The Effect of Source Water Quality on Water Treatment Costs: Evaluation of Source Water Protection Practices.

by

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Abstract

A few high-profile forest fires and floods in recent history has exposed the vulnerability of Canadians' drinking water supply systems to extreme events and their long-lasting consequences. Elevated levels of contaminants in surface waters can force downstream communities to engage in costly adaptive behaviors, increase public health risks, and force the implementation of expensive infrastructure investments. The conventional way of dealing with such challenges is investing in grey infrastructure. However, public infrastructure investment is costly, and there is evidence of underinvestment in conventional water treatment infrastructure. This creates the need for finding alternative solutions to improve the resilience of our communities for drinking water safety.

The main objective of this thesis is to improve understanding of the effects of water quality and water quality distributions on expected water treatment costs. For this, we develop an investment framework that incorporates community costs that arise when there are disruptions to water supply into total cost analysis. The framework allows us to estimate the benefits of different investment options in terms of avoided water supply costs, including both green and grey infrastructure projects. We conduct a proof-of-concept case study using in-plant data from the Glenmore water treatment plant in Calgary. We model the future distribution of water quality based on 11 years of daily data on water quality and quantity at the in-take and model future distributions of water treatment costs based on five years of costs and operational data.

Using the total cost distributions, we conduct scenario analysis to assess the benefits of different investment options. Namely, we consider two scenarios of increased resilience of the plant and two scenarios of improved source water quality. We conclude that previous studies may have significantly underestimated potential benefits from green infrastructure projects by excluding

community costs from the analysis. Moreover, we conclude that investing in source watershed protection practices can yield benefits in terms of avoided water treatment costs and avoided community costs. However, a cost-effectiveness assessment is needed to compare green and grey alternatives.

Our study evaluates alternative capital investment options that can be considered along with conventional grey investment to tackle challenges presented by extreme events, aging infrastructure, and population growth. Investing in ecosystem infrastructure can be one such alternative as it has the potential to reduce water treatment costs as well as outside community costs.

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Table of contents

List of Figures

List of Tables

Chapter 1: Introduction

In 2013 a heavy rainfall event led to severe flooding across Southern Alberta. The flood was later recognized as the most expensive natural disaster in the history of Canada (Pomeroy et al., 2016). The flood was partially caused by three days of heavy rain and snowmelt (Pomeroy et al., 2016). It is estimated that damage and recovery would exceed CAD$6 billion; the flood-damaged roads, bridges, and dams, about 100,000 people had to be evacuated, and five people died (Pomeroy et al., 2016). In addition to the damage to infrastructure, ecosystems, property, and people, the 2013 flood affected the quality of water in the Bow and Elbow rivers – rivers that supply the City of Calgary with drinking water. The turbidity of the water at the intake to one of Calgary's water treatment plants exceeded 4000 NTU during the flood (Kundert, 2014), while the plant's designed capacity was 1000 NTU. Such poor water quality caused the local authorities to issue a water use advisory. Despite poor source water quality, the treatment plant continued operating.

In 2003, the upper Elbow River watershed was affected by the Lost Creek wildfire – one of the worst forest fires to affect the region in recorded history (Emelko et al., 2011). Wildfires – such as the 2003 Lost Creek wildfire – have significant implications for communities that draw water from the affected watersheds. The 2003 wildfire altered water quality by elevating concentrations of organic matter and chemical contaminants, as well as decreasing the clarity of the water in streams and rivers (Emelko et al., 2011). More importantly, such shifts in water quality in source watersheds can be long-term and may persist for several years (Emelko et al., 2011). This means that downstream communities need to adapt to such sudden shifts to keep producing clean and healthy tap water. For some communities, where existing water treatment facilities cannot handle such changes, post-fire adaptation may imply costly infrastructure investments.

The 2013 flood and 2003 forest fire events raised concerns for water treatment authorities of whether water treatment systems are adequate to handle such extreme events and their long-lasting consequences. Given the potential vulnerability of our water treatment systems to these natural disturbances, it is important to understand the potential costs and probabilities of extreme events for individual communities. Climate change can put more pressure on the safety of drinking water supply by increasing the frequency and magnitude of forest fires and floods.

Aging infrastructure and rapid population growth in Canada are putting pressure on water treatment authorities to find the most cost-effective ways to address infrastructure needs. In the following subsections, we discuss how extreme events, aging infrastructure, and rapid population growth are seen as challenges to the safety of water treatment.

1.1 Extreme natural disturbances: floods and forest fires

In addition to physical damage to property, heavy rainfalls and floods bring large amounts of sediment and organic matter into the river systems. Water treatment facilities that draw water from affected rivers and groundwater wells have to deal with the increased contamination of source water and removal of the sediment in order to supply water to their respective communities. Sudden shifts in water quality create additional costs for water treatment in terms of additional chemical use (Dearmont et al., 1998; Price et al., 2017), loss of reservoir capacity, and costly sediment removal activities such as dredging (Crowder, 1987). Spikes in the contamination of source waters put additional stress on the treatment plants due to contamination of water with bacteria, pathogens, and other contaminants. In the cases when the technological capabilities of a treatment plant cannot keep up with elevated stress on the plant and there are health-related risks to the serviced community, water use advisories are issued. Cases, when such advisories are issued, can be very costly. This is due to the costs of boiling water, of looking for clean drinking water alternatives and other adapting behavior costs. Moreover, boil water advisory (BWA) cases can be associated with increased health risks; the risks might arise for a number of reasons: there might be people who did not receive an advisory notice, some people might ignore the advisory for some reasons, or other potential reasons. To avoid such BWA cases, community water authorities and plant decision-makers need to adapt to newfound challenges from flooding activity.

Severe wildfires burn vegetation which can leave bald slopes on the landscape. As a result, rainfall will wash off greater amounts of sediment, heavy metals, and nutrients that flow into the river systems (Bladon et al., 2014). Moreover, forest fires add to the degradation of natural ecosystem infrastructure that performs vital water purifying services. The adverse effects of the wildfires on the quality of water for downstream communities may persist for many years (Bladon et al., 2014). Such long-lasting effects can increase daily expenditures on water treatment plants meant to deal with increased contamination. Moreover, such shifts in water quality might potentially necessitate costly water treatment infrastructural and technological responses. This is because water treatment plants (WTPs) are pre-designed to deal with certain characteristics of water quality (such as levels of turbidity, or specific contaminants) (Emelko et al., 2011, Crittenden et al., 2012) that can be altered by a high-profile wildfire.

In addition to the individual effects of forest fires and floods on the water quality, there is a potential for these extreme events to exacerbate the effects of each other. Studies show that the amount of sediment and chemical contaminants released from the wildfires is linked with the intensity and sequencing of rainfall and floods (Moody et al., 2008). Such interaction effects between forest fires and floods can have important implications if both of these types of extreme events are expected to increase in the future. Canada is already experiencing an increase in flooding resulting in increasing annual damages measured through insured losses (Moudrak et al., 2018). Moreover, global climate change is forecast to alter the variation in the occurrence of extreme events (Flannigan et al., 2005; Westerling et al., 2016; Goodess, 2013). Thus, the North-Western US and Western Canada are forecast to experience an increase in the frequency and intensity of precipitation events that can further lead to devastating floods (Goodess, 2013). Severity and frequency of high-profile forest fires in Canada and the Western US are also projected to grow with time under different climate change scenarios (Flannigan et al., 2005; Westerling et al., 2016).

1.2 Ageing infrastructure is becoming an issue for towns in North America

Given that the costs of extreme natural disturbances can be high, it is important to evaluate the preparedness of Canadian communities to changes in water quality. A large portion of the Canadian population is served by public infrastructure that is reported to be in fair, poor, and very poor conditions (Canada Infrastructure, 2016). In addition to challenges posed by extreme events, the safety of the water supply is vulnerable due to aging pipes and treatment facilities. Furthermore, the investment approach towards public infrastructure has been very conservative, with reinvestment rates being lower than recommended rates (Canada Infrastructure, 2016). The rates of reinvestment are suggested by asset management practitioners and reflect the levels of reinvestment necessary to maintain the full functionality of the infrastructure (Canada Infrastructure, 2016). The 2016 reinvestment rates in potable water, as reported by the Canadian Infrastructure Report Card (CIRC) (Canada Infrastructure, 2016), were lower than the target rates. The CIRC (2016) estimates $60 billion to be the combined value of replacement of potable water infrastructure that is in very poor, poor, and fair conditions. Given the scale of underinvestment, the condition in potable water infrastructure is projected to decline even further in the future (Canada Infrastructure, 2016). Increasing expenditures in replacing retired infrastructure are considered key in maintaining the safety of the drinking water supply (AWWA, 2001; Canada Infrastructure, 2016).

Underinvestment in aging public water infrastructure is becoming a more prominent issue in some of the northeastern United States cities (Love et al., 2019). There, water infrastructure such as pipes and plants have outlived the design lifespans, and there are insufficient public funds to pay for infrastructure reinvestment (Love et al., 2019). Cities like Flint, Michigan (Love et al., 2019) and Baltimore, Maryland (Broadwater, 2019) are already experiencing lead leakages into the tap water, partially caused by underinvestment in aging infrastructure. Such leakages possess high health-related risks. Thus, the lack of public expenditure on conventional infrastructure replacement projects and underestimation of the problem can pose high risks to the health of the serviced population. Such cases expose urgency to consider alternative and more cost-effective water treatment infrastructure solutions for existing plants and shed light on issues in infrastructure planning such as lack of design adaptability.

1.3 Growing urban population is increasing pressure on water treatment infrastructure

The rapid growth of urban populations is creating pressure on the safety of drinking water through multiple channels. Water treatment plants are designed to serve a certain level of population, and this level is seeded as a plant's capacity during the planning. The prospect of exceeding such a population threshold requires water suppliers to expand the existing water treatment facility or build a new plant, given that the source of raw water is sufficient to meet the demands of a growing population. If the original source of raw water is not sufficient for new demand, then the community needs to search for new sources of water. On the other hand, a growing population also implies a territorial expansion of the cities that increases human presence in the surrounding environment. Such expansions are accompanied by the conversions of land to human use in the source watersheds, disturbing existing ecosystem infrastructure. This, in turn, can lead to a decrease in the source water quality (e.g., see Price and Heberling, 2018).

Population growth is an important factor to account for in infrastructure planning given the additional pressure it can pose on water facilities.

1.4 What is the response to the uncertainties in extreme events, population growth, and aging infrastructure?

A conventional response to the challenges discussed above would be infrastructural and technological responses. For instance, a purely infrastructural response to the expected increase in the frequency of the wildfires would be to analyze a variety of potential water quality effects and design a robust plant (Woodward et al., 2011). Designing large robust plants that outperform all other alternatives in the range of different future projections has been a conventional approach to infrastructure planning (Smet, 2017). However, building bigger and better plants is a costly solution. Thus, water treatment engineers started to look into incorporating flexibility and adaptability in the infrastructure design (e.g., Neufville and Scholtes, 2011). Such innovative approaches are meant to improve the resiliency of water infrastructure in the face of future uncertainty. However, infrastructural and technological adaptation to the challenges of decreasing water quality is aimed at tackling the consequences: such a consequence-based approach ignores the dynamics in the source water quality. Thus, source watersheds are left unprotected that can lead to further exacerbation of the problem.

1.5 Ecosystem infrastructure as an alternative solution

Natural ecosystems are considered to be an alternative infrastructure and are referred to as green infrastructure. This term is used as opposed to the *built* infrastructure, which is also known as grey infrastructure. Natural ecosystems provide valuable services such as river flow control, keeping moisture in soils, water purification, and other services listed in Table 1.1 (Postel, 2008).

Table 1.1 Life-Support Services Provided by Rivers, Wetlands, Floodplains and Other Freshwater Ecosystems

Provision of water supplies for irrigation, industries, cities, and homes
Provision of fish, waterfowl, mussels, and other foods for people and wildlife

Water purification and filtration of pollutants
Flood mitigation
Drought mitigation
Groundwater recharge
Water storage
Provision of wildlife habitat and nursery grounds
Soil fertility maintenance
Delivery of nutrients to deltas and estuaries
Delivery of freshwater flows to maintain estuarine salinity balances
Provision of aesthetic, cultural, and spiritual values
Provision of recreational opportunities
Conservation of biodiversity, which preserves resilience and options for the futuref

Source: Sandra Postel, *Liquid Assets: The Critical Need to Safeguard Freshwater Ecosystems* (Washington, D.C.: WorldWatch Institute, 2005) as used in (Postel, 2008, p.77)

The challenges that aging infrastructure, rapid population growth, and extreme events are putting on water treatment require novel solutions. This is partly due to financial constraints that communities have – upgrading of water purification facilities can be costly while building new or upgrading aging infrastructure can be cost-ineffective. This creates the need for communities to come up with cost-effective solutions. Moreover, building bigger and better plants as a response to the changes in the environment almost entirely ignores the dynamics in the population or source water quality. Thus, regulating the ecosystems and source watersheds can help mitigate the constant need for technological adaptation. Investing in green infrastructure such as planting forests, restoring wetlands or investing in fire regulation can help us address potential future problems by improving average source water quality and regulating water flows or decreasing probabilities of devastating wildfires and floods.

Introducing green infrastructure projects in conventional asset management can be one such novel approach that is cost-effective and can contribute to sustainable solutions on mitigating negative dynamics in water quality and flow issues. Natural infrastructure solutions can substitute or complement existing grey projects by relieving some of the existing pressure. Green infrastructure projects are being widely implemented in urban-planning for stormwater management and flood prevention. Wetlands, for instance, can decrease the pressure from stormwater flows and increase protection from flooding for downstream communities (Moudrak et al., 2018). The scales of such projects vary from street gardens and green rooftops (e.g., see USA Environmental Protection Agency, n.d.) to city-scale projects, wetland restoration, and reforestation activities (e.g., see City and County of Denver, n.d.a). Increasing the implementation of such projects adds to the evidence that investing in ecosystem infrastructure can help in mitigating growing pressures on the safety of water supply.

New York City (NYC) implemented a successful green infrastructure development project that allowed the city to avoid costly infrastructure investment (Chichilnisky and Heal, 1998). In the 1990s, New York had been experiencing the problem of source water quality degradation that would have required a USD$ 10-billion investment into the WTP (Bloomberg and Holloway, 2010). The city opted to invest in source watershed management in the Catskill Mountains and aimed at improving the water quality in the raw water source (Bloomberg and Holloway, 2010). As a result of this commitment, NYC had initially spent USD$ 1.5 billion and was able to avoid the costly grey infrastructure investment. The NYC example is one of a few successful implementations of green infrastructure for improving water quality. While such case studies and projects exist, the benefits of investing in green infrastructure are largely unknown in the context of water treatment.

1.6 Objectives of this study

The broad objective of this thesis is to increase understanding of the effects of water quality and water quality distributions on expected water treatment costs. The existing economic literature mainly focuses on the costs of chemicals, while we extend the analysis to include potential social costs of water supply when the source water quality hits lowest values associated with extreme events such as wildfires and floods. Such extreme events can be very costly in terms of water supply, community adaptation costs because such cases can pose a threat to public health and force serviced communities to engage in averting and adaptive behavior, as well as to consider alternative sources of drinking water. Understanding the impacts that water quality has on costs can help us evaluate the benefits of improving upstream or source water quality. In turn, it would enable us to assess the cost-effectiveness of investing in such alternative options. While green infrastructure projects have already been implemented in several cases, we plan to incorporate green options into capital investment frameworks. This will allow water treatment decision-makers to compare green and grey investment options.

The main objective of this thesis is to develop a total cost framework that incorporates community costs that arise when a water treatment plant is stressed under extremely poor water quality conditions, along with in-plant water treatment costs. This framework allows the investigation of the benefits of different investment options for water treatment, including source watershed protection practices. To achieve the main objective, we focus on three specific tasks:

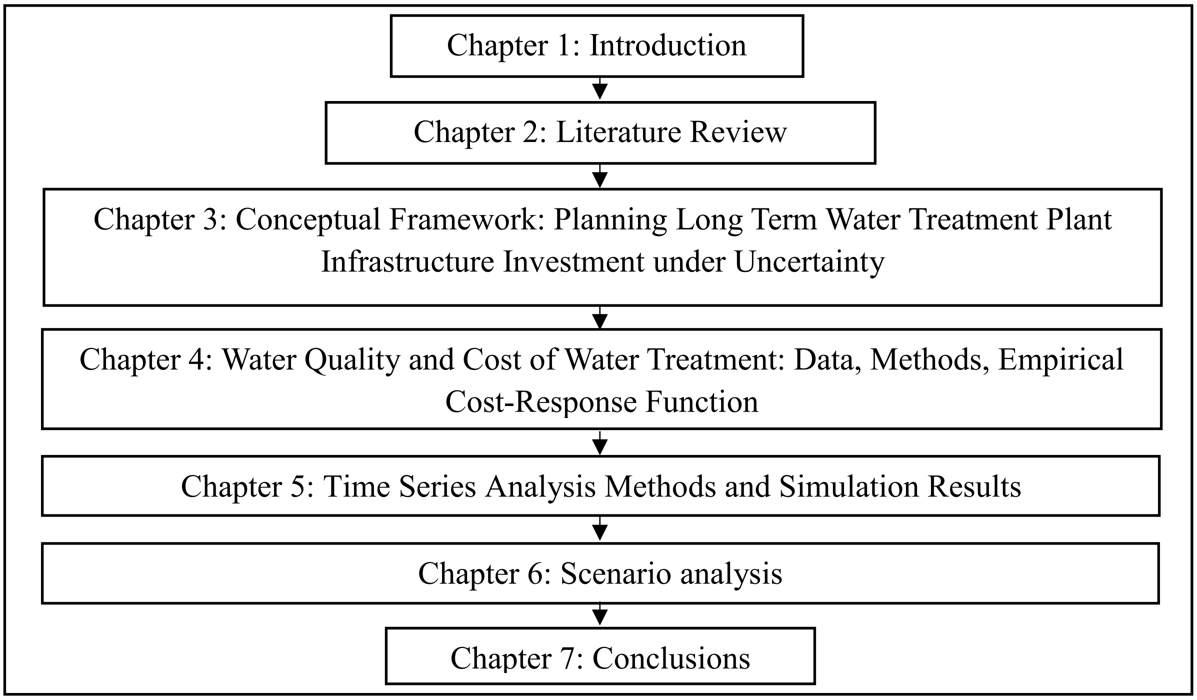
1) To develop a conceptual framework that will allow us to understand the impacts of changes in source water quality on total costs of water supply, and assess the cost-effectiveness of grey and green infrastructure investment projects.
2) To identify and analyze the uncertainties in water treatment costs for a specific plant. For this task, we analyze the engineering as well as economic literature and focus on Calgary's Glenmore WTP for the case study. We model the future distribution of water quality based on 11 years of daily data on water quality and quantity at the in-take and model future distribution of water treatment costs based on five years of cost and operational data.

3) To predict a distribution of the Glenmore water treatment plant's total costs for 20 years from 2015 to 2035, and conduct an assessment of avoided costs due to different investment options in a scenario analysis. The scenario analysis allows us to look into the benefits of investing in grey and green infrastructure options.

The thesis is structured in 7 chapters. The first chapter has focused on the background that motivates the research, highlights the importance of this work, and introduces the objectives of the study. Chapter 2 reviews background knowledge on the state of the art in the relevant literature and identifies gaps that this study aims to address. In chapter 3, we develop a conceptual framework of long-term infrastructure investment planning and discuss what knowledge, information, and data are needed to apply the conceptual framework successfully. In chapter 4, we analyze the available data, develop an empirical cost-response model, and estimate a cost-response function for the Glenmore WTP. In chapter 5, we discuss the time series analysis methods and present the water quality and total variable costs simulation results that precede the scenario analysis. Chapter 6 is the scenario analysis results chapter, where we outline the scenarios used for investment options assessment and discuss the results of the scenario analysis. In Chapter 7, we discuss the results of our empirical cost response model, conclude the results of the scenario analysis, and outline the limitations that our study has at this stage.

Figure 1.1 is a schematic roadmap of this thesis. It highlights the role of an individual chapter in the entire work.

Figure 1.1 Roadmap of the thesis



Chapter 2: Literature Review

The main objective of this research is to develop a capital investment framework that incorporates the analysis of in-plant water treatment costs with expected social costs that arise when the plant does not fit the regular operating schedule. The capital investment framework allows us to understand the effects of investing in grey or green infrastructure options. This literature review chapter focuses on two objectives. The first is to survey the relevant background literature on water quality concepts as well as principles of water treatment infrastructure investment. The second is to survey the relevant economic literature and identify gaps in the knowledge that need to be addressed. To achieve these objectives, this chapter is structured in the following way.

First, we introduce the concept of water quality and determinants of water quality. We will specifically focus on the impacts that wildfires and floods may have on the quality of water in affected watersheds. Second, literature that links water quality and water treatment costs are presented. Third, this chapter surveys the relevant literature in water treatment engineering with a focus on investment and infrastructure planning. Fourth, the ecosystem services literature is reviewed, outlining methods for valuing ecosystem services and practices in green infrastructure.

2.1 Water Quality: Determinants of the Quality of Water in Source Watersheds

Most of the usable water supply in North America – about two-thirds of all water – originates in upstream forested watersheds (Emelko et al., 2011). Communities that largely rely on water from forested watersheds are thus vulnerable to the changes in water quality. There are several sources of pollutants of source surface water drawn by these communities. Khatri and Tyagi (2015) divide these sources into two – natural and anthropogenic. Natural sources of pollutants include precipitation and water run-off, air pollution, degradation of rocks and soils, climate change, and natural disasters (such as forest fires, floods, droughts, etc.) (Khatri and Tyagi, 2015). Anthropogenic sources of pollution are a direct result of human activity. Agriculture, industrial and natural resource development, infrastructure building, land-use change, etc. (Khatri and Tyagi, 2015). Thus, both anthropogenic and natural sources of water pollution contribute to the variation in the quality of the source water and affect the distribution of water quality. Among all sources, natural disasters can be the most disturbing source of water pollution, and yet their effect on the costs of the water supply has not been studied thoroughly.

Forest Fires

Wildfires are one source of natural disasters. Forest fires burn vegetation, which is, in turn, responsible for the regulation of the quality and volumes of water runoff (Martin, 2016). Thus, a decrease in vegetation leads to decreases in evaporation rates, higher levels of soil moisture, and volumes of water runoff (Emelko et al., 2011). Several studies show the link between wildfires and specific components linked to the water quality. Bladon et al. (2008) and Mast and Clow (2008) are studies conducted on source watersheds in southern Alberta and Glacier national park, Montana, US, respectively. They both conclude that wildfires have a significant impact on nitrogen concentration in the forest fire affected watersheds compared to unaffected areas. Continued research on the effects of the same 2003 Lost Creek wildfire in southern Alberta (Silins et al., 2009) further shows that wildfires increase the release of sediments into water streams as compared to unaffected watersheds. Silins et al. (2009) show that the post-fire total suspended solids (TSS) concentration is higher in affected watersheds at least four years post-fire, although the difference is decreasing with time.

Rhoades et al. (2011) explore the effects of the Hayman Fire wildfire (Colorado, US, 2002) on the chemical composition of water streams, sedimentation, and temperature. The study showed that water turbidity increases in forest fire affected watersheds, while the fire effects on turbidity last for several years post-fire. Studies conducted to measure the effects of wildfires on water quality (Moody et al., 2008; Bladon et al., 2008; Mast and Clow, 2008; Silins et al., 2009; and Rhoades et al., 2011) have two important implications for our study. First, wildfires alter the water chemistry significantly, and the effects are long-lasting. Second, the severity of the effects is partly dependent on weather variability. This implies that heavier and more frequent rainfalls would release more sediments and chemicals into the water.

Floods

In addition to bringing costly physical damage to affected communities and ecosystems, high profile floods can cause drinking water supply disruptions. Due to the massive scale of physical destruction caused by high-profile floods, the quality of floodwater is often overlooked (Rui et al. 2018, Hrdinka et al. 2012). Most of the data collection and analytical activity is thus associated with measuring the physical scale of the flood (Hrdinka et al. 2012); moreover, some regions do not have real-time monitoring of water quality during floods, which complicates the research on floodwater quality even further (Rui et al. 2018). Such an approach to flood water quality measuring led to the lack of understanding of the effect of floods on drinking water. It is known, however, that flooding can increase health risks connected with contamination of water (Rui et al. 2018, Hrdinka et al. 2012, Talbot et al. 2018, Sun et al. 2016).

Hrdinka et al. (2012) study the effect of droughts and floods on aquatic ecosystem services. The authors analyze the changes in water quality for a major flood of 2006 (Luznice River basin) and drought of 2003 (Skalice River). The study finds that the concentration of suspended solids increased 30 times in the studied river at the start of the flood (Hrdinka et al., 2012). The concentration of dissolved solids, however, decreased with the course of the flood; the decrease is attributed to the dilution effect (Hrdinka et al. 2012). They further conclude that the 2006 floods significantly affected the concentration of organic matter in the water, the concentration of toxic metals and fecal bacteria (Hrdinka et al., 2012).

Talbot et al. (2018) conduct a review of the literature study to understand the effects of floods on ecosystem services provided by aquatic systems. They divide floods into two categories – small magnitude frequent floods and extreme floods – to see if the floods that are different in scale affect ecosystems differently. The authors identified 117 relevant studies, with 12 ± four studies per each ecosystem service. Relevant to our work, Talbot et al. (2018) analyze the effect of floods on the regulation of water flow, regulation of water quality, regulation of human disease, and provision of drinking water ecosystem services. Other ecosystem services provided by aquatic systems considered in work are supporting services, regulation of climate, provision of food, and cultural value. The authors (Talbot et al., 2018) find the difference in the effects of floods of different scales on the ecosystems.

Huntington and Aiken (2013, as cited in Talbot et al., 2018) show that total suspended solids and dissolved carbon concentrations in forested watersheds and wetlands increase due to floods of all scales, which means that the quality of water is decreasing because of floods. However, other studies (Hale et al., 2014, as cited in Talbot et al., 2018) show that contamination from point sources can be diluted due to the higher discharge of water. Thus, the concentration of some pollutants like heavy metals and fecal bacteria can be decreased due to flooding. The longer-term effects of the flooding on water quality ecosystem service, however, are more difficult to assess and can be ambiguous (Talbot et al., 2018). The impact can depend on the area affected by the flood, size of the watershed, geological specifics of the river basin, and other factors. Directly related to drinking water, Zahoor et al. (2016, as cited in Talbot et al., 2018) show that the concentration of heavy metals (Cr, Ni, Fe, Pb) in the tap and ground waters increased due to extreme flooding in their study sites in Pakistan.

Moreover, large-scale floods were found to be the leading cause of waterborne diseases outbreaks among studied water-related weather events in both developing and developed countries (Cann et al., 2013, as cited in Talbot et al., 2018). While some small scale floods can be beneficial to the provision of ecosystem services and have no significant impact on the quality of surface water, extreme floods are responsible for spikes in water quality and destruction of ecosystems. Such sudden decreases in the water quality can compromise the supply of drinking water and increase risks to human health in both short and longer terms.

Land-use change

Another source of water pollution in source watersheds is land-use change. Differences in water quality of rivers are partly attributed to the differences in land use in the watersheds. The effect of forests and the conversion of forested lands into alternative use on water quality is a well-studied area (Fiquepron et al., 2013). For instance, Tang et al. (2005) estimate the effects of land-use change on the water quality in the Muskegon River watershed. The authors find that land-use change due to urbanization increases runoff and water pollution in the affected watersheds. They also conclude that total water runoff can increase by 5-12% from 1978 to 2040, depending on the development scenario. Nutrient pollution increases due to soil releasing nitrogen and phosphorus by less than 3% in the same period. The study finds that nutrient pollution decreases due to land-use change from agriculture to urban uses, and forecasts a significant increase in water contamination with heavy metals and oil and grease in the studied area (by more than 65%).

Hascic and Wu, in their study (2006), name land-use change the most “pervasive” force disturbing the watersheds. They conduct a study to estimate the effect of land-use change on water quality and aquatic ecosystems in the US. They use various indicators to represent water quality. One is a *conventional ambient water quality* indicator (CONVWQ); it is constructed with readings of concentrations of phosphorus, ammonia, dissolved oxygen, and pH in the water samples. Another indicator they use is *toxic ambient water quality*, and it shows concentrations of toxic heavy metals such as copper, zinc, nickel, and chromium. The third indicator they use is

SPERISK (*species-at-risk*), and it measures the number of endangered animal and plant species inhabiting in the watersheds. They conclude that converting lands from forests to alternative uses (such as agriculture, roads, mining, etc.) has a statistically significant effect on the water quality measured, although the effect is different across land uses. Thus, transportation and mining are mostly responsible for contamination of water with toxic pollutants, while agriculture is responsible for adverse effects related to the concentrations of phosphorus, ammonia, pH, and oxygen in the water. Thus, the study (Hascic and Wu, 2006) establishes a causal link between watershed land disturbances and water quality.

Climate change

Several studies have investigated the potential effects of climate change on the future of extreme weather events and forest fires in Canada and the US. Westerling et al. (2006) study the time series data from 1970 to 2003 on wildfire occurrence in the western US. The authors find that the forest fires became more frequent with time, while the effect is attributed to the earlier spring arrival and increasing temperatures as well as land-use change. Flannigan et al. (2013) come to similar conclusions in their study. The authors look into different climate change scenarios and conclude that North America will experience an increase in the severity of fires in the coming 20-30 years. Moreover, the Canadian Rocky Mountains are forecast to experience both increases in the severity of forest fires and the length of forest fires seasons. Given that western Canada will most likely experience an increase in the number and severity of forest fires, Canadians can expect to have more stress on the safety of the water supply because of the impact of wildfire on water quality.

Mailhot et al. (2012) conduct a simulation study and evaluate future changes in precipitation in Canada due to climate change. Using available climate change projections from the North American Regional Climate Change Assessment Program (NARCCAP), the authors forecast future *annual maxima* precipitations for the period of 2041-2070, using multiple models. They conclude that Canadian prairies and Ontario will experience the highest increase in extreme precipitation events when compared to other provinces. In general, an increase in high precipitation events suggests that there might be increases in the frequency and intensity of flooding in the future. Tohver et al. (2014) analyze the potential effects of climate change on the floods and low flows in the Northwestern US for the 21st century. The analysis of flood risks is based on climate change scenarios and time series data for the 20th century. Although Southwestern Canada is different from the Northwestern US, important insights can be drawn from the study due to geographical proximity. Thus, warming temperatures provided by climate change scenarios are forecast to shift precipitation, snowpack formation, and snowmelt regimes that will eventually affect the distribution of the water runoff for most of the region. Flood and low flow risks for river basins in the region are thus expected to increase, even for colder regions, including US parts of the Rocky Mountains.

Turbidity and TOC

Several parameters are used to describe the quality of water. Some studies are as detailed to analyze the water contents in detail and measure levels of specific heavy metals, nutrients, oxygen (e.g., Hascic and Wu, 2006) or rely on aggregate measures such as the concentration of total suspended solids (TSS) and dissolved organic carbon (e.g., Hrdinka et al., 2012). Moreover, these indicators are meaningful in themselves as they are directly relevant to public health and water treatment processes. For instance, concentrations of heavy metals in tap water are related to the increase in diseases (Hascic and Wu, 2016); and such indicators as TOC and turbidity are used by the water treatment plant operators to control the use of some chemicals (Dearmont et al., 1998). There is also a difference in the water quality metrics used across regions and water treatment plants. For instance, Price et al. (2018) conduct a review of literature that links water quality and water treatment costs, and report elasticities from different studies. Among others were elasticities of costs with respect to sediment load, nitrogen, total organic carbon (TOC), phosphorus load, and pesticide load. However, *turbidity* was the most used measure of water quality among all the studies and is most often used to indicate the quality of water.

Moreover, Alberta's water treatment plant operators report (Alberta Operators Survey, 2015) that turbidity is the main source of concern. Thus, operators make their chemicals use decisions in response to the changes in water turbidity. In our study, we rely on the measures of *turbidity* and *TOC* as water quality indicators because they are collected by in-plant meters and serve as the basis for chemical use at the Glenmore water treatment plant (GWTP). We define turbidity and TOC as follows:

Turbidity is an "optical characteristic of water and is an expression of the amount of light that is scattered by material in the water when a light is shined through the water sample" (USGS, *2016). The higher values of turbidity mean the cloudier and the muddier is the water, and this, in turn, may indicate higher concentrations of sand, salt, and mud and could be a signal to worry about bacterial or chemical contamination of the source water (USGS, 2016).*

TOC is a measure of organic levels in the water (Singh, 2006), and is important to the water treatment analysis as the concentration of organic carbon indicates the cleanness of water (Horn, 2011). In particular, the organic carbon in water is a source of nutrients for microbial and algal growth. It could also lead to the fouling and clogging of membrane filters by accumulating on the filters.

2.2 Water treatment costs: effects of the changes in water quality

Drinking water treatment and supply are only one of the aspects affected by water quality. Keeler et al. (2012) provide a framework for a comprehensive valuation of water quality changes. This framework links final ecosystem services to water quality through biophysical and economic models. Rather than looking at water quality as the end service, the authors consider water quality as an "important contributor" (Keeler et al., 2012, p. 18619) to other ecosystem services. The framework emphasizes the importance of water quality to the provision of ecosystem services. The purpose of the framework is to increase understanding of biological and economic mechanisms by which changes in specific aspects of water quality can affect final ecosystem services and the value of these services. For instance, phosphorus concentration in the surface source water can affect the value of swimming in the given water body by affecting the water clarity and algal blooms. Similarly, phosphorus concentration (as one indicator of water quality) can affect the safety of drinking water and thus the value of avoided water treatment by affecting pest and parasite abundance in the source water.

The framework described in Keeler et al. (2012) connects six water quality characteristics with nine ecosystem goods and services and nine changes in value driven by water quality changes. Water quality is characterized by six components: concentrations of nitrogen, phosphorus, sediment (dissolved organic carbon (DOC)), toxins/pesticides/bacteria, and temperature. As identified by Keeler et al. (2012, p. 18621), changes in these water quality parameters can trigger changes in water bodies such as water clarity and algal blooms, fish abundance and productivity, and pest or parasite abundance. Thus, changes in water quality parameters, in turn, affect several final ecosystem goods and services either directly or through the abovementioned changes in water bodies. Let us consider a change in the concentration of toxins/pesticides/bacteria as an example. The concentration of these contaminants can drive changes in lake and river fishing, swimming, commercial fishing, and the safety of drinking water as final ecosystem goods and services. Changes in these ecosystem goods and services, in turn, affect values of swimming, lake fishing, trout angling, commercial fishing, boating, avoided deaths and illnesses, and the value of avoided water treatment.

Moreover, the value of avoided deaths and illnesses, for instance, can be effected through changes in various ecosystem goods and services, such as swimming, fishing, and safe drinking water. This framework emphasizes the complexity in biophysical and economic relationships and interconnectedness between water quality and the value of ecosystem goods and services. Thus, conducting a comprehensive valuation of changes in water quality requires an understanding of the abovementioned relationships. In this work, we consider the provision of drinking water quality and direct human health impacts as the services affected by the water quality.

Several studies have investigated the effect of various water quality parameters on the costs of drinking water treatment or consumer prices of tap water. The majority of studies were conducted using data from United States water treatment plants. Price and Heberling (2018) summarize the studies that estimate the relationship between source water quality and water treatment costs. We summarize the conclusions that are shared by most of the studies in this domain of literature. First, the effects of water quality are different across water treatment plants, geographies, and types of water sources. Second, the effects of water quality on water treatment, represented by costs or consumer prices, are negative, meaning that the worse the quality of source water, the higher are the costs and consumer prices. Third, land use in the source watersheds is important in determining water quality.

We support the first conclusion by looking into two different domains of literature. First, the theory of water treatment plants' design suggests that specific water contaminants in the source water have to be addressed with different technologies. Second, we review the economic literature on water quality and treatment costs and find that the magnitude of estimated effects of water quality on costs varies across different studies.

Some of the heterogeneity in the responsiveness of the variable costs can be explained by the water treatment plants' design and planning processes. Characterization of the source water is one of the stages of the process of designing water treatment facilities (McGivney and Kawamura, 2008). The technology at WTPs is chosen to address specific characteristics of the source water, and the water quality standards, which then affect the distribution of operating costs (Emelko et al., 2011). In the following subsection, we briefly review the processes of water purification in a conventional water treatment plant to summarize the purification process and better understand how the source water quality can affect the in-plant costs.

2.2.1 How a Water Treatment Plant Operates

Since at least 4000 B.C. people have known that water treatment is necessary before human consumption (Crittenden et al., 2012). The ways that water is treated for drinking purposes have changed throughout history with the evolution of technology and knowledge about chemical and physical properties of water and its components, and health. However, the purpose of the water treatment process remained mostly unchanged – to remove potentially harmful components from the source water and prepare it for final consumption. Nowadays, some communities use simpler technology, while others employ sophisticated processes to treat the source water.

A conventional water treatment plant uses 7 main processes to treat water. Namely, they are screening, pH control, coagulation, flocculation, sedimentation, filtration, and disinfection (Crittenden et al., 2012). Screening is the first part of the treatment process, where the bigger solid materials are removed from the raw water at the water intake. Then, water is treated to control for a pH level, which is important for further chemical treatment of the water as the acidity of the raw water affects the interaction between chemicals in the water. After a pH is leveled to an acceptable range, processes of coagulation and flocculation take place to remove excess sediment from the raw water. These two processes are used in a sequence to facilitate the sedimentation of particulate matter during which non-organic as well as organic and dissolved organic compounds are separated and removed from liquid water (Crittenden et al., 2012). It is important to remove particles from the water as they affect the color of water, can be potentially infectious and possess toxic components (Crittenden et al., 2012, p. 543). In a conventional WTP, various chemicals are used to conduct pH control, coagulation and flocculation processes. For instance, the Glenmore water treatment plant in the City of Calgary uses aluminum coagulants (alum) and polymers for coagulation. After most of the solids are removed, water is treated through filters to remove residual particulate matter and then disinfected and stored in a storage (Crittenden et al., 2012, p.12).

In a conventional WTP or WTPs that use conventional processes in addition to modern technology, the use of chemicals is an essential part of the water purification process. The use of chemicals can constitute a major share in variable costs, whereas the source water quality has a direct effect on the use of chemicals (Dearmont et al., 1998). In the coming subsections, we explore some factors that can affect the changes in water quality, and how water quality, in turn, drives water treatment costs.

2.2.2 Diminishing Water Quality Increases Treatment Costs

To support the conclusion number two, we summarize some studies conducted to estimate the effect of water quality on the treatment of drinking water.

Depending on data availability and research objectives, studies use various indicators to represent water quality. Several studies investigating US WTPs use turbidity as the main water quality parameter. Forster and Murray (2007), for instance, analyze annual panel data from 11 water treatment plants spanning five years. They estimate the elasticity of costs to changes in turbidity to be 0.3, and the cost elasticity with respect to pesticide load is estimated to be 0.27. Heberling et al. (2015) conduct a time series analysis of 5 years of daily data obtained from the Bob McEwen WTP in-plant data. Estimated long term cost elasticity to turbidity is 0.11, while the effect of other parameters like the concentration of total organic carbon (TOC) and pH of the water were found to be insignificantly related to costs.

In contrast, Warziniack et al. (2017) find a statistically significant relationship between TOC and costs. The authors conduct a two-step analysis of cross-section data obtained from 37 WTPs using a survey. WTPs that source their water from forested watersheds were selected for the survey. In the first step, Warziniack et al. (2017) estimate the ecological function that relates water quality and watershed characteristics. In the second step, economic benefits function is estimated to measure the effect of water quality on the treatment costs. To estimate the cost elasticities to water quality, the authors control for treatment technology and the volume of produced water. The study estimated the cost responsiveness with respect to turbidity and TOC to be 0.19 and 0.46, respectively.

Moreover, the study finds that the share of the forested areas in the watershed has a positive effect on the quality of water (the more forested watersheds are associated with better water quality). While the study (Warziniack et al., 2017) supports the conclusion that poorer water quality is associated with higher treatment costs, and that forests can improve the quality of water, the reported elasticities need to be considered with caution. The study does not record changes in water quality and costs with respect to time. Thus we cannot interpret cost elasticity as the responsiveness of costs to the changes in water quality. Reported elasticity rather reports within-sample differences in costs against average levels of TOC and turbidity. The study omits confounding factors (e.g., weather, land use, etc.) in the analysis that may lead to the omitted variable bias in the estimation of the elasticities (Warziniack et al., 2017).

Moreover, there might be potential for endogeneity between treatment costs and the treatment technology (Price et al., 2017) that can lead to biased estimators. From the biophysical function, the authors (Warziniack et al., 2017) find that afforestation of an additional 1% of the land would lead to a 2.8% reduction in turbidity. The cost elasticity obtained from the economic function of 0.19 tells us that a 2.8% reduction in turbidity will lead to a 0.5% reduction in costs.

Price et al. (2017) conduct a stochastic cost frontier analysis using data from Canadian water treatment facilities. The analysis is based on cross-sectional data from 944 plants and includes characteristics of in-plant technology, source water, and operation and maintenance costs. Their analysis shows that the elasticity of treatment costs with respect to turbidity varies across different treatment technologies, averaging at 0.1. Depending on the technology, elasticities were estimated to be as low as 0.06 (for plants classified as *disinfection* systems) and as high as 0.14 (for plants classified as *membrane*). Similarly to Warziniack et al. (2017), Price et al. (2017) is a cross-sectional study, and estimators can potentially be affected by the endogenous relationship between the costs and technology (Price et al., 2017).

2.2.3 The Effects of Land Use on the Costs of Water treatment

While some of the abovementioned studies have established the link between the land-use change and water quality, and the impact of the change of water quality on the treatment costs, some other studies make a direct inference of the relationship between land use and water treatment costs.

A 2013 study estimated the impact of land-use change on water quality and attempted to quantify the value of forests for water quality (Fiquerpon et al., 2013). The authors use cross-section data on department level from across France. They estimated the effects of various land uses on water quality characteristics (nitrates and pesticides), and the effect of water quality on end drinking water consumer prices at the national level. They use simultaneous equations estimation and generalized method of moments to account for endogeneity and heteroscedasticity in the water quality model. They conclude that forests and grasslands, as opposed to other land uses, improve water quality and decrease consumer prices. The impact of forests on the end prices can be interpreted as the economic value of forests in terms of drinking water (Fiquerpon et al., 2013). They estimate the value of 1 hectare of afforestation at €22[1] (2015 CAD 31.07) on household water bills. A one-point increase in the proportion of forests can lead to a relatively low decrease in consumer prices (€0.0034 per m^3), while the nation-wide savings are estimated to be €11.71 million (2015 CAD 16.54 million) per year.

Similarly, Abildtrup et al. (2013) analyze cross-section data from 232 water supply services located in the Vosges department, France, to estimate the effect of land-use change on the costs of water treatment. They estimate equations of costs and a demand function simultaneously. Similarly to Fiquerpon et al. (2013), Abildtrup et al. (2013) address the issues of endogeneity as well as spatial autocorrelation by doing instrumental variables estimation and employing the generalized method of moments. Water treatment costs are found to be significantly decreasing with increasing forest cover. Using estimated elasticities, the authors then calculate the value of increasing forest cover (at the cost of decreasing agricultural land cover) in an average water services supplier's region and neighboring regions. Thus, afforestation of 1 ha of agricultural and non-agricultural lands leads to €99 (2015 CAD 139.8) and €138 (2015 CAD 194.9) reduction on household bills for an average water service supplier.

Vincent et al. (2015) conduct a detailed study on the valuation of forests in terms of water quality ecosystem services. They use monthly data from 41 plants in Malaysia that span the period from 1994 to 2007. They conduct an econometric analysis of the effect of the share of the forested areas in the watershed on monthly average water treatment costs. The study supports the

[1]Value was adjusted to 2015 Euro, using 2013 and 2015 CPIs for France (https://data.oecd.org/price/inflation-cpi.htm). Values is then converted to 2015 CAD$ using 2015 average exchange rate of 1.42 (https://www.statista.com/statistics/412804/euro-to-canadian-dollar-average-annual-exchange-rate/)

conclusions of previous studies that the maintenance of virgin forests contributes to the improvement of water quality and reduced treatment costs. They find that virgin forests do a better job than the logged equivalents; the cost elasticity with respect to undisturbed forests was -0.47 compared to the elasticity of -0.32 for logged forests. The marginal value that 1 hectare of forests produced during the studied period is estimated to be RM67.75[2] per hectare per year (2015 CAD 23.05). Comparing the value of water purification alone does not offset the value of converting forests to commercial use, where 1 hectare of land brings RM2,360 (2015 CAD 802.93) and RM2,812 (2015 CAD 956.71) annually when used to produce rubber and palm oil respectively (Vincent et al., 2016). Looking at a variety of different plants, the authors conclude that the value produced by forests varies across treatment plants, suggesting that the cost-impact of forests is contingent upon the characteristics of both the source water and the technology employed by the plant.

2.2.4 Gaps in the Literature on the Effects of Water Quality on Treatment Costs

While the cost impacts of water quality have been studied for more than thirty years, we identify two research gaps. First, the cost reduction associated with the improvement of water quality was solely estimated as avoided treatment or variable costs. Second, to the best of our knowledge, no study has tried to bring in knowledge about the effect of green infrastructure such as forests into a capital investment framework to compare green and grey infrastructure. This study addresses the first gap by including the costs of avoided water treatment plant failure into the cost analysis.

To the best of our knowledge, all of the studies that relate water treatment costs and water quality report elasticities at the means. Thus, there is sufficient knowledge about the cost-response to the water quality changes around the mean. In contrast, little is known about how water treatment facilities deal with the extreme values of water quality. Extreme events associated with spikes in turbidity and specific contaminants have shown to be costly to the public. In this work, we address the gap in the literature and model the response of WTPs to the values in the right tail of water quality distribution.

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[2] Value was converted from 2015 Malaysian Ringgit to 2015 USD using 2015 average exchange rate of 0.256 (https://www.statista.com/statistics/863826/malaysia-exchange-rate-between-ringgit-and-us-dollar/), and converted to 2015 CAD using 2015 average exchange rate of 1.329 (https://www.irs.gov/individuals/international-taxpayers/yearly-average-currency-exchange-rates).

The second gap lies in the intersection of the economic and engineering literature. We lay the groundwork to incorporate green infrastructure options into a capital investment framework along with grey infrastructure options. In the next section, we explore the existing literature on capital investment planning. We then develop a conceptual framework in the third chapter; the framework brings the outside-of-plant costs (as opposed to in-plant variable costs) into the analysis and discusses how green infrastructure can be added to the capital investment framework. Thus, we address the two gaps identified in the Economics literature of drinking water quality.

2.3 Capital Infrastructure Investment in Water Resource Management: What are the Decision-Making Processes and Current Practices?

In this section, we briefly review the relevant literature in the domain of long term infrastructure planning and design. Net present value (NPV), internal rate of return (IRR), and benefit/cost ratio analysis are considered as conventional approaches to infrastructure planning (Dixit et al., 1994; Neufville and Scholte, 2011; Deng et al., 2013). These approaches assume that the investment takes place at a specified time, while the costs and benefits are then calculated as a discounted cash flow (Deng et al., 2013). These methods have been heavily criticized for more than two decades (e.g., Dixit et al., 1994; Neufville and Scholte, 2011; Deng et al., 2013). One of the criticisms of this approach is that these methods are unable to internalize future uncertainties, meaning that the best design is determined based on a predicted most-likely scenario, while not accounting for the possibility of other future scenarios (Neufville and Scholte, 2011). Another criticism is that conventional planning approaches are incapable of accounting for the shifts in future circumstances (Neufville and Scholte, 2011). An example of the change of circumstances might be obtaining new information in the periods after the infrastructure is built. Thus, for instance, a sudden shift in the river water quality due to a high profile wildfire, while affecting source water quality significantly, would require plant managers' adaptations. A plant designed using conventional methods would likely be less adaptive to sudden changes because the design-flexibility was not seeded as a design objective. Flexibility here is defined as an ability of an infrastructure project to be gradually upgraded as a measure to adapt to changing conditions. The Real Options (RO) approach was developed partly as a response to the inadequacies of conventional decision-making methods (Dixit et al., 1994).

The real options (RO) approach to infrastructure planning allows decision-makers to introduce adaptability to the design (Deng et al., 2013). The RO method eliminates two of the flaws of conventional planning practices by allowing the decision-makers to account for uncertainty in future scenarios and allowing them to internalize the timing of the investment or allowing the comparison to other investment options. The RO approach has been increasingly applied in project evaluation both in the literature and practice. For example, Kim et al. (2017) conduct an RO analysis of hydropower plant adaptation to climate change. Park et al. (2014) evaluate a drainage infrastructure project accounting for the impact of climate change. Some work in the real options literature has been done in the area of water supply infrastructure evaluation. Zhang and Babovic (2012) use the RO framework to analyze a combination of several alternative sources of water and technologies. They claim that conventional methods are inadequate for such complex tasks. Deng et al. (2013) build on the analysis of Carding et al. (2007, as cited in Deng et al., 2013), and apply the RO framework to introduce the flexibility of water systems in the design analysis.

The RO framework's origins lie in the theory of options valuation in finance (Dixit et al., 1994). The RO literature partly draws on the methodology in the finance literature; for instance, Hauer et al. (2017) apply Longstaff and Shwartz's (2001) method for the valuation of American options in the RO analysis. Thus, the RO literature lies on the intersection of the Engineering, Finance, and Economics literature. Some of the literature on RO explores methodology. For example, Gamba (2003) discusses the use of the Monte Carlo method in the Real Options framework, while Cortazar (2000) discusses simulation and numerical methods. Other studies present empirical findings from applications of the framework in different contexts. Kim et al. (2017) apply RO analysis in the context of renewable energy in developing countries. Woodward et al. (2014) apply the framework in a flood management context. Some studies use the framework to advance engineering design as a tool to give greater adaptability to the decision-makers and operators. Zhang and Babovic (2012) evaluate innovative technologies (such as desalination and recycling water for tap water use) applied in Singapore within the RO framework. Deng et al. (2013) assess the value of flexibility in the design of water supply infrastructure.

The reason for the real options approach slowly taking over from the conventional approaches is the amount of flexibility that it offers. This flexibility is especially useful given the rapid global (e.g., climate change) and local (e.g., population growth, change in health standards) changes that the world is experiencing. The real options framework for project valuation suits the needs of this study in several important ways. First, it allows us to incorporate a number of future scenarios, including population growth or climate change scenarios, into our analysis. Second, RO is a convenient and efficient framework to introduce and evaluate green infrastructure options along with grey infrastructure options in a water treatment setting. The real options framework adds flexibility and complexity to conventional analysis. However, the application of the RO framework requires careful analysis of uncertainties, costs of engineering options (grey infrastructure), an in-depth analysis of green infrastructure options, as well as developing, programming, and implementing the model. While the motivation for this study is comprehensive and requires the application of the RO framework, the actual implementation of the RO model goes beyond the scope of this thesis. We conduct the preliminary analysis of uncertainties and develop a framework to introduce green infrastructure into the capital investment analysis framework. We then implement the framework using a net present value (NPV) analysis of generalized grey and green infrastructure projects, as a precursor to an RO analysis.

2.4 Introduction to Ecosystem (Green) Infrastructure

In this study, we use terms *ecosystem infrastructure* and *green infrastructure* interchangeably because both of them are relevant in the context of capital investment and are used in the literature. One way to define green infrastructure is as "*an interconnected network of green space that conserves natural ecosystem values and functions and provides associated benefits to human populations"* (Benedict and McMahon, 2002, p.12). In the context of river systems and source watersheds, green infrastructure includes soil systems, water systems, grasslands, wetlands, forests, and other "green spaces" (Benedict and McMahon, 2002). An important feature of green infrastructure is that it eventually provides services to people. Postel (2008) provides a good summary of the types of services that water systems provide communities with:

> *"Healthy rivers, floodplains, wetlands, and forested watersheds supply more than water fish. When functioning well, this "eco-infrastructure" stores seasonal floodwaters, helping to lessen flood damages. It recharges groundwater supplies, which can ensure that water is available during dry spells. It filters pollutants, purifies drinking water, and*

delivers nutrients to coastal fisheries. Perhaps most importantly, it provides the myriad habitats that support the diversity of plants and animals that perform so much of this work" (Postel, 2008, pp. 75-76).

The importance of ecosystem conservation is increasing because people are becoming more aware of types and the value of services that ecosystems provide. This study contributes to the understanding of the value of ecosystem services that green infrastructure has for water treatment. In this section, we review case studies where the use of green infrastructure proved to be useful for water treatment. We use these examples to provide the reader with a better understanding of the kinds of infrastructure that can be used to improve water quality. We then discuss what co-benefits green infrastructure projects might have. Finally, we outline methods that are used in the economic literature to value ecosystem services and indicate how this paper relates to the field of environmental valuation.

2.4.1 Examples of Ecosystem Infrastructure Investment

In this subsection, we explore what green infrastructure is needed to regulate or improve water quality.

2.4.1.1 New York City's Experience of Green Infrastructure implementation

One of the most cited and well-known examples of the use of ecosystem infrastructure is the New York City (NYC) case (Chichilnisky and Heal (1998) cited in Vincent et al., 2016). Due to diminishing quality in the water that New York City was drawing from, the city had to invest in new costly filtration infrastructure (Chichilnisky and Heal, 1998). In turn, the city made a decision not to build the new infrastructure, but instead to focus on watershed protection practices (Bloomberg and Holloway, 2010). Thus, instead of tackling the consequences of the diminishing quality of water, they focused on the source of the problem. The decision resulted in more than $1.5 billion of investment into preserving the quality of the source water and delayed grey infrastructure investments estimated at more than $10 billion.

The $1.5 billion investment included buying out and protecting lands in the upstream watersheds and improving wastewater treatment systems (Bloomberg and Holloway, 2010). Wetlands and forests played a major role in preserving the quality of water. Since the early 1990s, New York City has been continuously investing in green infrastructure projects. They complement watershed protection practices and wastewater treatment systems by improving city green spaces. Thus, there are programs to encourage the use of green roofs, to require green parking lots, and support other city sustainability projects (Bloomberg and Holloway, 2010). Thus, New York City avoids costly and cost-ineffective investment into grey infrastructure and preserves one of the best quality tap water systems in the world.

2.4.1.2 Portland, Maine Case Study

Talberth et al. (2013) conduct a benefit-cost analysis of green infrastructure versus grey infrastructure projects in a Portland, Maine case study. Portland is a small town of about 67,000 people. The town draws its drinking water from Sebago Lake located north-west of the town. Similarly to the NYC case, Portland wanted to avoid costly filtration infrastructure development projects required by the U.S. Environmental Protection Agency (EPA) and thus analyzed green infrastructure projects. Investing in grey infrastructure was used as a baseline case, and green infrastructure projects were then weighed against the baseline. For this town, an alternative infrastructure project was to rely on forests to provide water purification services. The green infrastructure project presented by the authors is a combination of different subprojects that are claimed to substitute the need for the filtration plant. Afforestation efforts were estimated to be the most expensive of all elements ($15-44 million per 9,395 acres), followed by investments into riparian buffers ($16-29 million per 367 acres) and conservation easements to maintain 80% of forest cover ($12-29 million per 13,215 acres), while culvert upgrades ($1-4 million per 44 units) and sustainability certification of timber harvest ($0.1 million per 4,699 acres) were among the cheapest elements (US Climate Resilience Toolkit, 2017). The baseline expenditure on grey infrastructure is estimated at $97-155 million, meaning that green infrastructure could potentially save $49-113 million in net present value. The authors, however, omit the description of the methods they used to estimate the costs and benefits of green infrastructure options. However, this case study provides an important outlook on how green versus grey infrastructure consideration should generally be executed based on the net present value approach. Moreover, the case study serves as an example of what ecosystem infrastructure can be used to improve water quality.

2.4.1.3 Summary

The essence of the green infrastructure approach to the treatment of water is the use of green or natural spaces (forests, wetlands, etc.) to reduce the number of pollutants going into waters, regulate water flows, and build sustainable ecosystems. Depending on the climate, geography, and the objectives of green infrastructure projects, a variety of tools can be used for water purification purposes. Thus, source water protection (SWP) is an important tool in protecting waters. However, SWP is not sufficient in some cases, and there is a need to act beyond protecting the source watersheds and complement the existing ecosystems (Emelko et al., 2011). Afforestation and reforestation have proven to be effective measures in restoring and expanding existing ecosystems to reduce water treatment costs in New York City (Bloomberg and Holloway, 2010) and India (see Gray and Srinidhi, 2013), and were estimated to be relatively more cost-effective (compared to grey infrastructure) in the Portland case study (US Climate Resilience Toolkit, 2017). In addition to forests, wetlands provide flow regulation and water storage services, and thus restoration and support of wetlands can be an important part of green infrastructure projects aimed at water purification and flood regulation.

2.5 Valuation of Ecosystem Services

It is difficult to put a value on services that ecosystems provide us with. Some services might be difficult to measure (e.g., how do we measure biodiversity?), while people can value the same services differently. For instance, forests in Amazonia are valued as timber by some people, while those same forests support living for other people; for instance, by providing hunting opportunities. However, we want to estimate the value that can be extracted from different ecosystem services for various reasons. One such reason is the evaluation of the provision of ecosystem services by the government (Boyd and Banzhaf, 2007). Here, an estimate of the value of benefits is important for a cost-benefit assessment of such projects. Often ecosystems and green spaces (e.g., forests) can be considered for competitive purposes. Wetlands, for instance, can be drained and used for the expansion of a city, while they can provide purification of water services for communities, support natural habitats for animals, and other services.

In the book “The Measurement of Environmental and Resource Values,” Freeman et al. (2014) suggest different ways to classify the different values provided by the environment and natural resources. One way is to distinguish values by “type of resource of environmental media”; such a classification approach is used to separate changes in value due to changes in the quality of water, air, land, etc. (Freeman et al., 2014, p. 12). The second way is to distinguish value according to how humans are affected – through marketable goods and services, such as timber or goods and services for which markets do not exist, such as health, some recreation opportunities, and others. The third type of classification suggested by Freeman et al. (2014) is to distinguish environmental goods and service flow on whether they affect humans directly or indirectly through other living things or other systems. Direct human effects would include such impacts as air and water quality directly affecting human or reduced water quality affecting swimming. The second channel of effects through living organisms and systems might include effects on the economic productivity of "agricultural croplands, commercial forests, and commercial fishing" (Freeman et al., p. 13), as well as, for instance, reduced fishing and hunting opportunities. The third channel would include indirect human impacts through affected infrastructure or property damages. The fourth way to classify values provided by ecosystem goods and services is to distinguish non-use (or passive use) values and use-values. The use-value would include goods and services that are valued for their usability, where the value can be extracted through some activity or consumption to improve the people's well-being. Nonuse values, by contrast, include the features possessed by the environment and natural resources that are valuable in and for themselves.

Different classifications allow us to look at the value provided by the environment and resources in different ways, and ones can be useful in specific contexts more than in others. Freeman et al. (2014) discuss channels through which producers utilize ecosystem services, and that they are reflected in the costs of production. In their book, in the instance of water treatment, water quality can be considered as an input into production. As discussed above, the diminishing quality of water can affect plant costs (Vincent et al., 2015). This way, a change in quality affects producer surplus (Freeman et al., 2014). We can thus improve welfare by improving the quality of the source water.

Freeman et al. (2014, p.240) explore the valuation of improved inputs such as water quality by examining the problem of cost minimization of a firm, where costs can be expressed as a function of environmental quality:

$$C = C[y*(q), q] \,, \qquad \textbf{[2.1]}$$

Where C is the aggregate variable cost for the industry, q is environmental quality, say water quality that enters the production of single product y, and $y*$ is an equilibrium quantity. The social welfare, in this case, can be expressed as:

$$W = \int_0^y p(u)du - C(y*, q), \quad \textbf{[2.2]}$$

Where W is social welfare expressed as the sum of consumer and producer surplus. Here, p is the market price, and u is the quantity demanded. The firm and consumers are price takers.

Freeman et al. (2014, p.241) then apply the envelope theorem to obtain the marginal change in welfare with respect to the changes in the quality of the environment; here, the quality of environmental good or service as an input. Here, q is assumed only to affect costs.

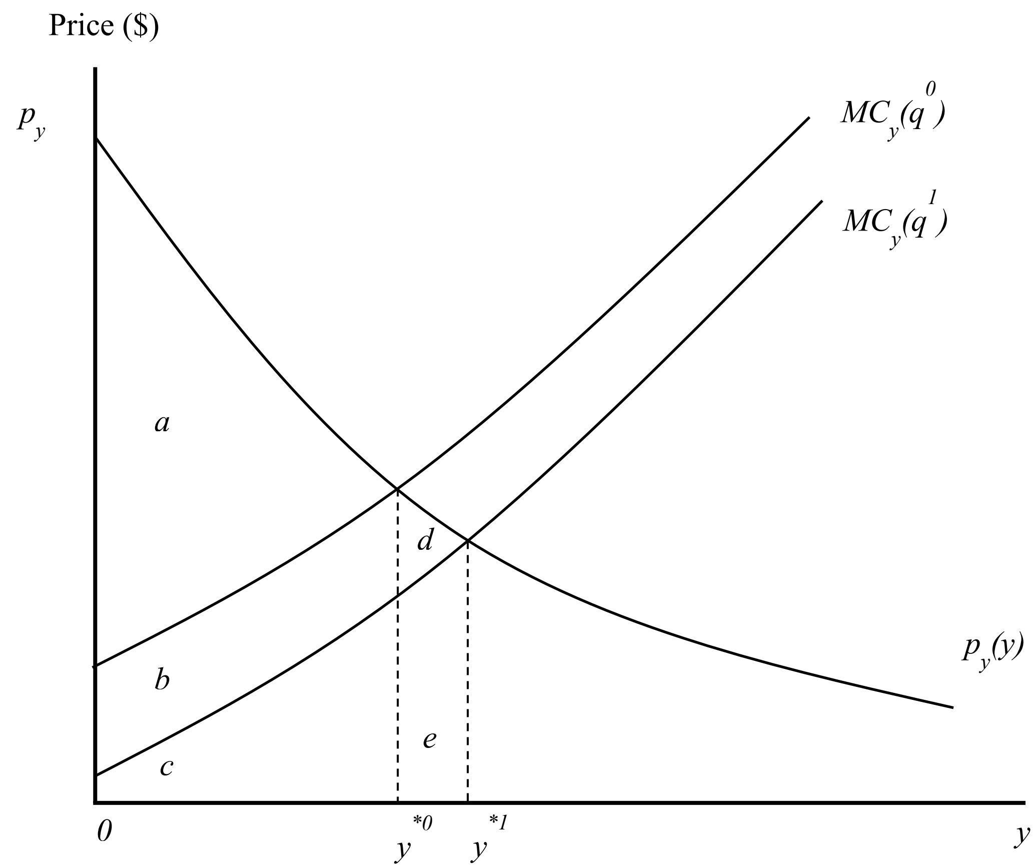
$$\frac{\partial W}{\partial q} = -\frac{\partial C(y*, q)}{\partial q}. \quad \textbf{[2.3]}$$

Thus, the marginal welfare change can be calculated using a cost function (Freeman et al., 2014). In the context of water treatment, we need to model costs as a function of water quality. Aggregate welfare gains (or losses) can be calculated by integration of marginal reduction in costs:

$$W = -\int_{q0}^{q1} \left\{\frac{\partial C[y*(q), q]}{\partial q}\right\} dq, \quad \textbf{[2.4]}$$

Where q^0 and q^1 are water quality before and after the change, respectively. The welfare change can be illustrated in the following figure:

Figure 2.1 The Welfare Change for Single-Product Firms.



Source: Freeman et al. (2014), p. 243, Figure 8.1

Here, the welfare change is:

$$W_q = (a + b + c + d + e) - (c + e) - (a + b + c) + (b + c) = (b + d), \qquad \textbf{[2.5]}$$

Thus, a change in welfare, when using a production (cost) approach, is simply the difference between total costs before and after of the quality change (*b + d)*. The initial assumption for the model was that the firms are price-takers, which is not usually the case for municipal water suppliers. A municipal water supplier is usually a natural monopoly and is not a price-taker. In the case of a natural monopoly, the equilibrium quantity is less than a socially optimum quantity observed in perfectly competitive markets. An assumption that we make about competitive firms or private monopolies is that they are profit maximizers. Here, a WTP, although privately owned, can be considered as a provider of a public good that maximizes social welfare (Perman et al., 2003). Thus, a socially optimal outcome can be achieved at quantities y^{*0} and y^{*1} (Perman et al., 2003), as illustrated in Figure 2.1 above.

The theoretical framework described in Freeman et al. (2014) provides a good starting point for analyzing the effects of changes in water quality on welfare. However, the framework is used under the assumption that environmental quality only affects in-plant water treatment costs. In the following chapter, we complement the analysis of water treatment costs with the analysis of external costs (social and private costs) that arise when a WTP falters due to decreased water quality.

2.6 Summary

In this literature review chapter, we have brought together pieces from different domains of the literature, including economics, engineering, and water resources. We started the chapter by reviewing studies on the relationship between the wildfires and water quality in affected watersheds. We conclude that wildfires can have devastating effects on the quality of water, and the effects can persist in the long term. Flooding can potentially be another disturbance that can decrease the quality of water. In addition to the individual effects of wildfires and floods, we have shown that the combination of floods and wildfires can have significant negative consequences for water quality in regions like western Canada. We further showed that climate change is forecast to increase the likelihood of high-profile forest fires and floods. The review of the economics literature, in turn, shows that such effects can be disruptive for downstream communities that draw water from stressed watersheds. Studies show a relationship between the changes in water quality and water treatment costs. The economic analysis of the effects of the water quality on water treatment costs solely focused on in-plant variable costs; the consideration of social costs of water supply disruption was left out of the analysis in most studies.

Section 2.3 discusses the developments in asset management and investment planning literature. We highlight the development of the *real options* approach that is used to evaluate infrastructure projects. The RO approach is considered superior to the conventional NPV approach in a way that it is more suitable for the consideration of investment under uncertainty. The benefits from and methods for the valuation of green infrastructure projects were discussed in sections 2.4 and 2.5. It is possible that communities can benefit from the introduction of innovative green infrastructure approaches. The benefits of including ecosystem infrastructure options, however, are largely unknown in the context of water treatment.

We identify that our work can contribute to the literature by developing a framework to introduce green infrastructure projects into investment analysis. Moreover, we extend the literature on the economics of water quality by incorporating the analysis of outside-of-plant-social costs along with the analysis of water treatment costs.

Chapter 3: Conceptual Framework: Planning Long Term Water Treatment Plant Infrastructure Investment under Uncertainty

In this chapter, we present a cost-effectiveness framework for long-term infrastructure investment planning under uncertainty for water treatment plants. This approach is innovative in the way that it incorporates the analysis of the impact that the distribution of source water quality has on operational costs into the framework of planning the investment. Moreover, the analysis of the impact of water quality on investment costs will allow us to value the benefits, in terms of treatment cost reductions, from different source water quality management practices as well as grey infrastructure options. This approach could be considered a general framework for water treatment plant investment planning, as it could handle various specific aspects of the plant, including technical sophistication of the plant, source-water quality, population growth expectations, and challenges that the future holds for the specific plant. In this chapter, first, we will outline the conceptual framework and steps needed to address the question of infrastructure investment planning. Second, this chapter will define the uncertainties that need to be addressed when planning the investment path. Third, we will outline the set of thresholds that differentiate normal in-plant operational costs for water treatment from extreme event costs that can include costs of community adaptation during different water use advisories. Finally, we consider how to use this approach for an assessment of the benefits of a source-water management strategy.

This approach consists of four steps. Step one defines the problem and important issues that managers of water treatment plants face, including future challenges that come with population growth, expected changes in water quality, and decreasing technological capacities of the facilities. Analysis and characterization of uncertainties is an important part of the problem definition. The second step is to define thresholds in uncertain parameters that define changes in the operational schedule of the WTP and affect the total variable costs. The third step is to formulate a total cost model for the water treatment plant that addresses the outlined uncertainties and incorporates the costs under various scenarios defined by those thresholds. The fourth step in this framework is to consider different strategies to address the uncertainties, including technological upgrading of an existing plant, building a new facility, or employing ecosystem infrastructure options. The final step is to compare the strategies, options, and choose the most cost-effective investment path.

3.1 Define the Problem

In this thesis, we will consider problems that a WTP could face in a 20-year planning horizon. We split the problem into two categories. The first category is described by a scenario in which the WTP is unable to meet the demand for water quantity from the population. This problem might have multiple sources – the rapid growth of the population, aging infrastructure resulting in decreased technical capabilities, or a shortage of source water. The second category of the problems covers the scenario of the plant's inability to meet output water quality standards. There might be several causes for this problem, such as aging infrastructure and machinery that is not able to process water to sufficient quality or decreasing water quality in the source water to the extent that the current technology becomes incapable of treating raw water to standards. Worsening water quality might include the overall gradual decrease in water quality (e.g., algae blooms, or increasing contamination in a river linked to urbanization and land-use change), or could be a reflection of an increasing probability of wildfires or floods that can affect the water quality. Correct identification and characterization of the problem is the necessary first step, as this step will identify the uncertainties and further define the tactics of how to deal with them.

3.2 Analyze the Uncertainties

This step is a central part of the suggested approach, as uncertainties are important inputs into the analysis of future scenarios. Depending on the accuracy of identifying and characterizing the uncertainties and assumptions around them are the end conclusions that could be drawn from the model. Moreover, ignoring the uncertainty limits the ability to address water treatment problems in the future (Walker et al., 2013). To identify the most relevant sources of uncertainty, one may need to refer to the existing studies on the sources of raw water, the literature on the water treatment plant and population growth, analyze historical data on water quality and extreme events, and consult with experts (Smet, 2017). To limit the number of sources of uncertainty to include in the analysis, they need to be selected based on significance to the performance of the plant.

One of the important sources of uncertainty for a water treatment plant is the dynamics of the demand for water. In turn, the demand for water is defined by several factors, of which the most important are population size, the average per person consumption of water, and water tariffs. Whether the population is expected to grow, decrease, or remain constant, a plant's decision-makers must understand the dynamics in demographics. Because their design capacity bounds WTPs, a plant's decision-makers must have the option of increasing the capacity of the plant in the future to satisfy the demand of the growing population. Water treatment plant designs also have to be reflective of expected shrinking populations when relevant, to optimize the infrastructure to reduce operational costs and avoid redundant designs.

Another source of uncertainty that the WTP decision-makers have to account for is the quality of the raw water source. There are two reasons why water quality is an important source of uncertainty for the plant. First, water quality is one of the major factors affecting operational costs. As shown in Dearmont et al. (1998) and Horn (2011), expenditures on water treatment chemicals are driven directly by such water quality characteristics as turbidity and total organic carbon (TOC). Moreover, an Alberta-wide plant operators' survey (Operators Survey, 2015) showed that in-plant decision-making on chemical use is driven by the level of turbidity at the in-take.

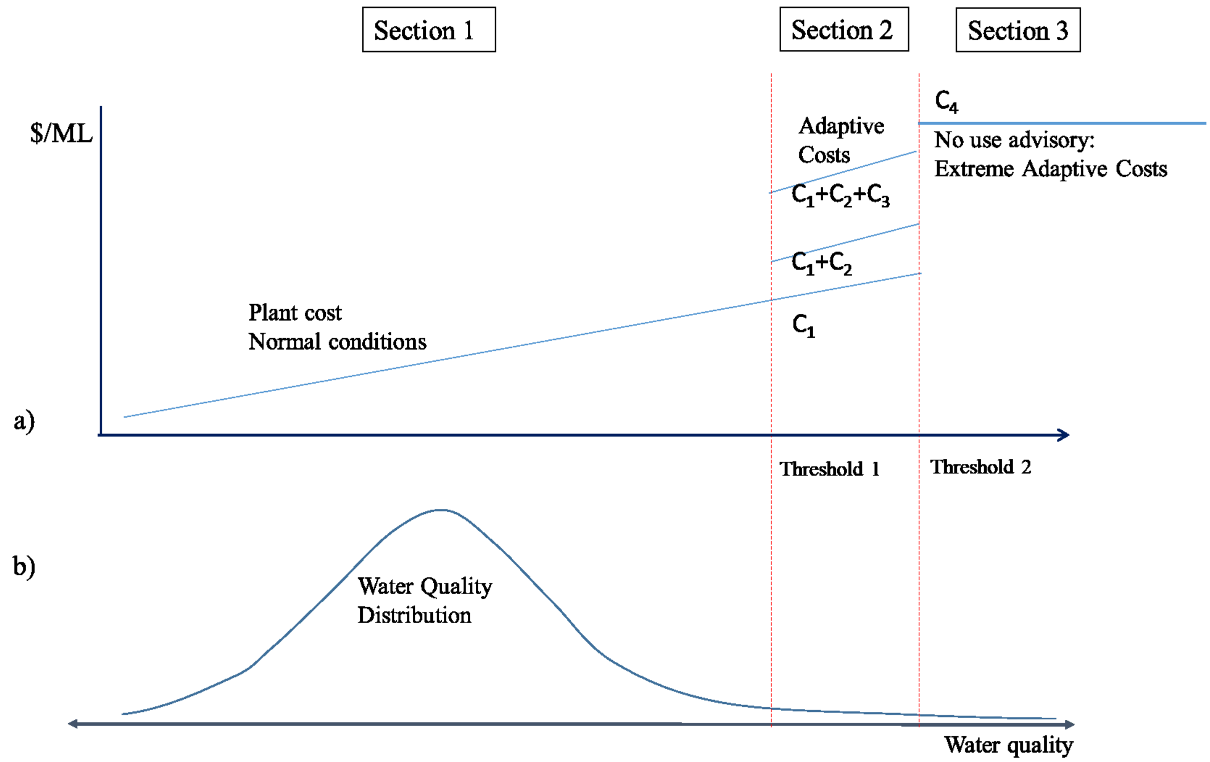
Increasing risks of extreme events such as wildfires and floods are the second reason to pay close attention to water quality characteristics. Wildfires and floods can lead to large decreases in water quality (Bladon et al., 2014). If these events affect large portions of the water source and are severe enough, the resulting decreases in water quality increase pressure on the water treatment plant. In the cases when such pressure is too high and output water quality parameters exceed safe levels, public health authorities might issue water use advisories (e.g. boil water advisory or no-use advisory) to warn the community of potential health risks from consuming the tap water. A WTP would keep operating in cases when the tap water is unsafe for drinking due to other water needs (e.g. to supply water to fire hydrants). However, even when BWAs are issued, there is probability that some people would either not see a notice or ignore it for various reasons. In such cases, the risks to public health arise. We assume that if the WTP's design threshold(s) for source water quality processing is exceeded, such risks increase. Thus, extreme values of water quality may lead to higher maintenance costs at the water treatment plants (such as maintaining machinery and filters, consequent removal of algae, etc.) as well as to the population served due to averting and adaptive behaviours and health risks. In the most extreme cases, it is possible that the quality of output water becomes inadequate for drinking and other household uses, and a no-use advisory could be issued. This, in turn, implies that a population that is served by the given WTP would be forced to search for alternative sources of drinkable and usable water. Such cases are very rare in a developed country context and we consider them in order to cover the wider range of possible outcomes, even if such possibility can be minimal.

The next step after characterizing and analyzing the sources of uncertainty is to consider the mechanisms of how these sources of uncertainty affect capital investment decision-making. Within the framework of capital investments, it is important to understand how these uncertainties interact with the structure of the total costs. For this, we characterize WTP operations as having breakpoints (thresholds) at which the water treatment plant no longer operates in the regular operating schedule but is required to take other actions such as calling a water use advisory. The description of the interactions between a WTP's costs and sources of uncertainties, and the role of the thresholds is the next step in constructing the WTP's complete costs model.

3.3. Define Water Treatment Thresholds

Water treatment thresholds define the ranges of cost functions under different outcome scenarios. A WTP can have a pre-designed capacity to serve a certain level of population. If the threshold is exceeded, the plant may experience significant increases in costs. If the level of population and water demand increases above the WTP's threshold, then an alternative source of water needs to be employed. At this point, we also assume that the employment of an alternative source of water is costlier because it may involve bringing in bottled water, water use advisories, or using other strategies that imply significant community costs. One way to avoid exceeding the threshold and incurring higher costs is to expand the facility by investing in the capacity of the plant. Turning to water quality as a source of uncertainty, then the cost function of the plant can be represented as in Figure 3.1 a):

Figure 3.1 Stylized costs graph of water treatment related to the water quality at a WTP. Panel a: costs schedule with respect to water quality; panel b: distribution of source water quality. C_1 – in-plant costs under normal operating conditions; C_2 – adaptive community costs; C_3 – adaptive in-plant costs; C_4 – community costs of bringing water from alternative sources.



In Figure 3.1 a), the horizontal axis represents water quality, where the water quality decreases from left to right, and the vertical axis is per unit cost of water supply. Section 1 of the graph is the portion of the cost function under normal water quality conditions. In other words, the plant is operating under normal conditions where it can treat the water effectively, but costs are higher when the source water is of worse quality. Section 2 of the graph is the section where water quality exceeds the first threshold. In the range between threshold 1 and threshold 2, the costs of supply include adaptations beyond the plant costs. These costs might include community costs of boiling, hauling and purchasing water, and costs associated with increased risks of morbidity and mortality (C_1), and in-plant adaptive costs (C_2) such as dredging and increased maintenance costs. Threshold 1 is defined as the level of water quality at which the water treatment plant can no longer provide water to the best health standards, although it continues to operate under some advisory.

Section 3 is associated with levels of water quality that exceed the second threshold. Threshold 2 corresponds to scenarios such as natural and human disturbances. The right tail of the water quality distribution beyond threshold 2 corresponds to another scenario when the water treatment facility cannot produce water to the health standards, and keeps operating under a no-use water advisory. Such no-use water advisories are issued because tap water poses serious health risks to the serviced community. In this scenario, the water production is limited and only used to supply vital water services to the city. Thus, section 3 of the graph depicts the costs of community adaptation, which include but are not limited to adaptive costs, costs of bringing water from outside, potential health risks, as well as damage to the water treatment facility (C_4). Due to limited production of water, we ignore the chemical use costs, and assume that water supply costs do not depend on the quality of source water.

These thresholds are very specific to the infrastructure and technology employed at a given plant. Installed technology is one of the factors that determine these thresholds, as it defines the capabilities of the plant to process water of a certain quality. Newer and more sophisticated plant designs, which are more expensive, are more likely to cope with levels of water quality in the right tail of the water quality distribution. Figure 3.1 b) illustrates the probability distributions of water quality throughout a year. As seen in the graph, these thresholds are located on the extreme right tail of the distribution and are, therefore, extremely rare events. This is due to the design of the existing plants, which typically ensure that the probability of faltering is very low. However, these thresholds are not fixed in time and are subject to change over time. Such changes might be induced by the changes in the environment (such as a change in the distribution of water quality), changes in the technology of the plant that would make it more (or less) resistant to a wider range of water quality, or changes in the tap water quality standards[3].

3.4 Alternative Investment Options: Including Ecosystem Infrastructure into the Analysis

An empirical application of the conceptual framework would include the simulation of water quality distributions using historical data. Once the distributions are obtained, the expected costs for various investment options can be determined and compared to select the most cost-effective solution given that other conditions, such as tolerance for risk, for example, are known. The way the framework is defined, we need to carefully assess the distributions of water quality,

[3] More stringent water quality standards could increase the average costs per every output level, or can shift the thresholds. The latter case can be triggered if the authorities decrease maximum allowed concentration of specific contaminants, while the former can be triggered if the authorities impose stricter regulations for mean and/or median concentrations.

especially the tails of these distributions and see how the nature of the tails affects the investment decisions.

In Figure 3.1 b), for example, the first and second thresholds correspond to levels on the water quality distribution, and the range to the right from the first threshold has its probability density. If water quality is in the range beyond the thresholds, the water treatment plant and population are experiencing higher costs, and there is a need to either invest in technology to reduce the costs or invest in approaches to reduce the probability of exceeding the threshold, such as investing in ecosystem infrastructure.

3.4.1 Set of Assumptions Made for Implementation of the Conceptual Framework

There are several assumptions in our conceptual framework that simplify the analysis and explain some mechanisms behind the way investments, outside costs, and cost schedules are modeled. We discuss them in this subsection.

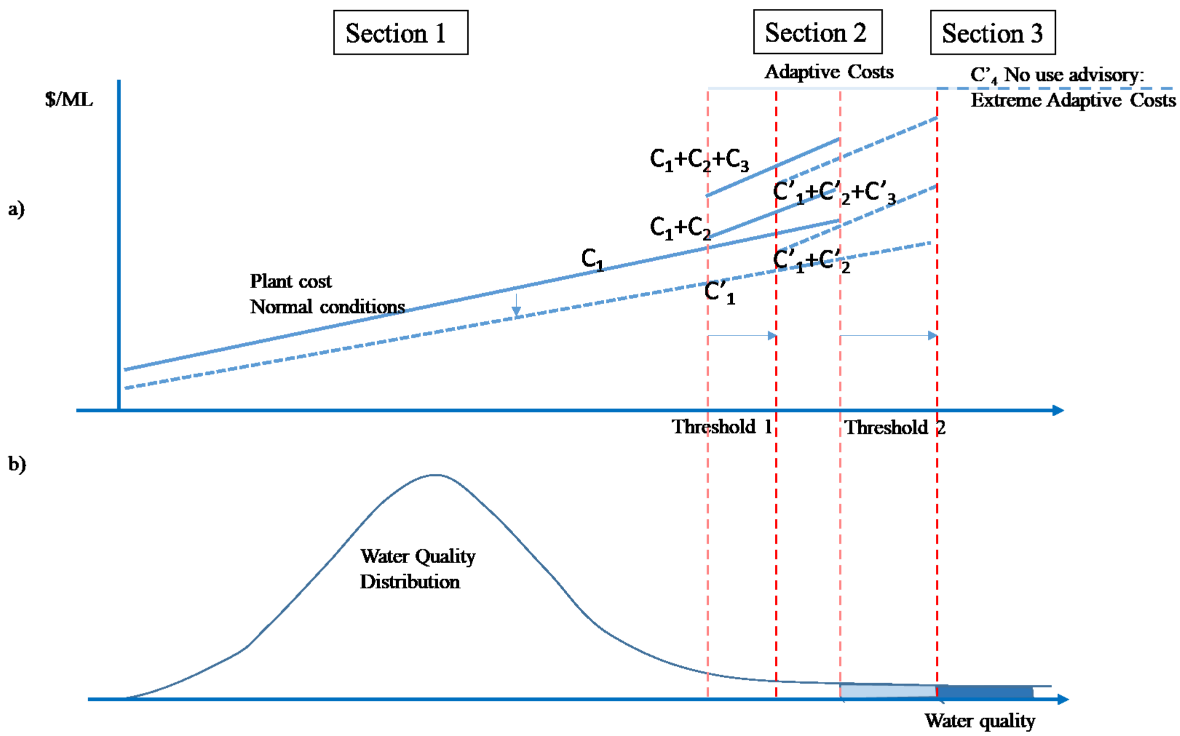
1. We assume that an outside-cost event happens if and only if the water quality threshold is exceeded in a given day.
    a. This implies that these costs are realized immediately and happen in a day when the water quality threshold is exceeded, and do not have spill-over cost effects on following days.
    b. This also implies that we assume the effectiveness of post-extreme events actions that remove the cost effects. Thus, for example, risks of morbidity and mortality are eliminated post-event. We can assume that increases in community costs thus include costs of elimination of adverse effects of the extreme event along with costs of the adverse effects.
2. We model the shifts in water quality distributions and threshold movements so that the effects on the costs take place immediately the day when the shift is made.
3. We assume *ceteris paribus;* in a sense, there is nothing else changing in the future except for the investment. We do not explicitly model changes to drinking water health standards, depreciation of natural capital, or other shocks.
4. We model scenarios in a way that the change (either threshold movement or shift in the water quality distribution) lasts for the length of the considered period, with no depreciation of the effect.

a. This also implies that technology and WTP’s capacity are the same for the entire period. Thus, costs are related to water quality in the same way before and after the upgrading.

3.4.2 Modelling Different Infrastructure Investments

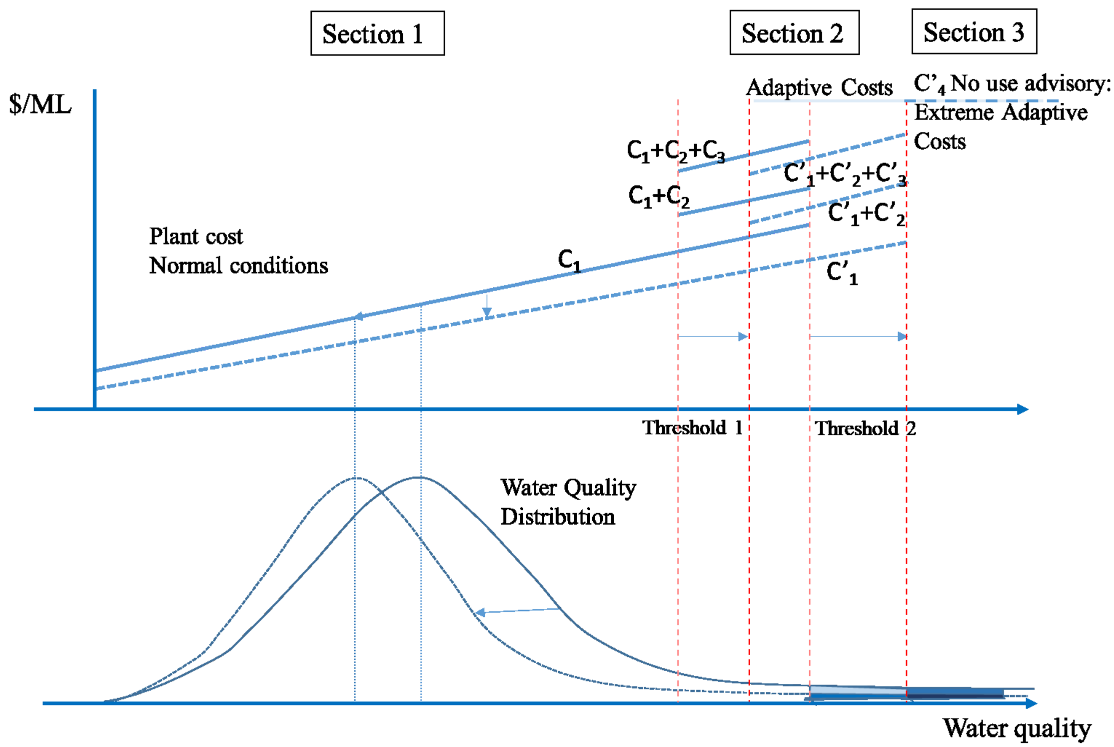
Figure 3.2 shows how an investment in infrastructure affects the costs and interaction between the costs and the thresholds. First, an upgrade to better technology would reduce the operational costs, shifting the plant's regular schedule cost down. This shift, in turn, also reduces total cost in section two, as the cost there is the sum of operational and adaptive costs. Second, a plant’s upgrade driven by capital investments increases the resilience of the plant, and this is represented by the shift of thresholds to the right. These shifts reflect the nature of the upgrades – now, the plant can handle wider ranges of water quality levels. This is also reflected in panel b) of the graph – now, the probability of exceeding the threshold is lower. However, considering that moving the threshold is associated with costly public infrastructure investments as the plant upgrade requires the upgrade of technology, there is a need to look at how moving thresholds are compared to improvement in water quality in terms of potential benefits.

Figure 3.2 Stylized costs graph of water treatment related to the water quality at a WTP: illustrating of modeling the effect of new technology on the water treatment plant’s total costs. Panel a: Cost schedule for the WTP; panel b: distribution of the source water quality. C_1 – in-plant costs under normal operating conditions; C_2 – adaptive community costs; C_3 – adaptive in-plant costs; C_4 – community costs of bringing water from alternative sources. C'_1 – in-plant costs under normal operating conditions after the threshold shift; C'_2 – adaptive community costs after the threshold shift; C'_3 – adaptive in-plant costs after the threshold shift; C'_4 – community costs of bringing water from alternative sources after the threshold shift.



The option of reducing the weight in the tails of the water quality distribution will not affect the infrastructure costs of the plant. However, it does affect the probability exceeding the thresholds (being in sections 2 or 3). Using investments to shift the water quality distribution as complementary to investment into grey infrastructure would result in the distributions reflected in Figure 3.3.

Figure 3.3 Stylized costs graph of water treatment related to the water quality at a WTP: illustrating of modeling the effect of new technology and shift of the water quality parameters' distribution on the total costs. Panel a: Cost schedule for the WTP; panel b: distribution of the source water quality. C_1 – in-plant costs under normal operating conditions; C_2 – adaptive community costs; C_3 – adaptive in-plant costs; C_4 – community costs of bringing water from alternative sources. C'_1 – in-plant costs under normal operating conditions after the threshold shift; C'_2 – adaptive community costs after the threshold shift; C'_3 – adaptive in-plant costs after the threshold shift; C'_4 – community costs of bringing water from alternative sources after the threshold shift.



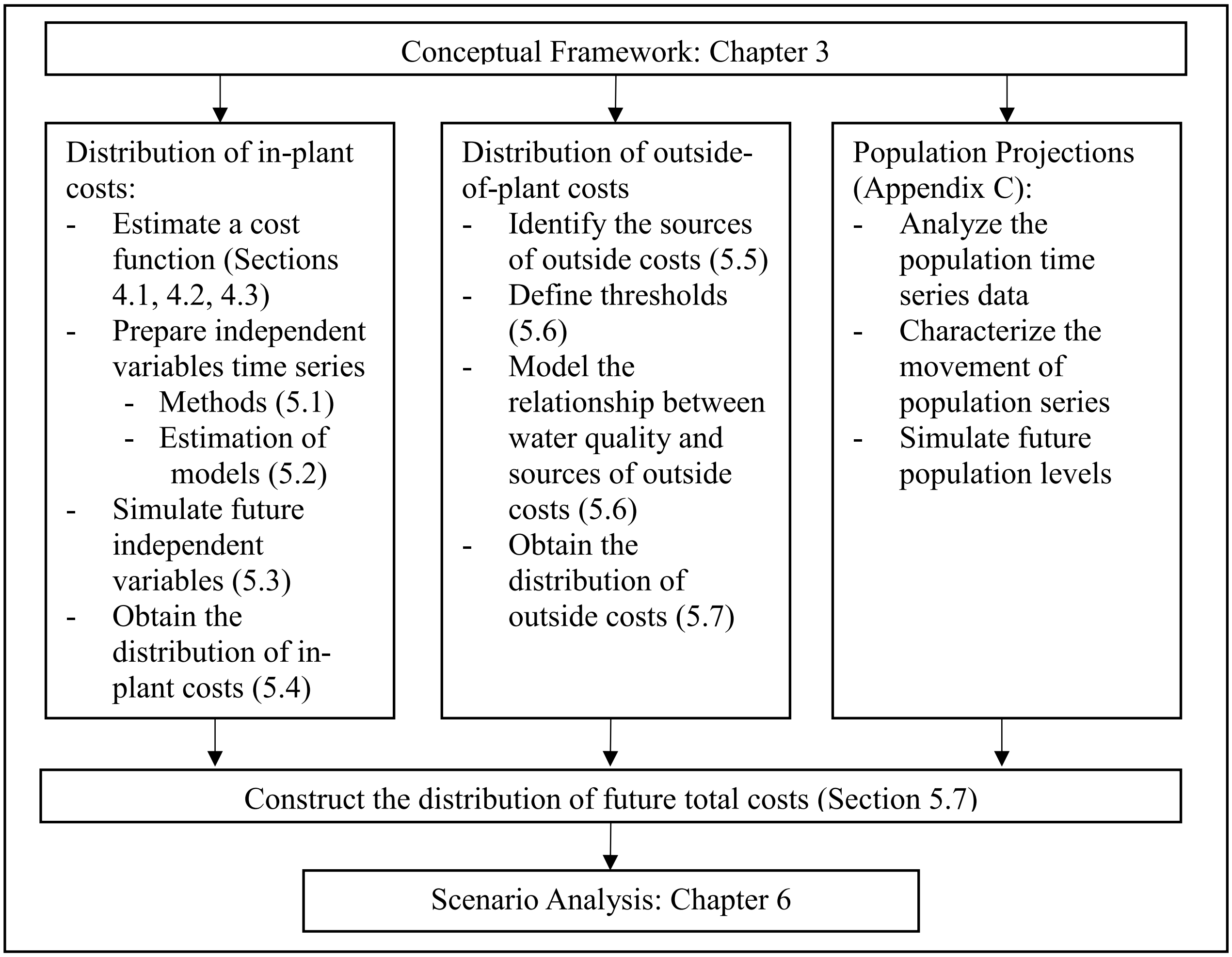
In the graph above, we see that the changes in the water quality distribution shift the mean of the distribution, meaning that the plant will be operating on the left side of the cost curve in panel a more often. More importantly, the thinner tail of the distribution decreases the probability of being in sections 2 or 3 of the costs where the thresholds are exceeded. This, in turn, decreases the expected costs of having such extreme events in the planning horizon.

We can apply this conceptual framework to the future distribution of total costs and evaluate the potential benefits (cost reductions) of different investment scenarios (grey or green). We can do so by moving thresholds and water quality distributions to simulate changes that can be brought by different investment options. To estimate the benefits, we first need to calculate the expected total costs of water treatment under a specific investment assumption (scenario). We can then compare them against the expected total costs under the status quo (no changes) scenario. The benefit of an investment will be the difference between net present values of the future flow of costs under an investment scenario and the status-quo scenario, assuming risk-neutrality. This allows us to conduct a valuation of the benefits of different methods of ecosystem infrastructure investments that could shift the distribution of water quality. One such method would be upstream forest management. Using biophysical models, we can determine the relationship between the amounts of effort (costs) put into the forest management and the benefit in terms of how much we could reduce the thickness of the tail of the water quality distribution. Furthermore, this, in turn, could then be evaluated using the suggested framework for the analysis of investment options.

Chapter 4: Water Quality and Cost of Water Treatment: Data, Methods, Empirical Cost-Response Function

The conceptual framework described in the previous chapter shows that the distribution of future costs serves as the basis for the cost-effectiveness investment analysis for water treatment plants. Implementation of the conceptual framework and proof-of-concept requires simulation of the complete distribution of future water supply costs, where the complete costs include in-plant treatment costs, external costs. The treatment costs reflect the plant's response to the changes in the water quality, while outside costs reflect the additional community and the WTP's adaptation costs[4]. Thus, simulation of the distribution of variables that determine the water treatment costs as well as the distribution of treatment costs serves as the basis for the analysis. In addition to obtaining the distribution of the costs, it is necessary to account for population changes. We discuss the data, methods, and results of obtaining the complete distribution of costs for the Glenmore water treatment plant for years 2015-2025 in chapters 4, 5, and 6. Chapter 4 focuses on the development of the empirical cost-response function that is then used to obtain the distribution of in-plant costs. In chapter 5, we discuss the process of preparing independent variables from the cost function, and sources of outside community costs to obtain the distribution of total costs. In chapter 6, we evaluate the benefits from four infrastructure investment scenarios using obtained total costs distribution and the conceptual framework described in chapter 3. We summarize the steps needed to conduct the scenario analysis and present a graphical representation of the roadmap to guide the reader through the process in the following figure:

[4] While water treatment plants are owned by public and a plant's costs would also be incurred by the public, we distinguish plant's costs from community costs to emphasize the channels of effects. Community effects and thus costs reflect the direct costs experienced by the serviced community, and include averting and adaptive costs such as costs of hauling water, buying bottled water, boiling water, etc. In-plant adaptive costs would include increased chemical costs, maintenance costs, dredging costs, etc.



In this chapter, we discuss the process of estimating the cost-response function. First, we develop an empirical model of cost response to analyze the effect of a change in water quality on in-plant costs. Second, we describe the available data from Calgary's Glenmore water treatment plant that we use to support our analysis. Finally, we estimate the cost-response function for the GWTP.

4.1 Specification of the Empirical Model: Predicting Costs Using Water Quality Characteristics

In this section, we analyze the effect of water quality characteristics on the cost of water treatment. To estimate the effects, we develop an empirical model of cost response to the characteristics of water quality. In our model, we incorporate source water quality characteristics directly into the cost function and thus estimate the cost-response function. We model the cost response in a log-log form and use per unit costs as the dependent variable. Thus, our empirical model is the following:

$$ln(cost_t) = \alpha + \sum\beta_i\,(ln(X_{it})\times spring_t) + \sum\gamma_i\,(ln(X_{it})\times winter_t) + \sum\delta_j ln(Z_{jt}) + \mu Q_t + \eta\times winter_t + \varepsilon_t, \quad \textbf{[4.1]}$$

Where:

cost – are the variable in-plant costs of chemical use,

X – are water quality characteristics that influence costs differently in spring and winter at time t,

Z – are weather characteristics at time t,

Q – is the quantity of water intake at time t,

spring – is a dummy variable that takes the value of 1 for when it is April – September, covering exactly half a year, and

winter – is a dummy variable that takes the value of 1 for January – March, and October – December months;

α – is the per-unit cost due to factors other than water quality and weather during spring,

β – is the elasticity of per-unit costs with respect to changes in the water quality during spring,

γ – is the elasticity of per-unit costs with respect to changes in the water quality during winter,

δ – is the elasticity of per-unit costs with respect to the changes in the weather,

μ – is the effect of the amount of influent water on the average daily costs,

η – is the difference in per-unit costs between winter and spring seasons,

ε – is the random error term.

In comparison to previous studies, we incorporate behavioral aspects of in-plant decision-making, such as the seasonal difference in response to changes in water quality. We have analyzed the dosage of chemicals, and have identified that dosage differs between spring-summer and fall-winter months (see Appendix B). Based on this finding, we define 2 operational periods: fall-winter and spring-summer. This finding partly reflects water treatment plants' managers' behavior expressed in the Alberta drinking water treatment plants operators' survey. Plant managers distinguish five seasonal operational periods: warm water season, fall transition period, cold water season, snow-melt period, and spring-transition period[5] (Operators Survey, 2015).

4.2. Data from Glenmore Water Treatment Plant on In-take Water Quality, Quantity, and Costs of Chemical Use

We employ data from the Glenmore water treatment plant – one of two plants that serve the city of Calgary's population. This dataset consists of daily time-series data and spans about eleven years, from January 1st, 2005 till October 1st, 2015. This dataset covers the performance of the plant during two major floods – of 2005 and 2013 and illustrates the changes that happened to the plant during the upgrading period[6] that finished in early 2011 for the GWTP. These upgrades, among other changes, encompass alterations to the combination of chemicals used in the plant, and these can be tracked in the dataset. This is of particular importance to our work because we use the costs of chemicals to proxy the variable costs in the plant. The change in the composition of chemicals during the upgrading directly affected the composition of costs. To preserve consistency in our analysis, we estimate the cost model on the upgraded plant period only.

4.2.1 Variable Costs: Costs of Chemical Use

The dataset does not contain complete information on the daily total operational costs. We have obtained the information on the daily use of chemicals, and per-unit costs of chemicals such as aluminum coagulants (alum), polymers, and sand. The use of these three chemicals is found to be responsive to the changes in water quality, while their share in total chemical costs is 70-80%

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[5] Alberta Drinking Water Plant Operators Survey is an online survey that was conducted between January and June of 2015. In the survey, 8 managers and operators of Alberta water treatment plants were asked various questions on plants' characteristics, characteristics of source water, and other questions related to water quality and costs relationship.
One question was asked to define operational periods by months. A common response among the plant operators was to distinguish following operational seasons:
Warm water season: July – August
Fall transition period: September – October
Cold water season: November – April
Snow melt period: March – June
Spring transition period: May – June

[6] City of Calgary initiated the upgrading of two plants that was completed in 2011. The driving concern for the upgrading of the plants were increasing population of the city and observed high values of turbidity (>1000 NTU) during the flood of 2005 (John Meunier, n.a.). As the result of the upgrade, daily capacity of the GWTP increased to enable the plant to supply the increasing population up to and after 2025 (Water Technology, n.d.). The plant have implemented the Actiflo technology for water treatment that allows the plant to process the water with higher range of turbidity. Implementation of Actiflo implied the change in composition of chemicals used in the water treatment (Associated Engineering, 2011).

after the upgrade. We thus use the daily costs of alum, polymer, and sand-use to approximate the total cost of chemicals use on the plant. Because the composition of chemicals and the plant's technology were not commissioned to use until early 2011, we will only use data that cover costs on the plant after the upgrade – from February 2011 to August 2015.

Table 4.1 presents descriptive summary statistics on variables used in the cost response model. *Total variable cost* is the dependent variable in our model and depicts total daily chemical use costs at the plant. Total variable costs are measured in Canadian dollars. Data are daily; there are 1565 data points that span the period from May third, 2011 to August fourteenth, 2015. From the table, it can be seen that in-plant costs are highly variable, with the standard deviation being higher than the mean and maximum values being greater than the mean and median by order of magnitude. However, understanding that these costs could be driven by the amount of water treated, we standardize the units and use costs per unit of input water in our analysis. Moreover, to address the high variance in the variable, we use the logarithm of costs in our final empirical model. Succeeding sections of this chapter discuss *turbidity, TOC,* and *total flow* variables in detail.

Table 4.1 Summary statistics for total daily variable costs, and in-take water quality variables for the Glenmore Water Treatment Plant, from 2005 to 2015.

Variable	Unit	Median	Mean	Minimum value	Maximum value	Standard Deviation
*Total variable costs**	$	14,598.3	25,104	197.9	313,465.1	26,347.28
Turbidity	NTU	1.1	9.06	0.26	1000.33	53.39
TOC	mg/L	1.2	1.64	0.011	11.92	1.38
Total Flow	ML/ day	181.1	195.7	13.2	493.9	65.64

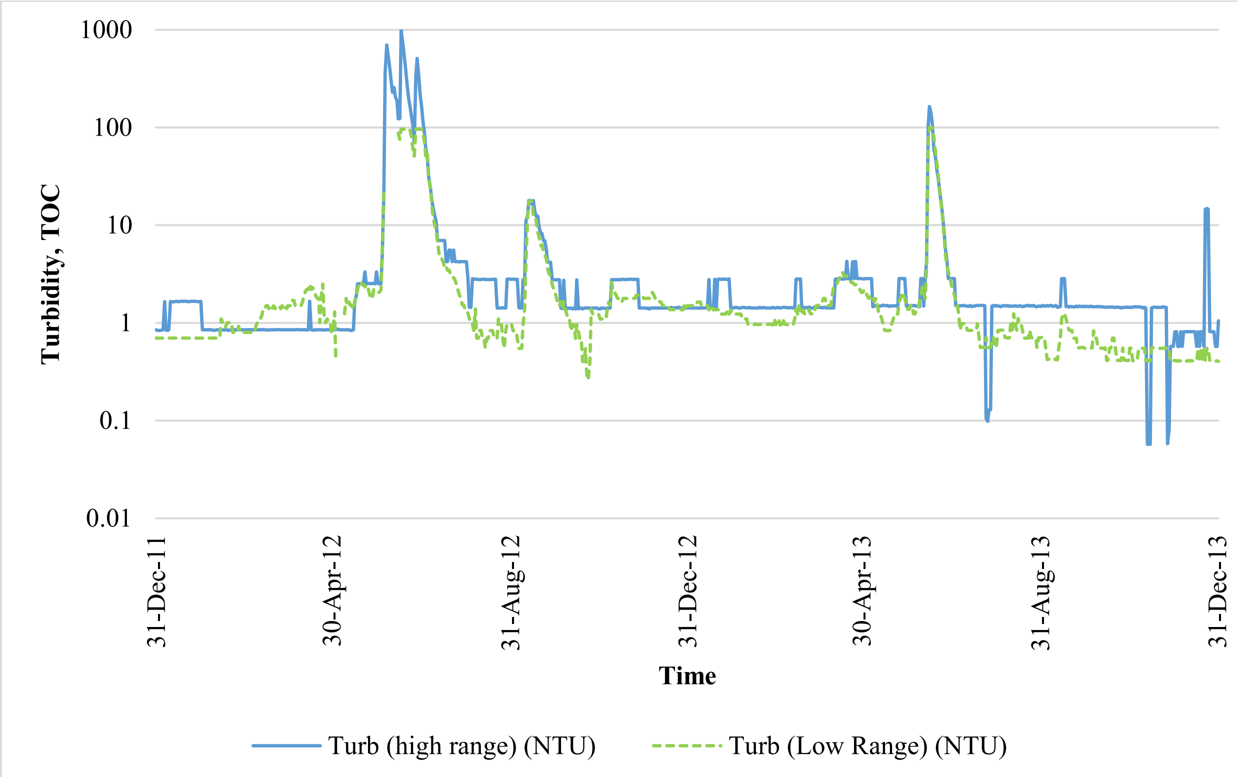
*- summary statistics for total variable costs are for data from 2011 to 2015.

4.2.2 Water Quality (X_i) and Quantity (Q) Variables: Turbidity, TOC, and Total Flow.

Water quality variables are described as X_i in our empirical model and are composed of turbidity and total organic carbon (TOC). Turbidity and TOC are commonly used to indicate the quality of the source water (Dearmont et al., 1998; Horn, 2011) and are used by the WTP engineers as a base for chemical use decision-making (Operators Survey, 2015). Both TOC and turbidity are measured by meters at the water in-take that send the data online. The recorded data, however, is the water quality at the beginning of a new day at 00-00.

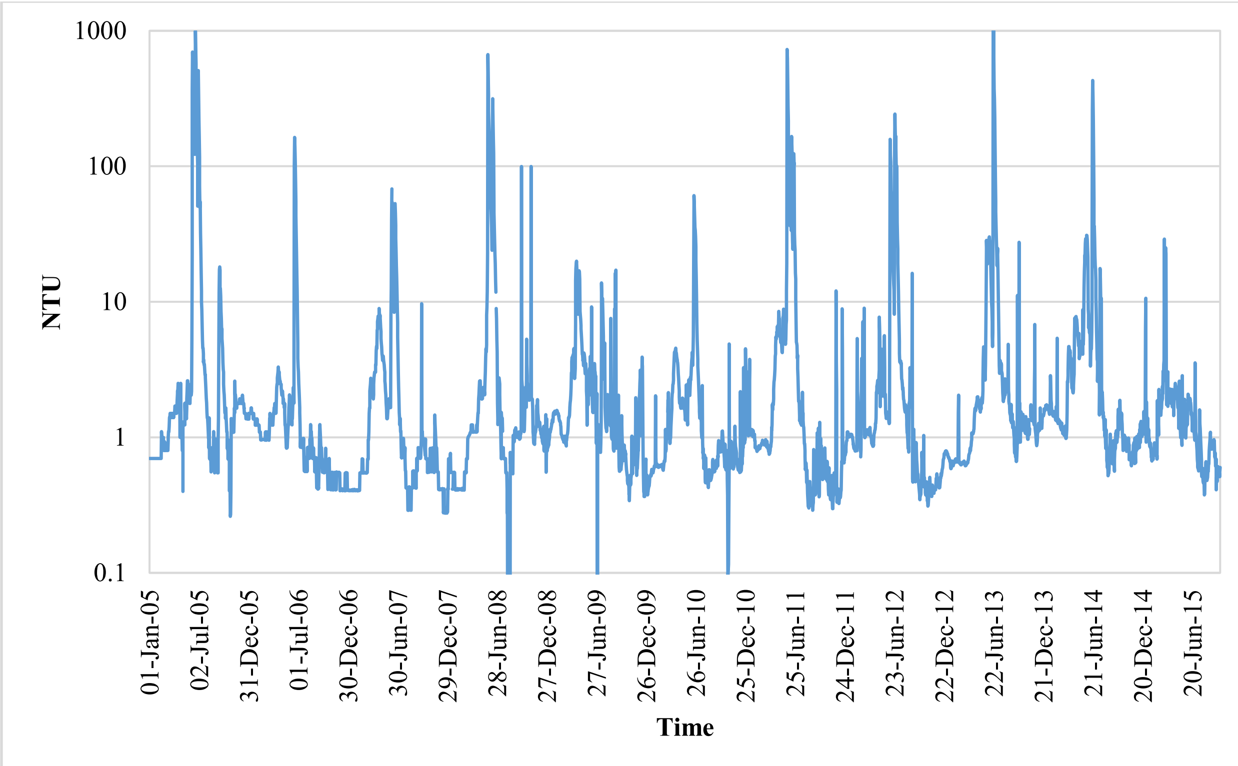
Turbidity is one of the main variables of interest as it is an indicator of water quality, and, unlike TOC, it is a decision driver at WTPs in Alberta that is similar to that of Glenmore WTP (Operators Survey, 2015). Turbidity values in our analysis are obtained from electronic meters that are located at the water intake and are measured in nephelometric turbidity units (NTU). There are two separate meters to capture low values of turbidity in the range of [0, 100], and high values of turbidity in the range of [100, 1000]. We combine values from two meters so that the low range turbidity levels are represented by the low-value meter, and higher ranges (above 100) are indicated by high-value meter readings. In addition to this, the high-value meter is truncated at 1000, meaning that levels exceeding 1000 NTU are recorded as 1000. Thus, online meters capture turbidity values in the range of 1-1000, while values from 1000 to 4000 are measured specifically from grab samples. In Figure 4.1, we present raw data from both meters for the years 2012 and 2013. In the graph, the solid blue line depicts the data points from a high range meter, while the green dashed line shows readings from the low range meter. Based on the detailed analysis of the data and a discussion with an engineer (Emelko, personal communication, 2018), it was decided to combine readings from these two meters into one series. The rule for merging the data is that our final turbidity data point takes values of the high range meter if the value from the high range meter is higher than 100. Otherwise, it takes the value of low range meter.

Figure 4.1 Turbidity time series for the Glenmore water treatment plant, 2005 – 2015, represented by two different meters to capture low and high values.



The illustration of the final turbidity series is given in Figure 4.2. The graph suggests that turbidity follows a seasonal pattern, with turbidity being low during winters, then rising to reach the highest values in spring and summer, and then falling to lower values during fall and winter. This can be seen in the following graph:

Figure 4.2 Turbidity time series for Glenmore water treatment plant, 2005 – 2015. Readings from high and low meters combined.

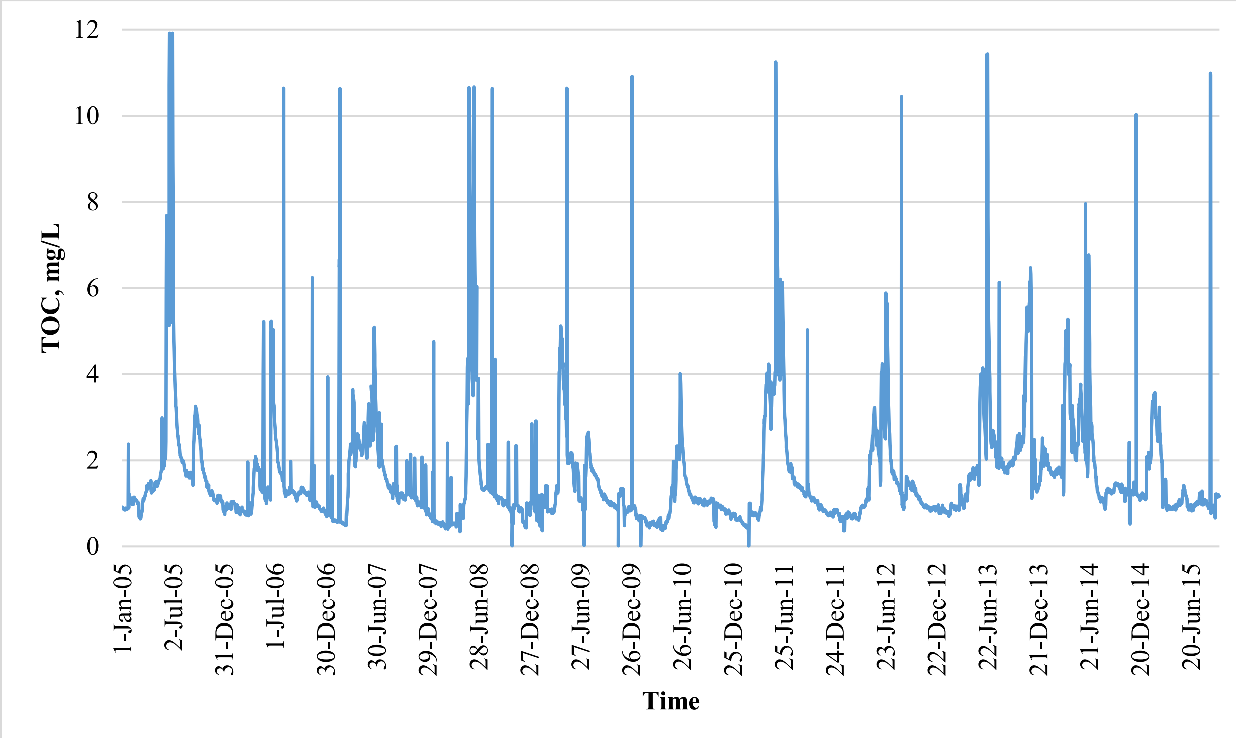


Turbidity reaches its highest values during the freshet and summer seasons, whereas its lowest values are typically in the fall and winter seasons. Peak points of 1000 NTU during 2005 and 2013 indicate the turbidity levels during floods that happened in Calgary during those years. In 2013, the turbidity levels exceeded 1000 NTU for at least three days (Kundert, 2014), while the readings from online meters show values of 1000 NTU. Special readings from grab[7] samples on June 21-23, 2013 show that turbidity in the water exceeded 1000 NTU for three days and exceeded 4000 NTU on June 21st (Kundert, 2014). This points out the need to recognize measurement errors in our analysis in general and address the problem that real data points above 1000 are not observed in the dataset. However, the analysis shows that this is a minor problem and does not affect the estimated parameters of our cost-response model.

The *TOC* values at the GWTP are obtained by a meter at the in-take of raw water, and these values are given in milligrams per liter. The dataset provides online readings from the meter that are taken at the same time each day.

[7] Grab samples are single samples collected at a specific time and place and are different from samples from online meters at the GWTP

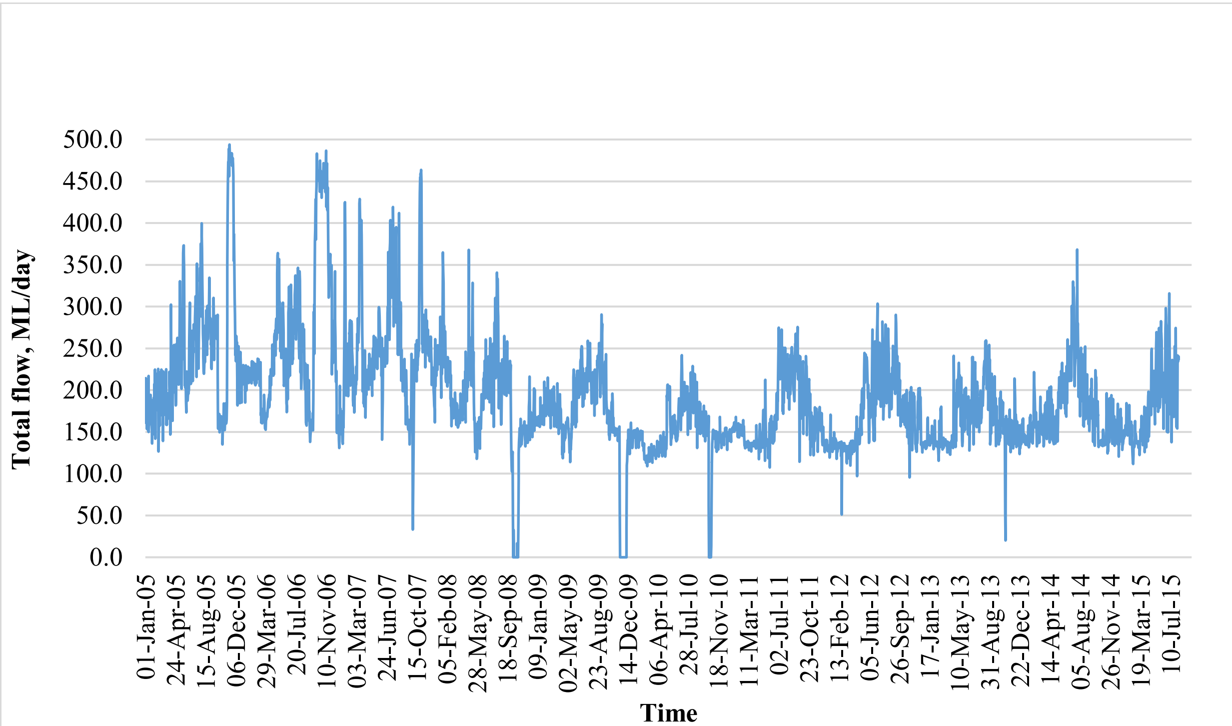
Figure 4.3 TOC time series for Glenmore water treatment plant, 2005 - 2015



From Figure 4.3, we can observe that the TOC follows seasonal patterns that are similar to that of turbidity. Thus, TOC is in its higher ranges during the spring snowmelt and the summer seasons, while the lowest values are associated with the fall and winter seasons. The maximum value of 11.9 mg/L is observed during the flood of 2005. Higher TOC values are also present during the flood of 2013, where the values reached the highest of 11.4 mg/L. Observations on TOC are also truncated, where the truncation threshold is at the point slightly lower than 12 mg/L. Values in the range exceeding 12 mg/L are measured from the grab sample. Kundert (2014) shows that on June 21 and 22, 2013, TOC exceeded 20 mg/L. There are sudden spikes that are observed throughout the entire time period, and they last for one or a few days. A water treatment plant engineer (Emelko, personal communication, 2018) suggests that these spikes could be a result of real changes in water quality and could, for instance, reflect the changes due to rain or snow.

Total flow is measured in ML/day, and it indicates the amount of water that enters the water treatment plant in a day. We expect the seasonality in total flow to reflect seasonal consumption patterns in the water demand. Thus, we expect peak water intakes to be in the spring-summer season, while the lowest total flow values to be in fall and winter.

Figure 4.4 Plant's total inflow of raw water time series for Glenmore water treatment plant, 2005 - 2015



Looking at the *total flow* series in Figure 4.4, we observe a shift in the pattern. Notably, the volatility of the data is lower in the more recent years (on the right side of the figure), where October of 2008 is the first break-point. This change in the pattern of flow is due to the upgrading of the plant that had started to take place in 2007 and finished in 2011. Thus, in our analysis of the total flow series, we divide the data into three parts: before October 2008, between October 2008 and May 2011, and onwards. May of 2011 is the month that the plant has been commissioned most recently.

4.3 Estimation of the Empirical Model of Cost Response

At the beginning of this chapter, we outlined an empirical model to estimate the effect of changes in water quality on in-plant chemical costs. Next, we described the series that will enter the empirical model as independent variables. In this section, we take the next step and estimate the empirical model that is necessary to estimate the effect of changes in the water quality on variable costs and to estimate the distribution of future variable in-plant costs.

On the left-hand side of the model is the natural logarithm of chemical costs per unit of water at the intake. The independent variables describing water quality are logarithms of turbidity (), TOC (*lnTOC*). Water quality variables are interacted with the seasonal dummy variables to reflect differences in dose-response and decision-making with respect to the time of the year. Previous research shows that the volume of intake water affects the average treatment costs, and we thus include the *total flow* as an independent variable in the final model specification.

The results[8] of the estimation are presented below:

$$\begin{aligned} lncost_t = \underset{(0.04)}{3.83^{***}} &+ \underset{(0.015)}{0.06^{***}}\, lnturb \times q1 + \underset{(0.009)}{0.22^{***}}\, lnturb \times q2 + \\ &\underset{(0.015)}{0.03^{\circ}} lnTOC \times q1 + \underset{(0.026)}{0.61^{***}}\, lnTOC \times q2 + \underset{(0.0002)}{0.003^{***}} toflo - \underset{(0.019)}{0.12^{***}} q1, \end{aligned} \qquad \textbf{[4.2]}$$

Significance levels codes: *** - 0.1%, ** - 1%, * - 5%, ° - 10%

The effect of turbidity on chemical costs is positive and statistically significant, and the elasticity of cost with respect to changes in turbidity is 0.06 and 0.22 during winter and summer seasons, respectively. The elasticity of cost with respect to TOC also differs between seasons: elasticity of costs with respect to TOC is 0.03 and 0.61 during winter and summer, respectively. A 1 ML increase in the volume of treated water increases average variable costs by 0.3 percent. The mean level of costs during the winter season is 12% less than in the non-winter season at a 0.1% significance level. The statistically significant constant suggests that there are factors other than the *turbidity*, *TOC,* and quantity of input water that affect average costs. Some of the effects could be attributed to the effects of pH and temperature that we omit.

[8] pH and temperature were initially included in the cost response model. PH does not have a statistically significant effect on variable costs. Temperature has a statistically significant effect on costs, which is, however, is small in magnitude. Elasticities of main variables are not affected if we eliminate these variables from the model. We thus eliminate these variables from the final model to simplify the process of simulation, and present the final model results in this section.

4.4 Summary

In this chapter, we have estimated the relationship between water quality and in-plant chemical use costs. In section 1 of this chapter, we developed an empirical model that relates in-plant variable costs and water quality. It is stated that in-plant chemical use costs are a function of water quality, weather characteristics, the quantity of influent water, and season. In section 2, we described data that are used as inputs to the empirical model and supports our analysis. In section 3, we estimated the cost-response equation for Calgary's Glenmore WTP and find that turbidity and TOC have statistically significant positive effects on average variable costs, meaning that decreasing water quality increases the costs of water treatment. Moreover, the effect of water quality on the costs is found to be contingent on the season. In turn, the quantity of influent water is estimated to increase average variable costs.

Chapter 5: Time Series Analysis Methods and Simulation Results

In the previous chapter, we developed and estimated an econometric model that will be used as the basis to obtain a distribution of future in-plant costs. To construct this distribution, we develop distributions of the relevant input variables over time. In this chapter, we construct a complete distribution of future water treatment costs for the years 2015-2035. These costs include in-plant variable costs and outside-of-plant costs, which we call community costs. First, we describe the methods employed for the time series analysis of the variables. Second, we develop time series models to characterize the independent variables. Third, we simulate the future values of independent variables and present the results. Simulated turbidity, TOC, and total flow values are then used as inputs in the cost-response function to obtain the distribution of the in-plant costs. Finally, we discuss the sources of outside-of-plant costs and add community costs to in-plant costs to obtain a complete distribution of future water treatment costs.

5.1 Methods to Develop Inputs for Simulation Analysis.

In this subsection, we describe the methods that are employed to analyze and characterize the independent variables to construct the distribution of in-plant costs. We employ Fourier series analysis to address seasonality in turbidity, TOC, and total flow. To choose seasonal models for the variables, we use an analysis of variance (ANOVA) procedure of stepwise selection of models. After defining deterministic seasonal mean models, we establish the stationarity of the error terms and characterize the residuals with autoregressive-moving average (ARMA) models. Overall, the water quality time series models take the general form:

$$Y_{mt} = S_{mt} + e_{mt}, \qquad \textbf{[5.1]}$$

Where the dependent variable, Y_m, is our water quality (X_i) or quantity (Q) variable at time t from equation [4.1], S_m is a seasonal component, and e_m is a composite error. In turn, the error term consists of a random error and a white noise parameter. We discuss methods used to analyze each component of this model in the following subsections.

5.1.1 Fourier Series Analysis

Fourier series analysis is used to estimate models of variables that can be described as seasonal processes (Woolhiser and Pegram, 1978). Woolhiser and Pegram (1978) suggest a model describe the Fourier transformation for a precipitation model, and we employ a similar model in our analysis. We define it as follows:

$$S_{mt} = A_{m0} + \sum_{k=1}^{l_m}\left\{A_{mk}\cos\left(\frac{nk}{T}\right) + B_{mk}\sin\left(\frac{nk}{T}\right)\right\}, \qquad \textbf{[5.2]}$$

Where $T = 365/2\pi$, and l_m is the number of harmonics needed to specify the parameter for each variable S_m, n is the calendar day, and A and B are estimated Fourier terms coefficients. To select the numbers k and l_m for our Fourier series analysis, we use ANOVA procedures of the stepwise selection of models.

5.1.2 ANOVA procedure for stepwise selection of models

Stepwise analysis of variance (ANOVA) is a statistical model selection method that uses information criteria (such as AIC) to choose the best model from the full set of models (Venables and Ripley, 2002). It starts from the full model, and then fits sub-models by using backward or forward selection – trying and removing and adding terms, and "compares using formal analysis of variance" (Venables and Ripley, 2002, p. 11). Understanding the shortcomings of the ANOVA procedure as being purely statistical and automatic in a way that it does not incorporate theory behind the described processes, and trying to address data limitations, we keep control over the choice of the number of degrees of freedom used as penalties for adding a variable in the statistical software. This allows us to avoid the overfitting of the model.

5.1.3 Autoregressive-Moving Average Models

An autoregressive-moving average model (ARMA) is the way to describe time series, and is a combination of autoregressive (AR) and moving average (MA) time series models. ARMA of order (p,q) uses a combination of $p+q+1$ weight parameters and p lags of series averages and q moving average lags of the error term (Box and Jenkins, 1976). In Box and Jenkins (1976, p.74), the linear ARMA(p,q) model is:

$$\tilde{z}_t = \varphi_1\tilde{z}_{t-1} + \cdots + \varphi_p\tilde{z}_{t-p} + a_t - \theta_1\tilde{a}_{t-1} - \cdots - \theta_q\tilde{a}_{t-q} \qquad \textbf{[5.3]}$$

Where $\tilde{z}_t$ is mean of the process, and is expressed as a weighted sum of past lags and of present and past lags of the a_t, where a_t is a "white noise" process, and φ_i and θ_j are weight parameters;

Further, equation [5.3] can be re-expressed as:

$$(1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p)\tilde{z}_t = (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)a_t, \quad \textbf{[5.4]}$$

or

$$\varphi(B)\tilde{z}_t = \theta(B)a_t, \quad \textbf{[5.5]}$$

Where $\varphi(B)$ and $\theta(B)$ are polynomials of degree p and q, in B, and B is a backward shift operator, such that:

$$Bz_t = z_{t-1}, \quad \textbf{[5.6]}$$

$$B^j z_t = z_{t-j}, \quad \textbf{[5.7]}$$

for $j > 1$.

For the model [5.3] to be applied, the time series need to satisfy stationarity conditions [5.8], and the process needs to be invertible [5.9]:

Characteristic equations $\varphi(B)\tilde{z}_t = 0$ **[5.8]** and $\theta(B) = 0$ **[5.9]** need to have all their roots lying outside of the unit circle (Box and Jenkins, 1976, p.74).

5.2 Developing the Independent Variable Series for The Cost Model

We use R statistical software to conduct our analysis of the variables, and in this subsection, we present the steps and resulting models for the analysis of turbidity, TOC, and total flow series. Before we proceed to the analysis, we address the issue of missing data in the variables and interpolate missing data points. We then need to establish the stationarity of the series. Since we have variables that have seasonal fluctuations, we cannot perform regular stationarity tests until we account for seasonality. To identify the seasonality, we conduct the Fourier series analysis.

Total flow was the variable with the most missing values, with 96 missing values. *Turbidity* and *TOC* series were missing 16 and 5 values, respectively. Turbidity, TOC, and total flow series have 3926 observations in total. Total variable costs data on the post-upgrade period did not have any missing points in the 1565 observations. To interpolate missing values for *turbidity, TOC,* and *total flow* series, we develop linear seasonal models with Fourier terms for each variable and then apply the Kalman filter to add in residuals (see Welch and Bishope, 1997, and Kalman, 1960 for reference). The Kalman filter is used in predicting the state of the process at a specified point in time; the filter uses the minimizing mean squared principle to construct the estimator (Lacey, n.a.). We use the s*tats* R package to apply the filter.

To specify the model outlined in equation [5.2], we use $k = 10$ to obtain a full model with Fourier transformed series, where the log of *turbidity,* log of *TOC,* and *total flow* are independent variables. We then apply a stepwise ANOVA model selection procedure based on the AIC to obtain final seasonal models. To avoid the issue of overfitting the model, we specified a high penalty for the addition of extra variables. The resulting models are reported in Table 5.1 below.

Table 5.1 Estimation of models according to final model specifications for the *turbidity, TOC,* and *total flow* seasonal mean models using the Fourier series.

Fourier terms	***lnTb***	***lnTOC***	***total flow[1]***
Intercept	0.38***	0.28***	170.02***
(se)	(0.015)	(0.008)	(1.019)
S1	0.5***	-	-22.74 ***
(se)	(0.022)		(1.160)
C1	-0.81***	-0.43***	-18.59***
(se)	(0.022)	(0.011)	(1.150)
S2	-0.44***	-0.18***	
(se)	(0.022)	(0.011)	
C2	0.34***	0.12***	
(se)	(0.022)	(0.011)	

Significance levels codes: *** - 0.1%, ** - 1%, * - 5%, ° - 10%

[1] – in this table, the seasonal model for total flow covers the performance of the plant after upgrading as we only use these coefficients for future variable costs estimation

To better understand the fit of the model, we can examine a graph that illustrates the fitted values for the seasonal mean model and the actual data. To avoid repetition, we discuss the performance of Fourier series seasonal mean models on the example of turbidity.

Figure 5.1 Turbidity time series from 2005 to 2015 and fitted values from Fourier series seasonal mean models. Here, *lnTb* – log of *turbidity* series. In red is the fitted full Fourier series model (k

= 10). In blue is the fitted Fourier seasonal model chosen by ANOVA stepwise selection procedure.

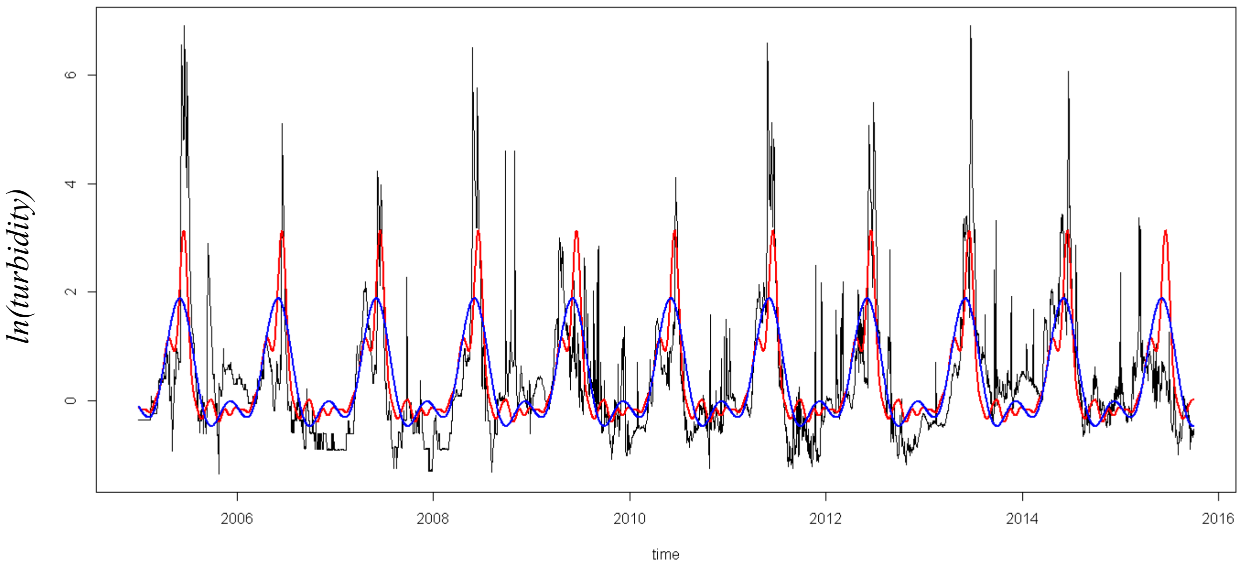
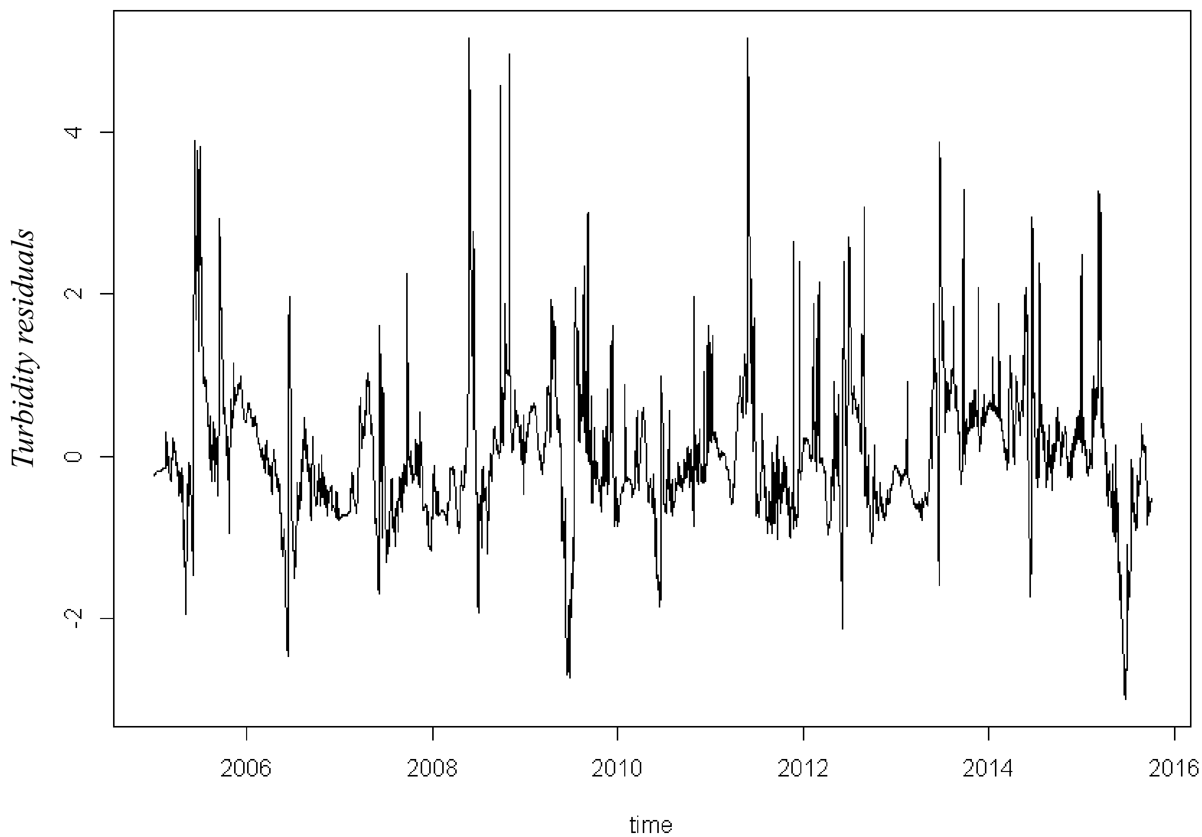


Figure 5.1 presents fitted values produced by the full model of Fourier transformation with k = 10, in red. Comparing the graphical representation of the full model and the final model in the figure above, we observe a couple of notable differences. First, the red line fits the data better in the peaks, suggesting that it could be a better model to simulate higher range values into the future. Second, the blue line is smoother between peaks, suggesting that the final model is not addressing some of the local peaks during the fall and winter seasons. This is due to fewer Fourier terms used in the final model compared to the initial specification. However, this is an intended result rather than a shortcoming of the model. The choice of the degrees of freedom used in the ANOVA procedure heavily penalized the addition of extra variables, and thus only 4 terms were chosen to characterize seasonality in turbidity (and 3 for *TOC* and *total flow*). The idea behind this is that the seasonality assumption about water quality suggests fluctuations from spring-summer season to fall-winter season, and thus we cannot justify patterns suggested by models that have more Fourier terms. The full model with 20 Fourier terms is overfitting the data, capturing random weather events that happened during the 11 years. After developing seasonal mean models for turbidity, TOC, and total flow, we analyze the residuals.

Due to the limited explanatory power of the seasonal mean model, we need to describe and characterize processes in the residuals. We extract the residuals from seasonal mean models for *turbidity, TOC,* and *total flow*, and consider them separately. In this chapter, we present the analysis done on the example of residuals from the turbidity model. In Figure 5.2 below are the residuals from the seasonal turbidity model.

Figure 5.2 Residuals from the Fourier transformation model for turbidity series, 2005-2015.



We conduct a Fourier series analysis on the squared residuals and find that the residuals have seasonal fluctuations. The final models for residuals from turbidity, TOC, and total flow are presented in Table 5.2.

Table 5.2 Final model specifications for the squared residuals from seasonal *turbidity* model, square root of residuals from the *TOC,* and *total flow* seasonal mean models.

Fourier terms	***res_turb^2***	***sqrt(res_toc^2)***	***sqrt(res_flow^2)[1]***

Intercept	0.73***	0.36***	20.37***
(se)	(0.028)	(0.005)	(0.5)
S1	-	0.13***	-3.01***
(se)		(0.007)	(0.71)
C1	-0.71***	-	-7.76***
(se)	(0.04)		(0.71)
S2	-	-	-0.67**
(se)			(0.71)
C2	0.5***	-	-
(se)	(0.04)		
C3	-	-	-2.17***
(se)			(0.71)

Significance levels codes: *** - 0.1%, ** - 1%, * - 5%, ° - 10%

[1] – in this table, we only include a seasonal model for squared residuals from the total flow seasonal model that covers the performance of the plant after upgrading.

We observe that the leftover volatility in residuals is the result of the seasonality of the original variable. The fit of the seasonal mean model illustrated in Figure 5.1 shows that the model fits better in valleys than in peaks. This is why we observe a non-constant variance that is dependent on seasons. We follow the regular procedure to obtain a valid estimator for variance (i.e., residuals) described in econometrics textbooks (see Wooldridge, 2002, p.250). We divide the residuals by the variance factor, and we obtain the variance factor from the seasonal model for the residuals. Thus, we adjust for the heteroscedasticity of the residuals:

deseasonalized residuals = residuals/ fitted values for residuals^2, **[5.10]**

In the case when the square root of squared residuals was simulated, deseasonalized residuals are obtained by the formula:

deseasonalized residuals = residuals/ sqrt(fitted values for residuals^2). **[5.11]**

The next step is to establish the stationarity of the series. We conduct an Augmented Dickey-Fuller (ADF) test to test for unit roots and then conduct a Kwiatkowski–Phillips–Schmidt–Shin

(KPSS) test to confirm stationarity of the series. The table below summarizes the test statistics from the tests conducted on residuals from turbidity, TOC, and total flow models, respectively:

Table 5.3 Summary statistics on ADF and KPSS tests on the stationarity of deseasonalized residuals from seasonal mean models for *turbidity, TOC, total flow*

Test	Test statistic from turbidity model	Test statistic from TOC model	Test statistic from total flow model
ADF, 27 lags	-10.69**	-8.02**	-12.21**
KPSS , 10 lags	0.54*	1.29**	0.32°

Significance levels codes: *** - 0.1%, ** - 1%, * - 5%, ° - 10%

By the ADF test, we reject the presence of unit root in the series, while the KPSS test result states that we reject the stationarity null hypothesis. Obtaining mixed results from KPSS and ADF tests does not seem to be widely discussed in the literature. One of the possible reasons that we reject stationarity in the residuals is that there might be leftover heteroscedasticity in the residuals, meaning that we have not eliminated it fully by removing the seasonal component. Given that the condition for the application of ARMA(p,q) models was for roots of characteristics equations [5.8] and [5.9] to lie outside the unit circle, we rely on the results of the ADF tests. However, we do not know how non-stationarity of different types (i.e., other than unit root) could affect the results of the estimated ARMA models. At this point in the analysis, we rely on the absence of the unit root to proceed with further analysis.

The next step in forecasting the variable costs is estimating ARMA(p,q) models to characterize the movement of residuals as autoregressive moving-average processes. We analyze the fit of the theoretical distributions to the empirical distribution based on the AIC and find that under the assumption of skewed student T distribution (sstd) of the error, we get the best ARMA models. The model results are presented in Table 5.4.

Table 5.4 Summary of ARMA models coefficients for deseasonalized residuals from turbidity, TOC, and total flow seasonal models

Component	Lag	ARMA model	ARMA model	ARMA model

		turbidity residuals	TOC residuals	total flow residuals[1]
AR	1	0.97***	0.99***	0.96***
		(0.014)	(0.004)	(0.013)
MA	1	0.027*	0.016***	-0.43***
		(0.013)	(0.005)	(0.013)
	2	(0.004)	0.021***	-0.14***
		(0.01)	(0.006)	(0.028)
	3	(0.005)	0.01*	-0.12***
		(0.71)	(0.004)	(0.026)
	4		0.009*	-0.05°
			(0.003)	(0.029)
	5			-0.04°
				(0.024)

Significance levels codes: *** - 0.1%, ** - 1%, * - 5%, ° - 10%

[1] – in this table, we only include a seasonal model for residuals from the total flow seasonal model that covers the performance of the plant after upgrading.

5.3 Analysis of Residuals from the Cost-Response Model

We analyze residuals from the cost-response model separately. We collect the residuals from the final model (equation [4.2]) and test for the presence of heteroscedasticity as a function of seasonality. We test the hypothesis with simple OLS models of squared residuals on summer and winter dummy variables, and find that residuals vary differently depending on the season:

$$\textit{cost response model residual}^\wedge 2_t = \underset{(0.006)}{0.045^{***}}q1 + \underset{(0.006)}{0.071^{***}}q2, \qquad \textbf{[5.12]}$$

Significance levels codes: *** - 0.1%, ** - 1%, * - 5%, ° - 10%

Where:

Cost response model residuals^2$_t$ – are the squared residuals collected from model [**4.2**], *q1* – is the dummy variable that takes the value of 1, when there's winter season (as defined in section 4.1), and 0 otherwise,

q2 – is the dummy variable that takes the value of 1, when there's summer season (as defined in section 4.1), and 0 otherwise;

We then divide the residuals by the fitted values from the model and thus account for heteroscedasticity in the residuals, and then characterize the residuals as an autoregressive-moving average process. ARMA(1,3) model fits the observed residuals best under a skewed student t distribution assumption of the error. The final normalized residuals model coefficients are summarized in the following table:

Table 5.5 Estimated ARMA model for normalized residuals from cost response model

Component	**Lag**	**ARMA model Cost residuals**
AR	1	0.92*** (0.016)
MA	1	-0.27*** (0.03)
	2	-0.16*** (0.029)
	3	-0.04*** (0.028)

Significance levels codes: *** - 0.1%, ** - 1%, * - 5%, ° - 10%

To summarize sections 5.2 and 5.3, we have obtained complete models that characterize the water quality and quantity variables as well as the residuals from the cost-response model. We have defined seasonal mean models using Fourier transformational terms and then analyzed the residuals. To analyze the residuals, we first recognized the seasonality in the residuals and developed seasonal models for the residuals. We then estimated these models and used fitted values from these models to deseasonalize the residuals. Finally, we have characterized residuals as ARMA processes and estimated ARMA models. Using this information, we now can simulate the three variables and obtain the distribution of future in-plant costs using the empirical model developed in section 4.1.

5.4 Obtaining the Distributions of Future Values of Turbidity, TOC, and Total Flow.

To obtain the distributions of future values for turbidity, TOC, and total flow, we use the models developed in chapter 4. We model seasonality in the logarithms of turbidity and TOC, and total flow with Fourier terms presented in Table 5.2, and further deseasonalize the residuals from the seasonal mean model by dividing the residuals by the fitted values from the seasonal model for the residuals presented in Table 5.2. Deseasonalized residuals from the cost model are then modeled as autoregressive moving-average processes summarized in Table 5.5, and the residuals from the ARMA model are assumed to follow the skewed Student T distribution.

We project the variables for 20 years from 2015 and assume that a year has 365.25 days, where the three years consist of 365 days, and the fourth of 366 days. Projected seasonal mean models for turbidity, TOC, and total flow series are presented in Figure 5.3.

Figure 5.3 Illustration of the fit of Fourier seasonal mean models for turbidity, TOC, and total flow variables. In black, are historical data; in blue are fitted values from seasonal mean models.

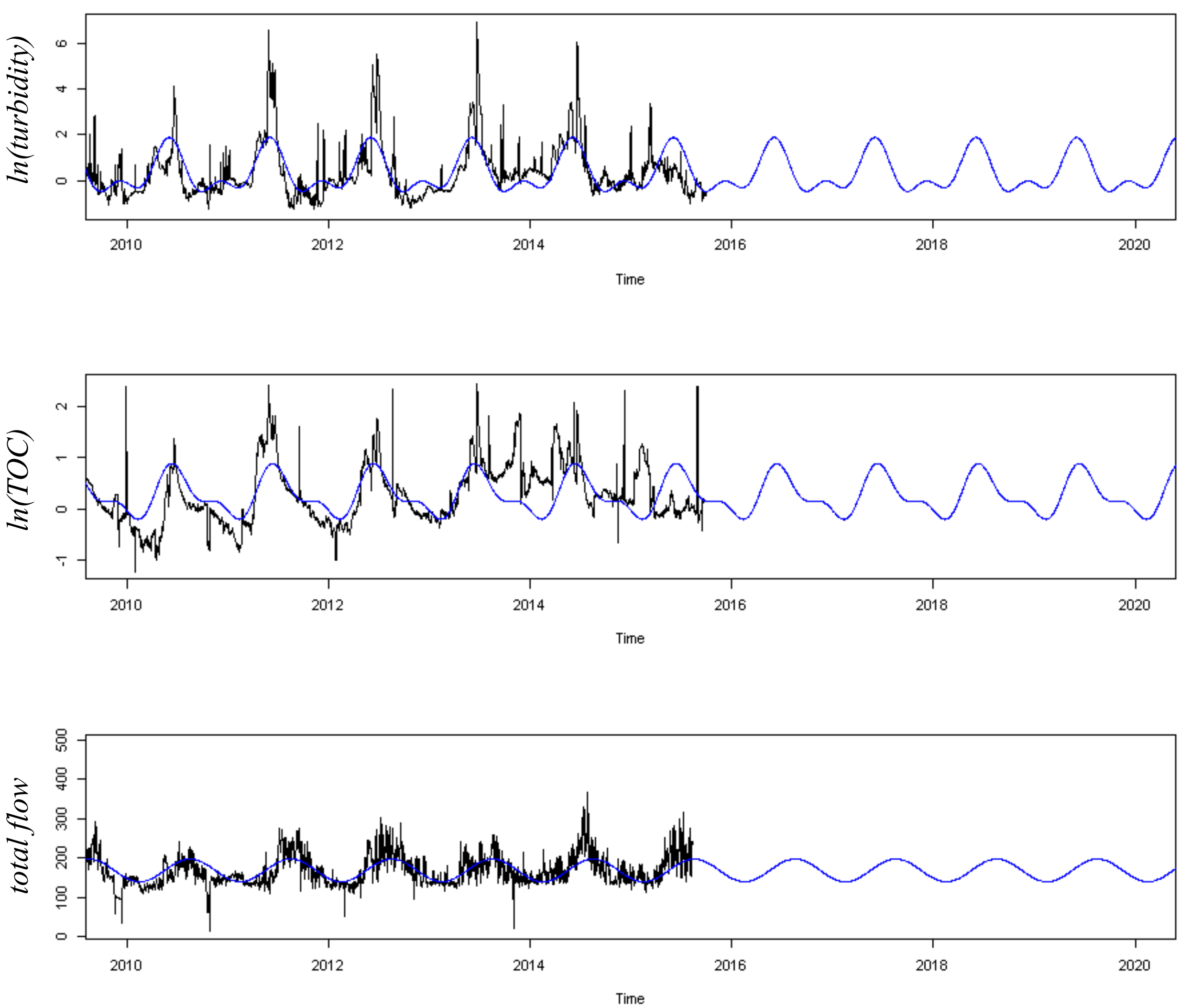
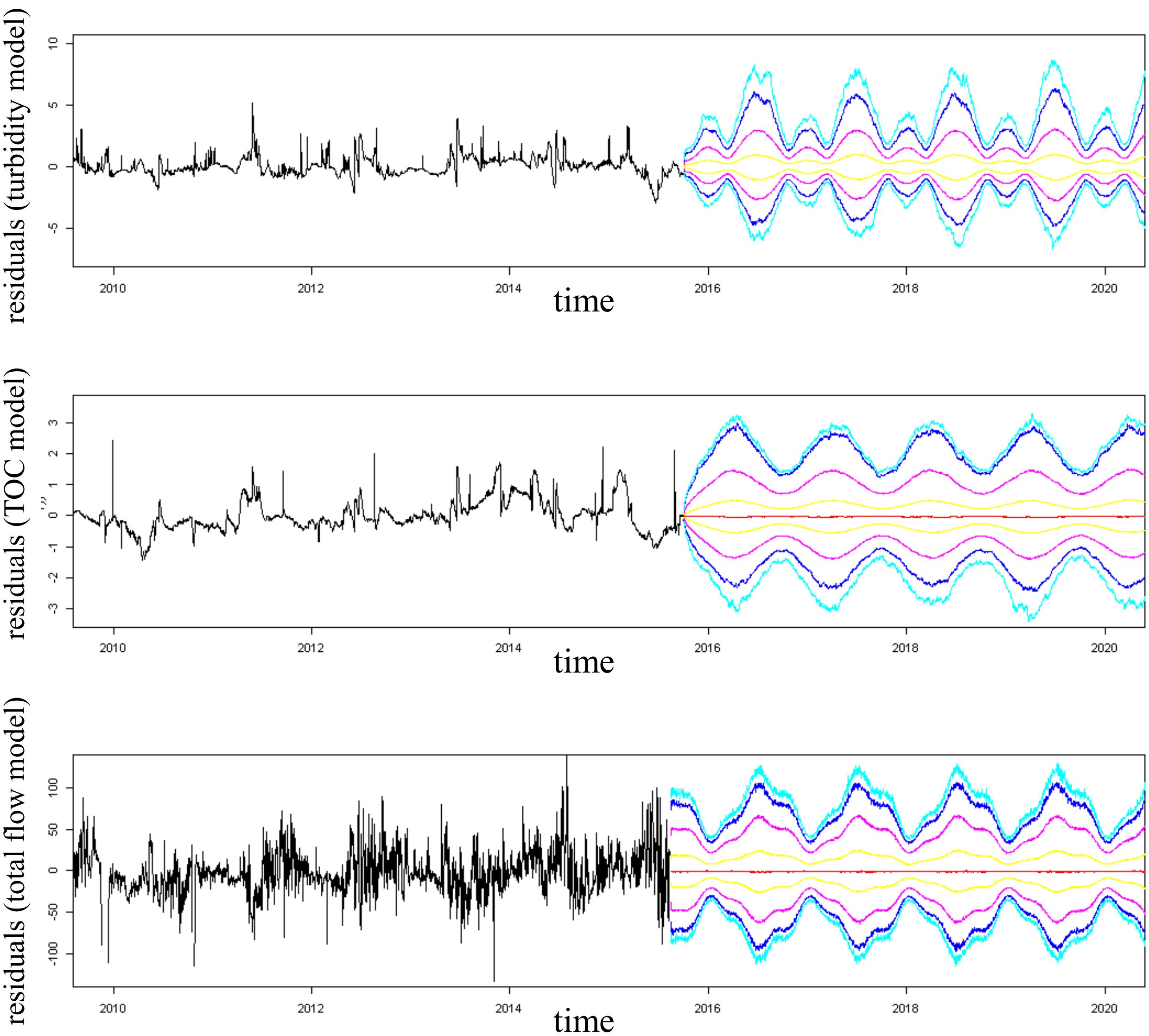


Figure 5.3 illustrates the fit and projection of the means for five years before and after the end data point of our dataset, respectively. From the figure, we can observe that seasonal mean models do not fit the empirical distribution well in peaks – this is the direct result from the construction of the models discussed in section 5.2. This is done to recognize the limitations of available data – only five years of daily data – and thus avoid overfitting of the models.

The next step is to simulate residuals that account for seasonal variation from the mean models and to combine them with the seasonal mean model. The simulation is done using an R-stats *rugarch* package, and ARMA models described in table 5.4, and the random error is assumed to follow a skewed Student T distribution. The results are illustrated in Figure 5.4.

Figure 5.4 Simulated residuals for turbidity, TOC, and total flow; ARMA models for years 2010-2020.



On the figure:

Black – residuals from seasonal mean models data,

Red – median simulated values

Yellow – 25th and 75th percentile simulated values

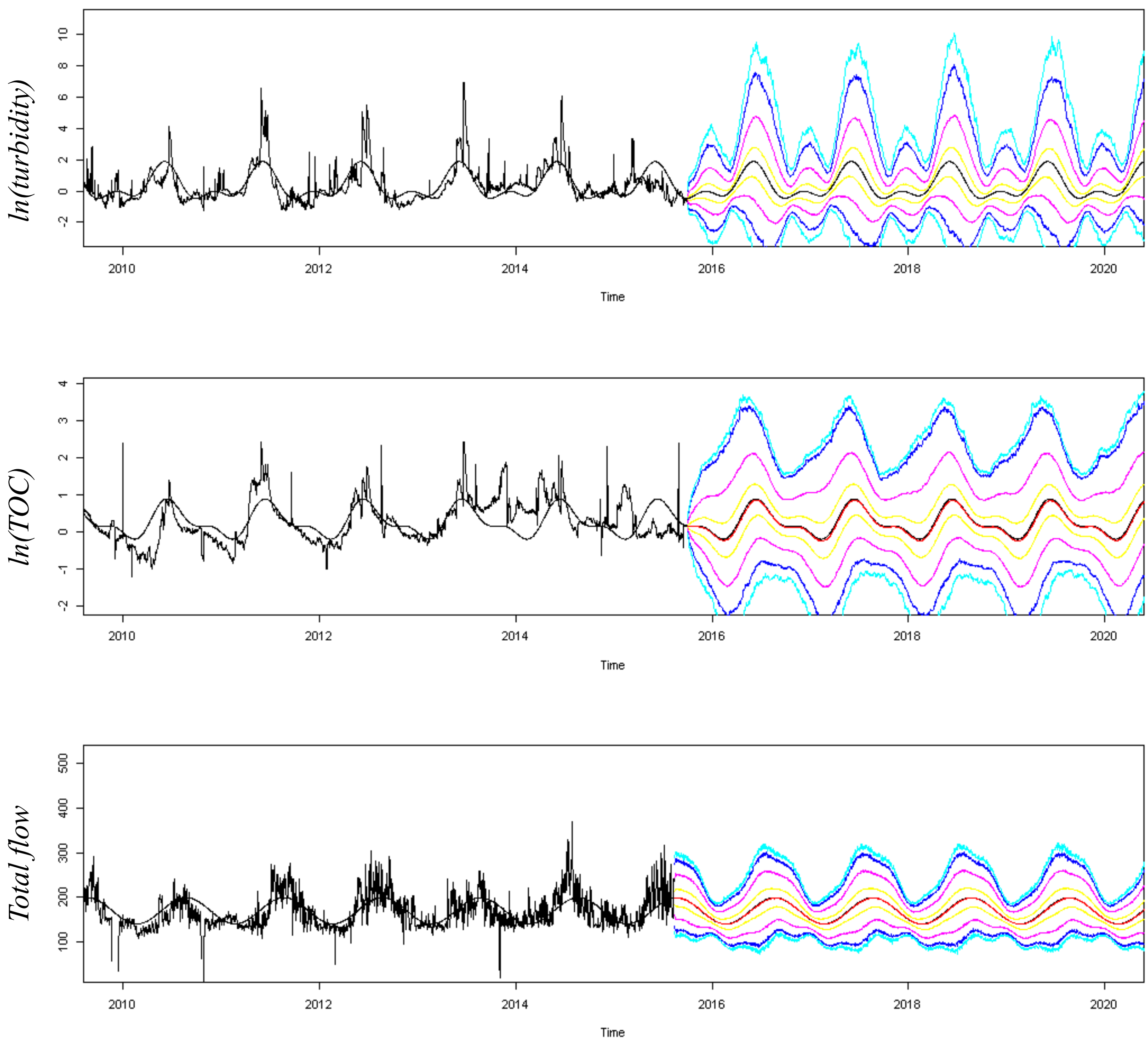
Purple – 10^{th} and 90^{th} percentile simulated values

Blue – 5^{th} and 95^{th} percentile simulated values

Light blue – 1^{st} and 99^{th} percentile simulated values

We then multiply the simulated residuals by the seasonal variance factor and obtain the residuals accounting for seasonal variation, and add them to the projected means to obtain the complete distribution for the three water quality variables. The results are illustrated in Figure 5.5.

Figure 5.5 Summary of simulated distributions of turbidity, TOC, and total flow variables for Glenmore WTP, 2010-2020.



In the figure:

Black – residuals from seasonal mean models data,

Red – median simulated values

Yellow – 25th and 75th percentile simulated values

Purple – 10th and 90th percentile simulated values

Blue – 5th and 95th percentile simulated values

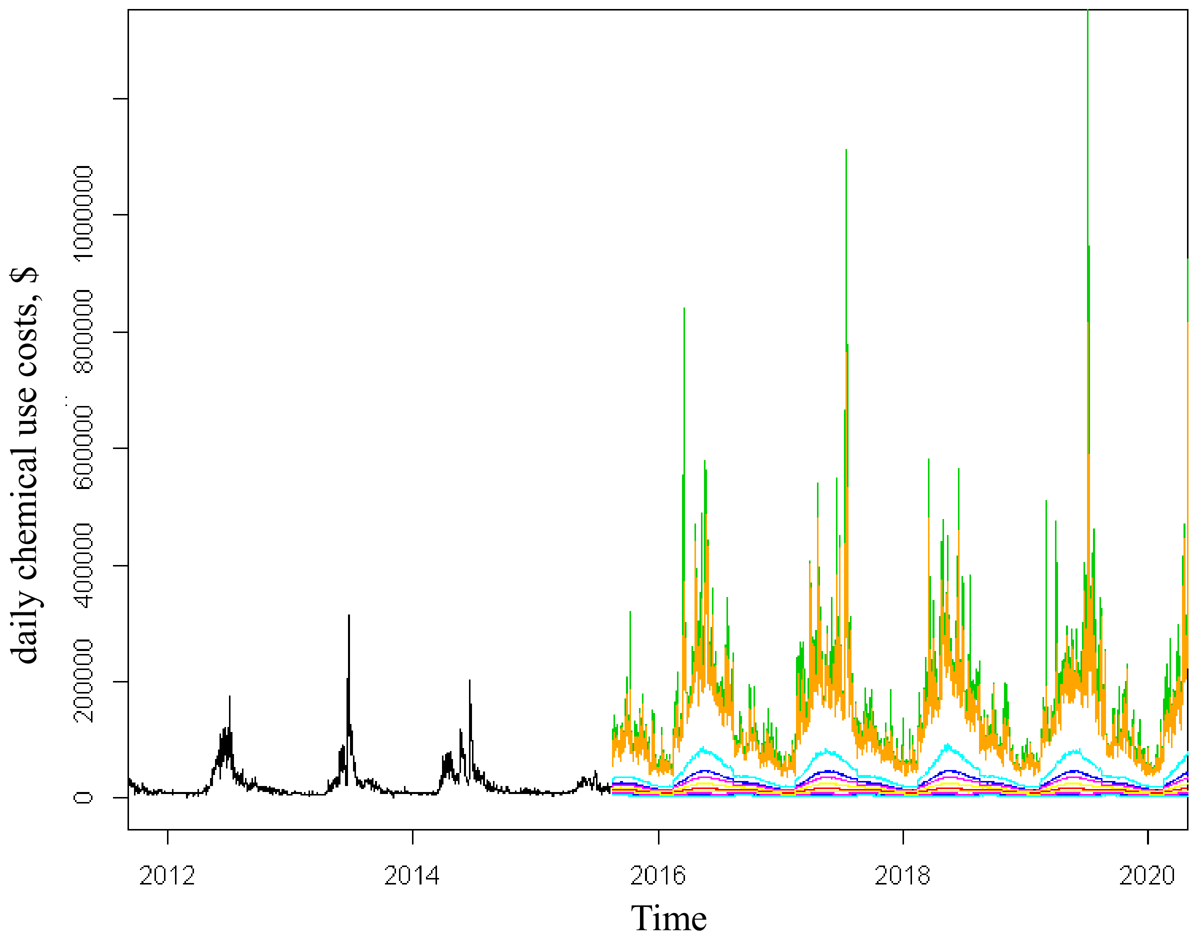
Light blue – 1st and 99th percentile simulated values

From Figure 5.5, it is evident that the **95th** percentile of simulated values covers the entire range of observed data points for turbidity and TOC, while the top 5 percent of maximum values of the simulated data points exceed the observed values. Simulations for total flow are less variant, and 99% of simulated data points are within the observed range.

Obtaining the distribution of future in-plant costs

In chapter 4, we developed an empirical model to estimate the effect of changes in the water quality on the in-plant chemical costs. On the left-hand side of the model is the natural logarithm of chemical costs per unit of influent water. The independent variables describing water quality are logarithms of turbidity (*lnturb*), TOC (*lnTOC*), while *total flow* is a water quantity variable. Water quality variables are interacted with the seasonal dummy variables to reflect differences in dose-response with respect to the time of year. Having developed the models to characterize the cost response model and movement of residuals, we predict the distribution of future costs using simulated distributions of water quality variables and add simulated residuals and a white noise parameter. As a result, we have 10,000 different simulations for 20 years that are summarized in the following graph:

Figure 5.6 Distribution of chemical use costs for Glenmore WTP, for years 2012 – 2020.



In the figure:

Black - observed total variable costs data,

Red – median simulated values

Yellow – 25th and 75th percentile simulated values

Purple – 10th and 90th percentile simulated values

Blue – 5th and 95th percentile simulated values

Light blue – 1st and 99th percentile simulated values

Orange – 99.94th percentile simulated values

Green – 99.95th percentile simulated values

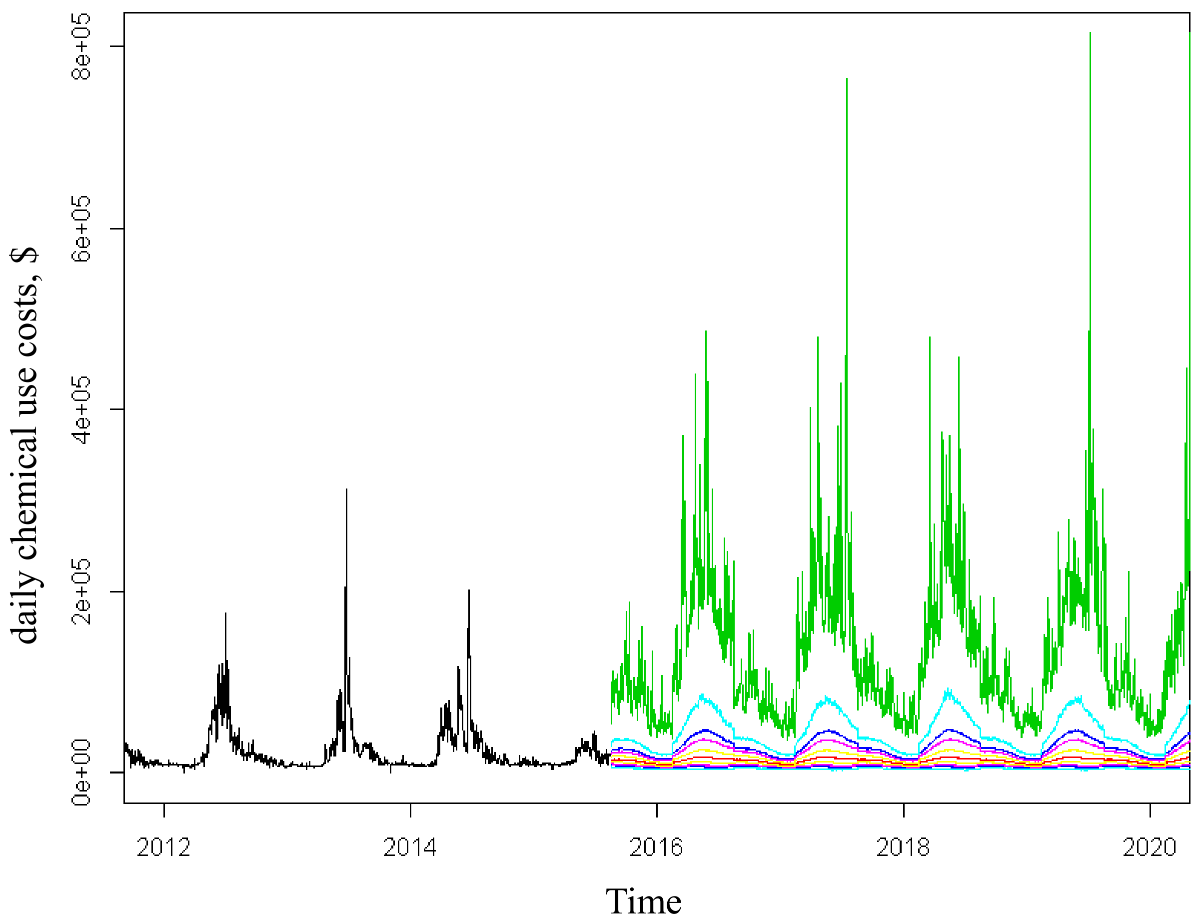
We have chosen a skewed Student T distribution for the error because it fits the empirical distributions better around the mean. Although the skewed T distribution fits the data well, the theoretical distribution does not tell us about possible boundaries beyond the observed data. Due to the chosen distribution having heavy tails (Aas and Haff, 2006), the upper bound for the simulated error is far beyond the observed maximum values, and we do not know where the possible theoretical upper bound lies. Some simulated cost values are as high as 10^{58}, while the maximum observed value is around 313,000. We analyze the upper range of values in closer detail to identify the point at which simulated costs exceed the maximum observed total variable costs.

Table 5.6 Maximum simulated values of in-plant costs for Glenmore WTP for years 2015-2035 at different percentiles of data.

Percentile	Maximum value, $
100th	$6.56*10^{58}$
99.96th	4,445,635
99.95th	1,529,595
99.94th	899,267.2
99.93rd	756,094.5
99.92nd	658,913.1
99.91st	395,268.1
99.90th	334,282.7
99.89th	332,498.1

Analyzing the simulated data, we find that simulations starting at the 99.95th percentile exceed the maximum observed value by more than five times. We are concerned with heavy outliers as they tend to skew mean values, while we base part of the analysis on the mean values (expected values). To deal with the outliers, we use a two-sided *Winsorization* technique described in Chambers et al. (2000). Winsorization is a method to adjust outliers using a pre-defined rule, leaving the rest of the distribution unchanged. Based on Table 5.6, we replace values above the 99.94th percentile and below 0.06th percentile with the previous highest and lowest values respectively for each day. Thus, a final distribution of total in-plant costs is illustrated in the following figure.

Figure 5.7 Distribution of total costs for Glenmore WTP, for years 2012 – 2020 Winsorized at 99.94th percentile.



On the figure:

Black - observed total variable costs data,

Red – median simulated values

Yellow – 25th and 75th percentile simulated values

Purple – 10th and 90th percentile simulated values

Blue – 5th and 95th percentile simulated values

Light blue – 1st and 99th percentile simulated values

Green – 100th percentile values

5.5 Costs of Water Treatment Outside of the Regular Operating Parameters

Up to this point, we have discussed the operating costs and developed an empirical model to estimate the effect of changes in water quality on average daily chemical use costs. In this section, we discuss what constitutes the costs during supply disruptions. First, we describe our assumptions about the thresholds for the water treatment plant's disruptions. Second, we consider cost components to the disruptions to the work of the WTP, including costs of averting and adaptive behavior, costs of increased risks of morbidity and mortality, and bringing in water to the city.

The thresholds depend on the quality of the source water, a technology employed at the treatment plant, and risk perceptions of the water supply decision-makers. Thus, the thresholds are not the only source- and geography-specific, but they are also plant-specific. A survey of Alberta's plant operators (2015) reveals that the Alberta water treatment plants similar to the one operating in Calgary could operate under a normal schedule until the level of turbidity reaches 4000 NTU[9]. Thus, we assume 4000 NTU turbidity to be the threshold at which the plant stops operating on a regular schedule. There is no literature that is known to the authors on the raw water quality thresholds that would make a plant to go off a regular schedule, and for authorities to call specific water use or no-use advisories. However, we know that a water advisory must be called when output water quality exceeds 1 NTU, wherein the range between 1 and 5 NTU the water quality is considered as "fair" and a water quality notice is given to customers; a boil water advisory (BWA) must be issued if output water turbidity exceeds 5 NTU (Guidelines for Canadian Drinking Water Quality cited in TNRD, n.d. and SEKID, n.d.) or high level of contaminants are detected in the output water (as outlined by the Guidelines). Environment and Climate Change Canada (2019) summarizes that from 2010 to 2017, boil water advisories were caused by E.Coli bacteria (on average, 6% of cases), other microbiological parameters (around 18% on average), while the rest are attributed to equipment and process issues[10]. Given that

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[9] The response of the water treatment plants' managers that operate a water treatment similar to GWTP in characteristics for a question *"How high would turbidity have to be for the plant to shut down temporarily? Please indicate the unit of measurement."* was ">4000 NTU"

[10] *"Data used in this indicator come from various agencies and jurisdictions across Canada that use or share information with the Canadian Network for Public Health Intelligence's Drinking Water Advisories application. They represent only a subset (less than 50%) of the Canadian population. Comprehensive national data are not*

cities like Calgary are equipped with water treatment plants, and drinking water is primarily supplied by these plants, it is safe to assume that water quality issues could arise from malfunctioning of the plant. Thus, if the water turbidity reaches 4000NTU, we assume that poor water quality is causing high stress on the water treatment facility. Operating under such pressure could mean that a plant's output water might potentially not meet the health standards (i.e., exceed 5 NTU or contain specific contaminants). This is why we assume that exceeding 4000 NTU input water quality threshold triggers some sort of a water use advisory. For the analysis, we choose 4000 NTU to be the threshold at which the plant experiences problems meeting the drinking water quality standards, and a water use advisory is called.

Partial disruptions of water treatment plant operations happen due to the inability of the plant to deliver their services to the population at required health standards. The disruptions on the consumers' side are perceived as water outages and water use advisories. Consultation with an expert in water treatment (Emelko, personal communication, 2018) suggests several sources of additional costs that would arise from a partial disruption of the water supply. In this subsection, we discuss the nature of these sources, costs from past experiences, and estimated costs under recommended health standards. The sources of outside costs that we identify include the following: new infrastructure costs, extra in-plant maintenance and restoration (e.g., reservoir dredging) costs, costs of boil-water advisories to the consumers, costs of risks of increased morbidity and mortality, and increased analytical costs.

5.5.1 Costs of Water Outages and Adaptive Behaviour.

Short and longer-term outages and boil water advisories have social costs. First, there are costs associated with buying bottled water, hauling water, the cost of time and energy of boiling water, and the cost of discomfort caused by the advisories. To complete the distribution of costs to cover various cases of water outages, we rely on previous studies and convert values to 2015 Canadian dollars using relevant indexes. There are different approaches to elicit consumers' willingness to pay for water quality and to assess the costs caused by drinking water supply disruptions. The following subsection presents a summary of studies that use an adaptive

available […] The Water quality, other microbiological parameters category includes detection of total coliform bacteria and high turbidity levels in drinking water systems. The Equipment and process category includes issues such as broken water mains, planned system maintenance, power failures or equipment problems."
Source: ECCC (2018) Canadian Environmental Sustainability Indicators: Drinking water advisories

behavior and expenditures approach that supply our cost model with lower and upper bound estimates.

Averting Behaviour and Adaptive Expenditures Approach

Cropper and Oates (1992, p. 680) describe averting behavior as "defensive behavior to mitigate the effect of pollution from which they suffer." In the case of drinking water, consumers avoid drinking contaminated water by switching towards clean sources of water - bottled water, or sources like wells, and hauling water from neighboring towns, or they boil or filter the tap water. A 1998 study by Whitehead et al. gives a summary of studies on averting behavior and diminished water quality. They summarize their findings in the following table.

Table 5.7 Summary of Costs from Averting and Adapting Expenditure Studies on the Costs of Boil Water Advisories.

Study	**Location**	**Nature and Duration of Episode**	**Averting Behaviors**	**Sample Size**	**Costs (b)**
Harrington, Krupnick, and Spofford (1989)	Luzerne County, Pennsylvania	*Giardiasis* outbreak (12/83 - 9/84)	1, 2, 3	50	$153 -483
Abdalla (1990)	College Township, Pennsylvania	Detection of *percholoroethylene* in wells (6/87 - 12/87)	1, 2, 3, 4	1012	$26 - 32
Abdalla, Roach, and Epp (1992)	Perkasie, Pennsylvania	Detection of *trichloroethylene* in wells (6/88 - 12/89)	1, 2, 3, 4	761	$16 - 35
Collins and Steinback (1993)	Rural West Virginia	Bacterial, Mineral and Organics detected in drinking water supplies (1/87 - 12/89) (c)	1, 2, 3, 4, 5	291, 151	$32 - 36 (d)

Laughland et al. (1993)	Milesburg, Pennsylvania	Giardia detected in (surface) drinking water supplies (1/89 - 4/89)	1, 2, 3	226	$16 - 42

(a) 1 = hauling safe water, 2 = boiling water, 3 = purchasing bottled water, 4 = installation of home water treatment system, 5 = clean or repair the water system
(b) Monthly averting costs are adjusted to the monthly household level using 4.3 weeks per month and 30 days per month in 1996 dollars
(c) Dates of water tests for nonpublic water systems, duration of episodes varied by household
(d) Bacterial - mineral contaminants.

Source: Whitehead et al., 1998. Table 1, p. 29.

To use the numbers in our study, we need to adjust prices to 2015 Canadian dollars. The summary table of adjusted and inflated costs from Table 5.7 is presented at the end of the section in Table 5.9.

5.5.2 Costs of Increased Risks of Morbidity and Mortality

Increased number of illnesses and deaths due to diminishing water quality is one of the costly outcomes that can come with decreased tap water quality. These high costs are due to medical costs, and the value of elevated mortality risk, loss of productivity as well as the other social costs. Higher risks of morbidity and mortality could be related to the decrease in water quality: if a large population is exposed to contaminated water, there is a risk that some people will get ill or even die. As discussed above, a water treatment plant that is operating under the stress can issue a water use advisory. However, even under such advisories, there exist public health risks related to the ineffectiveness of communication of a notice or people's non-compliance. In our study, we use *turbidity* as an indicator of overall water quality. We assume that a higher concentration of particles in the source water is correlated with the concentration of other chemicals and microorganisms and can obstruct the normal operation of the plant. In the case when the turbidity threshold is exceeded and the quality of output water is compromised, with the BWA in action, public health risks arise. Ex-post costs of water-related disease outbreaks can be very costly.

For instance, Corso et al. (2003) have conducted a detailed study of the costs of the 1993 Milwaukee cryptosporidium outbreak. They found that the total cost of illness was $96.2 million (1993 US dollars), where $31.7 million were medical costs, and the rest is due to the losses in productivity. The plant's abnormal condition in the referenced case lasted for 17 days from March 23rd to April 8th. About 25% of the population became ill, whereas the BWA lasted for 10 days, and one of the plants was shut down for approximately 2 months. Sixty-three deaths were linked to the outbreak of the bacteria, which constituted 0.00039% of the population. We use the costs from the Milwaukee case as inputs to our model to approximate the costs from increased morbidity and mortality risks. There potentially could be a number of reasons for such outbreaks, as well as the distribution of possible outcomes in terms of costs. However, we use the Milwaukee costs only to approximate the potential consequences from the outbreak in a larger city. One of the reasons to use these numbers is that Milwaukee is one of the few cases in which the economic costs of a waterborne disease outbreak were studied carefully. Another reason is the comparability of Milwaukee, Wisconsin, with Calgary, Alberta in terms of the population (1.6 million compared to 1.2 million respectively), and that the Milwaukee plant was one of two plants serving the population at the time, supplying approximately 880 thousand residents.

A cryptosporidium outbreak caused illness to more than a third of North Battleford's population of 15000 in 2001 (Woo and Vincente, 2003). It took more than a month to recognize the emergency and declare a boil advisory, and then three months to lift the advisory. 39-47% became ill as the result of the outbreak, but economic losses from the crisis have not been estimated. A similar waterborne-disease related tragedy happened in Walkerton, Ontario, in May 2000. Raw water became contaminated with an E. coli bacteria and caused illness to about 48 percent of the population – 2300 out of the total population of 4800 people, and death to 7 people. The case of Walkerton, Ontario, could serve as an example of an upper bound case, where the negligence of the local government and lack of adequate technology have led to the lagged reaction to the crisis (Woo and Vincente, 2003). The Walkerton-like case is an extremely unlikely event in larger cities, especially as a result of poor source water quality. However, we refer to the Walkerton case as an example of possible consequences of disease outbreaks and community response to such crises. Moreover, not accounting for such cases in the analysis as one of the possibilities can lead to an underestimation of potential outcomes. The economic damage was estimated to be $64.5 million (Woo and Vincente, 2003). The Walkerton tragedy was partly the result of inadequate technological sophistication of the plant that did not correspond to the riskiness of the source water, and partly due to poor handling of the situation. The water advisory was not issued for fourteen days allowing for the disease to spread (O'Connor, 2002). The advisory lasted for 7 months before it was lifted in December of 2000.

5.5.3 Costs of Sedimentation and Reservoir Dredging

Soil erosion and sediment formation could cause additional costs to the maintenance of the water treatment facilities. According to Moore and McCarl (1989), high levels of sediment in a river increase costs:

> *Erosion, sedimentation and/ or deposition directly or indirectly increase costs to society in terms of facility maintenance (e.g., ditch cleaning), facility replacement (e.g., building new dams), erosion mitigation (e.g., increased water purification), and/ or effect prevention (e.g., sediment settling ponds)* (Moore and McCarl, 1989, p.42).

The reduction in reservoir capacity and contents of the sediment necessitate dredging after longer events that are characterized by high levels of turbidity and TOC. Thus, untouched organic contents of the sediment in the reservoir may lead to the formation of algae, and cause an outbreak of a bacterial disease. The US Army Corps of Engineers (2017) provides an analysis of dredging costs. The summary of the dredging costs is presented in the following table.

Table 5.8 US Army Corps of Engineers summary of costs of dredging (2017)

	Dollar Value (000s)	**m^3(000s)**	**Cost/m^3**
Total Dredging	1,359,376.5	176,463.34	7.70
Total Maintenance Dredging	1,173,202.4	167,482.85	7.00
Total Emergency Dredging	835.7	67.51	12.38
Total Non-Hopper Dredging (Maintenance)	810,693.9	123,471.56	6.57
Total Non-Hopper Dredging (Emergency)	835.7	67.51	12.38

5.5.4 Increased analytical costs

An additional source of costs to society in cases of an unusual operational schedule is the increased analytical cost. The examples of North Battleford and Walkerton crises illustrate the lack of water treatment specialists, whereas the emergency and unusual events require an accurate and professional reaction. Sourcing external analysts and consultants to the place of the emergency is the solution to supply for the need of a professional and/or expert group. However, we believe that increased analytical costs are low compared to other sources of external costs, and thus we omit the use of analytical costs as extra costs.

5.5.5 Costs of Bringing in Water in Trucks or in Bottles

To this point, we have discussed the costs that may arise with water supply disruptions. In addition to the costs of increased chemical consumption on the plant and direct in-plant adaptive costs of dealing with water advisories, society also faces costs of increased illnesses and deaths, costs associated with the reservoir dredging due to increased sedimentation and contamination with microorganisms, and increased analytical costs. In this subsection, we discuss the costs of supplying water to the city from alternative sources during a no-use advisory. No-use water advisory implies that tap water is no longer safe for consumption or use by the households, and there is a need to source water from other alternatives, which include bringing in bottled water (e.g., Toledo, Ohio in 2014 and Flint, Michigan in 2016), bringing water in trucks, or developing new raw water sources. In this section, we approximate the costs for the GWTP case study using historical costs from past cases with no-use advisories and provide estimates of lower and upper bounds of costs when water is supplied in accordance with the health standards during emergencies suggested by the World Health Organization. Cases when cities have to issue a no water use advisory are very improbable in larger cities. However, we consider such cases as the most extreme cases that can potentially happen if the WTP is experiencing an extreme amount of pressure from the source water quality. We thus obtain a range of values to approximate the costs of supplying water to the community when the tap water is found to be unsafe to use.

Costs of Hauling Water During a No-use Advisory in Recent History

Flint, Michigan. 2016.

From 2014 to 2016, residents of Flint, Michigan, had been experiencing a water crisis that cost more than $70 million to the city and state to deal with the crisis (Gostin, 2016). Flint is a town located near the Great Lakes and was populated by about 100,000 residents from 2014 to 2016. In the context of this subsection, the Flint water crisis is important to study as it provides important insights into how the state dealt with cases when the community cannot use the tap water and has to find alternative water sources. For instance, the local government and other governmental and non-governmental institutions organized the delivery of bottled water to distribution stations (Fonger, 2018). The expenditures for the supply of bottled water averaged $653,000 (2016 US dollars) a month, which could be translated into $.22 per person per day.

Toledo, Ohio, 2014

The Toledo, Ohio 2014 water crisis is another example where a ban on tap water drinking was issued. The ban lasted for two days – August 2nd and 3rd of 2014 (AWWA, 2016). During that time, 500,000 residents were advised not to use contaminated water, and residents turned to sources of bottled water. On the first day, the National Guard provided 48,000 gallons (181700 L) of bottled water for people in need (CBC, 2014). No further information about water purchases, hauling, or transporting by other state entities is available in the open sources. However, we can use the value of 48,000 gallons as the lower bound estimate of how much water was delivered for people in need during the crisis that day. We compare the costs from Toledo and Flint, and then use the numbers in our model with adjustment to inflation, and population sizes.

World Health Organization Emergency Situation Standards

Reed and Reed from the Water Engineering and Development Center (WEDC) developed technical notes for the World Health Organization (WHO) on drinking water during emergencies (Reed and Reed, 2011). In the notes, there are recommended levels of water per person for domestic and non-domestic uses to sustain basic needs. Recommended levels of water supply per person are 7.5 to 15 liters per day. We use these recommendations and available data on the costs of bringing water to Calgary to obtain the costs of water supply in an emergency of poor water quality. Actual no-use advisory case costs can be extremely high and include costs other than hauling water. For instance, when a no-use advisory is issued, serviced populations are forced to engage in costly behavior, among which are buying and hauling water for drinking and other household purposes, and other costs related to losses of productivity, lost business opportunities, and others. While these aspects of water supply cut-offs are important, they are difficult to estimate, and there is a lack of case studies on the topic. While potentially considerably underestimating the actual costs of such cases, cost approximations form Flint, Toledo, and using WHO guidelines, are important referencing points for lower bound estimates. We summarize these costs in Table 5.9, along with other sources of outside costs.

Table 5.9 Summary of community costs incurred when water quality is beyond the assumed quality threshold for a portion of the Calgary population that is served by the Glenmore WTP in 2015 CAN$. Highlighted in light and dark grey are values used in the analysis as outside costs as lower and upper bound estimates, respectively.

Source of costs	**Reference**	**Original cost or volumes**	**Currency and unit**	**Cost per unit in 2015 CADs[a]**	**Cost per unit per day in 2015 CADs[b]**
Averting and adaptive behavior	Harrington et al. (1989)	$153 - 483	1996 US dollars per household per month	$321-1014	$10.7-33.8
	Abdalla (1990)	$26 - 32	1996 US dollars per household per month	$55-67	$1.83-2.23
	Abdalla, Roach and Epp (1992)	$16 - 35	1996 US dollars per household per month	$34-73	$1.13-2.43
	Collins and Steinback (1993)	$32 - 36 (d)	1996 US dollars per household per month	$67-76	$2.23-5.53
	Laughland et al. (1993)	$16 - 42	1996 US dollars per household per month	$34-88	$1.13-2.93

Increased morbidity and mortality	Milwaukee, Wisconsin (Corso et al. 2003)	$96.2 million	1993 US dollars for 17 days for 880000 residents	$219.3 million	$14.66 per person per day
	Walkerton, Ontario	$64.5 million	2000 Canadian dollars per 21 days	$85.6 million	$849.2 per person per day
Cost of reservoir dredging	US Army Corps of Engineers	$6.57 – $12.38	2017 US dollars per m^3	$8.83-16.64	$4.42 – 8.3 million [f]
Bringing water from alternative sources	Flint, Michigan	$0.22	2016 US dollars per capita per day	$0.30	$0.30
	Toledo, Ohio	48,000 G	Gallons per day	$0.147[c]	$0.147
	WEDC notes for WHO	7.5 – 15L	Liters per day per person	$0.19-0.38[d] $1.5-3[e]	$0.19-0.38 $1.5-3

a - US Consumer price index is obtained from U.S. Department of Labor Bureau of Labor Statistic, Canada CPI is obtained from Statistics Canada; prices are converted to 2015 Canadian Dollars (CCD)

b – half of Calgary's population served by GWTP = 620,000 residents or 279,455 households in 2015

c – the cost of water per person per day; wholesale $1.1 per gallon of water is assumed

d – the cost of water per person per day; water is brought in 2500G trucks for an average of $237.5; from Alberta Water Services

e – the cost of water per person per day; water is brought in 500mL bottles; Real Canadian Spring water 24x packs for $2.4

f – Calgary Glenmore reservoir's estimated capacity of 10 million cubic meters was used for the calculation. Dredging volume is assumed at 5% of the total reservoir volume.

After we have obtained various estimates of per-person costs that can arise under different assumptions, the next step is to combine the estimates with population growth and discuss how these numbers add to the variable costs.

5.6 Modelling Outside-of-plant Event Costs

We now proceed to build the distribution of outside costs. We consider two cases that could happen when water quality exceeds the design threshold. These cases illustrate ways that a community adapts to different levels of output water quality. They are mainly characterized by the sources and nature of the costs. One case is when a WTP is unable to provide water to required health standards and continues to operate under a boil water advisory, and people have to engage in adaptive and averting behavior, and there are morbidity and mortality risks; we refer to such instances as *case One*. The second case is respectively referred to as *case Two*. In this case, the output water quality is even worse than during a *case One*, and is also triggered when the raw water quality threshold is exceeded. The plant keeps operating, providing a limited supply of water to support key public services; authorities issue an advisory advising the population to avoid any use of tap water. There are two sources of outside costs in this case: costs of hauling water to the city, and costs of health risks. In the instance of a *case Two*, individual adaptive and averting behaviors are assumed to be costless.

Case One covers a wider range of community adaptation costs, including buying bottled water by individuals, hauling water, and boiling water, while *case Two* only includes public costs of hauling water to the entire city as one of the sources of community adaptations. The boil-water-advisory-case (*case One*) can be assigned a higher probability of occurrence than a no-use-case (*case Two*). This is due to the need for a WTP to operate to supply water to support vital community services with non-drinking water use (e.g. have water available for fire emergencies). The scenario that results in *case Two* is the less likely of the two cases in reality. However, we do not assign weights to the occurrence of one of the two scenarios. The reason is that we do not know the distribution of cases outside regular operating schedules between these two cases. We acknowledge that both cases are possible, although the *case Two* is far less likely. We assume that no-use-advisory-cases can be triggered by some event at which the water quality exceeds the threshold of 4000 NTU. We evaluate the costs of both cases in our analyses to construct a range of possible scenarios. In this section, we will consider the mechanism of how we obtain the distribution of outside costs and combine them with the distribution of in-plant costs.

Modeling Outside Community Costs in a Case One Instance.

We identified the water quality threshold at 4000 NTU for the GWTP, and it will be the point at which the output water quality is below the advised health standards, but the plant continues to operate under the assumption of an issued BWA or no-use advisory. In the *case One* event, the plant's total costs when the threshold is exceeded will consist of variable operational costs and costs of adaptive and averting behaviors adjusted for the population levels. In addition to adaptive and averting behavior, contaminated water poses risks of an outbreak of waterborne diseases. We thus add the costs of increased risks of illnesses and deaths into consideration. Therefore, each *case One* instance is represented by the sum of variable in-plant costs, costs of adaptive and averting behaviors as discussed above, and expected costs of having a disease outbreak.

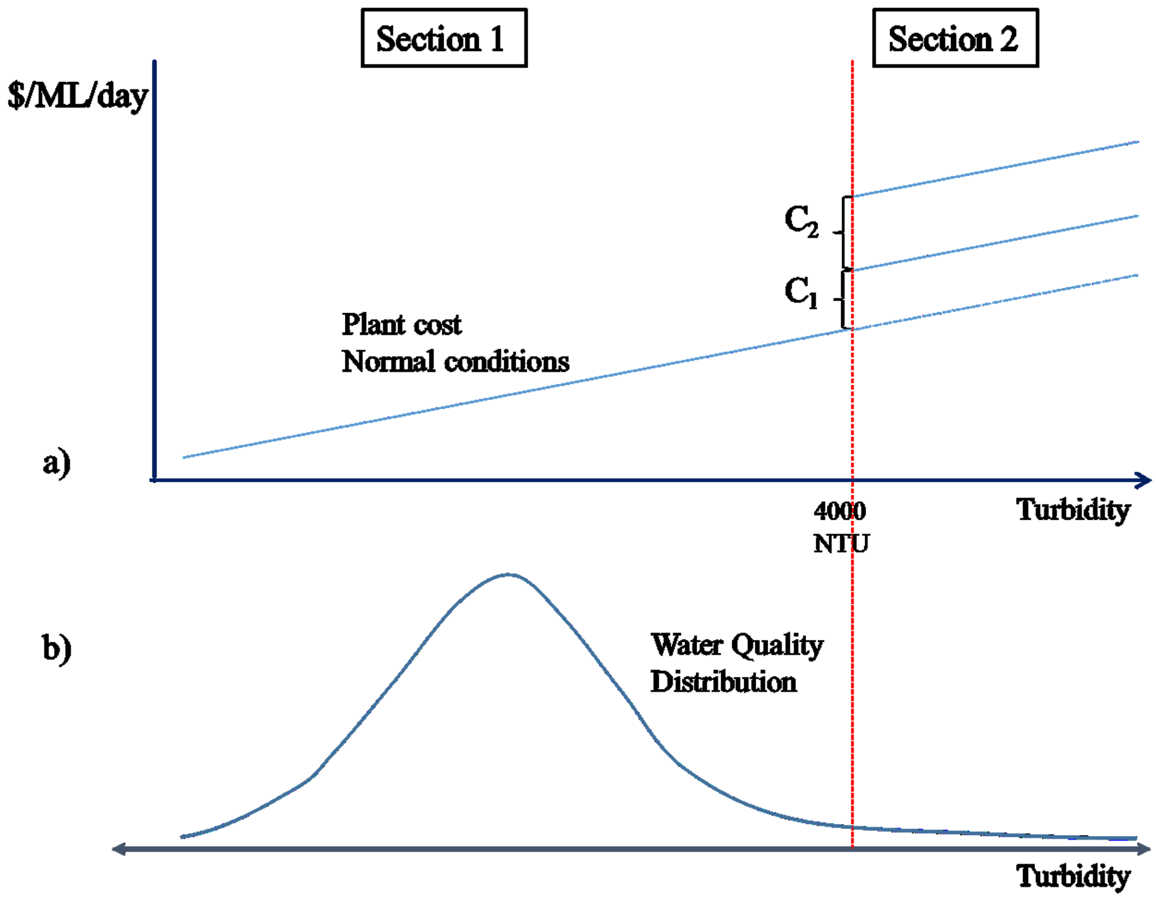
In turn, the expected costs of a disease outbreak are:

$$E(costs\ of\ disease\ outbreak) = p_d \times (costs\ of\ disease\ outbreak), \qquad \textbf{[5.13]}$$

Where p_d is the probability of a disease outbreak.

The *case One* water supply costs can be illustrated as a two-section stylized cost graph.

Figure 5.8 Stylized costs graph of water treatment costs during a *case One* event for the Glenmore WTP. Panel a: cost schedule for the GWTP; panel b: distribution of the source water quality. C_1 –adaptive and averting behavior costs; C_2 – costs of increased risks of morbidity and mortality.



In Figure 5.8, panel a) of the graph shows the relationship of turbidity to the average daily costs of water treatment; panel b) here is the statistical distribution of turbidity. The costs consist of two sections. Section 1 covers the average in-plant chemical use costs, where costs are an upward sloping line. The line continues in section two, where constant C_1 and C_2 costs are added to the costs and shift the cost curve upwards. The breakpoint in the cost is at 4000NTU, as discussed above. Thus, total costs in a *case One* event can be represented as follows:

$$\text{Total Costs} = \begin{cases} in - plant\ costs, if\ turbidity\ \in [0, 4000), \\ in - plant\ costs + C_1 + C_2, if\ turbidity \geq 4000 \end{cases} \quad \textbf{[5.14]}$$

C_1 are the costs of adaptive and averting behaviors. We define a range of costs for adaptive behavior (see Table 5.9), where the lower bound is from Laughland et al. (1993) and Abdalla et al. (1992) with $1.13 per person per day. The upper bound is $33.8 per person per day from Harrington et al. (1989). We assume that this case is triggered every time the level of turbidity enters the range above 4000 NTU. Population level-adjusted outside costs, in this case, are added directly to the in-plant costs, as is shown in the graph.

C_2 are the costs of increased risks of morbidity and mortality. Here, we explicitly associate risks of output water contamination with higher turbidity of input water and account for risks of outbreaks of waterborne diseases that lead to more illnesses and deaths. To the best of our knowledge, there are no estimates of risks of having a waterborne disease outbreak given the WTP's failure. Thus, we approximate the number of water treatment plants' failures by the number of boil-water advisories (BWAs). We use data on waterborne disease outbreaks and the number of BWAs in Canada to approximate the probability of a disease outbreak conditioned on the occurrence of a boil water advisory. Moffatt and Struck (2011) in "Water-borne Disease Outbreaks in Canadian Small Drinking Water Systems" report that there were 48 disease outbreaks from 1993 to 2007 – on average, 3.2 outbreaks per year. Lloyd Smith (2018) calculates that there were, on average 54 boil advisories in a year in Alberta. Adjusting for the Canadian population, we approximate that roughly about 1084 BWAs happen in Canada in a year. We assume that a disease outbreak would only happen if there is a BWA, and thus could estimate a conditional probability of having an outbreak given the BWA installment. Thus, a conditional probability is a number of disease outbreaks in a year over the total number of BWAs in a year, which is 3.2/1084 = 0.003. We thus estimate the probability of a waterborne disease outbreak conditional on a BWA installment (p_d in equation [5.13]) to be 0.003. In other words, the third cost component enters the calculation of the total costs as expected costs:

$$C_2 = E[\text{costs of disease outbreak given BWA}] = 0.003*(\text{costs of disease outbreak}), \quad \mathbf{[5.15]}$$

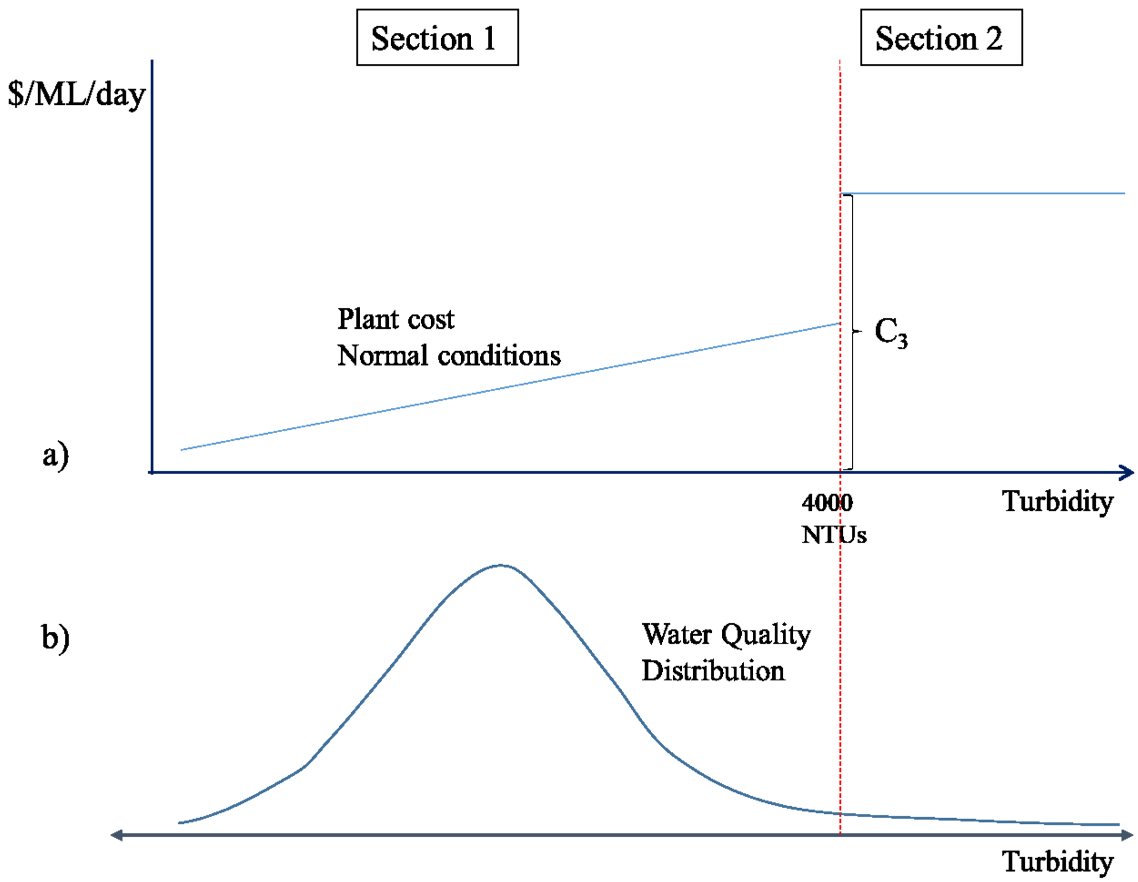
We use the Milwaukee, 1993 costs of $14.66 per day per person as a lower bound estimate for C_2, where the Walkerton, 2000 costs of $849.2 per person per day are used for the upper bound estimate of costs of a disease outbreak that can potentially cause illnesses and deaths.

Modeling Outside Community Costs in a Case Two Instance.

In this case, when the source water quality reaches the threshold level, we assume that the plant's water production is limited, and thus the chemical costs are not included in the calculation of the total cost when this case is triggered, as opposed to *case One.* In addition to bringing water in trucks, and increased health risks, higher contents of sediment in the river and high concentration of organic matter in the water present another source of costs. High sediment and organic matter contents pose risks to the development of algae in the reservoir or filling of the reservoir with the sediment. Thus, such costly reservoir management practices as dredging might be required; however, we exclude reservoir dredging costs from the final calculation[11]. Excluding reservoir dredging costs means that *case Two* event costs are comprised solely of bringing water from alternative sources costs and costs of increased health risks. If all sources of costs in a no-use advisory case are incorporated into the analysis, we suppose that this case would be costlier than cases when boil water advisories are issued. This is due to the magnification of consequences from risks of water contamination due to poor raw water quality. In our model, however, the no-use case assumes no other costs but costs of hauling water and increased health risks, and thus is modelled as a lower bound in the scenario analysis. We can summarize the case in the following graph.

Figure 5.9 Stylized costs graph of water treatment costs in an instance of *case Two*. Panel a: cost schedule for the GWTP; panel b: distribution of the source water quality. C_3 – external costs of bringing water from alternative sources.

[11] The cost approximations for reservoir dredging are presented in Table 5.9. The dredging for Glenmore reservoir could be as costly as $4.7-8.3 million per activity. Reservoir dredging might result from a one-time event (e.g. flood), or could be due to long-term accumulation of sediment. Including dredging in total costs consideration would require adjusting site-specific water quality thresholds, and accounting for the diversity in accumulating processes. We thus leave the dredging costs out of the simulation due to difficulties of determining conditional probabilities for the need of dredging.



Similar to Figure 5.8, panel a) Figure 5.9 illustrates the cost function that responds to the changes in turbidity. Thus, total costs in the *case Two* instance can be represented as follows:

$$\text{Total Costs} = \begin{cases} in - plant\ costs, if\ turbidity\ \in [0, 4000), \\ C_3, if\ turbidity \geq 4000 \end{cases}, \qquad \textbf{[5.16]}$$

Where C_3 are the costs of bringing in water and increased risks of morbidity and mortality. We use various sources of costs to approximate C_3 in the sensitivity analysis. For one part of C_3, we use the Toledo, Ohio 2014 costs of $0.15 per person per day (see Table 5.9) of supplying water to vulnerable parts of the population with zero transportation costs as a lower bound estimate of bringing in water. We add costs of increased morbidity and mortality (C_2 in Figure 5.8 and as discussed in the *case One* event description) to the hauling costs to obtain the total value of C_3. In *case Two*, we use the same values to approximate costs of morbidity and mortality risks, as in *case One*. The upper bound costs of bringing water in are approximated by the calculated costs of hauling water in 500ml bottles of $3 per person per day, and supplying the entire affected population with accordance to WHO standards.

Combining Population Growth and Outside Costs Simulations

We use population growth projections (see appendix C) in combination with the simulated per person outside-of-plant costs to obtain population-level costs. Given that the Glenmore WTP serves only half of the City's population, we assume that the demand between two treatment plants is split in the same ratio for the years 2015-2035. Moreover, we assume the same population-to-households ratio of 2.4 (obtained from the 2016 census data) for the entire length of the planning horizon. This is needed to adjust household-level costs (e.g., costs of averting and adaptive behavior) to the population level. To obtain the distribution of population-level total costs, we multiply per person (or per household) annual outside costs by the population levels and add them to the in-plant variable costs.

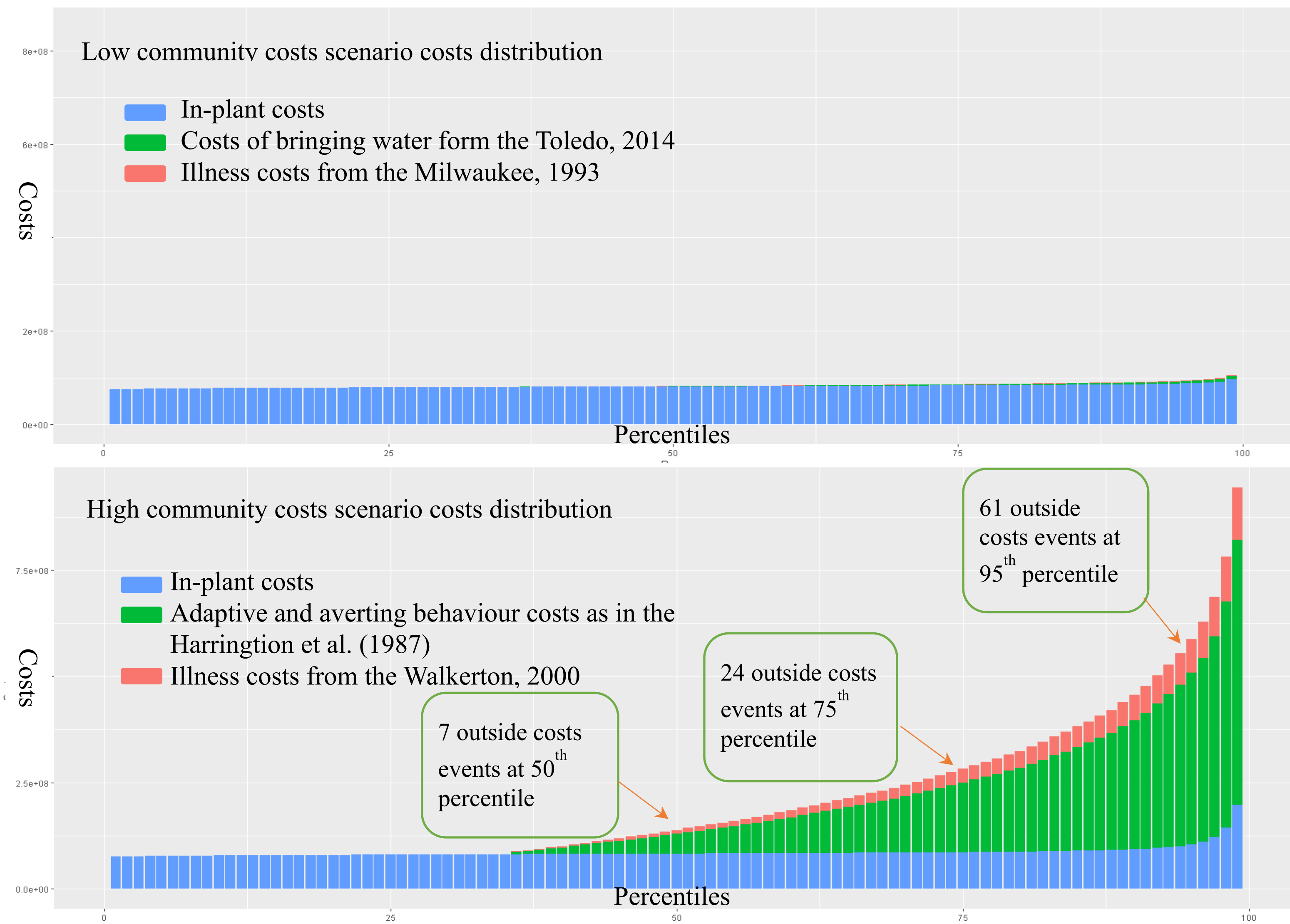
5.7 Simulation of Total Cost Distribution: Results

For the investment performance evaluation, we conduct a sensitivity analysis, constructing the range of community costs with the lowest and highest values obtained from Table 5.9. To define the boundaries, we compare the costs from different sources (Table 5.9). We identify the lowest per-person costs as the lower boundary, while the highest estimates are used as the upper boundary. The lower boundary is defined by the costs from Toledo, Ohio 2014 case for bringing in bottled water, and costs of morbidity and mortality from the Milwaukee, Madison 2003 case study. Thus, the lower boundary is characterized by relatively mild morbidity and mortality risks and supplying vulnerable parts of the population with bottled water. The upper boundary, on the other hand, is a case with high averting and adapting behavior costs and high morbidity and mortality risks. Here, we use values from Harrington et al. (1989) study to approximate averting and adapting behavior costs and costs from the Walkerton, Ontario 2000 case study for increased health risks costs. Lower and upper boundaries describe the 20 year period in which the costs of a WTP failure are the same on each occasion of the turbidity exceeding 4000 NTU threshold. However, total costs in-between the boundaries can have different combinations of cases (either case *One* or *Two*) from event to event. For instance, one event in a 20 year period can consist of costs similar to those in the Toledo 2014 case, while another event can be as costly as it is described in Laughland et al. (1993).

We simulate total costs for 7305 days (20 years of daily data) and obtain 10,000 different simulated values for each day. We then annualize the total costs for each of the 10,000 simulations by adding daily costs. We then estimate the net present values (NPVs) and thus create the distribution of NPVs of future flows of total costs. Figure 5.10 illustrates the ranked distribution of NPVs of total costs under status quo assumptions. The status quo is defined by the 2015 year's state of capacity and technology of the plant, of the environment, and of the water quality.

The NPV of in-plant cost changes little from the lowest (1^{st} percentile) to the highest (99^{th} percentile) costs in comparison to the outside-of-plant costs. The increase in the outside costs is associated with the increase in the total number of outside-costs events from least costly to most costly simulations. Thus, there are no such events of exceeding the turbidity threshold of 4000 NTU until the 36^{th} percentile; there are 7 such events at the median, 24 at the 75^{th} percentile, 61 at the 95^{th}, and 175 in costliest of all simulations. In-plant costs make up the majority of total costs at the lower bound for 1^{st} to 99^{th} percentiles of the total costs distribution. Chemical use costs constitute the majority of total costs at the upper bound only up to 57^{th} percentile of costs. At the lower bound, the costs of bringing water in bottles constitute the majority of outside costs, while the averting and adaptive behavior costs are major sources of costs at the upper bound. The mean and 99^{th} percentile NPVs of total costs at the upper bound are 2.6 and 8.95 times higher than at the lower bound. At both the lower and upper bounds, the outside costs are observable at the 36^{th} percentile costs, meaning that the majority of 10,000 simulated projections have at least 1 outside-costs event in 20 years.

Figure 5.10 Distribution of net present values of 2015-2020 costs for Glenmore Water Treatment Plant. Left figure: low community costs scenario; right figure: high community costs scenario



The lowest total costs of the water supply for Glenmore WTP for years 2015-2025 can be about CAD$ 75 million, as seen in the 1st percentile total costs. These $75 million are comprised solely of the chemical use costs. The median total costs range from CAD$ 82 -138 million, and in-plant costs constitute from 60% to 99%, while the rest is made up by the outside community costs. The 99th percentile total costs range from CAD$ 106 to 946 million. The respective share of in-plant costs at the 99th percentile is in the range from 21% to 91%, with the share of in-plant costs decreasing with increasing total costs. Thus, the average total costs of water supply are approximately CAD$ 4.2 – 10.8 million in a year, or about CAD$ 7 – 18 per person per year. Historical average annual costs of chemical use in the period from 2011 – 2015 were $CAD 9.2 million, given that outside costs were not included in the calculation. Per person costs over the same period were about CAD$ 15.3 in a year. For comparison, investment costs of upgrading the GWTP in the years 2005-2011 cost the city about CAD$ 130 million (Water Technology, n.d.a). The upgraded capacity was projected to be capable of supplying the population before it exceeds the population capacity in 2025 or beyond, which is about 20 years from the beginning of the upgrading period and 10 years from the year of the final commission of the plant.

5.8 Summary

To summarize, in this chapter, we have simulated the distribution of total daily chemical use costs for the Calgary Glenmore WTP for the years 2015-2035. For this, we first developed times series models that characterize processes that water quality parameters follow. We then used these models to simulate turbidity, TOC, and total flow variables to obtain the distribution of daily observations for a 20-year period. These simulated variables were then used as inputs in the average chemical use cost response model to obtain the distribution of total variable costs. Finally, we completed the variable costs by adding the outside-of-plant costs, accounting for population growth. The next step in our analysis is to conduct scenario analysis and estimate the effect of green and grey infrastructure investment options on the distribution of costs.

Chapter 6: Scenario Analysis

In this chapter, we conduct scenario analyses and examine how various investment options affect future costs. The chapter is structured in the following way. First, we discuss the modeling of the effects of various investment options on the net present value of future costs, given different assumptions regarding the outside costs. Then, we conduct scenario analyses and present the results. Finally, we look at the expected net present values from the scenario analyses.

6.1 The effect of adaptation investments on expected costs: scenario analysis

In this section, we discuss the assessment framework of the effect of various investment decisions on the flow of future costs. We base our analysis on the conceptual framework discussed in chapter 3, where we distinguish options that alter the resilience of the plant and options that alter the distribution of water quality. We associate an investment into grey infrastructure with a movement of the thresholds to make the plant more resilient to the values at the right tail of the distribution of water quality – rare extreme events. On the other hand, alteration of the water quality distribution (shifting to the left and/ or reducing the left tail) is associated with the investment in so-called ecosystem infrastructure or enhanced forest management practices.

6.1.1 Modelling the Effect of Investments in Grey Infrastructure or Upstream Watershed Protection Practices.

The scenario analysis is conducted under the conceptual framework discussed in chapter 3. The analysis starts from a conceptual framework, where the initial set up is illustrated in Figure 3.1. Figure 6.1 is an adapted version of the initial figure, and it reflects the assumptions made in the steps preceding the scenario analysis.

Figure 6.1 Stylized costs graph of water treatment related to water quality for the Glenmore WTP in the instance of *case One*. Panel a: Cost schedule for the GWTP; panel b: distribution of the source water quality. C1 – adaptive and averting behavior costs; C_2 – costs of increased risks of morbidity and mortality.

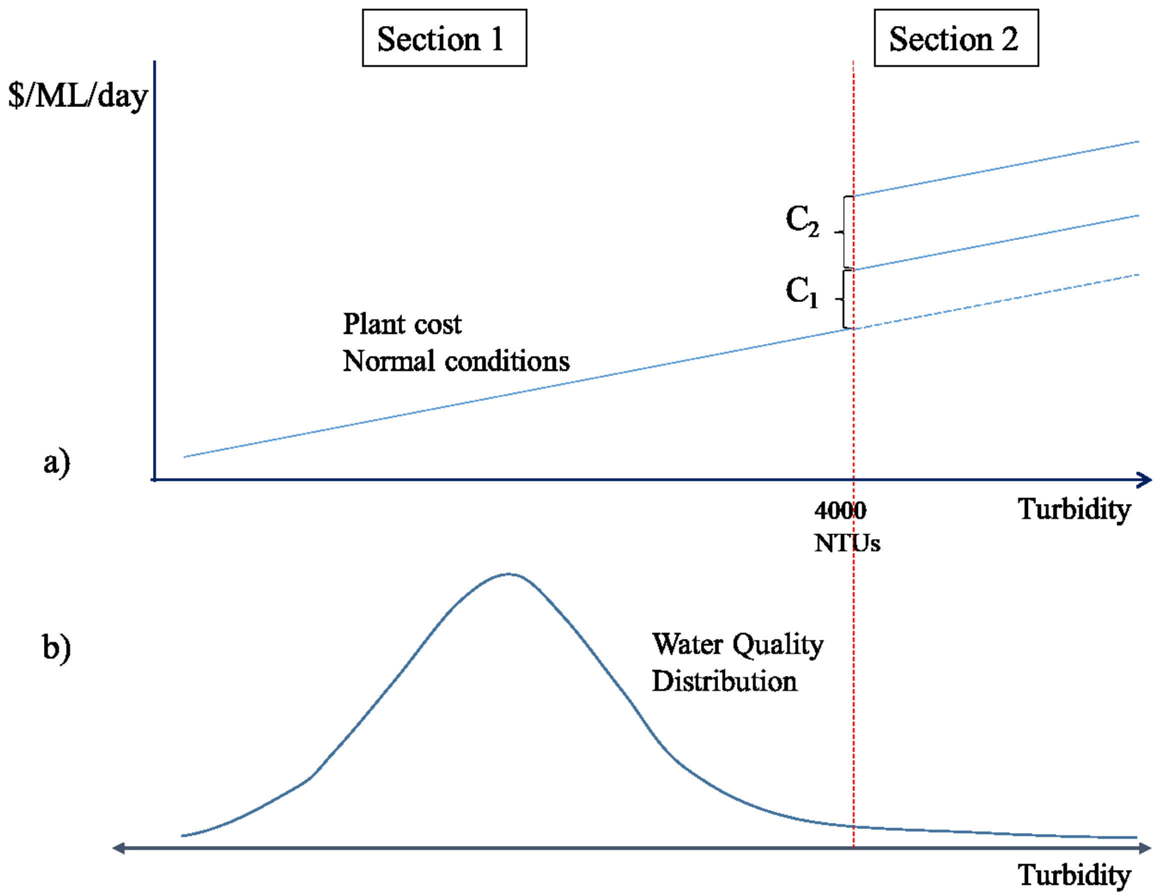


Figure 6.1 is split into two panels so that panel a) represents the average daily water treatment costs (on the vertical axis) with respect to the changes in water quality (horizontal axis), and panel b) represents the distribution of water quality.

Section 4.1 and 4.2 in this thesis focused on the analysis of Section 1 costs. Equation [4.2] is the cost-response function that estimates the effect of the water quality parameters on the average treatment costs. The estimated cost function is upward sloping with respect to two water quality parameters, namely, turbidity and TOC. Specific to the Glenmore WTP, we find that the elasticity of the costs of the chemicals with respect to water quality depends on seasons, and thus the costs are more responsive to the changes in raw water quality in the spring-summer season (elasticities of 0.22 and 0.61 w.r.t. turbidity and TOC respectively) than in fall-winter months (elasticities of 0.06 and 0.03 w.r.t turbidity and TOC respectively).

Original regions 2 and 3 of the costs in Figure 3.1 were combined into one region 2 in Figure 6.1. Region 2 costs are divided from region 1 by the threshold. In section 5.5, we defined the turbidity level of 4000 NTU as the breakpoint at which the plant is incapable of operating in the regular schedule. Thus, we distinguish between cases *One* and *Two*, where the former case assumes zero operation costs (i.e., we assume that water production is limited), and the latter assumes chemical costs in addition to outside community costs. In the first case, the plant experiences C_3 average costs; these costs are summarized in Table 5.9 and are approximated with costs from the Flint, Michigan 2016 and the Toledo, Ohio 2014 cases, and calculations from the WHO handbook on handling emergency situations.

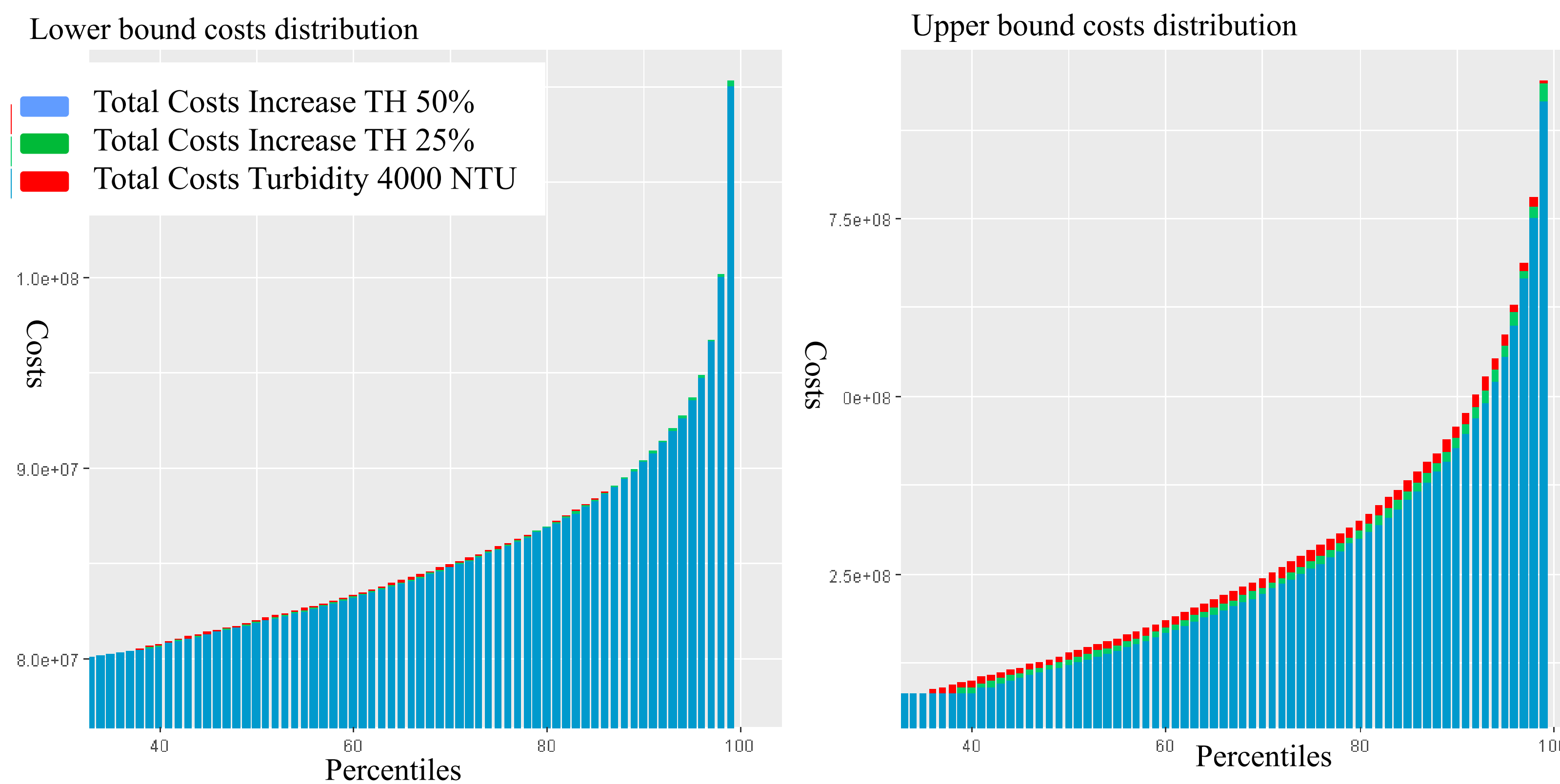
In the case when the plant continues its regular operation and a BWA is issued when the turbidity is above the 4000NTU level, in addition to the chemical costs of water treatment, there are community costs of C_1 and C_2. We assume that if output water quality is below health standards, then the city would issue a boil water use advisory, and we would be in the high community costs case. Then, C_1 are BWA adaptive and averting behavior costs, and C_2 are the costs of increased morbidity and mortality risks. We discussed the C_1 and C_2 costs in chapter 5 of this work.

Water quality is represented by the levels of turbidity and TOC. In chapters 4 and 5, we describe and characterize the statistical properties of the empirical distributions of these two water parameters. We obtain distributions of future turbidity and TOC values and illustrate them in Figure 5.5. These values are then used as the inputs into a cost-response function that establishes the vertical connection between panels a) and b); the distribution of future costs is thus summarized in Figure 5.7.

6.1.1.1 Scenarios 1 and 2: Investing in Grey infrastructure. Moving the threshold by 25 and 50 percent.

We explore the effect of improving the plant resilience to incurring outside (community) costs by moving the threshold by 25% and 50% to the right. The new threshold is 5000NTU and 6000NTU, respectively. The effect of moving thresholds on the costs is illustrated in Figure 3.2. We expect that the number of simulated occurrences of outside costs events (defined as events when turbidity exceeds the threshold) will decrease, thus driving the community costs down. The change in NPVs of costs of making the plant more resilient by 25% and 50% is illustrated in Figure 6.2.

Figure 6.2 Potential Changes in the Distribution of Future Costs for years 2015-2035 at GWTP due to Technology Change.

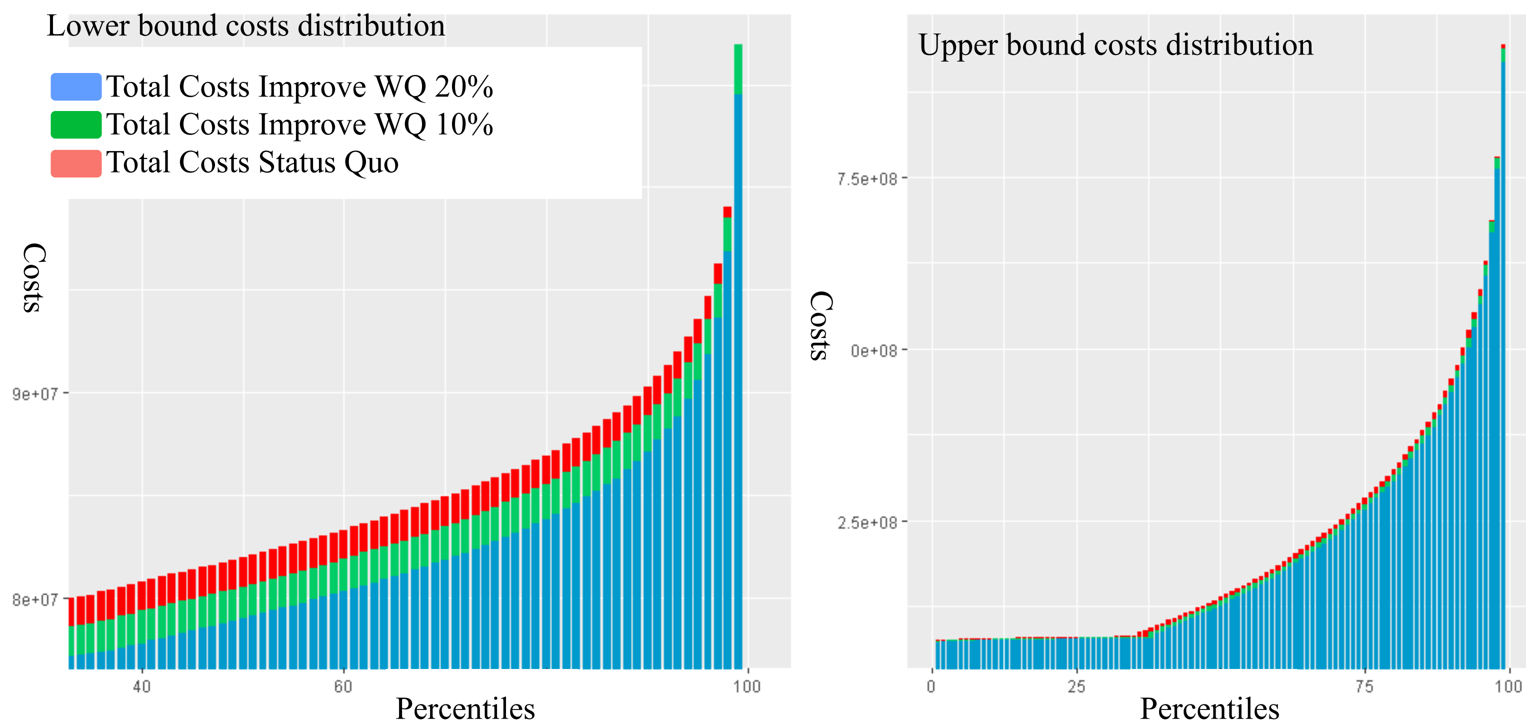


The 25% increase in the threshold had almost no effect on the median NPV of total costs, and both status quo and 25% threshold moving scenarios have mean NPVs of CAD$ 84 million at the lower bound, while the upper bound costs decreased from CAD$ 215 million to CAD$ 207 million. The decrease in the costs is shown as the red portion of bars in Figure 6.2, and cannot be clearly seen on the lower bound community costs graph. Moving the threshold does not affect the distribution of NPVs significantly: the difference between status quo and scenario 1 NPVs ranges between (–CAD$ 70,000) and CAD$ 24,000 while the minimum NPV of total costs at the lower bound is $75 million. The 25% shift in the threshold can potentially increase or decrease the total costs. If the costs are decreasing due to the shift, this suggests that avoided community costs are higher than additional in-plant costs that occur due to the higher range of water quality being treated by the plant. On the other hand, an increase in the total costs is due to higher additional in-plant costs compared to the value of avoided community costs. The scale of the effect of the 25% and 50% shifts of the threshold is small because there are only a few simulated values in the range between 4000 and 6000 NTU that are affected by the change in the threshold. The community cost events do not occur until 39th and 41st percentiles for 25% and 50% threshold movements respectively. Thus, the 25% increase in the threshold decreases the median NPV of total costs to CAD$ 81.8 – CAD$ 128 million (decrease in costs is seen as the red bars in the graph) or less than 1% and 7.2%. On the other hand, the green bars are not clearly seen on both graphs in Figure 6.2, because the effect of moving the threshold from 5000 NTU to 6000 NTU is relatively small.

6.1.1.2 Scenarios 3 and 4: Investing in Green Infrastructure Approach. Improving Water Quality by 10 and 20%

We model the effect of green infrastructure on water quality by shifting the distribution of water quality on the left. We achieve this by reducing each simulated value of both turbidity and TOC by 10% and 20% for two scenarios, respectively. We illustrate the results in Figure 6.3.

Figure 6.3 Potential Changes in the Distribution of Future Costs for years 2015-2035 at GWTP due to Water Quality Improvement



The 10% improvement in water quality parameters affects the distribution of costs is comparable to the effects of moving thresholds. Thus, the 10% decrease in turbidity and TOC leads to between a 1.8% and 4.1% decrease in the median NPV of total costs at the lower and upper bound community costs respectively; costs decrease from $82-138 million to $80.5-133 million (improvement is seen as the red bars in the figure). The 20% improvement in water quality decreases the total median NPV of costs even further to $79 – $126. This is seen as a 3.7% and 8.7% decrease in the total costs for two scenarios. The occurrence of community cost events is not observed until the 38th and 39th percentiles for 10% and 20% source water quality improvements respectively.

6.2 Analysis of Expected Net Present Values

The effect of different investment options can be analyzed by examining the expected NPV. We present a summary of mean NPVs under different scenarios in Table 6.1. We do not observe a significant difference between the scenarios in the share of simulations that do not have any community-cost events in the 20 year period. In the status quo, 35 percent of all simulations do not have any water treatment plant's failures. Thus, outside-cost events are starting to occur in the 36th percentile costs in the status-quo scenario. The 25% and 50% increases in the threshold have a marginal impact on the occurrence of the outside-cost events. Increasing the threshold to 5000 NTU shifts the occurrence of outside-cost events to the 39th percentile. The threshold movement to 6000 NTU shifts the occurrence of outside costs events to 41st percentile. In the scenarios where the water quality is improved by 10% and 20%, 37 and 38 percent of all simulations do not experience any community-cost events reflecting a minor difference from the status quo.

Movement in the threshold by 25% results in almost no change in expected NPVs of total costs at the lower bound and a 3.8% decrease at the upper bound. Moving the threshold from 4000 NTU to 6000 NTU does not change the expected NPV at the lower bound and decreases the upper bound costs by 6.8%. A 10 percent improvement in turbidity and TOC decreases total costs by 1.6%, and 2.5% at the two community cost boundaries respectively. Improving water quality by 20% brings a higher deduction in total costs – 3.5% and 5.3% at the lower and upper boundaries, respectively.

Table 6.1 Summary of Expected Net Present Values under Different Scenario Assumptions for Glenmore water treatment plant, years 2015-2025. Dollar values are presented in millions of 2015 CAD$.

Scenarios	**Percentile**	**In-plant costs**		**Outside Costs**		**Total Costs**	
		Lower $	Upper $	Lower $	Upper $	Lower $	Upper $
Status quo	36	81.9	87.5	1.6	127.7	83.5	215.2
25% increase in threshold	39	82.1	87.8	1.5	119.4	83.6	207.1
50% increase in threshold	41	82.1	87.8	1.4	112.9	83.5	200.6
10% change in distribution	38	80.7	86.2	1.5	123.7	82.2	209.9
20% change in distribution	39	79.1	84.5	1.5	119.4	80.6	203.9

6.3 Potential Benefits from Different Investment Options: a Risk-Neutral Decision Maker Perspective

Table 6.1 provides us with an important benchmark of benefits that different investment options can potentially bring to the public in a 20-year period. Part of the benefits come from the avoided water treatment costs that can be seen in the difference between in-plant costs in the status quo and across different scenarios. Upgrading the in-plant treatment technology that is seen as the threshold movement from 4000 NTU to 5000 NTU and 6000 NTU respectively in two scenarios, increases the in-plant costs, while the total costs still decrease. An increase in the in-plant costs in the first two scenarios is expected. Under the status quo assumptions of *case Two*, the WTP is producing a limited amount of water and is required to issue a no-use advisory whenever the turbidity level exceeds 4000 NTU, and in-plant costs are considered zero. When the threshold is 5000 NTU and 6000 NTU, the outside-cost events are less frequent. Thus some of the zero-in-plant-cost days now have positive in-plant chemical costs. On the other hand, fewer number of outside-cost events mean that the community is experiencing health risks and adaptation costs less frequently. For this reason, the expected community costs are smaller under upgraded technology scenarios compared to the status quo. Upgrading the Glenmore WTP to move the threshold to 5000 NTU can yield from (- CAD$ 55,000) to CAD$ 8.1 million in avoided costs. Moving the threshold up to 6000 NTU can result in CAD$0 to CAD$ 14.6 million of benefits in terms of avoided costs.

In contrast, improving water quality by 10% and 20% yield less in terms of avoided supply costs. Thus, improvement in raw water TOC concentration and turbidity level by 10% results in cost reductions of CAD$ 1.3 – CAD$ 5.3 million. Of these, CAD$ 1.2 – CAD$ 1.3 million result from avoided in-plant chemical use alone. A 20% improvement in the source water quality yields CAD$ 2.9 – CAD$ 11.3 million worth of expected benefits. Of these, CAD$ 2.8 – CAD$ 3 million are benefits in terms of avoided water treatment, while the rest are due to avoided community costs. While these numbers provide important insights into the potential benefits of ecosystem infrastructure projects, it is important to put these numbers in comparison with the potential costs of such projects.

6.4 Costs of Different Infrastructure Investment Projects

Grey Infrastructure projects

When compared to potential benefits from grey infrastructure investments, as suggested by the model, grey infrastructure projects are much more expensive. It is difficult to estimate the costs of suggested 25% and 50% improvements in the resilience of the plant. Water treatment plants are usually complex structures, and upgrading of plants' technology can be accompanied by increasing volume-processing capacities and renewal of some infrastructure. This makes it difficult to elicit the share of costs spent on making a plant more resilient by X%. However, we can look into past investments in the region for relative numbers.

Upgrading at the Glenmore and Bearspaw WTPs in Calgary is relatively recent, with the GWTP being commissioned to use in 2011. Upgrading of two plants cost the City of Calgary CAD$300 million, with BWTP taking $170 million and $130 million left to GWTP upgrading (Water Technology, n.d.a). The GWTP's capacity was upgraded to produce 550 ML/day, while an improvement of technology increased the plant's resilience to turbidity from 1000 NTU to current 4000 NTU. Upgrading at the Saskatoon WTP in Saskatchewan was estimated at $130 million, where the installation of an ultraviolet (UV) disinfection[12] system was estimated to cost $13 million, and an upgrade and expansion of the filtration plant were estimated to cost $17 million (Water Technology, n.d.b). While these numbers add some more context on the potential costs of WTP upgrading and upgrading costs breakdown, the thresholds and specific details on the improvement in technology are not reported. The potential benefits of a maximum of $14.6 million obtained from our model are considerably lower than the grey infrastructure projects implemented recently. It is also important to recognize that numbers reported in our analysis are expected costs and assume risk-neutrality, whereas drinking water authorities can be expected to be risk-averse. Moreover, our analysis underestimates the total costs of the GWTP due to the exclusion of some variable and maintenance costs from the analysis of in-plant costs, and due to exclusion from potential outside costs, such as dredging costs.

A study by Warziniack et al. (2017) on land-use change and water treatment costs have estimated that afforestation of 1% of the land (at the expense of agricultural use) would lead to a 2.8% reduction in turbidity in the US. The reported elasticity is the elasticity of turbidity to land-use change around the mean. If we assume a constant elasticity, we may conclude that an afforestation project of approximately 3.6% of land from the mean value would lead to a 10% improvement in water quality, and a 7.14% afforestation project would be required to achieve a 20% improvement in the water quality. The Warziniack et al. (2017) study was conducted using data from WTPs in forested watersheds (Eastern Temperate Forest and Northwestern Forested Mountains in the US). The mean forested area in the study was 56%, with an average drainage area of 40,500 km^2. For comparison, the Elbow river watershed area is 1,238 km^2, and forests cover 44% of it (Wijesekara, 2013). Assuming that elasticities from Warziniack et al. (2017)

[12] A UV disinfection technology is used to purify water from organic contaminants, including bacteria; UV disinfection also decreases TOC concentration in the water (Oram, n.d.)

study are true in Elbow river watershed, forest cover needs to be increased from 44% to 47.6% and 51.14% to achieve 10% and 20% improvements in source water quality. This, in turn, means that 44.5 – 88.3 km^2 of land has to be planted with mature trees. The cost of afforestation of 1 ha is estimated to be in the range from $1000 - $3000 per hectare ($100,000 - $300,000 per km^2) (Yemshanov et al., 2005) if the land is assumed to be in the public property. Thus, a project to afforest 44.5 km^2 would cost between CAD$ 4.5-13.4 million and can potentially bring benefits valued at CAD$ 1.3 – CAD$ 1.5 million. Similarly, the project of afforestation of 88.4 km^2 would cost CAD$ 8.83 – 26.5 million, and can potentially result in CAD$ 2.9 – CAD$ 11.3 million in avoided costs.

However, there is some uncertainty towards whether the land is readily available for afforestation. For instance, if the land is in public property, the costs afforestation of $1000 - $3000 per hectare are realistic and can be applied in the analysis. However, if the land necessary for afforestation is in private property, then the costs of land acquisition can be added to the costs of afforestation. Moreover, as the conversion of land from agricultural use to forests brings the greatest improvements in terms of water quality, it is important to account for the costs of private commercial land acquisitions. A 2018 report on the farmlands in Alberta puts the value of an acre of farmland in the range from CAD$ 1,000 to CAD$ 14,100 per acre or from CAD$ 2470 to CAD$ 35,000 per hectare (FCC, 2019). Thus, costs of afforestation of $1000 - $3000 per hectare can be viewed as lower bound costs, where an upper bound can go as high as up to CAD$2,000 - $CAD 38,000 when acquisition costs are accounted for. Accounting for land acquisition widens the range of possible costs of afforestation programs. Thus, the cost of 10 and 20-percent water quality improvements can potentially cost from CAD$ 8.9 – CAD$ 335.5 million. The avoided costs from 10% water quality improvement scenario can purchase only from 0.8 – 15% of the required area of land at the lower bound of benefits, and 1.6 – 60% of the land with the maximum expected benefits. Avoided cost from a 20% water quality improvement project can buy from 2 – 38% at the lower bound of avoided costs and from 0.9 – 64% of necessary agricultural land if upper bound expected benefits are assumed.

Denver, Colorado, has implemented a green infrastructure project to improve source water quality. It is a project aimed to help the city with stormwater management, avoid floods, and improve source water quality (Novick, 2019). It is a comprehensive green infrastructure project that includes city infrastructure, parks, roofs, university campus management, as well as source watershed management. The project was estimated at $400 million (2011 CAD$395.7 million) (City of and County of Denver, n.d.b). Stormwater management is the main part of the project, suggesting that water quality improvement costs are a smaller share of the total costs of the project.

While the costs presented above are the "back-of-the-envelope" calculations, these values provide important reference points. Both green infrastructure and grey infrastructure projects can be costly and valued at more than $100 million. At the same time, back-of-the-envelope calculations tell us that desired water quality improvements can be achieved cost-effectively. Thus, projects to achieve desired 10% water quality improvements can cost from CAD$ 8.9 – CAD$ 169 million and result in CAD$ 1.3 – CAD$ 5.3 million in avoided costs. A 20% water quality improvement afforestation project can cost CAD$ 17.7 – CAD$ 335.5 million and can save CAD$ 2.9 – CAD$ 11.3 million worth of costs if we assume a risk-neutral decision-maker. These results suggest that watershed management projects aimed at water quality improvement are not cost-effective in the water treatment context alone. However, to reach final conclusions regarding the cost-effectiveness of specific projects, we need to study such programs in detail.

6.5 Summary

In this chapter, we have conducted scenario analyses to estimate the effect of different investment options on the net present value of the flow of future costs for the GWTP. For this, we developed 2 scenarios for each of grey and green infrastructure investment options and estimated the effect using low and high community cost assumptions. Grey infrastructure options were viewed as the shift in the threshold. For scenarios 1 and 2, we moved the threshold by 25% and 50% respectively, so that the new thresholds are 5000 NTU and 6000 NTU compared to initial 4000 NTU. We modeled the green infrastructure investment option as a shift of the entire turbidity and TOC distributions. For scenarios 3 and 4, we consider 10% and 20% improvement in source water turbidity and TOC. We find that investments in both grey and green infrastructure options decrease NPVs of future costs. We conclude with the results of the scenario analyses and address the limitations of our work in the next chapter.

Chapter 7: Conclusions

This dissertation's main objective was to develop an investment framework to estimate the effect of water quality and water quality distribution on the costs of water supply. As discussed in chapters 1 and 2, there are gaps in knowledge about the relationship between water quality and water treatment. More specifically, we believe that, first, the value of water quality in the context of drinking water may have been underestimated in the literature. Partly this is because previous studies, when estimating the value of water quality in terms of drinking water, have mainly focused on the avoided costs of water treatment in terms of in-plant variable costs. Thus, previous analyses have avoided the consideration of the costs that lie outside of the normal operating schedule – costs of WTPs faltering. Second, as discussed in the review-of-literature chapter, the economic and engineering literature has so far generally avoided, including green infrastructure solutions in the water treatment infrastructure context. In this chapter, we summarize the steps and analyses undertaken to address the abovementioned gaps. Second, we discuss the results of our work. In doing so, we discuss the cost-response function and elasticities of in-plant costs with respect to changes in source water quality. We then discuss the results of the scenario analyses and compare the magnitudes of changes obtained by different investment options. Third, we go over the limitations of our analysis and outline further work that will move this analysis forward.

7.1 Summary

Chapter 1 outlined the challenges that water treatment is facing today, and suggested that including the ecosystem infrastructure in investment planning may be able to help address these challenges. The challenges mentioned in chapter 1 are the aging infrastructure, rapid population growth, and extreme weather events that compromise the safety of water supply. We have outlined that the traditional approach in water treatment decision-making to address the challenges is inadequate. This is due to public expenditure constraints and that the conventional approach relies on outdated concepts of robustness while building flexible and resilient water treatment systems might be a better solution.

In the literature review chapter, we have surveyed the literature to establish the connection between water quality and the costs of water treatment. Moreover, we discussed the factors that can alter the quality of water in source watersheds. Namely, the conversion of land toward agricultural and other human needs was one of the contributing factors to the long-term degradation of sources of water. Forest fires coupled with increased precipitation are found to be factors that can shift the distribution of water quality. Chapter 2 then explored the relevant economic and engineering literature and identified the following gaps in the literature:

1) The existing economic literature that estimated the effect of water quality changes on water treatment costs focused solely on the cost or price responses to the changes in water quality. Such approaches were potentially underestimating the value of water quality in the context of drinking water. Most previous analyses have not explored the expected costs of a WTP failure. Adverse water quality consequences from forest fires and/ or floods that can lead to such failures can result in costly impacts on the public. Thus, diminished water quality can pose health risks to the serviced communities, can potentially result in high maintenance costs to the plant, or can invoke costly adaptive activities. Therefore, consideration of WTP failures should not be omitted.
2) Consideration of green infrastructure in investment planning for drinking water infrastructure is not frequently discussed in the literature. Existing evidence has shown that the improvement of water quality can bring the costs of water treatment down. However, the literature contains only a few examples of the benefits of green infrastructure projects being examined using an expected value framework.

In chapter 3, we developed a conceptual framework that addresses the gaps in the literature.

1) The conceptual framework introduces outside-of-plant costs into the total costs model. For this, we define water quality thresholds. The threshold is such that below the water quality threshold, the WTP is operating in a regular schedule, and raw water is treated in-plant with available chemicals. When the source water quality passes the threshold, a WTP is no longer capable of treating the water to health standards, and that is where the WTP's faltering scenario happens. By bringing the analysis of the water treatment process beyond the threshold, we analyze the performance of the plant on the entire length of the source water quality distribution.
2) The conceptual framework then describes how we can model different investment options, including both grey and green infrastructure projects. We model grey infrastructure as an investment in new infrastructure and/ or new technology that

improves the resilience of the plant and shifts the water quality threshold up. We model green infrastructure projects as activities that improve the source water quality by shifting the entire distribution.

In the following chapters, we conducted a case study based on data from the Calgary Glenmore WTP. The case study is the application of the conceptual framework. In chapter 3, we stated the need to obtain the distribution of future total costs that include both in-plant and outside-of-plant costs. Thus, chapters 4 and 5 focused on obtaining the distribution of future costs. We have estimated the cost-response function and analyzed historical data on turbidity, TOC, and total water intake to obtain the distribution of future in-plant costs. In chapter 5, we described how we complemented in-plant costs with outside costs by accounting for the costs of averting and adaptive behavior, costs of hauling water, and costs of increased risks of morbidity and mortality. In chapter 6, we analyzed the effects of four investment options on the NPV of the future flow of costs, two grey, and two green infrastructure options. The following sections of this chapter will discuss the empirical cost-response function and conclude with the results from the scenario analyses.

7.2 Effect of Water Quality on the Costs of Chemical Use

We have estimated the cost-response function in chapter 4 and obtained the Equation [4.2]. We account for seasonality in the cost response and find that seasonal differences are statistically significant. We find that the plant is less responsive to the changes in water quality in fall and winter compared to spring and summer seasons. Previous literature has not explored the difference in in-plant decision-making with respect to seasons. One of the possible reasons to not account for seasonality is the difference in the analyzed water treatment plants and the use of cross-section data in some studies, which does not allow to capture seasonal variation in the distribution of costs. Glenmore WTP had undergone major upgrading in the period before 2011 that changed the in-plant technology. More specifically, a plant was upgraded to withstand turbidity levels above 1000 NTU (John Meunier, n.d.). The GWTP could be overdesigned for fall and winter seasons, where the water quality is generally of better quality (Emelko, personal communication, 2019). Another reason is that different chemicals and technologies can be used in-plant to tackle different levels of turbidity (Emelko et al., 2011). This could potentially have led to a difference in the use of chemicals in fall and winter compared to spring and summer. To the best of our knowledge, fall and winter elasticities of costs with respect to turbidity and TOC have not been reported before.

We find that turbidity has a statistically significant effect on the costs of the chemicals at the Glenmore WTP. The estimated spring and summer cost elasticity with respect to turbidity is 0.22. The lowest estimated elasticity in the literature was 0.06 (Price et al., 2017) and 0.07 (Holmes, 1988, and Abdul-Rahim and Mohd-Shahwahid, 2011). The highest estimated elasticity is in Forster and Murray (2007) – the elasticity of 0.3. Warziniack et al. (2017) estimated the cost elasticity to the turbidity of 0.19, Moore, and McCarl (1987) estimate the elasticities of 0.21 and 0.22.

We find that chemical costs are relatively more responsive to the changes in total organic carbon concentration. We estimate the spring-summer elasticity of 0.61, meaning that costs increase by 0.61 percent when TOC increases by 1 percent. The estimates of TOC elasticity were as low as 0.06 (Horn, 2011), and as high as 0.77 (Freeman et al., 2008). Similarly, Warziniack et al. (2017) estimate the TOC elasticity as 0.46, while Heberling et al. (2015) find no statistically significant effect of TOC on the costs.

We estimate that a 1 ML increase in the volume of treated water increases costs by 0.3%. Warziniack et al. (2017) and Heberling et al. (2015) find a statistically significant negative relationship between costs and the volume of the total product; they estimate the elasticity to be -0.19 and 0.21, respectively. Shih et al. (2004) find the presence of economies of scale in water treatment plants that can explain the negative relationship between average costs and the level of output. In contrast with previous studies, we find that the volume of treated water has a positive effect on the costs.

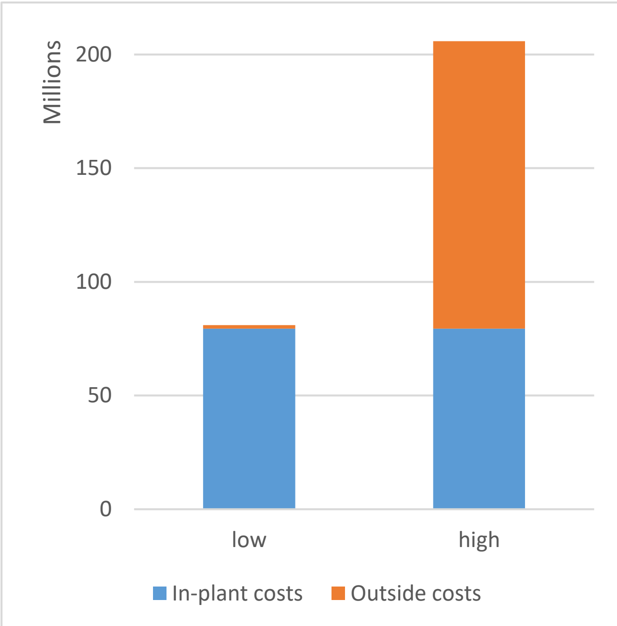
7.3 Scenario analysis results

In chapters 5 and 6, we finalized the distribution of total water treatment costs and obtained the net present values using lower and upper bound community costs estimates. In this section, we discuss the results of the scenario analyses and present key findings.

7.3.1 Including the Community Costs of in the Analysis Increases the Total Costs of Water Supply Substantially.

Figure 7.1 is an illustration of the first row of Table 6.1 and summarizes the net present value of the future flow of total costs for Glenmore WTP for years 2015-2025. From the figure, we can see that excluding outside costs from the analysis leads to underestimating the costs of water treatment. Excluding outside costs from the analysis underestimates the total costs by 2-58%, depending on the cost assumptions. As we show in chapter 6, both grey and green infrastructure investments have a relatively small effect on the in-plant costs of water treatment. However, we see that improvement of the overall quality of source water can have a larger effect on total costs when outside costs are accounted for. A few cases in recent history (e.g., the Walkerton, 2000, and Baltimore cases discussed in chapter 1) have shown that contamination of water with bacteria or heavy metals can be very costly. Decision-makers can proactively address extreme events in capital infrastructure planning, considering such events as a source of uncertainty. On the other hand, excluding potential outside community costs from the analysis can lead to underestimating the benefits that either of green and grey infrastructure options can potentially bring.

Figure 7.1 Comparison of a GWTP's expected net present values for lower and upper bound community costs assumptions in the status quo for 2015-2035. In blue are the NPVs of in-plant costs, and in orange are the NPVs of community costs estimated in millions of Canadian dollars.



While expected total costs provide an important piece of information, relying on mean NPVs assumes the risk-neutrality of decision-makers. Water treatment decision-makers are likely to be risk-averse, and thus it is important that we consider the entire distribution of costs as we do in Figure 5.10. A risk-averse decision-maker would be willing to avoid high-cost scenarios, and thus providing a full view on possible scenarios may provide economic justification for investment in ecosystem infrastructure as means to decrease the likelihood of costly natural disturbances. For this to be meaningful, however, there needs to be evidence that it is possible to thin out the right tail in the water quality distribution using ecosystem infrastructure and upstream management techniques.

7.3.2 Benefits from Green and Grey Infrastructure Investments

Ex-post case studies on the consequences of decreased source water quality show us how costly such events can be. While such costs can be extremely high, the probability of having such events and having adverse consequences from these events are very small. Such extreme events lie in the right tail of the distribution, and there are not much historical data to precisely understand and forecast these costs. In our analysis, we try to incorporate these costs *ex-ante* and find that expected community costs can be high.

Among the scenarios considered in our work, total water treatment costs decrease more under the improved water quality scenarios than under grey infrastructure scenarios. The net present value of the future flow of total costs is CAD$ 83.5 - CAD$ 215.2 million under status quo conditions. We measure the benefits from investment options as the avoided total costs due to the investment. We estimate that a 25% increase in the threshold brings benefits of up to CAD$ 8.1 million. Moving the threshold by 50% to 6,000 NTU can be valued at a maximum of CAD$ 14.6 million. On the other hand, the expected benefits from improving water quality by 10% are from CAD$ 1.2 million to CAD$ 5.3 million. Improving water quality by 50% can bring the benefits of CAD$ 2.9 million to $11.3 million in terms of avoided total costs. In chapter 6, we have discussed the potential costs of different infrastructure projects.

Grey infrastructure projects costs are higher than avoided costs due to improved plant's resilience as estimated by our model. Infrastructure upgrading projects can serve multiple functions, including infrastructure renewal, increasing capacity, and improving resilience, and thus it is unclear what portion of expenditures was targeting the improvement in resilience. Moreover, we find that water quality improvement strategies suggested and modelled in our analysis are not cost-effective in the context of drinking water supply alone. This is especially true if the land is considered to be in the private property. It is important to note that our analysis underestimates the benefits of investment options by excluding such potential avoided costs as costs of reservoir and river dredging or some operational and maintenance costs.

One of the important reasons of why the water quality improvements did not significantly decrease the expected net present value of total costs is that the majority of costs at the upper bound are comprised of community costs. Community costs, in turn, lie in the right tale of the water quality distribution. The suggested overall improvement in the water quality distribution does not specifically target the tail, and thus the benefits are expectedly low. However, the results that we obtained in chapter 6 stress the importance of analyzing the tail of the distribution and the need to potentially come up with such policies that would focus on thinning out the right tail of the water quality distribution. Such alternative options should be explored along with conventional investment options in the drinking water context. Further cost-benefit and cost-effectiveness analysis would require more information on the costs of each of the options or their combinations. However, the capital investment framework developed in this thesis can incorporate additional information on cost-effectiveness. In this work, the scenario analysis serves as a proof of concept and demonstrates the application of the framework. While we model grey and green infrastructures this way, we do not know if these are feasible investment options.

7.4 Limitations and further research

The main objective of this thesis is to develop a conceptual capital investment framework and conduct a proof-of-concept case study using real data. While the case study is conducted using real data from Calgary's Glenmore water treatment plant, the major limitation of the study concerns data issues. First, a more accurate prediction requires more data. Here, we only have 11 years of data, while we forecast future values for twenty years. We relied on even shorter time series of chemicals use costs - 5 years of daily data – to estimate the cost-response model that is then used to predict future costs for 20 years. This limitation is even more constraining when we consider the right tail of the turbidity and TOC distributions. In the span of 11 years, we had 2 major floods that were associated with the highest values of turbidity and TOC. For the analysis and more accurate characterization of the higher values of the water quality distributions, we need more data that might have more data points in the right tail. We believe that longer datasets will give us a better idea of the probabilities of extreme events and their impact on water quality.

The scenario analyses is sensitive to the definition of outside community costs. First, the correct understanding of in-plant technology and related thresholds (capacity and technology) is the key to define the distribution of costs accurately. In our study, we relied on the Alberta WTP operators' survey responses and GWTP's upgrading technology supplier's publicly available information to define the threshold. However, the 4000 NTU threshold was exceeded during the flood of 2013, while a significant increase in waterborne related risks of morbidity and mortality was not observed, whereas a water use advisory was issued to reduce quantity pressure from the plant. Moreover, we have omitted the dredging costs in our final analysis due to a lack of understanding of processes behind the sediment formation and impacts of natural disturbances on the formation of sediment. This implies that we need a better understanding of potential in-plant and community responses to poor source water quality, and to assign accurate conditional probabilities to such scenarios.

Second, the structure of community costs and accurate identification of potential costs of a WTP faltering is important for investment planning. In our study, we relied on a few case studies to assign costs for outside cost events. Although we have considered the range of costs, a calibration of community costs is necessary to obtain meaningful insights for capital investment planning.

Analysis of the right tail of a water quality distribution within the framework is one of key contributions of our work. Previously, the analyses of water quality and water treatment costs were mostly concentrated around the regular operating schedule – on the costs of chemical use and other variable costs. We extended the analysis and estimated potential costs of the events caused by water quality events in the right tail of the distribution in *ex-ante* sense. For this, we conducted a simulation case study using the in-plant data from the Glenmore WTP and surveyed existing studies to identify *ex-post* estimates of the potential community costs. During the analysis, we identified the gap in the knowledge about extreme events that significantly decrease the water quality. And we identify this gap in the knowledge as one of the limitations to our study. Historical data available for the studied river and the GWTP does not have rich information about the tail of turbidity and TOC distributions. To approximate the distribution of turbidity and TOC, we assumed that they fit theoretical skewed Student-T distribution (SSTD). This distribution, in turn, is heavy-tailed and we do not know how accurately the SSTD characterizes the true tail of the turbidity and TOC distributions. Improving the understanding of the tail in water quality or frequency of extreme rare events is important to continuing the research on this topic.

The next step to move this research forward is to address the abovementioned limitations and extend the application of the investment framework and conduct a real options analysis of green and grey investment options. For this, we need a more careful characterization of investment options. More specifically, for example, one needs to employ biophysical models to understand what actions can be taken to produce 10% or 20% improvements in water quality. Information on potential costs of both grey and green infrastructure investments would be useful to move the analysis forward. Using knowledge about how much a 10% improvement in water quality would cost, we could provide a cost-effectiveness assessment of the efficiency of the investment project. Thus, it is important to understand both physical needs to implement desired changes in water quality and the costs of such investments to put the benefits into the context of cost-effectiveness. We can then use the conceptual framework and apply real options analysis to both consider the timing of investments and find optimal investment strategies. An RO analysis is important in that it would allow us to compare investment portfolios that include combinations of green and grey infrastructure options and to assess substitutability and complementarity of these options.

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Appendix

Appendix A

In this appendix, we present a theoretical formulation of the economic problem of WTP decision-makers. The problem of cost minimization and avoiding costly events motivated the development of the conceptual framework described in chapter 3. We formalize the challenges faced by water treatment plant decision-makers into two mathematical problems. First, a decision-maker is facing uncertainty in population growth, which affects the distribution of future costs and, thus, capital investment decision-making. Second, water quality is introduced as the uncertainty into the costs minimization framework, and the WTP decision-maker is facing two sources of uncertainty.

Model 1: Water Plant Investment with Stochastic Population Growth

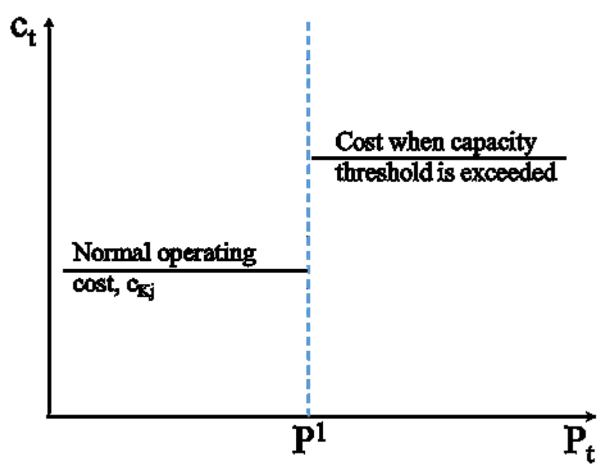
Consider a town with population P_t, which demands d_t quantity of water at time t. The time horizon for this problem is [0, T]. P_0 is the initial population level, and the quantity demanded is the function of population level: $d_t(P_t)$. There is a water treatment plant that processes the raw water from the surface water source and supplies the demand for water. This water treatment plant uses a specific technology to treat the water, and the output of water is limited by the plant's capacity. If the capacity of the WTP is reached or exceeded, the serviced community will face additional costs that arise from the need to attract additional sources of clean water to satisfy the demand for water. When the population grows such that the demand can no longer be met by the existing plant, and expected costs of expanding the plant are lower than without the investment, then the decision to upgrade the plant is made. To define the intertemporal problem of total cost minimization, we first define the in-plant marginal cost function of the WTP.

We define costs $c(q_t, K_j)$ depending on whether the WTP is able to satisfy the demand d_t for water given its technology K_j. Here, j is the set of technology, so that the technology j =1 is different from the set of technologies j = 2. If the demand is not satisfied, then the costs are based on those that are experienced when the threshold Q_{Kj} is exceeded. Q_{Kj} is the plant's output capacity. The cost function when the entire demand is met is expressed as the function of the raw input water q_t multiplied by a factor of δ. Here, δ is the technology factor and defines how input water is transformed into output. When the demand exceeds the plant's capacity of Q_{Kj}, the costs take the value of C_{Kj} that is greater than the regular schedule costs. Thus, the costs are the following:

$$c(q_t,K_j) = \begin{cases} c_{Kj}(\delta q_t), if\ d_t \leq Q_{Kj}\ \ , Q_{K_j} > 0 \\ C_{K_j} > c_{K_j}(\delta q_t)\ if\ \mathrm{d}_t > Q_{K_j} \end{cases} . \quad \textbf{[a.1]}$$

We can draw the relationship between the population level P_t and the plant's volume capacity Q_{Kj} and define the level of population for which the WTP cannot meet the entire demand. Thus, there is a population level P^1 for which the WTP cannot meet the entire demand. Thus, for the population levels below P^1, the WTP's operating in the regular schedule. For the population levels greater than P^1, C_{Kj} is the new cost. This is illustrated in the following figure:

Figure a.1 Stylized costs graph of water supply related to the population level of the serviced community. Plant's marginal costs are on the vertical axis; population level is on the horizontal axis. P^1 – population threshold.



There might be high external social costs from the inability to meet the water demand; these can include political costs, people's discontent, and discomfort in addition to costs of bringing water from the outside. Thus, the plant faces the decision of whether to adapt to the growing demand in the form of investing in the plant's capacity or bringing water from alternative water sources. The decision will be to go with the least costly solution. Thus, the decision-maker is facing a cost-minimization problem. We consider the problem from the intertemporal perspective, where the WTP managers make their adaptation decisions through time, thus minimizing the expected costs - $Vt(q_t,k_t)$. Here, k_t is the state of the technology at time t. In the initial period $t = 0$, $k_0 = K_1$. If the plant is switching from one capital-technology combination to another, the capacity of the WTP is increased, such that $Q_{K1} < Q_{K2}$. Plant's technology is upgraded if an investment of cost i_t takes place. Here, i_t is the investment level at time t, and it can be either 0 or I_{Kj}. The upgrading takes place immediately in the period when the investment is made such that: $k_t = k_{t-1}$ if $i_t=0$, and $k_t = K_2$ if $i_t = I_{K2}$. Formally, the costs minimization problem is the following:

$$\mathbb{P}\text{: } Vt(q_t,k_t) = \min\left(c(q_t,k_t) + i_t + \frac{EV_{t+1}(q_{t+1},k_{t+1})}{1+r}\right) \quad \textbf{[a.2]}$$

subject to: $\delta q_t = d(P_t)$, where $\delta<1$

$i_t = 0$ or I_{Kj}

$k_0 = K_1$

$k_t = k_{t-1}$ if $i_t=0$, and $k_t = K_2$ if $i_t = I_{K2}$

$i_t = 0$ if $k_t = K_{2}$.

Here, the expected value of total costs at time t is the sum of the current time period in-plant costs, level of investment, and the net present value of the discounted flow of future costs. Here, r is a discount rate. If we expand the expectation operator, we get the following:

$$\mathbb{P}\text{: } Vt(q_t,k_t) = \min\left[c(q_t,k_t) + i_t + \frac{E\min[\, c(q_{t+1},k_{t+1}) + it + \frac{EV_{t+2}(q_{t+2},k_{t+2})}{1+r}]}{1+r}\right]. \quad \textbf{[a.3]}$$

The water treatment plant's problem is to choose the optimal level of investment i^*_t for each time period to minimize costs, given the set of constraints. WTP managers decide when to upgrade the plant from the capital-technology combination K_1 to K_2.

Model 1 shows how a growing population would drive capital investments into the plant. The population level defines the quantity of water demanded. Potential high expected costs of WTP failing to meet the water demand enter the capital investment decision-making by affecting the flow of costs. Identification of a P^1 threshold is an important part of uncertainty characterization that allows the WTP managers to plant the investment. The population was the only source of uncertainty faced by WTP decision-makers. Model 2 describes a case when the WTP managers are facing two sources of uncertainty – population level and water quality distribution.

Model 2: Water Plant Investment with Stochastic Population Growth and Source Water Quality

Consider a town with population P_t that demands clean water for household purposes of d_t quantity. Time is defined as t, and the time horizon is [0, T]. Water that the population uses has to meet certain quality standards. There is a water treatment plant that processes water from the river. This water treatment plant uses a specific capital-technology combination K_j; this capital-technology combination defines the coefficient δ - a fraction of output water from a unit of input water such that $q_t^o = \delta q_t^i$, and limits the amount of produced water Q_{Kj}. There are costs associated with water purification and supply, expressed as the function $c_i\left(q_t^i, m_t; S, k_t\right)$. The costs of water supply depend on the quantity of input water q^i_t, quality of incoming raw water m_t, quality standards for output water S, and the plant's capital-technology combination k_t. Higher values of m_t mean worse water quality; for instance, turbidity can be one such indicator. Costs of supplying clean water differ with respect to different scenarios. Thus, costs are expected to be higher when the amount of water demanded exceeds the capacity of the plant Q_{Kj}; or when the plant cannot meet the quality standards for the output water because of the conditions of the quality of the source water; or when standards could not be met and the demand exceeds what could be provided by the plant. The cost function of the plant is:

$$c_i\left(q_t^i, m_t; S, \mathrm{Kj}\right) =$$
$$\begin{cases} c_1\left(q_t^i, m_t; S_t, \mathrm{Kj}\right), if\, q_t^o = \delta q_t^i,\ \mathrm{d}_t = \delta q_t^i \le Q_{Kj}, Q_{K_j} > 0, m_t \le \widehat{m}_i(S_t, \mathrm{Kj}) \\ c_2\left(q_t^i, m_t; S_t, \mathrm{Kj}\right) > c_1 x\left(q_t^i, m_t; S_t, \mathrm{Kj}\right)\ if\ \mathrm{d}_t > Q_{K_j} > 0, m_t \le \widehat{m_1}(S_t, \mathrm{Kj}) \\ c_3\left(q_t^i, m_t; S_t, \mathrm{Kj}\right) > c_1\left(q_t^i, m_t; S_t, \mathrm{Kj}\right)\ if\ 0 < \mathrm{d}_t \le Q_{Kj}, \widehat{m}_1(S_t, \mathrm{Kj}) < m_t < \widehat{m}_2(S_t, \mathrm{Kj}) \\ c_4\left(q_t^i, m_t; S_t, \mathrm{Kj}\right) > c_3\left(q_t^i, m_t; S_t, \mathrm{Kj}\right)\ if\ 0 < \mathrm{d}_t \le Q_{Kj}, m_t > \widehat{m}_2(S_t, \mathrm{Kj}) \end{cases} \quad \textbf{[a.4]}$$

The first row of the function describes the regular operating costs. Here, the plant is experiencing regular schedule costs if the demand is not exceeding the plant's capacity: $\mathrm{d}_t = \delta q_t^i \le Q_{Kj}$ and input water quality is less than the water quality threshold of the plant $\widehat{m}_i(S_t, \mathrm{Kj})$. The water quality threshold is the maximum level of contaminants or sediment in the source water that the WTP can process to meet the health standards. If the input water quality exceeds the threshold, then the technology of the plant K_j becomes inadequate to process the water to output water quality standards S. The WTP can have multiple water quality thresholds $\widehat{m}_i$ that serve as breakpoints to the costs; in this model, the plant has 2 thresholds such that i = 1 or 2.

The second row of the function describes the costs when the demand for water exceeds the plant's volume capacity, and input water quality is below the threshold. The slope of the function has to be established empirically as some plants experience economies of scale, while others do not. However, $c_2 > c_1$, meaning that it is cheaper for the plant to treat water in-plant than allocating the additional supply of water from alternative sources.

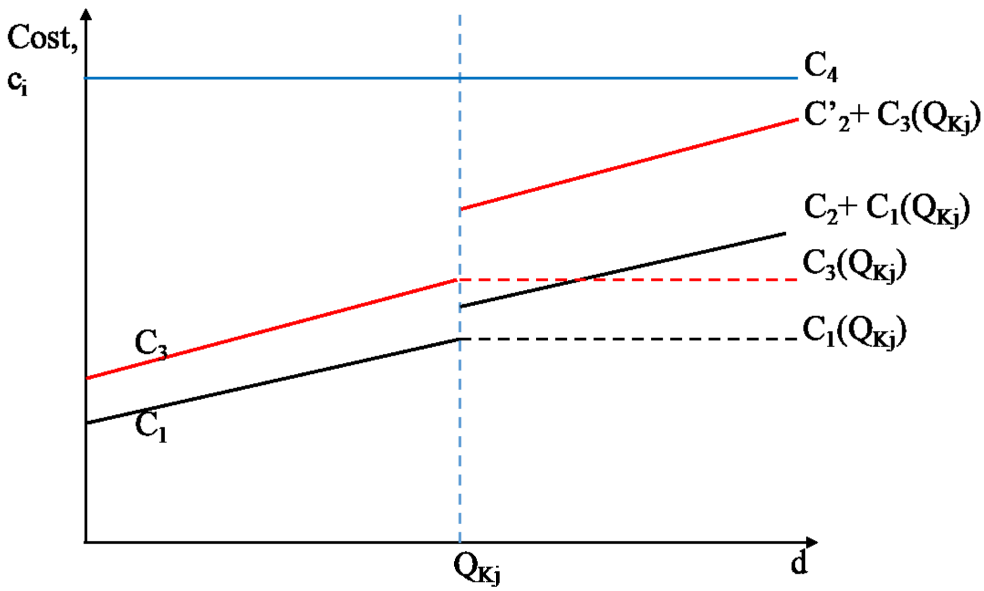
The third row of the function describes the cost schedule when the demand for water is below the plant's capacity, and water quality is such that it is in the range between two thresholds. The plant continues its operation. In this range of water quality, the costs of water treatment are higher than the regular costs. This is due to additional in-plant and community adaptive costs. Thus, increased contamination of the source water might require the plant managers to target specific contaminants with additional chemicals; maintenance costs can increase. Unusual levels of the source water contamination can lead to increases in the risks of output water contamination. On the serviced community side of costs, people might need to engage in costly adaptive behaviors such as buying bottled water and boiling water, with risks of output water contamination posing health risks and risks of disease outbreaks.

The last row in the cost function describes the costs schedule when the source water quality exceeds the threshold $\widehat{m}_2(S_t, \mathrm{Kj})$. Similarly to exceeding the $\widehat{m}_1(S_t, \mathrm{Kj})$ threshold, there arise additional costs from both on-plant and community side. We consider the second threshold to be as high as when the water quality is worse than the $\widehat{m}_2(S_t, \mathrm{Kj})$, the WTP has to issue no-use water advisory due to high potential health risks to the population and damages to water treatment technology. When the plant stops operating, then there are costs due to increased health risks, costs of bringing water from alternative sources, high plant maintenance costs due to poor water quality, etc. The $c_4\left(q_t^i, m_t; S_t, \mathrm{Kj}\right)$ costs are higher than $c_3\left(q_t^i, m_t; S_t, \mathrm{Kj}\right)$ costs.

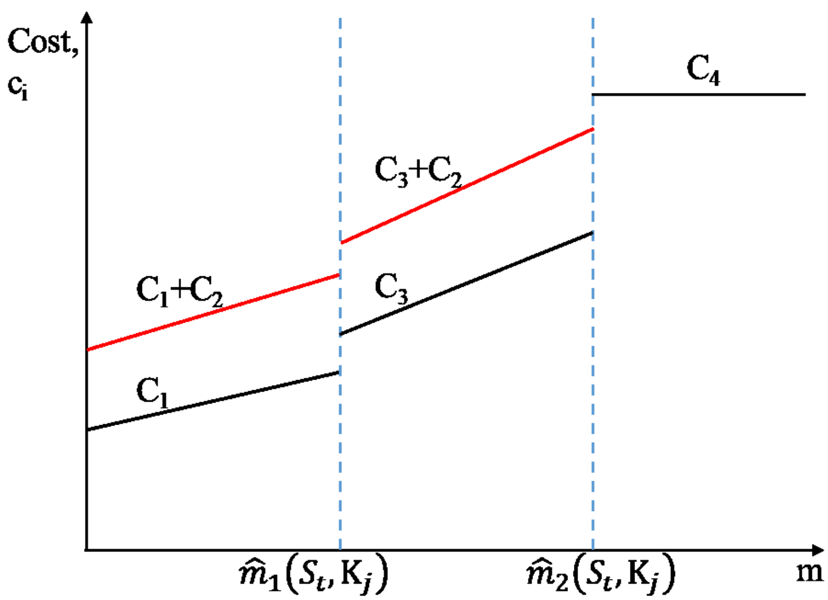
We can summarize the cost function in the two following figures:

Figure a.2 Stylized costs graphs of water supply. Panel a: costs are related to the population level. Panel b: costs are related to water quality costs.

$\widehat{m}_1(S_t, \mathrm{Kj})$ and $\widehat{m}_2(S_t, \mathrm{Kj})$ – water quality thresholds. Q_{Kj} – WTP's water volume capacity. C_1 – regular costs schedule. C_2 – costs of water treatment when the WTP's quantity threshold is exceeded. C_3 – costs, when demand is under the quantity capacity, and water quality is exceeding the threshold $\widehat{m}_1(S_t, \mathrm{Kj})$, but below $\widehat{m}_2(S_t, \mathrm{Kj})$. C_3 – costs, when the $\widehat{m}_2(S_t, \mathrm{Kj})$ a threshold is exceeded. S_t – output water quality standards. K_j – the capital-technology combination at the WTP.



a.



b.

Figure a.2 a) describes the cost schedule for the water treatment plant in relation to the output water quantity. Black solid lines represent the costs of the plant when the source water quality is under the first water quality threshold. Similarly, solid red lines represent the costs of the plant if the first water quality threshold is exceeded. Marginal costs change at the breakpoint Q_{Kj}; when the demand for water exceeds the quantity threshold, the WTP is experiencing C_2+$C_1(Q_{Kj})$, and C_2+$C_3(Q_{Kj})$ costs for two water quality scenarios, respectively. We sum the costs because the WTP is still operating, and the public has to supplement the deficit by bringing water from alternative sources and experience additional costs of elevated health risks and adaptive behaviors. By contrast, if the water quality exceeds the second threshold, then the public has to haul water from the outside due to the no-use water advisory. Thus, the water quantity threshold does not affect C_4 costs. When the WTP is closed, the public experiences additional costs of increased health risks and adaptive behavior.

Figure a.2 b) describes the cost schedule for the WTP in relation to the water quality. As defined in the cost function, there are two water quality thresholds that affect the marginal costs of water supply. The solid black line is the cost function in the case when the water quantity threshold is not exceeded, and the red line is the cost function if the demand is above the quantity capacity. As described in the cost function, the cost of water supply is lower for water quality levels below the $\widehat{m}_1(S_t, \mathrm{K}_j)$ threshold, as the costs are comprised solely of the in-plant treatment costs. As the water quality becomes worse, between two water quality thresholds, the costs are higher, and they follow the c_2 function described in the equation [a.4]. When the water quality exceeds the $\widehat{m}_2(S_t, \mathrm{K}_j)$ threshold, the water supply from the WTP is cut off and the public engages in the costly adaptation behavior. The c_4 cost does not depend on the water quality anymore, because the supply from the WTP is cut off.

The costs depend on the water quality standards S_t and capital-technology combination K_j that are exogenous in this model. More stringent water standards can increase costs due to additional compliance efforts. Changes in health standards can also shift the water quality and capacity thresholds that can further affect the distribution of costs. K_j directly affects the distribution of costs; we assume that improved technologies make the WTP more resilient to water quality. This means that the water quality threshold $\widehat{m}_2(S_t, \mathrm{K}_2) > \widehat{m}_2(S_t, \mathrm{K}_1)$ and $\widehat{m}_1(S_t, \mathrm{K}_2) > \widehat{m}_1(S_t, \mathrm{K}_1)$. If we consider water quality distribution, then an upgrade implies that the plant is less likely to experience cases with water quality or quantity thresholds exceeded. Thus, society, including the plant people, are less likely to engage in costly adaptation behavior. The investment, however, is costly and can only be made once within the planning horizon of [0, T]. The cost of investment is

i_t. An investment of i_t changes the capital-technology combination from K_1 – the initial technology at the plant – to K_2 in the same time period that the investment is made. We define k_t as the capital-technology combination at the plant at time t.

The problem for the decision-maker is to minimize the expected cost of (maximize the expected value from) operating the plant - $V_t\left(q_t^i, m_t; S_t, k_t\right)$. Expected costs are the sum of current costs, discounted future costs, and investments into the plant. An upgrade of the plant would allow it to meet water quality standards, or to respond to the demands of a growing population because it increases the capacity of the plant. The WTP's decision-makers problem then is:

$$\mathbb{P}: V_t\left(q_t^i, m_t; S, k_t\right) = \min \left(c_i\left(q_t^i, m_t; S_t, k_t\right) \right) + i_t + \mathbb{E}\,\frac{V_{t+1}\left(q_{t+1}^i, m_{t+1}; S_{t+1}, k_{t+1}\right)}{1+r})$$

subject to: $\delta q_t = d(P_t)$, where $\delta<1$

$i_t = 0$ or I_{Kj}

$k_0 = K_1$

$k_t = k_{t-1}$ if $i_t=0$, and $k_t = K_2$ if $i_t = I_{K2}$

$i_t = 0$ if $k_t = K_2$.

$m_t, P_t, q_t \in R^+$

In this equation, V_t be the value function; i.e. expected cost of the project including discounted flow of future costs at time t. The plant's decision variable is i_t – the plant decides on the optimal investment level in each time period given the constraints involving capital-technology combinations, levels of investment and water quality levels.

Model 2 shows how water quality distribution and population growth affect the costs of water supply. Specifically, an interaction between water quality and quantity and capital technology defines the distribution of costs. The case when the water quality exceeds the designed thresholds can be associated with extremely high social costs, thus encouraging the water authorities to avoid such scenarios. Incorporating water quality and population growth into an expected value framework of investment decision-making allows us to account for such costs in ex-ante sense and plan infrastructure investments accordingly.

Appendix B

We estimated a linear model to analyze the relationship between the use of chemicals and water quality. We present the result of intermediate analysis on the example of Alum, and it has the largest use share among all chemicals. We estimate the initial model and plot the predicted costs against the observations in a scatter plot in Figure b.1. On the left pane of Figure b.1, we see that there is a cluster of points in the bottom left, where the fit of the model is not as good as for the rest of the points. We then discover that this cluster of points is the set of winter observations, where the use of Alum was low, and the pattern was not captured by the general model. We thus distinguish summer and winter seasons, where half of the year from April to September is summer, and the rest of the months are coded as winter. This seasonal model predicted points are plotted on the right panel of Figure b.1. We can observe that a seasonal model, where we introduce the seasonal dummy variable as well as seasonal slope variables, has a better fit for winter observations. We conduct a similar procedure with chemical use costs and plot the results in Figure b.2. Similarly, the seasonal model predicts observations in the winter season better than the general model. Thus, we use the seasonal model in our final cost-response model specification estimated in Section 4.3.

Figure b.1 Scatter plot of logarithm of average use of Alum per day against the level of logarithm of turbidity on that day. Black points –observations on the use of alum against the level of turbidity; red points – points predicted by the model for summer; purple – predictions for winter. Left pane – seasonality is not accounted for. Right panel – model predictions with seasonality accounted for.

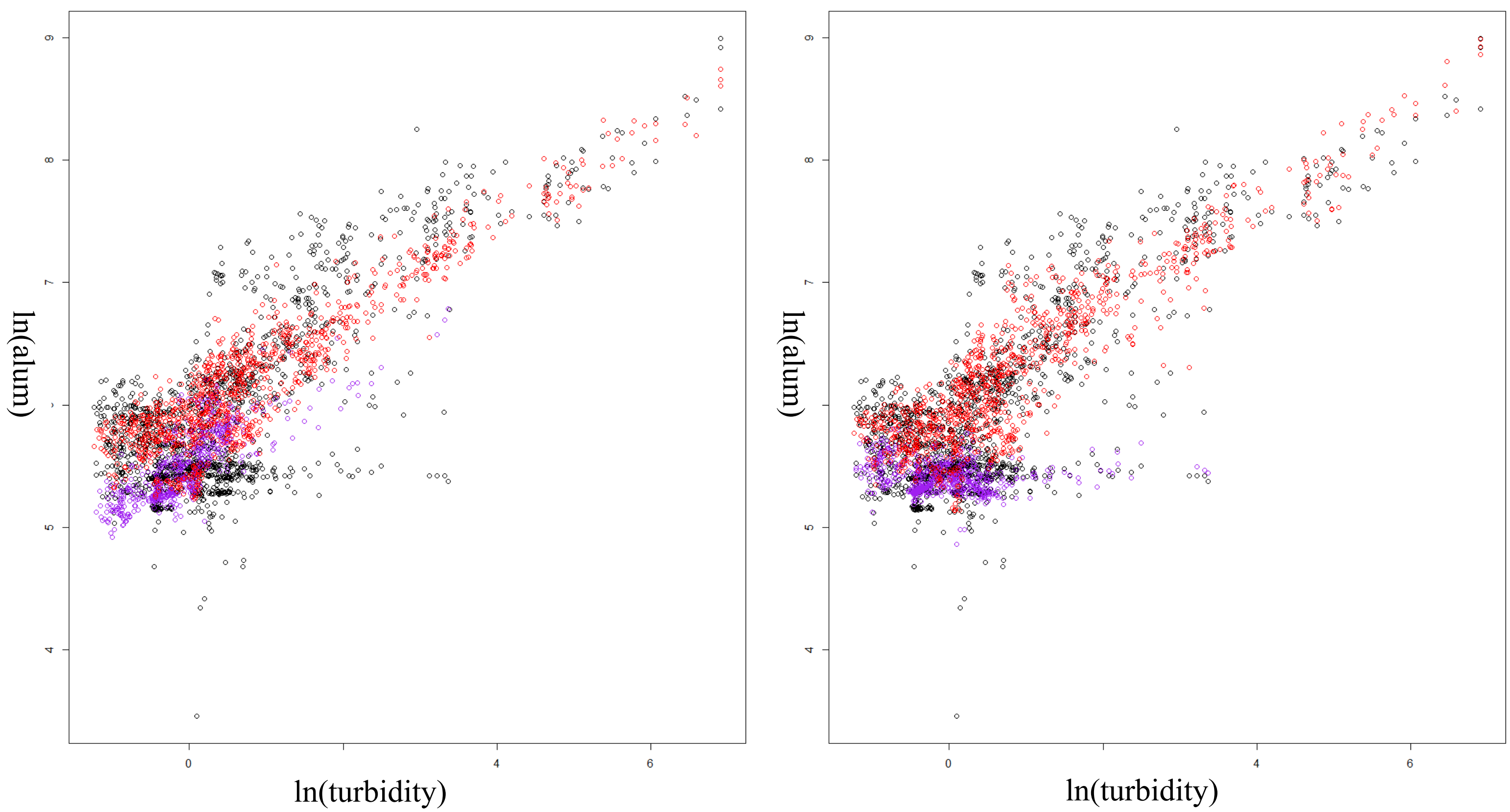
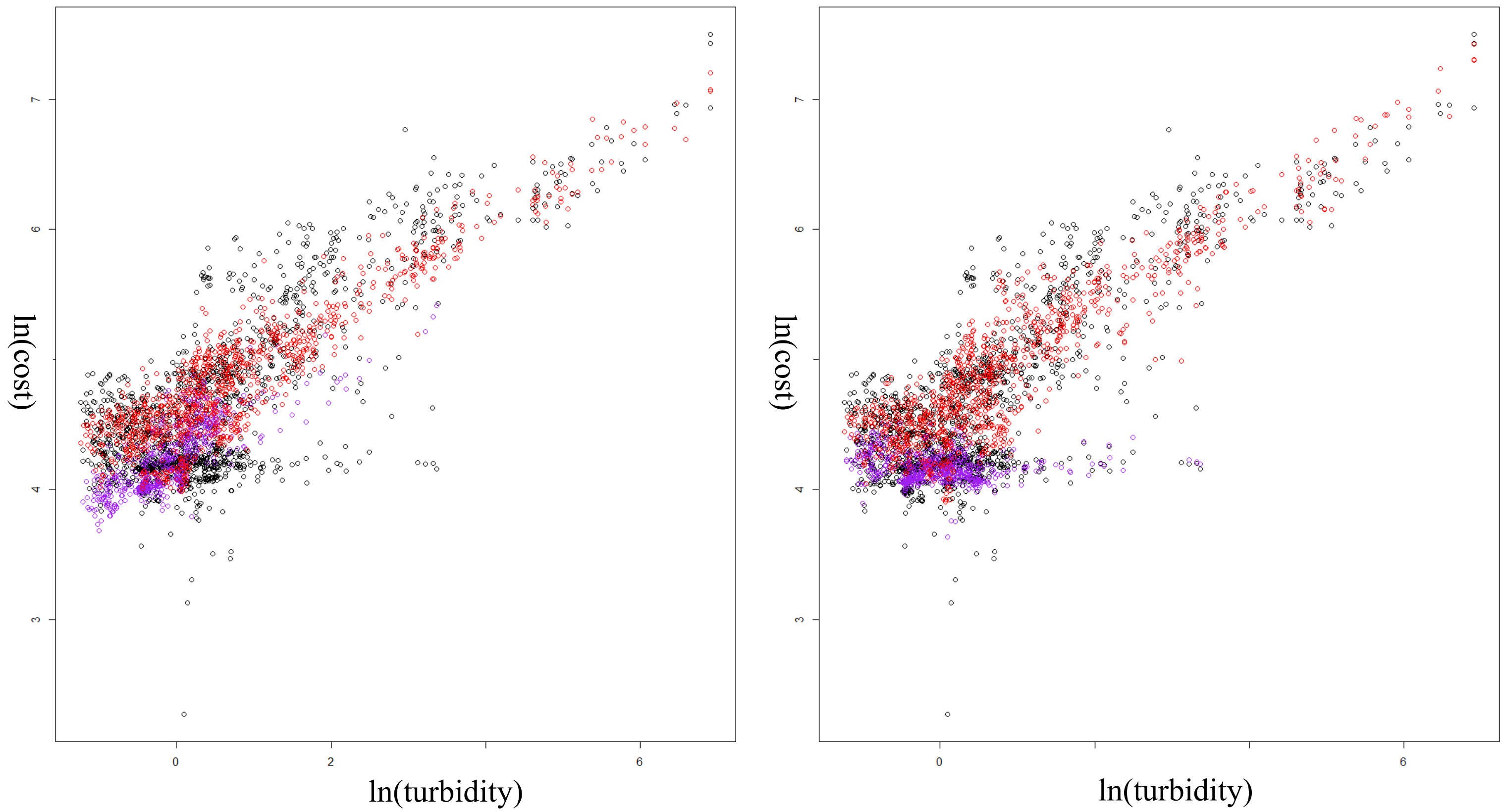


Figure b.2 Scatter plot of logarithm of average daily chemical use costs against the level of logarithm of turbidity on that day. Black points – observations on the chemical use costs against the level of turbidity, red points – points predicted by the model for summer; purple – predictions for winter. On the left: seasonality is not accounted for. On the right: model predictions with seasonality accounted for.



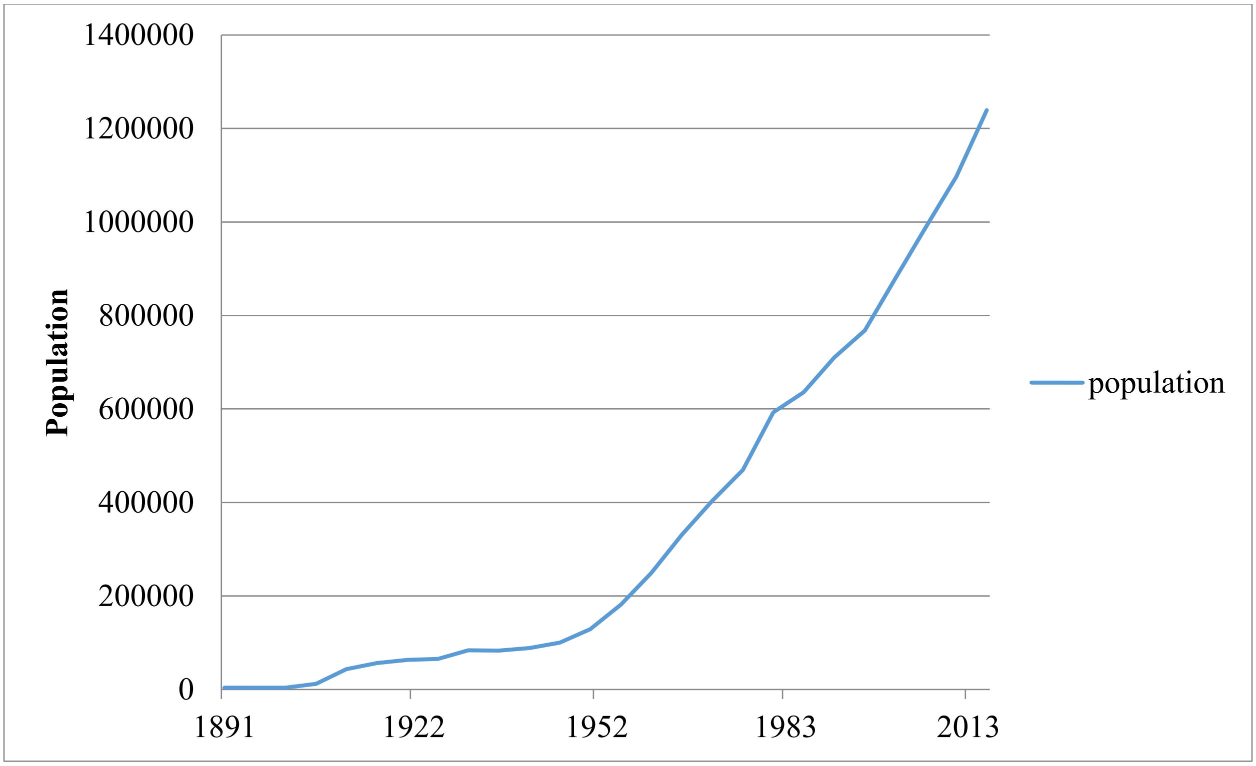
Appendix C

Modelling Calgary's population growth

To account for uncertainty in the growth of the population, we forecast the population until 2025. We analyze Calgary census population data from 1891 to 2016 and obtain 10,000 simulated projections of yearly population data. We then use population simulations in combination with the simulated outside-of-plant costs simulations, and thus per person outside-of plant costs projections are adjusted to the population level.

The population of Calgary had grown significantly since 1891, when the population of the town was 3,876 (Government of Canada (1907), cited in Wikipedia, n.d), and reached 1,285,711 by 2019, according to 2019 census data (City of Calgary Civic Census, 2019) (see table c.1). Calgary has experienced the most rapid growth rates at the beginning of the 20th century. The population almost doubled in 5 years from 1901 to 1906 and increased by 265% during the following 5 years (Government of Canada (1927), cited in Wikipedia, n.d). The 5-year population growth during the following century averaged at 18.7%. Calgary has experienced the only 5-year population drop during the years of the Great Depression; the town's population dropped by 0.4% from 83,761 to 83,407 from 1931 to 1936. Calgary has been seeing a steady growth of its population during the beginning of the 21st century, with annual growth rates averaging at 2.14% (City of Calgary Civic Census, 2019). The population of the city is forecast to hit 1.42 million in 2024 (City of Calgary, 2019), with the projected annual population growth averaging at about 2% from 2018 to 2024.

Figure c.1 Historical population of Calgary from 1891-2016.



To start the analysis of the population data, we test for stationarity with the Augmented Dickey-Fuller test, and present the results in the following table:

Table c.1: Augmented Dickey-Fuller test results for *population* and population's first- and second- difference time series

Test	**Test statistic for Population series**	**The test statistic for population first difference**	**Test statistic from total flow model**
ADF, 1 lag	2.55	1.23	-2.94***

Significance levels codes: *** - 0.1%, ** - 1%, * - 5%, ° - 10%

We cannot reject the null hypothesis of the presence of the unit root for the original series and its first-difference. However, we conclude that the second-differenced population series is stationary, and we thus use this series for population forecasts.

The second-differenced population series can be interpreted as the population's growth rate's growth rate. In other words, it represents how fast or slows the population grows.

We then estimate the AR(1) model for the series:

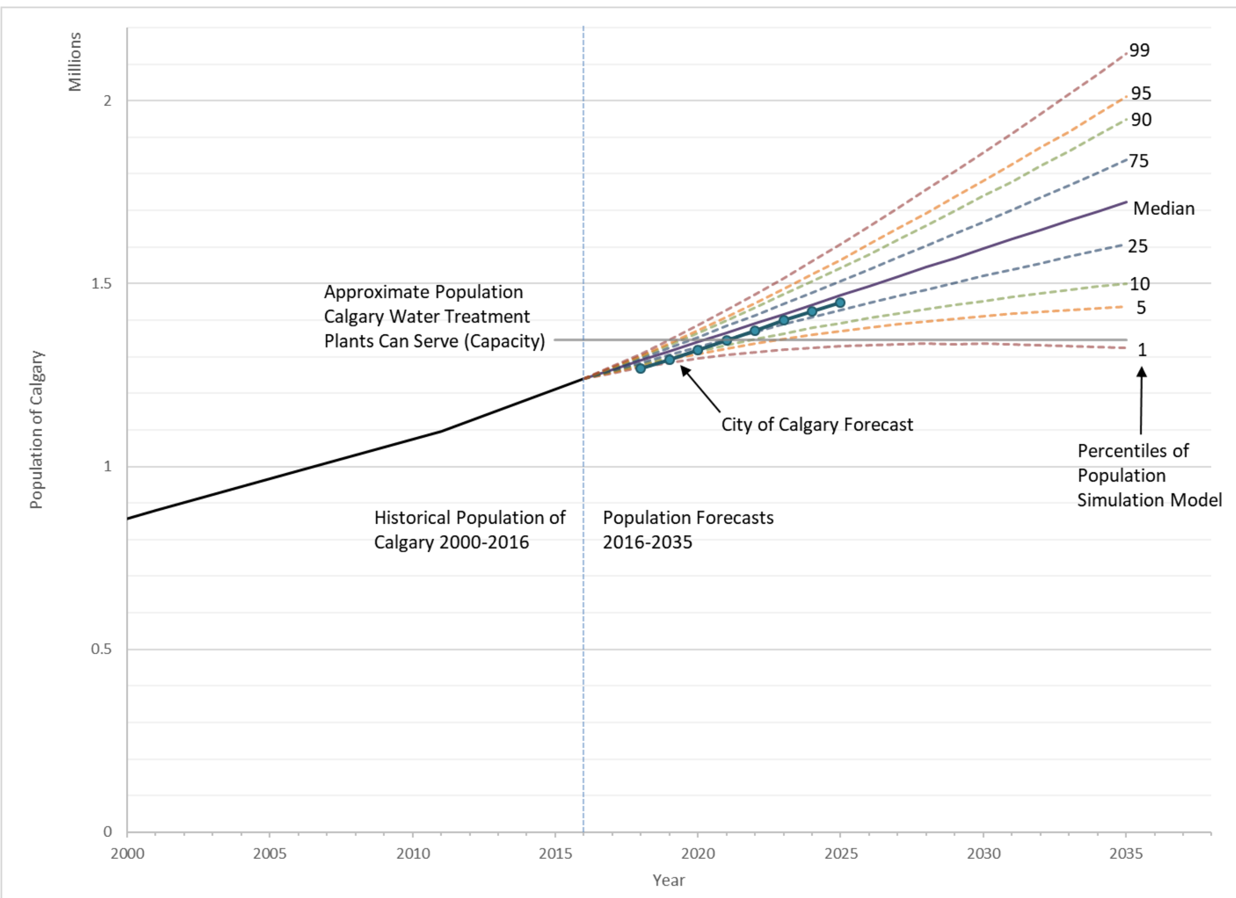
Table c.2 Summary of AR(1) model for the population's second difference.

Component	**AR(1)** **Population second-difference**
AR	-0.52* (0.22)

Significance levels codes: *** - 0.1%, ** - 1%, * - 5%, ° - 10%

We use the AR(1) model to forecast the population until 2035. We thus obtain a matrix of 10,000 simulations for 20 years. We summarize the population forecast in the following figure:

Figure c.2 Simulation of Calgary's population for 2016-2035



In the figure, the black line represents the observed data. The purple line is the median of forecast scenarios. We draw a blue line on top of the graph to compare our model's prediction to the forecasts provided by the City of Calgary. Colored dashed lines represent respective percentiles of future population projections.

Our model forecasts that Calgary's population will exceed the design capacity of two water treatment plants by 2021 in 50% of the simulations. The designed capacity threshold is reached even earlier – in 2019 – if we consider the 99^{th} percentile projection of the population's growth.