half the Tgoal of 0.1 NTU, which explains the TRI categorization. The consistently robust performance of the filters compensated for the weeks of low robust CFS performance.


Intake (reservoir) TRI
Effluent turbidity
Raw water turbidity
TRI
Effluent Turbidity (NTU)
Week Number (2019-2020)

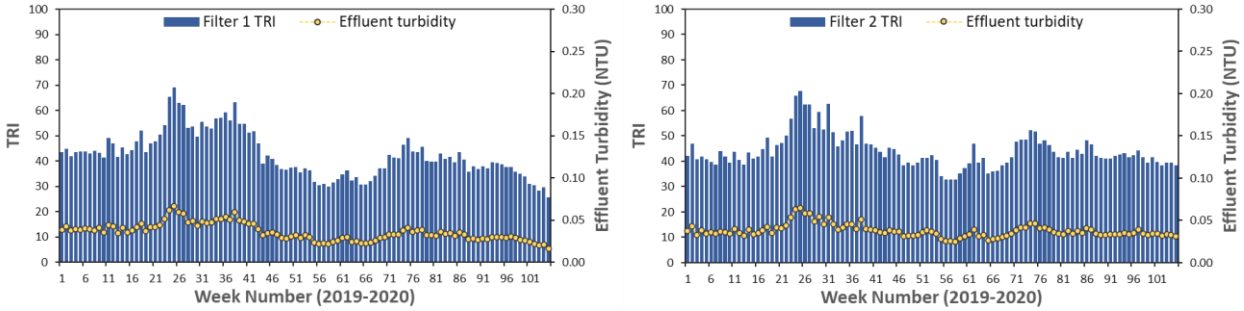
A


CFS Train 1 TRI
Influent Turbidity
TRI
Influent turbidity (NTU)
Week Number (2019-2020)

B

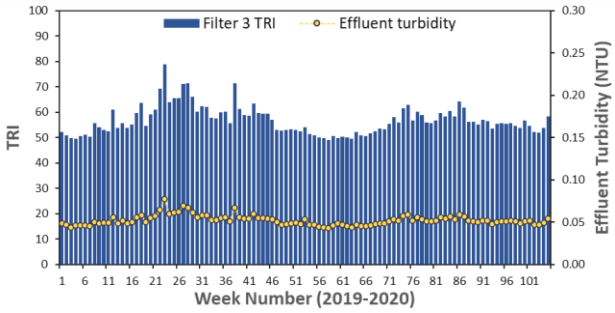


C

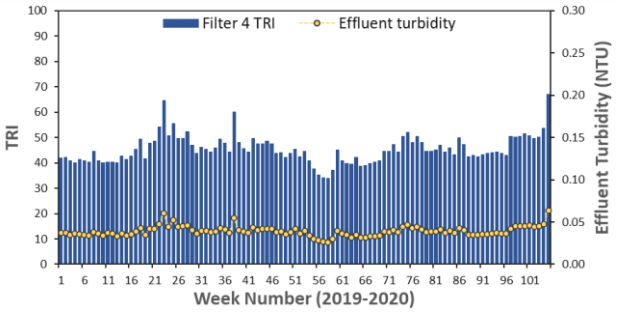


D

E



F



G

Figure B.1: TRI evaluation results (scenario 1 and 2) for Plant A critical treatment processes (intake, CFS, filtration)

2.2. Plant A, Step 4: Evaluation: extremely high turbidity (scenario 3)

For generating high raw water turbidities with natural sediment at Plant A, sediment from the bottom of the intake chamber, cell 1 was collected when the cell was drained for maintenance. Composite samples of the sediment in the form of a slurry were collected from the four corners and the centre of the basin and mixed in equal portions. This slurry was then mixed in small volumes (0.5-5 ml approximately) with raw water to obtain turbidities from 50-1000 NTU. Coagulant, coagulant aid preparation and dosages were kept the same as in Nemani et al. (2023) (section 3.3.3).

Extremely high turbidity simulation for CFS using jar test was demonstrated using kaolin for plant A in Nemani et al. (2022). In addition, sediment from Plant A intake basin was also utilized to generate raw water with extremely high turbidity and to compare to the results of the kaolin high turbidity waters (Fig B.2). It was seen that the removals of simulated turbidity using sediment were better than those with kaolin and were below the CFS Tgoal of 2 NTU. However, student's t-test on the two data sets resulted in a $p=0.08$ ($\alpha=0.05$) for 16 mins settling time and $p=0.0019$ ($\alpha=0.05$) for 30 mins settling time indicating that, while there was no significant difference in using sediment vs. kaolin for the shorter settling time, there is a significant difference between the two for the longer settling time. It should also be noted that the sediment used for this purpose comprises mainly of particulate matter that naturally settles out in the intake basin, so may not be entirely representative of the particle size distribution entering the plant. It may also not be possible to replicate this method for other plants such as plant B, that do not have an intake reservoir.

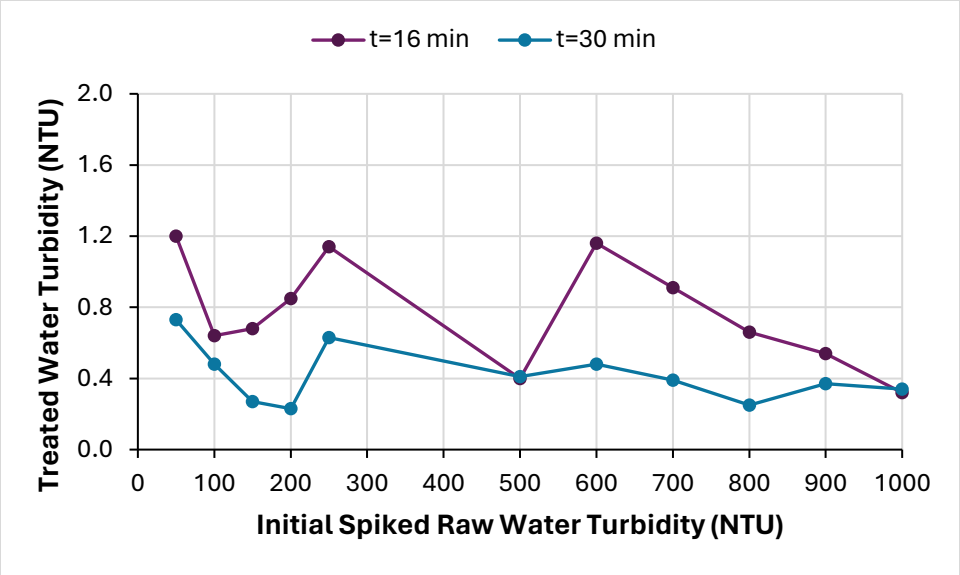


Figure B.2: Scenario 3 bench-scale turbidity simulation test with reservoir sediment for Plant A. Coagulant STERN PAC (Kemira) was dosed at 30 mg/L and the polymer at 0.3 mg/L

2.3. Plant A, Step 5 and 6: overall plant assessment and adaptation

The individual TRIs for the three critical treatment processes were converted into robustness categories (RCs), following the methodology outlined by Nemani et al. (2023). Of the four weighting cases presented in the pervious work, the combination weight (high weight for intake during raw water turbidity>=25 NTU) and higher CFS weight scenario was found to be the most conservative, resulting in 8 weeks of 'slightly disturbed' ORI (Table B.3) (Nemani et al., 2023). For the overall assessment, the combination weight approach has been used for further analysis.

The bench scale simulation for the scenario 3 adaptation for plant A has been demonstrated in Nemani et al. (2023), which shows that the current coagulant and polymer doses already achieve desirable settled water turbidities even for high turbidity ranges and increasing the dosages or settling time were not found to be statistically significant.

Table B.3: Combination weighting ORI approach for Plant A weeks 27-105

Week Number	Raw water turbidity	Intake TRI	RC	Intake Weight	CFS TRI	RC	CFS Weight	Filtration TRI	RC	Filtration Weight	ORI	Overall system robustness

	(NTU)											
27	0.9	36	1	0.10	29	1	0.40	61	2	0.50	2	Stable
28	0.8	31	1	0.10	107	3	0.40	58	1	0.50	2	Stable
29	1.0	21	1	0.10	39	1	0.40	57	1	0.50	1	Very stable
30	2.3	20	1	0.10	145	4	0.40	52	1	0.50	2	Stable
31	2.3	20	1	0.10	47	1	0.40	57	1	0.50	1	Very stable
32	2.3	16	1	0.10	113	3	0.40	53	1	0.50	2	Stable
33	1.9	18	1	0.10	218	6	0.40	50	1	0.50	3	Slightly Disturbed
34	2.4	25	1	0.10	65	2	0.40	52	1	0.50	1	Very stable
35	3.5	17	1	0.10	73	2	0.40	55	1	0.50	1	Very stable
36	2.9	16	1	0.10	177	5	0.40	55	1	0.50	3	Slightly Disturbed
37	2.4	17	1	0.10	46	1	0.40	51	1	0.50	1	Very stable
38	2.3	18	1	0.10	36	1	0.40	63	2	0.50	2	Stable
39	1.8	22	1	0.10	24	1	0.40	53	1	0.50	1	Very stable
40	1.4	21	1	0.10	38	1	0.40	51	1	0.50	1	Very stable
41	3.3	25	1	0.10	36	1	0.40	50	1	0.50	1	Very stable
42	2.2	23	1	0.10	61	2	0.40	52	1	0.50	1	Very stable

43	2.2	21	1	0.10	40	1	0.40	49	1	0.50	1	Very stable
44	1.7	21	1	0.10	34	1	0.40	48	1	0.50	1	Very stable
45	10.3	26	1	0.10	47	1	0.40	49	1	0.50	1	Very stable
46	4.3	43	1	0.10	39	1	0.40	47	1	0.50	1	Very stable
47	2.7	28	1	0.10	144	4	0.40	44	1	0.50	2	Stable
48	2.9	28	1	0.10	303	6	0.40	43	1	0.50	3	Slightly Disturbed
49	5.8	38	1	0.10	45	1	0.40	43	1	0.50	1	Very stable
50	4.0	44	1	0.10	107	3	0.40	43	1	0.50	2	Stable
51	7.0	32	1	0.10	57	1	0.40	44	1	0.50	1	Very stable
52	4.4	28	1	0.10	54	1	0.40	43	1	0.50	1	Very stable
53	1.9	22	1	0.10	230	6	0.40	44	1	0.50	3	Slightly Disturbed
54	7.0	32	1	0.10	57	1	0.40	42	1	0.50	1	Very stable
55	48.2	25	1	0.25	66	2	0.25	39	1	0.50	1	Very stable
56	7.2	80	1	0.10	25	1	0.40	37	1	0.50	1	Very stable
57	5.5	66	1	0.10	61	2	0.40	37	1	0.50	1	Very stable
58	3.8	28	1	0.10	94	2	0.40	36	1	0.50	1	Very stable
59	3.3	28	1	0.10	40	1	0.40	39	1	0.50	1	Very

												stable
60	3.6	22	1	0.10	33	1	0.40	41	1	0.50	1	Very stable
61	3.6	22	1	0.10	44	1	0.40	41	1	0.50	1	Very stable
62	5.1	22	1	0.10	58	1	0.40	43	1	0.50	1	Very stable
63	15.9	27	1	0.10	45	1	0.40	40	1	0.50	1	Very stable
64	10.5	32	1	0.10	52	1	0.40	42	1	0.50	1	Very stable
65	6.4	41	1	0.10	35	1	0.40	39	1	0.50	1	Very stable
66	13.7	40	1	0.10	49	1	0.40	39	1	0.50	1	Very stable
67	2.1	30	1	0.10	51	1	0.40	40	1	0.50	1	Very stable
68	1.6	23	1	0.10	144	4	0.40	41	1	0.50	2	Stable
69	1.2	25	1	0.10	33	1	0.40	43	1	0.50	1	Very stable
70	2.0	24	1	0.10	51	1	0.40	44	1	0.50	1	Very stable
71	1.5	20	1	0.10	36	1	0.40	48	1	0.50	1	Very stable
72	1.3	21	1	0.10	25	1	0.40	49	1	0.50	1	Very stable
73	2.0	20	1	0.10	33	1	0.40	47	1	0.50	1	Very stable
74	1.5	27	1	0.10	38	1	0.40	53	1	0.50	1	Very stable
75	1.4	28	1	0.10	45	1	0.40	54	1	0.50	1	Very

												stable
76	1.7	24	1	0.10	31	1	0.40	49	1	0.50	1	Very stable
77	0.9	19	1	0.10	28	1	0.40	51	1	0.50	1	Very stable
78	1.4	19	1	0.10	31	1	0.40	50	1	0.50	1	Very stable
79	1.9	19	1	0.10	47	1	0.40	46	1	0.50	1	Very stable
80	3.7	20	1	0.10	71	2	0.40	45	1	0.50	1	Very stable
81	2.5	20	1	0.10	45	1	0.40	46	1	0.50	1	Very stable
82	2.7	21	1	0.10	36	1	0.40	48	1	0.50	1	Very stable
83	3.1	20	1	0.10	52	1	0.40	46	1	0.50	1	Very stable
84	5.4	20	1	0.10	60	2	0.40	48	1	0.50	1	Very stable
85	5.3	22	1	0.10	66	2	0.40	46	1	0.50	1	Very stable
86	3.5	20	1	0.10	41	1	0.40	51	1	0.50	1	Very stable
87	5.5	25	1	0.10	44	1	0.40	49	1	0.50	1	Very stable
88	8.4	23	1	0.10	43	1	0.40	44	1	0.50	1	Very stable
89	3.3	25	1	0.10	35	1	0.40	45	1	0.50	1	Very stable
90	3.8	24	1	0.10	65	2	0.40	44	1	0.50	1	Very stable

91	2.1	24	1	0.10	62	2	0.40	45	1	0.50	1	Very stable
92	2.5	22	1	0.10	52	1	0.40	45	1	0.50	1	Very stable
93	3.0	20	1	0.10	34	1	0.40	45	1	0.50	1	Very stable
94	3.1	21	1	0.10	55	1	0.40	46	1	0.50	1	Very stable
95	5.2	22	1	0.10	67	2	0.40	45	1	0.50	1	Very stable
96	5.7	22	1	0.10	63	2	0.40	45	1	0.50	1	Very stable
97	6.3	29	1	0.10	121	3	0.40	47	1	0.50	2	Stable
98	3.9	26	1	0.10	338	6	0.40	46	1	0.50	3	Slightly Disturbed
99	3.3	19	1	0.10	1190	6	0.40	45	1	0.50	3	Slightly Disturbed
100	3.7	25	1	0.10	63	2	0.40	46	1	0.50	1	Very stable
101	2.8	24	1	0.10	78	2	0.40	44	1	0.50	1	Very stable
102	3.1	22	1	0.10	76	2	0.40	43	1	0.50	1	Very stable
103	5.8	21	1	0.10	397	6	0.40	42	1	0.50	3	Slightly Disturbed
104	4.4	32	1	0.10	37	2	0.40	44	1	0.50	1	Very stable
105	4.3	29	1	0.10	37	2	0.40	47	1	0.50	1	Very stable

3. Plant B turbidity robustness framework application additional details

3.1. Plant B, Step 4: Identification and evaluation of scenarios 1 and 2

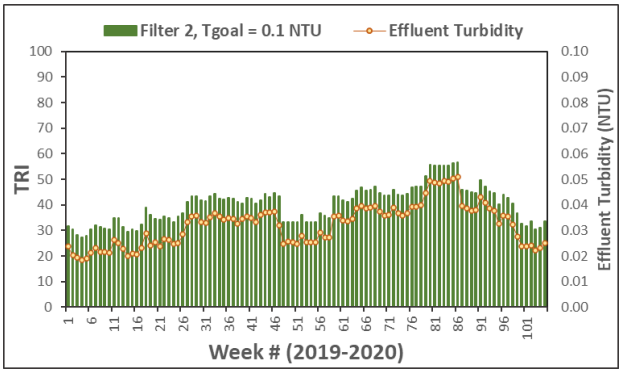
Table B.4: Seasonal medians and median thresholds for two methodologies

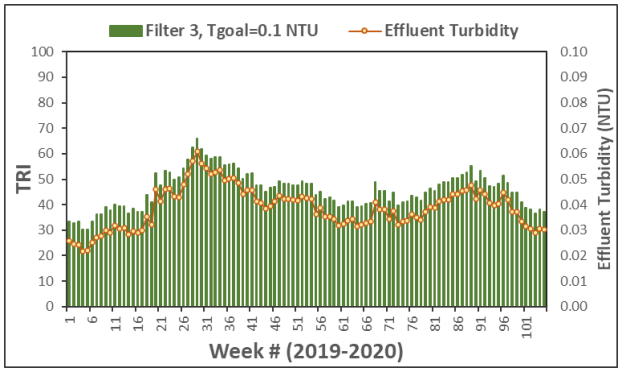
Season	Jan-Feb 2019	Mar-May 2019	Jun-Aug 2019	Sep-Nov 2019	Dec-Feb 2020	Mar-May 2020	Jun-Aug 2020	Sep-Nov 2020	Dec 2020
Seasonal median	5.3	3.2	1.3	2.8	5.8	6.8	1.1	3.8	22.0
Method 1, seasonal threshold	7.9	4.8	1.9	4.2	8.7	10.2	1.65	5.7	33.0
Method 2, seasonal threshold	15.5	11.4	7.6	10.6	16.6	18.6	7.2	12.6	49

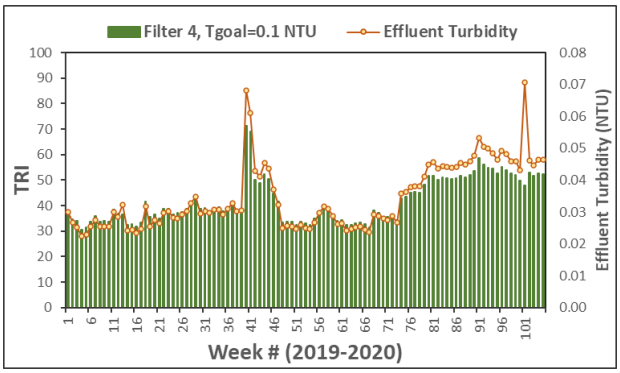
Table B.5: Weeks corresponding to scenario 2 (historical turbidity events) for methods 1 and 2. Tick marks represent a turbidity event and blank cells represent normal turbidity range.

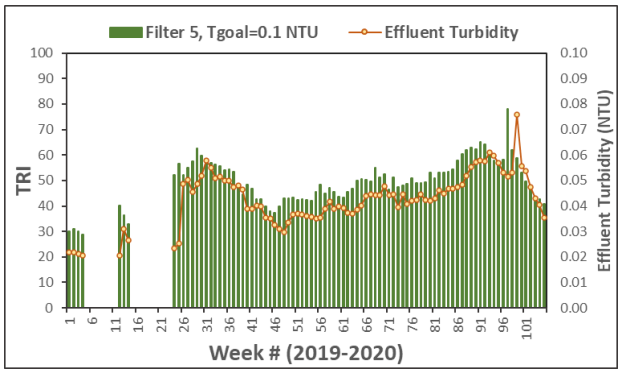
Week #	**Method 1**	**Method 2**	**Week #**	**Method 1**	**Method 2**
1	✓		53		
2	✓	✓	54		
3	✓	✓	55		
4	✓	✓	56	✓	✓
5	✓		57	✓	✓
6	✓	✓	58	✓	✓
7	✓	✓	59	✓	✓
8	✓	✓	60	✓	✓
9	✓		61	✓	✓
10	✓		62	✓	✓
11	✓		63	✓	✓
12	✓	✓	64	✓	✓
13	✓	✓	65	✓	✓
14	✓	✓	66	✓	✓
15	✓		67		
16	✓	✓	68	✓	✓

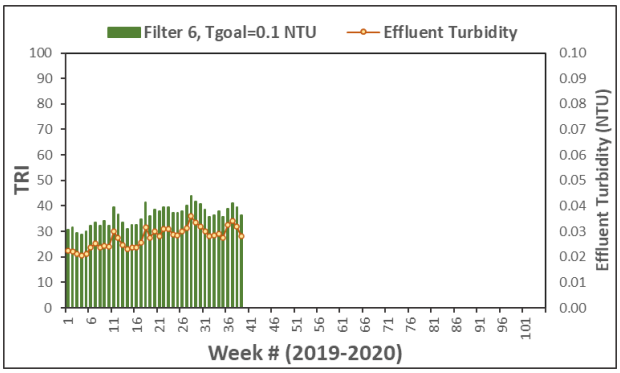
17	✓	✓	69	✓	✓
18	✓	✓	70	✓	✓
19	✓		71	✓	✓
20			72	✓	✓
21			73	✓	✓
22			74		
23	✓		75		
24	✓	✓	76	✓	
25	✓	✓	77	✓	
26	✓	✓	78	✓	
27			79	✓	
28	✓		80		
29	✓		81	✓	
30	✓		82	✓	✓
31			83	✓	
32	✓		84	✓	✓
33	✓		85	✓	✓
34	✓		86	✓	✓
35	✓	✓	87	✓	
36	✓	✓	88	✓	
37			89	✓	✓
38	✓	✓	90	✓	✓
39	✓		91	✓	
40			92	✓	✓
41	✓	✓	93	✓	✓
42	✓	✓	94	✓	
43	✓	✓	95	✓	✓
44	✓	✓	96		
45	✓	✓	97	✓	
46	✓	✓	98	✓	✓
47	✓	✓	99	✓	✓
48	✓	✓	100	✓	✓
49	✓	✓	101	✓	✓
50	✓	✓	102	✓	✓
51	✓	✓	103	✓	✓
52			104	✓	✓
			105	✓	

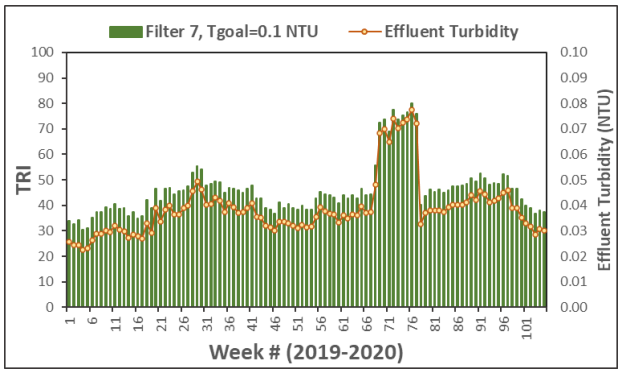

Filter 2, Tgoal = 0.1 NTU
Effluent Turbidity
TRI
Effluent Turbidity (NTU)
Week # (2019-2020)

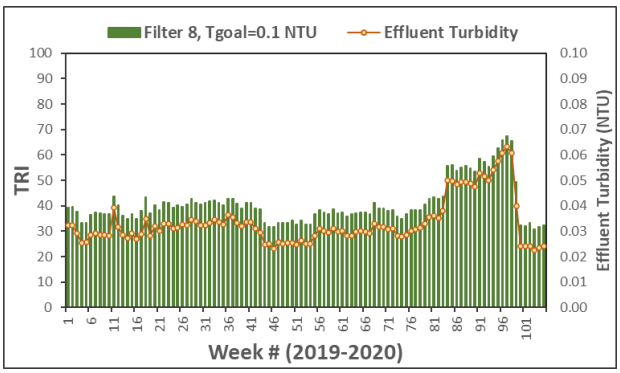

Filter 3, Tgoal=0.1 NTU
Effluent Turbidity
TRI
Effluent Turbidity (NTU)
Week # (2019-2020)

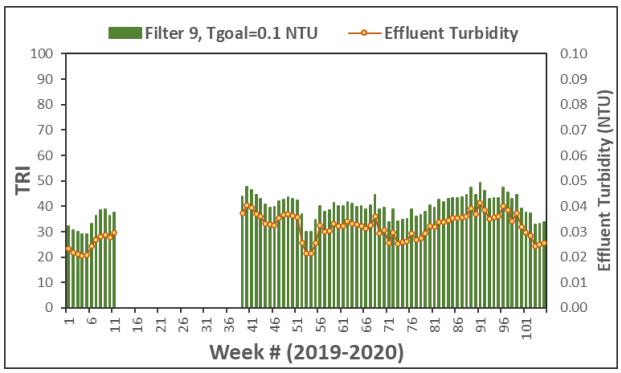

Filter 4, Tgoal=0.1 NTU
Effluent Turbidity
TRI
Effluent Turbidity (NTU)
Week # (2019-2020)


Filter 5, Tgoal=0.1 NTU
Effluent Turbidity
TRI
Effluent Turbidity (NTU)
Week # (2019-2020)


Filter 6, Tgoal=0.1 NTU
Effluent Turbidity
TRI
Effluent Turbidity (NTU)
Week # (2019-2020)


Filter 7, Tgoal=0.1 NTU
Effluent Turbidity
TRI
Effluent Turbidity (NTU)
Week # (2019-2020)


Filter 8, Tgoal=0.1 NTU
Effluent Turbidity
TRI
Effluent Turbidity (NTU)
Week # (2019-2020)


Filter 9, Tgoal=0.1 NTU
Effluent Turbidity
TRI
Effluent Turbidity (NTU)
Week # (2019-2020)

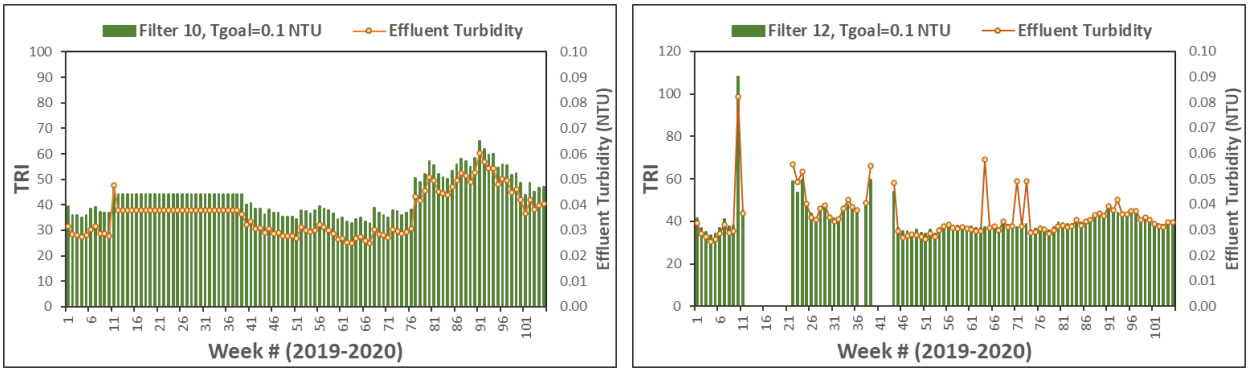


Figure B.3: TRI assessment of remaining filters at Plant B

3.2. Plant B, Step 5: overall plant assessment

Table B.6: ORI Scenario 1- Equal weights for CFS and filtration

Week Number	Combined CFS TRI	RC	CFS Weight	Filtration TRI	RC	Filtration Weight	ORI	Overall system robustness
1	26	1	0.50	35	1	0.50	1	Very stable
2	25	1	0.50	33	1	0.50	1	Very stable
3	26	1	0.50	32	1	0.50	1	Very stable
4	30	1	0.50	30	1	0.50	1	Very stable
5	28	1	0.50	31	1	0.50	1	Very stable
6	31	1	0.50	34	1	0.50	1	Very stable
7	31	1	0.50	36	1	0.50	1	Very stable
8	28	1	0.50	36	1	0.50	1	Very stable
9	26	1	0.50	37	1	0.50	1	Very stable
10	24	1	0.50	45	1	0.50	1	Very stable
11	30	1	0.50	41	1	0.50	1	Very stable
12	27	1	0.50	42	1	0.50	1	Very stable
13	31	1	0.50	39	1	0.50	1	Very stable
14	28	1	0.50	37	1	0.50	1	Very stable
15	32	1	0.50	39	1	0.50	1	Very stable
16	29	1	0.50	38	1	0.50	1	Very stable
17	27	1	0.50	39	1	0.50	1	Very stable
18	28	1	0.50	44	1	0.50	1	Very stable
19	27	1	0.50	42	1	0.50	1	Very stable
20	27	1	0.50	45	1	0.50	1	Very stable
21	24	1	0.50	42	1	0.50	1	Very stable
22	24	1	0.50	44	1	0.50	1	Very stable

23	23	1	0.50	43	1	0.50	1	Very stable
24	24	1	0.50	43	1	0.50	1	Very stable
25	23	1	0.50	43	1	0.50	1	Very stable
26	24	1	0.50	43	1	0.50	1	Very stable
27	26	1	0.50	44	1	0.50	1	Very stable
28	26	1	0.50	47	1	0.50	1	Very stable
29	32	1	0.50	49	1	0.50	1	Very stable
30	30	1	0.50	47	1	0.50	1	Very stable
31	27	1	0.50	45	1	0.50	1	Very stable
32	27	1	0.50	45	1	0.50	1	Very stable
33	29	1	0.50	46	1	0.50	1	Very stable
34	26	1	0.50	46	1	0.50	1	Very stable
35	24	1	0.50	44	1	0.50	1	Very stable
36	25	1	0.50	45	1	0.50	1	Very stable
37	23	1	0.50	45	1	0.50	1	Very stable
38	24	1	0.50	44	1	0.50	1	Very stable
39	27	1	0.50	44	1	0.50	1	Very stable
40	23	1	0.50	47	1	0.50	1	Very stable
41	23	1	0.50	47	1	0.50	1	Very stable
42	23	1	0.50	42	1	0.50	1	Very stable
43	21	1	0.50	41	1	0.50	1	Very stable
44	28	1	0.50	41	1	0.50	1	Very stable
45	59	1	0.50	39	1	0.50	1	Very stable
46	41	1	0.50	38	1	0.50	1	Very stable
47	31	1	0.50	39	1	0.50	1	Very stable
48	26	1	0.50	37	1	0.50	1	Very stable
49	22	1	0.50	38	1	0.50	1	Very stable
50	27	1	0.50	37	1	0.50	1	Very stable
51	24	1	0.50	37	1	0.50	1	Very stable
52	25	1	0.50	38	1	0.50	1	Very stable
53	21	1	0.50	36	1	0.50	1	Very stable
54	18	1	0.50	36	1	0.50	1	Very stable
55	19	1	0.50	38	1	0.50	1	Very stable
56	29	1	0.50	41	1	0.50	1	Very stable
57	28	1	0.50	39	1	0.50	1	Very stable
58	24	1	0.50	39	1	0.50	1	Very stable
59	26	1	0.50	40	1	0.50	1	Very stable
60	27	1	0.50	38	1	0.50	1	Very stable
61	26	1	0.50	39	1	0.50	1	Very stable
62	27	1	0.50	38	1	0.50	1	Very stable
63	29	1	0.50	39	1	0.50	1	Very stable
64	29	1	0.50	39	1	0.50	1	Very stable
65	28	1	0.50	40	1	0.50	1	Very stable

66	27	1	0.50	39	1	0.50	1	Very stable
67	24	1	0.50	39	1	0.50	1	Very stable
68	30	1	0.50	45	1	0.50	1	Very stable
69	31	1	0.50	44	1	0.50	1	Very stable
70	31	1	0.50	44	1	0.50	1	Very stable
71	28	1	0.50	41	1	0.50	1	Very stable
72	33	1	0.50	44	1	0.50	1	Very stable
73	31	1	0.50	41	1	0.50	1	Very stable
74	23	1	0.50	42	1	0.50	1	Very stable
75	26	1	0.50	43	1	0.50	1	Very stable
76	25	1	0.50	45	1	0.50	1	Very stable
77	27	1	0.50	45	1	0.50	1	Very stable
78	28	1	0.50	42	1	0.50	1	Very stable
79	24	1	0.50	45	1	0.50	1	Very stable
80	30	1	0.50	47	1	0.50	1	Very stable
81	27	1	0.50	47	1	0.50	1	Very stable
82	24	1	0.50	47	1	0.50	1	Very stable
83	23	1	0.50	47	1	0.50	1	Very stable
84	22	1	0.50	49	1	0.50	1	Very stable
85	24	1	0.50	56	1	0.50	1	Very stable
86	22	1	0.50	50	1	0.50	1	Very stable
87	21	1	0.50	50	1	0.50	1	Very stable
88	22	1	0.50	51	1	0.50	1	Very stable
89	28	1	0.50	52	1	0.50	1	Very stable
90	21	1	0.50	51	1	0.50	1	Very stable
91	24	1	0.50	56	1	0.50	1	Very stable
92	21	1	0.50	53	1	0.50	1	Very stable
93	20	1	0.50	51	1	0.50	1	Very stable
94	19	1	0.50	51	1	0.50	1	Very stable
95	22	1	0.50	51	1	0.50	1	Very stable
96	22	1	0.50	54	1	0.50	1	Very stable
97	25	1	0.50	55	1	0.50	1	Very stable
98	23	1	0.50	50	1	0.50	1	Very stable
99	25	1	0.50	48	1	0.50	1	Very stable
100	22	1	0.50	42	1	0.50	1	Very stable
101	25	1	0.50	40	1	0.50	1	Very stable
102	30	1	0.50	41	1	0.50	1	Very stable
103	32	1	0.50	38	1	0.50	1	Very stable
104	30	1	0.50	39	1	0.50	1	Very stable
105	27	1	0.50	39	1	0.50	1	Very stable

Table B.7: ORI Scenario 2- CFS high weight (0.8) and filtration low weight (0.2)

Week Number	Combined CFS TRI	RC	CFS Weight	Filtration TRI	RC	Filtration Weight	ORI	Overall system robustness
1	26	1	0.80	35	1	0.20	1	Very stable
2	25	1	0.80	33	1	0.20	1	Very stable
3	26	1	0.80	32	1	0.20	1	Very stable
4	30	1	0.80	30	1	0.20	1	Very stable
5	28	1	0.80	31	1	0.20	1	Very stable
6	31	1	0.80	34	1	0.20	1	Very stable
7	31	1	0.80	36	1	0.20	1	Very stable
8	28	1	0.80	36	1	0.20	1	Very stable
9	26	1	0.80	37	1	0.20	1	Very stable
10	24	1	0.80	45	1	0.20	1	Very stable
11	30	1	0.80	41	1	0.20	1	Very stable
12	27	1	0.80	42	1	0.20	1	Very stable
13	31	1	0.80	39	1	0.20	1	Very stable
14	28	1	0.80	37	1	0.20	1	Very stable
15	32	1	0.80	39	1	0.20	1	Very stable
16	29	1	0.80	38	1	0.20	1	Very stable
17	27	1	0.80	39	1	0.20	1	Very stable
18	28	1	0.80	44	1	0.20	1	Very stable
19	27	1	0.80	42	1	0.20	1	Very stable
20	27	1	0.80	45	1	0.20	1	Very stable
21	24	1	0.80	42	1	0.20	1	Very stable
22	24	1	0.80	44	1	0.20	1	Very stable
23	23	1	0.80	43	1	0.20	1	Very stable
24	24	1	0.80	43	1	0.20	1	Very stable
25	23	1	0.80	43	1	0.20	1	Very stable
26	24	1	0.80	43	1	0.20	1	Very stable
27	26	1	0.80	44	1	0.20	1	Very stable
28	26	1	0.80	47	1	0.20	1	Very stable
29	32	1	0.80	49	1	0.20	1	Very stable
30	30	1	0.80	47	1	0.20	1	Very stable
31	27	1	0.80	45	1	0.20	1	Very stable
32	27	1	0.80	45	1	0.20	1	Very stable
33	29	1	0.80	46	1	0.20	1	Very stable
34	26	1	0.80	46	1	0.20	1	Very stable
35	24	1	0.80	44	1	0.20	1	Very stable
36	25	1	0.80	45	1	0.20	1	Very stable
37	23	1	0.80	45	1	0.20	1	Very stable
38	24	1	0.80	44	1	0.20	1	Very stable
39	27	1	0.80	44	1	0.20	1	Very stable
40	23	1	0.80	47	1	0.20	1	Very stable

41	23	1	0.80	47	1	0.20	1	Very stable
42	23	1	0.80	42	1	0.20	1	Very stable
43	21	1	0.80	41	1	0.20	1	Very stable
44	28	1	0.80	41	1	0.20	1	Very stable
45	59	1	0.80	39	1	0.20	1	Very stable
46	41	1	0.80	38	1	0.20	1	Very stable
47	31	1	0.80	39	1	0.20	1	Very stable
48	26	1	0.80	37	1	0.20	1	Very stable
49	22	1	0.80	38	1	0.20	1	Very stable
50	27	1	0.80	37	1	0.20	1	Very stable
51	24	1	0.80	37	1	0.20	1	Very stable
52	25	1	0.80	38	1	0.20	1	Very stable
53	21	1	0.80	36	1	0.20	1	Very stable
54	18	1	0.80	36	1	0.20	1	Very stable
55	19	1	0.80	38	1	0.20	1	Very stable
56	29	1	0.80	41	1	0.20	1	Very stable
57	28	1	0.80	39	1	0.20	1	Very stable
58	24	1	0.80	39	1	0.20	1	Very stable
59	26	1	0.80	40	1	0.20	1	Very stable
60	27	1	0.80	38	1	0.20	1	Very stable
61	26	1	0.80	39	1	0.20	1	Very stable
62	27	1	0.80	38	1	0.20	1	Very stable
63	29	1	0.80	39	1	0.20	1	Very stable
64	29	1	0.80	39	1	0.20	1	Very stable
65	28	1	0.80	40	1	0.20	1	Very stable
66	27	1	0.80	39	1	0.20	1	Very stable
67	24	1	0.80	39	1	0.20	1	Very stable
68	30	1	0.80	45	1	0.20	1	Very stable
69	31	1	0.80	44	1	0.20	1	Very stable
70	31	1	0.80	44	1	0.20	1	Very stable
71	28	1	0.80	41	1	0.20	1	Very stable
72	33	1	0.80	44	1	0.20	1	Very stable
73	31	1	0.80	41	1	0.20	1	Very stable
74	23	1	0.80	42	1	0.20	1	Very stable
75	26	1	0.80	43	1	0.20	1	Very stable
76	25	1	0.80	45	1	0.20	1	Very stable
77	27	1	0.80	45	1	0.20	1	Very stable
78	28	1	0.80	42	1	0.20	1	Very stable
79	24	1	0.80	45	1	0.20	1	Very stable
80	30	1	0.80	47	1	0.20	1	Very stable
81	27	1	0.80	47	1	0.20	1	Very stable
82	24	1	0.80	47	1	0.20	1	Very stable
83	23	1	0.80	47	1	0.20	1	Very stable

84	22	1	0.80	49	1	0.20	1	Very stable
85	24	1	0.80	56	1	0.20	1	Very stable
86	22	1	0.80	50	1	0.20	1	Very stable
87	21	1	0.80	50	1	0.20	1	Very stable
88	22	1	0.80	51	1	0.20	1	Very stable
89	28	1	0.80	52	1	0.20	1	Very stable
90	21	1	0.80	51	1	0.20	1	Very stable
91	24	1	0.80	56	1	0.20	1	Very stable
92	21	1	0.80	53	1	0.20	1	Very stable
93	20	1	0.80	51	1	0.20	1	Very stable
94	19	1	0.80	51	1	0.20	1	Very stable
95	22	1	0.80	51	1	0.20	1	Very stable
96	22	1	0.80	54	1	0.20	1	Very stable
97	25	1	0.80	55	1	0.20	1	Very stable
98	23	1	0.80	50	1	0.20	1	Very stable
99	25	1	0.80	48	1	0.20	1	Very stable
100	22	1	0.80	42	1	0.20	1	Very stable
101	25	1	0.80	40	1	0.20	1	Very stable
102	30	1	0.80	41	1	0.20	1	Very stable
103	32	1	0.80	38	1	0.20	1	Very stable
104	30	1	0.80	39	1	0.20	1	Very stable
105	27	1	0.80	39	1	0.20	1	Very stable

Table B.8: ORI Scenario 3- CFS low weight (0.2) and filtration high weight (0.8)

Week Number	**Combined CFS TRI**	**RC**	**CFS Weight**	**Filtration TRI**	**RC**	**Filtration Weight**	**ORI**	**Overall system robustness**
1	26	1	0.20	35	1	0.80	1	Very stable
2	25	1	0.20	33	1	0.80	1	Very stable
3	26	1	0.20	32	1	0.80	1	Very stable
4	30	1	0.20	30	1	0.80	1	Very stable
5	28	1	0.20	31	1	0.80	1	Very stable
6	31	1	0.20	34	1	0.80	1	Very stable
7	31	1	0.20	36	1	0.80	1	Very stable
8	28	1	0.20	36	1	0.80	1	Very stable
9	26	1	0.20	37	1	0.80	1	Very stable
10	24	1	0.20	45	1	0.80	1	Very stable
11	30	1	0.20	41	1	0.80	1	Very stable
12	27	1	0.20	42	1	0.80	1	Very stable

13	31	1	0.20	39	1	0.80	1	Very stable
14	28	1	0.20	37	1	0.80	1	Very stable
15	32	1	0.20	39	1	0.80	1	Very stable
16	29	1	0.20	38	1	0.80	1	Very stable
17	27	1	0.20	39	1	0.80	1	Very stable
18	28	1	0.20	44	1	0.80	1	Very stable
19	27	1	0.20	42	1	0.80	1	Very stable
20	27	1	0.20	45	1	0.80	1	Very stable
21	24	1	0.20	42	1	0.80	1	Very stable
22	24	1	0.20	44	1	0.80	1	Very stable
23	23	1	0.20	43	1	0.80	1	Very stable
24	24	1	0.20	43	1	0.80	1	Very stable
25	23	1	0.20	43	1	0.80	1	Very stable
26	24	1	0.20	43	1	0.80	1	Very stable
27	26	1	0.20	44	1	0.80	1	Very stable
28	26	1	0.20	47	1	0.80	1	Very stable
29	32	1	0.20	49	1	0.80	1	Very stable
30	30	1	0.20	47	1	0.80	1	Very stable
31	27	1	0.20	45	1	0.80	1	Very stable
32	27	1	0.20	45	1	0.80	1	Very stable
33	29	1	0.20	46	1	0.80	1	Very stable
34	26	1	0.20	46	1	0.80	1	Very stable
35	24	1	0.20	44	1	0.80	1	Very stable
36	25	1	0.20	45	1	0.80	1	Very stable
37	23	1	0.20	45	1	0.80	1	Very stable
38	24	1	0.20	44	1	0.80	1	Very stable
39	27	1	0.20	44	1	0.80	1	Very stable
40	23	1	0.20	47	1	0.80	1	Very stable
41	23	1	0.20	47	1	0.80	1	Very stable
42	23	1	0.20	42	1	0.80	1	Very stable
43	21	1	0.20	41	1	0.80	1	Very stable
44	28	1	0.20	41	1	0.80	1	Very stable
45	59	1	0.20	39	1	0.80	1	Very stable
46	41	1	0.20	38	1	0.80	1	Very stable
47	31	1	0.20	39	1	0.80	1	Very stable
48	26	1	0.20	37	1	0.80	1	Very stable
49	22	1	0.20	38	1	0.80	1	Very stable
50	27	1	0.20	37	1	0.80	1	Very stable
51	24	1	0.20	37	1	0.80	1	Very stable
52	25	1	0.20	38	1	0.80	1	Very stable
53	21	1	0.20	36	1	0.80	1	Very stable
54	18	1	0.20	36	1	0.80	1	Very stable
55	19	1	0.20	38	1	0.80	1	Very stable

56	29	1	0.20	41	1	0.80	1	Very stable
57	28	1	0.20	39	1	0.80	1	Very stable
58	24	1	0.20	39	1	0.80	1	Very stable
59	26	1	0.20	40	1	0.80	1	Very stable
60	27	1	0.20	38	1	0.80	1	Very stable
61	26	1	0.20	39	1	0.80	1	Very stable
62	27	1	0.20	38	1	0.80	1	Very stable
63	29	1	0.20	39	1	0.80	1	Very stable
64	29	1	0.20	39	1	0.80	1	Very stable
65	28	1	0.20	40	1	0.80	1	Very stable
66	27	1	0.20	39	1	0.80	1	Very stable
67	24	1	0.20	39	1	0.80	1	Very stable
68	30	1	0.20	45	1	0.80	1	Very stable
69	31	1	0.20	44	1	0.80	1	Very stable
70	31	1	0.20	44	1	0.80	1	Very stable
71	28	1	0.20	41	1	0.80	1	Very stable
72	33	1	0.20	44	1	0.80	1	Very stable
73	31	1	0.20	41	1	0.80	1	Very stable
74	23	1	0.20	42	1	0.80	1	Very stable
75	26	1	0.20	43	1	0.80	1	Very stable
76	25	1	0.20	45	1	0.80	1	Very stable
77	27	1	0.20	45	1	0.80	1	Very stable
78	28	1	0.20	42	1	0.80	1	Very stable
79	24	1	0.20	45	1	0.80	1	Very stable
80	30	1	0.20	47	1	0.80	1	Very stable
81	27	1	0.20	47	1	0.80	1	Very stable
82	24	1	0.20	47	1	0.80	1	Very stable
83	23	1	0.20	47	1	0.80	1	Very stable
84	22	1	0.20	49	1	0.80	1	Very stable
85	24	1	0.20	56	1	0.80	1	Very stable
86	22	1	0.20	50	1	0.80	1	Very stable
87	21	1	0.20	50	1	0.80	1	Very stable
88	22	1	0.20	51	1	0.80	1	Very stable
89	28	1	0.20	52	1	0.80	1	Very stable
90	21	1	0.20	51	1	0.80	1	Very stable
91	24	1	0.20	56	1	0.80	1	Very stable
92	21	1	0.20	53	1	0.80	1	Very stable
93	20	1	0.20	51	1	0.80	1	Very stable
94	19	1	0.20	51	1	0.80	1	Very stable
95	22	1	0.20	51	1	0.80	1	Very stable
96	22	1	0.20	54	1	0.80	1	Very stable
97	25	1	0.20	55	1	0.80	1	Very stable
98	23	1	0.20	50	1	0.80	1	Very stable

99	25	1	0.20	48	1	0.80	1	Very stable
100	22	1	0.20	42	1	0.80	1	Very stable
101	25	1	0.20	40	1	0.80	1	Very stable
102	30	1	0.20	41	1	0.80	1	Very stable
103	32	1	0.20	38	1	0.80	1	Very stable
104	30	1	0.20	39	1	0.80	1	Very stable
105	27	1	0.20	39	1	0.80	1	Very stable

3.3. Plant B, Step 6: adaptation

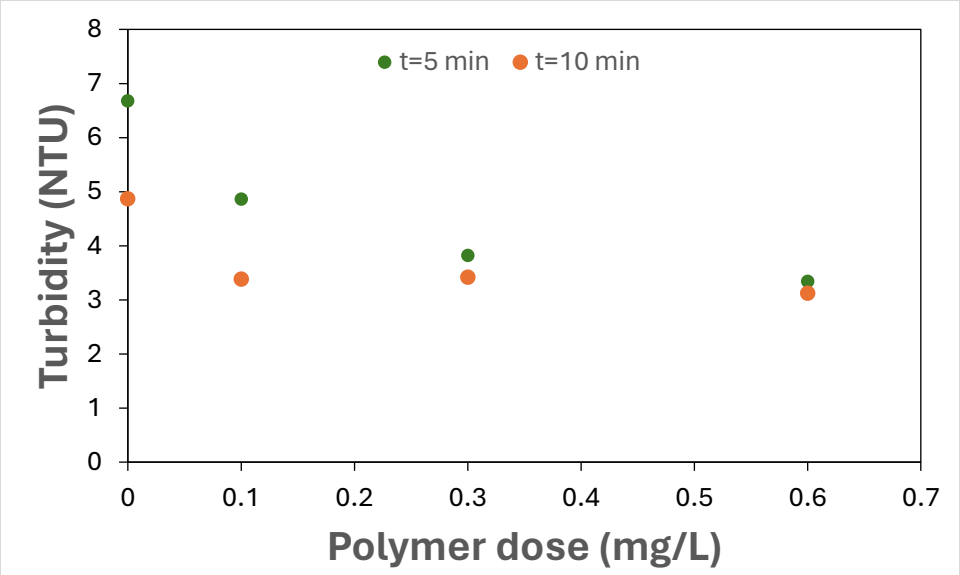


Figure B.4: Initial jar test experiment to check the effectiveness of polymer addition at typical plant coagulation dosage of 35 mg/L alum and two settling times of 5 min and 10 min

Table B.9: ANOVA results of the factorial design experiment. p-values highlighted in red show the significant factors and interactions.

Source	Effect	p-value
Coagulant	-8.5825	0.004
Polymer	-10.9275	0.004
Settling Time (T)	-6.9325	0.006
CXP (coagulant-polymer interaction)	3.7475	0.010
CXT (coagulant-settling time interaction)	2.0225	0.019
PXT	5.3975	0.007

(polymer-settling time interaction)		
CXPXT (coagulant-polymer-settling time interaction)	-1.1475	0.033

C. Appendix C

Supporting Information for Chapter 5

1. Overview of general robustness framework

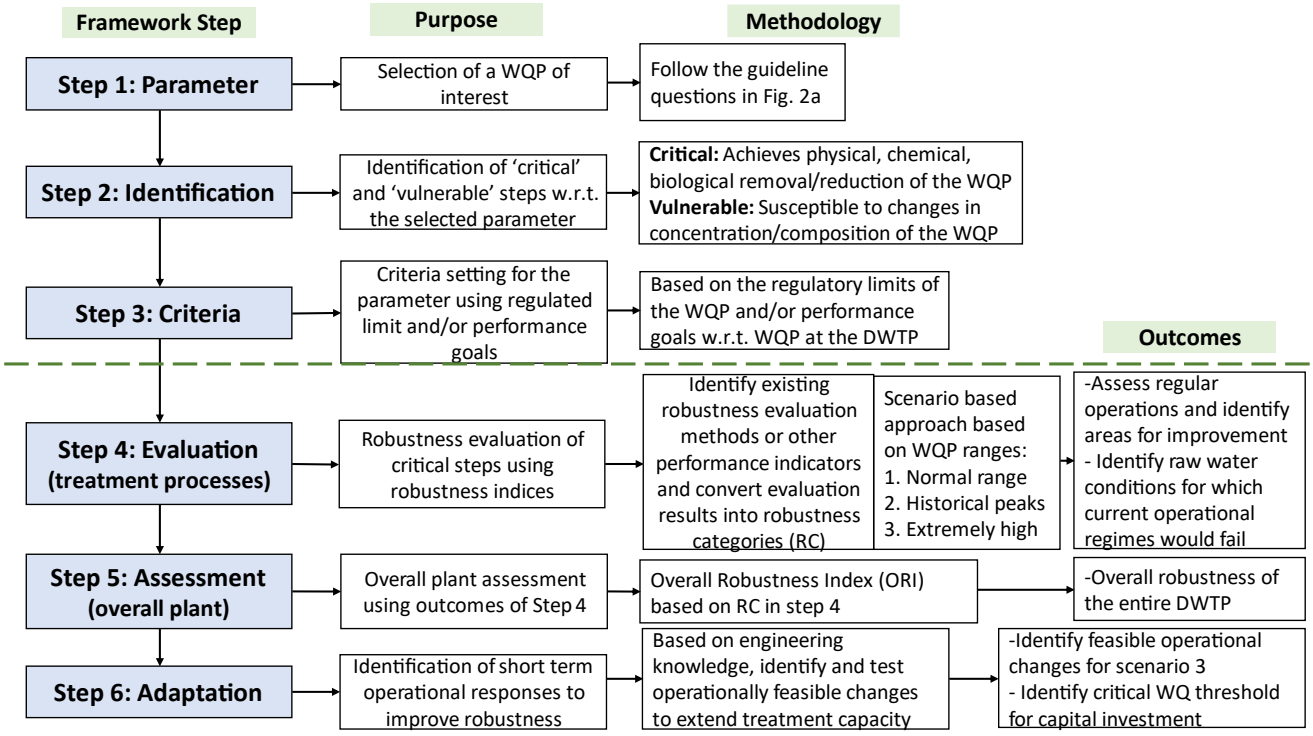


Figure C.1: General Robustness framework.

2. TRI sensitivity analysis

Table C.1: Results of TRI sensitivity analysis with two data sets and two averaging methods.

Averaging method #	**TRI Value**			**Standard Deviation**
	Data set 1, 1700 points	**Data set 1, 170 points**	**Data set 1, 17 points**	
1	33	33	33	0
2	33	33	33	0
Averaging method #	**Data set 2, 2000 points**	**Data set 2, 200 points**	**Data set 2, 20 points**	**Standard Deviation**

1	63	58	56	3.6
2	63	63	63	0

3. Plant specific framework: plant B additional information

   a. Plant B treatment train and sampling locations

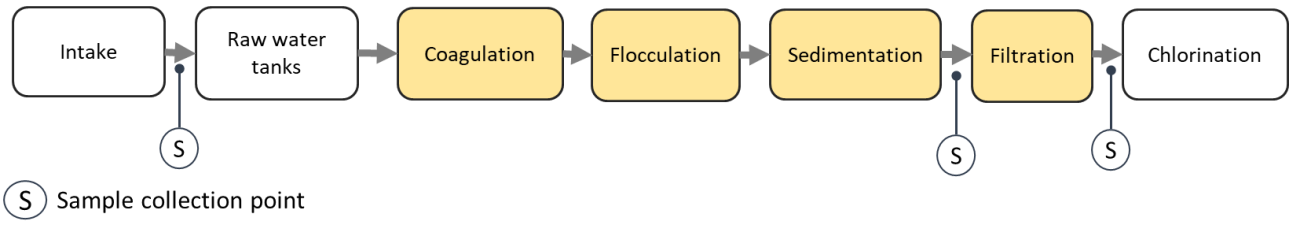


Figure C.2: Plant B process flow chart and sample collection points

   b. DOC, UV 254, THMFP trends and correlation

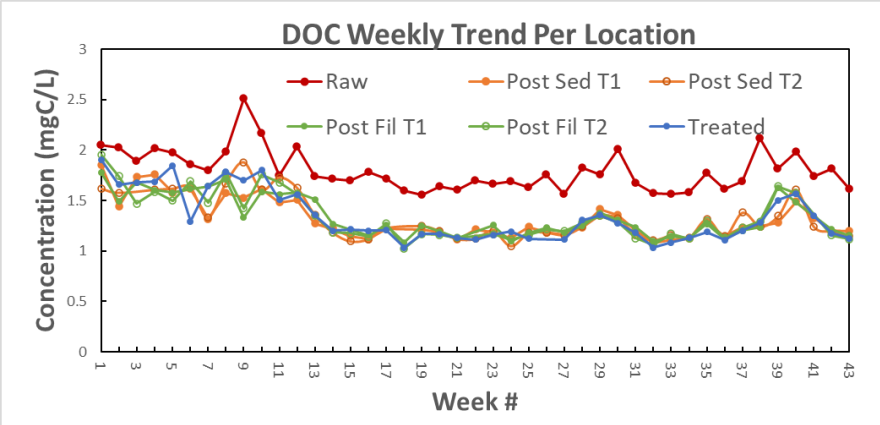


Figure C.3: DOC weekly trends at Plant B

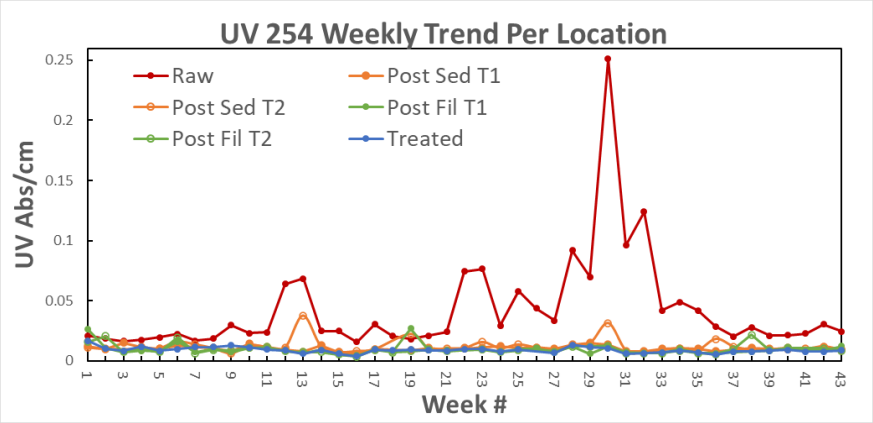


Figure C.4: Weekly UV absorbance at 254 nm at Plant B

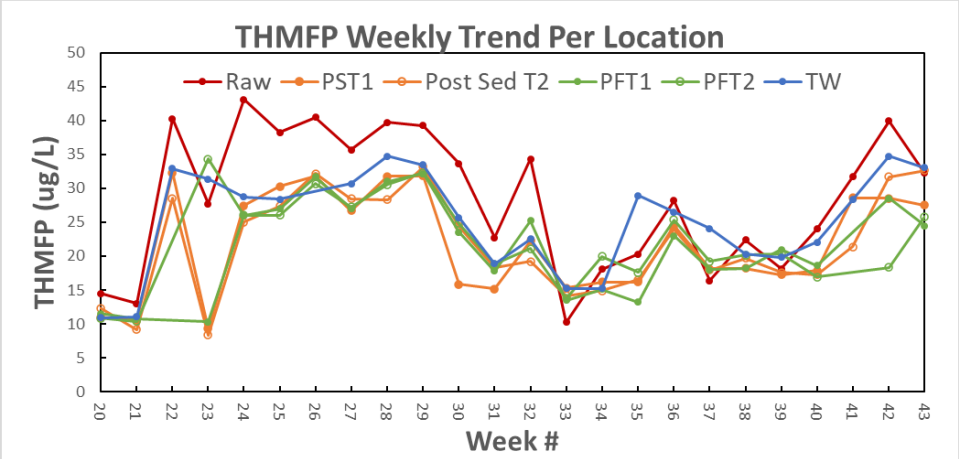


Figure C.5: Weekly THMFP at Plant B

Table C.2: Plant B surrogate parameters and correlations for different sample locations data

Water quality parameters	Raw	Post Sed Train 1	Post Sed Train 2	Post Fil Train 1	Post Fil Train 2	Treated
TOC, DOC	0.7	0.8	0.6	0.9	0.8	0.9
TOC, UV254	0.4	0.4	0.5	0.2	0.6	0.6
DOC, UV254	0.0	0.4	0.0	0.3	0.5	0.6
THMFP, TOC	0.3	0.1	0.2	0.4	0.2	0.2
THMFP, DOC	0.1	0.1	-0.1	0.1	0.0	0.0
THMFP, UV254	0.3	0.3	0.2	0.2	0.1	0.3

c. OMRI data for different process locations

a. Raw water

Table C.3: Plant B raw water surrogate parameter data and OMRI for 4 weighting scenarios

Week #	WQP			OMRI			
	DOC (mgC/L)	**UVT (%)**	**THMFP (µg/L)**	Case 1	Case 2	Case 3	Case 4
20	1.6	95.2	14.5	0.5	0.7	0.5	0.3
21	1.6	94.5	13.0	0.5	0.7	0.5	0.3
22	1.7	84.2	40.3	0.9	0.9	1.3	0.6
23	1.7	84.8	27.7	0.9	0.9	1.2	0.5
24	1.7	93.4	43.1	0.6	0.8	0.7	0.5
25	1.6	87.5	38.3	0.8	0.8	1.1	0.6
26	1.8	90.4	40.5	0.7	0.8	0.9	0.6
27	1.6	92.7	35.7	0.6	0.7	0.7	0.5
28	1.8	81.0	39.8	1.1	1.0	1.5	0.7
29	1.8	84.5	39.2	0.9	0.9	1.3	0.6
30	2.0	56.2	33.7	1.9	1.4	3.3	1.0
31	1.7	87.3	22.7	0.8	0.8	1.1	0.5
32	1.6	75.0	34.3	1.2	1.0	1.9	0.7
33	1.6	90.8	10.2	0.6	0.7	0.8	0.3
34	1.6	90.0	18.1	0.7	0.7	0.9	0.4
35	1.8	90.8	20.3	0.7	0.8	0.8	0.4
36	1.6	93.8	28.2	0.6	0.7	0.6	0.4
37	1.7	95.5	16.4	0.5	0.7	0.5	0.3
38	2.1	93.7	22.4	0.6	0.9	0.6	0.4
39	1.8	95.3	18.2	0.5	0.7	0.5	0.3
40	2.0	95.1	24.0	0.6	0.8	0.5	0.4
41	1.7	95.3	31.7	0.6	0.7	0.5	0.4
42	1.8	93.3	39.9	0.7	0.8	0.7	0.5
43	1.6	94.6	32.3	0.6	0.7	0.5	0.4

b. Coagulation-flocculation-sedimentation

Table C.4: Plant B CFS surrogate parameter data and OMRI for 4 weighting scenarios

Week #	WQP			OMRI			
	DOC (mgC/L)	**UVT (%)**	**THMFP (µg/L)**	Case 1	Case 2	Case 3	Case 4
20	1.2	97.4	11.6	0.3	0.5	0.3	0.2
21	1.1	97.7	9.9	0.3	0.4	0.3	0.2

22	1.2	97.6	30.4	0.4	0.5	0.3	0.3
23	1.2	96.5	8.8	0.3	0.5	0.3	0.2
24	1.1	97.8	26.2	0.3	0.5	0.3	0.3
25	1.2	97.4	28.8	0.4	0.5	0.3	0.3
26	1.2	97.5	32.0	0.4	0.5	0.3	0.3
27	1.2	97.9	27.6	0.4	0.5	0.3	0.3
28	1.2	96.9	30.0	0.4	0.5	0.4	0.3
29	1.4	96.5	32.5	0.5	0.6	0.4	0.4
30	1.3	96.2	20.1	0.4	0.6	0.4	0.3
31	1.2	98.2	16.7	0.3	0.5	0.2	0.2
32	1.1	98.0	20.7	0.3	0.4	0.2	0.3
33	1.1	97.0	14.7	0.3	0.5	0.3	0.2
34	1.1	97.7	15.5	0.3	0.5	0.3	0.2
35	1.3	97.0	16.4	0.4	0.5	0.3	0.3
36	1.1	96.9	24.2	0.4	0.5	0.3	0.3
37	1.3	97.5	18.0	0.4	0.5	0.3	0.3
38	1.2	97.7	19.0	0.3	0.5	0.3	0.3
39	1.3	97.9	17.4	0.3	0.5	0.3	0.2
40	1.5	97.6	17.5	0.4	0.6	0.3	0.3
41	1.3	97.9	25.0	0.4	0.5	0.3	0.3
42	1.2	97.2	30.1	0.4	0.5	0.3	0.3
43	1.2	97.9	30.1	0.4	0.5	0.3	0.3

c. Filtration

Table C.5: Plant B filtration surrogate parameter data and OMRI for 4 weighting scenarios

Week #	WQP			OMRI			
	DOC (mgC/L)	**UVT (%)**	**THMFP (µg/L)**	Case 1	Case 2	Case 3	Case 4
20	1.2	98.0	11.2	0.3	0.5	0.2	0.2
21	1.1	98.1	10.6	0.3	0.4	0.2	0.2
22	1.1	97.8	32.9	0.4	0.5	0.3	0.3
23	1.2	97.9	22.3	0.3	0.5	0.3	0.3
24	1.1	98.3	26.0	0.3	0.5	0.2	0.3
25	1.2	97.9	26.5	0.4	0.5	0.3	0.3
26	1.2	97.7	31.2	0.4	0.5	0.3	0.3
27	1.2	98.3	27.2	0.3	0.5	0.2	0.3
28	1.3	97.3	30.8	0.4	0.5	0.3	0.3
29	1.4	97.9	32.2	0.4	0.6	0.3	0.4
30	1.3	97.2	24.2	0.4	0.5	0.3	0.3

31	1.2	98.4	18.3	0.3	0.5	0.2	0.2
32	1.1	98.5	23.2	0.3	0.4	0.2	0.3
33	1.2	98.6	13.6	0.3	0.5	0.2	0.2
34	1.1	98.4	17.5	0.3	0.4	0.2	0.2
35	1.3	98.6	15.4	0.3	0.5	0.2	0.2
36	1.1	98.7	24.2	0.3	0.5	0.2	0.3
37	1.2	98.1	18.6	0.3	0.5	0.2	0.2
38	1.3	96.3	19.2	0.4	0.5	0.4	0.3
39	1.6	98.0	20.6	0.4	0.6	0.3	0.3
40	1.5	97.6	17.8	0.4	0.6	0.3	0.3
41	1.3	98.3	28.3	0.4	0.5	0.3	0.3
42	1.2	97.7	23.4	0.4	0.5	0.3	0.3
43	1.1	97.6	25.2	0.4	0.5	0.3	0.3

d. Step 4: Extreme NOM (scenario 3) bench scale test results

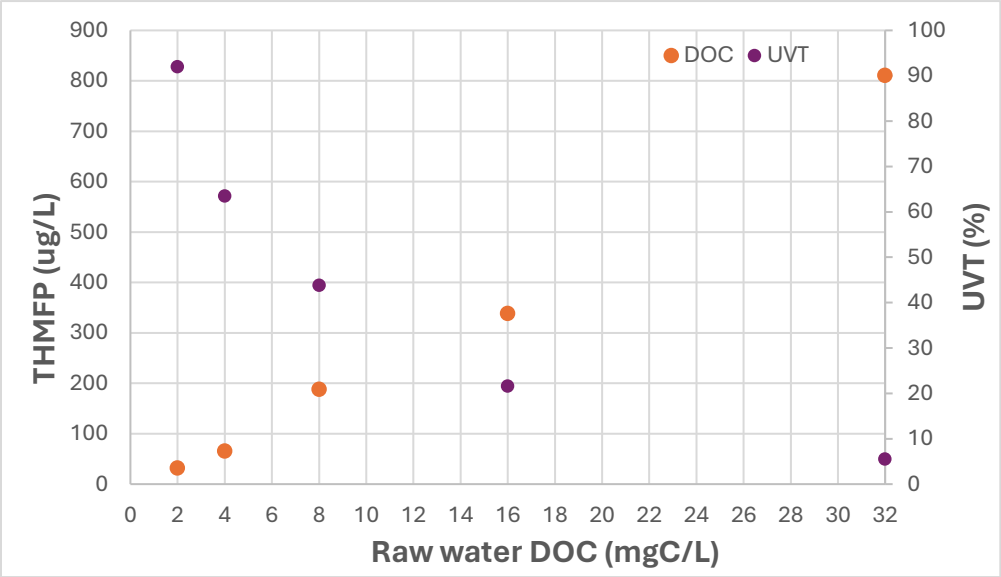


Figure C.6: Initial jar test results employing plant coagulant dosage of 35 m/L alum to identify limitation of plant coagulation regime

e. Step 6: Factorial design experiment

Table C.6: Significance of operational factors on water quality parameters determined using ANOVA. Bold values indicate significant effects at α=0.05

Parameter		Coagulant dose (A)	Polymer dose (B)	Settling time (C)	AXB	AXC	BXC	AXBXC
DOC	p-value	**0.009**	**0.023**	0.062	**0.027**	0.080	0.090	0.085
UVT	p-value	**0.001**	**0.003**	**0.005**	**0.004**	**0.006**	**0.006**	**0.006**
THMFP	p-value	0.216	0.128	0.137	0.102	0.562	0.186	0.223

Table C.7: OMRI results of factorial design experiment with coded factors. '+' indicates high level and '-' indicates low level of the factor.

Coded factors (coag-poly-time)	**DOC (mgC/L)**	**UVT (%)**	**THMFP (µg/L)**	**OMRI**	**Category**
(- - -)	5.9	44.8	303.0	3.8	Severely Upset
(+ - -)	4.4	58.5	257.7	3.0	Severely Upset
(- + -)	6.6	48.4	231.9	3.6	Severely Upset
(+ + -)	3.3	87.1	83.2	1.3	Moderately disturbed
(- - +)	6.7	45.5	131.5	3.4	Severely Upset
(+ - +)	3.5	78.3	192.7	1.9	Moderately disturbed
(- + +)	7.0	48.5	241.7	3.7	Severely Upset
(+ + +)	3.1	87.8	35.6	1.0	Slightly disturbed
(0 0 0)	4.4	80.1	61.4	1.6	Moderately disturbed
(0 0 0)	4.2	80.2	53.9	1.5	Moderately disturbed