A theoretical and empirical investigation into the economic relationship between forested watersheds and water treatment costs

by

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Author's Declaration

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

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Statement of Contributions

The second, and fourth chapter is co-authored with my supervisor, Dr. Roy Brouwer, the third chapter is co-authored with Dr. Roy Brouwer and my Internal-External Member, Dr. Monica B. Emelko. For all chapters, I have contributed to all aspects of the research, including development of research objectives, utilizing econometric models and analyzing results.

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Abstract

Forests around the world are believed to perform important chemical and nutrient retention functions. Chemical concentration levels have been found to be lower in surface water bodies located in areas with a higher forest cover. There is increasing interest from both academics and policymakers in understanding the economic value behind these nature-based services provided by forests. Including forest cover as green infrastructure in integrated source water protection and management strategies is believed to enhance their overall economic efficiency by improving water treatability. However, the empirical evidence base linking forest cover and forest management to water treatability and treatment costs is limited, and largely absent in Canada, one of the most resource-abundant regions in the world. In order to justify investments in forest cover as green infrastructure it is vital to understand the economic benefits involved, in particular in relation to drinking water treatment. The main objective of this PhD thesis is to further analyze the relationship between forest land and water treatment, both theoretically and empirically using Canada as a case study area.

The first chapter of this PhD thesis aims to provide a theoretical framework for better understanding the costs and benefits of investment decisions in the provision of safe drinking water. More specifically, a cost minimization function is specified to reach a given water quality standard, for example based on World Health Organization guidelines. The costs are based on two possible treatment approaches that can be adopted, denoted as grey and green infrastructure, where grey infrastructure represents the traditional water treatment technologies and green infrastructure consists of forest cover (e.g. forest protection or re-afforestation).

Compared to grey infrastructure, green infrastructure has been found to be less costly, but riskier to implement than grey infrastructure to improve water treatability due to the lack of engineering control and environmental uncertainties surrounding causal dose-response relationships between forest cover and water quality. An optimal control model is developed to guide social planners in combining these two complementary types of infrastructure in the most cost-effective way given assumptions about the age structure of forests, risk levels, risk aversion, and the discount rate used to value future water service delivery from green infrastructure. Any optimal allocation between grey and green infrastructure is based on balancing the marginal net benefits of both types of infrastructure. Including wildfires as an additional risk, makes green infrastructure less attractive, among others because of the introduction of additional costs such as forest protection costs and reforestation costs. More forest means a higher risk of forest fires and hence damage costs and increases the uncertainty surrounding the delivery of the water service. Accounting for the co-benefits of forests as a carbon trap increases the likelihood of investing in green infrastructure, because it reduces the risk of forest fire in the long term and hence the forest protection costs, but is highly dependent on the applied discount rate to factor these long-term benefits into present-day decision-making.

The second chapter in this PhD makes use of available empirical data for the province of Ontario in Canada, and focuses on the potential role of forest cover in potentially reducing drinking water incidents, reflecting on concerns in the first chapter about the effectiveness of green infrastructure as a means of source water protection. The publicly available Ontario drinking water quality and enforcement data base contains all drinking water incidents over a particular fiscal year that failed existing water quality standards in Ontario. The database lists all incidents, so-called adverse events, related to municipal water sources. By linking this database (n=228) to geographical information retrieved from the Ontario Land Cover (GIS) database, a set of interconnected spatial regression models are estimated, aiming to assess the relationship between forest cover and drinking water rates and between drinking water rates and drinking water safety. In the latter case, the drinking water rates are used as a proxy for the drinking water treatment costs. To this end, a spatial instrumental variable model is estimated to improve our understanding about the aforementioned (reverse) causal relationships, i.e. how drinking water rates influence incidence rates and vice versa incidence rates in turn impact water rates. A key finding is that forest cover significantly reduces the number of adverse events and drinking water rates.

In the third and final chapter of this PhD thesis, use is made of another important database, the biennial Drinking Water Plants Survey conducted by Statistics Canada for the country as a whole. The survey aims to gain insight into the financial treatment costs, water treatment characteristics, and water plant customers. The survey data are confidential and can only be accessed on-site in Statistics Canada in Ottawa after requesting permission and going through an extensive (legal) screening procedure of both student and supervisor. The collected data provides detailed insight in different treatment cost categories that can help to assess how specific cost categories are influenced by surrounding land cover across Canada. Using the detailed water treatment costs in similar spatial econometric regression models (n=1,373), accounting for potential spillover effects between neighbouring water service units, a significant negative relationship is found for Canada as a whole between forest cover and total drinking water treatment costs and the material costs incurred in drinking water treatment, whilst accounting for a range of individual water treatment plant characteristics, such as treatment capacity, treatment technology, and population served.

In conclusion, in this PhD thesis I demonstrate that surrounding forest cover has a significant negative effect on water rates and incidence rates in Ontario and I show that surrounding forest cover significantly reduces water treatment costs across Canada as a whole. However, the regression models estimated in this PhD thesis are based on various far-reaching assumptions which could not be verified. These include, most importantly, the assumption that there exists a direct relationship between water rates and water treatment costs in Ontario and the assumption that the spatial analysis conducted at the level of census sub-divisions in both Ontario and Canada as a whole is able to capture upstream-downstream relationships between land cover upstream and the quality of the water intake downstream in the watersheds providing water to the drinking water treatment plants. More research is needed to validate these key assumptions.

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Chapter 1
Introductory Chapter

1.1 Overview of the thesis

Green infrastructure is a wide range of natural-based solutions that provide essential natural services, including drinking water treatment. The drinking water treatment rate or costs will be reduced, given further forest land cover available in the watersheds. However, there is limited Canadian research addressing the drinking water treatment functions of forests. Most importantly, to my best acknowledgement, no research indicates the economic benefit of water treatability, which is received from forest land cover. As one of the most resource-abundance regions globally, Canada has 347 million HA of forests, which accounting 9% of total forests on earth (Food and Agriculture Organization of the United Nations, 2018). Simultaneously, the municipal drinking water system in Canada is accounting for surface water mostly. It is reported that around 87.8% of potable water, related to municipal water treatment, is coming from surface water sources, according to Statistics Canada (2021). Therefore, it is vital to understand the economic benefit of forest land covers in drinking water treatment.

Forests, among many widely adopted green infrastructures, have been analyzed for their root fortification effect. It is believed that this specific natural function plays a crucial role during the water circulation process. For instance, certain nutrients and chemicals can be restored in soils instead of recharging back to water bodies(Guo et al., 2001; Futter et al., 2016). Downstream treatment plants, thus, can save chemical inputs, which reduce total water treatment costs. Based on the substitution effect between green-based solutions like forests and grey infrastructure, the integrated water treatment combination is believed to enhance the overall drinking water treatment's cost-efficiency. Moreover, the green-infrastructure-based solution is widely conducted and analyzed for the global future. In the sustainable development goal(SDG) target 6.6, restoration and conservation forest for securing safe drinking water source is one of the targets that shall be reached before 2020(United Nations, 2021). In one of the most recent research reports, the Intergovernmental Panel on Climate Change(IPCC) states the demand to find climate change resilient solutions for the future. This includes the green infrastructure of this paper(IPCC, 2021). The Canadian government also strengthen the importance of forest conservation. In one of the most recent forest governance frameworks, forests management should prioritize forest-related products, including water, instead of timber production only(Natural Resource Canada, 2021).

There is an emerging trend in decomposing the substitution effect between forests and grey infrastructure. The traditional procedure is a target-based substitution method. For instance, two potential solutions can achieve the same water treatment target, while one of them is dominated by green infrastructure. It is analyzed that the natural-based solution tends to be more cost-efficient than another. Therefore, the cost reduction between projects can be mapped as a proxy of cost reduction and benefits of the natural-based solution(Pu-mei et al., 2001; Biao et al., 2010). Labour substitution can be considered as an extension to the target-based solution. Das et al. (2019) illustrate the labour requirement reduction of water transportation given the source water protection function provided by forests.

Besides the engineering target-based models, economists evaluate the substitution effect by using empirical data directly. Abildtrup et al. (2013) propose a spatial-instrumented model in modelling the relationship between French land cover and municipal drinking water rates. Warziniack et al. (2017) plotted the causal impact of water treatment costs reduction due to further forests. Besides cross-section setups, Mulatu et al. (2019) documented panel data in Ethiopia detailing the water treatment cost changes given forests land cover variation between years.

The main objective of this thesis is scoping on the Canadian drinking water treatment, which is influenced by the forest lands. There is no Canadian research addressing water treatment costs or rate reduction based on forest shares variation, according to Price and Heberling (2018). In that sense, this research is mainly in understanding the economic effect of Canadian forests on drinking water treatment. Specifically, the drinking water costs reduction due to fewer chemical and other inputs caused by more forest land covers. On top of the cost reduction caused by substitution effects between forests and chemical inputs, the risk of drinking water treatment, mapped by adverse incidents, is modelled revolving around forest land covers and disturbances. This thesis further provides the fisrt framework in evaluating drinking water treatment investment decisions made by social planners, while accounting the risk of water treatment.

In chapter 2, a theoretical framework is proposed in understanding the investment strategy between green and grey infrastructure. The social planner will implement a combination of infrastructure, green and grey, to satisfy the drinking water standard. Several concerns regarding forests will alter the social planer's optimal investment decision. For instance, the wildfire risk may deter a social planner from expanding the level of investment. On the other hand, the carbon fixation effect that can reduce the long-term climate change pace may attract a social planner's interest in investment. This chapter is mainly utilizing a theoretical framework to understand the concerns of social planners in facing the risk and uncertainties revolving around green infrastructure.

In chapter 3, an empirical study is conducted to understand the economic benefit of forests better. By using Ontario drinking water quality and enforcement data, together with forest land cover and water rate information, the study aims to plot the relationship between forest land cover and drinking water rate. Merging the drinking water rate info collected by phone surveys and public adverse events, the final dataset is the first case study focusing on the land-use variation and drinking water safety that municipal drinking water plants are facing.

The final chapter is mainly scoping on the financial information of drinking water treatment plants. Other than the drinking water rate, this study narrows the scope of water treatment costs from a confidential dataset across Canada. Other than Price et al.(2015), this paper builds the connection between forest land cover and final water treatment costs directly. While accessing the dataset from Statistics Canada, the research highlights the forest land cover differences across Canada and its influences on annual water treatment costs. Finally, it compares the complementary effect between different chemical input costs, related with forests or not.

Chapter 2

A Theoretical Modeling Framework to Support Investment Decisions in Green and Grey Infrastructure under Risk and Uncertainty

Zehua Pan and Roy Brouwer

Abstract

Green infrastructure for source water protection in the form of forest protection and afforestation is gaining interest worldwide. It is considered more sustainable in the long-term than traditional engineering-based approaches. This paper presents a theoretical model to support investment decisions in green and grey infrastructure to deliver safe drinking water. We first develop a static optimal control model accounting for the uncertainties surrounding green infrastructure. This model is then extended to factor in key characteristics surrounding investment decisions aimed at optimizing the stock of green and grey infrastructure. We first include dynamic forest growth, followed by the risk of wildfires and finally the potential offsetting effect of carbon sequestration on long-term climate change and the reduced risk of wildfires. We provide a numerical example to analyze the performance of the different model specifications, interpret their outcomes and draw conclusions to guide future investment decisions in green and grey infrastructure.

Key words: Green Infrastructure, Drinking Water Safety, Optimal Control, Forest Management, Wildfire Risk, Climate Change

2.1 Introduction

Forests provide a wide variety of essential ecosystem services, including valuable hydrological ones (Ovando and Brouwer, 2019). They have been found to be able to reduce the concentration levels of water pollutants compared to other non-forested land uses (e.g., Clark et al., 2000; Guo et al., 2001; Jussy et al., 2002; Bastrup-Birk and Gundersen, 2004; Schelker et al., 2012; Warziniack et al., 2017). Forests can retain nutrients and other chemical components in the soil instead of discharging them immediately into the water. Maintaining forest land instead of harvesting trees for timber production or converting forests into agricultural land also reduces the amount of sediments entering rivers. Soil erosion may result in the discharge of the chemicals contained in the soils (Guo et al., 2001; Futter et al., 2016), affecting water quality. Besides improving water quality, forests may also enhance water supply in a watershed. Trees can store water that will then be released again during a drought period (Guo et al., 2001; Mastrorilli et al., 2018). This water storage and release capacity can ease possible water shortage problems in increasingly urbanized watersheds.

A number of studies exist that try to estimate the economic value of forests in watersheds and the hydrological services they provide. These studies demonstrate, among others, that there exists a negative correlation between forest cover and water treatment costs (e.g., Abildtrup et al., 2013; Warziniack et al., 2017). Compared to conventional (grey) water treatment facilities, the costs of this natural (green) water treatment capacity of forests has been shown to be significantly lower (Ernst et al., 2004; Warziniack et al., 2017). This has substantially increased interest in the water storage, supply and purification performance of forest land as a nature-based approach instead of engineering a water treatment facility or dam reservoir (e.g., Pu-Mei et al., 2001; Biao et al., 2010). New York City's long history of dependence on the Croton and Catskill-Delaware watersheds for its freshwater supply is one of the best-known examples of the early recognition of the importance of sustainable land use management in urbanizing watersheds (Mehaffey et al., 2005). The supply of water from forested watersheds is expected to benefit urban water demand in a more sustainable way than conventional water management

(Mastrorilli et al., 2018), whilst at the same time playing a crucial role in reducing carbon emissions and the social costs from deforestation and forest degradation (Phan et al., 2014).

Quantifying the economic benefits of the hydrological functions performed by forested watersheds is crucial to inform policy and decision-making related to the implementation of green and grey water infrastructure, and the optimal mixture of the two. Research in this area is emerging, but still somewhat limited. Existing forestry economics studies have focused on economic valuation of water services provided by forests in the context of forest conservation (e.g., Ojea and Martin-Ortega, 2015), or on substituting grey infrastructure with green infrastructure by either minimizing the total costs of water supply or maximizing the effectiveness of water supply provision (e.g., Honey-Rosés et al., 2013; Lopes et al., 2019; Das et al., 2019). Here, we introduce a new optimal control modelling framework where a safe drinking water standard can be reached using both grey and green infrastructure, and the objective function consists of a cost minimization function. The baseline model is extended to account for some of the key characteristics related to the implementation of green infrastructure and associated positive and negative externalities. We investigate how these influence the outcome of the optimization model.

First of all, there exists considerable uncertainty related to the effectiveness of relying on (more) forests to protect drinking water sources. Due to the limited amount of control over influencing environmental variables (e.g., weather conditions), the hydrological impacts of forests are hard to quantify precisely (Fischbach et al., 2015). Counting entirely on forests to treat water may increase the risk of failing water safety standards. Secondly, the time it takes for water protection to become effective may differ between grey and green infrastructure. In the case of afforestation, water quality may take years to become notable (Waters and Jenkins, 1992). Hence, afforestation may be a future investment instead of a real-time solution, and therefore a less favourable solution for urgent water demands. Third, besides positive externalities such as carbon sequestration and biodiversity conservation, green infrastructure is also associated with a possible negative externality, namely the risk of forest fires. Fire prevention and the potential wildfire damage costs, in particular the impact of a forest fire on water quality in the watershed, will have to be taken into account in policy and decision-making (Jones et al., 2017). The extra forest protection costs will make the green forest-based solution furthermore more costly.

The main objective of this paper is to develop a theoretical economic model that informs the investment decision in green and grey infrastructure to secure safe water supply in an urbanized watershed, taking into account the hydrological impacts of forested land as a nature-based solution on water supply security. The investment decision is presented as a cost minimization problem to meet society's demand for safe and clean drinking water. Following the development of a simple static baseline optimal control model, the constraints listed above will be incorporated one by one in an extended version of the model, accounting for (1) the uncertainty surrounding the effectiveness of forested watersheds in water supply security, (2) the time it takes for forests to maximize water supply security in a dynamic version of the baseline model, (3) the risks of wildfires, and (4) the co-benefits of sustainable management of forested watersheds on climate change. Differences between the different models will be illustrated using numerical simulation.

2.2 Baseline model

In this section, first, the baseline model is presented where a social planner (e.g., government) is responsible for delivering treated water at a certain quality standard. The social planner aims to minimize the cost of delivering that quality standard. For water supply, there are two main investment decisions that the social planner can make, that is, adopting green or grey infrastructure, or a combination of the two. These will be referred to as C for green and D for grey infrastructure. We furthermore categorize infrastructure costs into three major components: construction costs, operation costs, and depreciation costs. The social planner will identify the optimal levels of green and grey infrastructure at the starting point of each investment decision. Construction costs (C_{con}) are assumed to be linear in the infrastructure (capital) levels:

$$C_{con} = \kappa_c C + \kappa_d D \tag{1}$$

where κ_c and κ_d describe the marginal construction costs. For simplicity sake, we initially assume that the construction of the infrastructure takes no time in the baseline model. That means that the green and grey capital stocks will be available to treat water instantly. In reality, the construction time between green and grey infrastructure will be different. We will relax this assumption later in the paper.

After construction, water will be treated during the rest of the time period until a new investment decision is needed. For each treatment period, the social planner will need to cover the operation and depreciation costs of each type of capital. The operation cost (C_{op}), which will guarantee that the infrastructure works properly, for each time period is:

$$C_{op} = \beta_c C + \beta_d D \tag{2}$$

where β_c and β_d are a constant fraction of the capital costs. The depreciation rate is a common feature of both types of infrastructure that influences the effectiveness of the capital stock to deliver water quality. At the end of each treatment period, we assume that the grey infrastructure has depreciated, while the green infrastructure has not. Existing studies on green infrastructure indicate that green infrastructure has a longer lifespan than grey infrastructure (e.g. Vincent, 1997). Furthermore, green infrastructure typically has a natural regeneration feature that may help to maintain the capital stock (Filoso et al., 2017). Taking these aspects into account, the depreciation rate of grey infrastructure is assumed to be larger than that of green infrastructure. The depreciation cost (C_{dep}) in each time period is hence:

$$C_{dep} = \gamma_d D \tag{3}$$

where γ_d are a constant fraction of the total capital costs. Fully accounting for these depreciation costs will ensure that the stock of grey infrastructure and hence its water quality service level will not change between periods. The total cost (TC) over time can be written in its present value form as follows:

$$TC = C_{con} + C_{op} + C_{dep} = \frac{1}{1-\zeta} * \left(\beta_c C + \beta_d D + \gamma_d D\right) + \kappa_c C + \kappa_d D \tag{4}$$

where ζ is the discount factor (equal to $\frac{1}{1+r}$) and r is the discount rate. Here we assume that both types of capital have the same discount factor.

We use Q to represent the quality of the treated water. Instead of a given constant number, we assume that water quality Q is represented by a probability distribution function to reflect the fact that the delivery of the water quality standard faces some degree of uncertainty. A Normal distribution is assumed to underly the water quality parameter Q with the following mean and variance:

$$Q \sim N(C^{\alpha} D^{1-\alpha}, C^{2\rho_c} D^{2\rho_d}) \tag{5}$$

where the mean of the distribution is a Cobb-Douglas constant returns to scale production function, following Malmsten and Lekkas (2010), including the two types of infrastructure C and D, α is the constant marginal productivity of green infrastructure and ρ is the variance parameter associated with green and grey infrastructure, reflecting the degree of uncertainty in delivering water quality. Contrary to Borsuk et al. (2002), who assume a constant level of delivery, we quantify the risk associated with the treatment process through the variance of the distribution, and assume that $\alpha > \frac{1}{2}$, $\alpha > \rho_c$, $1 - \alpha > \rho_d$ and $\frac{\rho_c}{\alpha} > \frac{\rho_d}{1-\alpha}$. $\alpha > \frac{1}{2}$ reflects that green infrastructure is more effective in treating water, while $\frac{\rho_c}{\alpha} > \frac{\rho_d}{1-\alpha}$ states that green infrastructure faces at the same time a higher degree of uncertainty than grey infrastructure in achieving the water quality standard. Even if a social planner adopts C and D such that their marginal productivity in treating water quality is the same, the risk of not being able to meet the water quality standard due to the use of green infrastructure is still larger than that related to grey infrastructure.

Turning to the demand side, consumers ask for safe drinking water. The water quality standard reflects societal demand for safe drinking water quality, including general consensus about the societal acceptance of the risk of not reaching this quality standard. The water quality standard $\bar{Q}$ is set exogenously based on, for example, global health standards provided by the World Health Organization. However, since the supply of water quality is surrounded by some degree of uncertainty, it is assumed to follow a random distribution. In other words, there is no $\bar{Q}$ such that $Q(C,D) > \bar{Q}$ with 100% probability. Hence, society is expected to define a probability p such that $Q(C,D) > \bar{Q}$. In practice, water quality assessment methods are based on sampling procedures where a water treatment facility will pass the test once, for example, 95% or more of the samples taken to satisfy the required quality standard (Smith et al., 2001). This testing procedure is identical to what we propose here for modelling the likelihood of achieving the water quality standard:

$$\Pr\left(Q(C,D) \geq \bar{Q}\right) \geq p \tag{6}$$

Equation (6) is the standard constraint that the water treatment plant as a supplier of safe drinking water needs to achieve, where p reflects the risk-averness of society. If a society is more risk-averseness, p will be greater. Hence, the larger p, the less risky the investment decision in water infrastructure ought to be that society is demanding.

From the social planner's perspective, the main goal is to meet consumer demand for access to clean and safe drinking water. We assume that the consumer has no incentive to demand water that is of better quality than the global health standard for safe drinking water quality. The social planner will, therefore, also not have an incentive to treat water more or better than the water quality standard. Hence, among all the potential water treatment infrastructure options that meet the water quality standard, the least cost option(s) will be the preferred by the social planner. Combining these assertions, the social planner's objective function looks as follows:

$$\min_{C\,D} \frac{1}{1-\zeta}(\beta_c C + \beta_d D + \gamma_d D) + \kappa_c C + \kappa_d D \tag{7}$$
$$s.t.\ Pr(Q(C,D) \geq \bar{Q}) \geq p$$

The standard constraint is equivalent to[1]

$$Q = C^{\alpha} D^{1-\alpha} - q * C^{\rho_c} D^{\rho_d} \geq \bar{Q}$$
(8)

where q equals $\Phi^{-1}(p)$. Φ is the cumulative normal probability distribution function, and q is the quantile of the distribution satisfying the constraint that the probability of water quality standard failure cannot exceed a certain threshold. In other words, if p is the accepted chance of failure, the associated quantile q is the minimum point in the distribution function that satisfies this condition. Once the quantile q exceeds the established target value, society is satisfied with the treated water quality. From equation (8), we see that the quantile value for q increases as more green and/or grey infrastructure is implemented.

The optimal level of investment in green and grey infrastructure is the set of C and D, where the ratio of the marginal productivity between green and grey infrastructure equals their marginal cost ratio[2]:

$$\frac{\alpha\, C^{\alpha-1} D^{1-\alpha} - q\rho_c C^{\rho_c-1} D^{\rho_d}}{(1-\alpha) C^{\alpha} D^{-\alpha} - q\rho_d C^{\rho_c} D^{\rho_d-1}} = \frac{\frac{1}{1+\zeta}\beta_c + \kappa_c}{\frac{1}{1+\zeta}(\beta_d + \gamma_d) + \kappa_d} \tag{9}$$

[1] Appendix Lemma 1.

[2] Appendix Theorem 1.

On the left-hand side of equation (9), the ratio illustrates the marginal rate of substitution between green and grey infrastructure. The term reflects the additional amount of green infrastructure that needs to be invested in exchange for one unit of grey infrastructure to keep the level of water supply constant at the lowest cost possible. The right-hand side gives the marginal cost ratio between the two types of infrastructure. In the optimal situation where the water quality standard is met, the marginal cost of green infrastructure is equal to the marginal cost of grey infrastructure. In that case, there is no incentive for the social planner to make further adjustments to the green and grey infrastructure investment portfolio since this would only make the provision of safe drinking water more costly than in the optimum.

A further transformation of equation (9) leads to:

$$\frac{\alpha\, C^{\alpha-1}D^{1-\alpha}}{\frac{1}{1+\zeta}\beta_c+\kappa_c}-\frac{q\rho_c\, C^{\rho_c-1}D^{\rho_d}}{\frac{1}{1+\zeta}\beta_c+\kappa_c}=\frac{(1-\alpha)C^{\alpha}D^{-\alpha}}{\frac{1}{1+\zeta}(\beta_d+\gamma_d)+\kappa_d}-\frac{q\rho_d\, C^{\rho_c}D^{\rho_d-1}}{\frac{1}{1+\zeta}(\beta_d+\gamma_d)+\kappa_d} \tag{10}$$

The two terms on the left-hand side of equation (10) reflect the marginal net benefit of the green infrastructure, and the terms on the right-hand side quantify the same marginal benefits of grey infrastructure. Equation (10) states that the performance of grey and green infrastructure at the margin should be the same in the optimum.

The first term on the left-hand side can also be interpreted as quantifying the marginal cost-effectiveness of the green infrastructure, while the second term on the left-hand side reflects the marginal risk premium of green infrastructure. The same applies to the terms on the right-hand side for grey infrastructure. This risk premium is the amount of money that the social planner is willing to sacrifice to avoid the risk. If the variance of the treated water quality distribution goes up, the risk premium will be larger. In the optimum, the risk premium is a cost that deters a social planner from adopting, for example, a vast proportion of green infrastructure for water treatment. For green infrastructure, the marginal cost-effectiveness is believed to be higher than for grey infrastructure. Hence, at the same level of C and D, the first term on the left-hand side is higher than the same term on the right-hand side. However, due to the larger degree of uncertainty surrounding water quality supply from green infrastructure, the green infrastructure risk premium (the second term on the left-hand side) is higher than for grey infrastructure (the second term on the right-hand side). The optimal investment decision will be based on both aspects of the performance of green and grey infrastructure.

An exogenous change in the parameters will change the optimal allocation between green and grey infrastructure. Suppose β_c increases, meaning that the cost-effectiveness of grey infrastructure will improve compared to that of green infrastructure. Ceteris paribus, the marginal net benefit of grey infrastructure will hence also be larger than that of green infrastructure. In other words, the social planner will be incentivized to allocate more of the original investment from green to grey infrastructure[3].

Similarly, if the probability of meeting the water quality standard p, reflecting the risk-averseness of society as a whole, increases, this implies that society demands more certainty that water quality meets the existing global health standard, and hence green infrastructure as a more uncertain choice will become less attractive. In that case, the risk premiums of both green and grey infrastructure will go up too since q goes up. If we furthermore assume that the marginal cost-effectiveness of green infrastructure is larger than that of grey infrastructure, the increase of the green marginal risk premium will be larger than that of grey infrastructure. This, too, is then expected to result in a choice more in favour of grey infrastructure due to the increase in its relative marginal net benefit. The social planner will consequently be less willing to spend a large portion of the funding on green infrastructure[4].

Hence, for a society that prioritizes drinking water safety, the optimal allocation between green and grey infrastructure will be influenced by the four terms in equation (10). Despite its more favourable outcome in terms of cost-effectiveness, the productivity of green infrastructure is

[3] Appendix Theorem 2.

[4] Appendix Theorem 3.

surrounded by more uncertainty, increasing the risk of failing existing water quality standards. The alternative choice, grey infrastructure, will in that case be more attractive for a risk-averse social planner, even if the cost-effectiveness of this grey infrastructure is relatively weaker. Grey infrastructure is believed to be more controllable. Due to, among others, unpredictable weather conditions, green infrastructure is expected to introduce significant uncertainty to public water supply, which comes at a price that is reflected in a relatively higher risk premium.

2.3 Dynamic Model

In this section, the baseline model is expanded by examining the hydrological effects of forest growth over the years. Older forests have been found to provide more developed hydrological functions than younger forests (Filoso et al., 2017; Walters and Jenkins, 1992). Therefore, planting forests for water treatment now will notably benefit the future, and is expected to play only a limited role in the short term. A social planner hence faces the challenge of finding a balance between the future sustainable return from forests and current drinking water demand. Based on the static-comparative baseline model, we will include a dynamic component to evaluate the cost-effectiveness of forest growth over an infinite time horizon.

To this end, we divide green infrastructure into two categories, C_y and C_o. C_y denotes young forests or regrowth forests, and C_o means old forests or old-growth forests. The investment strategy will be determined at the beginning of each treatment period and can only be made in relation to the level of C_y and D. As in the baseline model, the social planner in the dynamic model faces the same water standard constraint. For each period, the treated water should pass the standard, and the social planner will need to find the optimal allocation of C_y and D to minimize the total water treatment costs. Compared to the baseline model, there are a number of important differences in this new dynamic model.

The first difference is the infrastructure stock change between periods. The technical lifetime of a typical water treatment facility is around 60 years (Bonton et al., 2012), after which the facility may be demolished. Forests older than 60 years still provide water services like water treatment (e.g. Waters and Jenkins, 1992; Sookhdeo and Druckenbrod, 2012). Adopting similar principles, we assume that after one period all D will be demolished, while for forests C_y will partially (i percent) grow in that period and become C_o and a proportion of C_o (l percent) from the previous period is expected to die off. As a result, the hydrological function of forests is rewritten as follows. For each period, if the current level of forest and grey infrastructure is C_y, C_o and D, the treated water quality in achieving the water standard now is: $N((\theta C_o + C_y)^{\alpha} D^{1-\alpha}, (C_o + C_y)^{2\rho_c} D^{2\rho_d})$. θ is a new variable capturing the age effect of old forests and is assumed to be larger than 1, indicating that the marginal effectiveness of older forest in providing water services is higher than that of younger forest (Filoso et al., 2017).

The second difference is the simplification of the cost structure. Construction costs are not discussed in this section because grey infrastructure construction and operation are happening in the same period. For green infrastructure, we use β_c^y and β_c^o to reflect the construction and operating cost. $\beta_c^y > \beta_c^o > 0$ since it is mainly young forest that will trigger construction costs, not so much old forest. Furthermore, depreciation costs for green and grey infrastructure are eliminated in the dynamic model. The young forest supplements the old forest and the share of the old forest that ultimately dies off. For simplicity reasons, we also assume that the social planner does not need to invest extra to facilitate the transition between time periods. The same forest capital stock will be maintained between periods, while the grey infrastructure is demolished and rebuilt. We merge these costs therefore also into a single infrastructure operation cost β_d.

For each period t, the dynamic problem can now be expressed as follows:

$$\min_{C_t^y D_t} \sum_{t=1}^{\infty} \zeta^{t-1} (\beta_c^o C_t^o + \beta_c^y C_t^y + \beta_d D_t) \tag{11}$$

$$s.t. \left(\theta\, C_t^o + C_t^y\right)^{\alpha} D_t^{1-\alpha} - q * \left(C_t^o + C_t^y\right)^{\rho_c} D_t^{\rho_d} \geq \bar{Q}$$

$$C_t^o = i * C_{t-1}^y + (1-l)C_{t-1}^o$$
$$C_0^o \geq 0$$

As specified in equation 11, the social planner at each discrete time t can modify the current investment in young forest or grey infrastructure. The state variable of the dynamic optimization problem is the old forest level that is still alive.

If we write this dynamic problem into the Hamiltonian, we get:

$$\mathcal{H} = -(\beta_c^o C_t^o + \beta_c^y C_t^y + \beta_d D_t) + \mu_t((\theta\, C_t^o + C_t^y)^{\alpha} D_t^{1-\alpha} - q * (C_t^o + C_t^y)^{\rho_c} D_t^{\rho_d} - \bar{Q}) + \zeta\lambda_{t+1}(i * C_t^y - l * C_t^o) \quad (12)$$

λ_t reflects the shadow price of forest in each period. This parameter indicates the scarcity of forest as its future water treatment benefit. μ_t is the Lagrangian multiplier, and ζ is as before the discount factor.

The marginal condition of the Hamiltonian has several components. The marginal effects of the grey and green infrastructure control variables D_t and C_t^y are set equal to zero. This gives us equations (13) and (15):

$$\frac{d\mathcal{H}}{dD_t} = -\beta_d + \mu_t((\theta\, C_t^o + C_t^y)^{\alpha} D_t^{-\alpha} * (1-\alpha) - q * (C_t^o + C_t^y)^{\rho_c} D_t^{\rho_d - 1} * (\rho_d)) = 0$$
(13)

which leads to equation (14)

$$\mu_t = \frac{\beta_d}{(\theta\, C_t^o + C_t^y)^{\alpha} D_t^{-\alpha} * (1-\alpha) - q * (C_t^o + C_t^y)^{\rho_c} D_t^{\rho_d - 1} * (\rho_d)} \quad (14)$$

$$\frac{d\mathcal{H}}{dC_t^y} = -\beta_c^y + \mu_t\left(\left(\theta\, C_t^o + C_t^y\right)^{\alpha-1} D_t^{1-\alpha} * (\alpha) - q * \left(C_t^o + C_t^y\right)^{\rho_c-1} D_t^{\rho_d} * \rho_c\right) + \lambda_{t+1} * \zeta * i = 0 \quad (15)$$

which can be rewritten as equation (16)

$$\lambda_{t+1} = 1/(i\zeta) * (\beta_c^y - \mu_t((\theta\, C_t^o + C_t^y)^{\alpha-1} D_t^{1-\alpha} * (\alpha) - q * \left(C_t^o + C_t^y\right)^{\rho_c-1} D_t^{\rho_d} * \rho_c)) \quad (16)$$

The marginal conditions above signify that the marginal net benefits for either further forest planting or grey infrastructure construction are zero in the optimum. Hence, any extra benefits due to the expansion of either type of infrastructure just offset the accompanying costs.

The marginal condition concerning grey infrastructure maps the Lagrangian multiplier λ_{t+1} towards the current marginal effectiveness and marginal cost. μ is the shadow price of changing the water standard. If the water quality standard goes up, μ indicates the additional amount of money it will cost to meet the new standard. In other words, if a social planner wants to change the hydrological service provided by either type of infrastructure, the shadow price converts the effect this has on reaching the water quality standard into a monetary value.

The second component of the Hamiltonian is the marginal condition concerning the state variable C_t^o:

$$\frac{d\mathcal{H}}{d\,C_t^o} = -\beta_c^o + \mu_t\left(\left(\theta\, C_t^o + C_t^y\right)^{\alpha-1} D_t^{1-\alpha} * \alpha * \theta - q * \left(C_t^o + C_t^y\right)^{\rho_c-1} D_t^{\rho_d} * \rho_c\right) - \lambda_{t+1} * \zeta * l = \lambda_t - \lambda_{t+1} * \zeta \quad (17)$$

This can be rewritten as:

$$\lambda_t = \mu_t\big(\theta\ C_t^o + C_t^y\big)^{\alpha-1}\ D_t^{1-\alpha} * \alpha * \theta - \beta_c^o - \mu_t * q * \big(C_t^o + C_t^y\big)^{\rho_c-1} D_t^{\rho_d} * \rho_c) + \lambda_{t+1} * \zeta * (1-l) \tag{18}$$

Here, λ_t reflects the current value of C_t^o. This value contains four important components that a social planner should take into account. The first term is the water treatment benefit. As more infrastructure is implemented, water quality will improve. The second term refers to the current operating cost. As more forests are planted and managed, the social planner will need to pay more operation costs. The third term can be considered a risk premium. In the baseline model, we already found that as more green infrastructure is implemented, the uncertainty of reaching the standard will increase. The final term refers to the expected net benefit for the future that is transferred by the remaining old-growth forest. The net benefit of the current forest stock hence consists of the current water treatment benefit and the future net benefit (i.e. minus the operation cost of green infrastructure) and the risk premium.

The final component is the transversality condition. Since we assume an infinite time horizon for this investment decision, there is no restriction on how much green and grey infrastructure can be implemented. The transversality condition then is:

$$\lim_{t\to\infty} \lambda_t = 0 \tag{19}$$

To find the optimal investment strategy, we can use the following condition and combine this with equations (16) and (18):

$$\lambda_t = 1/(i\zeta) * (\beta_c^y - \mu_{t-1}((\theta\ C_{t-1}^o + C_{t-1}^y\big)^{\alpha-1}\ D_{t-1}^{1-\alpha} * (\alpha) - q * \big(C_{t-1}^o + C_{t-1}^y\big)^{\rho_c-1} D_{t-1}^{\rho_d} * \rho_c)) \tag{20}$$

Combined, this yields:

$$\left(\beta_c^y - \mu_{t-1}\left(\left(\theta\, C_{t-1}^o + C_{t-1}^y\right)^{\alpha-1} D_{t-1}^{1-\alpha} * (\alpha) - q * \left(C_{t-1}^o + C_{t-1}^y\right)^{\rho_c-1} D_{t-1}^{\rho_d} * \rho_c\right)\right) = i\zeta * (\mu_t\left(\theta\, C_t^o + C_t^y\right)^{\alpha-1} D_t^{1-\alpha} * \alpha * \theta - \beta_c^o - \mu_t * q * \left(C_t^o + C_t^y\right)^{\rho_c-1} D_t^{\rho_d} * \rho_c) + \zeta * (1-l) * 1/(i\zeta) * (\beta_c^y - \mu_t((\theta\, C_t^o + C_t^y)^{\alpha-1} D_t^{1-\alpha} * (\alpha) - q * \left(C_t^o + C_t^y\right)^{\rho_c-1} D_t^{\rho_d} * \rho_c))) \quad (21)$$

The left-hand side reflects the net benefits resulting from the last period's young forest, while the right-hand side projects the present value of the net benefits for the next period. In the optimum, the net benefits from the current level of young forest are equal to the net discounted benefits in the future.

We can reorder the terms in equation (21) to get:

$$-\left(\beta_c^y + i\zeta\beta_c^o\right) + \left\{\mu_{t-1}\left(\theta\, C_{t-1}^o + C_{t-1}^y\right)^{\alpha-1} D_{t-1}^{1-\alpha} * (\alpha) + i\zeta\mu_t\left(\theta\, C_t^o + C_t^y\right)^{\alpha-1} D_t^{1-\alpha} * \alpha * \theta\right\} - \left\{\mu_{t-1} q * \left(C_{t-1}^o + C_{t-1}^y\right)^{\rho_c-1} D_{t-1}^{\rho_d} * \rho_c + i\zeta\mu_t * q * \left(C_t^o + C_t^y\right)^{\rho_c-1} D_t^{\rho_d} * \rho_c\right\} + 1/i * (1-l) * (\beta_c^y - \mu_t((\theta\, C_t^o + C_t^y)^{\alpha-1} D_t^{1-\alpha} * (\alpha) - q * \left(C_t^o + C_t^y\right)^{\rho_c-1} D_t^{\rho_d} * \rho_c))) = 0$$
(22)

The first term is the present value of the total operating cost. The second term is the intertemporal marginal water treatment benefit received from the forest investment, while the third term is the present value of the two-state sum of the risk premium. The final term projects the future net benefits of the remaining forest. The intertemporal net marginal benefit should be zero to minimize the total treatment cost. The above equation (22) hence gives social planners a guide to allocate the available funding.

Green infrastructure is in this section the sum of young and old forests. Compared with the baseline model, the future increase in water treatment benefits incentivizes investment decisions in current young forest. This future benefit induces the social planner to allocate a larger proportion of the available budget to green infrastructure. If the social planner values the future, the level of green infrastructure in the new dynamic model presented here will be larger than in the baseline model, holding other parameters and conditions constant.

Despite the future benefit of green infrastructure, having old forest may discourage investments in young forest. Suppose a social planner has a considerable amount of old forest already in the infrastructure portfolio. This might discourage investing more in young forest since the marginal benefit of these young trees is relatively low. The second term in equation (22) can explain this behaviour. The current marginal benefit of green infrastructure is small, while the intertemporal marginal risk premium (the third term) is at the same time increasing. This discourages a social planner to invest in more young forest and instead choose to invest more in grey infrastructure. Due to the increasing risk of potential loss of water services (i.e. not reaching the water quality standard) in the distant future associated with increasing green infrastructure, the social planner may face a high total cost in the future. The potential risk of having an abundance of forest may, in that case, offset the benefits of green infrastructure in terms of being relatively speaking more cost-effective than grey infrastructure.

Another interesting observation from the dynamic model is the composite effect of ζ and θ. As mentioned, future benefits are an important consideration in the social planner's decision making. However, the discount factor ζ may reduce the present value of any future advantage. ζ reflects how impatient a social planner is. If the social planner's ζ is small, (s)he will undervalue future outcomes. This is not implausible since studies in this field indicate that the time horizon is around 60 years. In other words, if ζ is close to zero, then this would make the cost minimization problem focus on the current period mainly. Hence, unless the future benefits from forest infrastructure offset the time preferences of a social planner, there might not be enough incentive for a social planner to invest in green infrastructure. The young forest survival rate, i, may furthermore reinforce the effect of discounting future benefits. Under increasing probabilities of young forest dying off, for example, due to wildfires, a social planner may be reluctant to invest more in green infrastructure if this adds to future outcome uncertainty. We discuss the expected impact of wildfires in the next section.

2.4 The Impact of Wildfires

Due to climate change, the frequency and intensity of extreme weather events are expected to increase (e.g., Cornwall, 2016). In the case of extremely dry weather conditions, the probability of wildfires increases (e.g., Flannigan et al., 2009). These wildfires can have significant detrimental effects on green infrastructure and the water services they provide (e.g., Emmerton et al., 2020). In this section, we extend the dynamic model to include the risk of a potential wildfire that will deplete part of the forest and hence harm the hydrological services provided by the forest in the watershed.

As before, the social planner faces the same standard constraint. In this new model, we distinguish between two possible periods: without or with wildfires. The regular period represents a period without a wildfire. This period is identical to the dynamic model in which C_t^y, C_t^o and D_t^r solve the water quality standard constraint, and the model follows a similar trajectory through time as the dynamic model. The social planner determines the optimal level of investment in young forest C_t^y and grey infrastructure D_t^r each period given the current amount of old-growth forest. During a wildfire period, the wildfire will destroy part of the forest. We assume that the destruction is a linear function of C and the age of the forest. Only τ_y amount of young forest and τ_o amount of old forest will be left after the fire. Given the fact that old-growth forest may have a higher burn intensity, it is expected to be more depleted after a wildfire (Parisien et al., 2020), and we therefore assume $\tau_y > \tau_o$. Since society will still demand the same water quality, the social planner needs to invest extra in grey infrastructure to meet the standard, both to replace the lost water services from green infrastructure and treat the extra polluted water after a wildfire (Burton et al., 2016). In addition, given the replanting challenges after a wildfire (Jones et al., 2017), we assume that a central planner also faces higher reforestation cost, where $R\left(C_{t+1}^y\right)$ reflects the forest volume loss. As before in the previous section, the depreciation cost of grey infrastructure are included in the operation costs. Hence, $\tau_y C_y + \tau_o C_o$, D_f and $R\left(C_{t+1}^y\right)$ will solve the objective function of cost minimization under the water quality constraint.

The forest fire rate is a function of the level of unprotected green infrastructure. Protected green infrastructure refers to the forest that is treated to reduce the risk of wildfires or mitigate wildfire damage costs. Protecting green infrastructure costs money, and is also referred to as fuel treatment costs (Jones, 2017). The proportion of forest that is unprotected will be denoted here as $\eta(C_y + zC_o)$. The parameter z, which is larger than 1, reflects the higher probability of old-growth forest catching fire (Parisien et al.,2020). η has a value between 0 and 1, where 0 implies that the whole forest is protected and 1 that none of the forest is protected. We assume that the protection cost is $T(\eta)(C_y + C_o)$. This protection cost function is decreasing with respect to η, where $T(1)$ is zero and $T(0)$ approaches infinity.

The goal of the social planner for this wildfire model is identical to the dynamic one, namely minimizing the total costs of water treatment, taking into account the potential wildfire risk. As before, the water treatment process needs to meet the standard. Once we combine all assumptions and conditions, the dynamic model with the wildfire extension looks as follows:

$$\min_{C_t, D_t^r, D_t^f, \eta_t} f(x) = \sum_{t=1}^{\infty} \zeta^{t-1} (P\left(\eta_t\left(C_t^y + zC_t^o\right)\right)\left(\beta_c^y \tau_y C_t^y + \beta_c^o \tau_o C_t^o + \beta_d D_t^f + \right.$$

$$T(\eta_t)\left(C_t^y + C_t^o\right) + R\left(C_{t+1}^y\right)) + (1 - P\left(\eta_t\left(C_t^y + zC_t^o\right)\right))\left(\beta_c^y C_t^y + \beta_c^o C_t^o + \beta_d D_t^r + \right.$$

$$\left. T(\eta_t)\left(C_t^y + C_t^o\right)\right))$$

$$s.t. \left(\theta\, C_t^o + C_t^y\right)^{\alpha} (D_t^r)^{1-\alpha} - q * \left(C_t^o + C_t^y\right)^{\rho_c} (D_t^r)^{\rho_d} \geq \bar{Q}$$

$$\left(\theta\, \tau_o C_t^o + \tau_y C_t^y\right)^{\alpha} \left(D_t^f\right)^{1-\alpha} - q * \left(\tau_o C_t^o + \tau_y C_t^y\right)^{\rho_c} \left(D_t^f\right)^{\rho_d} \geq \bar{Q}$$

$$C_{t+1}^o = \left(1 - P\left(\eta_t\left(C_t^y + zC_t^o\right)\right)\right) * \left(C_t^y * i + (1-l)C_t^o\right) + P\left(\eta_t\left(C_t^y + zC_t^o\right)\right) * (\tau_y C_t^y * i + \tau_o(1-l)C_t^o)$$

$$C_0^o \geq 0 \tag{23}$$

This extension characterizes wildfire risk and associated costs separately in the objective function instead of incorporating the risk in the variance of the green infrastructure production function or in a separate forest transition function. Compared to the dynamic model, this extended model describes a pathway where during a wildfire period, the social planner will incur extra costs. These damage costs consist of two main categories: direct capital loss and indirect treatment loss. For the capital loss, the social planner will incur additional reforestation costs at the beginning of the next period. The treatment loss is offset by the implemented additional grey infrastructure.

Fire prevention makes green infrastructure more expensive. Compared to the dynamic model, the optimal C_t^y considering wildfires should hence be less than in the dynamic model. Considering that the chance of wildfire increases with extra green infrastructure, also the uncertainty surrounding the effectiveness of green infrastructure in reaching the water quality standard increases. In this wildfire model, green infrastructure is, therefore, less preferred than in the baseline or dynamic model.

We can transform the model into the following Hamiltonian:

$$\underset{C_t, D_t^r, D_t^f, \eta_t}{\mathcal{H}} = -\left(P\left(\eta_t\left(C_t^y + zC_t^o\right)\right)\left(\beta_c^y \tau_y C_t^y + \beta_c^o \tau_o C_t^o + \beta_d D_t^f + T(\eta_t)\left(C_t^y + C_t^o\right)\right) + \left(1 - P\left(\eta_t\left(C_t^y + zC_t^o\right)\right)\right)\left(\beta_c^y C_t^y + \beta_c^o C_t^o + \beta_d D_t^r + T(\eta_t)\left(C_t^y + C_t^o\right) + R\left(C_{t+1}^y\right)\right) + \mu_1\left(\left(\theta\, C_t^o + C_t^y\right)^\alpha (D_t^r)^{1-\alpha} - q * \left(C_t^o + C_t^y\right)^{\rho_c} (D_t^r)^{\rho_d} - \bar{Q}\right) + \mu_2\left(\left(\theta\, \tau_o C_t^o + \tau_y C_t^y\right)^\alpha \left(D_t^f\right)^{1-\alpha} - q * \left(\tau_o C_t^o + \tau_y C_t^y\right)^{\rho_c}\left(D_t^f\right)^{\rho_d} - \bar{Q}\right) + \zeta\lambda_{t+1}\left(C_t^y * i * \left(1 - P\left(\eta_t\left(C_t^y + zC_t^o\right)\right)\left(1 - \tau_y\right)\right) - C_t^o\left(l + P\left(\eta_t\left(C_t^y + zC_t^o\right)\right) * (1 - \tau_o)(1 - l)\right)\right) \tag{24}$$

Similar to the previous dynamic model description, the first-order conditions underlying equation (24) yield equations (25) and (27):

$$\frac{d\mathcal{H}}{dC_t^y} = -\left\{\left(\beta_c^y + T(\eta)\right) * \left(1 - P\left(\eta_t\left(C_t^y + zC_t^o\right)\right)\right) + \left(\beta_c^y \tau_y + T(\eta)\right) * P\left(\eta_t\left(C_t^y + zC_t^o\right)\right)\right\} - P'\left(\eta_t\left(C_t^y + zC_t^o\right)\right) * \eta_t * \left(\beta_d\left(D_t^f - D_t^r\right) - \beta_c^y C_t^y\left(1 - \tau_y\right) - \beta_c^o C_t^o(1 - \tau_o)\right) + \mu_1\left(\left(\theta\, C_t^o + C_t^y\right)^{\alpha-1}(D_t^r)^{1-\alpha} * \alpha\, - q * \left(C_t^o + C_t^y\right)^{\rho_c - 1}(D_t^r)^{\rho_d} * \rho_c\right) + \mu_2\left(\left(\theta\, \tau_o C_t^o + \tau_y C_t^y\right)^{\alpha-1}\left(D_t^f\right)^{1-\alpha} * \alpha\tau_y\, - q * \left(\tau_o C_t^o + \tau_y C_t^y\right)^{\rho_c - 1}\left(D_t^f\right)^{\rho_d} * \rho_c \tau_y\right) + \zeta\lambda_{t+1}\left(i * \left(1 - P\left(\eta_t\left(C_t^y + zC_t^o\right)\right)\left(1 - \tau_y\right)\right)\right) - \zeta\lambda_{t+1}\left(i * \left(P'\left(\eta_t\left(C_t^y + zC_t^o\right)\right) * \eta_t\left(1 - \tau_y\right)\right)\right) = 0 \tag{25}$$

Equation (25) highlights some new aspects of young forest compared to equation (15). First of all, due to the potential wildfire threat, the current hydrological benefits are reduced. Moreover, the extra costs related to forest protection reduce the cost-effectiveness of green infrastructure and consequently the incentive for the social planner to invest in more young forest. Secondly, the long term benefit of having more forest also becomes more uncertain because of potential future wildfire depletion. Both the expected depletion and the effect of wildfires on the young forest's survival rate i, specified in the previous section, will negatively impact the long-term benefits. Besides the reduction in cost-effectiveness, having a larger stock of forest will also influence the future fire probability, as can be seen in the last term of equation (25). Together, these modifications make green infrastructure a less preferable alternative for drinking water treatment. We can reorder equation (25) into:

$$\lambda_{t+1} = \Bigg(-\left\{\left(\beta_c^y + T(\eta)\right) * \left(1 - P\left(\eta_t\left(C_t^y + zC_t^o\right)\right)\right) + \left(\beta_c^y \tau_y + T(\eta)\right) * P\left(\eta_t\left(C_t^y + zC_t^o\right)\right)\right\} - P'\left(\eta_t\left(C_t^y + zC_t^o\right)\right) * \eta_t * \Big(\beta_d\left(D_t^f - D_t^r\right) + R\left(C_{t+1}^y\right) - \beta_c^y C_t^y\left(1 - \tau_y\right) -$$

$$\beta_c^o C_t^o(1-\tau_o)\Big) + \mu_1\left(\left(\theta\, C_t^o + C_t^y\right)^{\alpha-1}(D_t^r)^{1-\alpha} * \alpha\ - q * \left(C_t^o + C_t^y\right)^{\rho_c-1}(D_t^r)^{\rho_d} * \rho_c\right) +$$

$$\mu_2\left(\left(\theta\,\tau_o C_t^o + \tau_y C_t^y\right)^{\alpha-1}\left(D_t^f\right)^{1-\alpha} * \alpha\tau_y\ - q * \left(\tau_o C_t^o + \tau_y C_t^y\right)^{\rho_c-1}\left(D_t^f\right)^{\rho_d} * \rho_c\tau_y\right)\Bigg) *$$

$$\left(-\frac{1}{\zeta} * \frac{1}{i*\left(1-P\left(\eta_t\left(C_t^y+zC_t^o\right)\right)(1-\tau_y)\right)-i*\left(P'\left(\eta_t\left(C_t^y+zC_t^o\right)\right)*\eta_t(1-\tau_y)\right)}\right) \tag{26}$$

For equation (26), the shadow price of the next period old forests should match with the current net benefit of young forests. The current net benefit includes the expected operation cost, the hydrological benefit and the risk premium similar to the previous extension.

The first-order condition of the state variable gives:

$$\frac{d\mathcal{H}}{dC_t^o} = -\Big\{\left(\beta_c^o + T(\eta)\right) * \left(1 - P\left(\eta_t\left(C_t^y + zC_t^o\right)\right)\right) + \left(\beta_c^o\tau_o + T(\eta)\right) * P\left(\eta_t\left(C_t^y +\right.\right.$$

$$\left.\left.zC_t^o\right)\right)\Big\} - P'\left(\eta_t\left(C_t^y + zC_t^o\right)\right) * \eta_t * z * \Big(\beta_d\left(D_t^f - D_t^r\right) + R\left(C_{t+1}^y\right) - \beta_c^y C_t^y\left(1-\tau_y\right) -$$

$$\beta_c^o C_t^o(1-\tau_o)\Big) + \mu_1\left(\left(\theta\, C_t^o + C_t^y\right)^{\alpha-1}(D_t^r)^{1-\alpha} * \alpha * \theta\ - q * \left(C_t^o + C_t^y\right)^{\rho_c-1}(D_t^r)^{\rho_d} *\right.$$

$$\left.\rho_c\right) + \mu_2\left(\left(\theta\,\tau_o C_t^o + \tau_y C_t^y\right)^{\alpha-1}\left(D_t^f\right)^{1-\alpha} * \alpha\tau_o\theta\ - q * \left(\tau_o C_t^o + \tau_y C_t^y\right)^{\rho_c-1}\left(D_t^f\right)^{\rho_d} *\right.$$

$$\left.\rho_c\tau_o\right) - \zeta\lambda_{t+1}\left(l + \left(P\left(\eta_t\left(C_t^y + zC_t^o\right)\right)(1-\tau_o) * (1-l)\right)\right) - \zeta\lambda_{t+1}\Bigg(\Bigg(P'\left(\eta_t\left(C_t^y +\right.\right.$$

$$\left.\left.zC_t^o\right)\right) * \eta_t * z * (1-l)(1-\tau_o)\Bigg)\Bigg) = \lambda_t - \zeta\lambda_{t+1} \tag{27}$$

This can be reformulated as follows:

$$\lambda_t = -\Big\{\left(\beta_c^o + T(\eta)\right) * \left(1 - P\left(\eta_t\left(C_t^y + zC_t^o\right)\right)\right) + \left(\beta_c^o\tau_o + T(\eta)\right) * P\left(\eta_t\left(C_t^y + zC_t^o\right)\right)\Big\} -$$

$$P'\left(\eta_t\left(C_t^y + zC_t^o\right)\right) * \eta_t * z * \Big(\beta_d\left(D_t^f - D_t^r\right) + R\left(C_{t+1}^y\right) - \beta_c^y C_t^y\left(1-\tau_y\right) - \beta_c^o C_t^o(1-$$

$$\left.\tau_o)\right) + \mu_1\left(\left(\theta\, C_t^o + C_t^y\right)^{\alpha-1}(D_t^r)^{1-\alpha} * \alpha * \theta\ - q * \left(C_t^o + C_t^y\right)^{\rho_c-1}(D_t^r)^{\rho_d} * \rho_c\right) +$$

$$\mu_2\left(\left(\theta\,\tau_o C_t^o + \tau_y C_t^y\right)^{\alpha-1}\left(D_t^f\right)^{1-\alpha} * \alpha\tau_o\theta\ - q * \left(\tau_o C_t^o + \tau_y C_t^y\right)^{\rho_c-1}\left(D_t^f\right)^{\rho_d} * \rho_c\tau_o\right) +$$

$$\zeta\lambda_{t+1}\left(1-l-\left(P\left(\eta_t\left(C_t^y+zC_t^o\right)\right)(1-\tau_o)*(1-l)\right)\right)-\zeta\lambda_{t+1}\left(\left(P'\left(\eta_t\left(C_t^y+zC_t^o\right)\right)*\eta_t*z*(1-l)(1-\tau_o)\right)\right) \tag{28}$$

Equation (28) states that in the optimum the shadow price of the current stock of old-growth forest equals its current and next period hydrological benefits minus the aggregate costs of providing these benefits. These costs include operation costs, potential wildfire damage costs, and the extra potential wildfire costs caused by higher levels of forests. Given the higher chance of wildfires and the risk associated with old-growth forest, a social planner with a higher stock of (old-growth) green infrastructure is less likely to expand the existing green infrastructure.

Another control variable that the social planner can apply is the proportion of forest receiving protection. The optimal level of protection should satisfy the following condition:

$$\frac{d\mathcal{H}}{d\eta}=-(P\left(\eta_t\left(C_t^y+zC_t^o\right)\right)(T'(\eta_t)\left(C_t^y+C_t^o\right))+(1-P\left(\eta_t\left(C_t^y+zC_t^o\right)\right))(T'(\eta_t)\left(C_t^y+C_t^o\right))-P'\left(\eta_t\left(C_t^y+zC_t^o\right)\right)\left(\beta_c^y(\tau_y-1)C_t^y+R\left(C_{t+1}^y\right)+\beta_c^o(\tau_o-1)C_t^o+\beta_d(D_t^f-D_t^r)\right)*(C_t^y+zC_t^o)+\zeta\lambda_{t+1}(C_t^y*i*\left(-P'\left(\eta_t\left(C_t^y+zC_t^o\right)\right)\left(1-\tau_y\right)*\left(C_t^y+zC_t^o\right)\right)-C_t^o(P'\left(\eta_t\left(C_t^y+zC_t^o\right)\right)*(1-\tau_o)(1-l)*\left(C_t^y+zC_t^o\right)))=0 \tag{29}$$

The above equation can be rewritten as:

$$P'\left(\eta_t\left(C_t^y+zC_t^o\right)\right)((\beta_c^y\left(\tau_y-1\right)C_t^y+\beta_c^o(\tau_o-1)C_t^o+R\left(C_{t+1}^y\right)+\beta_d\left(D_t^f-D_t^r\right))+\zeta\lambda_{t+1}(C_t^y*i*\left(1-\tau_y\right)+C_t^o*(1-\tau_o)(1-l)))*\left(C_t^y+zC_t^o\right)=(T'(\eta_t)\left(C_t^y+C_t^o\right) \tag{30}$$

The left-hand side of equation (30) represents the marginal cost difference between the period without and with a wildfire. This includes the extra water treatment costs for the current period and the loss of green infrastructure for future water treatment. Having a smaller η can reduce the probability of a wildfire, which can then further reduce the expected damage costs. Since old forest may trigger a higher chance of wildfire and causes more damage, the existing level of old-growth forest will alter the optimal level of η. Suppose there is a substantial stock of old forest to treat water at the start of the decision period, then the wildfire risk factor z will increase the potential damage under the current situation. The potential damage cost of the current situation will hence be higher than a situation with a relatively lower stock of old forest. This will incentivize the social planner to adopt a lower level of η to reduce the chance of a wildfire. The term on the right-hand side refers to the expected cost increase if the social planner demands a lower η. Having a relatively high η is risky for society, whilst spending too much on fire prevention will be less cost-effective. Equation (30) indicates, as expected, that the optimal level of η is found where the marginal cost of wildfire protection equals the marginal net benefits of reducing the risk of having a wildfire on water treatment.

2.5 The Impact of Long-term Climate Change

Global warming will increase the probability of extreme weather events like droughts, and droughts impact the risk of wildfires. Hence, once we include climate change into our model, the wildfire probability will increase over time, and it will become more likely for social planners to face a wildfire in the future. This will change various aspects of the dynamic model. At the same time, green infrastructure contributes significantly to carbon sequestration. In a global context, forests' carbon sequestration capacity reduces the speed of climate change (Law et al., 2018; Smyth et al., 2018). Thus, investing in green infrastructure and increasing the forest area is expected to slow down the pace of global warming and reduce the potential risk of future wildfires compared to relatively low levels of green infrastructure.

From equation (30), we can see that an increasing probability of wildfires will have an influence on the optimal level of η. Increasing the level of forest protection, in turn, reduces the potential wildfire probability and at the same time better-protected forest or green infrastructure has a positive effect on wildfire risk. Put differently, if forest wildfire prevention becomes more effective under increasing drought conditions, then the social planner will be incentivized to adopt more fire prevention measures. Combined with the moderating effect of green infrastructure on global warming, this will reduce the risk of wildfires due to extreme weather events. The extension of the model presented in the previous section would, therefore, consist of the potential wildfire risk reduction effect of forest investments due to their impact on climate change. Although it may be hard to demonstrate that the potential effect of slowing down climate change will reduce wildfire risks in the short run, there may be a long-run benefit to mitigate the negative impacts of climate change on increasing drought conditions and enhance forest safety.

In order to reflect this long-term climate change effect, we define a drought variable $d(C_{t-1}^{y})$, which will become effective one period after the social planner decides about the water treatment infrastructure portfolio. It has been argued that young forest has a higher carbon sequestration capability than old-growth forest (Pugh et al., 2019). We simplify this finding in the literature by assuming that only the stock of young forest in the previous period has a moderating effect on droughts and hence wildfire risk in the current period. $d(C_{t-1}^{y})$ is a decreasing function, reflecting the negative correlation between future drought conditions and the current stock of young forest. In this section, the probability of a potential wildfire thus will be $P(d(C_{t-1}^{y}) * \eta_t\left(C_t^y + zC_t^o\right))$, meaning that a future drought will increase the wildfire rate. Integrating this new feature into the dynamic model, we obtain the following objective function:

$$\min_{C_t, D_t^r, D_t^f, \eta_t} f(x) = \sum_{t=1}^{\infty} \Big(P\left(d(C_{t-1}^{y})\eta_t\left(C_t^y + zC_t^o\right)\right)\left(\beta_c^y \tau_y C_t^y + \beta_c^o \tau_o C_t^o + \beta_d D_t^f + T(\eta_t)\left(C_t^y + C_t^o\right) + R\left(C_{t+1}^y\right)\right) + \left(1 - P\left(d(C_{t-1}^{y})\eta_t\left(C_t^y + zC_t^o\right)\right)\right)\left(\beta_c^y C_t^y + \beta_c^o C_t^o + \beta_d D_t^r + T(\eta_t)\left(C_t^y + C_t^o\right)\right)\Big)$$

$$s.t. \left(\theta\, C_t^o + C_t^y\right)^{\alpha} (D_t^r)^{1-\alpha} - q * \left(C_t^o + C_t^y\right)^{\rho_c} (D_t^r)^{\rho_d} \geq \bar{Q}$$

$$\left(\theta\, \tau_o C_t^o + \tau_y C_t^y\right)^{\alpha} \left(D_t^f\right)^{1-\alpha} - q * \left(\tau_o C_t^o + \tau_y C_t^y\right)^{\rho_c} \left(D_t^f\right)^{\rho_d} \geq \bar{Q}$$

$$C_{t+1}^o = \left(1 - P\left(d(C_{t-1}^y)\eta_t\left(C_t^y + zC_t^o\right)\right)\right) * \left(C_t^y * i + (1-l)C_t^o\right)$$

$$+ P\left(d(C_{t-1}^y)\eta_t\left(C_t^y + zC_t^o\right)\right) * (\tau_y C_t^y * i + \tau_o(1-l)C_t^o)$$

$$C_0^o \geq 0 \tag{31}$$

The Hamiltonian of the cost minimization problem is:

$$\underset{C_t, D_t^r, D_t^f, \eta_t}{\mathcal{H}} = -(P\left(d\left(C_{t-1}^y\right)\eta_t\left(C_t^y + zC_t^o\right)\right)\left(\beta_c^y \tau_y C_t^y + \beta_c^o \tau_o C_t^o + \beta_d D_t^f + T(\eta_t)\left(C_t^y + C_t^o\right) + R\left(C_{t+1}^y\right)\right) + (1 - P\left(d\left(C_{t-1}^y\right)\eta_t\left(C_t^y + zC_t^o\right)\right))\left(\beta_c^y C_t^y + \beta_c^o C_t^o + \beta_d D_t^r + T(\eta_t)\left(C_t^y + C_t^o\right)\right)) + \mu_1\left(\left(\theta\, C_t^o + C_t^y\right)^{\alpha}(D_t^r)^{1-\alpha} - q * \left(C_t^o + C_t^y\right)^{\rho_c}(D_t^r)^{\rho_d} - \bar{Q}\right) + \mu_2\left(\left(\theta\, \tau_o C_t^o + \tau_y C_t^y\right)^{\alpha}\left(D_t^f\right)^{1-\alpha} - q * \left(\tau_o C_t^o + \tau_y C_t^y\right)^{\rho_c}\left(D_t^f\right)^{\rho_d} - \bar{Q}\right) + \zeta\lambda_{t+1}(C_t^y * i * \left(1 - P\left(d\left(C_{t-1}^y\right)\eta_t\left(C_t^y + zC_t^o\right)\right)\left(1 - \tau_y\right)\right) - C_t^o(l + P(d\left(C_{t-1}^y\right)\eta_t\left(C_t^y + zC_t^o\right)) * (1 - \tau_o)(1 - l))) + \zeta o_{t+1}(C_t^y - C_{t-1}^y) \tag{32}$$

The first order condition with respect to the stock of young forest then becomes:

$$\frac{d\mathcal{H}}{dC_t^y} = -\left\{\left(\beta_c^y + T(\eta)\right) * \left(1 - P\left(d\left(C_{t-1}^y\right)\eta_t\left(C_t^y + zC_t^o\right)\right)\right) + \left(\beta_c^y \tau_y + T(\eta)\right) * P\left(d\left(C_{t-1}^y\right)\eta_t\left(C_t^y + zC_t^o\right)\right)\right\} - P'\left(d\left(C_{t-1}^y\right)\eta_t\left(C_t^y + zC_t^o\right)\right) * \eta_t * \left(\beta_d\left(D_t^f - D_t^r\right) + R\left(C_{t+1}^y\right) - \beta_c^y C_t^y\left(1 - \tau_y\right) - \beta_c^o C_t^o\left(1 - \tau_o\right)\right) + \mu_1\left(\left(\theta\, C_t^o + C_t^y\right)^{\alpha-1}(D_t^r)^{1-\alpha} * \alpha - q * \left(C_t^o + C_t^y\right)^{\rho_c - 1}(D_t^r)^{\rho_d} * \rho_c\right) + \mu_2\left(\left(\theta\, \tau_o C_t^o + \tau_y C_t^y\right)^{\alpha-1}\left(D_t^f\right)^{1-\alpha} * \alpha\tau_y - q * \left(\tau_o C_t^o + \right.\right.$$

$$\tau_y C_t^y\Big)^{\rho_c-1}\left(D_t^f\right)^{\rho_d} * \rho_c\tau_y\Big) + \zeta\lambda_{t+1}\left(i * \left(1 - P\left(d\left(C_{t-1}^y\right)\eta_t\left(C_t^y + zC_t^o\right)\right)\left(1-\tau_y\right)\right)\right) -$$

$$\zeta\lambda_{t+1}\left(i * \left(P'\left(d\left(C_{t-1}^y\right)\eta_t\left(C_t^y + zC_t^o\right)\right) * \eta_t\left(1-\tau_y\right)\right)\right) + \zeta o_{t+1} = 0 \qquad (33)$$

The result presented in equation (33) is similar to equation (25) in the previous section. The climate change mitigation effect in the next period from the investment in young forest in the current period, ζo_{t+1}, is included as an additional benefit that a social planner will take into account. The shadow price of this climate change mitigation effect is o_{t+1}. To find the exact value of the Hamiltonian multiplier, we examine the first-order condition with respect to the state variable C_{t-1}^y :

$$\frac{d\mathcal{H}}{dC_{t-1}^y} = -P'\left(d\left(C_{t-1}^y\right)\eta_t\left(C_t^y + zC_t^o\right)\right) * d'\left(C_{t-1}^y\right) * \eta_t * \left(\beta_d\left(D_t^f - D_t^r\right) + R\left(C_{t+1}^y\right) -\right.$$

$$\left.\beta_c^y C_t^y\left(1-\tau_y\right) - \beta_c^o C_t^o(1-\tau_o)\right) - \zeta\lambda_{t+1}\left(C_t^y i\left(1-\tau_y\right) * P'\left(d\left(C_{t-1}^y\right)\eta_t\left(C_t^y + zC_t^o\right)\right) *\right.$$

$$\left. d'\left(C_{t-1}^y\right) - C_t^o(1-\tau_o)(1-l) * P'\left(d\left(C_{t-1}^y\right)\eta_t\left(C_t^y + zC_t^o\right)\right) * d'\left(C_{t-1}^y\right)\right) - \zeta o_{t+1} = o_t -$$

$$\zeta o_{t+1} \qquad (34)$$

which we can reorder into:

$$o_t = -P'\left(d\left(C_{t-1}^y\right)\eta_t\left(C_t^y + zC_t^o\right)\right) * d'\left(C_{t-1}^y\right) * \eta_t * \left(\beta_d\left(D_t^f - D_t^r\right) + R\left(C_{t+1}^y\right) -\right.$$

$$\left.\beta_c^y C_t^y\left(1-\tau_y\right) - \beta_c^o C_t^o(1-\tau_o)\right) - \zeta\lambda_{t+1}\left(C_t^y i\left(1-\tau_y\right) * P'\left(d\left(C_{t-1}^y\right)\eta_t\left(C_t^y + zC_t^o\right)\right) *\right.$$

$$\left. d'\left(C_{t-1}^y\right) - C_t^o(1-\tau_o)(1-l) * P'\left(d\left(C_{t-1}^y\right)\eta_t\left(C_t^y + zC_t^o\right)\right) * d'\left(C_{t-1}^y\right)\right) \qquad (35)$$

The shadow price of the marginal effect of climate change mitigation includes several benefits generated by the young forest in the previous period. First, having more young forest, carbon sequestration reduces the probability of having a wildfire one period later. As the first term of equation (35) indicates, if we assume that having a wildfire triggers additional operation costs, the cost difference between a period without and with a wildfire can be considered as the avoided cost of not having a wildfire. Thus, the additional young forest can reduce the expected operation cost in an indirect way other than described in the section with the dynamic model. By reducing the risk of wildfire, the stock of forest that will remain intact will continue to generate further long-term benefits. In that sense, the additional benefit of investing in green infrastructure under these conditions is the sum of wildfire mitigation and long-term water treatment.

If we compare equation (33) with the solution without the modelled climate change effect, as in equation (25), the drought mitigation effect is expected to encourage the social planner to expand the stock of young forest to reduce future wildfire risks. Investment behaviour in green infrastructure now will influence the future benefits obtained from a change in wildfire probability. This future benefit is different from the one we observed in the dynamic model. Instead of a direct impact on the provided water service, moderating climate change will mainly alter the probability of a wildfire. However, many of the dynamic model interpretations continue to hold for this extended model. For instance, the discount factor applied by the social planner will affect the allocation between green and grey infrastructure. A positive discount factor will play down any potential future risk. For a social planner with a high discount factor, the drought mitigation effect may not be significant. Under such conditions, it will not be optimal to invest in green infrastructure now to protect benefits in the future.

The drought effect $d\left(C_{t-1}^{y}\right)$ influences future outcomes. If society values the future and invests in green infrastructure, the risks of droughts and wildfires will reduce. This behaviour may potentially reduce future water treatment costs and the loss of water services as indicated in equation (35). Based on the additional benefits provided by forests as a green solution to slow down climate change, the optimal level of green infrastructure should increase compared to the investment decision in the dynamic model without climate change. However, increasing the stock of forest at the same time increases the cost of current forest management as this will increase the probability of wildfires. In other words, investing more in forests now will transfer part of the future climate change risks to the present. A social planner will need to find a balance between these two risks. Finally, our model only captures the damage related to the provision of safe drinking water. Once we include additional social welfare losses associated with wildfires, like public unrest, social and economic disruptions, society may become more inclined to avoid them. In that case, the social planner is expected to be willing to incur more costs for fire prevention.

2.6 Simulation results

In this section, we numerically simulate the optimal investment levels across the three previously presented models, measured as the total costs of green and grey infrastructure, based on different assumptions related to initial levels of old forests in the software R. The starting values for the key parameters in the numerical simulation are presented in Table 2.1. The parameter values follow the assumptions described in the previous sections. In order to increase the level of realism, we change the infrastructures' stocks and flows over time, and impose a restriction on space. We assume that the average lifetime of a water treatment plant is about 60 years (Bonton, 2012), and the forests in our study mature in around 20-30 years (Asbjornsen et al., 2017). To keep things simple, we define the time it takes for young forests to grow into a mature forest to be 30 years. We define discrete investment decision periods to last 30 years and grey infrastructure hence to last for two discrete periods, while young forest grows old and then partially dies off in one discrete period. The total time horizon for the simulation is set to be 300 years. Thus, a social planner is expected to decide 10 times at the beginning of each investment period how to choose between grey and green infrastructure. The discount factor for costs and benefits occurring over time is less than one. Due to spatial limitations, we assume that there exists a physical maximum to implement green infrastructure, and we indicate this as a percentage, where 100% means that green infrastructure has reached its full capacity.

The operating cost parameters follow the following ranking: $\beta_c^o < \beta_c^y < \beta_d$. In the model with wildfire risk, we assume that the reforestation cost is higher than these three operating costs. Thus, facing a risk of wildfire is expected to negatively influence decision-making for green infrastructure due to the significant recovery cost. Due to the assumption that grey infrastructure provides a flow of water services over two time periods, we identify a separate grey infrastructure construction cost that the social planner incurs when deciding to invest more in the current stock of grey infrastructure. Green infrastructure provides hydrological services over a longer period of time unless the forest dies off or is destroyed due to a wildfire. For the overall water treatment performance of grey and green infrastructure, the green infrastructure is as before more cost-effective but riskier. The Cobb-Douglas parameter for green infrastructure's treatment capacity α is greater than the variance parameters ρ_c and ρ_d in securing a unique solution. The water quality standard and safety threshold value are both positive, reflecting a risk-averse society as defined in the baseline model.

Table 2-1 Starting Values for Parameters Used in the Simulation

Parameter	Description	Value
β_c^y	Operation cost of young forests	200
β_c^o	Operation cost of old forests	100
β_d	Operation cost of grey infrastructure	300
K_d	Construction cost of grey infrastructure	100
$R(C)$	Recovery cost after a wildfire	$400 * C$
$\bar{Q}$	Water quality standard	100
q	Water safety threshold	1.96
i	Young forest survival rate	0.9
l	Old forest death rate	0.2
α	Green infrastructure water treatment effectiveness	0.7
θ	Old forest water treatment ageing effect	1.2
ρ_c	Green infrastructure risk parameter	0.3
ρ_d	Grey infrastructure risk parameter	0.2

τ_y	Residual young forest post-fire ratio	0.6
τ_o	Residual old forest post-fire ratio	0.4
z	Old forest fire risk factor	1.2
$P(C)$	Wildfire probability function	tanh $((1-\eta)$C/1000)
$T(\eta)$C	Fuel treatment cost function	$10* \eta\left(C_t^y + C_t^o\right)^2$
$d\left(C_{t-1}^y\right)$	Carbon sequestration effect of green infrastructure (young forest)	$\dfrac{1}{C_{t-1}^y * 0.5 + 1}$
T	Time horizon	300 years
C_0^o	Initial old forest (green infrastructure capacity)	0-100%
ζ	Discount factor	0.9

A key parameter in the simulation presented here is the initial stock of old forest reflecting different baseline scenarios across a continuum of forest abundance, from an abundance of forest to a complete lack of forest. Depending on the presence of different degrees of old forest at the start of the decision-making period, the social planner may exhibit different decision-making behaviour with regards to investing in young forests. The set of parameters that focus on the characteristics and age composition of forests is aligned with our assumptions in the dynamic model described in section 3. The survival rate of old forest $(1-l)$ is higher than the survival rate *i* for young forest (Lorimer et al., 2001). Similarly, the ageing effect of old forest on water treatment is larger than one, implying that old forest provides higher hydrological benefits than young forest. For the sake of simplicity, we do not account for forest management practices that involve thinning forests to reduce forest levels. Therefore, under the specification of the dynamic model, tree death is the only way to reduce the current level of forests.

The fire damage ratio τ also includes risk differences between young and old forests. The probability function for wildfire is specified as a hyperbolic tangent function, where $tanh(0) = 0, \lim_{x\to\infty} \tanh(x) = 1$, and the function is differentiable when $x > 0$. This means that unlike a linear probability function, a large stock of initial old forest is almost certainly facing a wildfire. This specification of the probability function is used to better represent the increasing wildfire risk of having an abundance of green infrastructure, which may deter a social planner from further investing in or maintaining this stock of old forest. A quadratic fuel treatment cost function is furthermore applied to reflect the disproportional marginal cost increase as the share of unprotected forest drops. In other words, it will be increasingly costly for the social planner to fully protect the forest and achieve 0% unprotected forest (Jones et al., 2017).

Finally, the amount of carbon sequestration that is expected to affect climate change and hence the risk of wildfires relies on the investment in young forest in the last period. When there is no investment in green infrastructure, we assume that the risk of wildfire will not change. An alternative specification of the wildfire probability would be an increasing function over time if no further investments were to be made in young forest.

Figure 2.1 presents the simulation results for investment decisions in green and grey infrastructure based on the three models presented before in sections 3, 4, and 5. Each line reflects the optimal path that minimizes the total costs, whilst guaranteeing that the water quality standard is met. Each dot on each line represents a different starting point for the initial stock of green infrastructure. The black line in Figure 2.1 is the dynamic model that triggers the least cost without wildfire risk. The convex shape of the line indicates that an optimal initial level of green infrastructure exists where the water quality standard is achieved at least total cost. The total costs steeply increase as the initial green infrastructure capacity increases to deliver the required water quality levels because the central planner's decision space becomes increasingly limited up to the point where investing in more costly grey infrastructure becomes the only option.

Figure 2-1 The simulated present value of the total investment and operating costs of green and grey infrastructure under the three models

Since the green infrastructure level can only be reduced if old trees die, starting at a higher percentage of green infrastructure may actually turn out to be a burden to provide clean drinking water. This is illustrated by the fact that the social planner may be willing to accept forest damage due to wildfires (the red line in Figure 2.1) to approach the optimal level of green infrastructure in the trajectory where the black line is higher than the red line (beyond approximately 70%). The same dynamic model including the risk of wildfires is expected to result in higher total costs because of increasing protection and damage costs. Figure 2.1 shows that this is indeed the case, but up to the point where the initial level of old forest is around 70%. Beyond this point the total water treatment costs accounting for wildfires are lower. Hence the reason that a central planner is expected to be willing to incur wildfire risks, also as a means to manage the forest as a green solution, and increase the available water treatment options in the planner's choice set. Extending the dynamic model with the risk of wildfires,that is, accounting for potential wildfire damage, fuel treatment and recovery costs, shifts the optimal pathway as expected substantially upwards. The slightly U-shaped line of the wildfire model has its lowest point at a higher proportion of green infrastructure compared to the dynamic model. Due to the wildfire damage, a social planner needs more green and grey infrastructure to offset the damaging impacts on water treatment. Therefore, the social planner is looking for more old forest initially.

If we also include the longer-term benefits of green infrastructure to sequestrate carbon and lower the risk of wildfires, this lowers the present value of the total costs (the green line in Figure 2.1). The moderating impacts of carbon sequestration on climate change and wildfire risk means that the green line is located between the black and red line. Carbon sequestration reduces forest wildfire damage costs and results in savings on forest protection costs. The lowest point of the green curve is found between the dynamic model and its extension with wildfire risk. Since carbon sequestration is most effective when planting young forest, a lower initial level of old forest encourages the social planner to invest more in young forest green infrastructure. This then further reduces the risk of wildfire, wildfire damage, and recovery costs. However, as the initial stock of old forest is larger, the amount of young forest that can be planted diminishes and hence the risk of wildfires increases. Consequently, the cost start increasing. As the risk of old forest accumulates, the social planner is discouraged to further invest in young forests. In response, the green line starts to converge with the red line as the moderating effect of carbon sequestration on wildfire risks diminishes. Approaching full capacity levels for green infrastructure, the total costs estimated under the model with wildfire risks and climate change become more or less the same.

The amount of green over grey infrastructure over the simulated time period under the three models is further illustrated in Figure 2.2. As expected, the ratio declines as the share of initially available green infrastructure increases. The existence of the old forest reduces the marginal hydrological benefit of young forest investments. In other words, the social planner is discouraged to further invest in young trees given a higher stock of old forest. Extending the dynamic model with wildfire risk, the social planner has the same incentive to invest in green infrastructure when there is no or hardly any green infrastructure available at the start of the decision-making period. The risk of wildfires is relatively low given the limited amount of green infrastructure, and due to its cost-effective features, the planner has an incentive to invest in more green infrastructure. The red line representing the model with wildfire risk is located above the black line representing the dynamic model because there is an incentive to invest more in young forest when facing wildfire risks to offset wildfire damages and the reduction in treatment capacity.

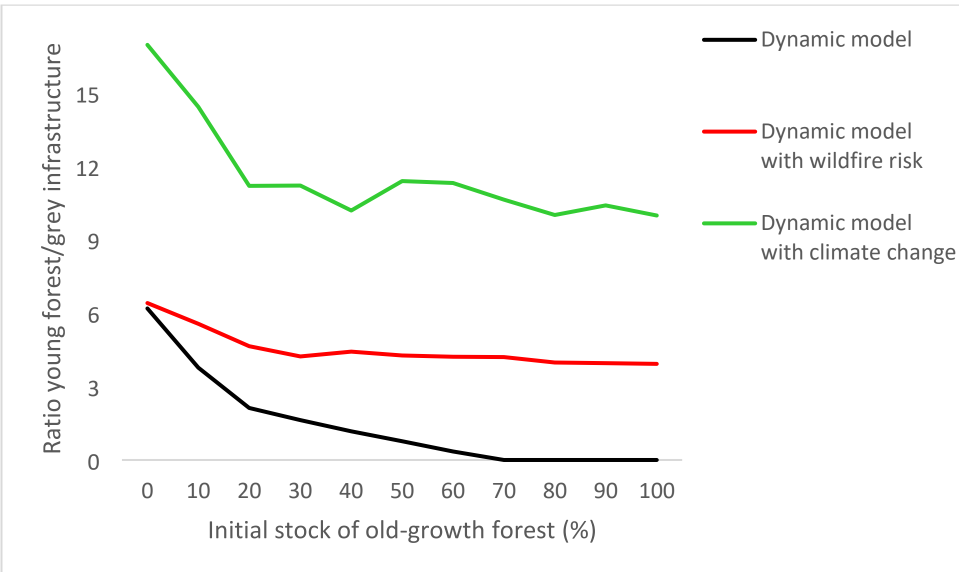


Figure 2-2 The ratio of green (young forest) and grey infrastructure over the simulated time period under the three models

The ratio is highest for the dynamic model including climate change (green line). Carbon sequestration increases the social planner's incentive to implement more green infrastructure because of the longer-term benefits involved. Carbon sequestration reduces the long-term wildfire risks and hence enhances the social planner's willingness to invest more in planting young forest as a more cost-effective water treatment method than grey infrastructure.

2.7 Conclusion

This paper explored the role of forested watersheds as a green, nature-based solution in investment decisions related to clean and safe drinking water provision, one of the United

Nation's Sustainable Development Goals. A simple baseline model was developed incorporating key features of forests' capacity to provide valuable hydrological services to society, as increasingly demonstrated in the scientific literature, accounting for the uncertainty associated with the delivery of the required water quality standards by green infrastructure. Despite the increase in payments schemes for forest watershed services and empirical studies analyzing their environmental and socio-economic impacts, no overarching theoretical framework exists to analyze the economic efficiency of such payment schemes. This is to our knowledge the first study to present an economic-theoretical framework to analyze optimum water treatment decision-making under risk and uncertainty based on the expected costs and benefits of green infrastructure vis-à-vis conventional grey infrastructure in increasingly urbanized watersheds worldwide. The static baseline model was modified to include forest growth dynamics and we discussed the consequences of this for the provision of the water treatment benefits and investment decision-making. This dynamic model was subsequently extended to include additional costs associated with forests as a cost-effective green solution to water treatment, in particular the risk of wildfires and associated damage and recovery costs. Forest protection costs were included to assess their role in finding the economic optimal level of green infrastructure, weighing the increasing protection costs due to wildfire risks against the avoided damage and recovery costs. Finally, the co-benefits of afforestation and reforestation in the form of carbon sequestration were added to the dynamic model to assess their impact on investment decisions in green and grey infrastructure to treat water and meet water quality standards. Carbon sequestration is expected to slow down climate change and as a consequence reduce the risk of wildfires, increasing decision-makers' incentive to invest more in green infrastructure. Differences between the dynamic versions of the model were further illustrated in a hypothetical numerical simulation.

We identified a number of key factors driving investment behavior in green infrastructure. Society may be less inclined to invest vastly in green infrastructure due to the uncertainties surrounding their cost-effectiveness. This is picked up in a risk premium that decision-makers may be willing to pay to avoid the risk associated with green infrastructure. Although there exists a variety of real-world risks with both types of infrastructure, all else being equal the higher the uncertainty surrounding the performance of green infrastructure, the higher society's willingness to pay this risk premiums, discouraging investments in green infrastructure.

Wildfire risks also play an important role. Besides the destruction of valuable water treatment capital, there is increasing evidence that wildfires have disastrous long-lasting impacts on water quality provision, resulting in high clean-up and treatment costs. Increasing protection costs may offset some of these costs incurred during the aftermath of a wildfire, but these protection costs make green infrastructure a less attractive solution compared to conventional grey infrastructure where furthermore much more control can be exercised over the water quality outcome.

The moderating impact of carbon sequestration co-benefits of forest conservation and afforestation on wildfire risks are rather uncertain, especially at local or regional level. A large-scale global transition to green water treatment infrastructure will be needed for this to have a real impact in the long term and reduce future risks of wildfires. The age composition of forests was shown to play a key role here too, especially the stock of old-growth forest available at the start of new investment decisions, and society's time preferences. The older the forest, the lower overall the carbon sequestration benefit and at the same time also the lower the survival rate in case of a wildfire, discouraging decision-makers from investing in new-growth forest. Given the long time horizon of the investment decisions involved over periods of 30 to 60 years, discounting of future benefits, besides risk attitudes towards green infrastructure's outcome uncertainty, profoundly influences the present value of future outcomes, which is expected to make forest protection and afforestation in urbanized watersheds less attractive than grey infrastructure.

In conclusion, although green infrastructure has gained significant interest worldwide for source water protection, some of the key factors we discussed in this paper may deter a social planner to fully embrace this option in practice. These factors will need to be taken into consideration when deciding to invest in green water treatment infrastructure.

Chapter 3

The Impact of Green Infrastructure on Water Rates and Drinking Water Incidents: A Spatial Instrumental Variable Regression Model

Zehua Pan, Roy Brouwer and Monica B. Emelko

Abstract

There is increasing interest in the cost-effectiveness and economic benefits of replacing traditional engineering-based ‘grey’ infrastructure with nature-based ‘green’ infrastructure in the water sector. This study builds on the emerging literature in this field and sets itself apart in several ways. New in this study is the focus on the interrelationship between green infrastructure, water treatment costs proxied by drinking water rates, and drinking water safety. The latter refers to adverse treated water quality incidents (AWQIs) such as unsatisfactory bacteriological test results that may lead to drinking water advisories when sufficiently severe. A new modelling framework is furthermore developed, accounting simultaneously for possible spatial spill-over effects due to watershed land cover and potential endogeneity embedded in the relationship between water treatment costs, drinking water billing, and the occurrence of AWQIs. Data from the water- and forest-abundant and densely populated Canadian province of Ontario were used and significant negative correlations between forested land area and both drinking water rates and AWQIs are observed. While causality underlying these relationships needs further investigation, these results indicate support for the use of techno-ecological nature-based solutions in drinking water risk management.

Key words: green infrastructure; ecosystem services; safe drinking water; water rates, nature-based solutions

3.1 Introduction

Drinking water treatment resilience and treated water safety are emerging as new environmental, social, and economic challenges as a result of global increases in the severity of climate change-exacerbated landscape disturbances such as wildfires and extreme precipitation events (Delpla et al., 2009; Emelko et al., 2011; Valdivia-Garcia et al., 2019). Safe drinking water is crucial for human health. Almost one in ten people around the world do not have access to clean drinking water (WHO, 2017). The World Health Organization (WHO) reported in 2019 that an estimated 829 thousand people died due to drinking-water-related diarrhea, of which 297 thousand were children under the age of six (UN Water, 2019). Even in countries such as the U.S., water rates increased more than 41% between 2010 and 2017, and more than a third of all households were estimated to be unable to afford water services on a full cost recovery basis at that rate of change in the future (Mack and Wrase, 2017), with the brunt of the impact being borne by low-income customers (Swain et al. 2020). In the long run, exposure to insufficiently treated drinking water increases public health costs and increasingly harm human capital in the labour market (Graff Zivin and Neidell, 2013).

Alternative nature-based (green) solutions for drinking water treatment are increasingly explored to supplement or even replace existing engineering-based (grey) treatment facilities (Pu-mei et al., 2001; Biao et al., 2010). A framework for advancing on the promises of techno-ecological nature-based solutions in water supply and treatment underscores that no such solutions are universal (Blackburn et al. 2021). Notably, however, in the provision of safe drinking water, conservation and source water protection have always played an important role that is complementary to treatment (Emelko et al., 2011; Mapulanga and Naito, 2019; Sing et al., 2017). Various authors have evaluated nature-based solutions in a watershed or river basin context and compared these green solutions in terms of their effectiveness with downstream grey treatment facilities (e.g., Bastrup-Birk & Gundersen, 2004; Warziniack, et al., 2017).

Among the various upstream land protection options, forested land plays a rather unique role in the provision of ecosystem services. Through its roots structure, healthy forest land provides natural filtration, retains and stores nutrients and other contaminants in the soil, and as such maintains or improves receiving water quality (Clark et al., 2000; Guo et al., 2001; Tong and Chen, 2002; Jussy et al., 2002; Bastrup-Birk and Gundersen, 2004; Schelker et al., 2012). Healthy forests also regulate hydrology through various processes including increased infiltration, which increases soil moisture, recharges aquifers, and often leads to gradual release of water throughout the year (Mastrorilli et al., 2018). By accounting these forest ecosystem services into integrated watershed management planning, policy and decision-makers can evaluate the costs and benefits of both grey and green infrastructure, which will be essential for future investment (Pan and Brouwer, 2021).

There is an emerging body of literature focusing on the interrelationship between healthy forested watershed area, the costs of drinking water treatment (e.g. Ernst et al., 2004; Abildtrup et al., 2013; Honey-Rosés et al., 2013; Lopes et al., 2018; Das et al., 2019; Westling et al., 2020), and the non-market valuation of the ecohydrological functions of forests (e.g. Ojea and Martin-Ortega, 2015). Understanding of the complicated causal relationships between green infrastructure and local water contamination problems and their economic implications is still rather limited (Ovando and Brouwer, 2019). This study provides new insights into the interrelationship between land cover and water treatment costs proxied by water rates and adverse treated drinking water quality incidents (AWQIs). Spatial regression models are estimated, accounting for potential endogeneity between AWQIs and the water rates paid by households. Depending on the type and number of AWQI, this may lead to increased efforts to improve drinking water treatment to ensure treated water quality and public health protection. In some cases, this may in turn result in higher water rates over the longer termand reduce the occurrence of AWQIs. Here, we use geo-referenced drinking water data from a drinking water survey conducted in the most densely populated province in Canada (Ontario) and link this to provincial land cover maps. Ontario is densely populated along its southern borders with the U.S., but also rich in water and forest, especially in the areas upstream of the more urbanized parts in the south of the province. First, we examine the relationship between land cover and water rates as a proxy for treatment costs and show that the share of forested land is significantly correlated with water rates when we account for potential spatial spillover effects in spatial lag and spatial error regression models. Secondly, we regress land cover on AWQIs, accounting for possible endogeneity between the AWQI and the water rate by including the latter as an instrumented variable and find that the share of forested land cover is also significantly associated with the reported incidence rates.

The remainder of this paper is organized as follows. Section 2 first describes the econometric modelling framework. This is then followed by a presentation of the collected data in this study to estimate the econometric models in Section 3. Results are presented in Section 4, and conclusions are drawn in the final Section 5.

3.2 Econometric modeling framework

The modelling framework developed in this study builds upon Abildtrup et al. (2013), who regressed available water rates on a combination of water treatment characteristics X_i and land cover characteristics Z_i in the watersheds where the water treatment facilities' sources for drinking water are located. A similar spatial econometric model is used here, where we test and account for spatial lags and/or spatially correlated errors, due to possible spatial spillover effects from areas neighboring the specific location where the water treatment takes place. The first null hypothesis we test in this study is that a significant negative correlation can be found between the share of forested land cover Z_i in the treatment unit *i* and the water rate P_i:

$$H_0^1 : \frac{\partial Z}{\partial P} < 0 \qquad (1)$$

A higher degree forested watershed area that serves as green, natural resource-based water treatment infrastructure was expected to correspond to lower treatment costs that are reflected in water rates.

New in this study is that we estimate the relationship between the water rate, treatment characteristics (e.g. source water intake types) and land cover characteristics as a first stage model and then relate this to the number of AWQIs in the same water treatment areas in a second stage model, accounting for potential reverse causation between water rates and drinking water incidence rates. A higher water rate implies a higher probability of treatment capacity that is able to effectively reduce the number of incidence rates, while vice versa a higher incidence rate may result in higher treatment costs, for example due to additional treatment effort, which in turn is expected to increase water rates. For this reason, the water rate explained in the first stage model is included as an instrumented variable in the second stage model to explain variations in AWQIs across treatment areas. The second hypothesis tested in this study is that a significant negative correlation also exists between the share of forested land cover Z_i in the treatment unit i and AWQIs I_i:

$$H_0^2: \frac{\partial Z}{\partial I} < 0 \qquad (2)$$

A higher forested watershed area can be considered analogous to green water treatment infrastructure (Ernst et al., 2004)[5]. Thus, it is also expected to reduce the number of AWQIs in a treatment unit due to the provision of natural pre-treatment that results in water quality improvement, widely understood in the water and forest management industry (Emelko and Sham, 2014) and demonstrated in practice (e.g., Ernst et al., 2004; Westling et al., 2020).

We furthermore extend the initial cross-sectional data analysis to a panel or cross-sectional longitudinal data analysis by also considering reported drinking water incidents in the past as possible drivers behind current water rates and incidence rates. The econometric modelling framework is visualized in Figure 1.

[5] Ernst et al. (2004) also suggest a non-linearity between forest land covers and water treatment cost. The results highlight that once reaching a potential cut-off point, the further forest land covers no longer reduce water treatment costs significantly.

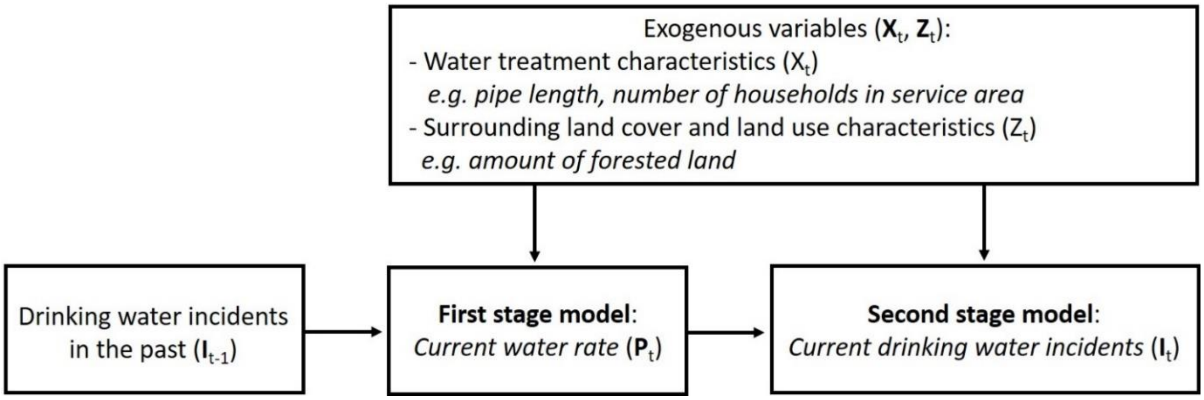


Figure 3-1 Visualization of the econometric modelling framework

The associated modeling structure, estimated in two steps, can be specified as shown below. In a first step, we define the first stage model:

$$\log\,(P_i) = W_j^{\alpha}\alpha + X_i\beta + Z_i\gamma + \delta I_{i,t-1} + \epsilon \tag{3}$$

where P_i is the water rate in treatment unit i, W^{α} is the spatial lag term, accounting for spatial spillover effects in the dependent variable from neighboring treatment units j, X_i represents the treatment characteristics (e.g. source water intake types) in unit i, Z_i the land cover characteristics in unit i, and I_{t-1} the number of AWQIs in the previous year. α, β, γ and δ are the coefficient estimates associated with W, X, Z and I_{t-1}, respectively. Note that the number of AWQIs in the past I_{t-1} is assumed to be an independent exogenous factor influencing the water rate in year t by increasing the water treatment costs, but not the number of AWQIs in the next year, thereby satisfying the restriction condition in the instrumental variable regression analysis. For this, we use the number of lead-related incidents, which are associated with treated water distribution system pipes (i.e., from leaded-brass fixtures, solder used to join pipes prior to 1990, and pipes in homes built before the mid-1950s) that corrode and breakdown, leading to lead (Pb) release to treated drinking water. Thus, lead-related AWQIs have no relationship to watershed land cover. An important assumption is that further water treatment efforts will be translated into higher drinking water rate increments and affect treated water quality in the same year. This assumption is perhaps too strong if the water treatment improvement requires substantial modifications in the treatment infrastructure instead of treatment operation only. Moreover, annual water rates are usually fixed administratively following laws and regulations, and hence less flexible to capture changes in treatment costs as assumed here. In our model specification, we assume that the water rate serves as a proxy for treatment costs and we test to what extent the water rate in a particular year influences the AWQI rate in that same year.

The spatial error term ϵ accounts for unobservable spatial spillover effects from neighboring treatment units and is defined as:

$$\epsilon = W_j^{\lambda}\lambda + u, \text{ with } u \sim iid(0, \sigma^2) \tag{4}$$

where lambda is the coefficient on the spatially correlated errors and u the residual error, assumed to be independent and identically distributed with a mean value of zero and variance equal to sigma squared.

In a second step, we define the incidence rate model, where the dependent variable P from the first step (water rate) is the instrumented variable:

$$\mathrm{I}_{\mathrm{i,t}} = W_j^{\alpha}\alpha + X_{i,t}\beta + Z_{i,t}\gamma + P_{i,t}\varphi + \tau \qquad (5)$$

In equation (5), $I_{i,t}$ is the number of drinking water incidents (AWQIs) in a specific year t in treatment unit i, W^{α} is as before the spatial lag term, X represents the water treatment characteristics, and Z the land cover characteristics. α, β, γ and φ are the coefficient estimates associated with W, X, Z and P respectively. The spatial error term τ accounts for unobservable spatial spillover effects from neighboring treatment units and is defined as before in equation (4):

$$\tau = W_j^{\lambda}\lambda + v, \text{ with } v \sim iid(0, \sigma^2) \qquad (6)$$

For both models, the Moran eigenvector method is used in the software package R to estimate the vector of eigenvalues λ in the error term (Dray et al., 2006; Griffith & Peres-Neto, 2006). The Moran's eigenvector minimizes the Moran's index, indicating spatial autocorrelation, and these eigenvectors are included in both models to filter out spatial spillover effects and identify the appropriate spatial regression model for our analysis. The spatial lag across neighboring treatment units is based on their common boundaries, after which variables are created describing the proportions of different land cover and land usages for all neighboring treatment units. Water rates and all other independent factors except the land cover variables (which are expressed as shares in each treatment unit) are converted into their natural logarithm to improve the model fit in an OLS regression model in the first stage, whereas the number of drinking water incidents in the second stage are assumed to follow a Poisson distribution in a count data regression model.

3.3 Data

The data used to estimate the spatial econometric models originate from multiple sources. The most important data source is the 2017-2018 Ontario Drinking Water Quality and Enforcement database (Ministry of the Environment, Conservation and Parks Ontario, 2019). In line with its monitoring responsibility and to ensure compliance with Ontario's drinking water laws, the provincial Ministry of the Environment, Conservation and Parks publishes this database every year online. The dataset contains records of all AWQI events that occurred in the province of Ontario in a particular fiscal year, in this case from 1 April 2017 until and including 31 March 2018 (n=6,698). Only one year was chosen because changes in land cover are only available every 10 years in Ontario. AWQI events are recorded when water samples submitted by the water treatment system owners fail existing water quality standards. For each record, the dataset indicates (1) the location and municipality where the event took place, (2) the type of water treatment facility, (3) the start and end date of the reported AWQI, and (4) the cause and type of AWQI. Here, we only examine incidents that might be linked to surrounding land cover (e.g. forest, water) and land cover such as agriculture, rrecently disturbed land or urban residential areas, and that are associated with a municipal water treatment facility. The latter criterion ensures that the reported AWQI in a municipality can be directly linked to the municipal treatment facility. Reported AWQI in municipalities that buy their drinking water from treatment facilities in other municipalities (n=207) are therefore excluded from the analysis here[6]. Lead-associated AWQIs comprised the majority (> 60%) of reported incidents (n=4,080). They were excluded from the analysis, as were

[6] Information about which municipalities have and which municipalities do not have their own treatment plants in Ontario is retrieved from online municipal websites. If a municipality does not have its own treatment facility, it typically purchases its drinking water from water providers in other municipalities.

operational failures like loss of power or pressure (n=451). AWQIs related to well supplies were also excluded (n=981) because groundwater does not typically require treatment beyond disinfection unless there are specific sources of natural (typically geologic) or anthropogenic contamination. The removal of these 5,719 observations from the 2017-2018 Ontario Drinking Water Quality and Enforcement database results in a much smaller dataset containing 979 observations only. The types of incidents remaining in the database and constituting the dependent variable in the second stage model (equation (5) in the previous section) are defined in the appendix to this paper. A map of the study areas, called census sub-divisions by Statistics Canada, in the province Ontario for which the number of incidents were reported over the period 2017-2018 is presented in Figure 2. Census sub-divisions (CSD's) are defined by Statistics Canada as the highest spatial resolution areas, usually corresponding to a municipality, at which census data and population statistics are available.

It should be noted that school boards are disproportionately represented in the data set because of concerns regarding lead. Since 2017-2018, Ontario school boards are obliged to submit water samples. During the fiscal year 2017-2018 all Ontario childcare and public schools were requested to submit their water samples for further testing. This increased the database's sample size substantially compared to previous years. The overall number of incidents more than doubled from around 2,000 in the fiscal year 2016-2017 to more than 5,000 in 2017-2018. In our analysis, we will also use the number of incidents reported in the fiscal year 2016-2017, but we expect that some degree of selection bias may have played a role in previous years before the new mandatory reporting rule was enforced. Without the new mandatory reporting rule, municipalities with a higher water safety awareness are expected to be more likely to conduct a water quality test and report incidents.

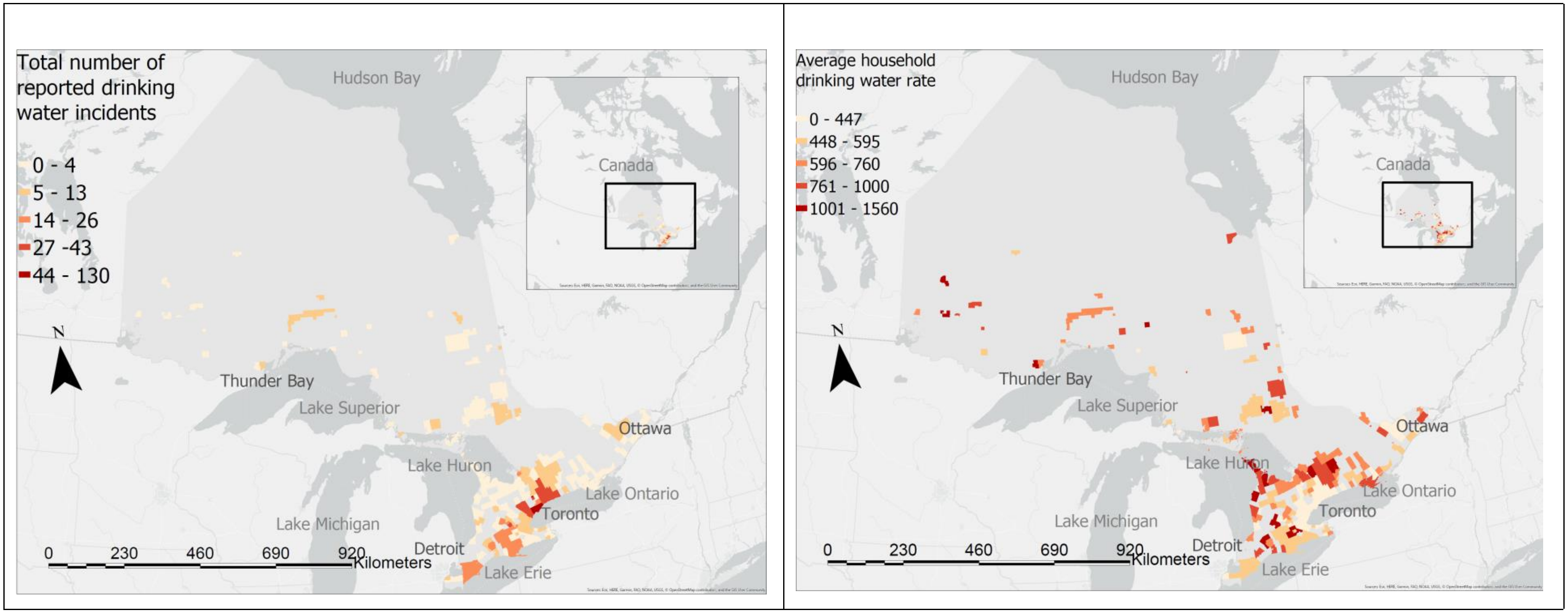


Figure 3-2 Map of the census sub-division study areas in the province Ontario in Canada included in the dataset with their total number of drinking water incidents (left-hand side) and average water rates (right-hand side) in the fiscal year 2017-2018

A second important information source is the Ontario Financial Information Return (FIR) database (Ministry of Municipal Affairs and Housing Ontario, 2018). The FIR is a tool used by the provincial Ministry of Municipal Affairs and Housing to collect financial and statistical information from municipalities. It is a standard annual reporting requirement. For the fiscal year 2017-2018, the number of households within the municipalities and the total length of the drinking water transmission pipes in each municipality were extracted from the database. However, data about the latter are not provided for all municipalities and the municipalities with missing values (less than 10%) for this variable are dropped from the analysis.

The average annual water rate per household in each municipality was also collected. Under the 2001 Ontario Municipal Act, municipalities can impose fees and charges for different public services, including municipal water supply. Water rate information is publicly available online, while a telephone survey was used to follow up with municipalities for which the relevant information was missing. In this telephone survey, municipalities were asked for information about the water rate structure in their townships for the 2017-2018 fiscal year. Due to differences in the structure of water rates, where some municipalities relied on a flat rate instead of a metered volumetric rate, the latter was converted into a total water bill based on available information about average household water consumption (Statistics Canada, 2019).

Finally, the data above were linked to the publicly available 2016 Ontario Land Cover Compilation v.2.0 Geographical Information System (GIS) published online by the Land Information Ontario (2016). This spatial database includes 26 land cover classes and has a spatial pixel resolution of

15 meters. Based on this dataset, we computed (1) the size of each municipality (in km^2) and (2) the share (%) of land in each municipality covered by (a) forest, (b) shrub, (c) agriculture, (d) urban area, (e) open water, (f) heath, and (g) forest that was recently harvested (referred to as disturbed). All these information are calculated by the summarize within function from the ArcGIS pro.

The summary statistics for the main variables in the model estimation are presented in Table 1. All the data presented in Table 1 refer to the fiscal year 2017-2018. The total number of observations is 154, meaning that we were able to extract data points for 154 CSD's for which we have full information to estimate the presented econometric models in Section 2. Some rural regions are excluded from the analysis, given the fact that they are importing water from neighboring regions. After excluding these systems, the average municipal area was 374 km^2. While it is recognized that utilization of catchment area rather than municipal boundaries would be preferable, the water treatment plant intake location data that would be required for this analysis were not available, thereby precluding it.

Table 3-1 Summary statistics for the municipalities (census sub-divisions) included in the data set over the fiscal year 2017-2018

Variable	Mean	St. Dev.	Min	Max	N
Municipal area (km^2)	534.58	686.01	1.77	3,621.89	154
Transmission Pipe Length(km)	353.4	989.46	4	8386	154
Number of households (10^3)	30.95	111.55	0.17	1,193.73	154
Annual household drinking water rate (Canadian Dollars)	638.86	232.12	214.20	1,560.00	154
Share using only surface water (%)	0.604	-	0	1	154
Total number of AWQIs per municipality[1]	6.35	15.71	1.00	130.00	154
Microbiological AWQIs per municipality	3.56	10.66	0.00	119.00	154

Inorganic chemical AWQIs per municipality	0.03	0.32	0.00	4.00	154
Organic chemical AWQIs per municipality	0.10	0.49	0.00	4.00	154
Other AWQIs per municipality	2.66	8.59	0.00	98.00	154
Previous year number of lead incidents per municipality	4.75	13.08	0	119	154
Urban land area (%)	0.106	0.182	0.000	0.913	154
Cultivated land area (%)	0.272	0.280	0.000	0.885	154
Forested land area (%)	0.383	0.256	0.012	0.876	154
Shrub land area (%)	0.083	0.079	0.000	0.326	154
Disturbed land area (%)	0.012	0.031	0	0.140	154
Open water area (%)	0.069	0.088	0.000	0.626	154

[1] All incidents as defined in the appendix of the paper.
[2] Land that was deforested over the last 10 years, either through land burning or cutting.

The average number of all different types of AWQIs per municipality as reported in the appendix to this paper was 6, varying from once per year to as many as 130 incidents across one municipality in one single year. Inorganic and organic drinking water contamination incidents were considerably lower compared to other incidents and microbiological incidents. The former include turbidity incidents which make up only 1% of all AWQIs. Average annual water rates also vary considerably across municipalities, with an average of 639 Canadian dollars per household over the year 2017-2018. The ten most expensive water rates were typically found in remote rural regions of Ontario; they ranged between $1,040 and $1,560 per household per year. Excluding these highest water rates, the adjusted mean was substantially lower at $598 per household per year.

3.4 Results

3.4.1 First Stage Model

The results from the first-stage model are presented in Table 2. Five different models are presented to explain the observed variation in drinking water rates across 154 municipalities in Ontario. A simple OLS regression model was used and then gradually extended to account for possible spatial autocorrelation surrounding drinking water rates and previous incidents with drinking water quality. The changes in goodness of fit between the estimated models are evaluated using an F-test, except for the first two models for which this could not be done due to the different number of observations. The test results help to assess to what extent spatial autocorrelation either in the deterministic or stochastic component of the estimated models and previous drinking water incidents help improve the first-stage OLS model. The OLS model was first extended with a spatial error term to capture unobserved spatial autocorrelation between neighboring water treatment units (municipalities) in Model II, then with a spatial lag term and converted to a spatial autoregressive Model III, and with both a spatial error and spatial lag term in the fourth model (Model IV). The number of lead-related drinking water incidents in the previous year was then added into the fifth model (Model V), combined with the spatial lag and spatial error. The last model (Model VI) tests nonlinearity associated with forested land cover by adding a quadratic term for this key variable in surrounding land cover of the treatment unit self and in the spatial lag terms. In every model we test the first hypothesis in this study, i.e. whether or not forested land cover significantly affects the observed variation in water rates, and if so, in which direction and by how much. The number of observations drops from 154 to 123 when including the spatial lag term in the baseline OLS model because this term can only be created for the 123 municipalities that share a border with each other. The spatial lags are calculated based on neighboring land cover, using a queen contiguity weighting matrix. This weighting matrix was considered most appropriate for the models presented here because it describes the relationship between locations using edge and corner contiguity (Anselin and Rey, 2014). If location *i* is adjacent and directly tangent to the location *j*, the matrix element ($w_{i,j}$) in the spatial lag term W in equation (3) has the value 1, if this is not the case, the element has the value 0.

Table 3-2 Estimated first-stage models explaining annual drinking water rates across the province of Ontario, Canada[a]

Explanatory factors	Model I	Model II	Model III	Model IV	Model V	Model VI
	OLS	Spatial Lag (SL)	Spatial Error (SE)	SL and SE	SL and SE and previous incidents	SL and SE and previous incidents and quadratic forest cover
Constant	6.595***	6.728***	6.658***	6.635***	6.606***	6.592***
	(0.096)	(0.190)	(0.119)	(0.194)	(0.196)	(0.119)
Area size (km^2)	0.087**	0.124***	0.101**	0.108**	0.105**	0.128***
	(0.040)	(0.046)	(0.044)	(0.046)	(0.046)	(0.047)
Number of households (1000's)	-0.091***	-0.110***	-0.083***	-0.088***	-0.074***	-0.107***
	(0.017)	(0.022)	(0.024)	(0.025)	(0.028)	(0.027)
Surface water intake (dummy 1=surface water, 0= groundwater)	0.022	-0.036	-0.037	-0.046	-0.040	-0.024
	(0.055)	(0.065)	(0.062)	(0.065)	(0.065)	(0.067)
Surrounding land cover						
Share built area (%)	-0.004**	-0.004**	-0.004*	-0.005**	-0.005**	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Share forest land (%)	-0.002	-0.004**	-0.003**	-0.004**	-0.004**	-1.407**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.559)
Square of share forest land (%)						0.363
						(0.470)
Share shrub land (%)	0.003	0.0001	0.003	0.001	0.001	-0.0005
	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Share open water (%)	0.001	-0.0002	0.0002	0.001	0.001	0.001
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)

Share disturbed land (%)	0.005 (0.009)	0.013 (0.010)	0.005 (0.009)	0.010 (0.010)	0.010 (0.010)	0.015 (0.010)
Spatial lags (influence of adjacent neighboring treatment units)						
Share built area (%)		-0.003 (0.005)		-0.002 (0.005)	-0.001 (0.005)	-0.003 (0.005)
Share forest land (%)		-0.0001 (0.002)		0.001 (0.002)	0.001 (0.002)	-0.138 (0.561)
Square of share forest land (%)						-0.403 (0.437)
Share shrub land (%)		0.009 (0.006)		0.011* (0.006)	0.011* (0.006)	0.007 (0.006)
Share open water (%)		-0.005 (0.004)		-0.005 (0.004)	-0.005 (0.004)	-0.006 (0.004)
Share disturbed land (%)		-0.001 (0.011)		-0.003 (0.011)	-0.003 (0.011)	-0.003 (0.011)
Model characteristics						
Spatial lag	No	Yes	No	Yes	Yes	Yes
Spatial error	No	No	Yes	Yes	Yes	Yes
Previous incidents	No	No	No	No	Yes	Yes
Summary statistics						
R^2	0.214	0.282	0.270	0.309	0.315	0.300
Model's own F-test statistic	4.949***	3.286***	4.137***	3.190***	3.051***	2.645***
Degrees of freedom (k;n-k)	(8; 145)	(13; 109)	(10; 112)	(15; 107)	(16; 106)	(17:105)
F-test statistic between models[a]		-[b]	0.60	1.22	0.97	0.626
Number of observations	154	123	123	123	123	123

Notes: both the dependent and independent variables are converted into their natural logarithmic form except the land cover variables for ease of interpretation. Standard errors are presented between parentheses. Degrees of freedom: k refers to the number of parameters and n the number of observations.
[a] The F-test statistic between models refers to the difference between the model in whose column the test is reported and the model in the previous column.
[b] The F-test statistic cannot be calculated due to different numbers of observations between columns.
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

The model fit gradually improves when we account for spatial correlation captured in the stochastic and deterministic parts of the models and additionally include control for the effect of drinking water incidents in the past, as indicated by increasing coefficient of determination (R^2) in Table 2. However, none of the improvements were statistically significant, as indicated by the F test statistics between models. The last model in which we account for AWQIs in the previous year has the highest explanatory power and is therefore considered the best fit model in the first stage of analysis. This model explains most of the variation in drinking water rates. The inclusion of a higher order of forest land cover to test for possible turning points does not yield any significant results and does also not improve the model's goodness of fit.

The constant terms are highly significant in all 6 models and consistently exhibit similar coefficient estimates. Interestingly, the first null hypothesis is confirmed in every spatial regression model in Table 2, but not in the first OLS model, and the coefficient estimate for the share of forested land is fairly constant across all first five models, varying between -0.003 and -0.004. The differences in coefficient estimates between the models are not statistically significant. Agricultural land cover is the baseline category for the different types of land cover. The coefficient estimates therefore have to be interpreted as compared to agricultural land. Accounting for the semi-logarithmic functional form of the estimated models, the negative coefficient estimates for forest cover imply that if the share of forest cover increases by 1 percent in a municipality in Ontario compared to agricultural land, the average drinking water rate per household is reduced by 0.3% to 0.4% per year. Compared to the sample's average annual water rate of $639 per year, this seems negligible.

However, multiplied over all households in Ontario in 2016 with access to municipal water sources[7], this amounts to a reduction of around $9 to 12 million on an annual basis.

Except for the share of urban land cover, none of the other land cover variables significantly influences the average water rates. The negative sign for urban land cover is in line with the negative sign for the number of households served in the treatment units, and suggests significant economies of scale in urban areas with higher population densities, as commonly recognized in the water industry. Examining the influence of land cover in neighboring areas, only a spatial spillover effect can be detected for the share of shrub lands in the last two models at the 10% significance level. The positive sign suggests that a higher share of shrub lands in neighboring areas results in a higher water rate, all else being equal. The same positive effect is found for the share of shrub lands inside the water treatment unit, but this direct effect of shrub lands on the water rate in one and the same treatment area is not statistically significant. In their study covering 95 departments in France, Fiquepron, Garcia, and Stenger (2013) found that shrubland has a significant impact on water quality and indirectly also on water prices. Also the share of disturbed land and the area of open water does not influence the water rates. The spatial lag term for land disturbance is not significant either. Previous research by Futter et al. (2016) highlights that treatment costs can go up considerably due to the increased discharge of nutrients and other chemicals after forest logging. The share of disturbed land has, as expected, a positive effect on the water rate, but the effect never becomes statistically significant in any of the estimated models.

[7] The total number of households in Ontario in 2016 was 5,169,000 (Government of Ontario, 2021), of which 89 percent is connected to municipal water sources (Statistics Canada, 2017).

Turning to the characteristics of the treatment unit, i.e. the size of the service area, the number of households served, and the source water types, only the first two play a significant role in explaining the variation in water rates. Although water treatment costs are generally expected to be lower if groundwater is used as the source of drinking water, no significant effect of the water source on the water rate can be detected in any of the estimated models. The area size has a relatively small positive effect on the water rates, most likely because of the increasing water infrastructure and supply costs when covering a larger service area, whereas the number of households has, as mentioned, a significant negative effect and suggests economies of scale. The number of households refers to the households living in each municipality and proxy the number of households served by water treatment plants. Information was also available about the length of the pipes to distribute the water to the households, but this variable was highly correlated with the area size and the number of households, and therefore omitted from the regression analysis here to avoid multicollinearity. Moreover, rural regions tend to have more frequent hybrid water systems, where households also have their own water well, but no data are available to account for this.

3.4.2 Second stage model

The results of the second-stage model are presented in Table 3. The second-stage model is a Poisson count model that is estimated using maximum likelihood regression techniques, where the dependent variable is the number of AWQIs as defined in the appendix to this paper that are expected to be related to land cover across the same 154 municipalities in Ontario. As before, different model specifications are used to statistically test the role of spatial autocorrelation and the incremental explanatory power of the instrumental variable model in the last column. First, the maximum likelihood estimated (MLE) Model VII is converted into a spatial lag model (Model VIII), followed by the spatial error Model IX. The number of observations for the spatial error model drops, as before, because of the omission of study areas that are not spatially connected. Model X is a combined spatial lag and spatial error model, and finally Model XI is the instrumental variable (IV) spatial lag-spatial error model, while Model XII is the same IV model including also quadratic terms for forest land cover to account for possible nonlinearity in the relationship between forest cover and AWQIs.

Table 3-3 Estimated second-stage Poisson regression models explaining the incidence rate of adverse drinking water events across the province of Ontario, Canada[a]

Explanatory factors	**Model VII** Maximum Likelihood Estimation (MLE)	**Model VIII** MLE Spatial Lag (SL)	**Model IX** MLE Spatial Error (SE)	**Model X** MLE SL-SE	**Model XI** Instrumental variable (IV)MLE SL-SE	**Model XII** IV-MLE SL-SE-and quadratic land cover
Constant	0.985	0.940	-0.252	0.382	6.677**	7.227***
	(0.956)	(1.074)	(1.062)	(1.118)	(2.819)	(2.782)
Annual water rate ($/household/year)	0.009	0.025	0.176	0.116	-0.814**	-0.880**
	(0.139)	(0.152)	(0.154)	(0.159)	(0.415)	(0.410)
Area size (km^2)	0.023	0.085*	-0.018	0.065	0.141**	0.085
	(0.045)	(0.049)	(0.048)	(0.050)	(0.060)	(0.062)
Number of households (1000's)	0.561***	0.600***	0.586***	0.573***	0.513***	0.547***
	(0.027)	(0.031)	(0.034)	(0.034)	(0.039)	(0.039)
Surface water intake (dummy 1=surface water, 0= groundwater)	-0.086	0.039	-0.103	0.055	0.009	0.003
	(0.085)	(0.096)	(0.096)	(0.099)	(0.101)	(0.100)
Surrounding land cover						
Share built area (%)	-0.021***	-0.020***	-0.020***	-0.018***	-0.022***	-0.022***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Share forest land (%)	-0.012***	-0.011***	-0.010***	-0.010***	-0.013***	-0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Square of share forest land (%)						-2.463***

						(0.650)
Share shrub land (%)	-0.020***	-0.013**	-0.021***	-0.014**	-0.012*	-0.017**
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Share open water (%)	-0.0004	-0.002	-0.004	-0.004	-0.005	-0.010
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Share disturbed land (%)	0.003	-0.025*	0.006	-0.021	-0.013	-0.036**
	(0.013)	(0.015)	(0.013)	(0.015)	(0.014)	(0.016)
Spatial lags (influence of adjacent neighboring treatment units)						
Share built area (%)		-0.044***		-0.040***	-0.048***	-0.050***
		(0.007)		(0.008)	(0.008)	(0.008)
Share forest land (%)		-0.007**		-0.007**	-0.008**	-0.010***
		(0.003)		(0.003)	(0.003)	(0.003)
Square of share forest land (%)						-0.347
						(0.699)
Share shrub land (%)		-0.013		-0.016*	-0.019*	-0.021**
		(0.009)		(0.009)	(0.010)	(0.010)
Share open water (%)		0.009		0.012**	0.012**	0.018***
		(0.006)		(0.006)	(0.006)	(0.006)
Share disturbed land (%)		0.089***		0.067***	0.067***	0.074***
		(0.014)		(0.016)	(0.016)	(0.016)

Model characteristics						
Spatial lag	No	Yes	No	Yes	Yes	Yes
Spatial error	No	No	Yes	Yes	Yes	Yes
Previous incidents	No	No	No	No	Yes	Yes
Summary statistics						
Log Likelihood	-475.128	-366.595	-389.025	-361.961	-360.350	-353.025
LR test[a]		-[c]	44.86***	54.13***	3.224***	17.023***
AIC	972.256	765.190	804.051	759.923	756.699	744.051
Number of observations	154	123	123	123	123	123

Notes: Standard errors are presented between parentheses. MLE is the maximum likelihood estimator, AIC is the Akaike Information Criterion and LR is the Likelihood Ratio test statistic.

[a] The list with incidence categories used in the regression analysis is presented in the appendix.

[b] The LR test statistic refers to the difference between the model in whose column the test is reported and the model in the previous column. The degrees of freedom for the 3 LR test statistics are the same as in Table 2.

[c] The LR test statistic cannot be calculated due to different numbers of observations between columns.

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

The instrumented variable in Model X is the annual household drinking water rate from the first stage-model. This variable is included as an independent regressor in Models VII-X and is estimated simultaneously using two-stage least squares (2SLS) regression in Model XI and XII. The coefficient estimate is only negative and statistically significant in the IV models XI and XII. This confirms our *a priori* expectation: the drinking water rate influences the number of AWQIs, where municipalities with higher water rates face significantly lower incidence rates. Examining the explanatory power of the spatial econometric models in Table 3, both the AIC and log-likelihood function show that model XII with the instrumented water rate and quadratic term for forest cover has the highest explanatory power. Although the differences in the log-likelihood function between models VIII, X, XI and XII are small, the LR test results show that they are statistically significant. The quadratic term in the last model is significant at the 1 percent level and negative, like the significant linear term, reinforcing that the effect is not constant and levels off as the share of forest cover increases. A higher forest cover compared to agriculture (the baseline category) results all else equal in a reduction in drinking water incidence rates, confirming the second hypothesis, but the extent to which this is the case depends on the amount of forest cover.

The spatial error model IX has a considerably lower fit than the other three spatial econometric models, including the IV models XI and XII. This is due to the inclusion of the spatial lag terms in the other models. These spatial lags are, somewhat contrary to the results in Table 2, highly significant for most of the land cover variables across all model specifications. The coefficient estimates are furthermore in most cases not significantly different from each other across the model specifications, indicating that they are robust. The share of forest cover has a significant negative effect in all models, as well as the share of shrubland and urban area. In view of the fact that a Poisson regression models the log of the expected count as a function of the predictor variables, a 1 percent increase in forest land results, all else being constant, compared to agricultural land cover in an almost equal reduction of 1 percent (0.99%) in the likelihood of an adverse drinking water event based on the linear model specifications in Table 3.

Although the share of disturbed land in neighboring areas consistently has, as expected, a significant positive influence on the number of AWQIs, the share of disturbed land in the treatment area self is significant and negative in two of the four models including spatial lags (models XIII and XII). Hence, compared to agricultural land cover, disturbed land is associated with fewer drinking water incidents in the treatment area self, whereas the reverse relationship is found in neighboring treatment units. The negative coefficient for the impact of land disturbance in the treatment area is half the size of the same coefficient in the surrounding area, suggesting that land disturbance in adjacent regions may outweigh the negative effect on AWQIs in the treatment area self. Also the share of open water in neighboring areas has a positive effect on the number of AWQIs compared to agricultural land. The coefficient estimates for the share of open water in the treatment area self are all negative, but not significant. The share of forest and shrubland cover and built area in neighboring treatment units all have a significant negative effect on the number of incidents. No significant quadratic effect exists for forest cover in neighboring areas.

Following Lopes et al. (2019), the land cover variables were also interacted with the source of water intake for drinking water (surface or groundwater), but these interaction terms did not yield any significant results and are therefore not included in the models shown in Table 3. As in Table 2, the water source is not statistically significant in any of the estimated models. Finally, the area size of the treatment unit is only significant and positive in the spatial lag and IV models (VIII and XI), while the number of households served in the treatment units is consistently significant and positive across all model specifications. These findings are as expected. The larger the area size and the more households served, the higher the risk of an adverse event, all else constant.

3.5 Conclusion

There is growing interest in the role of nature-based solutions such as forested watersheds in water supply security under increasing pressures such as climate change. In this paper, we tried to assess whether such a relationship can be established using existing public data sources between the water rates households pay as a proxy for water treatment costs and the land cover surrounding drinking water intake across 154 different municipalities in Ontario, Canada. Ontario has an abundance of 71 million hectares of forest, 17 percent of all the country's forest land. On average, there are 6.5 hectares of forest for every citizen of the province (Ministry of Natural Resources and Forestry, 2021). Besides being one of the first applications in Canada, new in this study is the modelling framework in which we combine a spatial econometric and instrumental variable model to account for possible spatial spillover effects of neighbouring land cover and drinking water rates and potential reverse causation between drinking water rates and drinking water incidences. The focus on drinking water incidence rates is also new. By gradually extending and step-wise testing the first-stage and second-stage models to account for these challenges, we show that this new modelling framework fits the collected data well. Whilst controlling for a limited number of treatment characteristics such as the size of the service area and the source of water supply, the share of forest cover systematically influences both drinking water rates and incidence rates in a negative way. Hence, the first hypothesis of a negative relationship between the share of forest cover and drinking water rates is confirmed, as well as the second hypothesis of a negative relationship between the share of forested land and drinking water incidence rates. As the share of forest cover increases by 1 percent in a municipality with its own drinking water supply system, the average drinking water rate per household is reduced by around 0.4 percent per year. Aggregated over all households in Ontario, this implies a waterbill reduction of approximately 12 million Canadian dollars per year. The same 1 percent increase in forest cover was furthermore associated with a similar 1 percent decrease in the likelihood of experiencing a drinking water incident. In this latter case, we detected a nonlinear relationship where the effect seems to wear off as the share of forest cover increases. Such a nonlinear effect could not be found in the first stage model.

These results have to be interpreted with caution for a number of reasons. First of all, the collected data was only available at the level of administrative census sub-divisions across Ontario. Although the analysis was restricted to neighbouring geographical units, and accounted for spatial spillover effects between these neighbouring units, and many of these geographical areas share the same watershed, it was not possible to factor in upstream-downstream relationships within watersheds between land cover upstream and water and incidence rates downstream. This would have required a more detailed spatial analysis with more detailed geo-referenced data. The currently available data are not suitable for such a spatial analysis at watershed scale.

Secondly, key assumptions underlying the data analysis presented here are that there exists a positive correlation between forest cover and water quality, a negative correlation between water quality and water treatment costs, and a positive correlation between water treatment costs and drinking water rates. The latter assumption seems reasonable given that drinking water pricing policies in Ontario since 2015 dictate that municipalities should fully fund the costs of their water treatment operations through the revenues obtained from customers paying their water bills (Kitchen, 2017). However, the other assumptions could not be verified in this study. Using water treatment cost data across Canada, Price et al. (2017) showed that turbidity is a significant determinant of water treatment costs, increasing treatment costs by 0.1 percent if the nephelometric turbidity units (NTU) increase by 1 percent (i.e. water quality deteriorates). In the study presented here, we were unable to detect a significant relationship between the share of disturbed land, typically resulting in an increase in water turbidity, and water rates, and only a significant positive relationship could be found between the share of disturbed land in neighboring areas and drinking water incidence rates. Drinking water treatment costs are confidential and not publicly available in Canada. Follow-up studies will need to show if the same relationships are found when using confidential water treatment costs instead of water rates.

Finally, ideally the same analysis would have been performed on longer-term data about land cover, drinking water rates, and incidence rates to test the robustness of the results over time. Given that land cover data are only updated every 10 years in Ontario, such a time series analysis may be challenging. The effects of land-use changes on incidence rates, water treatment costs and drinking water rates may only show up after a number of years. Although we included information about drinking water incidences reported the year before, one year may not have been sufficient to control and manage incidences in the future.

Chapter 4
Economics benefit of the green infrastructure

4.1 Introduction

Forests provide essential natural services in watersheds to secure water supply and improve water quality (e.g. Creed et al., 2016). In particular, forests can store chemical pollutants and thus reduce the total amount of chemical residuals entering water bodies (Emelko et al., 2011; Mapulanga and Naito, 2019; Sing et al., 2017). This specific natural function plays a critical role in integrated water management (Blackburn et al., 2021). Water treatment facilities have been shown to save on water treatment costs costs when located downstream of a forested watershed (e.g. Bastrup-Birk & Gundersen, 2004; Warziniack et al., 2017). The water provision function of forests furthermore eases water shortages under drought spells, because of the ecosystem's ability to store and recharge water back into the water system. These ecosystem functions and processes stabilize the water treatment process for treatment plants that directly depend on surface water sources.

There is increasing interest in assessing these natural processes and functions provided by forests and their societal and economic benefits (Ojea and Martin-Ortega, 2015; Ovando and

Brouwer, 2019), especially the impact of watershed degradation on water treatment costs (McDonald et al., 2016). Abildtrup et al. (2013) identified, for example, significant water rate reductions related to increasing forest land cover across French municipalities. Water rates were used in this study as a proxy for water treatment costs. The latter are generally much harder to obtain than the former, especially at individual plant level (Pan et al., 2021). In the few existing case studies where land cover could be linked to drinking water costs, treatment chemical costs have been observed to be negatively correlated with forests near water treatment plants, both in the developed and developing world.

For example, based on data from 37 treatment plants in different ecoregions in the US, Warziniack et al. (2017) first examine the effect of changes in land cover on water quality through an ecological production function, and then examine the effect of changes in water quality on the cost of treatment through an economic benefits function. They show that a 1% increase in turbidity increases water treatment costs by 0.19%, and 1% increase in Total Organic Carbon increases water treatment costs by 0.46%. Mulatu et al. (2020) skip the first step in Warziniack et al. (2017) and link forest cover directly to treatment chemical costs for 8 urban treatment plants in Ethiopia over a 13 year time period (2002-2014), yielding 104 observations. Compared to non-forest cover, forest cover contributes significantly to a reduction of these costs, but this contribution declines as the buffer distance increases (from 2.5 to 30 km).

The only study in Canada by Price et al. (2017) found a significant impact of turbidity of water intake on overall treatment costs, but did not relate turbidity directly to changes in land cover or land disturbance. Their results suggested that a landscape disturbance resulting in a 50% increase in median turbidity (NTU) would increase short-term treatment cost by 4.95% in the average treatment facility based on 944 water treatment facilities across Canada. Land disturbance such as severe wildfires in Fort McMurray in northern Alberta, Canada in 2016, destroying almost 600 thousand hectares of land, have been shown to result in a significant increase of the water treatment chemical costs of 50% or higher (Thruton, 2017).

In this study, we aim to add to the empirical evidence base of studies that try to make a direct link between land cover and drinking water treatment costs. We do this based on the Canadian Survey of Drinking Water Plants, the same one as used as in Price et al. (2017), but for 2015 instead of 2011, and focusing not so much on the relationship between water intake quality and total treatment costs, but land cover around the individual water treatment facilities using different buffers, varying between 1 and 10 km, and different variable and fixed cost categories, whilst accounting for the possible influencing effects of the drainage basins in which the treatment plants are located, available key characteristics of the treatment facilities, including treatment technology, and the served population. Surrounding forest cover as green infrastructure is expected to influence both the capital costs in grey infrastructure to treat water and chemical treatment costs. The latter relationship has been investigated in the literature before, but not the former. Another novelty of this study is the use of spatial econometric models to account for observed and unobserved spatial spillover effects between neighboring treatment facilities.

Canada is considered a very suitable case study country here in view of the fact that it is one of the most forest and water abundant regions in the world. At the same time, the total drinking water treatment costs in 2015 serving over 26 million inhabitants were around 5.3 billion Canadian dollars (CAD) (Statistics Canada, 2015). Canada is covered by 347 million hectares of forest, which is equivalent to approximately 10% of all forests on the planet (FAO, 2018). Lakes and rivers cover about 12% of the country's surface area (Statistics Canada, 2016). These lakes and rivers are under increasing pressure from surrounding land intensification including agriculture, mining, industrialization and urbanization. The municipal drinking water system in Canada relies almost entirely on surrounding surface waters. Around 88% of all potable water is from surface water sources (Statistics Canada, 2021). There is therefore a lot of interest in gaining a better understanding of the influence of the surrounding land cover on water treatment costs and possible cost savings as a result of land cover change.

4.2 Model

Different fixed effects models will be presented in this chapter, focusing on the role of land cover in explaining (1) the total drinking water treatment costs, and (2) different treatment categories making up the total costs, in particular the fixed capital expenditures related to water treatment and their variable labour, materials and energy costs. Following previous research

(Mulatu et al., 2021), different spatial scales will be used to assess the role of land cover, i.e. 1, 2, 5 and 10 km radius around the location of the water treatment facility. A key assumption here is that the source water used in each treatment facility is located within these radius in view of the fact that only the geographical coordinates of the treatment facilities are available from the Canadian Survey of Drinking Water Plants (SDWP) (see section 3), not the exact location of the source waters feeding the treatment facilities. The models will initially be specified using simple Ordinary Least Squares (OLS) regression analysis, and then extended to also account for possible spatial spillover effects from landcovers surrounding neighboring treatment facilities in a spatial error model (e.g. Abildtrup et al., 2013). All the models furthermore account for the fact that the drinking water treatment facilities are located in different drainage basins across Canada. These drainage basins represent the network of connected rivers and lakes in a particular part of the country that are typically characterized as homogeneous in terms of climate, precipitation levels and hydrogeology. We therefore adopt a drainage basin fixed-effects model for all models. There are 25 drainage basins across Canada, as can be seen in Figure 1 in the next section.

The OLS models specify the relationship between forest land cover and total water treatment costs per capita, whilst controlling for a number of additional influencing factors. These other covariates are based on key factors identified in previous research (e.g. Abildtrup etc., 2013; Price et al., 2017; Mulatu etc., 2021). The inclusion of these additional covariates is meant to isolate as much as possible the impact of forest land cover on the water treatment costs so as to minimize omitted variable bias insofar possible based on the available data. The additional factors hence aim to explain as much as possible the variation in water treatment costs across treatment facilities and include the main characteristics of the water treatment plants such their size, capacity and source water type, but also the implemented treatment technologies, and the characteristics of their customers. This is specified in model 1, where we assume that these factors will linearly influence the natural logarithm of the total water treatment costs per capita:

$$\text{NatLog}\left(costs\ per\ capita_{ij}\right) = forest\ cover_{ij} * \beta_1 + other\ \ land\ cover_{ij} * \beta_2 + water\ treatment\ facility\ characteristics_{ij} * \beta_3 + treatment\ technologies_{ij} * \beta_4 + customer\ charatceristics_{ij} * \beta_5 + \epsilon_{ij} \qquad (1)$$

The β's refer to the marginal effects to be estimated for each of the various explanatory factors, and the subscript *ij* to each individual treatment plant *i* located in one of the 25 Canadian drainage basins j. The error term ϵ_{ij} is assumed to be an independent and identically distributed (iid) random variable. In the extended spatial error model, this error term accounts for unobservable spatial spillover effects from neighbouring treatment facilities and is specified as follows:

$$\epsilon_{ij} = W_{ij}^{\lambda} + u_{ij} \text{ with } u \sim iid(0, \sigma^2) \qquad (2)$$

where W is a sptial weighting matrix, λ the coefficient on the spatially correlated errors and u the residual error, assumed to be independent and identically distributed (iid) with a mean value of zero and variance equal to σ^2. The Moran eigenvector method is used in the software package R to estimate the vector of eigenvalues λ in the error term (Dray et al., 2006; Griffith & Peres-Neto, 2006). The Moran's eigenvector minimizes the Moran's index, indicating spatial autocorrelation, and these eigenvectors are included in the spatial error model to filter out spatial spillover effects and identify the appropriate spatial regression model in the analysis.

4.3 Data

The primary data source for this study comes from Statistics Canada's confidential Survey of Drinking Water Plants (SDWP) (Statistics Canada, 2017b). Statistics Canada requires all municipal water treatment plants serving more than 300 residents to participate in this survey biennially. This setup excludes private water treatment systems and systems serving First Nations. The 2015 SDWP was the last year that data were collected at individual treatment plant level. The surveys after 2015, i.e. in 2017 and 2019, are collected at the level of municipalities. Municipalities that operate more than one plant can aggregate information, like costs and amount of water processed, and the summation of responses will therefore make the link between surrounding land cover and water treatment costs weaker. Therefore, we decide to adopt the 2015 version for this research. The main characteristics of the treatment facilities are included in Table 1. The top and center part of Table 1 refers to data that is directly based on Statistic Canada's confidential 2015 SDWP, while the bottom part refers to publicly available Government of Canada's 2015 Land Cover of Canada[8]. The ArcGIS land cover dataset has a 30m spatial resolution and uses observations from Operational Land Imager (OLI) Landsat sensor. An accuracy assessment based on 806 randomly distributed samples shows that land cover data produced with this approach achieved an almost 80 percent accuracy.

It is important to point out that access to the 2015 SDWP was preceded by an extensive Statistics Canada application and training procedure, including oath-taking by both the PhD student and his supervisor to not share any of the confidential data with anyone else. Data access was only granted on Statsitics Canada computers whilst being on Statistics Canada premises in Ottawa during office hours. All data requests had to be submitted beforehand, no data could be downloaded or taken home, all the analyses presented in this paper were conducted on-site during a one-week stay at Statsitics Canada, and the release of the results had to be approved before they could be used in this paper. Due to the specific confidentiality requirement that no individual treatment plants can be identified and publishable aggregated data have to include a minimum of at least 10 observations, much information cannot be directly released in the tables presented in this chapter. The 2015 SDWP contains 1,613 observations, 240 of which did not disclose the location of water treatment plants. These 240 observations were therefore excluded from further analysis, resulting in a total number of 1,373 water treatment plant observations across the whole country. Due to the strict confidential

[8] https://open.canada.ca/data/en/dataset/4e615eae-b90c-420b-adee-2ca35896caf6.

requirements from Statistics Canada, we cannot present the summary statistics for the 240 plants that were dropped from the database, but no obvious systematic patterns (e.g. related to their key characteristics) could be detected in this group of treatment plants. The summary statistics of the 1,373 treatment facilities is presented in Table 1. Note that all of the variables that are expressed as a percentage in Table 1 do not add up to 1, because the baseline group is omitted from the summary statistics Table. This setup aligns with the confidentiality requirement from Statistics Canada.

Table 4-1 Summary statistics of the collected 2015 survey data across drinking water treatment facility

Variable	Mean	St. Dev.	Median	N
Treatment facility characteristics				
Total share where source is surface water[1] (%)	40.15	48.46	0.00	1,373
Total share where source is groundwater (%)	53.11	48.92	100.00	1,373
Average number of days per year operating at more than 90% treatment capacity	16.51	66.82	0.00	1,373
Number of facilities having at least 1 day operating at more than 90% treatment capacity	241	-	-	1,373
Number of facilities operating more than 1 plant	331	-	-	1,373
Average amount of treated water (m^3/year)	3,073,527	16,226,950	270,323	1,373
Number of facilities with pre-treatment	398	-	-	1,373
Number of facilities applying coagulation	428	-	-	1,373
Number of facilities with filtration	657	-	-	1,373
Customers				
Total share residential (%)	67.919	21.47	70.00	1,373
Total share industry and commercial (%)	18.73	15.33	15.00	1,373
Total share water loss (%)	9.93	10.81	6.00	1,373
Average population served (number of people)	19,140	95,437	1,600	1,373
Costs per capita (CAD/year) by category				
Average capital expenditures	85.79	368.94	4.90	1,373

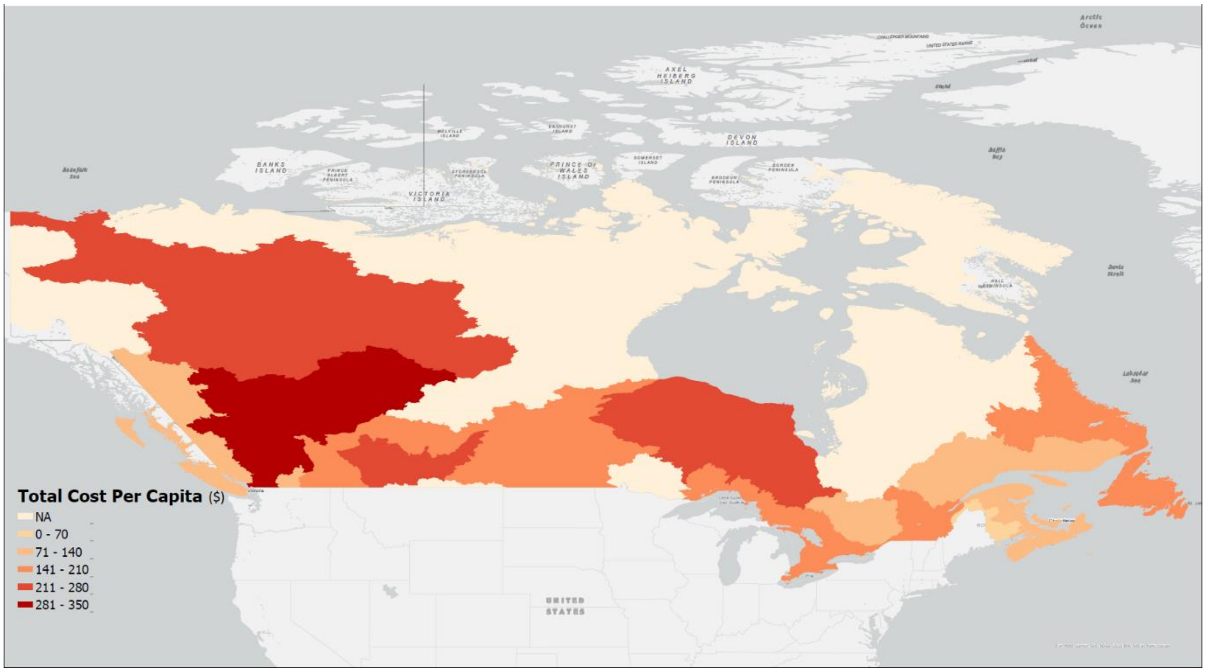
Average chemical costs	25.59	37.06	14.50	1,373
Average labour costs	52.04	67.15	31.70	1,373
Average energy costs	22.03	29.61	14.80	1,373
Average other costs	16.84	43.63	3.60	1,373
Average total costs	202.28	308.84	121.10	1,373
Source water quality				
E-Coli (most probable number per 100 milliliter)	67.08	219.89	4.58	467
Turbidity(nephelometric turbidity units)	20.67	51.54	4.33	530
Land cover and land cover around facility				
Average share urban within 1 km (%)	32.3	22.6	30.0	1,373
Average share forest within 1 km (%)	24.1	24.0	20.0	1,373
Average share urban within 2 km (%)	20.8	17.5	20.0	1,373
Average share forest within 2 km (%)	28.8	24.5	20.0	1,373
Average share urban within 5 km (%)	11.2	12.7	10.0	1,373
Average share forest within 5 km (%)	34.6	25.4	40.0	1,373
Average share urban within 10 km (%)	7.7	10.2	10.0	1,373
Average share forest within 10 km (%)	37.9	26.1	40.0	1,373

Note: 1. There are three sources of drinking water intakes, denoting ground, surface, and ground under the influence of surface. Groundwater under influence of surface water is the omitted baseline in this Table. 2. There are four types of water uses, denoting residential, commercial, losses, and wholesale. The latter category is the omitted baseline in the Table. 3. Other Costs including all other variable costs other than chemical, labour, energy. For example, acquisition of water, disposing of waste, or contractors costs.

Within the survey, a significant portion elaborates the financial costs that the treatment plants incur in the past year. This includes capital expenditures, costs for materials, labour, energy, and other costs. In contrast to past literature (e.g. Warziniack et al., 2017), this explicit cost information gives a unique opportunity to test the effect of surrounding land cover, in particular of forests, on different water treatment costs. Fixed costs like capital expenditures are more associated with the design and capacity of the plants and make up 42 percent of the total costs, while variable costs like materials (chemicals), energy and labour are more related to the plants' operation and management, constituting 13, 11 and 26 percent of the total costs, respectively. Land cover may have a different influence on fixed or variable costs, while abrupt disturbances in the landscape such as forest harvesting or wildfires are expected to significantly influence especially the operational treatment costs (e.g. extra use of chemicals to treat polluted water) (Emelko et al., 2015). The average total water treatment costs per capita served across the 25 main drainage basins in Canada are presented in Figure 1. Note that in Figure 1 many rural regions have less than ten observations. In line with the confidentiality requirements, the summary statistics are therefore not direct visible in the map.

Besides these financial aspects, a variety of plant design and operation characteristics are available from the SDWP. This includes information about the drinking water source, such as the share of ground and surface water intake, the total amount of treated water, and water loss. Water treatment amounts were available on a monthly basis and hence allowed us to also calculate seasonal variation in monthly water processing. We use natural logarithm of the standard deviation of the monthly water quantities being processed to reflect any seasonal effects. If a water treatment plant has a large standard deviation, i.e. the volume changes dramatically between months, this is used as a strong indicator for seasonal effects and fluctuations. Also the population served by the treatment plants is included in the analysis, and the breakdown in different customer groups (share residential, industry and commercial).

Figure 4-1 Total Costs per capita across the 25 drainage basins in Canada (2015 CAD)



The scale of operation and the use of the available treatment capacity have been shown to affect the operation costs (e.g. Plappally & Lienhard, 2012), and the share of the operating scale over the design capacity may at the same time influence the cost-effectiveness of the treatment system. The operation may trigger more costs if the plant operating scheme is close to its design capacity most of the time. In reflecting this pattern, we used the responses to the question asking treatment plants for the number of days that the plant is operating at more than 90 percent of its capacity. In addition to the total number of days, we also created a dummy for those plants that have more than one day operating at more than 90 percent of their capacity. This novel setup compared to previous studies is meant to create a regression by discontinuity where the cutoff point is zero days. Following Plappally & Lienhard (2012), there is a potential cluster difference between the group of treatment plants with zero days of water treatment beyond 90 percent capacity and water treatment plants that bypass the threshold. Therefore, the coefficient of days operating at more than 90 percent capacity should be interpreted as the log value changes regarding total water treatment costs within the group of plants with at least one day operating more than 90% capacity in this setup.

The survey also includes questions related to source water quality. Monthly parameter values for Escherichia coli (E-Coli), temperature, and water turbidity are asked and provided. However, these variables have a lot of missing values and are subject to strict confidentiality requirements from Statistics Canada. The latter (confidentiality) reinforces the former (more missing values) in some cases. That is, due to limited numbers of observations in some of the drainage basins, they violate confidentiality rules and therefore had to be removed from further analysis, adding to the already large number of missing observations. Therefore, only the average E-Coli and turbidity values are reported in Table 1 with the summary statistics. The monthly data are used to compute the annual means for these water quality parameters for each plant, and these are subsequently aggregated and summarized across all treatment plants. The number of observations for these source water quality parameters drops to just over a third to 40 percent of the total number of observations for all treatment plants. In view of the fact that water quality information is missing for most of the water treatment plants, they were not included in the regression analysis presented in the Results section.

A final group of water treatment plant characteristics are the different technologies they use during the treatment process. The different categories identified in the SDWP are listed in the annex to this paper. They are clustered here into three categories: pre-treatment, coagulation and filtering. Coagulation and filtereing are the two main water treatment processes in Canada (Statistics Canada, 2017b). As stated by Statistics Canada, around 73% of the total processed water in quantity has been treated with aluminum-based coagulation. However, only 428 out of the 1,373 plants reported they use at least one coagulation technology specified in the list of the appendix (Statistics Canada, 2017b). This pattern holds similarly for filtration technology, while 74.4% of the total quantity of water has been reported to be filtered by granular media, while only a little more than one-half of respondents indicate that they have filtering technology involved for the water treatment process. Therefore, there is a potential difference between water treatment plants that claim to have filtration and coagulation technology with the rest that do not. The created dummy variable intends to reflect the difference. The pre-treatment process is believed to increase the overall water treatment process significantly, while keeping other factors constant (Hackney & Weisner, 1996). Therefore, we included also this step in the regression analysis to test its impact on the variation in costs.

We also include further data sources into consideration. The land cover covariates are generated from the Canadian Land Cover 2015 and integrate the urban and forest land cover, based on the plants' GIS coordinates in the original dataset. The land usage shares are computed using the QGIS buffer function in percentage values for a 1km radius circle around the plants' address. Here, all tree species are aggregated into one class. The literature suggests that the quality and species of forests may have an effect on the quality of source water(Babur et al., 2021; Voss, 2018), but this is not something we are able to pick up in this study due to a lack of more detailed information about these variables.

In the results section, we will present a sensitivity analysis by using different proximities, ranging from 1k to 2km to 10km. One of the limitations may also arise. As mentioned, some plants may have intake spots away from the plant. The dataset does not provide the location of source water intake, and there is a potential measurement error for the land cover information, given the land cover of water treatment plants and intake spots vary. However, we argue that there is not a clear trend that this measurement error is correlated with any independent variables. Therefore, we assume that this measurement error is random. Agriculture land cover together with wetlands and shrublands are treated as the baseline land cover, and hence the β_1 coefficient in equation 1 and 2 is therefore interpreted as the change in the log cost per capita as a result of a 1 percent change in forest land cover compared to this combined land cover. Agricultural land cover tends to discharge nutrients into water bodies, which in turn increases the total water treatment costs (Abildtrup et al., 2013). Changing the baseline category to another land cover did not change the results in this study. We used urban and forests land share to best represent the major land usages that influence the total costs, as also indicated in past research (Abildtrup, et al., 2016; Warziniack, et al., 2017).

4.4 Results

4.4.1 Explaining the variation in total drinking water treatment cost

First the regression results focusing on the total treatment costs per capita are presented, both using OLS and a spatial error model to account for possible spatial spillover effects. Table 2 presents the OLS regression results, where the four columns specify the relationship between total costs per capita and land cover across the four different spatial resolutions (distances) around each treatment facility. The other covariates are identical across the four columns. Only the land cover variables are generated based on different proximity radius, ranging from 1km to 10km. This setup aims to test whether land cover impacts total treatment costs under different spatial resolutions or distances from the treatment facility. The R^2 and F-test statistics are the same across all 4 model specifications, which suggests that the explanatory power of the four specifications is the same. Although the estimated models are highly significant, their explanatory power is not very high. Only around 35 percent of the variation in the total costs per capita is explained by the model specification.

The coefficient estimates for all explanatory factors are very similar. The major changes can be noticed from the land cover variables. First, the forest land cover is only weakly significant at the 10 percent level at a 1km radius, while it is not statistically significant for the other three. This suggests that potential land cover impacts decay as proximity to the water treatment plant increases. The negative sign on the coefficient indicates that the total treatment costs are reduced as the share of forest cover increases in a radius of 1 km around the water treatment facility compared to the baseline land cover of agriculture, wetlands and shrubs. A one percent increase in forest cover in a radius of 1 km around a water treatment facility results all else equal in a proportionate reduction (0.99%) in total treatment costs per capita.

Second, urban land cover illustrates a different trend, other than forests land cover. A significant positive relationship exists between urban land cover and total water treatment costs, but this relationship is only statistically significant when the radius is enlarged to 5 or 10 km. The total costs per capita are on average and ceteris paribus 1.03 percent higher if the share of urban land cover increases by 1 percent within a 5 or 10 km radius. These results are in line with previous studies that show that the costs may increase due to increasing human activity and associated pollution levels (Price & Heberling, 2020).

Table 4-2 Annual drinking water treatment costs OLS regression results with drainage basins fixed effects and using four proximity specifications for land cover

	Dependent variable:			
	Log(Total Cost Per Capita)			
	1km	2km	5km	10km
Land cover/use				
Forests (%)	-0.012*	-0.009	-0.005	-0.009
	(0.006)	(0.006)	(0.006)	(0.006)
Urban (%)	0.002	0.012	0.030**	0.028*
	(0.007)	(0.010)	(0.014)	(0.017)

Treatment facility characteristics				
Source: share of ground water (%)	-0.010^{***}	-0.010^{***}	-0.010^{***}	-0.010^{***}
	(0.004)	(0.004)	(0.004)	(0.004)
Nat. Log total amount of water treated (m^3/year)	1.454^{***}	1.482^{***}	1.525^{***}	1.547^{***}
	(0.294)	(0.294)	(0.294)	(0.294)
Seasonality (natural log of standard deviation in m^3/year)	0.152	0.135	0.113	0.108
	(0.147)	(0.146)	(0.146)	(0.146)
Operating More than One plant (dummy)	0.851^{***}	0.837^{***}	0.872^{***}	0.869^{***}
	(0.300)	(0.300)	(0.301)	(0.301)
Has at least one day operating at more than 90% capacity (dummy)	0.187	0.182	0.183	0.176
	(0.575)	(0.575)	(0.575)	(0.575)
Number of Days operating at more than 90% capacity	-0.297^{*}	-0.301^{*}	-0.305^{*}	-0.305^{**}
	(0.156)	(0.156)	(0.155)	(0.155)
Pretreatment (dummy)	0.409	0.411	0.398	0.385
	(0.302)	(0.302)	(0.302)	(0.302)
Application of coagulation (dummy)	0.942^{**}	0.927^{**}	0.939^{**}	0.926^{**}
	(0.424)	(0.425)	(0.424)	(0.424)
Filtration (dummy)	2.169^{***}	2.167^{***}	2.166^{***}	2.183^{***}
	(0.353)	(0.353)	(0.353)	(0.353)

Customers				
Nat. Log Population Served	-3.240***	-3.315***	-3.413***	-3.389***
	(0.265)	(0.270)	(0.277)	(0.276)
Water Use: Share Residential (%)	0.010	0.010	0.009	0.009
	(0.009)	(0.009)	(0.010)	(0.010)
Water Use: Share Commercial and Industry(%)	0.002	0.002	0.001	0.002
	(0.011)	(0.011)	(0.011)	(0.011)
Water Use: Share Water Loss (%)	0.013	0.012	0.011	0.012
	(0.014)	(0.014)	(0.014)	(0.014)
Constant	19.676***	19.858***	20.122***	19.962***
	(2.084)	(2.105)	(2.135)	(2.111)
Number of observations	1,373	1,373	1,373	1,373
R^2	0.371	0.371	0.371	0.371
Adjusted R^2	0.353	0.353	0.353	0.353
Residual Std. Error (dof = 1334)	4.687	4.687	4.686	4.686
F Statistic (dof = 38; 1334)	20.710***	20.699***	20.720***	20.718***

$^{*}p < 0.10$; $^{**}p<0.05$; $^{***}p<0.01$

Interestingly, almost the same results are found for the land cover variables when accounting for possible unobserved spatial spillover effects between neighbouring treatment facilities (see Table 3). This spatial correlation is statistically significant, as can be seen from the outcome of the LR test statistic, comparing the log likelihood values for the unrestricted (with unobserved spatial correlation) and restricted model (without unobserved spatial correlation). In addition to finding the same significant negative coefficient estimate within a 1 km radius for forest cover, now also the coefficient estimate within a radius of 10km is statistically significant at the 10 percent level and, as expected, negative. The same positive coefficient estimate is found for urban cover, but this coefficient estimate is only statistically significant within a radius of 5 km. Hence, the estimated OLS model results are robust when also taking the unobserved spatial correlation between neighbouring treatment plants into consideration. In view of the fact that the OLS and spatial error model results are the same, we will discuss them here together.

Turning to the other covariates, we notice that the total costs per capita are positively correlated with the total amount of water that has been processed during the year. The significant positive coefficient estimate demonstrates that, as expected, the drinking water treatment costs increase as the amount of treated water increases. Treatment plants are facing higher costs in meeting higher demands from customers. The standard deviation of the average amount of treated water, used as an indicator here to reflect seasonal changes in drinking water demand and supply, does not have a statistically significant impact. One potential explanation is that the seasonality has already been accounted for during the plants' design process. Whilst controlling for the amount of treated water, the population size coefficient is expected to exhibit a negative coefficient, reflecting economies of scale. Keeping the amount of treated water constant, as the number of people served by the treatment plants increases, the total treatment costs per capita go down, indicating that water treatment plants serving more people are more likely to operate in a cost-efficient manner. A 1 percent increase in the number of customers results ceteris paribus (and as a result of the double-log functional form) in a 3.2 to 3.4 percent decrease in total water treatment costs per capita in both the OLS and spatial error regression models. Note that the specification of the customers (and their shares in total water supplied) does not have any influence on the total treatment costs.

From the regression Tables, it can be seen that managing multiple water treatment plants results in increasing treatment costs, whereas a higher share of groundwater as source water reduces the total water treatment costs significantly, as expected. Water underground is better protected and the soils have a natural cleansing capacity, reducing pollution risks in source water and reducing total treatment costs.

Although the dummy variable representing a continuity break is not statistically significant, the number of days the plant operates at more than 90% of its capacity is significantly negatively related to the total treatment costs. Total costs seem to reduce as plants are managed more days near the limit of their treatment capacity. However, the potential cost reduction shall also come with further risk. The risk of not meeting the drinking water demand of customers may force water specialists in charge of extra costs, e.g. transfer water from other municipalities. This risk aspect cannot be plotted due to the limitation of the survey.

Finally, different technologies were also included in the regression models. Contrary to prior expectations (Hackney & Weisner, 1996), pre-treating the source water before it enters the treatment plant does not affect the total treatment costs. However, the dummy variables indicating if the treatment system includes coagulation and filtering significantly increase the total treatment costs per capita compared to the other technologies listed in the appendix to this chapter. This statistical difference also iterates that water treatment cost dynamics may vary significantly between plants that adopt these two technologies or not. The decision for one or the other technology is caused by demand, source water quality etc. One of the key assumptions we have in this paper is that all plant officers will adopt the most cost-efficient solution for water treatment plants, accounting for the aggregate demand and source water quality. Noting that less than half of the treatment plants indicate they adopt filtration and coagulation procedure within the water treatment process, while these plants account for more than 74% of total water being treated in quantity, it is obvious that water treatment plants that are serving larger population are more likely to adopt these two technologies. Therefore, including these two variables will also give a robust estimation of the effect of households and water quantity being processed.

Table 4-3 Annual drinking water treatment costs spatial error regression model results with drainage basins fixed effects and using four proximity specifications for land cover

	Dependent variable:
	TotalCost

	1km	2km	5km	10km
Land cover				
Land Cover: Forests (%)	-0.012*	-0.008	-0.006	-0.011*
	(0.006)	(0.006)	(0.006)	(0.006)
Land Cover: Urban (%)	0.004	0.013	0.027**	0.024
	(0.006)	(0.009)	(0.013)	(0.015)
Treatment facility characteristics				
Source: Ground Water (%)	-0.010***	-0.010***	-0.010***	-0.010***
	(0.004)	(0.004)	(0.004)	(0.004)
Log Total Annual Water Processed (Cubic Meters)	1.410***	1.437***	1.478***	1.505***
	(0.293)	(0.292)	(0.292)	(0.293)
Dummy: Operating More than One plant	0.887***	0.878***	0.909***	0.910***
	(0.290)	(0.290)	(0.290)	(0.291)
Seasonality	0.136	0.115	0.093	0.086
	(0.158)	(0.158)	(0.158)	(0.158)
Number of Days operating more than 90% capacity	-0.396***	-0.395***	-0.396***	-0.396***
	(0.153)	(0.153)	(0.153)	(0.153)
Dummy: Has at least one day operating more than 90% capacity	0.510	0.493	0.485	0.469
	(0.564)	(0.564)	(0.564)	(0.564)
Dummy: Has at least one machine listed as pretreatment	0.367	0.368	0.357	0.339
	(0.292)	(0.292)	(0.292)	(0.292)
Dummy: Has at least one machine listed as coagulation	0.893**	0.879**	0.895**	0.895**
	(0.408)	(0.408)	(0.408)	(0.408)
Dummy: Has at least one machine listed as filtration	2.064***	2.060***	2.061***	2.075***
	(0.345)	(0.345)	(0.345)	(0.344)

Customers				
Log Population Served	-3.237***	-3.307***	-3.388***	-3.369***
	(0.258)	(0.262)	(0.268)	(0.268)
Water Use: Residential(%)	0.004	0.004	0.003	0.004
	(0.009)	(0.009)	(0.009)	(0.009)
Water Use: Commercial and Industry(%)	0.0002	-0.0001	-0.001	0.0001
	(0.011)	(0.011)	(0.011)	(0.011)
Water Use: Losses(%)	0.008	0.007	0.007	0.008
	(0.013)	(0.013)	(0.013)	(0.013)
Constant	21.102***	21.299***	21.586***	21.476***
	(2.019)	(2.037)	(2.067)	(2.046)
Observations	1,373	1,373	1,373	1,373
Log Likelihood	-3,891.195	-3,891.438	-3,891.349	-3,891.141
σ^2	16.938	16.945	16.944	16.941
Akaike Inf. Crit.	7,872.389	7,872.875	7,872.698	7,872.281
Wald Test (df = 1)	2.274	2.008	1.815	1.534
LR Test (df = 1)	2.136	1.887	1.699	1.439

$^{*}p < 0.10$; $^{**}p<0.05$; $^{***}p<0.01$

4.4.2 Explaining the variation in fixed and variable costs

We also include different costs by categories as the dependent variable, see Table 4. The objective in this section is to utilize the categorical cost differences to explore the heterogeneity of variables, which may influence types of costs differently. As shown in the regression analysis in the previous section, the differences in explanatory power using different proximities to the treatment facilities are minimal. We were able to show that forest cover signifacntly reduces the total costs per capita, but only when adopting a smaller radius around the water treatment plants. Thus, we use the same 1km radius in the model specifications to explain variations across different cost categories (see Table 4), where the capital expenditures are used as a proxy for the total annual fixed costs, while other cost items are variable costs. Only the OLS regression model results are presented in this section. As before, the 25 drainage basins are included as a fixed effect in each of the model specifications, and the dependent variable is converted into its natural logarithmic form to improve the goodness of fit of the estimated regression models.

Table 4-4 Variable and fixed annual drinking water treatment costs OLS regression results with drainage basin fixed effects

	Variable Cost			**Fixed Cost**
	Labour Cost	Chemical Cost	Energy Cost	Capital Expenditure
Land cover				
Land Cover: Forests (%)	-0.0010	-0.0017	-0.0010	-0.0053^{*}
	(0.0013)	(0.0015)	(0.0013)	(0.003)
Land Cover: Urban (%)	-0.00050	-0.0012	-0.00049	0.0069^{**}
	(0.0014)	(0.0016)	(0.0014)	(0.0033)
Treatment facility characteristics				
Source: Ground Water (%)	-0.002^{***}	-0.006^{***}	-0.002^{***}	-0.003^{*}
	(0.001)	(0.001)	(0.001)	(0.001)
Log Total Annual Water Processed (Cubic Meters)	0.450^{***}	0.347^{***}	0.450^{***}	0.015
	(0.060)	(0.069)	(0.060)	(0.143)

Dummy: Operating More than One plant	0.028	0.049	0.028	0.142
	(0.061)	(0.070)	(0.061)	(0.145)
Seasonality	-0.024	-0.007	-0.024	0.105
	(0.030)	(0.034)	(0.030)	(0.071)
Number of Days operating more than 90% capacity	-0.012	-0.025	-0.012	-0.105
	(0.032)	(0.036)	(0.032)	(0.076)
Dummy: Has at least one day operating more than 90% capacity	-0.146	0.095	-0.146	0.322
	(0.117)	(0.135)	(0.117)	(0.280)
Customers				
Log Population Served	-0.649***	-0.593***	-0.649***	-0.217*
	(0.054)	(0.062)	(0.054)	(0.129)
Water Use: Residential(%)	-0.001	-0.001	-0.001	-0.003
	(0.002)	(0.002)	(0.002)	(0.005)
Water Use: Commercial and Industry(%)	-0.002	-0.0004	-0.002	-0.002
	(0.002)	(0.003)	(0.002)	(0.006)
Water Use: Losses(%)	0.0003	-0.002	0.0003	0.006
	(0.003)	(0.003)	(0.003)	(0.007)
Constant	1.985***	2.914***	1.985***	2.953***
	(0.424)	(0.488)	(0.424)	(1.016)
Observations	1,373	1373	1,373	1,373
R^2	0.252	0.261	0.252	0.081

Adjusted R^2	0.232	0.241	0.232	0.057
Residual Std. Error (df = 1337)	0.955	1.100	0.955	2.289
F Statistic (df = 35; 1337)	12.866***	13.477***	12.866***	3.353***

$^{*}p < 0.10$; $^{**}p<0.05$; $^{***}p<0.01$

The overall goodness of fit of the estimated OLS models is lower when breaking up the total costs in different subcategories. The fixed costs model has the lowest explanatory power with no more than 10 percent, while the three other models explain approximately 25 percent of the variation in the variable costs.

Starting with forest land cover, this appears to have different impacts across the cost categories. The capital expenditure model is the only model where forest cover is statistically significant at the 10 percent level and negative (as expected) compared to the basleine category (agriculture, wetlands and shrubland). Considering fixed costs related to grey infrastructure and 'green' forest infrastructure (measured through the share of forest cover within a radius of 1 km of each drinking water treatment plant) as two different mechanisms to deliver safe drinking water as discussed in Pan and Brouwer (2021) is not possible here, but the significant negative relationship in Table 4 does suggest that investing more in green infrastructure would reduce the grey infrastructure watrer treatment costs. Interestingly, the urban land cover is also only statistically significant in the fixed cost model and and as before positive. The coefficient estimates are, however, considerably smaller in Table 5 than they were in Tables 3 and 4.

The chemical costs are particularly of interest here (e.g. Mulatu et al., 2020), but contrary to prior expectations none of the land cover variables are significantly of influence. Interestingly though, the share of groundwater intake has a much bigger (three times higher) negative impact on the chemical costs than the other two cost categories. The difference in coefficient estimates is statistically significant at the 1 percent level. This is in line with what is stated by Environmental and Climate Change Canada (2013), namely that the quality of groundwater sources is more stable, which reduces the excess demand of chemical inputs. The correlation between groundwater intake and fixed costs is also lower and only significant at the 10 percent level.

As for the total treatment costs, a significant positive relationship is found between the amount of treated water and variable costs, but not for fixed costs. The amount of treated water during the year has moreover a 22 percent lower impact on the chemical costs than on the variable labour and energy costs. No significant effect can be found for the number of plants to treat the drinking water.

Similarly, significant economies of scale are detected for the number of people served by the treatment plants, keeping the amount of treated water constant, but this effect is much smaller and less significant for the fixed costs than the variable costs. This is as expected, as the fixed costs are literally ‘fixed’ and are not expected to change as a result of higher treatment quantities or a higher number of people served.

As for the total costs, the type of customers does not significantly influence the variable or fixed costs, and also no seasonal effect can be detected for any of the cost categories. This time, also no significant capacity limit effect can be found, neither for the dummy variable or the number of days that a plant operates at more than 90 percent of its capacity. Note that contrary to the total costs per capita no control is included in the regression models for the type of technologies used to treat the water or whether the source water was treated before it was treated in the treatment plant.

4.5 Discussion and Conclusion

This is one of the first studies in Canada focusing on the relationship between forested land and drinking water treatment costs. Based on Statsitics Canada's 2015 SDWP, we are able to demonstrate that forest land cover significantly reduces the total costs per capita in Canada, albeit at a relatively lower significance level (10%) and in a model that only explains around 35 percent of all the variation in the observed drinking water treatment costs. Increasing forest cover in the direct surroundings of the drinking water treatment plant within a radius of 1 km by one percent results in a more less proportionate decrease in the total drinking water treatment costs of one percemt. This estimation is higher than the previous evaluation of the role of forests, in Europe (Abildtrup et al., 2016) and North America (Warziniack et al., 2017). For Ontario, the previous chapter showed that a similar increase in forest cover reduces the average water rate by 0.4 percent.

Simultaneously, tree planting is expensive. Suppose a tree plant will cost $0.2 while 1500 trees roughly take 2.5 acres of land, estimated by Nottawasaga Valley Conservation Authority in Ontario (2021), the total planting costs around $0.13 billion by increasing forest land cover by 1% for all land use 1km near water treatment plants, disregarding the proceeding costs like management costs. This amount exceeds the aggregate use benefit evaluated above. This seems to align with Price and Heberling (2018), which indicates that the drinking water use benefit tends to be less than the cost of source water protection programs. However, the non-use value, denoting economic benefits that residents near watersheds receive, is also another crucial component for project evaluations. Price and Heberling (2018) argue that the sum of drinking water use values and the non-use value may bring a positive net benefit for forest expansion projects. We cannot exploit the accurate sum in this paper, given the limitation of this research.

The categorical regression comparison may give a new direction in understanding the economic benefit of drinking water treatment. Fixed costs, reflected by capital expenditure, is relatively lower for the forest-abundant region. This pattern confirms the substitution effect between green and grey infrastructure, identified by Pan and Brouwer (2021). The chemical costs and other variable portions are not statistically significantly related to forest land cover amount. However, the boundary definition may still not fully reflect the land disturbances within the watershed. Thus, these results may not fully exclude the potential significant relationship between forests and variable costs.

Given the spatial dispersal, we do not find variations between non-spatial and spatial models. This pattern may not hold if we can cluster the data on a spatial scale. However, this lower scale analysis, e.g. based on drainage region, cannot be performed due to the confidential requirement of the data source. While the lower scale may result in a potential leakage of data, this analysis cannot be presented in this research.

One of our key assumptions suggests the water treatment function is only related to forest amount, while it is not totally valid empirically. The healthiness and species may alter the expected treatability. This research cannot include further heterogeneous discussion due to the limitation of data.

The water quality information is crucial in understanding the challenges that water treatment plants are facing. On top of source water quality, it will be essential to enlarge the focus on the variation of parameters across the year. The high fluctuation can increase the difficulties in drinking water treatment while increasing the total cost as a response. This feature is partially explored while analyzing the source water types. From the results, we can observe that groundwater sources, which are believed to provide more source water protection, cost less for the water treatment, either variable or fixed.

One last limitation of this research is the lack of inter-temporal variations. This study only focuses on the costs of water treatment facilities in 2015. Given the lifetime variation between plants, it is likewise that the temporal variation of plant usages may also shake the robustness of this result. For instance, old plants may require further maintenance and updates, which our data inputs cannot directly adjudicate.

Chapter 5 Conclusions

5.1 Contribution to the current literature

This thesis has contributed multiple aspects to the current research field and explored some novel relationships that have not been analyzed before.

First, this thesis first plotted the theoretical framework in understanding the policy makers' responses toward green and grey infrastructure for the water treatment services. Inspired by multiple historical research(Abildtrup et al., 2013; Mulatu et al., 2021;Warzniack et al., 2017), water treatment is modelled as a public service that social planners are responsible for securing drinking water safety and minimizing the total treatment cost. This framework is first modelled explicitly in the economic context. On top of the baseline scenarios, wildfire, tree growth, and climate change effects are expressed explicitly to different submodels and extensions. These further expressions enrich the existing framework and plot multiple essential concerns within the policy makers' decision-making lists.

The third chapter inherited the basic setup from the historical research(Abildtrup et al., 2013). The key objective is aiming to investigate and discuss the correlation between forest land cover and water treatment costs proxied by water rate. This study has been widely conducted globally(Abildtrup et al., 2013; Mulatu et al., 2021; Warzniack et al., 2017).

However, it has not been conducted in Canada before. The closest one is Price et al. (2017), where the relationship is drawn from source water parameters and water treatment costs instead of modelling land cover information within the analysis. Building upon the existing model, there are still multiple innovative structures that the new model within chapter three added. Firstly, it addresses the relationship between adverse water quality incidents(AWQI) and forest land covers. This variable has not been analyzed before in this setup before. Furthermore, the model provides a robust estimation while accounting for the endogeneity effect between drinking water rate and AWQI. Water rates tend to go higher, as a response to historical AWQI. This negative correlation between AWQI and drinking water rates will leave a biased estimation. The instrumented model in chapter three firstly provides an unbiased estimation method that can solve both the endogeneity, and the spatial spillover effect once the model includes the spatial error and lag specifications. The results clearly state that there exists a negative correlation between drinking water rate and forest land cover. Furthermore, further forest land cover and higher drinking water rates are both pointing to a lower AWQI rate. These findings align with existing international research, thus providing the first economic benefit analysis of drinking water treatment given further forest land cover in Canada.

The fourth chapter attempts to narrow the existing gap between water treatment rate and water treatment costs. The Federation of Canadian Municipalities stated in the third edition of the National Guide of Sustainable Municipal Infrastructure(FCM, 2006); the drinking water rate should satisfy the cost recovery standard. However, the drinking water rate usually takes years to be designed while relying mainly on the historical information with estimation to the future treatment. This setup makes a potential lag between drinking water rate and costs, which shakes the robustness of the third chapter estimations. In solving this specific concern, the fourth chapter is analyzed by using confidential survey data from Statistics Canada. The new dataset also granted novel findings in comparison with historical research. The fourth chapter analysis sub-cost components that contribute to the total cost factors. Beyond the chemical or material costs that have been studied historically(Mulatu et al., 2021), the fourth chapter also expands the scope onto the fixed costs – capital expenditures. The statistically significant negative correlation between capital expenditures and forest land covers echoes the main findings in Chapter two, where there is a potential substitution effect between green and grey infrastructure that can be expressed in monetary terms. Furthermore, this study compares fixed and variable costs components to understand better the potential heterogeneity effect of forest land on water treatment costs. These findings are firstly explored on a site level among the existing literature.

These three papers also provide internal linkages through findings and models. The first chapter provides a theoretical framework that is transformed into the empirical specifications in the latter two chapters. Meanwhile, as stated above, the green and grey substitution effect is firstly noticed in the fourth chapter, which confirms the theoretical findings of the second chapter. Finally, the third and fourth chapters can be considered as the comparison of modelling drinking water treatment benefits by costs and rates. The drinking water rate, the dependent variable in chapter three, faces the designed lag issue. This limitation is encountered in the fourth chapter, once the cost component is included in the analysis. From findings, capital expenditure, which will be transformed into future drinking water rate, is negatively correlated with forest land cover. This finding is robust while controlling spatial errors and drainage basin fixed effects. Therefore, all three chapters complement each other and provide a systematic analysis of the relationship between drinking water treatment costs and forest land covers.

5.2 Limitation and future works

However, this paper still possesses multiple limitations that can be exploited by future research. Within the second chapter, the social planner is believed to make the best investment decision given the parameters associated with water treatments. Results are simulated, given the expected return of initial investment decisions. The parameter selection is one of the potential scenarios. However, it will be more robust if more scientific research is available in suggesting more robust parameters that should be considered. This update will make the result more policy-relevant.

Second of all, the empirical analyses are based on the administrative boundaries of census subdivisions, the highest spatial resolution more or less equal to municipalities in Canada, at which water and incidence rate data are publicly available. The influence of forested land cover on water treatability is typically measured within the hydrological boundaries of watersheds. Agreements exist, in several places around the world (e.g. Wunder et al., 2018), for example, between upstream landowners and land users and downstream water utilities to manage the land in such a way so as to minimize any disturbance to the water services provided by the watershed, such as erosion or pollution. The spatial regression models employed in this PhD thesis are hence based on the administrative boundaries of neighbouring census subdivisions (CSD's), not spatial relationships between upstream land cover and downstream water or incidence rates, for example. In the second study, it was impossible to create or restore watershed boundaries based on the spatial delineation of CSD's. Typically, a watershed consists of multiple CSD's. Land cover shares in the CSD's were used in the second paper, without knowing where the water intake sources were located exactly in each CSD. The main selection criterion of the CSD's was that each one had at least one drinking water plant. However, where they received their water from was unknown. It could therefore be the case, especially in the southern part of Ontario in urban areas along the shores of Lake Ontario, that these areas received their water from different areas than where the CSD's are located. This is an important caveat in the presented analysis here. In the third study, analyzing the water treatment data at watershed level was not allowed due to the breaching of data confidentiality. Here, the only scale at which the analysis was allowed was at the level of the 25 drainage basins in Canada. These were included as fixed effects in the spatial regression models. Hence, although the water treatment costs were based on the exact location of the drinking water treatment facilities, concentric circles were used around these drinking water plants to calculate surrounding land cover and land use, and hence also here the observed and unobserved spatial correlation between forest cover and water treatment costs has to be interpreted with the necessary care. The spatial relationships captured in the spatial regression models are also in this second empirical study not based on the hydrological boundaries of the watersheds in which the drinking water treatment plants are located; or without knowledge of where exactly these water treatment plants get their intake water from, from within the watershed in which they are located or from outside that watershed. In none of the two studies was a direct causal relationship established between (1) forest cover and water quality (based on available water quality monitoring data), (2) water quality of the drinking water intake sources and water treatment costs. The estimated relationships in this PhD thesis skipped these two important causal relationships and directly investigated the impact of forest cover on treatment costs (or water rates or incidence rates) without knowing exactly how forest cover affects water quality in the sources used by the drinking water plants that were surveyed in the 2015 Survey of Drinking Water Plants. A key assumption therefore is that the forest cover information used in the two empirical studies in this PhD thesis include the relevant water intake sources for the drinking water plants involved.

The limitation described above will also alter the policy scenarios as well. The empirical studies of chapter three adopt a municipalities level for all analyses. Therefore, potential investment recommendations will be assigned to the municipality level, while watershed catchment conditions will be ignored. However, if analysis can be conducted with watershed boundary information included, then coordination between plants in the same watershed will be more efficient. Unlike investment to the plant level, systematic changes and improvements will be captured for all water treatment plants in the same watershed. With that being said, the overall cost-effectiveness will be further improved.

The heterogeneity of forest species and forest qualities are not examined in both papers. Within chapter 2, the model only demonstrates the age difference between forests, while it assumes it has no water treatment implications. For chapters 3 and 4 on the empirical aspects, forest land cover is computed as a sum of all tree species, disregarding the type and condition. It has been noticed that these attributes will influence the final drinking water delivery outcomes, by United States Trust for Public Lands and American Water Works Association (2003) and World Bank and WWF Alliance for Forest Conservation and Sustainable Use (2003). Within their reports, it is noted that forest expansion, disregarding tree species and forest conditions, will not reach an ideal solution for water treatment purposes. Future research should explicitly model forest land cover by species. This change will provide a clear picture for policymakers. The ideal investment is never planting more trees near the water treatment plants but to restore the forest system near the water sources.

The financial aspects of water treatment plants are examined limited. On top of water treatment costs or water rates, the water plants' debt and investment represent the stagnations and potentialities of water treatment plant management. The drinking water rate and costs only reflect part of the financial aspects of water treatment facilities. Drinking water rates are usually designed for years in a row in recovering the annual water treatment costs. This cost refers to both actual treatment cost and debt in the past. However, it is still unclear to what percentage are treatment projects are in debt. The financial condition will alter the long-term investment that social planners are willing to make. For instance, the limited funding sources may limit the updating incentives of social planners, and in turn, the future water treatment cost is expecting to increase.

This limitation may also draw severe policy implications. Within chapters three and four, water rates and water costs are compared between municipalities and plants. Therefore, we are assuming the monetary variables, either rates or costs, are directly comparables with observed variables in the regression specification. In other words, the financial condition, i.e. cost-recovery capability that is not included in the model, is assumed the same across all plants. With this assumption, one of the policy suggestions will be adopting adequate infrastructure/technology with Federal investment to municipalities that want to improve the drinking water condition. However, if there exists a negative correlation between cost-recovery capability and water treatment costs, this policy will further enlarge the aggregate future water treatment costs, which will be transformed into water bills according to the cost-recovery scheme by the Federation of Canadian Municipalities' guide(FCM, 2006). Therefore, there is an urgent demand to examine the relationship between these two factors.

This limitation may also provide a future research potentiality as well. Green infrastructure, with an adequate balance of grey infrastructure, will improve the cost-effectiveness of the water treatment, as drawn for the conclusion of Chapter two. Therefore, it will be more important to examine the relationship between forest land cover and the cost-recovery capability of water treatment plants over time. Suppose a positive relationship exists between forest land cover and financial recovery factors. In that case, we shall conclude that there are potentialities that expanding green infrastructure can enhance cost-efficiency in Canada. With that being said, then the policy implication will be proposed as investing in general green infrastructure to enhance the overall water treatment cost-efficiency, which will benefit the financial capability of water treatment plants.

There is a factor that is not included in the empirical research, while it has been discussed in the model, denoting climate change. Climate change is one of the founding reasons that researchers and policymakers are expanding the research and investment toward green infrastructure. According to US EPA(2021), challenges in water treatment due to climate change include 1. Water supply shortage, 2. Water supply uncertainties, 3. Source water quality changes, 4. Source water quality uncertainties, etc. Together with wildfire risk, these factors impose a costly water treatment barrier to the current system. Most importantly, as discussed in chapter two, grey infrastructure has zero climate change resilience in severe climate change scenarios. Therefore, in chapters three and four, the cost reduction is assumed to be held of the environmental condition remain the same. However, for the severe climate change cases, grey infrastructure will not operate as efficiently as right now, and the cost reduction evaluation will significantly underestimate the cost reduction function, given the omitted climate change mitigation function.

It is noteworthy to include the climate change mitigation function and climate resiliency factors into account with the climate change discussion. Concrete policy recommendations should be drawn from the results, including the worst scenario simulation of climate changes. More scientific results should be plotted to describe the operation and financial condition of the extrema cases to provide a systematic policy recommendation in that sense.

Alongside the climate change factors, another variable not included in all models is the water treatment system difference between private, public, and First Nation. In this thesis, the baseline group is targeted toward large public residential water treatment plants, i.e. serving more than 300 residents in chapter 4. The water treatment infrastructure is not adequate for Canada's current First Nation population, reported by Indigenous Canada(2021). As a result of land cover changes, the source water quality dispersion may cause more damage to the First Nation indeed. Recalling results from the third chapter, a positive correlation is observed between land disturbance and AWQI. This relationship will be even stronger for the First Nation, ceteris paribus. Therefore, separate research is required to understand the economic dynamic among the First Nation water treatments.

Therefore, it will also be highly suitable to conduct a financial variations panel regression model. This model can better exclude the unobserved plantwise effect. The dynamic of plant financial condition over the years can be explicitly spelled out. This robust result will give precise policy recommendations given modelling over the financial condition changes over the years. However, it is still hard to achieve given Statistics Canada's inconsistent census setups. Over the past five versions of the Survey of the drinking water plants(DKWP), Statistics Canada has changed the data resolution from plants to municipalities, making observation tracking impossible. Therefore, a consistent data structure is demanded to achieve the research requirement proposed.

As a concluding remark, the green infrastructure is providing essential economic function toward drinking water services. It reduces the total adverse drinking water incidents while improving the total water treatment cost efficiencies. The risk associated with wildfire damage is inevitable. This risk will impose further fuel treatment costs, which alter the willingness to invest; the simulation demonstrates that in the second chapter. This paper tries to explicitly understand forest as a new type of infrastructure that may provide similar functions as well-establish grey infrastructure in that sense. It setups several basic concerns and model frameworks that indicate the future research direction in understanding the norm of forests and green infrastructure.

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Appendix A

Proof

Lemma 1: The standard constraint is equivalent to $C^{\alpha}D^{1-\alpha} - q(C^{\rho_c}D^{\rho_d}) \geq \bar{Q}$ such that $q = \Phi^{-1}(p)$ and Φ is the normal cumulative distribution.

Proof: For C, D that fulfill the standard constraint,

$$Pr\{Q(C,D) \geq \bar{Q}\} \geq p$$

Denote $F = Q(C,D), Q(C,D) \sim N(C^{\alpha}D^{1-\alpha}, C^{2\rho_c}D^{2\rho_d})$. We then get

$$1 - (Pr\{Q(C,D) \geq \bar{Q}\}) \leq (1-p)$$

$$Pr\{Q(C,D) \leq \bar{Q}\} \leq (1-p)$$

$$F^{-1}(Pr\{Q(C,D) \leq \bar{Q}\}) \leq F^{-1}(1-p)$$

$$\bar{Q} \leq C^{\alpha}D^{1-\alpha} + \Phi^{-1}(1-p)(C^{\rho_c}D^{\rho_d})$$

$$\bar{Q} \leq C^{\alpha}D^{1-\alpha} - \Phi^{-1}(p)(C^{\rho_c}D^{\rho_d})$$

$$\bar{Q} \leq C^{\alpha}D^{1-\alpha} - q(C^{\rho_c}D^{\rho_d})$$

Lemma 2: The function $g(C,D) = C^{\alpha}D^{1-\alpha} - q * C^{\rho_c}D^{\rho_d}$ is a strictly increasing concave function with respect to C and D at the given domains of C and D.

Proof: $\frac{dg}{dC} = \alpha C^{\alpha-1}D^{1-\alpha} - \rho_c\, q * C^{\rho_c-1}D^{\rho_d}$

Since we assumed $\alpha > \rho_c$ and $1-\alpha > \rho_d$, that means for $\frac{dg}{dC}$, $\exists \bar{C}, \bar{D}$, such that $\forall C$ and D, $C \geq \bar{C}\ D \geq \bar{D}$, the derivative is positive. In that domain, the function is increasing.

$$\frac{d^2g}{dC_2} = \alpha\,(\alpha-1)C^{\alpha-2}D^{1-\alpha} - \rho_c\,(\rho_c-1)\,q * C^{\rho_c-2}D^{\rho_d}$$

$\alpha - 1$ and $\rho_c - 1$ are negative. Since $\alpha > \rho_c$, $1 - \alpha > \rho_d$, that means for $\frac{d^2 g}{dC_2}$, $\exists \bar{C}', \bar{D}'$, such that $\forall$ C and D, $C \geq \bar{C}' D \geq \bar{D}'$, the second derivative is negative. In that domain, the function is concave.

Then, denote $\bar{C}'' = max\{\bar{C}', \bar{C}\}$ and $\bar{D}'' = max\{\bar{D}, \bar{D}'\}$. Then $\forall$ $C \geq \bar{C}''$ and $\forall$ $D \geq \bar{D}''$, the function $g(C, D)$ is an increasing concave function with respect to C. It is the same to prove this function is an increasing concave function with respect to D. \\

Corollary 1: For the production function $g(C, D) = C^{\alpha} D^{1-\alpha} - q * C^{\rho_c} D^{\rho_d}$, the isoquant function is strictly convex.

Theorem 1: For $g(C, D) = C^{\alpha} D^{1-\alpha} - q * C^{\rho_c} D^{\rho_d}$, given for some $\bar{Q}$ and p, there is a unique C, D such that $g(C, D) = \bar{Q}$ and

$$\frac{\alpha\, C^{\alpha-1} D^{1-\alpha} - q \rho_c C^{(\rho_c - 1)} D^{\rho_d}}{(1-\alpha) C^{\alpha} D^{-\alpha} - q \rho_d C^{\rho_c} D^{\rho_d - 1}} = \frac{\frac{1}{1+\zeta} \beta_c + \kappa_c}{\frac{1}{1+\zeta} (\beta_d + \gamma_d) + \kappa_d}$$

Proof: Given a $\bar{Q}$ that is large enough, there is an isoquant curve for $g(C, D) = \bar{Q}$. According to corollary 1, this isoquant curve is convex. The marginal rate of technical substitution is $\frac{\frac{dg}{dC}}{\frac{dg}{dD}} = \frac{\alpha\, C^{\alpha-1} D^{1-\alpha} - q \rho_c C^{(\rho_c - 1)} D^{\rho_d}}{(1-\alpha) C^{\alpha} D^{-\alpha} - q \rho_d C^{\rho_c} D^{\rho_d - 1}}$. Due to the strict convexity, for any constant b, there exists unique C and D such that the marginal rate of technical substitution equals to b. Denote $b = \frac{\frac{1}{1+\zeta} \beta_c + \kappa_c}{\frac{1}{1+\zeta} (\beta_d + \gamma_d) + \kappa_d}$. There exists a unique combination C and D such that

$$\frac{\alpha\, C^{\alpha-1} D^{1-\alpha} - q \rho_c C^{(\rho_c - 1)} D^{\rho_d}}{(1-\alpha) C^{\alpha} D^{-\alpha} - q \rho_d C^{\rho_c} D^{\rho_d - 1}} = \frac{\frac{1}{1+\zeta} \beta_c + \kappa_c}{\frac{1}{1+\zeta} (\beta_d + \gamma_d) + \kappa_d}$$

Theorem 2: For C_1, D_1 and C_2, D_2 that are solutions of β_1 and β_2 the following equation, while $\beta_1 > \beta_2$

$$\frac{\alpha\, C^{\alpha-1}D^{1-\alpha} - q\rho_c C^{(\rho_c-1)}D^{\rho_d}}{(1-\alpha)C^{\alpha}D^{-\alpha} - q\rho_d C^{\rho_c}D^{\rho_d-1}} = \frac{\frac{1}{1+\zeta}\beta_c + \kappa_c}{\frac{1}{1+\zeta}(\beta_d+\gamma_d) + \kappa_d}$$

Then either $C_1 < C_2$ or $D_1 > D_2$

Proof: Denote $K(C,D) = \frac{\alpha\, C^{\alpha-1}D^{1-\alpha} - q\rho_c C^{(\rho_c-1)}D^{\rho_d}}{(1-\alpha)C^{\alpha}D^{-\alpha} - q\rho_d C^{\rho_c}D^{\rho_d-1}}$

Since $\beta_1 > \beta_2$, while C_1, D_1 and C_2, D_2 are solutions for the above equations.

Then we have:

$$K(C_1, D_1) > K(C_2, D_2)$$

In that sense, we will get either:

either

$$\alpha\, C_1^{\alpha-1}D_1^{1-\alpha} - q\rho_c C_1^{(\rho_c-1)}D_1^{\rho_d} > \alpha\, C_2^{\alpha-1}D_2^{1-\alpha} - q\rho_c C_2^{(\rho_c-1)}D_2^{\rho_d}$$

Or:

$$(1-\alpha)C_1^{\alpha}D_1^{-\alpha} - q\rho_d C_1^{\rho_c}D_1^{\rho_d-1} < (1-\alpha)C_2^{\alpha}D_2^{-\alpha} - q\rho_d C_2^{\rho_c}D_2^{\rho_d-1}$$

Combining the above equation with Lemma 2, where g(C,D) is increasing in both C and D, we will get either $C_1 < C_2$ or $D_1 > D_2$

Theorem 3: For C_1, D_1 and C_2, D_2 that are solutions of q_1 and q_2 in the following equation, while $q_1 > q_2$

$$\frac{\alpha\, C^{\alpha-1}D^{1-\alpha} - q\rho_c C^{(\rho_c-1)}D^{\rho_d}}{(1-\alpha)C^{\alpha}D^{-\alpha} - q\rho_d C^{\rho_c}D^{\rho_d-1}} = \frac{\frac{1}{1+\zeta}\beta_c + \kappa_c}{\frac{1}{1+\zeta}(\beta_d+\gamma_d) + \kappa_d}$$

Then either $C_1 < C_2$ or $D_1 > D_2$

Proof: Denote $h(C,D,q) = \frac{\alpha\, C^{\alpha-1}D^{1-\alpha} - q\rho_c C^{(\rho_c-1)}D^{\rho_d}}{(1-\alpha)C^{\alpha}D^{-\alpha} - q\rho_d C^{\rho_c}D^{\rho_d-1}}$

Then, $\frac{dh}{dq} = \frac{(\alpha*\rho_d-(1-\alpha)*\rho_c)*C^{\alpha+\rho_c-1}*D^{\rho_d-\alpha}}{\left((1-\alpha)C^{\alpha}D^{-\alpha}-q\rho_d C^{\rho_c}D^{\rho_d-1}\right)^2}$

Since $\frac{\alpha}{\rho_c} > \frac{1-\alpha}{\rho_d}$, $\alpha*\rho_d > (1-\alpha)*\rho_c$

Therefore, $\frac{dh}{dq} > 0$

That means, $h(C_1, D_1, q_1) > h(C_1, D_1, q_2)$

Given that $h(C_1, D_1, q_1) = h(C_2, D_2, q_2)$, then either:

$\alpha\, C_1^{\alpha-1} D_1^{1-\alpha} - q_2 \rho_c C_1^{(\rho_c - 1)} D_1^{\rho_d} < \alpha\, C_2^{\alpha-1} D_2^{1-\alpha} - q_2 \rho_c C_2^{(\rho_c - 1)} D_2^{\rho_d}$

Or:

$$(1-\alpha) C_1^{\alpha} D_1^{-\alpha} - q_2 \rho_d C_1^{\rho_c} D_1^{\rho_d - 1} > (1-\alpha) C_2^{\alpha} D_2^{-\alpha} - q_2 \rho_d C_2^{\rho_c} D_2^{\rho_d - 1}$$

Once we combine this with Lemma 2, we will get either $C_1 < C_2$ or $D_1 > D_2$

Appendix B

Types of incidents included in the database for the second-stage regression model(Chapter three)

Inorganic Chemical:

Chlorite, Nitrate (As Nitrogen)

Organic Chemical:

Dichloromethane, Trihalomethane, Atrazine

Management Incidents:

Turbidity violates the standard, Low UV dosage, Colour violates the standard, Combined Chlorine Residual, Free Chlorine Residual, Ph violates the standard, Low Chlorine, High Chlorine, Boiling Water Advisory, Loss Of Process

Micro-biological:

Total Coliform, Escherichia Coli

Appendix C

Types of incidents that are not included in the database for the second-stage regression model(Chapter three)

Inorganic Chemicals:

Arsenic, Cadmium, Chloride, Chromium, Fluoride, Lead, Mercury, Sodium

Organic Chemicals:

Naphthalene

Other Incidents:

Equipment Malfunction, Loss Of Power, Loss Of Pressure, Water Main Break

Appendix D

Water treatment infrastructure by categories

Pretreatment:

Microscreening, Other Pre-treatment

Disinfection/oxidation:

Chlorination, Chlorine Dioxide, Chloramination, Ultraviolet Irradiation, Ozonation, Potassium Permanganate, Other Reagents

Chemical treatment or addition:

Fluoridation, Alkalinity Adjustment - Process control, pH Adjustment - Process control, pH Adjustment - Corrosion control, Alkalinity Adjustment - Corrosion control, Corrosion Inhibitors

Coagulation/flocculation and filter aid:

Aluminum-based Coagulation, Ferric-based Coagulation, Other Coagulant, Enhanced Coagulation, Flocculation

Clarification/sedimentation:

Sedimentation, Dissolved Air Flotation, Other Clarification

Filtration:

Granular Media, Granular Activated Carbon - Filter media, Granular Activated

Carbon - Separate process, Microfiltration, Ultrafiltration, Cartridge/Bag, Slow Sand

Other processes:

Aeration, Air Stripping, Lime Softening, Activated Alumina, Ion Exchange, Sequestering, Greensand Filtration, Powdered Activated Carbon, Reverse Osmosis or Nano Filtration, Other Processes