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Spatial Modeling of Decentralized Wastewater Infrastructure: The Case for Water Reuse and Nitrogen Recovery

Author
Kavvada, Olga

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Spatial Modeling of Decentralized Wastewater Infrastructure: The Case for Water Reuse and Nitrogen Recovery

by

Olga Kavvada

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of the
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Committee in charge:

Professor Arpad Horvath, Co-Chair
Professor Kara L. Nelson, Co-Chair
Professor Scott Moura
Professor Stefano Schiavon

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Abstract

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Climate change and increasing patterns of drought throughout the world are challenging the effectiveness of conventional water systems. A growing population in conjunction with more extreme weather events, threatens water supply infrastructure and increases uncertainty about how utilities will meet demand without sacrificing water quality. This issue has recently manifested in California, prompting utilities to invest in alternative water sources as a means of ensuring that water infrastructure is resilient to climate change scenarios.

Decentralized wastewater treatment is a promising option for increasing the sustainability of water infrastructure as it spatially merges supply and demand, minimizing large conveyance requirements. Decentralization can also promote nutrient management and recovery as it enables the source separation of the different wastewater sources. Specifically closing the nitrogen loop, by capturing it and reusing it to generate valuable high-end products can potentially improve the efficiency of the system and create revenue streams.

However, smaller decentralized water treatment units are potentially more energy intensive and costly than their centralized alternatives per unit of water treated. Due to these efficiency tradeoffs, planning tools and frameworks for holistically assessing decentralized water treatment systems need to be developed to optimally manage the new urban water supply paradigm. Better data management and data-driven decision support tools can provide valuable insight on the benefits and impacts of implementing future water systems.

This research assesses the technical performance of emerging decentralized technologies and implementation scenarios for residential uses, by assessing the feasibility of integrating decentralized facilities in cities with existing wastewater infrastructure. This work aims to create algorithmic models that integrate the spatial design of a wastewater treatment and distribution network with a life-cycle assessment to determine the associated environmental impacts. This dissertation utilizes spatial modeling to contextually evaluate the implementation and distribution potential and uses a life-cycle assessment approach to provide an extensive analysis of all the life-cycle impacts. By incorporating environmental indicators and metrics, a planning support framework can be created to help guide the water industry towards smart investments for a less energy-intensive future. Specifically, this work will 1) investigate how spatial terrain variability, demographics and distribution affect the performance of decentralized water treatment systems, 2) analyze the major parameters that affect the energy intensity, cost and greenhouse gas emissions of these systems, 3) quantify the unit processes that mostly impact the prementioned metrics and 4) identify the optimal system scale for decentralized infrastructure implementation under various spatial and demographic conditions.

The insights from this dissertation can help wastewater researchers and practitioners understand the complex relationships between the system scale and system performance. By evaluating the potential benefits and tradeoffs, this work can lead to management tools that will help transition away from traditional water management and create a water supply that (1) is resilient to changes in climate, (2) uses local water sources, and (3) leaves more water in natural ecosystems. This dissertation further adds to the growing body of literature on decentralized wastewater treatment assessing optimal scales, reuse potential, resource recovery and sewerage connections to investigate key factors affecting future implementation.

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Chapter 1.

Introduction

1.1 Motivation

Climate change, population growth, and rapid urbanization are increasing the stress on and unreliability of the water supply in many areas around the world.[1] In most developed countries, there exists an inherent expectation of sufficient water quantity and quality at all times. This expectation, however, comes with a large cost as water and wastewater are inherently energy intensive services. In the United States (U.S.), the energy for treatment and delivery of water emits more than 45 million tons of greenhouse gases (GHG) annually.[2] This is equivalent to 10% of all the annual GHG emissions occurring in California per year[3]. In California, 7.7% of electricity consumption is dedicated to energy for pumping and treatment of water, not accounting for the electricity used inside the households.[4]

Understanding the relationship between water, energy and GHG emissions is important for decision-making, especially when in the context of managing our limited water sources. Energy is used throughout the water sector, for collection, treatment and conveyance and it leads to production of GHG emissions. Several authorities have created initiatives to reimagine how water infrastructure might comply with GHG mitigation strategies.[5] For example, the California Water Plan promotes maximum efficiency in water management through identifying, developing and researching new technologies and implementation potentials.[6] Efficiency can be further improved though better data management and decision support tools that provide valuable insight on the benefits and impacts of implementing future redesigned systems.

The water scarcity threat, particularly in drought-prone regions, increases uncertainty around how utilities will meet demand without sacrificing water quality. The need to reinvent the water infrastructure paradigm becomes even more apparent with the realization that the conventional approach of large centralized infrastructure is failing to meet the growing water demands. This issue has revealed itself recently in California where more than 18% of all urban uses as well as a significant volume for agriculture and environmental uses is supplied by the State Water Project and Colorado River Aqueduct and could be significantly impacted by climate change.[7] The unsustainable practice of groundwater overdrafting along with the failure of these large projects to satisfy demands, has led to a critical assessment of the sustainability of the current water system.[8] As dry years magnify disagreements in the allocation distribution of the limited water supply, local utilities have been investing in alternative water sources to make sure that their new water infrastructure is resilient to climate change scenarios.

Closing the loop in the water systems can increase the system reliability by providing efficient and cost-effective solutions to the increasing water challenge. Closed-loop systems refer to systems that identify opportunities for generating value out of the generated waste products. In the water world, the major waste product is the wastewater. Water reuse, nutrient management, and other forms of resource recovery, promote efficient resource utilization and can help mitigate the environmental and energy impacts associated with water and wastewater treatment facilities.

New technological advances in decentralized wastewater treatment systems provide feasible alternatives to centralized infrastructure. Economies of scale do exist in the treatment of water[9,10], making small units more energy intensive than their centralized alternatives. However, the spatial setting in which the water treatment system exists can affect the overall system efficiency. As innovative technologies emerge the ability to understand the tradeoffs between system scale and performance become significant in order to minimize the systems economic and environmental impacts. Two new paradigms of water treatment are considered within this work, water reuse and nitrogen recovery. For both, decentralization can offer efficiency benefits as it merges supply and demand by having the systems be closer to the point of use and the large conveyance costs and environmental impacts can be avoided. Due to these efficiency tradeoffs, planning tools and frameworks for holistically assessing decentralized systems and their distribution networks need to be developed to optimally manage the urban water supply and help minimize the climate change effect of the water sector.

1.2 Research Overview and Questions

This dissertation assesses the technical performance of emerging decentralized technologies and their implementation in a variety of scenarios for residential uses. It evaluates the feasibility of integrating decentralized facilities in cities with existing wastewater infrastructure and identifies opportunities for economic and environmental gains. The main objective of this research is to assess different options of utilizing wastewater as a resource in various settings and scales. This work aims to create algorithmic models that integrate the spatial design of a wastewater treatment and distribution network with a life-cycle assessment to determine the associated economic and environmental impacts. It utilizes spatial modeling techniques and algorithms to holistically evaluate the implementation and distribution potential and uses a life-cycle assessment approach to provide an extensive analysis of all the life-cycle impacts. By incorporating environmental indicators and metrics, a planning support framework is created to help push the water industry towards smart investments for a less energy intensive future.

This dissertation aims to assess two decentralized resource recovery options, namely *water reuse* and *nitrogen recovery*. The first part focuses on non-potable water reuse and provides a framework and a modeling process for optimally integrating the decentralized infrastructure to achieve maximum water savings with the minimum economic and environmental impacts. It aims to create a planning support tool for optimizing level of decentralization and implementation of residential non-potable water reuse facilities in an urban setting. The study assesses a wide range of possible system scales to estimate the threshold where decentralization would be the best choice in specific spatial conditions. Some of the key questions that are addressed in the first part include:

- How does spatial variability affect the performance of water reuse?
- What are the major contributors to the economic cost, energy intensity and GHG emissions of water reuse systems?
- Which are the most important unit processes in treatment that drive the energy intensity and GHG emissions from a life-cycle perspective?

- What is the optimal scale for infrastructure planning that would minimize the economic and environmental impacts?
- Can decentralized water reuse provide environmental benefits to justify the redesign of the water infrastructure under a GHG emissions constrained future?
- Can decision-making be assisted by generalizable model development that enables scenario planning in various settings?

The second part, concerning nitrogen recovery, aims to assess an emerging decentralized technology for recovering nitrogen from wastewater (ion exchange and electrochemical stripping) to minimize the economic and environmental impacts of effluent discharge in the receiving bodies. This technology is still under development in the laboratory, so this research can provide valuable preliminary insight on which parameters are the most impactful to cost, energy and GHG that need further research. This part plans to also address the question of optimal scale of decentralized nitrogen recovery technologies via process modeling and assess the spatial parameters that affect the implementation potential in an urban setting. The key questions addressed here include:

- How would nitrogen recovery technology perform in a real setting?
- Which are the key factors that affect the systems' cost, energy intensity and GHG emissions that could benefit from further research?
- How do spatial and distribution parameters (logistics) affect the overall system's cost, energy intensity and GHG emissions?
- What is the optimal scale for implementing nitrogen recovery given certain demographic and topographical conditions?
- Can we offset the cost and energy of centralized wastewater treatment to meet stringent nutrient discharge regulations, and does decentralization provide any benefits?

1.3 Research Challenges

Assessing decentralization as an approach for optimal water management to promote resource recovery is a complex endeavor for multiple reasons:

- The major friction between closing the loop for water is the disconnect between the water and wastewater industries. In many locations, the two industries are not in close proximity and are operated separately. Each has its own complexities and interests to prioritize. Achieving a high adoption of closed-loop systems requires the two industries to coordinate, cooperate and have mutual goals in place. That is hardly the case at the present. Even in cases where the same utility is responsible for both water and wastewater services, they are considered separately with minimal resource sharing and separate management systems. This is a major drawback, as the two industries share their most valuable resource, water. By combining the goals of the two industries, the dynamics of the system can change as the output of one system can be the input of the other. However, to make this process efficient and economically acceptable, it requires careful planning and change in the approach that service providers have utilized in the last decades.

- Factors that currently determine water system management are primarily related to economic cost. However, successful implementation of a new system should consider environmental impacts along with the long-term sustainability of the project. Understanding all of the factors and their contribution to economic and environmental impacts requires complex and multivariable analyses that are not always in the interest of the stakeholders. Making these analyses accessible to decision-makers and emphasize their importance is a non-trivial task.

- Similarly, determining the optimal system size or trying to minimize the economic and environmental impacts may not be the key driver to decision-making. Sometimes decisions around how the systems are implemented or where they are placed are based on externalities and site-specific conditions that cannot be modeled by engineering approaches. There is a disconnect between the context specific, political considerations and decision-makers needs and engineers that aim for optimal planning.

- Finally, developing frameworks that accurately assess and estimate metrics of interest is not trivial. Water infrastructure is highly site specific, involves a lot of moving parts and the infrastructure sizing can be challenging. Trying to develop generalizable models that can be applied in different settings with minimal customization is a complicated task that requires interaction between engineering principles and empirical approaches.

Research Contributions

This research aims to address the major challenges identified above to promote the sustainable implementation of water reuse and nitrogen recovery systems. By identifying the major parameters that affect the economic and environmental impacts of water reuse and nitrogen recovery this research intends to promote solutions that try to close the loop in our water systems and their nitrogen management. Closed-loop systems tend to be more sustainable and efficient and this research tries to bridge the gap between the water and wastewater industries by proposing solutions that could potentially benefit both. By identifying the key parameters that lead to economic and environmental impacts of the proposed closed-loop systems, this work intends to educate future research by highlighting the areas that need to be improved upon to increase the systems' efficiency and their implementation potential.

Secondly, this research quantifies the environmental impacts of the water reuse and nitrogen recovery systems along with their economic requirements. Economic cost is usually the primary factor that influences development decisions. However, the energy and GHG emissions impacts are equally important from a societal and environmental point of view and should be prioritized as decision metrics. Moreover, by quantifying both economic and environmental metrics, this research enables decision makers to reach optimal decisions by considering the tradeoffs between the various metrics in a comprehensive, holistic and consistent way.

A major challenge that was identified in the previous paragraph is the issue of implementation scale when considering decentralized solutions. This research tries to address this issue by identifying the effect of scale between treatment and distribution systems. These non-linear relationships are crucial and significantly affect the overall economic and environmental performance of the systems. Water reuse systems tend to also be highly location specific as the impacts of technology and distribution scaling will significantly differ with location and technology selection. This research addresses this challenge by developing generalizable models with the ability to assess the systems implementation in local conditions. This is a critical component for the realistic and holistic assessment of water reuse systems.

1.4 Organization

The analyses presented in this dissertation include multiple applications of advanced spatial analysis to address issues of optimal system implementation for water reuse and nitrogen recovery. These applications illustrate the importance of detailed spatial modeling for the holistic assessment of the economic and environmental costs of systems implementation.

Chapter 2 includes background information on the two main subjects studied here, namely water reuse and nitrogen recovery. This chapter will motivate the subject area and provide the basic knowledge for understanding the chapters to follow. It also provides background information on the main methods used in this research, specifically spatial analysis and life-cycle assessment.

Chapter 3 analyzes water reuse implementation potential in a city-scale application. It describes a high-level decision methodology that assesses various scales of water reuse implementations and compares their environmental performance. It explores the difference between centralized and decentralized non-potable water reuse, from a life-cycle perspective. Decentralized and centralized options are assessed for the same context area to identify at which locations decentralized systems would achieve environmental advantages over centralized alternatives.

Chapter 4 extends the previous chapter to a finer-scale resolution of decentralization for non-potable water reuse. The goal of this chapter is to model water reuse implementation down to the building scale. It assesses the economic and environmental impacts of decentralization by identifying the tradeoffs between various levels of decentralization. The development of a decision support software is described to enable optimal decision-making for water reuse applications. The development and implementation of the decision support software involves locating wastewater facilities, calculating water balances and infrastructure design and estimation of the environmental and economic impacts.

Chapter 5 moves towards the subject of resource recovery, specifically for nitrogen. This chapter aims to assess, from a life-cycle perspective, an innovative decentralized approach to nitrogen recovery: ion exchange of source-separated urine. To provide insight into how this decentralized technology would be implemented, an enhanced economic and environmental assessment approach is developed by combining spatial analysis, system-scale evaluation and detailed last-mile logistics modeling.

The overall major findings are summarized in Chapter 6 along with the major research contributions to the academic and professional field. Future research and extensions of this study are also included in the concluding chapter.

Chapter 2.

Background

2.1 Water Reuse

2.1.1 Why water reuse?

Today's world is characterized by an uneven distribution of the population which is increasingly tending towards urbanization.[11] Over 54% of the world's population live in urban regions. In North America, this percentage rises to 80%.[12] This tendency leads cities to face significant pressures to respond and fulfill all of the needs of the continuously increasing populations. Drinking water infrastructure is one of them. Historically, the location of the cities was strongly connected to the water availability. Water constraints have been significant friction factors to growth. Technological advances have enabled large water transport projects, which has disentangled growth from local water availability. However, this leads to inadequate supply and compromises the ability of the system to meet the quantity and quality expected by its users when considering aging infrastructure, climate change and competition over the available water sources.

Worldwide, water suppliers are investigating alternative water sources and efficient distribution designs that increase self-sufficiency and supply reliability of systems.[13] Self-sufficiency is defined as enabling water use in cities or regions that is sourced from within each city or region.[14] Currently, the most common water sources, particularly within urban metropolitan areas, are surface water and groundwater. Alternative water sources, such as stormwater capture and water reuse, have the potential to be promising solutions. Conventional approaches to manage wastewater involve collection via centralized sewerage networks and treatment in large wastewater treatment plants (WWTPs) prior to discharge. Wastewater treatment plants can provide a sustainable supply of recycled water and have the potential to address the stressors on traditional water sources. Water reuse, especially in water-limited regions, could directly augment available water resources and therefore offers the potential to significantly increase the nation's total available water resources. Recycled water is highly-treated wastewater that has been purified through multiple levels of treatment to meet quality and safety standards and can be reused for non-potable or potable applications.

Many utilities are currently deciding to implement or expand water reuse systems as extended drought conditions and water supply stressors are becoming more prevalent under climate change scenarios. For example, the California Water Plan requires maximum efficiency in water management through identifying, developing and researching new technologies and implementation potentials[6] and the California State Water Board has set an ambitious goal to increase the water reuse by 30% by 2020.[15] Water reuse can help reduce the environmental impact associated with wastewater treatment and increase the resiliency in water management. However, the economic and environmental benefits depend on various factors such as treatment technology, resource recovery strategy, and system size.[16]

2.1.2 Energy in water

Understanding the relationship between water, energy and GHG emissions is important for decision-making, especially when it's connected to managing the limited water sources. Energy is used throughout the water sector leading to production of GHG emissions. This relationship can support actions to reduce such emissions and to be compatible with the state's GHG mitigation strategies.[5]

Energy and water infrastructure are inherently connected. Water is an important component of energy production and water infrastructure requires energy inputs to be constructed and operate. As energy is directly related to GHG emissions, planning around water infrastructure should have an environmental focus as well. The internationally accepted goal of limiting global temperature increases to two degrees Celsius over pre-industrial levels will involve reducing GHG emissions by 40-70 % below 2010 levels by 2050[17], requiring water and wastewater infrastructure to substantially reduce their GHG footprints along with many other components of modern economies. It is essential that future water planning scenarios maximize water efficiency, minimize energy intensity and provide the same level of service to consumers, even as water demand increases.[18]

Water and wastewater are energy-intensive services. A study by Goldstein and Smith reports that 4% of total electricity use in the United States goes to the conveying and treating of water and wastewater.[19] In the U.S., the energy for treatment and delivery of water emits more than 45 million tons of greenhouse gases (GHG) annually.[2] This is equivalent of 10% of all the annual GHG emissions occurring in California.[3] In California, 7.7% of electricity consumption is dedicated to energy for pumping and treatment of water not accounting for the electricity used at the end use.[4] The California State Water Project is the largest single user of energy in California accounting for about 2-3% of all electricity consumed in the state.[20]

Energy requirements in water infrastructure are strongly site-specific. The energy required for the production and distribution of water can depend significantly on the technology, topographical characteristics and population density. For treatment, the "economies-of-scale" tend to benefit larger systems.[9,10] However, large systems tend to require large distribution networks and more uphill pumping that significantly affects energy requirements (Figure 1). Localization of water cycles can eliminate the distribution requirements as it spatially merges supply and demand, thus closing a loop within the water system. Decentralized systems can service a variety of scales ranging from individual homes to communities and usually function independently of a centralized system.[21,22] New technological advances in decentralized wastewater treatment systems challenge the strong dependency on the centralized infrastructure. Especially when considering water reuse, where the connection between supply and demand is significant, decentralization can offer efficiency benefits as the systems are closer to the point of use and large conveyance costs are avoided.

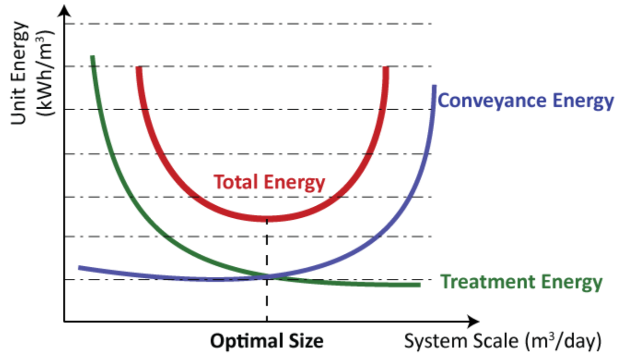
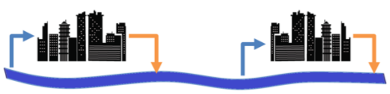
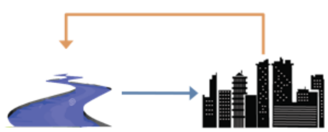
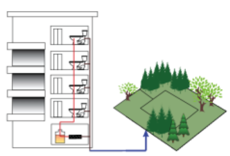


Figure 1: Optimization tradeoffs between treatment "economies-of-scale" and conveyance "diseconomies-of-scale"

2.1.3 Types of reuse

Water reuse can come in several different forms depending on the reused water application, the wastewater treatment plant technology, the location, water quality requirements and public policy. The different types of reuse can vary significantly in the output water quality, energy intensity, cost, volume, and discharge limits. An important benefit of flexibility inherent to water reuse technology is that water reuse projects can be "fit-for-purpose", meaning that the water quality can satisfy the standards for the required application and no more. This is a significant benefit when considering cost or energy intensity as the water is only treated to its appropriate standard, which can be achieved with significantly less economic and environmental impacts. There are two main types of water reuse, potable and non-potable water reuse which differ from each other at the required level of treatment. Water reuse can be performed as a direct process, which involves the introduction of the recycled water directly into the water system, or as an indirect process, where the recycled water is passed through an environmental buffer before it can be mixed with the water supply. Table 1 provides a breakdown of the different types of water reuse.

Table 1: Types of water reuse

Type of reuse	*Description*
De facto reuse 	De facto reuse is the simplest type of reuse and it can be referred to as the conventional process. Fresh surface or groundwater is extracted, treated and used as the water source, wastewater is generated, treated appropriately for discharge, discharged into a water body and used as input from downstream users where it would be treated again.
Indirect potable reuse 	Indirect potable reuse occurs when the discharged wastewater is returned to its original natural source so it can be reused by the same user. This is a type of potable reuse as the water quality level is not distinguished by application, but it is treated by a water treatment plant to a potable standard after it was gone through an environmental buffer.
Direct potable reuse 	Direct potable reuse is similar to the indirect potable reuse but there exists no environmental buffer between the wastewater and the water source. In this case the wastewater is treated to a potable level by the wastewater treatment plant and it is introduced directly to the water system or upstream of a water treatment plant for reuse.
Non-potable reuse 	Non-potable reuse is a separate type of reuse as it differs in its water quality level. In this case the wastewater is treated to an appropriate level for applications other than drinking, such as industrial uses, agriculture, landscape irrigation or other residential non-potable uses (e.g. toilet flushing).

Non-potable water volume, the main focus of this work, is a significant percentage of the overall water demand for residential and commercial uses. As illustrated in Figure 2, non-potable water can encompass up to 50% of the residential uses and up to 95% of the commercial water uses.[23] Non-potable water reuse can satisfy most water demands as long as it has been appropriately treated for that purpose. Non-potable water systems typically have lower water quality standards but their level of treatment reflects the type of application they are used for. These systems, require a separate distribution network ("purple pipe" network) as it cannot be mixed with the conventional water supply.

Incorporating multiple end-uses in the non-potable water reuse portfolio, can result in a more complex distribution structure but potentially more widespread application of the wastewater. For example, allowing for recycled water to be used indoors for toilet flushing and outdoors for landscape irrigation, increases the infrastructure complexity as more pipes are needed but at the same time achieves a much higher percentage in the offset of fresh water supply. In addition, allowing for more water sources to be treated and reused, such as greywater (wastewater originating from showers, bathroom and kitchen taps and washing machines) and blackwater (wastewater originating from toilets) can increase the available water for other uses. Depending on the extent of it application, the distribution network can have a significant impact on the overall systems cost and energy requirements.

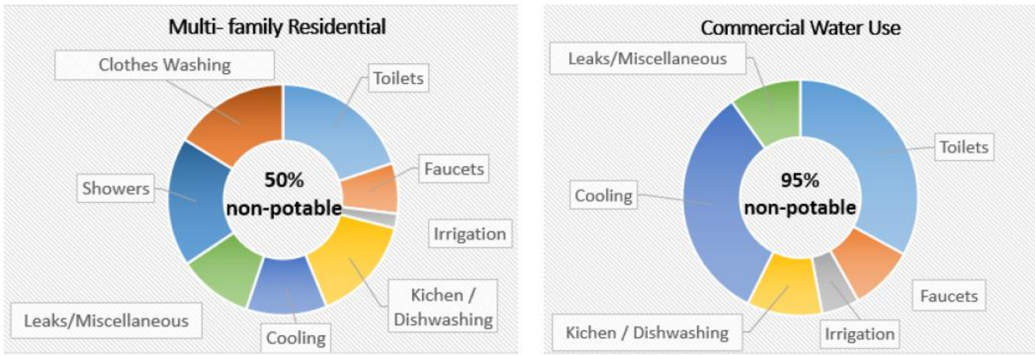


Figure 2: Breakdown of water uses for residential and commercial customers. (Adapted from San Francisco Public Utilities Commission[24])

2.2 Nitrogen Recovery

2.2.1 Nitrogen cycle

Wastewater is a source of other elements, such as nutrients, metals and heat. This work focuses on the nitrogen aspect of wastewater. Understanding the connections between a waste product, such as wastewater, and its constituents that can be recovered to generate high value products is of major significance. Figure 3 presents the main nitrogen cycle in wastewater treatment along with the Haber-Bosch process for fertilizer production.

Nitrogen is considered a pollutant when its located in the discharged wastewater, as it can cause eutrophication and damage aquatic ecosystems. The San Francisco Bay in the recent years has an increasing concern of nutrient loading. The WWTPs discharging in the Bay are responsible for about 50% of the nitrogen loading in wet periods rising up to 80% in dry years.[25] For this reason, wastewater treatment plants use an energy intensive process to remove nitrogen out of the wastewater before they discharge in sensitive ecosystems. Technologies for nitrogen reduction at the treatment plant do exist and usually involve biological processes to enhance nitrification and denitrification processes that convert ammonia to dinitrogen gas and allow it to escape in the atmosphere. However, these processes are costly and include high energy requirements that make them unattractive for the plant operators[26].

Besides the impact of nitrogen on the ecosystems and its energy intensive removal process, it can also be identified as a potential nutrient in agriculture processes. Nitrogen is a major constituent of most conventional fertilizers. Capturing the nitrogen from the atmosphere and incorporating it into the fertilizer products is also an energy intensive process, called Haber-Bosch, which consumes about 1% of global energy.[27] By creating a process that can eliminate the Haber-Bosch process and instead use the nitrogen present in the wastewater as a potential fertilizer can potentially lead to economic and environmental benefits. The removal of nitrogen from wastewater at the wastewater treatment plants and the capturing of the nitrogen from the atmosphere during fertilizer production are processes that essentially reverse each other as the wastewater treatment converts the NH_4^+ to N_2 gas and the fertilizer production industry converts N_2 gas back to NH_4. Closing the loop between the nitrogen present in conventional fertilizers and the nitrogen in the waste stream of wastewater treatment can not only generate a revenue source but it can also prevent potential environmental impacts caused by uncontrolled nitrogen discharge in aquatic bodies.

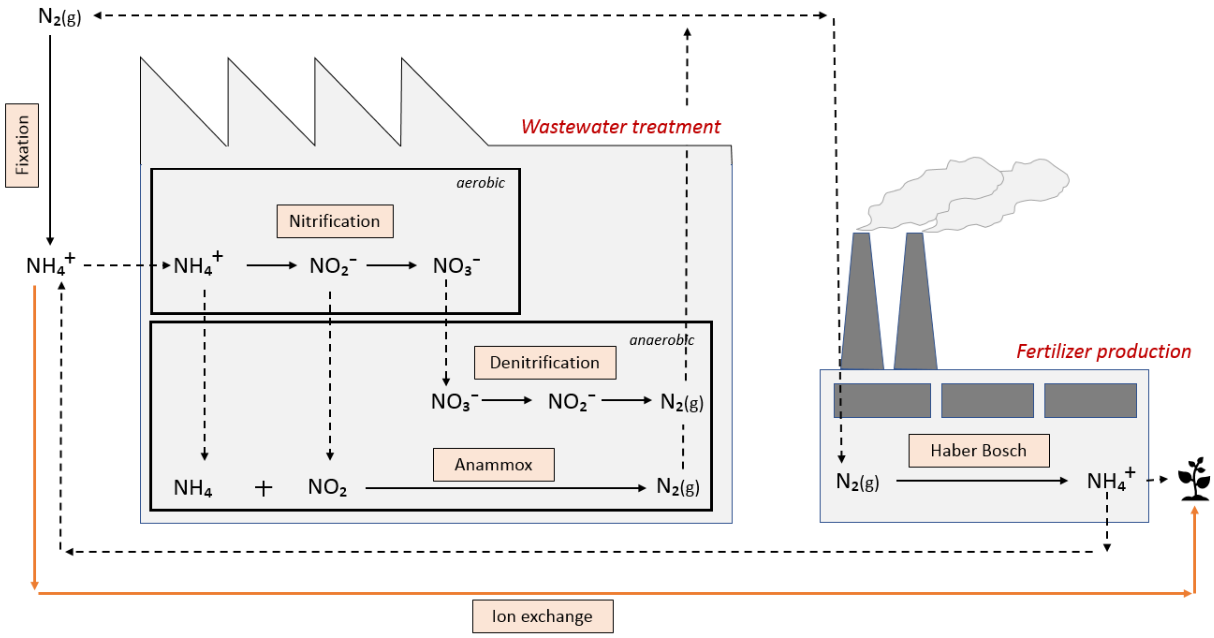


Figure 3: Schematic illustrating connecting the relationships between ammonia from urine and production of fertilizer

2.2.2 Source separation

Nitrogen is a main constituent of the wastewater but it is mostly present in urine (80% of the nitrogen in wastewater (Figure 4))[28] while, urine only represents 1% of the total wastewater volume.[29] Separating the urine from the rest of the wastewater, source separation, can significantly increase the ability to remove and recover key compounds such as nitrogen. Source separation generates a highly concentrated stream of nitrogen, enabling recovery. Separate collection and treatment of urine can potentially reduce treatment costs at the wastewater treatment plants, environmental pollution due to nutrient discharges, and can potentially substitute energy intensive processes for synthetic fertilizer production. Source separation though requires specific infrastructure, such as special toilet fixtures, so the urine can be successfully separated from the rest of the wastewater before it gets diluted.

Nutrient removal standards for wastewater discharge in aquatic bodies are becoming more stringent and require wastewater treatment plants to reduce the nitrogen concentration in their effluent. There are currently few restrictions for nutrient discharge in the San Francisco Bay but it is projected that the state's officials will start regulating nitrogen flows heavily and specify the allowable limits for discharge.[30] The conventional approach is to upgrade treatment by adding a nitrification/denitrification process, which is energy intensive and costly. A promising alternative is source separation and nitrogen removal from urine with the potential for recovery to produce fertilizer. Distributed nutrient treatment and nitrogen extraction at the source can reduce nutrient flows in the receiving bodies by diverting it before it reaches the wastewater treatment plant. This process can have significant benefits as it reduces the need for nitrogen treatment at the treatment plant. Compared to the conventional approach, extracting the nitrogen at the source can create high value products and can potentially have lower energy and greenhouse gas emissions compared to centralized nitrogen removal.

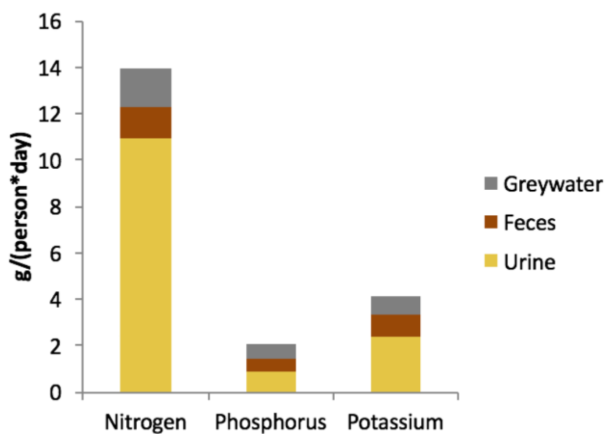


Figure 4: Wastewater stream composition by nutrient.[28]

2.2.3 Ion exchange

Ion exchange is a well-established technology for removing impurities from water. Recently its application has been extended to remove nitrogen from urine to promote nitrogen recovery.[31] Ion exchange is a promising alternative to the centralized biological nitrogen removal as it is modular, compact and can be installed in a decentralized fashion.

The main process behind the operation of ion exchange resins to remove nitrogen from a highly-concentrated source is illustrated in Figure 5. The ion exchange cartridges can be installed at the source, where urine can be selected as a highly concentrated source of nitrogen. As the urine flows through the cartridge, the nitrogen in the ammonium is adsorbed by the resin. To revert the process and recover the nitrogen for other applications, a strong acid can flow through the nitrogen rich cartridge. This way, the nitrogen is released from the resin and ends up in the output product. In this case the output ammonium sulfate ($(NH_4)_2SO_4$) can be used as an alternative fertilizer product to satisfy the plants needs on nitrogen. This process is referred to as regeneration.

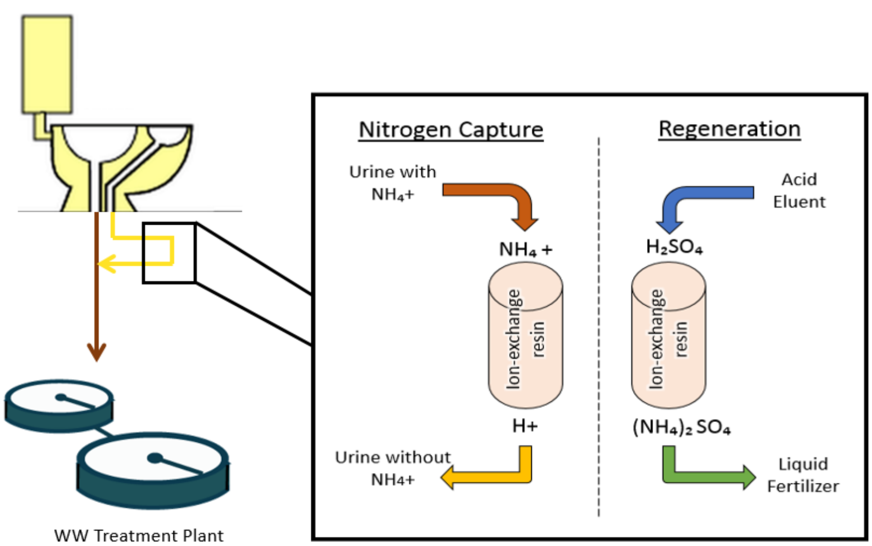


Figure 5: Using ion exchange resin for nitrogen capture and regeneration

2.3 Economic and Environmental Assessment

Life cycle assessment (LCA) provides a framework for holistically quantifying the environmental impact of a process or product over its lifetime, including raw material extraction, construction, operation and end-of-life. LCA enables us to quantify the complex relationship between activities and their environmental impacts using a "cradle to grave" approach. By including the whole life-cycle in the analysis, the results are more comprehensive as they include the impacts of all stages from material production and delivery to operation and maintenance. The framework is composed of the inventory phase (LCI) which identifies and quantifies the energy use and emissions of all the stages of a process or product, the impact assessment phase (LCIA) where the environmental effects are converted to environmental or health related impacts based on the outputs of the LCI and finally the interpretation stage, where the impacts are interpreted and evaluated.[32] This stage involves the uncertainty estimation of the previous methods and re-evaluates and improves the processes. Decision makers use LCA to quantify the breakdown of impacts through the different processes that occur in a system, and identify opportunities for improvement and efficiency gains.

Life-cycle cost assessment (LCCA) provides a methodology for assessing different options regarding their overall economic cost performance. LCCA includes all aspects that could potentially contribute to economic costs including purchasing, owning, operating, maintaining and disposing costs and can refer to any type of material, product or system. LCCA follows a similar methodology as LCA but instead or environmental impacts it refers to economic costs.[33] LCCA combined with LCA can provide valuable insight on the tradeoffs that may occur regarding more environmentally friendly solutions and associated economic cost. It can also elucidate the challenges associated with promoting sustainable solutions and multiobjective optimizations.

LCA and LCCA has been widely used to evaluate water and wastewater systems and can offer valuable insights into the energy intensity and cost of the system holistically.[34–38] This study incorporates the LCA and LCCA methodologies to holistically assess the impacts of water reuse and nitrogen recovery. The system boundary includes material extraction, component manufacturing, distribution and operation. The end-of-life phase is omitted as previous research has shown it does not significantly affect the total energy, GHGs and cost of these systems.[36,39,40] The outcomes of this research focus only on the first part of the LCA methodology, specifically the LCI and the quantification of energy intensity and GHG emissions of the systems as well as the uncertainty and sensitivity of the systems. The functional unit used to characterize the energy intensity, GHG emissions and cost in this industry is a m^3 of water treated, or in the case of nitrogen recovery a m^3 of urine treated. This allows for a direct comparison between various alternatives and different scales.

This study used both process-based and economic input-output (EIO-LCA) emission factors to minimize uncertainty. Process-based LCA refers to a bottom-up approach in which the processes that fall inside the system boundary are assessed.[41] This method characterizes the life-cycle inventory by assessing each unit process including their corresponding up-stream impacts. In contrast, input-output LCA takes a top-down approach and relies on aggregate data that models the entire system but lacks detail on specific processes.[42] This method tries to map the interactions of each process with the entire economic sector to produce an inventory that would include all the impacts of the supply chain. A hybrid approach, as used in this study, utilizes the benefits of the previously mentioned methods to quantify impacts in a comprehensive manner.[43]

The major components of the wastewater infrastructure that are assessed in this work to identify the impacts of the systems are treatment infrastructure, piping and pumping infrastructure for water collection and distribution and storage options. All these system components need to be assessed for their material requirements for construction as well as for their operational impacts. The component assessment model part of the LCA and LCCA evaluates the material inputs, operation requirements and maintenance and evaluates their life-cycle performance. Identifying and assessing all the unit processes and components, the overall energy, GHG emissions and cost can be calculated for all system stages given specific energy intensity requirements, emission factors and unit costs [Eq. 1].

$$T_x = \frac{\sum_i^N \left(\sum_a^M (\frac{m_{a,i} \times ef_{a,i}}{L_{a,i}})\right) + \sum_i^N \left(\sum_p^K (P_{p,i} \times ef_{p,i})\right)}{Q_x} \qquad \text{[Eq. 1]}$$

where:

T_x is the total energy/emission/cost of the system of scale x,

i is the system component, $\forall$ i = 1, 2, ...N,

$m_{a,i}$ is the mass of material a used in component i, $\forall$ a = 1, 2, ...M,

$ef_{a,i}$ is the energy/emission/cost factor of material a used in component i,

$L_{a,i}$ is the lifetime of material a used in component i,

$P_{p,i}$ is the power requirement of process p used in component i, $\forall$ p = 1, 2, ...K,

$ef_{p,i}$ is the energy/emission/cost factor of process p used in component i,

Q_x is the total input processed in the system of scale x.

2.4 Spatial Analysis

Water and wastewater systems are inherently site-specific and sensitive to location and topographic characteristics. Geographic Information Systems (GIS) have the potential to improve and enhance the decision-making process regarding the management of water and wastewater services. One of the biggest challenges in water and wastewater infrastructure modeling is the strong connection to demographic and street network characteristics along with the topography of an area. To accurately model these systems and make informed infrastructure improvement decision, a deep understanding of the underlying urban data is required, as is access to large amounts of diverse information.

A GIS system offers the combined power of both geography and information systems making it possible to address water and wastewater infrastructure issues accurately and in detail. A major advantage of using GIS is the increased productivity and the ability to generate and assess scenarios in a timely manner. By organizing information in a geographically aware way it is possible to combine layers of information to generate data, assess individual infrastructure aspects separately and design hypothetical systems for scenario development.

The performance of a water distribution system depends on variations in ground surface elevation. An important application of spatial modeling in this research is identifying the Digital Elevation Model (DEM) of an area of interest, which enables the assessment of water and wastewater infrastructure design and assessing pumping and piping needs. Figure 6 illustrates the development of a DEM which contains information that continuously varies over space, allowing for an understanding of the ground elevation values, slopes and trends of all the overlaying infrastructure.

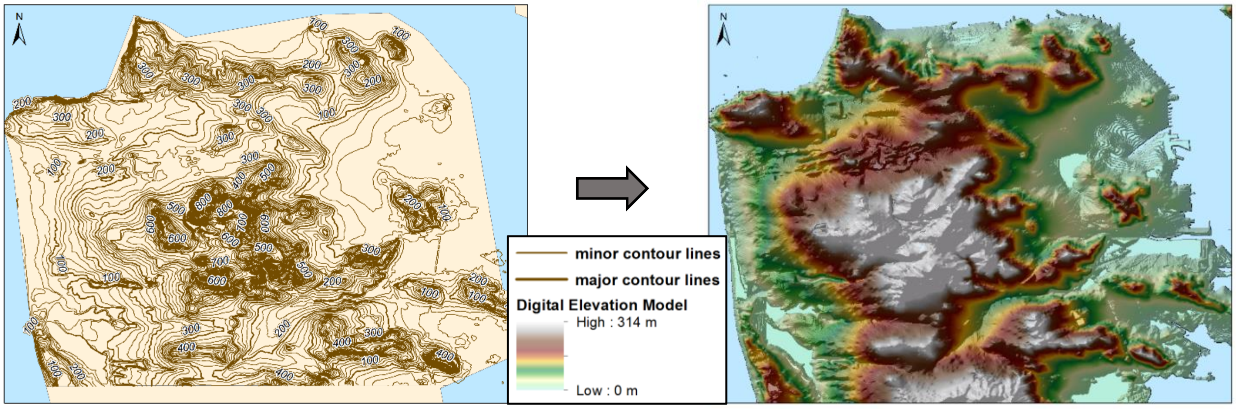


Figure 6: Constructing the digital elevation model from contours

Spatial analysis promotes realistic water infrastructure modeling as it allows for detailed piping design. Pipe infrastructure is complicated to accurately model as it is usually installed along the street networks for easier access rather than straight lines across the topography. Using spatial analysis this complexity can be parameterized in the models and piping network can be designed based on a predefined street network (Figure 7). This added complexity allows for accurate estimation of the required piping length, slope and location according to the specific inputs of the area of interest. Piping infrastructure can be modeled using a shortest path algorithm between the water source and the water end users. This approach minimizes the required pipe length between supply and demand selecting the appropriate path along the street networks. Additional complexity can be added by using the elevation information described before, which would penalize the shortest path algorithm for increases in elevation which would require additional pumping. In this work, the elevation was accounted for when designing piping networks as will be described in detail in Chapter 3.

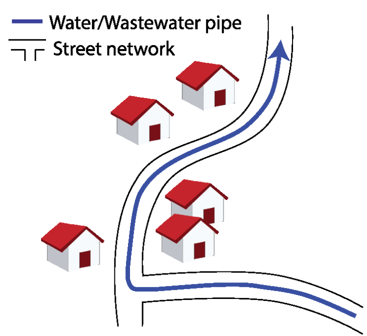


Figure 7: Example of designing and estimating piping infrastructure according to the road network

Population density and population distribution is another important aspect that can be effectively modeled using spatial analysis. Population values usually come from the Census Bureau and they correspond to large geometries, covering a couple of city blocks at best. Getting finer resolution of population distribution and population density requires some spatial analysis and combinations of various forms of data. For example, landuse information can be used to eliminate areas of blocks that are vacant. Building locations and their characteristics (type, number of floors, footprint area, etc.) can also be used as inputs to achieve a finer grain understanding about where people live. Combining various levels of information, using spatial analysis, we can better estimate higher resolution population distributions and more precise population density values (Figure 8). Several other "tricks" can be used to identify higher resolution population values, as more complex models are designed, e.g. population synthesizer tools, that are developed to imitate and model population characteristics and create virtual communities with detailed descriptions of the people living in them.[44]

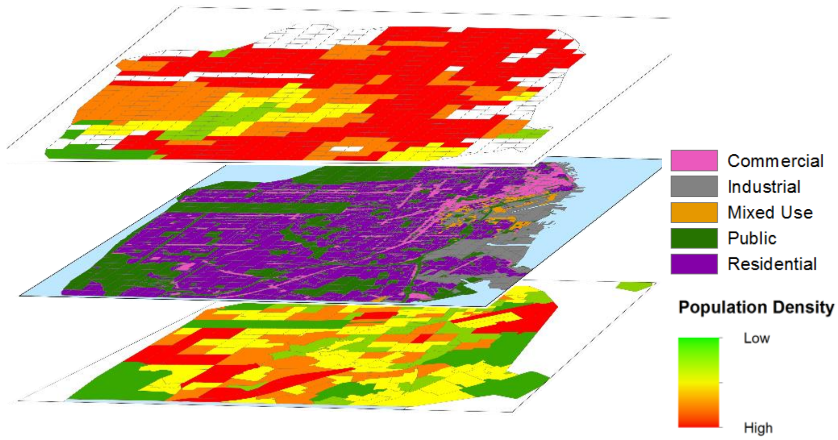


Figure 8: Disaggregation of population from census tract to grid cell size

Additionally, spatial algorithms can enhance our understanding of "connection" and lead to optimal planning. In this work, mathematical algorithms have been used to estimate and accurately model logistics impacts as well as facility location planning. The ability to understand connection between similar objects, their spatial distribution and optimal routing strategies, can increase the precision of infrastructure models, as they become more site-specific. This can address an important limitation of most infrastructure models that are based on generic data that is not representative of the conditions of the point of interest. Figure 9 illustrates some examples of computer science algorithms that were used in this research to better understand the impact of infrastructure planning and the impacts of logistics given certain site-specific conditions.

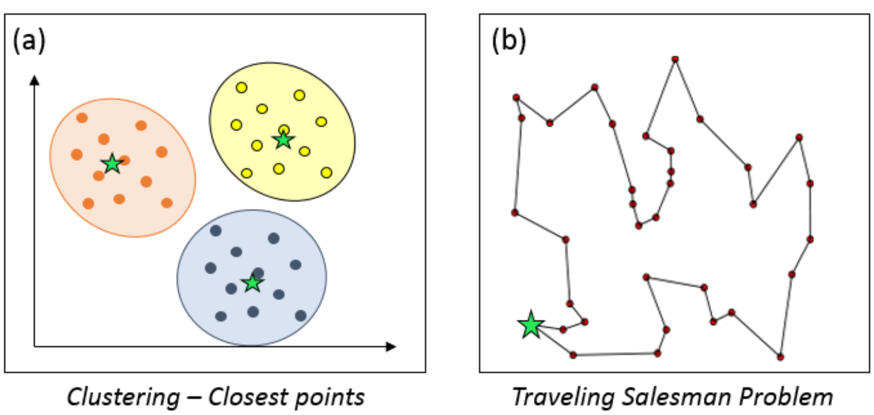


Figure 9: Examples of computer science algorithms that were used in this research to estimate (a) facility allocation and (b) transport distances

Chapter 3.

Urban Non-Potable Water Reuse: Location Variability Analysis

The following chapter is adapted from Kavvada et al. (2016) Assessing Location and Scale of Urban Nonpotable Water Reuse Systems for Life-Cycle Energy Consumption and Greenhouse Gas Emissions. Environmental Science & Technology, (50)24, 13184-13194, with permission from Arpad Horvath, Jennifer R. Stokes-Draut, Thomas P. Hendrickson, William A. Eisenstein and Kara L. Nelson. Copyright 2016, ACS Publications.

3.1 Introduction

Climate change, population growth, and competition over available water resources threaten the viability of conventional water sources globally. Drought conditions in many parts of the world are increasing in duration, severity, and frequency.[17] Proactive cities are moving to increase water supply resiliency and security by investing in conservation policies and diversifying water supply portfolios to include water reuse, stormwater harvesting, and desalination.[45]

Simultaneously, the world faces the need to reduce greenhouse gas (GHG) emissions. Urban water and wastewater services have significant GHG emissions associated with their energy use and direct emissions from the treatment processes. For example, in California, 7.7% of electricity consumption is dedicated to pumping and treatment of water.[4] Given the large energy requirements of water services, it is important to assess these environmental implications of infrastructure when diversifying a water supply portfolio. The internationally accepted goal of constraining global temperature increases to two degrees Celsius over pre-industrial levels will involve reducing GHG emissions by 40-70% below 2010 levels by 2050.[17] Meeting this goal will require water and wastewater utilities, along with other economic sectors, to substantially reduce their operational and embedded GHG footprints. In California, bill SB32 calls for GHG emissions statewide to be reduced by 40% relative to 1990 levels by 2030.[46]

Conventional approaches to managing wastewater involve collection via centralized sewerage networks and treatment in large wastewater treatment plants (WWTP) prior to discharge. Approximately 120 million m^3 (32 billion gallons) of treated wastewater are discharged into the environment in the United States every day.[47] Reusing some of that water could reduce demand on fresh water sources and alleviate the effects of drought. Non-potable reuse (NPR) involves using recycled water for toilet flushing, irrigation, and similar uses. Potable reuse requires more advanced wastewater treatment to ensure the water is safe for human consumption. NPR can increase per-capita water use efficiency with lower treatment requirements, fewer regulatory hurdles than potable reuse, and potentially lower cost.[48] However, because NPR requires separate distribution from potable water, dual plumbing systems are required.

Water reuse has been identified as the most efficient form of resource recovery for urban water systems.[49] However, centralized WWTPs are often located at low elevations within their collection areas to enable wastewater collection by gravity over large service areas to benefit from economies of scale in treatment (i.e., decreasing cost, energy use and GHG emissions with increasing system capacity). Centralized WWTPs are therefore often far from reuse customers, requiring large conveyance distances for a separate non-potable distribution network and, depending on topography, significant pumping requirements for NPR distribution.[50] Thus, it has been suggested that decentralized approaches may be preferable to centralized NPR water production in some cases[51] as it spatially matches supply and demand, decreases conveyance needs,[22] offers a fit-for-purpose approach, and potentially reduces the economic and environmental costs of water supply.[52]

Previous studies have assessed the costs associated with alternative water supply options (water recycling, stormwater capture and rainwater harvesting) and their corresponding environmental benefits (resiliency, reliability, health, energy, flood mitigation, ecosystem impact).[53] These factors are extremely dependent on site-specific criteria. No one-size-fits-all solutions are possible. Spatial modeling and site-specific information must be used to estimate the associated energy use, GHG emissions, and costs. Recently, a method was presented to assess the cost-optimal degree of centralization in wastewater infrastructure accounting for spatial and demographic parameters, but this study did not consider reuse.[54] Another study performed a location-specific multivariable analysis to assess the cost and resource recovery potential (non-potable water and biogas) for satellite wastewater treatment systems and identified hybrid solutions that involve a mixture of centralized and satellite treatment systems as having the best performance.[55]

The effect of scale can be a driving factor for treatment system efficiency. Several authors have tackled the mathematical relationship defining economies of scale for cost of treatment processes[9] as well as for cost and GHG emissions of alternative water sources.[10,49] One study assessed the cost of direct potable reuse with respect to system size by performing hypothetical modeling studies for retrofits of residence halls, and concluded that direct potable reuse in an urban area would only be cost competitive in medium-size facilities (about 10,000 residences per reuse facility).[56] Several previous studies have assessed the life-cycle implications of water and wastewater systems[34,57] and a few have focused on decentralized systems, producing varied results depending on specific technologies and locations assessed.[58–60] These prior studies provide context and lay important groundwork. Nonetheless, optimization of NPR systems has not yet been researched thoroughly, especially considering the effect of site-specific conditions and system scale.

The goal of this study was to assess residential NPR and create a planning support framework for recycling water with the lowest energy requirement and GHG emissions. The two reuse scenarios evaluated were centralized water reuse through the existing large WWTPs (which requires the addition of tertiary treatment and new pipelines to deliver the recycled water) and decentralized water reuse (new treatment facilities and short pipelines built inside or directly adjacent to the building(s)). For the purposes of this paper, decentralized reuse refers to systems that recycle wastewater for between 100 and 10,000 people. The size at which the decentralized facility has lower energy use and GHG emissions was identified for specific population density and topographic conditions (Figure 10).

We created a methodology that integrates the spatial design of an NPR treatment and distribution network with a life-cycle perspective to determine the associated energy intensity and GHG emissions. The study considered different options for NPR (centralized vs. decentralized) and assesses the level of decentralization given specific spatial and demographic conditions. The method described is generic and the input parameters (e.g., topography, population density, types of NPR) can be adjusted for analysis of any city or urban water system. We applied this methodology to the demographics, spatial parameters, and existing infrastructure of San Francisco, a city positioned as an innovation leader in the area of decentralized urban water reuse due to policies and incentives implemented to promote alternative water supply.[61] The specific conditions evaluated for San Francisco are described later in the text.

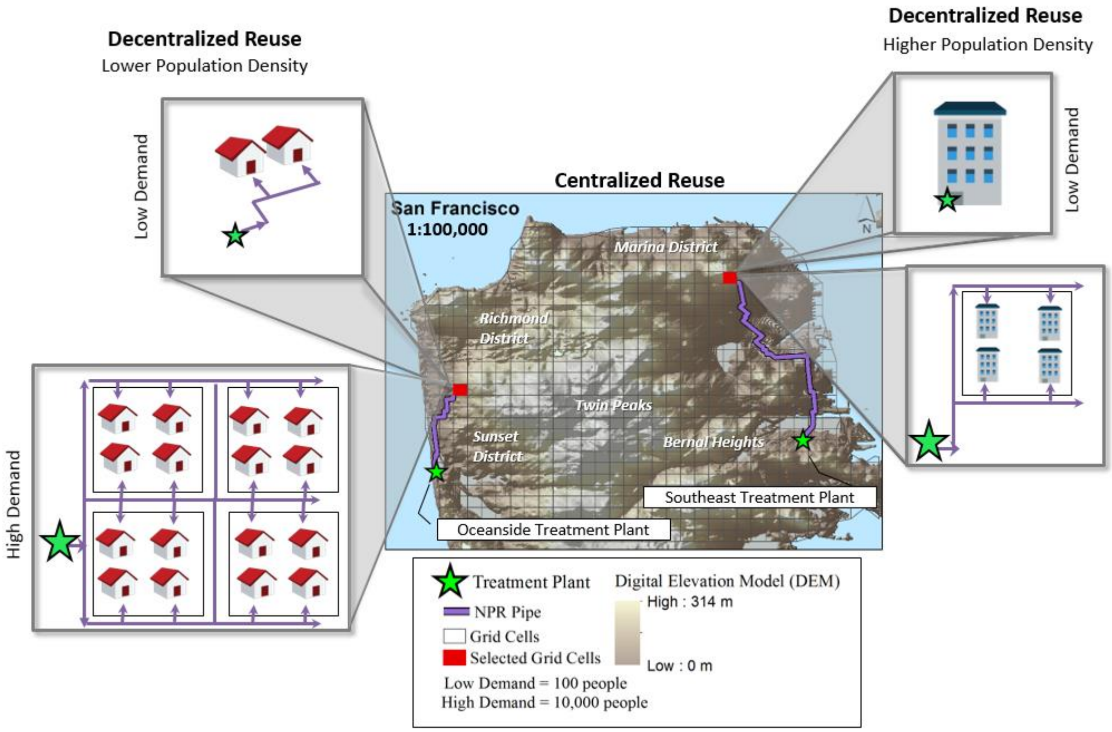


Figure 10: System options assessed for residential NPR in the San Francisco case study region (the contours used to generate the Digital Elevation Model from[62]).

3.2 Methods

The modeling approach is illustrated in Figure 10. For each grid cell (representing a neighborhood of a city), we assessed centralized and decentralized NPR. For centralized reuse, it was assumed that the recycled water was piped from an existing centralized WWTP (located outside of the cell) to the cell. For decentralized reuse, the WWTP was located within the cell and a range of realistic system scales are evaluated.

3.2.1 Overview of the Modeling Approach

The modeling process was partitioned into two functional models: the spatial analysis model and the life-cycle model. Figure 11 illustrates these two models and their integration. The spatial analysis model uses a digital elevation model (DEM) (see Figure 10), to estimate the piping length and pumping head required for the distribution of recycled water from either the decentralized or centralized treatment facility, taking into account the population density, grade profile and road network of the area of interest using network analysis. Based on these inputs the spatial analysis model estimates the system component sizes needed for distribution of the recycled water in the decentralized and centralized reuse scenarios (see Appendix 1 for more details).

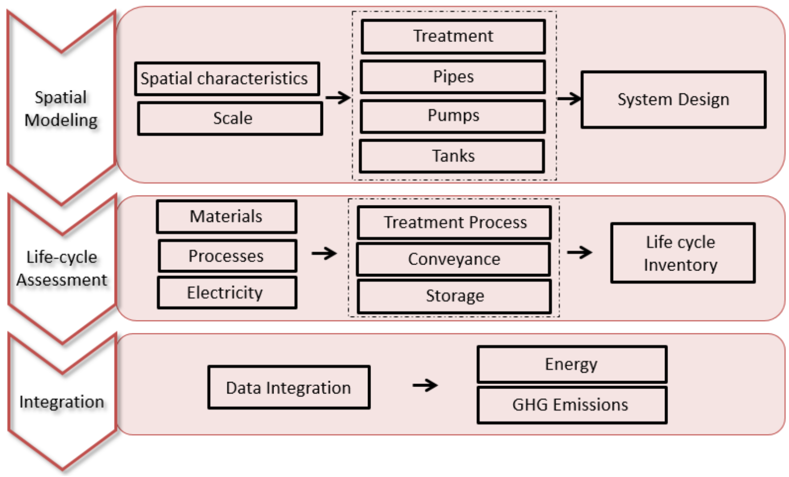


Figure 11: Modeling framework presented in this study

The life-cycle model utilizes the output of the spatial analysis model to evaluate the environmental impacts of all the required infrastructure components described in the next section. We quantified the life-cycle energy use and GHG emissions for material production and delivery, system construction, operation, and maintenance. End-of-life was not considered as previous research has shown that it does not significantly affect the total energy consumption and GHG emissions.[36,39,40] The system components evaluated are described in the next section and presented in Figure 12. The integrated spatial and life cycle modules provided estimates of the site-specific energy and GHG intensity of NPR systems.

To test the robustness of the model and the results, uncertainty and sensitivity analyses were performed using the Monte Carlo method programmed in Python. The uncertainty analysis generated a probability distribution for the energy use and GHG emissions given a range of realistic values for the model parameters. The uncertainty analysis aims to quantify the confidence intervals of the model output by assessing the uncertainties in the inputs. The parameters, ranges, probability distributions, and data sources can be found in the Appendix 1 (Table S - 5). We performed 25,000 simulations to get an accurate representation of the uncertainty.

A sensitivity analysis was used to estimate the effect of each parameter's value independently on the result to identify the relationship between the model's input and outputs. The sensitivity analysis was performed using a variance-based global sensitivity analysis method to estimate each parameter's effect on the variance of the energy use and GHG emission results. Sensitivity analysis was performed to estimate the effect of perturbing each parameter on the final results to explore the relationships between the input and outputs of our model. A perturbation of 10% of the original value was assumed for all the parameters. We simulate the perturbation effect by taking the derivative of the output model with respect to each normalized parameter. A mathematical formulation is presented below (Eq. 2 - Eq. 5).

$$S = \frac{\partial f}{\partial \theta}(\theta) \quad , \text{ where } \quad \theta = [\theta_1, \theta_2, ..., \theta_N]^T \qquad \text{[Eq. 2]}$$

$$\bar{\theta} = \frac{\theta - \theta_{min}}{\theta_{max} - \theta_{min}} \rightarrow \bar{\theta} \in [0, 1] \qquad \text{[Eq. 3]}$$

$$S = \frac{\partial f}{\partial \bar{\theta}} = \frac{\partial f}{\partial \theta} \times \frac{\mathrm{d}\theta}{\mathrm{d}\bar{\theta}} = \frac{\partial f}{\partial \theta} \times (\theta_{max} - \theta_{min}) \qquad \text{[Eq. 4]}$$

$$\Delta\theta = \frac{1}{10} \times (\theta_{max} - \theta_{min})$$ [Eq. 5]

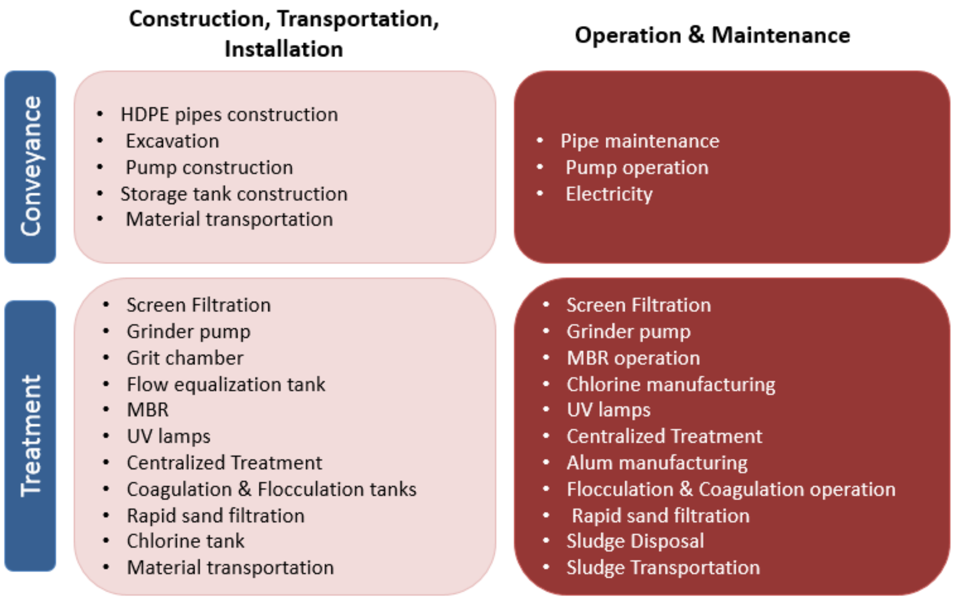


Figure 12: System components assessed and data sources[10,34–36,55,60,63–74]

3.2.2 Case Study Description

The NPR model was applied and tested using a scenario based on the city of San Francisco. San Francisco obtains high-purity fresh water from the Hetch Hetchy Reservoir in the Sierra Nevada Mountains, which is transported to San Francisco by gravity (the energy intensity is 1.7 kWh/m^3).[60] California has recently experienced one of the most severe droughts on record and policymakers are currently diversifying the water portfolio to increase drought resiliency.[6] In 2013, San Francisco passed an ordinance to allow district-scale sharing of NPR water (i.e., between buildings in close proximity) and require installation of purple (non-potable) pipe within certain new construction. In July 2015, the ordinance was amended to require new buildings of 23,000 m2 (250,000 sq. feet) or more to provide alternative water sources.[61] This ordinance lays the groundwork for expanded implementation of NPR, making San Francisco an early adopter in this field. NPR anticipated common end-uses are irrigation (representing only $2-5$ % of total water use) and toilet flushing (which can vary between 25% - 50% of total water use in a residential building and up to 75% - 95% in a commercial building).[24]

San Francisco is a densely populated city with substantial elevation changes over a compact surface area, an interesting topography for a case study. Though building a centralized NPR distribution network would cause major construction disturbances and is unlikely to be implemented for small flows, a wide range of flows are included in our analysis for comparison (20 m^3/day to 2,000 m^3/day per grid cell). Wastewater generation for sizing facilities was assumed to equal 0.2 m^3/person-day.[75] Residential water use was also assumed to equal 0.2 m^3/person-day given that outdoor water use and irrigation are low in San Francisco.[24,76] NPR water demand was assumed to be 50% of residential water use[24] a realistic assumption for an urban mixed use setting. The electricity used by the local water utility, the San Francisco Public Utilities Commission

(SFPUC), is 100% hydropower (a low carbon electricity source). The carbon intensity of SFPUC's electricity mix was assumed to be 83 gCO_2/kWh.[60]

We compared the decentralized approach to a hypothetical centralized water reuse scenario that would provide the same quantity and similar quality of water to locations throughout San Francisco. We estimated elevation, population density, and scale using spatial GIS analysis for San Francisco (Figure 10). We divided the city into 766 grid cells with dimensions of 500x500 m each and applied the model to each grid cell independently. The grid cell size was selected using heuristics, to provide granularity in the assessment while at the same time being large enough to illustrate realistic district-scale decentralized systems. The optimal grid cell size for analysis may vary for other locations, based on the area's topography and population density. The maximum number of people served by a single decentralized facility was a function of the grid cell size and the actual population density of that cell. The number of people served represents people whose wastewater is treated; the population that uses the NPR water is double that number, given our assumption that 50% of water demand can be met with the recycled water. The other 50% of the recycled water is used by the closest neighbors. For each grid cell, the digital elevation model (DEM) was calculated based on the elevation contours of San Francisco.[62] Using the DEM, we located the lowest elevation point as the assumed location of the cell's decentralized WWTP to obtain gravity-fed wastewater collection. Population density of each cell was estimated using a weighted average approach from census tract data[62] to estimate the piping distances required to serve a specific demand in each grid cell. Since this project focused on residential NPR, areas that were described as "public" or "commercial" in the zoning maps of San Francisco were excluded.[62]

3.2.3 Water Reuse Infrastructure Modeling

We used a life-cycle approach to evaluate the embodied and operational energy and GHG emissions for the infrastructure components described below. Our assessment included impacts associated with the construction, operation and maintenance[35] of NPR pipes (including excavation and backfilling for average trench depths for the selected pipe diameter[37]), storage tanks, treatment facilities and pumps for sewage collection and NPR distribution, and production and transportation of materials.[66] The impacts of sewer construction were not included in the assessment as we evaluated infill development assuming the wastewater network already exists and will continue to be operational.

For the centralized scenario, the SFPUC's two WWTPs, the Southeast and the Oceanside plants, were assumed to be the source of NPR water. Their locations are shown in Figure 10. For the treatment phase, the actual operational energy use was based on existing secondary treatment at the WWTP,[60] augmented with hypothetical typical tertiary treatment processes to achieve adequate water quality for NPR. Additional treatment processes included coagulation and flocculation with appropriate alum doses,[70] using rapid sand filtration and chlorination, which were each modeled independently (Figure 13). It was assumed that tertiary treatment was constructed at the equivalent scale of the existing plant (241,000 m^3/day) and that it was not necessary to size for peak flows, as they would receive only secondary treatment water and not be recycled. For the decentralized facilities, it is also appropriate to design based on average flows, because the equalization tank at the beginning of the treatment train is sized sufficiently to buffer the daily variations in flow rate. It is not necessary to accommodate increases in flow due to storm events, because infiltration/inflow does not occur in building systems. The biosolids resulting from anaerobic digestion at the centralized WWTP were assumed to be disposed in equal parts (by mass) via land application and daily cover at a landfill, with transportation requirements and landfill emissions estimated.[34] In reality, the planned treatment process for centralized NPR in San Francisco is more complex and energy intensive because saltwater intrusion in the sewer system requires reverse osmosis to be implemented for water used to irrigate parks.

For the decentralized treatment process, we evaluated a hypothetical treatment train with a membrane bioreactor (MBR), shown in Figure 13. Raw wastewater goes through pre-treatment (screen filter and a grinder pump to remove solids), a grit chamber, a flow equalization tank, and an MBR for primary and secondary treatment. The effluent is disinfected with UV (primary disinfectant) and chlorine (disinfectant residual) and then stored until needed. The sludge generated from primary and secondary treatment is stored onsite and periodically transported by truck to the closest centralized WWTP for further processing.

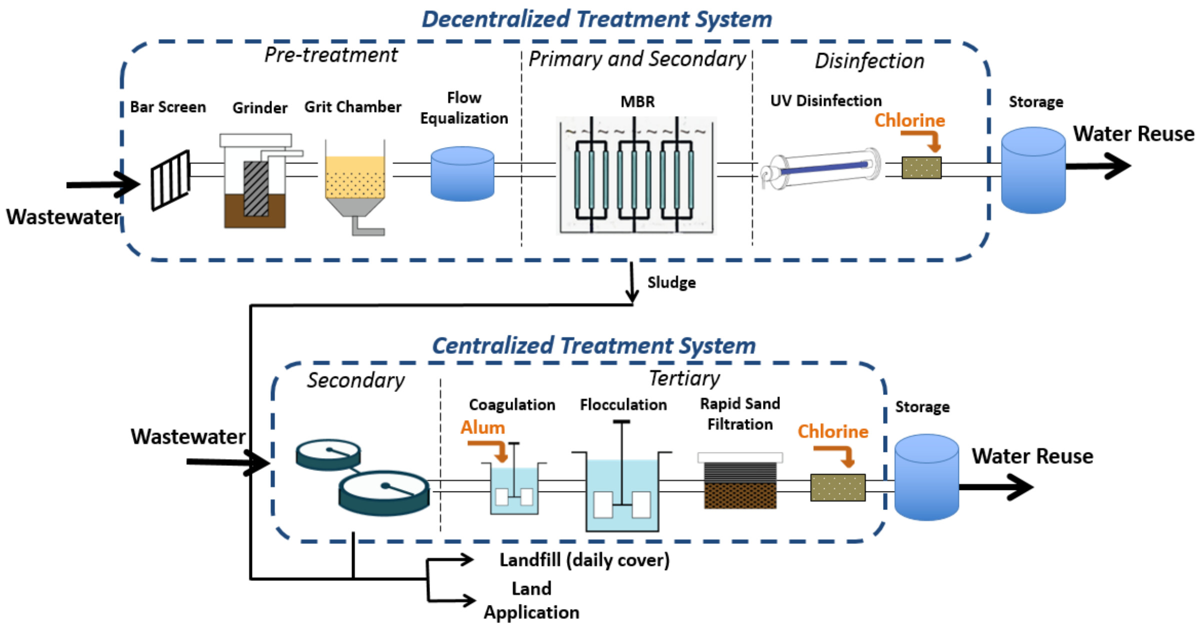


Figure 13: Treatment train for the decentralized and centralized scenarios

For the MBR, the operational energy was estimated from literature data and scaled to a range of possible flow conditions using a regression analysis based on literature data for installed small-scale MBRs as shown in Figure 14.[77–80] The embodied energy of the MBR was estimated based on the materials used and the associated emission factors.[68] The MBR data were benchmarked with other technology data and larger MBR systems for comparison.[60,80–82] Regression analysis details can be found in the SI. The energy use and GHG emissions for sludge handling were calculated based on the contribution of the decentralized plant to overall sludge production at the WWTP.

Small scale MBR technologies are not yet mature and have a large potential for improved operational efficiencies.[83] To simulate potential future conditions, we also evaluated a scenario in which the operation of the MBR treatment is 20% more energy efficient than that shown in Figure 14. This analysis illustrates how decentralized technologies with improved performance would compete against the already-efficient centralized treatment.

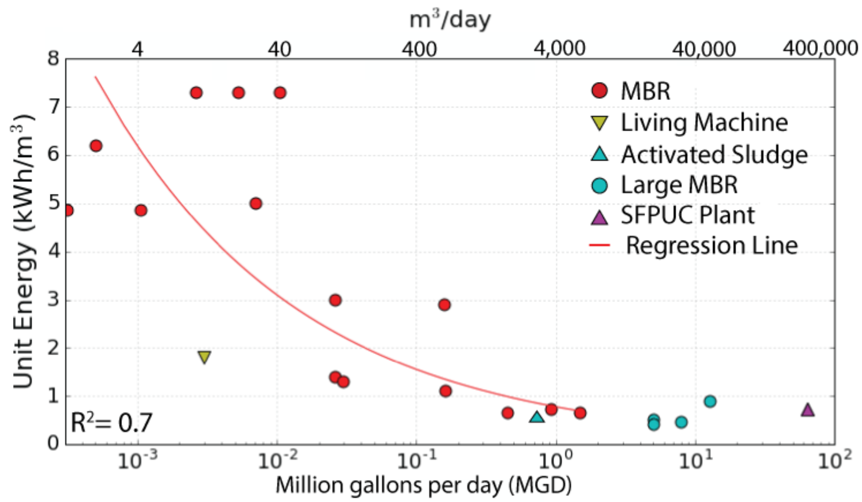


Figure 14: MBR Operational Energy Regression Analysis[60,77–80,81,82]. Data points shown in red were used in the regression; other data points are shown for context.

The direct GHG emissions released as CO_2 from wastewater systems are considered biogenic and, per IPCC protocols, were not accounted for.[84] For the centralized treatment scenario, the direct emissions of methane reported by the utility were minimal, as emissions in the form of CH_4 and N_2O are avoided through oxidation in cogeneration, boilers or flares. The direct emissions of CH_4 and N_2O from the biological treatment processes of both systems are sensitive to the treatment design, operation, and specific microbial processes.[85] Therefore, they are highly uncertain and likely vary depending on level of nitrification/denitrification occurring. Due to this uncertainty, they were not included in the analysis for either of the two systems, though they may potentially represent a significant portion of total GHG emissions. More research and data are needed to accurately estimate these emissions and identify strategies to reduce them.

For reuse distribution, the conveyance phase accounts for the distance and elevation change from the centralized or decentralized WWTP to the demand location and scales based on the modeled demand. For the decentralized scenario, the distribution network was modeled based on average city block sizes and the specific population density of the area with the WWTP modeled at the lowest elevation point. For the centralized scenario, each grid cell was connected to one of the two WWTPs based on a shortest path algorithm for the road network of San Francisco.[86] Selected routing results are illustrated in Figure 10. The shortest path algorithm (Dijkstra's algorithm) accounted for distance and elevation change between the WWTP and the target grid cell to minimize both piping and pumping needs (more information can be found in the next section). Therefore, the pipeline optimal route between the grid cell and the WWTP was not always the minimum distance, but the one that minimized the total cost for conveyance along the road network. Using the optimal route, the maximum elevation point along the route was identified and used to estimate the hydrostatic pressure for the pumping energy calculations. The total distance was used to estimate the head losses and piping construction and installation needs.

While modeling a hypothetical NPR distribution network, we generated two scenarios to evaluate the piping needs for each grid cell. The first scenario was called the "completely dispersed" scenario, where each grid cell is independently connected to the centralized WWTP (i.e., no pipe sharing between grid cells). This extreme scenario was used as the upper bound of the analysis. For the second, the "completely connected" scenario, piping was shared between cells such that the construction and installation of the pipes and pumps were allocated among grid cells served by the same infrastructure based on the network layout. In this case, the allocation of embodied energy and GHG emissions for pipe manufacture, construction, and maintenance was much smaller for each grid cell, giving the lower bound of the analysis. Realistically, the network would perform in a state between the two scenarios, which cannot be modeled accurately without knowing the actual network design. More details can be found in the next section (3.2.3.1 - Detailed spatial modeling description).

Pumping was included in the analysis both for the wastewater collection system and for the NPR system when there is not enough pressure to satisfy the total head requirement for pressurized distribution. For each network condition, we modeled a single pump with specifications to meet the overall head requirement; this simplifying assumption increases the uncertainty of our results but makes it possible to assess the network in a generalized way. Pump sizes for collection and distribution were estimated to minimize cost and head losses based on the elevation grade and flowrate. Embodied energy and GHG emission values for each pump were calculated for manufacturing and transportation.[65] Operational energy was calculated using Bernoulli's equation for total head. Wastewater collection pumping needs were estimated using the utility's pump sizes and flows for each area.[87] In water reuse, supply and demand are not necessarily synchronized. Storage is required for pre-treatment flow equalization as well as for treated wastewater until it is distributed for NPR. Above-ground water tanks located adjacent to the WWTP were assumed for storage. More details can be found in the following section (3.2.3.2 - Detailed LCA Description).

3.2.3.1 Detailed spatial modeling description

- Landscape

The model uses topographical elevations generated from contour data of San Francisco[62]. Each landscape is generated by performing an iterative finite difference interpolation method on the elevation values of the contours to produce a raster dataset. This raster, the digital elevation model, consists of pixels with the corresponding elevation values that describe the topography of the area. The digital elevation model is used during the system design, the piping distribution and to account for the pumping requirements in the area.

- Street network

The piping infrastructure layout is modeled over the street network of San Francisco[86]. To generate the street network for the model the road segments are connected with nodes to establish connectivity. The road segments represent the edges of the network and the intersections the junctions. These network attributes control the ability to traverse the network. The length of the road segments (in 3D) is calculated and the junctions are assigned an elevation value when overlaid on the digital elevation model. The road segment is then assigned an elevation value which corresponds to the difference of the elevation between the two junctions that characterize it. These elevations are used later to analyze the piping path, described below.

- Grid cells

To assess the water reuse scenarios and get better resolution on the results, the model divides the area of interest into small cells with a size of 500x500 m. Individual grid cells focus the analysis into smaller areas of interest to estimate the energy and GHG emissions for the water reuse scenario occurring in each individual grid cell. The grid cell size was selected to allow sufficient demand of water given the range of population densities in the study.

- **Population resolution**

Since the resolution of the analysis is at the grid cell level, we allocated population to each grid cell. However, population density data are given by a census tract which usually covers multiple grid cells, and/or multiple tracts cross grid cell boundaries. We disaggregated the population density from the tract area to the grid cell using a weighted average approach based on the area which the different census tracts overlapped in each affected grid cell. Using zoning data for San Francisco[62], we excluded areas that were characterized as public spaces or industrial and commercial areas when disaggregating the population values. Figure 15 illustrates the process and shows the estimated total population of each grid cell.

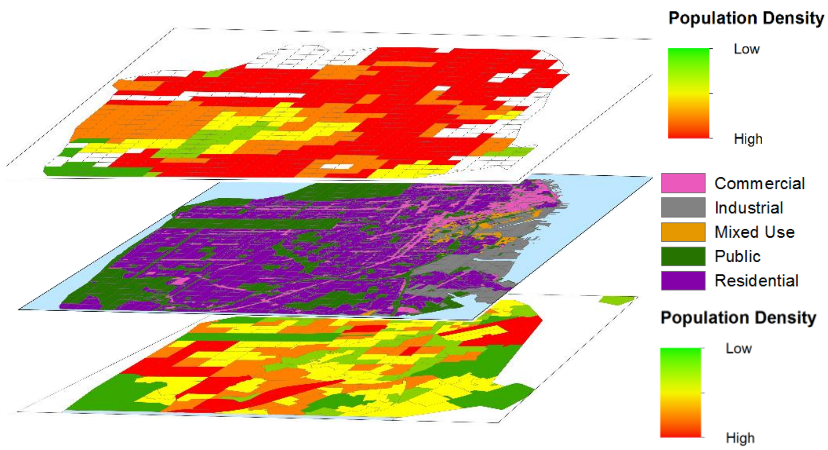


Figure 15: Disaggregation of population from census tract to grid cell size

- **Piping networks**

In each individual grid cell, a piping network is modeled to satisfy the required non-potable water demand. The piping network is modeled around the residential blocks. The assumed size of the residential blocks is 80x80 m. According to the estimated population density in each grid cell, the required area to fit the selected population, and the piping length needed to serve them, is calculated. The required piping length is calculated for each grid cell given the calculated population to be served (Figure 16). This means that by estimating the area covered by the population served (a function of population density for each grid cell), the piping infrastructure length corresponds to the circumference of the number of city blocks occupied. Low population density grid cells would require more piping to serve the equivalent population (population more dispersed) than high density areas as illustrated in Figure 16.

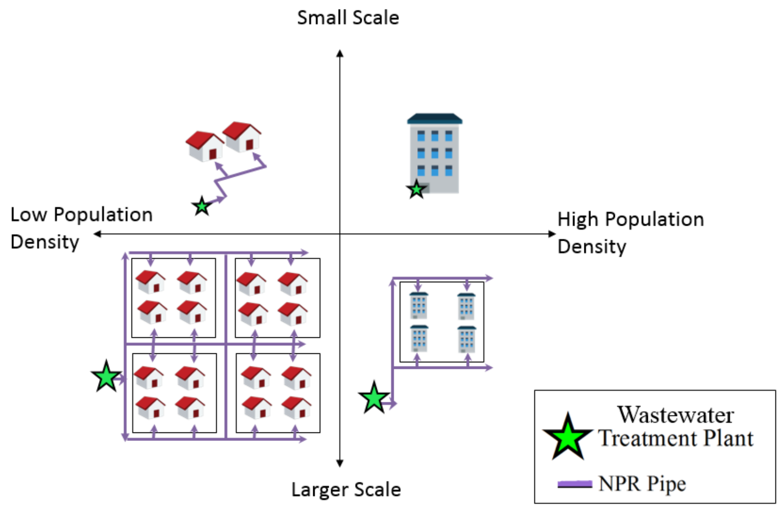


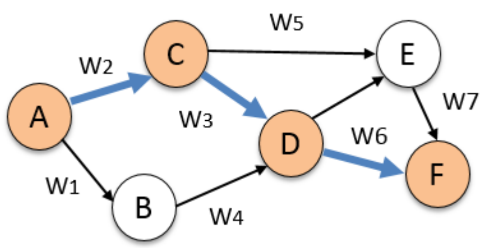
Figure 16: Example of estimating piping length for the same population served for different population densities and system scales

For the centralized scenario only, in addition to the in-cell piping requirements, NPR piping length is calculated to connect each grid cell with the closest centralized treatment plant based on Dijkstra's shortest path algorithm using the street network as the connection path (Figure 17). Using this algorithm, a path is created between the centralized treatment plant and the minimum elevation point of each grid cell based on the street network of the area. The algorithm ensures all possible paths are evaluated and the shortest path is found recursively by minimizing the overall distance between of all the possible road segments. The lowest elevation point of the grid cell is found using the digital elevation model and accounting for the elevation of every pixel that falls inside the grid cell. This is the starting point of the grid cell that connects to the centralized treatment plant. The cost function for the shortest path algorithm is to minimize costs for piping distance and pumping requirements. Thus, this algorithm minimizes the network distance between origin and destination and considers the topography. Examples of selected routes are presented in Figure 18.

The pumping requirements at every road segment are estimated based on the elevation difference of two junctions that characterize it. They are calculated for each road segment and input into the cost function. Pumping calculations are further discussed in the following section. For the piping costs, an estimation of pipe cost per length is used and added to the cost function of each road segment.

To analyze the infrastructure that corresponds to each grid cell, two scenarios were considered. The dispersed scenario and the completely connected scenario. For the completely dispersed scenario, an individual pipe was assumed from every grid cell connecting it to the corresponding centralized treatment plant, based on the shortest path algorithm. This scenario would model an independent development scenario where the NPR network is not yet established and only a few areas have access to NPR water. The completely connected scenario assumes that the NPR infrastructure is shared by multiple grid cells in an optimal way, reflecting a system where the NPR network is highly integrated in the city and all grid cells have access to NPR water. To model this from the optimized pipe network generated from the shortest path algorithm, each pipe segment was allocated to the corresponding number of grid cells that it serves. Every grid cell was then allocated only a fraction of the total piping infrastructure that was required to serve it based on the total water demand of all cells served by the same pipe. The number of cells served by an individual pipe segment was estimated based on the network connectivity. The main pipes would serve more grid cells than the branches off the main pipes. Intuitively, in this scenario, the infrastructure impacts were smaller for every grid cell compared to the dispersed scenario. Because NPR supply exceeds demand in San Francisco, and most urban areas, a fully built-out completely connected network is not possible. These two scenarios, therefore, correspond to the upper and lower bounds of what a realistic situation would look like.

The sewer piping construction was not included in the assessment as we are considering infill development where the sewage piping already exists and will be maintained regardless of the presence of decentralized systems. If this is not the case, the sewer piping construction, installation, and maintenance would have to be considered in the analysis. However, as the city requires some pumping for the collection of the sewage, this impact was evaluated appropriately for the centralized scenario.



$$w_i = d_i \times c_d + e_i \times c_e$$

Where w_i is the cost of each segment, d_i is the distance between nodes, c_d is the piping cost, e_i is the elevation difference between nodes and c_e the pumping cost

Figure 17: Shortest path algorithm

3.2.3.2 Detailed LCA Description

The study's scope includes all the supply chain elements of the materials considered, except the end of life, which has been shown in the past to not significantly affect the results.[36,39,40] Transportation of materials was individually calculated for all materials assessed in this study, and Class 8b trucks (tractor trailers) were assumed for the calculations. Transportation energy use and associated emission factors were sourced from [66] and the associated distance was estimated for San Francisco based on literature values.[88]

Our study's LCA focused on the treatment technologies for NPR and the distribution which includes piping, pumping and storage infrastructure. This study used both process-based and economic input-output (EIO-LCA) emission factors to minimize uncertainty. Process-based LCA refers to a bottom-up approach in which the processes that fall inside the system boundary are assessed.[41] In contrast, EIO-LCA takes a top-down approach and relies on aggregate data that models the entire system but lacks detail on specific processes.[42] A hybrid approach, as used in this study, utilizes the benefits of both the previously mentioned methods to quantify impacts in a comprehensive manner.[43] Figure 12 presents the specific components assessed and the corresponding literature citations. The specific processes are analyzed in detail below. Process-based LCA methods were used to assess each stage of the life-cycle where data were available, while EIO-LCA, which tracks the interactions of 400 U.S. economic sectors[65] for the rest. The GHG emissions associated with the operational electricity used were assumed to be from the San Francisco electricity provider which uses hydropower and has the relatively low emission factor of 83 $kgCO_{2(eq)}/kWh$.[60]

- **Piping**

Water distribution networks were designed to satisfy network requirements and design constraints. The pipes were sized according to the Manning – Strickler design equations to minimize cost (minimum possible diameter) that would provide a minimum velocity of 2 m/s and minimize headlosses. If the constraints were not satisfied, a larger diameter pipe was selected based on commercially available sizes. The friction factor for the pipes was evaluated with a standard engineering approach using the Reynolds number and the relative roughness of the pipes based on their material. We used the Moody diagram to approximate the friction factor.

The pipe network was assessed using life-cycle energy and emissions numbers based on previous studies.[35,36] High density polyethylene (HDPE) was assumed for the pipes as it has been assessed to have small environmental impacts associated with its construction, moderate costs, and wide range of available diameters.[36] It also satisfies local requirements for distributing NPR water as PVC use is discouraged in San Francisco and is being regulated.[89] Only commercially available pipe diameters were considered. A lifetime of 50 years was conservatively assumed for all the piping infrastructure. Table S - 1 in the Appendix 1 presents the data that were used to assess each pipe diameter size.

For piping installation, excavation and backfilling were also considered. The excavation volume was calculated for each pipe diameter following the dimensions described in [37] and the trench depth requirements for water reuse.[90] The trench depths were considered constant along the terrain. The energy and GHG emissions for installation were calculated based on the speed of excavation in medium soil (0.2 h/m^3) and the volume of diesel required for an excavator (20 L/h).[10] For the excavation and backfilling, diesel fuel was assumed with a specific energy of 42.8MJ/kg, a density of ρ =0.84 kg/L and carbon fraction f_c=0.86. Piping maintenance was also included in the scope with a break rate given by equation [Eq. 6].[35]

$$N(t) = N(t_0) \times e^{A(t-t_0)} \quad \text{[Eq. 6]}$$

where N(t) is the expected number of breaks per unit length in year t, $N(t_0)$ the number of breaks in the installation year and A growth rate factor appropriate to HDPE pipes equal to 0.08 y^{-1}.[36] An average break length of 0.6 m was used[36] and energy and GHG replacements of 393 kWh/m and 287 kg$CO_{2(eq)}$/m, respectively.[35]

- **Pumping**

To calculate the energy and GHG emissions from pumping, the dynamic, static and hydrostatic pressures are estimated along with the head losses. The dynamic pressure corresponds to the velocity head [Eq. 7]. The static pressure is associated with the minimum pressure for consumption at the endpoint and was assumed equal to 20 m. The hydrostatic pressure [Eq. 9] corresponds to the elevation head (z) (maximum point along route) and the pressure losses (hf) can be calculated from Darcy's equation [Eq. 8]. The total head (h_{tot}) to estimate the pumping requirements was given using Bernoulli's equation [Eq. 10]. The main contributor to pumping needs is the elevation head which accounts for about 50-90% of the total energy needed and the static pressure needs that are required for minimum pressure at the point of consumption. Head losses account for about 10% of the total pumping needs.

$$P_{dyn} = \frac{1}{2}\varrho u^2 \quad \text{[Eq. 7]}$$

$$h_f = f\frac{L}{D}\frac{u^2}{2g} \quad \text{[Eq. 8]}$$

$$P_{hydrostatic} = \varrho g z \qquad \text{[Eq. 9]}$$

$$h_{tot} = \frac{p}{\gamma_w} + z + \frac{u^2}{2g} + h_f \qquad \text{[Eq. 10]}$$

where f is the friction factor, ρ is the water density, v is the water velocity in the pipe, L is the pipe length, D is the pipe diameter and g is the gravitational acceleration. Given the total head and the volume of water required the pumps were sized appropriately. The required energy to satisfy the pressure head is estimated using the following equation [Eq. 11]:[63]

$$E_{pump} = \frac{\gamma_w Q_{avg} h_{tot} d_t}{n_{pump} n_{motor}} \qquad \text{[Eq. 11]}$$

where γ is the specific weight of water, Q_{avg} the average flow, d the pumping duration and n_{pump} and n_{motor} the efficiency for the pump[10] and motor[63], respectively, based on size.

For the decentralized system, the pumping head was estimated by calculating the slope index of each cell based on the digital elevation model. Given the population density and the existing demand, we estimated the required area of the cell and, using the specific slope index, we calculated the maximum elevation head between the highest point to be served and the treatment plant. For the centralized scenario, the same calculated elevation head was used for pumping within each cell, plus the maximum elevation and pipe length along the pipeline route that connects each cell to the centralized treatment plant.

The energy and GHG emissions for the pump construction and transportation were also considered (Table S - 2 in the Appendix 1). A lifetime of 25 years was assumed for the pumping components given in Table S - 2 to get the annualized values.

- Storage

Tanks were designed to store the treated wastewater before treatment or use. Tanks are assumed to be reinforced concrete (98% concrete, 2% steel rebar) with a retention time of 3 days.[55] The storage tanks were assessed using life-cycle energy and emissions for manufacturing and transporting the concrete material.[88] The tanks were considered to be built adjacent to the WWTP.

- Decentralized Treatment

For the decentralized treatment scenario, a WWTP of the required size was modeled at the point of lowest elevation in each grid cell. The plant receives raw wastewater by gravity and includes a screen filtering process before the wastewater is treated. The bar screen is selected from commercially available sizes. EIO-LCA was used to account for the embodied energy of and GHG emissions from materials manufacturing. The operational energy of pumps was estimated based on published data.[67] The coarse solids are then pumped out of the system using a grinder pump modeled as a 2-hp pump operating approximately 4 h per day. Wastewater overflows to the concrete grit chamber for particle settling and into the concrete flow equalization tank. Sizing for these two tanks was based on the retention times of each, taken from published data.[67] The wastewater then enters the main treatment process, a membrane bioreactor (MBR) system. The materials for manufacturing the MBR were based on a previous LCA study done of MBRs[68] and assessed for energy and GHGs using EIO-LCA. The lifetime for the membranes was assumed to be 10 years.[70] The operational energy for the different scales of MBRs assessed was based on an ordinary least squares regression algorithm described below. The literature data for MBR technologies used in this study is shown in Table S - 3 in the Appendix 1. Published lab- and pilot-scale MBR results were not included in the analysis.

We fit a power curve to represent the data shown in Table S - 3. The power regression curve will be of a form $y = ax^{\beta}$ which we can bring into a linear form,

$$ln(\alpha) + \beta \times ln(x) - ln(y) = 0 \quad \text{[Eq. 12]}$$

where x is the scale of the system and y the energy intensity.

We can transform this system to a matrix form:

$$A = \begin{bmatrix} 1 & ln(x_1) \\ 1 & ln(x_2) \\ & \vdots \\ 1 & ln(x_n) \end{bmatrix}, c = \begin{bmatrix} ln(a) \\ \beta \end{bmatrix}, y = \begin{bmatrix} ln(y_1) \\ ln(y_2) \\ \vdots \\ ln(y_n) \end{bmatrix} \quad \text{[Eq. 13]}$$

For ordinary least squares regression, we want to minimize the squared error,

$$\min_c \frac{1}{2} \|Ac - y\|^2 = \frac{1}{2} (Ac - y)^T (Ac - y) = \frac{1}{2} c^T A^T Ac - yAc + \frac{1}{2} y^T y \quad \text{[Eq. 14]}$$

which is a quadratic program with a solution

$$c^* = (A^T A)^{-1} A^T y \quad \text{[Eq. 15]}$$

By applying the values of Table S - 3, we get an output for the coefficients of ln(a) = 2.26 (standard deviation of 0.24) and β = -0.30 (standard deviation of 0.05). This gives the power regression equation [Eq. 16] to fit the data with an R^2 =0.76.

$$y = 9.5 \times x^{(-0.30)} \quad \text{[Eq. 16]}$$

Figure 14 presents the regression curve.

The sludge generated on site is assumed to be transported by truck to the nearest centralized WWTP. The distance between the grid cell and the centralized plant was estimated by the shortest path algorithm using the road network. The study also included the energy and emissions from transporting the dry sludge to either a landfill for daily cover or land applications as well as the direct emissions from the landfill.[34]

After the MBR, the wastewater is disinfected using low-pressure mercury UV lamps rated 9.5 W/m^3-day which are used for 12 h/day.[60] The embodied energy and GHG for the UV lamps were estimated using EIO-LCA and the operational energy and GHG from the onsite electricity consumption. The UV lamps were assumed to have a lifetime of 4 years.[70] Chlorination follows the UV disinfection for NPR residential uses. A loading factor of 15 mg/L was assumed of hypochlorous acid (HOCl).[67] To estimate the amount of calcium hypochlorite $Ca(OCl)_2$ used, a simple reaction was assumed:

$$Ca(OCl)_2 + 2H_2O \rightarrow 2HOCl + Ca(OH)_2 \quad \text{[Eq. 17]}$$

The corresponding embodied energy and GHG is from EIO-LCA. The treated water is then stored in a concrete storage tank with a storage capacity of 3 days.[55]

- **Centralized Treatment**

For the centralized reuse scenario, existing secondary-treatment plants were assumed to remain the same and additional treatment added to reach the water quality provided by the MBR system for NPR (shown in Figure 13). After the existing secondary treatment, the wastewater undergoes coagulation with the addition of alum in a dose of 10 mg/L.[67] Flocculation follows for particle settling and the water enters a multilayer rapid sand filtration system which consists of anthracite and sand for complete removal of solids. The filtration system is assumed to be enclosed in a steel casing with parameters described in Table S - 4 in the Appendix 1. Chlorination is assumed for disinfection purposes, as described in the previous section. The treated water enters a concrete storage tank until it is distributed for NPR.

3.3 Results

For each grid cell in San Francisco, we determined the corresponding energy intensity and GHG emissions for NPR under the decentralized and centralized scenarios. By comparing the results over a range of facility sizes (20 m^3/day – 2,000 m^3/day to serve approximately 100 – 10,000 people), we identified areas of the city where decentralized reuse would have lower energy intensity and GHG emissions compared to centralized reuse, as well as the minimum treatment scale for this to occur.

Figure 19 presents the comparative results for energy intensity and GHG emissions for the two water reuse scenarios (decentralized and centralized) for four example conditions modeled in the case study, which were chosen to illustrate the most extreme conditions (greatest differences in scale and elevation). Low demand and high demand values correspond to facility sizes of 20 m^3/d and 2,000 m^3/d, respectively. For the centralized reuse scenario, the low elevation values correspond to a grid cell that is relatively close to the centralized WWTP and the elevation difference between them is low (elevation = 32 m, distance = 2.4 km). The high elevation values correspond to a grid cell with high elevation difference from the WWTP and maximum distance (elevation = 205 m, distance = 11.5 km). The locations of the selected grid cells (#149 and # 375) are shown in Figure 18.

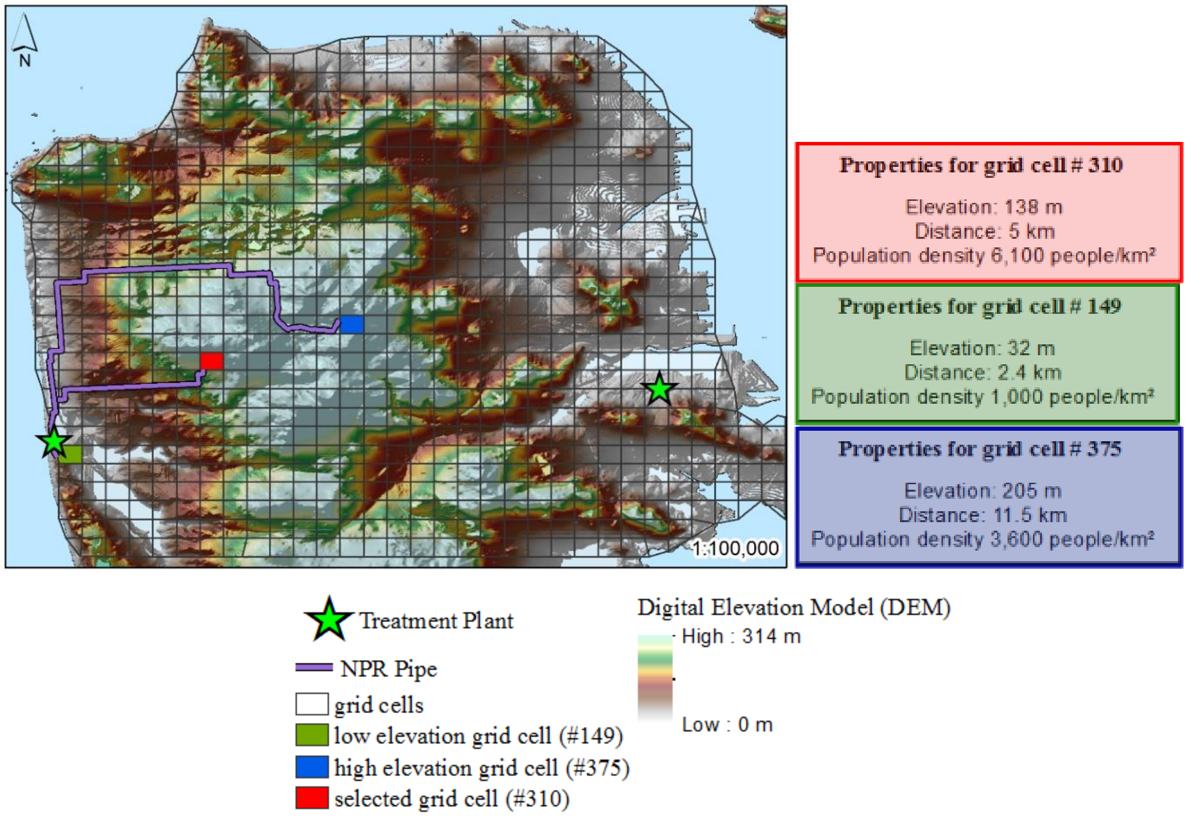
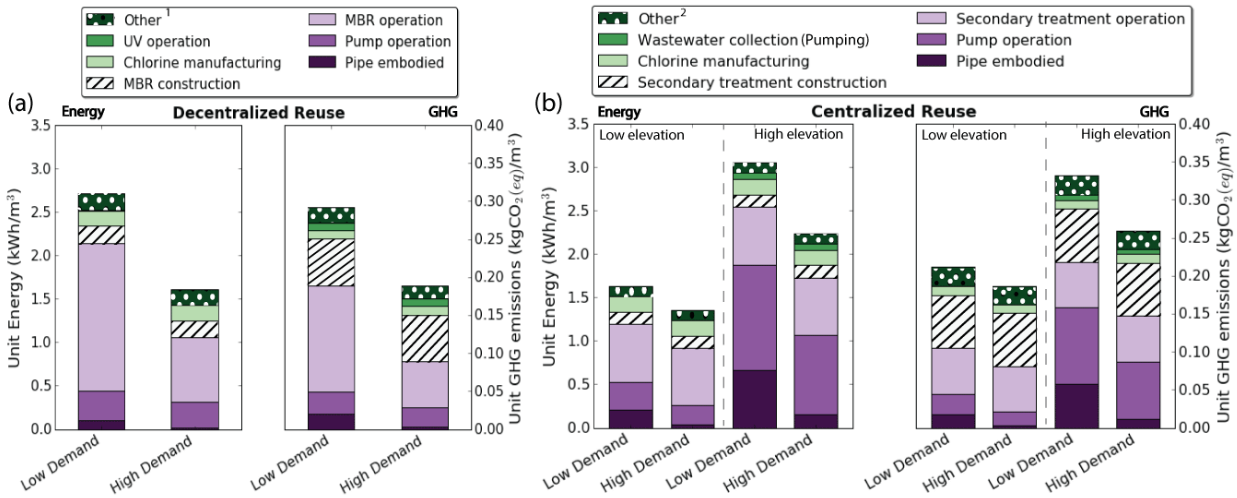


Figure 18: Case study elevation map with specific grid cell locations

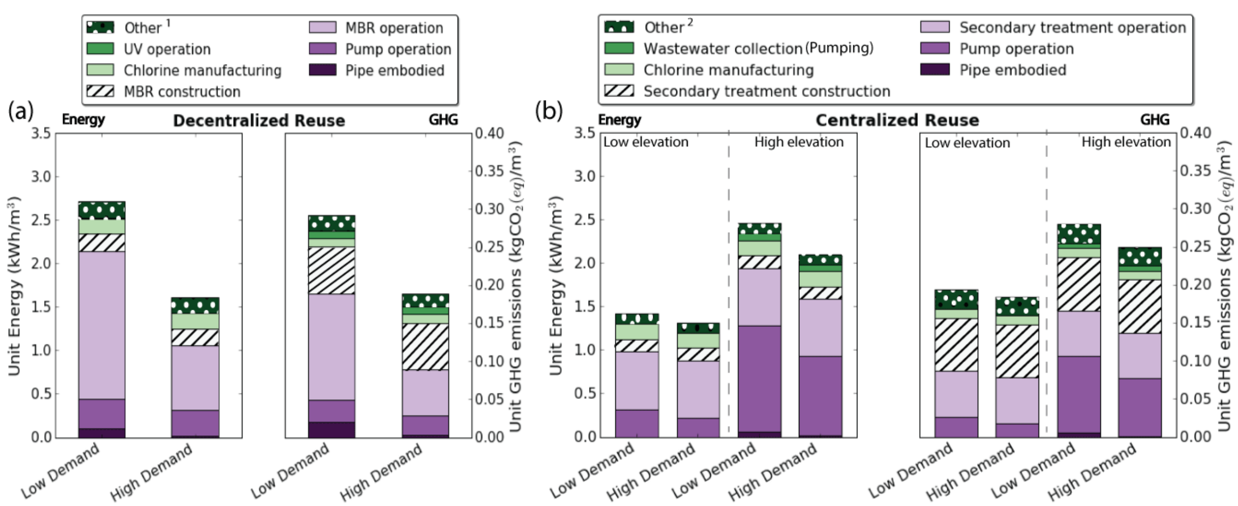
Figure 19 reports the contribution of each component of the energy intensity and GHG emissions for the two systems in the "completely dispersed" pipe configuration. In the decentralized reuse scenario, most of the impacts are due to the operation of the MBR. The major contributors to energy use in the centralized reuse scenario are the construction and installation of the piping infrastructure (including the embedded energy of the pipe materials), the pumping energy for water distribution, and the primary and secondary treatment operation. The high elevation scenario is also far from the centralized WWTP (high elevations in San Francisco are inland but the WWTPs are located near the coasts), so the piping infrastructure for conveyance is significant. Similar results for the "completely connected" pipe configuration, with much lower pipe embodied energy, are shown in Figure 20.



[1] Other includes:
Pipe maintenance, pump construction, tank construction, filter construction and operation, grinder pump construction and operation, grit chamber construction, UV construction, sludge management, transport and disposal

[2] Other includes:
Pipe maintenance, pump construction, tank construction, coagulation/flocculation construction, rapid sand filter construction & operation, sludge management, transport and disposal

Figure 19: Energy intensity and GHG emissions by process for representative scenarios for ranges of demand (low: 20 m^3/day, high: 2,000 m^3/day) and elevation difference (low: elevation=32 m and distance=2.4 km, high: elevation=140 m and distance=12 km) in (a) the decentralized and (b) the centralized alternatives, for a "completely dispersed" recycled water pipe network



[1] Other includes: Pipe maintenance, pump construction, tank construction, filter construction and operation, grinder pump construction and operation, grit chamber construction, UV construction, sludge management, transport and disposal

[2] Other includes: Pipe maintenance, pump construction, tank construction, coagulation/flocculation construction, rapid sand filter construction & operation, sludge management, transport and disposal

Figure 20: Energy intensity and GHG emissions by process for representative scenarios for ranges of demand (low: 20 m^3/day, high: 2,000 m^3/day) and elevation difference (low: elevation=32 m and distance=2.4 km, high: elevation=140 m and distance=12 km) in (a) the decentralized and (b) the centralized alternatives, for a completely connected scenario

Figure 21 presents the minimum facility size for residential areas in each grid cell for which the decentralized reuse scenario is preferable to a centralized scenario for lifecycle energy use (Figure 21) for both the "completely dispersed" (a1) and "completely connected" (a2) pipe configurations (recall that an actual centralized NPR project would likely fall between these bounding scenarios). In other words, when meeting equivalent reuse demand equal to or greater than the minimum decentralized facility size the decentralized approach is more energy efficient than the centralized approach. For each grid cell, the intersection point at which decentralized reuse becomes more efficient than the centralized alternative was calculated and illustrated in the graphs in Figure 21. The results for lifecycle GHG emissions can be found in Figure 22a. Another key result is that the economies of scale in the decentralized treatment process are significant in terms of energy use and GHG emissions; larger facilities can provide energy savings of up to $1.5 - 2.4$ kWh/m^3 (i.e., if the system is built for a demand of 2,000 m^3/d instead of 20 m^3/d) and avoided GHG emissions of $0.2 - 0.4$ kg$CO_{2(eq)}$/m^3 depending on the grid cell location. This relationship is not explicitly addressed in this paper, but optimizing the scale of decentralization can provide significant energy and GHG savings.

Overall, the results indicate that spatial characteristics (i.e., elevation and distance) often outweigh treatment economies of scale that would otherwise favor centralized solutions. Figure 21a shows that as the elevation difference increases between the reuse location and the centralized WWTP, smaller and smaller decentralized systems become more optimal than centralized reuse, even though they require more energy per unit of wastewater treated. The best-case scenario for decentralization is implementing a large facility (2,000 m^3/day) in a high elevation area. In this scenario, we identified savings of up to 0.7 kWh/m^3 and 0.07 kg$CO_{2(eq)}$/m^3 in lifecycle energy and GHG emissions relative to the centralized system, respectively for the "completely dispersed" and 0.5 kWh/m^3 and 0.06 kg$CO_{2(eq)}$/m^3 for the "completely connected" pipe scenarios. These results correspond to up to 29% lower energy consumption and 28% lower GHG emissions in the higher elevation areas of the city.

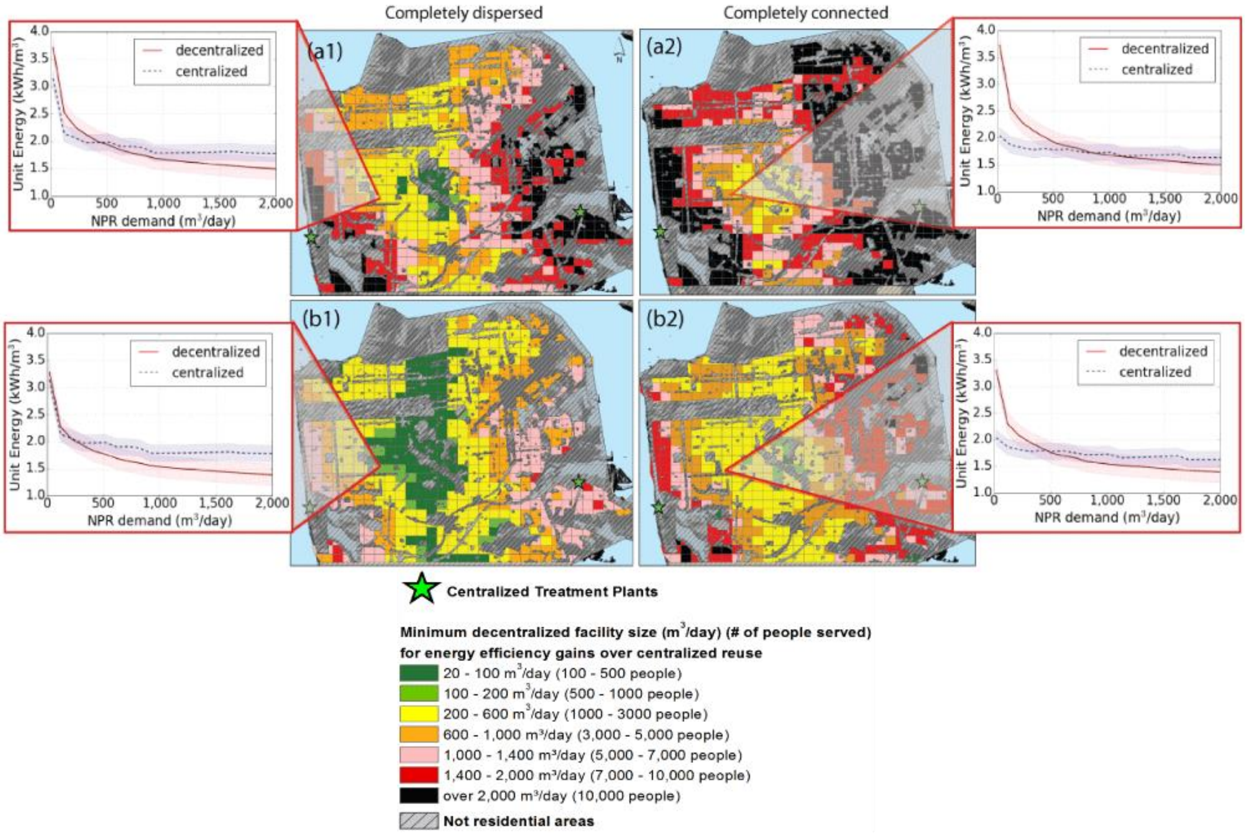


Figure 21: Minimum facility size for each grid cell for decentralized reuse to be more efficient than a centralized reuse scenario for (1) "completely dispersed" and (2) "completely connected" recycled water pipe networks. Lifecycle energy intensity for (a) current MBR performance and (b) future scenario in which the MBR treatment has gained 20% operational efficiency. Uncertainty bounds correspond to the 15th and 85th percentile probability according to the Monte Carlo method.

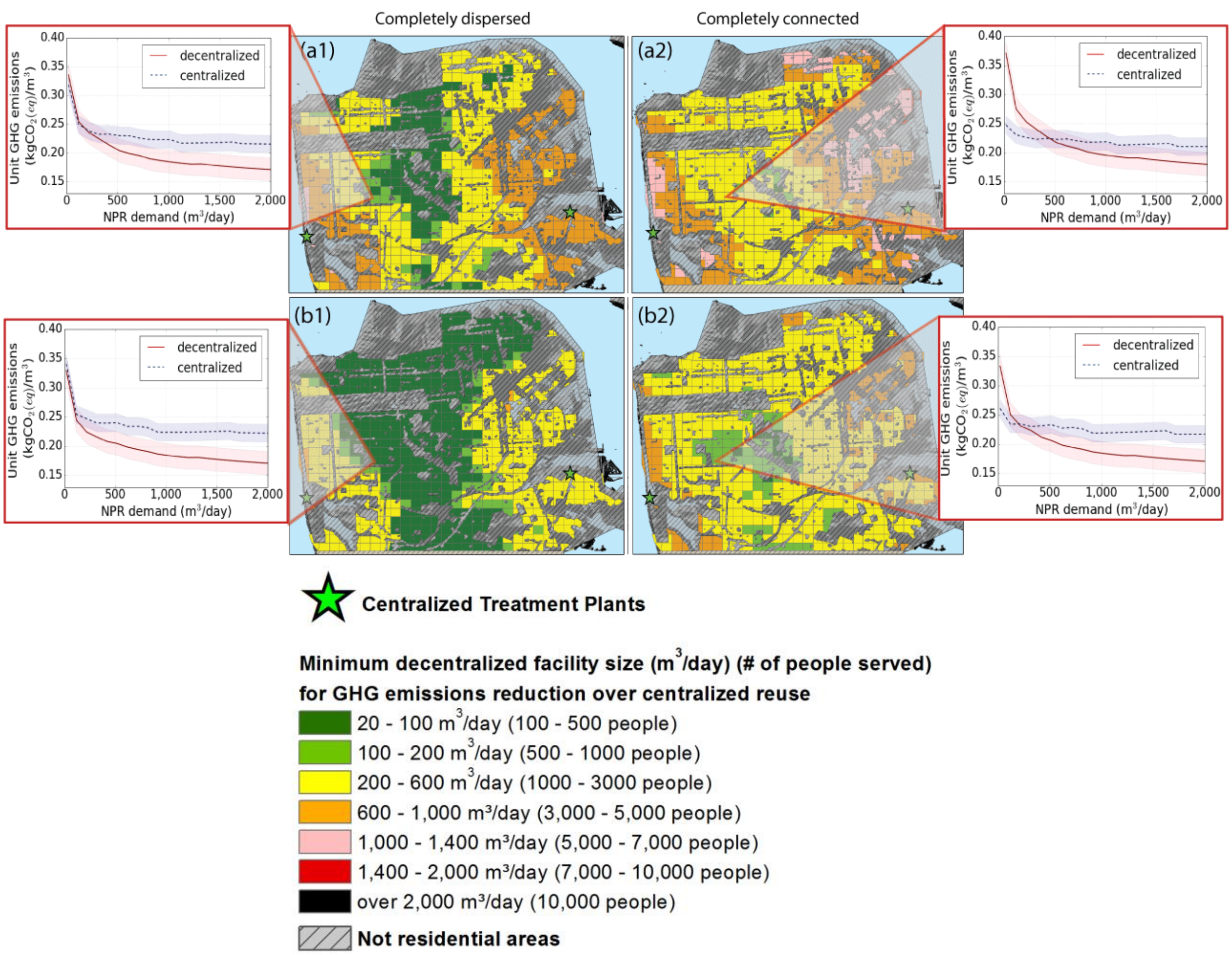


Figure 22: Minimum facility size for each grid cell for decentralization to be more efficient than a centralized reuse scenario for (1) "completely dispersed" and (2) "completely connected" scenario, (a) current GHG intensity and (b) GHG intensity for a future scenario in which the MBR treatment has gained 20% operational efficiency. Uncertainty bounds correspond to the 15th and 85th percentile probability according to the Monte Carlo method.

On the other hand, in the worst-case scenario, implementing a small facility (20 m^3/day) at low elevation near a centralized WWTP, the results indicate that decentralized systems would have higher energy intensity and GHG emissions than a centralized system by 1 kWh/m^3 (61%) and 0.08 $kgCO_{2(eq)}/m^3$ (37%) for the "completely dispersed" and 1.2 kWh/m^3 (85%) and 0.09 $kgCO_{2(eq)}/m^3$ (49%) for the "completely connected" scenarios. The energy and GHG emissions ranges do not track each other in the different scenarios as the GHG emissions also reflect life-cycle embodied emissions unrelated to electricity consumption. These results refer to the extreme cases of elevation difference and facility size and therefore reflect the maximum difference between the decentralized and centralized approaches. The detailed map and location-specific results for energy are shown in Figure 23 and for GHG savings in Figure 24.

It is likely that decentralized systems can be more competitive if the energy efficiency of MBRs and other emerging decentralized treatment technologies are improved.[82,83] To simulate potential future conditions, we evaluated scenarios in which the operation of the MBR treatment is 20% more energy efficient than current technology. Applying a similar methodology to compare decentralized and centralized scenarios, the decentralized system was found to be more efficient than the centralized system with up to 34% lower lifecycle energy consumption and up to 31% lower GHG emissions in the best-case scenario. Implementing small-scale facilities (20 m^3/day) in the low elevation areas results in losses in energy and GHG of up to 46% in energy consumption and up to 27% in GHG emissions compared to the centralized alternative at an equivalent scale. As shown in Figure 21, the decentralized treatment efficiency makes small systems even more competitive in most areas of the city, expanding areas where decentralized systems could prove more efficient. The 20% efficiency assumption is a reasonable, even conservative, estimate for future efficiency improvements given the progress that has already been made.[91] These results for the futuristic scenarios are shown in Figure 21 for both the "completely dispersed" (b1) and "completely connected" (b2) scenarios for lifecycle energy and Figure 22b for the GHG emissions.

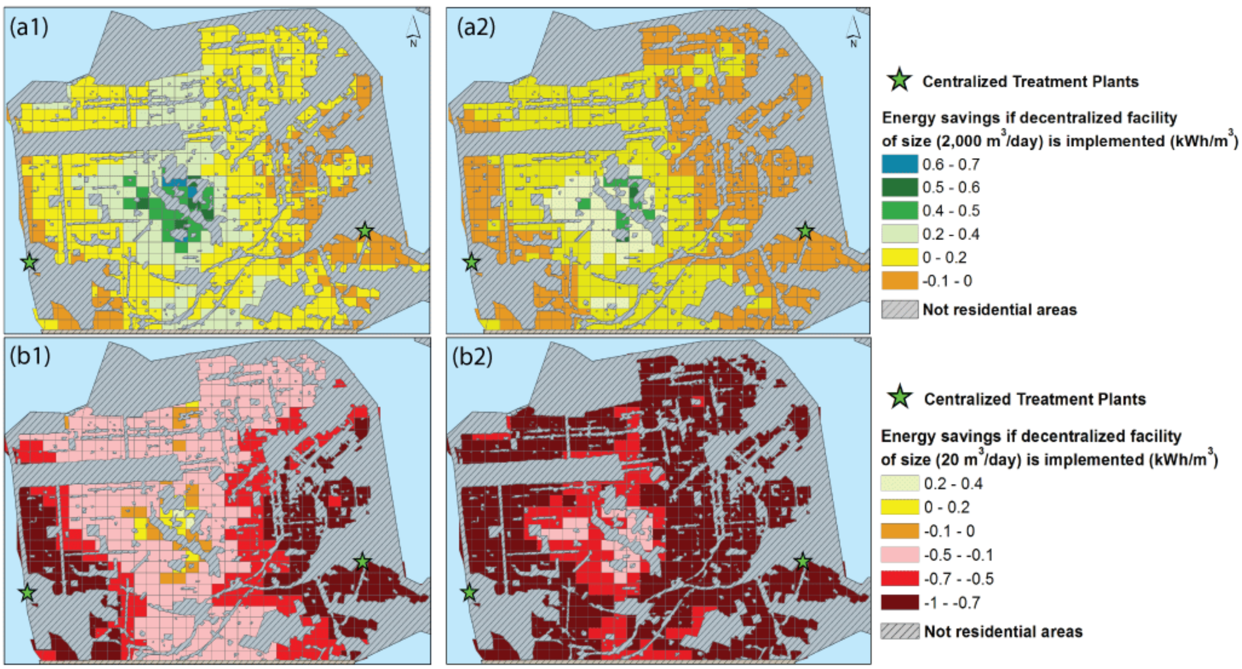


Figure 23: Energy savings if implementing a decentralized facility in the (1) "completely dispersed" and (2) "completely connected" scenario, at each grid cell of size (a) 2,000 m^3/day and (b) 20 m^3/day, instead of performing centralized reuse at the equivalent scale. Positive numbers indicate savings and negative numbers indicate losses of the decentralized system compared to the centralized alternative.

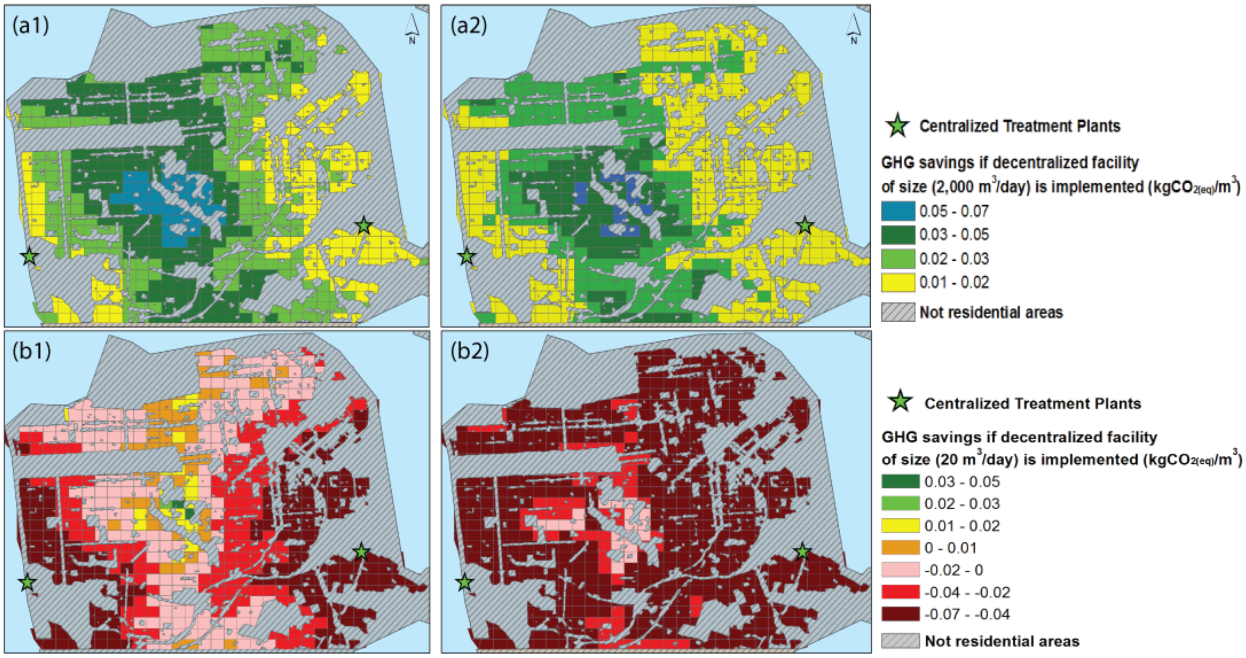


Figure 24: GHG savings if implementing a decentralized facility in the (1) "completely dispersed" and (2) "completely connected" scenario, at each grid cell of size (a) 2,000 m^3/day and (b) 20 m^3/day instead of performing centralized reuse at the equivalent scale. Positive numbers indicate savings and negative numbers indicate losses of the decentralized system compared to the centralized alternative.

As noted earlier, real-world centralized NPR in San Francisco will necessitate the use of reverse osmosis, significantly increasing the energy intensity associated with the centralized reuse scenario. If the treatment train planned for SFPUC's Oceanside plant were analyzed, rather than the more typical treatment processes selected, the energy and GHG benefits of decentralized systems would be more widespread throughout the city, even using current MBR technology.

To test the robustness of the model and results, an uncertainty and sensitivity analysis was performed using the Monte Carlo method (described in the 3.2 - Methods section). The model results were most sensitive to the parameters representing the scale of the system (NPR demand), the treatment operations, and the elevation head between the centralized plant and the point of use. Table 2 presents the sensitivity of the key parameters on the output results for the decentralized and centralized model, respectively. A plus sign indicates that an increase in the parameter value would lead to an increase in the end results. Parameters are presented in ranked order depending on the magnitude of the sensitivity on the results.

Table 2: Sensitivity Analysis Results. A plus sign indicates that an increase on the parameter value results in an increase on the overall energy intensity and GHG emissions and a minus sign indicates that an increase on the parameter values would result in a decrease on the overall energy intensity and GHG emissions.

PARAMETER	*DECENTRALIZED SCENARIO*	*CENTRALIZED SCENARIO*
DESIGN VOLUME	+	+
MBR OPERATION	+	+
ROUTE ELEVATION	N/A	+
CENTR. TREATMENT OPERATION	N/A	+
CENTR. TREATMENT CAPITAL	N/A	+
PIPE DIAMETER	+	+
SLOPE INDEX	+	+
UV OPERATION TIME	+	N/A
INFRASTRUCTURE LIFETIME	-	-
TREATMENT LIFETIME	-	-
UV LIFETIME	-	N/A
COAGULATION & FLOCCULATION MIXING	+	+

3.4 Discussion

Typically, decisions about where and when to implement water reuse are based primarily on economic costs. Although cost-effectiveness is critical, energy use and GHG emissions must be considered in decision making. Infrastructure planners, especially in areas where water supplies are constrained, should seek opportunities to maximize overall system resiliency while minimizing adverse environmental impacts. To achieve California's climate change objective of reducing GHG by 40% by 2030 while meeting water demand with constrained supplies,[46] energy- and GHG-efficient planning and investments in the water and wastewater sector are necessary.

Water infrastructure is spatially sensitive; optimal solutions will vary depending on location, scale, number of treatment facilities, and topography. The results for the centralized systems indicate that distribution pumping dominates energy and GHG effects while treatment requirements are key for the decentralized systems. For the centralized scenarios, the distribution systems can correspond to up to 60% of the total energy consumption which gives a significant advantage to the decentralized systems when the point of use is far away or at a significant elevation from the centralized plant. The treatment phase for the decentralized scenarios can reach up to 85% of the total energy, making the centralized approach more advantageous in the low elevation areas and closer to the centralized plant due to the economies of scale in treatment.

As presented in this paper, system scale should be coupled with the specific spatial parameters to identify optimal system designs. Not surprisingly, even relatively small decentralized systems have lower energy and GHG footprints in the areas of San Francisco that are far, in distance and elevation, from the centralized WWTPs, where energy requirements can be as much as 20% lower than centralized reuse for the "completely dispersed" scenario. Near the centralized WWTPs, the difference between decentralized and centralized reuse (for "completely dispersed") is smaller for the largest scale considered in our analysis (2,000 m^3/day system), with a decentralized system requiring about 8% more energy. On the other hand, small systems ($\leq$ 100 m^3/day) near the centralized treatment plant would require substantially more energy than for "completely dispersed" centralized systems (61% more energy). This can be translated to other geographical areas as the topography of the system can provide insight on which system is more likely to have lower environmental impacts.

Centralized infrastructure, though perceived as more reliable and with benefits of economies of scale, presents barriers for NPR as large scale dual-distribution systems can be costly and disruptive to implement in dense urban areas like San Francisco.[92] Decentralized infrastructure allows for a flexible, incremental approach for system expansion with uncertain growth patterns. Although important, these societal impacts were not considered in comparing the two systems and we did not make assumptions about future population dynamics. In either case, it should be noted that there is not enough demand for NPR to recycle all of San Francisco's wastewater, making complete build-out of either system unlikely. In less compact cities with significant irrigation, the demand for NPR would be higher.

More research is needed to reduce uncertainties in the analysis, particularly related to treatment process energy use at various scales- and how it may change over time with advances in treatment technology and direct GHG emissions. Few empirical performance data are available on wastewater reuse technologies over the range of small scales that captures decentralized systems. The results of this study are based on several assumptions for the treatment performance that could be improved if monitoring data were available for actual installations of small-scale treatment technologies. Another aspect that deserves further analysis is managing sludge from decentralized systems. Our study assumed that sludge was transported periodically by truck to a centralized WWTP. However, some projects may involve discharging solids to the existing sewer network, which could have the unintended consequence of increasing corrosion if flows are insufficient to flush them.

In addition, there is potential for new innovations, such as anaerobic MBRs, to have significantly lower energy requirements or even be energy positive.[82,93] Although research on lab and pilot scale systems is promising, more work is needed to characterize how these technologies will perform when integrated into complete treatment trains and deployed in actual installations.[82,94,95] Tracking and releasing measured performance data for a wide variety of technologies and scales will be crucial in developing and improving future systems. Increasing treatment energy and resource efficiency as well as optimizing the system's operating scale could improve the performance of decentralized systems. For example, rather than designing decentralized systems that receive wastewater from individual or groups of buildings, mining interceptor sewers can be practiced at the larger scales shown to be more energy and GHG efficient in our analysis and may also have operational advantages such as ability to treat a constant, continuous flow rate. However, operating at larger scales, whether in buildings or via sewer mining, will also require a larger distribution network, triggering similar spatial tradeoffs as analyzed in this paper. System resiliency could be improved using "looped networks" to avoid interrupted service and other problems when there are system failures or maintenance issues. This level of detail was not included in the analysis but, based on the sensitivity assessment, the added infrastructure would not likely change the results.

Energy use and GHG emissions are largely coupled through electricity consumption, but some GHG emissions are not directly tied to electricity- for example, equipment fuel use. Direct GHG emissions from the biological treatment processes at the centralized and decentralized facilities were assumed to be zero. This assumption is a major source of uncertainty in our analysis. The main source of GHGs are the microbiological processes involved in nitrogen conversions (ranging from negligible to several percent of influent N[96,97]). EPA has estimated that emissions from wastewater treatment may contribute as much as 3% of annual N_2O emissions in the U.S.[98] Ongoing research aims to develop improved approaches to model emissions based on parameters that describe the specific treatment processes.[99,100] The two centralized treatment plants operated by SFPUC do not practice nitrification, and likely have low N_2O emissions; however, direct measurements of emissions were not available. Although there is research to estimate GHG emissions from MBRs,[101] it is not known what configurations might be built in San Francisco, nor are scale effects well understood. Thus, because the uncertainty is so high, the most appropriate assumption for our analysis was to not include direct GHG emissions.

However, the impact of technology choices on N_2O emissions at the centralized and decentralized plants should be a priority for future research. For example, if biological nutrient removal is used and the N_2O emissions rate is 1.8% g N_2O per g influent N (high end value),[97] the GHG emissions for decentralized or centralized approach could increase by approximately 0.27 $kgCO_{2(eq)}/m^3$ over our current estimates (i.e., increase our current GHG emission estimates by $60-100\%$). Clearly, if the emissions rates are higher for centralized than decentralized (or vice versa), it could impact our findings on the conditions under which decentralized has a lower carbon footprint.

Novel approaches and technologies for decentralized reuse are emerging. However, to become consistently competitive with mature, energy-efficient, large-scale treatment systems, small-scale systems will benefit from additional optimization of energy use and GHG emissions. The framework described here can be applicable to other geographic settings, enabling infrastructure planners to evaluate the role and scale of NPR, and to compare NPR with other emerging options for diversifying water supply portfolios, such as direct potable reuse, while minimizing energy use and climate change impacts.

Chapter 4.

Urban Non-Potable Water Reuse: Spatial Optimization and Data-Driven Decision-Making

4.1 Introduction

As the world is facing frequent water shortages while at the same time water demands are increasing due to population growth and affluence, identifying energy-efficient and cost-effective alternative water supplies seems inevitable[45]. Wastewater is a sustainable water source that exists as long as water is used, and by treating it to an appropriate standard and reusing it, significant fresh water sources can be conserved. Non-potable water reuse (NPR) is one option for reusing water that promotes resilience and has the potential to lower economic and environmental impacts of the water infrastructure[48,102]. Non-potable uses of recycled water include toilet flushing, landscape and agricultural irrigation, and cooling systems, thus allowing fit-for-purpose approaches that minimize the energy and costs for water treatment compared to a potable stream of water for all uses.

A key factor for sustainable NPR implementation is the issue of system scale. Urban wastewater infrastructure usually consists of centralized systems to take advantage of economies of scale in treatment as larger facilities are more efficient[102,103]. However, by implementing water reuse, a tradeoff occurs: in a centralized system non-potable reuse requires delivering the recycled water back to the where demand exists, which may require substantial piping and upgradient conveyance[50,104]. Decentralized water reuse, on the other hand, produces recycled water close to its point of use[51,105]. New technological advances in small scale wastewater treatment challenge the reliance on centralized infrastructure and allow decentralized technologies and hybrid systems to be perceived as functional and comparable infrastructure options[106–108]. An important consideration is determining the optimal degree of decentralization, which can range from a single household to a cluster of buildings or an entire neighborhood. This work aims to add to the growing literature on the optimal scale of wastewater treatment and reuse to improve the sustainability of wastewater management by minimizing either the energy intensity, the greenhouse gas (GHG) emissions, or the financial cost of the system.

Experience with urban decentralized water reuse systems is still limited, but a few systems have been established using commercially-available technologies. To support data-driven water management, we aim to provide quantitative information of the impacts of scale and spatial conditions on decentralized NPR systems and expand the understanding of their environmental and economic performance. Previous studies have pointed out the importance of data-driven approaches in urban water management, which use optimization tools and novel methods for a deeper understanding of system performance[109]. An algorithm has been proposed in previous research to address the optimal scale for wastewater collection, which confirmed and quantified the expected result that the optimal scale of centralization decreases with topographic complexity and a more disperse population[54]. The same authors in a newer study reported that low population densities increase the costs of both decentralized and centralized systems, but they scale differently as they require different management approaches that should be modeled in detail for an accurate comparison[110].

Treatment technology selection is an important aspect of assessing decentralized systems. The performance of different technologies may scale differently, which authors have tried to characterize with respect to cost[9,10,111], energy intensity[104], and GHG emissions[10,104]. This characterization is especially useful in decentralized systems whose performance is highly sensitive to system size.

Combining the treatment performance with the distribution impacts under various topographic conditions is a necessary step for holistically assessing the overall system to promote optimal planning. Resource recovery has been getting increased attention. For example, multivariable analysis was conducted to understand the effect of location on recovery potential and economic cost, pointing out the need for hybrid solutions[55]. Another study assessed the cost performance of a real-world case study to model direct potable reuse and identify the optimal scale with respect to cost[56]. These authors determined that direct potable reuse is too expensive for low-density populations, and is more appropriate for urban settings serving more than 10,000 residences.

To our knowledge, spatial models and algorithms for identifying optimal decentralization scale for NPR with respect to energy intensity, GHG emissions, and economic cost do not yet exist. Case study focused work does not offer the potential to generalize to other settings, which is a major shortcoming identified in the current literature. This study aims to develop a generalizable modeling framework applicable to any location, given that appropriate data are available to enable the assessment of decentralized non-potable water reuse under local conditions. The model can assist decision makers and researchers in understanding the performance of different NPR system designs using economic and environmental metrics and their optimal implementation scale accounting for actual conditions.

The objective of this study was to develop a generalizable model to identify the decentralization scale for NPR for toilet-flushing that minimizes energy intensity, GHG emissions, or economic cost given certain topography, population density, building area and number of floors. Treatment technology design is important due to the effects of economies of scale[9]. We include treatment technology performance as a variable in the assessment so different realistic and hypothetical technology designs can be combined to estimate the optimal water reuse scale. Also, we perform a detailed spatial analysis for estimating distribution requirements for the recycled water. We incorporate the algorithmic model into a web-based decision-support platform that allows users to provide custom treatment technology and conveyance system design data to explore the impact of local conditions (topography and population density) and different scenarios. To illustrate uses of the platform, we apply it to a real-world case study to quantify how scale changes the impacts of decentralized NPR based on local conditions. We also model an optimal implementation plan for NPR under a constrained GHG emissions scenario.

4.2 Methods

The algorithmic process developed for this research aims to identify the optimal NPR system scale that minimizes the metric of interest by considering the relevant site-specific conditions. It is based on treatment technology performance and network design assumptions to deliver the recycled water to buildings for toilet flushing. The algorithm is divided into two main components: (1) the impact module, including the treatment submodule and spatial conveyance submodule; and (2) the spatial expansion module for identifying the optimal scale. The impact module considers the impact of treatment and distribution (piping and pumping) by determining the treatment performance and sewer and distribution requirements. The spatial expansion module accounts for the impact of expanding the system size one building at a time until the optimal scale is reached. A detailed description of the two modules is presented in the next sections.

We define the scale of the system as the population served by the recycled water (non-potable reuse for toilet flushing). We assume this demand is 50% of the total wastewater produced by that population[24], a realistic assumption for an urban mixed use setting. Thus, the population whose wastewater is collected and treated is only half that of the population served by recycled water. We assume that buildings that do not provide wastewater for recycling are served by an existing centralized sewer system and do not consider that infrastructure in our analysis.

4.2.1 Impact module

The impact module quantifies the total impact of each metric for NPR of a certain scale. Given building locations and characteristics and the population served in those buildings, the impact module is responsible for identifying the requirements for treating the NPR water and distributing it to buildings for toilet flushing. The impact module has two submodules, the treatment submodule and the spatial conveyance submodule. By combining the two submodules, the total impact for both treatment and distribution of the specific scale is calculated. The objective function of the algorithmic process [Eq. 18] is the minimization of the metric of interest, which can be economic cost, energy intensity, or GHG emissions. The objective function is solved numerically to identify the system scale that minimizes the treatment and conveyance requirements (Figure 25).

$$\text{Min } C\ (Q_{WWTP},\ L,\ Q_{PUMP},\ H) \qquad \text{[Eq. 18]}$$

where C is the total metric of interest (energy intensity, GHG emissions or economic cost), Q_{WWTP} is the flow rate of the wastewater treatment plant (WWTP), L is the collection and distribution piping length, Q_{PUMP} is the pumped flow rate of water, and H is the pumping head. In this work Q_{WWTP} and Q_{PUMP} are considered equal, but that is not the case if the entire treated volume cannot be reused.

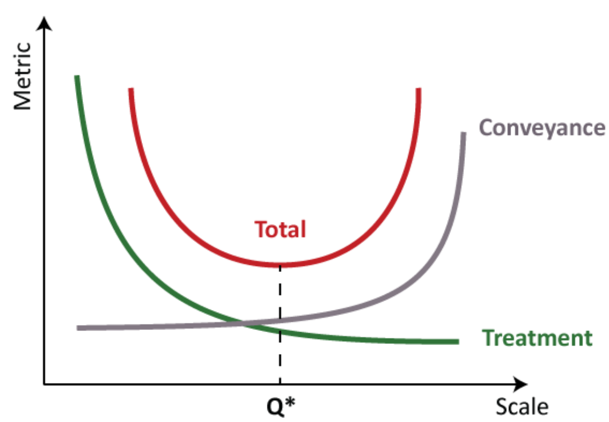


Figure 25: Optimization tradeoffs between treatment economies of scale and conveyance diseconomies of scale

4.2.1.1 Treatment submodule

The treatment submodule quantifies each of the metrics (economic cost, energy intensity, GHG emissions) for treating wastewater to an appropriate NPR standard. It takes as an input the system scale (residential and commercial people to be served) and calculates the operating requirement for treatment and the capital requirement for the manufacturing the treatment unit for that system scale. The impacts are based on published data that describe wastewater treatment capital and operation requirements at different scales and are expressed by a polynomial equation based on the treatment size for economic costs for membrane bioreactor (MBR) technologies [Eq. 19 - Eq. 20][112]. These cost functions are based on a regression analysis of several wastewater treatment installations in Europe for full-scale MBRs.

$$\text{Capital expenditure: } C\left[\frac{\$}{person}\right] = 82147 \times Q^{-0.495} \times 1.18 \qquad \text{[Eq. 19]}$$

$$\text{Operational expenditure: } C\left[\frac{\$}{person-year}\right] = 4.5 \times Q^{-0.34} \times 1.18 \qquad \text{[Eq. 20]}$$

where Q is system capacity in (m^3/day).

The operational treatment energy is calculated based on the polynomial equation[104] [Eq. 21].

$$T_E\left[\frac{kWh}{m^3}\right] = a \times Q^b + c \times Q + d \qquad \text{[Eq. 21]}$$

where the energy intensity T_E is estimated by defining Q as the plant capacity in average flow per day and factoring in the user-defined coefficients a, b, c, d. As the default, the impact module uses the estimated equation [Eq. 22] for treatment energy for membrane bioreactors from previous work by the authors:[104]

$$T_E\left[\frac{kWh}{m^3}\right] = 9.5 \times Q^{-0.3} \qquad \text{[Eq. 22]}$$

The embodied energy and GHG emissions refer to the energy and GHG impacts of system manufacturing (material inputs and transportation). The embodied energy for treatment is estimated based on previous work of the authors as a function of the system size as 0.3 kWh/m^3 of water treated[104]. The economies of scale for the embodied energy for treatment has been found to be negligible, thus it was not accounted for in this work. The GHG emissions for the operation are estimated based on the treatment's energy performance curve (assuming all energy use is in the form of electricity). The embodied GHG (calculated by the authors in previous work based on system size) is 0.06 $kgCO_2/m^3$ of water treated[104]. No direct GHG emissions from the treatment process are accounted for, but this input can also be changed by the user if better information is available.

4.2.1.2 Spatial conveyance submodule

The spatial conveyance submodule calculates the cost of delivering the NPR water to the customers. It considers the locations of buildings and the building demographic and size characteristics to estimate the amount of piping that would be required, along with the ground elevation and number of floors in the buildings, to estimate the pumping needs to deliver water to the bathrooms. The piping lengths to be installed are simulated as a minimum spanning tree (MST) algorithm based on the buildings locations. The MST represents the minimum length path to connect all buildings (nodes) without any line segments overlapping. This approximates what the actual pipe network would look like in a real implementation[54,113,114]. The wastewater collection piping was not explicitly modeled or optimized in this study. It was, however, included in the analysis with the simple assumption that the sewer collection pipes would be half the length of the NPR pipes given that the NPR demand (for toilet flushing) is assumed to be 50% of the total water demand.

The in-building piping is calculated based on the area of the buildings and the number of floors with a constant factor of average piping per area. The average piping length per building area was based on measurements of an existing building with water reuse infrastructure[115]. The piping costs are calculated as directly related to the piping length for economic cost [116] and energy intensity and GHG emissions[35] and are reported in Table S - 6 in Appendix 2. Piping costs include only material costs; note that installation costs may be significant and could be substantially higher for retrofits compared to new construction. The pumping needs for water conveyance between buildings are estimated based on the pumping head, using the ground elevation, assuming that the treatment technology would be installed in the building with the lowest elevation, and for the in-building pumping needs directly related to the building height (number of floors, enough to deliver water to the top floor). The pumping needs are calculated based on the standard engineering calculation for sewer pumping [Eq. 23]:

$$E_{pump} = \frac{\gamma_w \times Q \times h_{tot} \times d_t}{n_{pump}} \qquad \text{[Eq. 23]}$$

where E_{pump} is the energy applied by the pump, γ_w is the specific weight of water, Q is the pumped flow, d_t is the pumping duration, and n_{pump} is the efficiency for the pump. The pumps were conservatively sized to handle twice the average flow, so the pumping duration was 12 hours per day for the average daily flow. A smaller pump with a duration of 24 hours per day could have been modeled instead, but that would not give any flexibility for peak hour demand flows. The pumps were assumed to be in the small to medium range with an efficiency of 45%[10].

4.2.2 System expansion module

To account for the site-specific conditions and to assess multiple levels of decentralization, the developed algorithmic model expands system size through an iterative process with an input of the existing buildings as illustrated in Figure 26. The system expansion part is solved using a heuristic approach where in each iteration step i the values of the variables are changed and the updated objective function C_{i+1} is generated and compared to the previous C_i. A heuristic approach to spatial optimization has been similarly applied to assess the impact of geography on power distribution networks[117,118]. To make the assessment realistic, the algorithm considers the existing topographic and demographic conditions of the area of interest by taking as an input the buildings' locations and characteristics (number of residents/employees, number of floors, square footage and ground elevation). At the end of the iterations, the minimum impact and thus the optimal system size is identified (Figure 25).

In the first step, the algorithm takes the building of interest as a starting point and runs the impact module for the specific building (as described in the previous section) for the specified metric in question. The result is the system total impact as of this point. Next, it identifies the closest building to the one before and clusters them to one system. The closest building in each iteration is identified by a k-d tree algorithm. A k-d tree is a data structure that allows for the organization of points in such a way that nearest neighbor searches are optimized. For this new cluster, the algorithm calculates the updated impact module and compares it to the previous one. If the updated total impact is lower than the previous one, the cluster of two buildings stays as is and the total impact is updated to match the newest one. If the new total impact is higher than the previous one, the newest added building is dropped from the cluster and the system total impact is not updated. This could happen if the building's population is low, such that the efficiency gains from a larger treatment system are smaller than the increase in the other per capita infrastructure requirements (pipes and pumping to distribute the recycled water to that building). This process iterates through all the buildings in a certain radius and terminates when all the buildings are assessed. The final buildings in the cluster along with the final total impact are the outputs of the model that illustrate the optimal system size and the systems impact for the specific area and metric.

A greedy algorithm is used to reach the final optimal result, which means that in each iteration the best option is selected. The disadvantage with this approach is that it does not guarantee a globally optimal solution[119], but given the problem's complexity, this reasonably approximate solution is the only possible outcome. To identify a globally optimal solution, all possible building combinations must be examined which exceeds the restrictions of computational intensity[120]. To enhance the performance of the algorithm and its runtime, the algorithm is programmed to terminate the system expansion if it has discarded 50 buildings consecutively. This avoids large gaps in the selected buildings and enables the algorithm to still identify the optimal system scale without searching for buildings that would be too far away to make a practical implementation possible. The buildings that remained unassessed after the termination of the algorithm are visualized with a light blue circle (Figure 27).

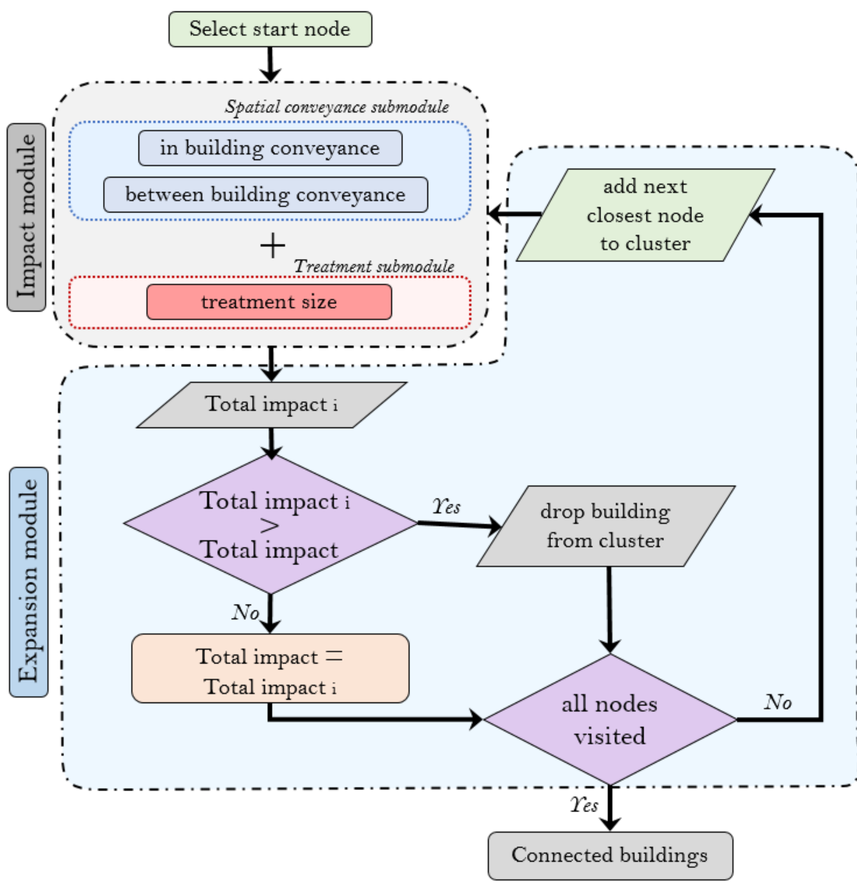


Figure 26: Algorithmic process for identifying the optimal system scale for non-potable water reuse

4.2.3 Web-based decision-support platform

To make the algorithm useful for scenario assessment, we developed a web-based platform that allows the user to select the location of interest and the algorithm runs in the background to estimate the optimal system scale at the point of interest. The web-based platform is still in beta version, but we anticipate a public release in the future. A snapshot of the developed web-based platform is shown in Figure 27. The platform allows the user to have flexibility to input different treatment technology criteria, as it is an important determinant of the optimal scale. The users can describe the treatment performance curve of the specific NPR technology they wish to test along with potential direct GHG emissions from the treatment that are not accounted for in the default model. Also, it allows selection of the desired metric the algorithm minimizes. By clicking on the desired location on the map, the user initiates the algorithm with the corresponding building location. The results illustrate which buildings should be clustered together to minimize the metric of interest. A summary table is also generated to present the number of clustered buildings and the final population served at the optimal scale.

Figure 27: Web-based platform snapshot highlighting the inputs and outputs of the model. The darker colored dots result from overlapping buildings.

4.2.4 Case study

To test the algorithm under varying system conditions and show the benefits of the optimization framework and how it can be used to drive optimal decisions with real-world data, we applied it to the case of San Francisco, a medium-sized U.S. city (865,000 citizens) with high population density (6,700 people/km^2) and an innovation leader in decentralized urban water reuse due to policies and incentives implemented to promote alternative water supplies[104]. San Francisco is very diverse in topography as well as in building sizes and population distribution, which make it an interesting example for exploration of the decentralization scales under various conditions.

To make our assessment realistic, we needed information on the locations and occupancy of all buildings in San Francisco. Building locations, footprints and number of floors were gathered from the City and County of San Francisco[62]. We then allocated residential and commercial population occupancy to each building. Residential population estimates were sourced from the Census Bureau[121] at a census block resolution (i.e., a few city blocks resolution). The population from the census tracts were allocated to each building proportionally to the building's total floor area. Commercial employment data were sourced from the ESRI Business Analyst database[122]. This framework has been described in previous work[123].

Apart from the building occupancy, to estimate water reuse impacts from distribution, we needed to estimate pumping and piping needs. Thus, the number of floors for each building was required to estimate the in-building piping and pumping along with the ground elevation to estimate pumping between buildings. The number of floors for all buildings in San Francisco were sourced from the City and County of San Francisco[62]. The ground elevation was sourced from the Digital Elevation Model of San Francisco that was extracted from the contours sourced from the City and County of San Francisco[62]. Specific parameter values used in the modeling process can be found in the Appendix 2 (Table S - 6).

4.3 Results

4.3.1 Location analysis

We used the web-based platform to explore the effect of location and population distribution on the optimal decentralization scale. To explore this, we developed an automated script that would iteratively make clicks on the map and store the result of the optimal scale and metric output. We ran the script for all three metrics and for 170 points equally distributed throughout the entire area of San Francisco. Every location is unique and the model results are a function of the local topography, population distribution, and building characteristics.

The platform is designed to be highly sensitive to local characteristics. This imposed a drawback when we used it for a city-wide assessment as even in the same neighborhood building characteristics can differ significantly (e.g., a high-rise apartment building next to a single-family home). To mitigate these locally-unique aspects, we increased the sampling by a factor of five to get a more accurate representation of the local conditions. Each of the 170 sampling points was surrounded with four other points in its vicinity for a total of 850 points. This allowed for a better understanding of the local conditions and eliminated errors based on extreme and outlier building characteristics. If the model results from one of the five points was significantly different (we used the 10^{th} and 90^{th} percentile to define dissimilarities), then it was discarded as a locality exemption. The included points were then averaged to get a smoother interpolation of the local conditions. The interpolation method used was nearest neighbor interpolation, which is a method for approximating the value of a function in a non-given point by using the value of the closest point around it. A more detailed outcome could be achieved by adding more points, but we were limited by computational intensity.

The location-specific results for running the analysis in the 850 points distributed throughout the city are presented in Figure 28. For each metric, we identified the optimal system scale, which is the system capacity (people served) to minimize the metric of interest, including both treatment requirements and distribution of the recycled water, as described earlier. We also present the value of each metric at the optimal scale, which represents the minimum value of the metric at that location.

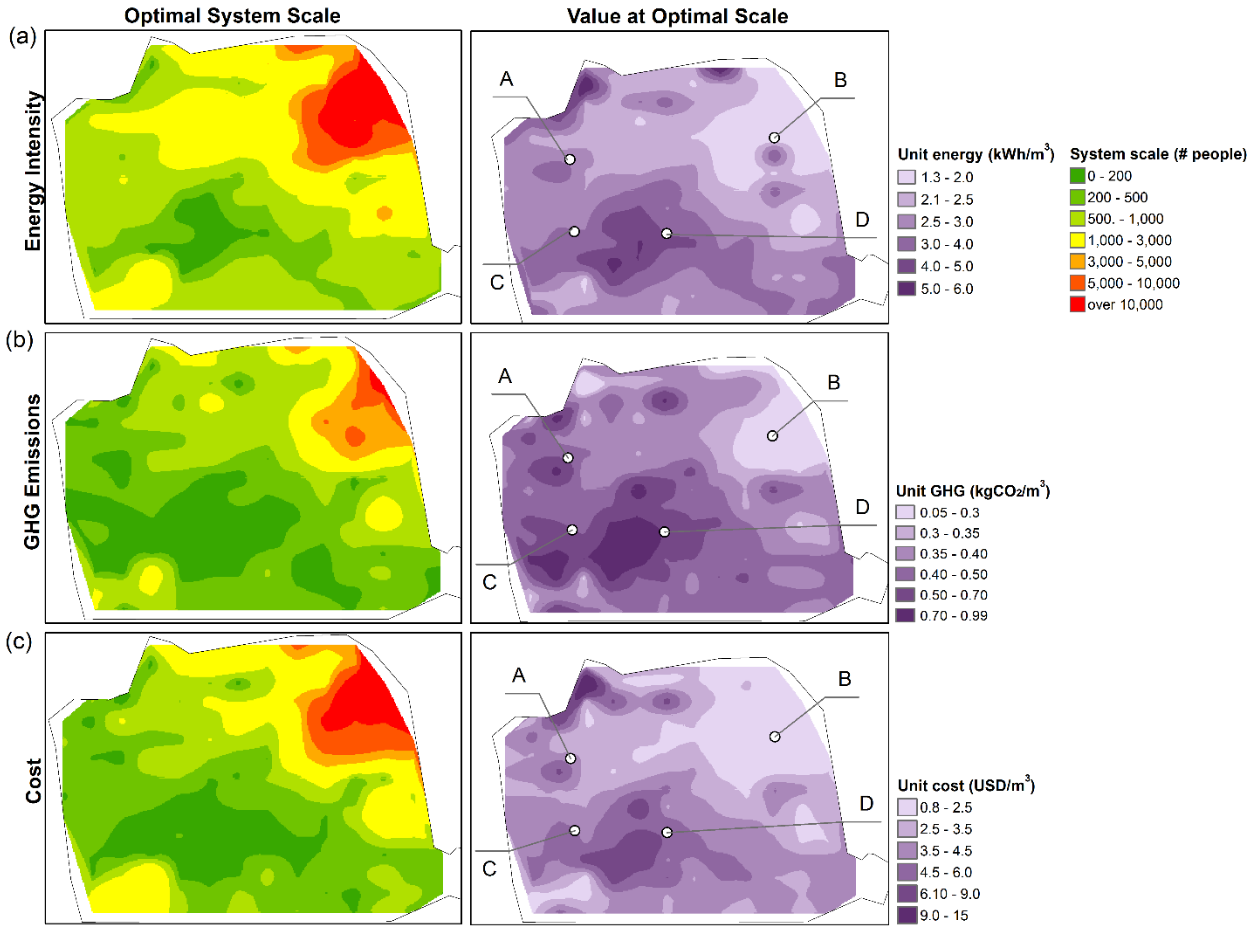


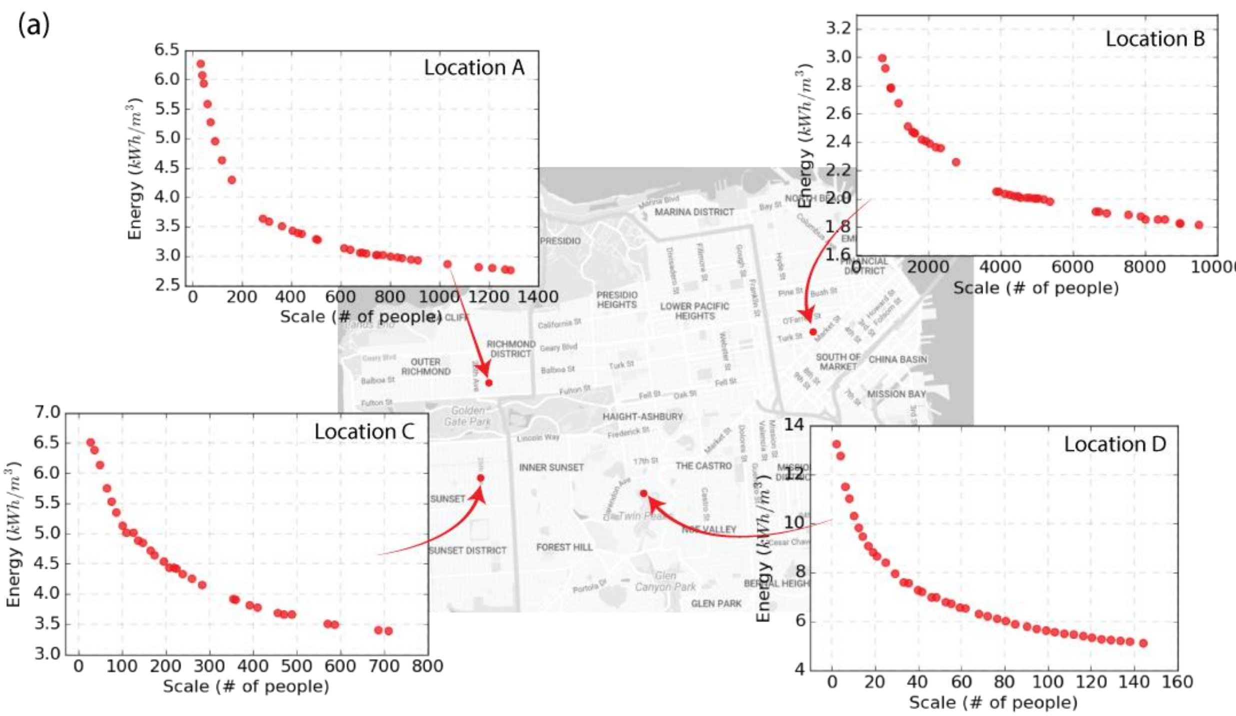
Figure 28: Location-specific results for San Francisco for (a) energy intensity, (b) GHG emissions and (c) cost. The results represent the optimal system scale for minimizing the metric of interest along with the metric's value at the optimal scale in space. The white dots labeled A, B, C, D illustrate the location of representative points for further analysis, shown in Figure 29.

As the results presented in Figure 28 are generated from a point estimation analysis and interpolating in between, there exist discontinuities that are an approximation of the existing conditions. Each point corresponds to a discrete system scale and an independent analysis area. By sampling enough points distributed throughout the entire city, we approximated each independent system. The optimal scale spans a large range, from less than 200 people served to more than 10,000 people served. In the areas with the largest population density and high-rise buildings (north east), the optimal system scale is larger because larger systems benefit from the treatment scale economies. In low population density areas where the buildings are more spread out, and significant pumping and piping needs are required to increase the system size, the optimal system scales are smaller. However, the value of each impact metric at the optimal scale is higher.

Figure 29 shows the sensitivity of the energy intensity to the system scale in various locations with different building types, elevation profiles and population densities. In Figure 29a, the magnitude of the economies of scale on the system energy intensity is shown for four different locations. The lowest point of the curve is the one identified by the algorithm as the optimal scale for that metric; after that point the energy increases with system scale. The shape of the curve provides valuable insight on the actual range of optimal scales. If some variance were allowed in the system output, the minimum optimal scale might range significantly in some locations. For example, if we allow for a 25% increase in the output energy intensity, we estimate that the optimal scale could decrease by 60-65% in the Locations A and B (where the optimal scale was larger) and about 45-55% in the Locations C and D. For example, at location A, the 25% variance corresponds to the population served ranging from about 500 to 1300. Due to other factors influencing the planning process, it may be preferable to design the system to serve 500 people, which may be acceptable even though the predicted energy or cost is 25% higher than the optimal value. By understanding the system performance at all scales, the tradeoffs between scale and the metric of interest can be quantified to assist with decision making.

Figure 29b illustrates the contribution of the main infrastructure components to the energy intensity of the system at each location. Treatment operation is responsible for the majority of the energy impacts while pumping is significant in the dense urban area with high rise buildings (10% of total energy). Treatment operation is characterized by large economies of scale (modeled as MBRs in this study), which can significantly affect the system performance at various scales. Piping infrastructure has a more prominent impact in low density areas where the required piping length is larger per person served. From Figure 29b it is also evident that optimizing scale for a particular location could have less impact than the location itself. For example, any scale of NPR at location B has lower energy impacts than the optimal scale NPR project at location D.

Related results for economic cost and GHG emissions are shown in Figure 30 and Figure 31. The component breakdown for GHG emissions follows a similar trend as the energy breakdown in all locations with a higher impact of piping construction as the embodied GHG emissions from that process are higher than the San Francisco electricity emissions which is 100% hydropower (a low carbon electricity source)[60]. The breakdown for cost reveals the high impact of the treatment capital costs and the piping infrastructure. This insight is useful because it illustrates that further improvements in small-scale treatment technologies that reduce the difference in unit cost for small versus larger systems have the potential to make smaller systems more viable financially. Most of the treatment operating costs are for energy, so reducing the scale effects of energy consumption will also help.



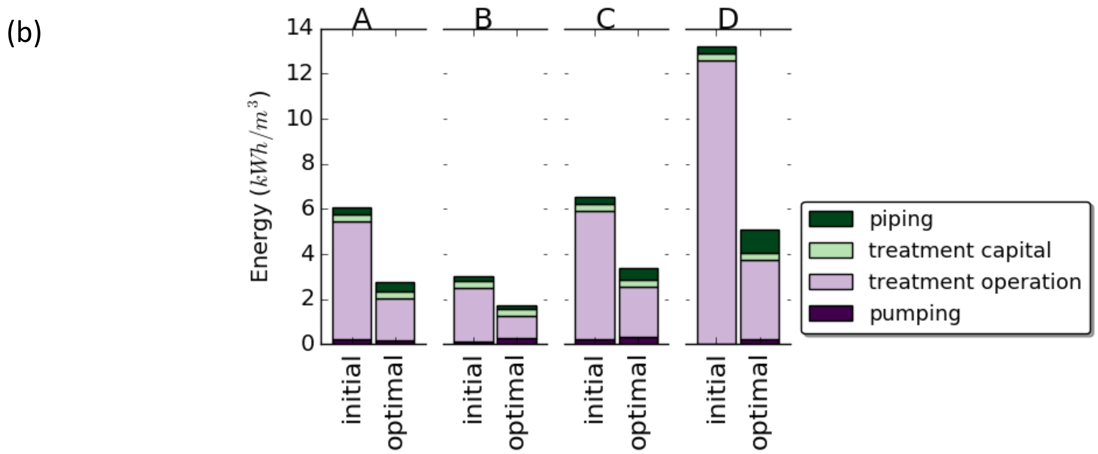
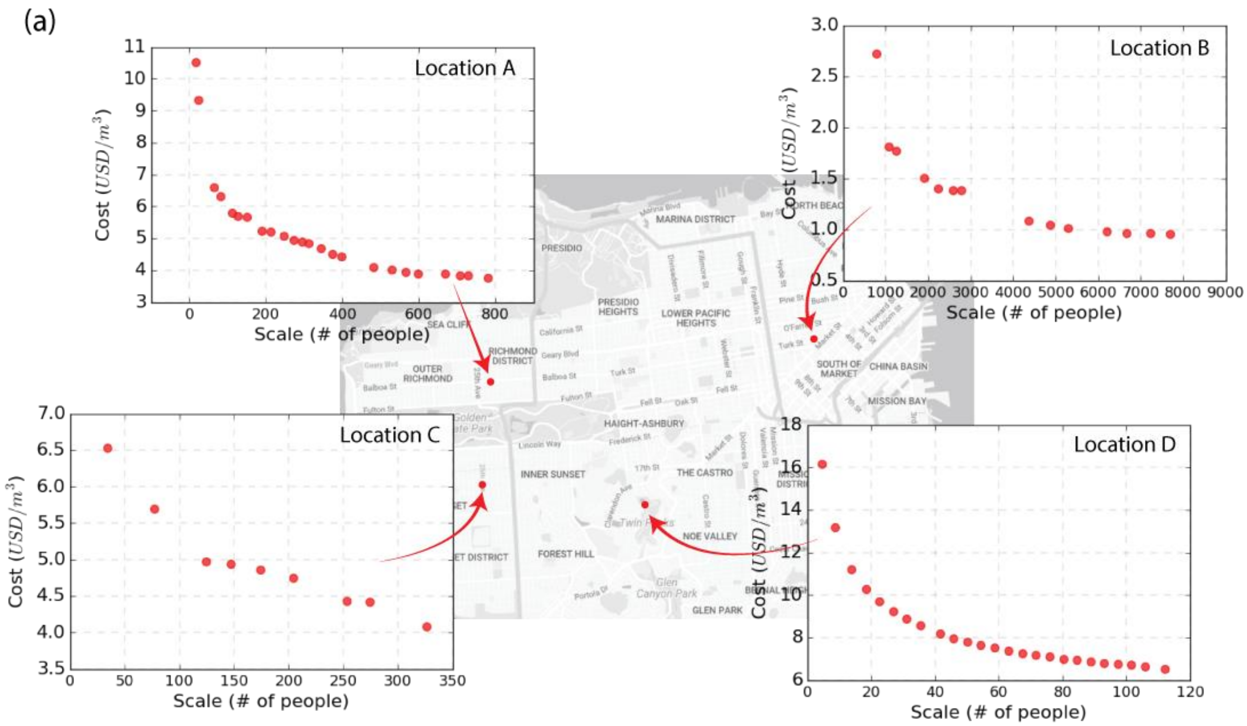


Figure 29: Location-specific scaling for San Francisco for energy intensity, (a) total energy at various system scales, and (b) infrastructure contributions at the initial and optimal scale for each location. The location of the points A, B, C and D is also shown in Figure 28.



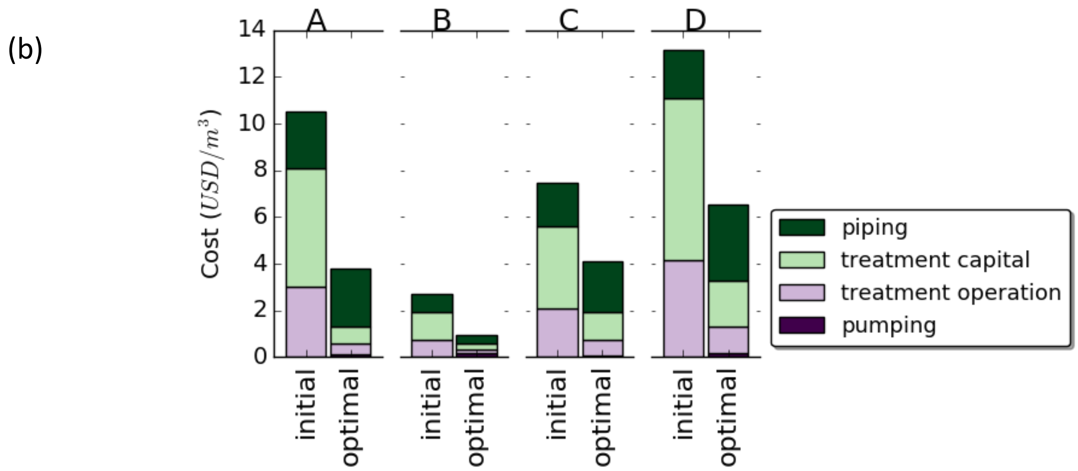
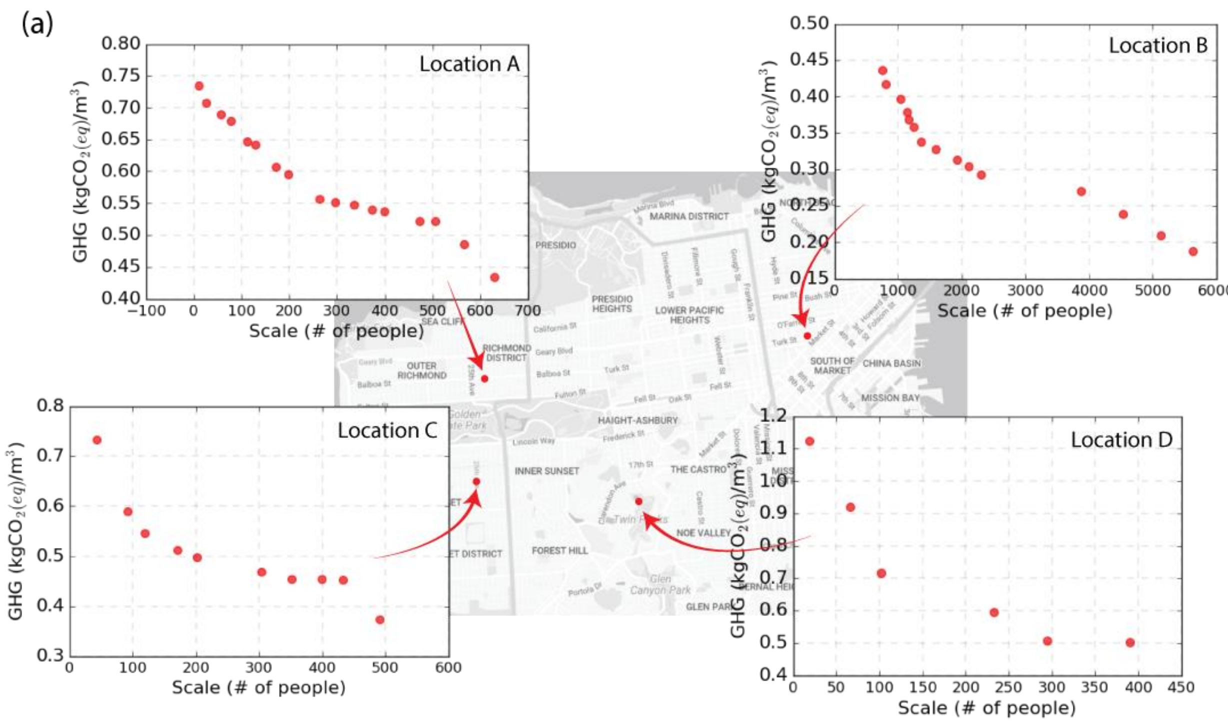


Figure 30: Location-specific scaling for San Francisco for economic cost, (a) total cost at various system scales, and (b) infrastructure contributions at the initial and optimal scale for each location. The location of the points A, B, C and D is also shown in Figure 28.



(b)

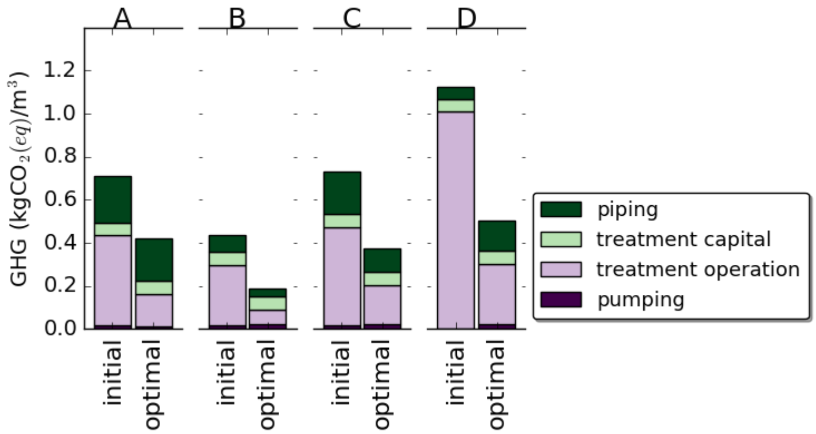


Figure 31: Location-specific scaling for San Francisco for GHG emissions, (a) total GHG emissions at various system scales, and (b) infrastructure contributions at the initial and optimal scale for each location. The location of the points A, B, C and D is also shown in Figure 28.

4.3.2 Treatment selection analysis

One of the largest contributors to energy, GHG, and cost metrics of decentralized reuse is treatment selection and performance. To understand the effects of treatment performance, we ran the model for different technology performance curves at the same location (the conveyance needs are the same). The unit energy and the scaling of the treatment performance could vary significantly for different technologies or with design improvements; the platform allows for exploration of different technology performance curves as it allows the user to set the polynomial coefficients and generate a custom curve. It also allows for flexibility in setting direct GHG emissions from the treatment process. We illustrate the potential impacts with three examples of treatment performance, one with exponential economies of scale, one flat, and one in between the two extreme cases.

Figure 32 presents the results for the three treatment options. As expected, once the economies of scale for treatment do not exist in the system, there is no motivation to generate larger systems by clustering buildings together (Figure 32 c), so building-level water reuse systems are preferred. On the other hand, if economies of scale exist, larger systems are preferable despite larger conveyance cost, as shown in Figure 32 a and Figure 32 b. From the difference in Figure 32 a and Figure 32b, we can identify that the more prominent the economies of scale in treatment are, the larger the preferred systems would be.

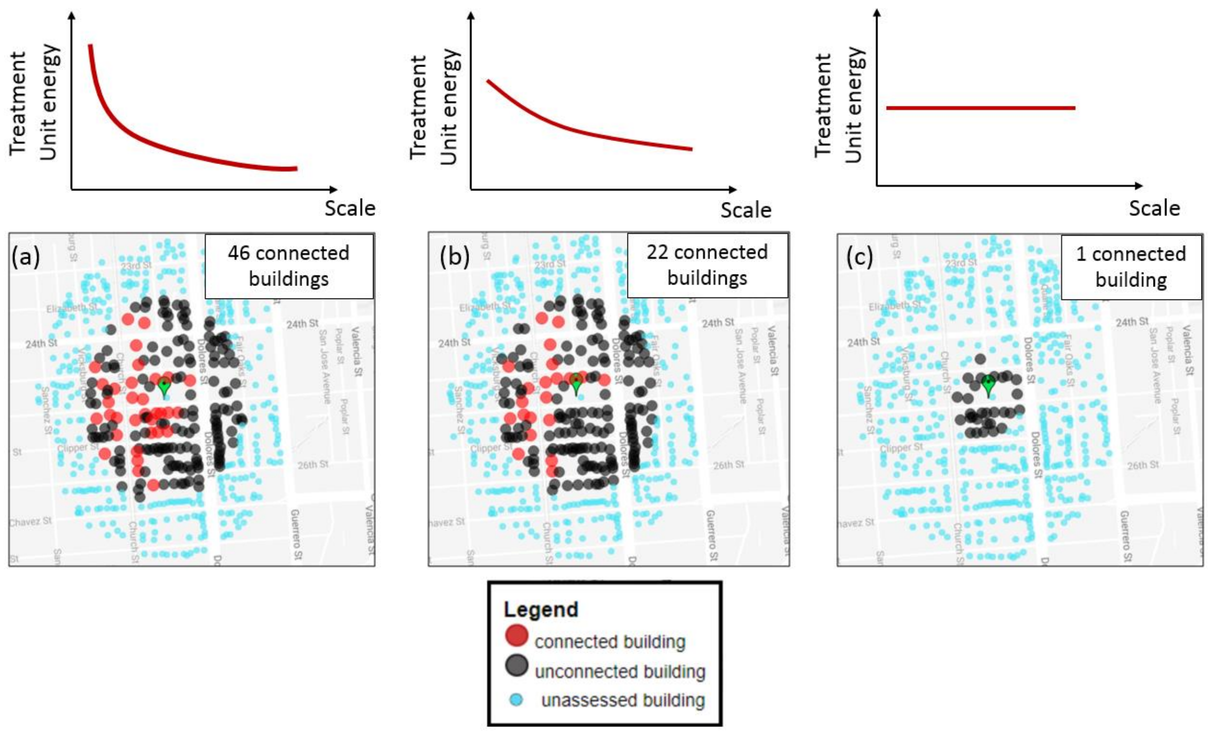


Figure 32: Assessing the optimal scale under different treatment options

4.3.3 Optimization analysis

To illustrate other potential applications of the web-based platform, we performed an optimization to identify the optimal areas for implementing water reuse under an emissions budget. To meet the climate goals of staying below a 2°C increase, it has been estimated that the maximum GHG emissions allowance would be 1 kgC/person-day[124]. As a reference, the GHG emissions for California in 2013 were about 7 kgC/person-day[125]. This emissions allowance accounts for all the activities of a person in a given day. To make our analysis realistic, we assumed that 10% of the emissions allowance can be attributed to water services as about 10% of the total energy in California is used for water related activities[126]. Further, water reuse is only a portion of the total water demand, so we assumed that 50% of the water emissions budget can be allocated to non-potable water reuse strategies[24]. This allocation ends up allowing 18 gCO_2/person-day (1 kgC/person-day * 10% * 50% * 12 gC/mol / 44 gCO_2/mol) to be emitted from NPR.

Having identified the optimal scale for decentralized reuse under different spatial conditions in San Francisco, we optimized the implementation of water reuse in space to serve the maximum amount of recycled water, i.e., save the maximum amount of fresh water sources while staying below the GHG emissions allowance. This problem can be described by a linear constraint optimization where the objective function is to maximize the implemented systems capacity. The optimization cannot be performed in continuous space, so we approximate space by dividing San Francisco into 170 grid cells in which we assume that the spatial characteristics remain constant. Each grid cell's center location is one of the 170 points described previously in the location analysis. Also, each grid cell is limited by the number of people that occupy that cell as that is the maximum number of people that can be served. To perform the optimization, we chose a realistic grid cell size (1000x800 m) and calculated the number of occupants in each by using the buildings' population, as estimated before. A mathematical formulation of the optimization model is given below.

Objective function:

$$\max \left(X_1 * C_1 + X_2 * C_2 + X_3 * C_3 + \cdots + X_N * C_N\right) \quad \text{[Eq. 24]}$$

where X_i number of systems installed in each grid cell and C_i optimal capacity of system

subject to:

$$\sum_1^N X_i \times C_i \times ef_i \leq emissions\ allowance \quad \text{[Eq. 25]}$$

where ef_i denotes the GHG emissions at the optimal scale of the system

$$\frac{X_i \times C_i}{a} \leq TP_i \quad \text{[Eq. 26]}$$

where TP_i enumerates the total people in grid cell and α is a coefficient representing the per person daily non-potable water consumption

By solving the linear constraint optimization, the grid cells that would maximize reuse capacity were identified. The result of the optimization is presented in Figure 33. To implement water reuse most successfully, by saving the most fresh water sources while at the same time remaining under the sustainable GHG emissions threshold, Figure 33 illustrates the areas that should be targeted. The gross water consumption in San Francisco is about 238,000 m^3/day (63 million gallons per day (MGD)), of which 155,000 m^3/day (41 MGD) are residential uses and 83,000 m^3/day (22 MGD) are commercial/municipal water uses[127]. We are not accounting for irrigation uses in this calculation since our model only accounts for in-building NPR. According to the San Francisco Public Utilities Commission (SFPUC), non-potable water accounts for 25-50% of the total water use for residential customers and about 75 - 95% for commercial customers[24]. Given these assumptions, the total non-potable water used in San Francisco is roughly 128,500 m^3/day (34 MGD). If decentralized reuse is implemented under this optimal scenario at maximum capacity in the illustrated region, there is potential to save 73,000 m^3/day, equal to about 56% of the total daily non-potable water use of San Francisco.

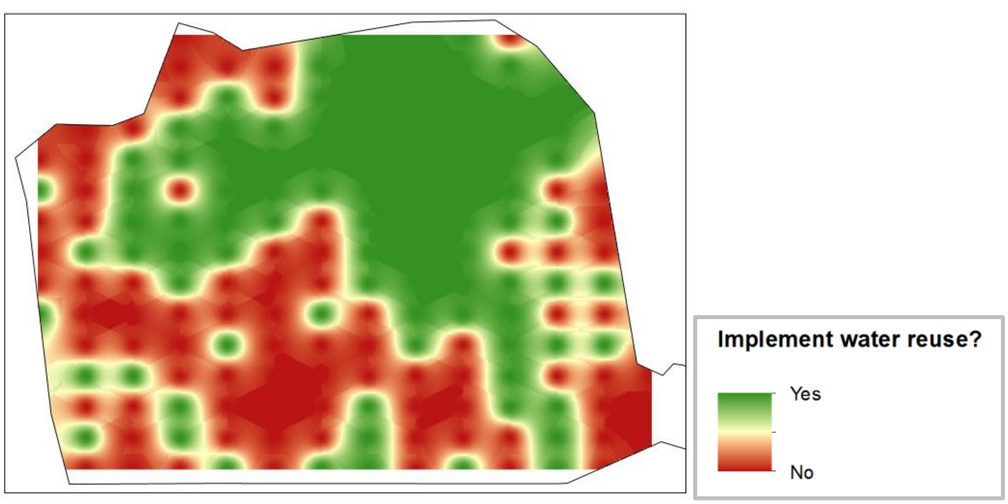


Figure 33: Implementation locations for maximizing adoption with constraint GHG emissions

By defining the optimization as a linear program, we can understand the relationships between the outcome (fresh water saved) and the problem constraint (GHG emissions). The GHG emissions constraint, the total allowable GHG emissions per day for reused water, is a binding constraint in our optimization problem, which means that it is the limiting factor. By relaxing the constraint, we can identify the additional potential for saved water. The linear optimization result allows us to extract that information. The percent increase in total saved water with respect to percent increase in per-capita GHG emissions allowance is shown in Figure 34. The curve presents a linear increase in saved water (as a percentage of total non-potable water calculated previously), and it flattens out when the maximum potential for the area is reached, meaning that the water reuse has served all potential customers in the area. (This assessment does not account for outdoor irrigation as it is highly variable and thus uncertain to model). Therefore, to be able to replace all toilet flushing water consumption with reused water, we would have to increase the GHG emissions allowance by 150% to 45 gCO_2/person-day.

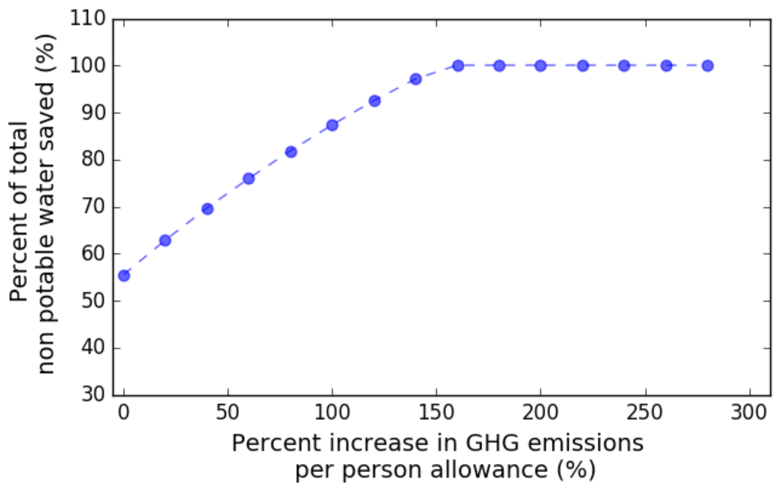


Figure 34: GHG emissions constraint sensitivity to fresh water saved

4.4 Discussion

This research aims to address the challenges of implementing decentralized NPR systems efficiently with respect to energy, GHG emissions, and cost. There are many drivers for implementing NPR. Decentralization is an intuitive approach to address the "purple pipe dilemma"[128], but because of the economies of scale in treatment, it is not trivial to estimate the implications of system size. As water reuse spatially merges the supply and demand of water, it requires careful planning with respect to treatment performance and distribution size. While energy, GHG, and cost may not always be the principle drivers for decision making, it is important to consider these effects in planning and policies. By developing a generalized algorithm that considers the specific local conditions, it enables decision makers to understand the implications of NPR and identify the optimal decentralization scale at the point of interest.

The algorithm developed in this research is generic and thus it is easily transferable to other locations and treatment technologies. The required data input file consists of a list of all the buildings, their floor area and number of floors, their occupancy (residents or employees), location, and elevation. This file can be modified to represent the existing or planned building infrastructure of any city. From the web interface, the user can also modify the equations describing the economies of scale for the treatment performance in terms of energy or cost. The sensitivity of the model to location-specific data demonstrates the importance of spatial analysis and promotes the need of detailed modeling in planning approaches.

An important aspect of the model is that it is based on multiple decision metrics that allows decision makers to understand the tradeoffs and make optimal decisions based on their priorities, not just economic efficiency. Cost is usually considered the most important factor when developments are proposed, however, that might not be the case for NPR systems as it is highly dependent on who bares that cost (utilities, developers, etc.) and how that cost would compare to the overall costs of a project. Optimizing for the lowest energy and GHG is important to consider in the context of city-wide or broader efforts to make our cities more sustainable.

One current limitation of the modeling approach is the lack of accurate and detailed treatment performance data for various technologies and multiple scales. This limitation is especially true for the MBR treatment requirements, which is a large contributor to energy, GHG emissions, and costs, and is based on literature values; as modeled, the curves highly penalize small systems due to lack of available data. This research seeks to drive innovation in decentralized treatment technologies and increase awareness on the significance of energy efficiency in small scale systems. The accuracy and relevance of the model results will improve if more data are collected on the energy demands and GHG emissions of actual installations, and for a wider range of technologies. Environmental performance and pressing climate change issues should influence behavior in optimal planning, especially in places like California where GHG reduction targets are set[46].

The development of a platform for a fast, relatively easy, and location-specific characterization of the optimal decentralization scale can be especially useful in the current context of changing infrastructure paradigms. The platform offers valuable insight regarding the implementation of water reuse systems as it accounts for specific local conditions and user-defined treatment processes. Our results illustrate that the unit values can vary by a factor of five depending on location, which illustrates the importance of careful master planning to inform decisions about where decentralized NPR systems are most appropriate. Although these ranges are high, they need to be assessed in comparison to the impacts of other alternatives or the conventional water supply. To capture the complexity of sustainable water management, holistic consideration based on multiple criteria is required to make optimal infrastructure decisions. Our platform can potentially be expanded to perform multicriteria analysis by assigning importance weights to the different metrics currently assessed.

An important aspect of the algorithm is the local-optimum approach. The algorithm does not try to converge on an overall system-optimal solution, rather it identifies a solution that would satisfy the local conditions. Thus, the platform identifies the optimal scale locally, and does not perform a global optimization for the entire city. This aspect is intentional as it is purposed for site-specific implementation of water reuse systems. System implementations are likely to occur in a step-by-step, modular fashion. As such, the model can be used to evaluate a specific proposed development and to explore the impact of a new technology or efficiency improvement. It can provide decision-makers with insight about the location-specific optimal system scale to assist with the planning process of implementing NPR while quantifying the expected energy, cost and GHG emissions. More broadly, it can be used in master planning of a city's water portfolio or water reuse program by identifying the areas that would benefit from more decentralized developments.

Based on our analysis, decentralized systems are generally more efficient at larger size because they benefit from the economies of scale for treatment. This finding is supportive of San Francisco's current policies to promote on-site water reuse, which focus on larger buildings (all new buildings larger than 250,000 ft^2 must identify alternate water sources to meet toilet flushing and irrigation demand)[61]. San Francisco has also put into place regulations to allow the installation of district scale systems, which is necessary for sharing of recycled water between buildings.

This research adds to the growing literature on optimal scale and system performance for various spatial conditions. It provides an understanding of how water reuse systems would perform in space given realistic topographic conditions, building structures, and population densities. The algorithm is generalizable and applicable to any building scale, which allows for the model to be valid in different locations with various spatial and population densities. The algorithmic process is modular to take as input the specific conditions of the location of interest and it does not have any information that ties it to a certain location. The web-based decision-support platform developed for the purposes of this research can be used as a decision-support tool for identifying optimal water reuse designs given specific local conditions.

Chapter 5.

Feasibility Assessment of Decentralized Nitrogen Recovery from Source-Separated Urine

The following chapter is adapted from Kavvada et al. (2017) Life-cycle cost and environmental assessment of decentralized nitrogen recovery using ion exchange from source-separated urine through spatial modeling. Environmental Science & Technology, 51(21), 12061-12071, with permission from William A. Tarpeh, Arpad Horvath, and Kara L. Nelson. Copyright 2017, ACS Publications.

5.1 Introduction

Nitrogen has become a contaminant of concern in surface waters because of its contribution to eutrophication, which deteriorates water quality, aquatic ecosystems, and aesthetic value.[129] A growing number of cities around the world are enacting nitrogen effluent controls to preserve receiving waters' quality.[130,131] In San Francisco, wastewater treatment plants (WWTPs) contribute 50-80% of nitrogen discharges.[132] Although nitrogen discharges to San Francisco Bay are not currently regulated, discharge limits are under discussion. On a global scale, about 90% of nitrogen in wastewater is discharged to receiving waters.[29]

Biological nitrogen removal has been successfully implemented at many WWTPs to control wastewater effluent nitrogen discharges[133]. Upgrading an existing treatment plant to convert ammonium (NH_4^+) to dinitrogen gas (N_2) via nitrification-denitrification requires additional costs and energy inputs. Paradoxically, N_2 is converted to NH_4^+ fertilizers in the Haber-Bosch process, which consumes about 1% of global energy.[27] In addition, nitrification-denitrification operates best in centralized treatment processes;[134] however, 25% of the United States population[135] and most people with sanitation access in developing regions[136] use on-site sanitation systems.

In contrast to biological nitrogen removal, separate urine collection facilitates recovery of nitrogen as valuable byproducts such as fertilizer. Urine is only 1% of municipal wastewater volume but contains the majority of excreted macronutrients, making it an ideal stream for nitrogen recovery.[29] A well-informed comparison between conventional nitrogen management and source separation with resource recovery requires improved understanding of life-cycle impacts and costs. Thus far, most research on nitrogen recovery from urine has focused on bench-scale studies of technologies such as ammonia stripping,[137] electrodialysis,[138] and nitrification-distillation.[139] Other nitrogen removal processes for wastewater include anammox[140] and the coupled anaerobic-anoxic nitrous decomposition operation (CANDO), which could also potentially be applied to urine.[141] In this study we focus on ion exchange, as it appears promising based on laboratory studies and can be implemented at a range of scales.

Ion exchange is a well-established technology for removing charged impurities from drinking water, wastewater, and landfill leachate. Removal of nitrogen from urine was first explored using zeolites,[142] with recent research demonstrating that synthetic resins have higher adsorption density and regeneration potential.[31] In fresh urine, nitrogen is present primarily as urea; during storage, the enzyme urease hydrolyzes urea to ammonium (NH_4^+), which can be adsorbed onto negatively charged adsorbents. Recovery requires a regeneration or elution step to create a concentrated product stream of nitrogen. In the proposed model (Figure 35, see Methods), NH_4^+ from urine is concentrated in cation exchange columns at the toilets; then the cartridges are trucked to facilities where the cation exchange resin is regenerated and ammonium sulfate fertilizer is produced. The regenerated cartridges are trucked back to the buildings and the fertilizer is trucked to a fertilizer distribution center. Although the use of ion exchange to recover ammonium from urine is still undergoing evaluation in the laboratory, an early assessment of its implementation at scale can provide valuable insight into the feasibility of the overall approach, as well as technical factors that require further research and development. In this study, we used three major tools to perform such an assessment: economic and environmental assessment, last-mile logistics modeling, and geospatial modeling.

Previous studies have reported several potential benefits of urine separation over centralized biological nitrogen removal.[143] Compared to biological nitrogen removal, separate collection of urine and application as fertilizer was reported to reduce treatment energy by 200 MJ/person/year [144] and to reduce greenhouse gas (GHG) emissions.[145] In another study, collecting urine in decentralized tanks had lower treatment costs than conventional treatment and similar capital costs, but dual plumbing from every building to the WWTP made total capital costs higher than conventional treatment.[146] Another potential benefit of urine separation could be avoidance of N_2O emissions (a potent greenhouse gas) during biological treatment due to incomplete nitrification.[147] Moreover, the trucking impacts can be significantly decreased with ion exchange by transporting and storing highly concentrated nitrogen rather than urine itself, which is 96% water.[148]

Implementing decentralized nitrogen recovery requires planning of the last-mile logistics for the system management between buildings and fertilizer distribution facilities. Last-mile logistics is a term used in supply chain management and refers to the transportation involved in the last step of the process, usually from a hub to people's homes.[149] Optimizing this aspect of the logistics could be particularly important for decentralized processes, but it has not been thoroughly explored in the development of alternative wastewater management and resource recovery strategies. One example of the significance of transportation modeling was illustrated for decentralized sludge management, showing the impact of population density on the overall system costs.[110] To provide a fair comparison of centralized and decentralized processes, it is also critical that these last-mile logistics are modeled in detail.

Evaluating the last-mile logistics in detail requires geospatial modeling to accurately estimate the required transportation distances and facility locations for different alternatives (Figure 35). Without this detailed assessment, general assumptions would need to be made that could introduce significant uncertainty and bias, limiting the ability to make well-informed planning decisions for decentralized infrastructure. Similar integrated models have been used to analyze the supply chains of recycling processes from the consumer source to the recycling terminal[150] and to optimize facility location for enhancing biofuel supply potential.[151–153] Advanced spatial modeling and last-mile logistics models have also been used to assess the economic impacts of electric vehicle battery recycling, illustrating the importance of quantifying the logistics impacts at a state-wide scale.[154,155]

The specific objectives of this study were to: (1) evaluate the life-cycle energy, GHG emissions and cost of ion exchange for recovery of nitrogen from source-separated urine, (2) develop geospatial models to analyze the last-mile logistics and identify the optimal scale for implementing this approach for a city, and (3) apply the framework to San Francisco as an illustrative case study. The results provide insights into the overall system performance and are benchmarked against centralized nitrogen removal. Conducting systems-level analysis while the development of novel unit processes is still at bench-scale helps identify research priorities, evaluate potential tradeoffs early in the technology development process, quantify potential benefits before scaling up, and improve the likelihood of progression to full-scale implementation. As more urban centers face restrictions on nitrogen discharges, the results of this study can provide decision makers with better information about the potential for source separation and resource recovery.

5.2 Methods

5.2.1 System Description

A schematic of the hypothetical process for decentralized nitrogen recovery via ion exchange is shown in Figure 35. At the building level, ion exchange cartridges are installed on urine-separating toilets. The effluent of the ion exchange cartridges is recombined with building wastewater and delivered to the wastewater treatment plant through the existing sewer network. A flow equalization tank, able to contain one day's worth of urine (volume based on our assumptions for daily urine production 1.4 L/d * 2.5 people per household), is installed prior to the ion exchange cartridge to regulate flow and achieve urea hydrolysis. Urea hydrolysis is necessary to produce ammonium prior to the ion exchange cartridge; a one-day residence time was considered a reasonable assumption, but further work is needed to develop effective designs that accelerate hydrolysis. Nitrogen loaded cartridges are collected from each household by a weekly truck collection service and replaced with a clean cartridge. The cartridges are sized such that the resin becomes saturated after one week, given the specific adsorption density measured in the laboratory (3.7 L volume, 12 cm diameter, 33 cm length). The collected cartridges are trucked to a regeneration facility where sulfuric acid is pumped through to regenerate the resin, and the cartridges are returned to buildings for reuse. The output liquid, ammonium sulfate (a common liquid fertilizer), is bottled on site and transported by trucks to a centralized fertilizer distribution facility where it can be sold.

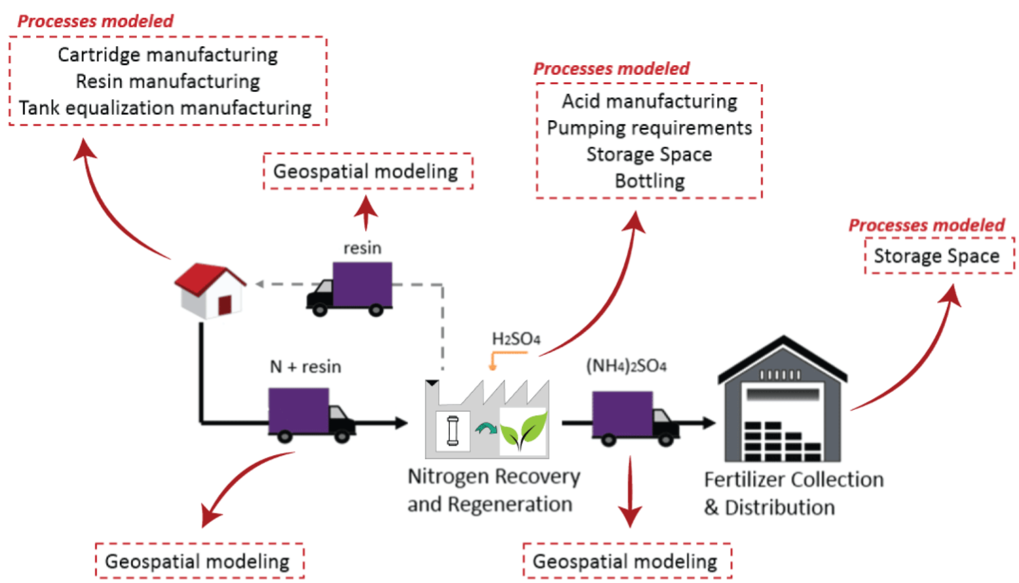


Figure 35: Process schematic

5.2.2 Description of Ion Exchange

In a previous study we evaluated several adsorbents for their ability to recover nitrogen from source-separated urine.[31] In this study, we focused exclusively on Dowex Mac 3, a synthetic resin that was determined to have high adsorption capacity (4.9 mmol N/g resin).[31] However, the life-cycle, geospatial, and logistics analysis could be applied to any adsorbent if the necessary parameters are defined (adsorption capacity, material density, hydraulic conductivity, cost, embodied energy and GHG emissions). Cation exchange cartridges reduce urine cation concentrations but leave anion concentrations unchanged. Protons desorb from Dowex Mac 3 into urine, consuming the alkalinity produced by urea hydrolysis (eq. S - 1 and eq. S - 2 in the Appendix 3). pH does not change with the use of ion exchange because of carbonate buffering in urine. The amount of sulfuric acid required for regeneration was calculated assuming stoichiometric exchange of protons and ammonium and commonly available stock concentrations (Table 3). The pumping requirements for resin regeneration with acid were calculated as the head loss through the cartridges; resin hydraulic conductivity was measured using the falling head method.[156]

Key parameters derived from laboratory experiments included resin density, adsorption density, time for regeneration, hydraulic conductivity, column headloss, regenerant volume required and cartridge sizing. All parameter values are presented in detail in Table S - 8.

5.2.3 Description of Economic and Environmental Assessment

To perform the economic and environmental analysis of the technology, the laboratory results were scaled and connected to the logistics methodology to estimate the performance of the entire system. The functional unit chosen for the analysis was 1 m^3 of urine treated (equal to 7.5 kg N treated). The system boundaries include the urine source at the toilet up to the fertilizer distribution center as shown in Figure 36.

The data inventory for this analysis involved all processes that contribute to the energy intensity, GHG emissions, and cost. The key components investigated were the ion exchange resin, the fiberglass cartridge, a plastic flow equalization tank to stabilize flow of urine through the cartridge and achieve urea hydrolysis, pumps at the regeneration facility, liquid sulfuric acid used for regeneration, rental space for the regeneration facility, bottling of the fertilizer (plastic bottles) and trucks used for the cartridge and fertilizer transport. The source-separating toilets were not included in the analysis, as it is assumed that they would be installed in new construction or during planned replacement of old toilets, and that they have comparable footprints to regular low-flow flush toilets. Material impacts were determined using either economic input-output life-cycle assessment (EIO-LCA)[65] or process-based life-cycle assessment (LCA) for specific inputs, a method called hybrid LCA.[157] Fertilizer offsets were determined on a mass nitrogen basis. The labor costs include truck driving (one driver per truck) and employees of the regeneration facilities (assuming each operator could handle 30 cartridges per hour and works an 8-hour workday). Labor requirements are quite speculative, and could likely be significantly reduced if automated processes are introduced. The wages were estimated based on the type of occupation.[158]

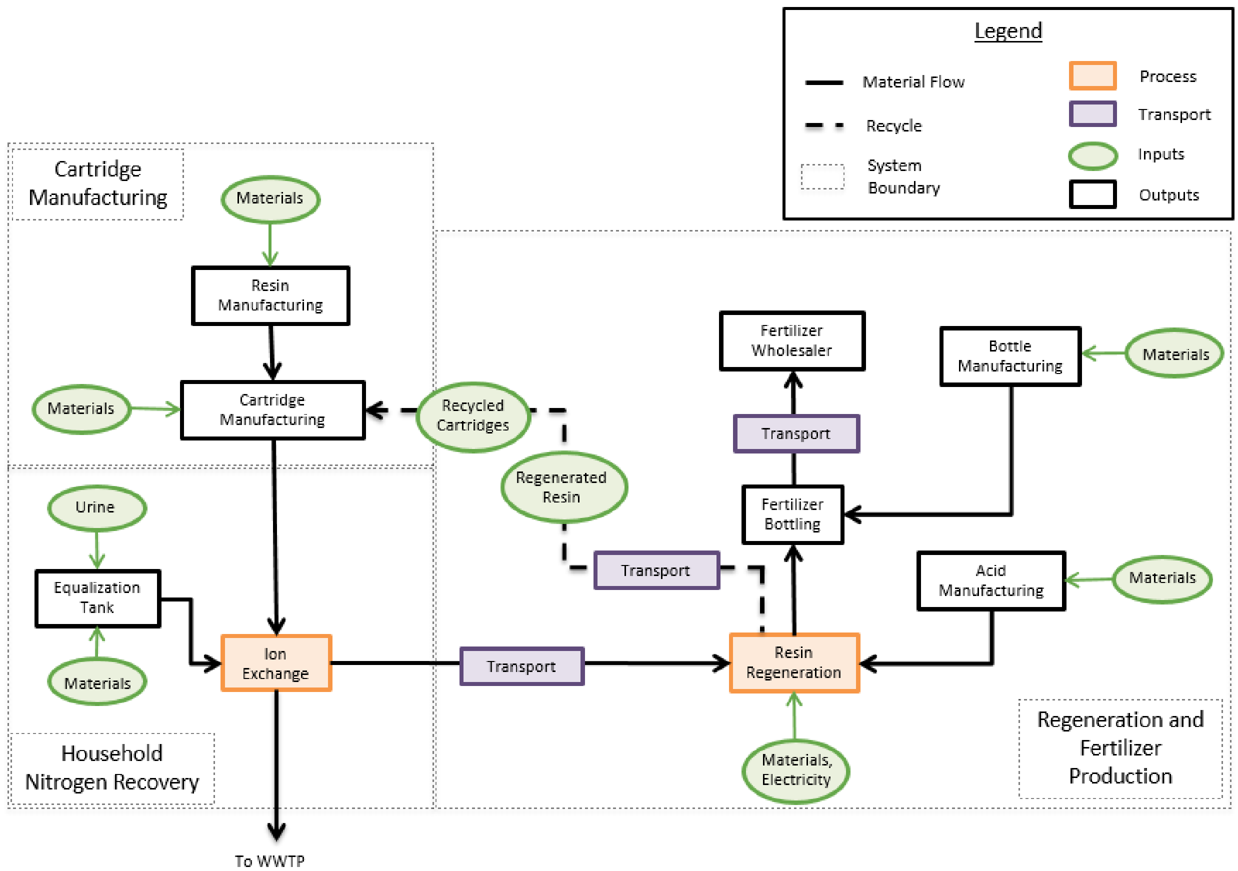


Figure 36: Process Diagram and system boundaries

5.2.4 Last-mile Logistics Modeling

Logistics modeling involved identifying the number and locations for the decentralized regeneration and fertilizer distribution facilities to identify the optimal level of decentralization to minimize the energy, GHG emissions and cost. Cartridge collection from buildings was assumed to be weekly, just as recycling and solid waste is collected in many urban settings. This interval was used to estimate the amount of urine produced by an average person and thus the dimensions of the toilet-level cartridge (resin mass and column volume). We assumed a per person urine production rate of 1.4 L/(person/day)[159] and 2.5 people per cartridge[160]). The total number of cartridges was increased by 2.5 times, as one cartridge would be installed in the household, one being regenerated, plus 50% more cartridges to account for households with more than one toilet or inefficiencies in logistics management. The estimates for urine diversion to eliminate the need for biological nutrient removal at the centralized plants vary from 50%[161,162] to 90%,[163] and depend on the centralized treatment processes and discharge limits. In this analysis, a urine diversion of 50% was assumed (i.e., decentralized nitrogen recovery was modeled to cover 50% of the population).

For the logistics modeling, we investigated the effect of the number of regeneration facilities along with the effect of facility location. Travel distances for collection of nitrogen recovery cartridges were modeled as a Traveling Salesman Problem (TSP). The TSP problem identifies the shortest possible route to visit a certain number of locations exactly once and return to the location of origin. By modeling transportation as a TSP given the location of the regeneration facilities, we could model the impacts of transportation with high resolution.

The effect of the number of regeneration facilities was identified by running multiple scenarios with different numbers of facilities in each iteration and allocating the buildings to the closest facility. We assessed scenarios ranging from one regeneration facility serving the entire city up to 100 smaller facilities being distributed throughout (Figure 41). The capacity of each facility in each run was calculated based on the number of people it would serve. To understand the effect of the location of the facilities, three scenarios were modeled.

The first scenario considers a custom-made facility location problem for identifying optimal locations for the nitrogen recovery facilities. In this scenario, the city is divided such that each facility would have an equal size service area to minimize the transportation distances for cartridge collection (iso-distant scenario). It was modeled by applying a clustering algorithm to all the building locations and the regeneration facility was placed in the cluster center (Figure 39a). The clustering algorithm used was K-Means clustering which partitions the buildings into k clusters, with each building being allocated to the cluster with the nearest mean (center).

In the second scenario, facilities are equidistant from each other and placed on a hypothetical grid overlaid on the city. In this scenario, the facilities were equally spaced throughout the city and each building was allocated to its closest facility using a Euclidean distance (grid scenario). The transportation distances were potentially higher, as the building locations are not considered for optimally placing the regeneration facilities and thus some trucks would have to travel long distances for cartridge collection.

In the third scenario, the facilities are placed randomly throughout the city (using a random number generator for their coordinates) and each building was allocated to its closest facility using a Euclidean distance (random scenario). This scenario is the one that most probably reflects reality, as facility locations would be based on location availability rather than transportation optimality.

5.2.5 Case Study

San Francisco, a medium-sized city with high population density (6,700 people/km^2)[164], was used as an illustrative case study to assess the implementation potential of decentralized nitrogen recovery. San Francisco was selected as it is located on the San Francisco Bay, an estuary in which wastewater agencies are required to evaluate treatment options and costs (financial, energy demand, and GHG emissions) for reducing nutrient discharges.[165] Also, geospatial data were available on building locations, size and number of floors, which made the logistics analysis feasible.

We modeled the entire city of San Francisco at building-scale resolution. The first step involved identifying the locations of all residential and commercial buildings in San Francisco, as well as their corresponding population. Building locations, footprints and number of floors were gathered from the City and County of San Francisco.[62] Residential population estimates were sourced from the Census Bureau[121] at a census block resolution. To allocate the population to the buildings in each census block, we first identified all the residential buildings by overlaying the city landuse mapping areas.[62] After calculating the entire area of the building (building footprint times number of floors), we allocated the population of each census block proportionally to the building area (see Section 5.2.6). For commercial buildings, we used commercial employment data from the ESRI Business Analyst database.[122] This dataset identifies the location of all businesses and their number of employees, and was used to estimate the number of people in each commercial building in San Francisco.

To model the logistics management scenarios for cartridge collection and regeneration, the three logistics scenarios (iso-distant, grid, and random) were modeled for San Francisco (Figure 37). Given the location of the facility and the number of buildings served by it in each scenario, logistic components (e.g. amount of resin, number of trucks, number of cartridges, size of facility, distances travelled) were sized appropriately and their impacts quantified. For the facility space cost, actual market data were used to estimate the cost for renting the space of a certain size and a regression line was calculated to estimate the average rent given the available commercial space (see Section 5.2.8).

The next step was to calculate the transportation distances for each scenario and for each number of regeneration facilities. From each regeneration facility, the overall transportation distance to visit all points was estimated using the TSP algorithm (as described in the previous section). A time constraint of 8-hour working days and pick-up occurring at the curb (similar to trash collection) were assumed, to estimate the number of trucks needed for the collection. To estimate the transportation distance for trucking the fertilizer to a centralized collection facility, regeneration facility locations were clustered with the fertilizer collection facility as the cluster center. To estimate the transportation impacts of this second step, the fertilizer collection, another TSP algorithm was solved with the predefined regeneration facilities as start points and the fertilizer collection facility as the end point.

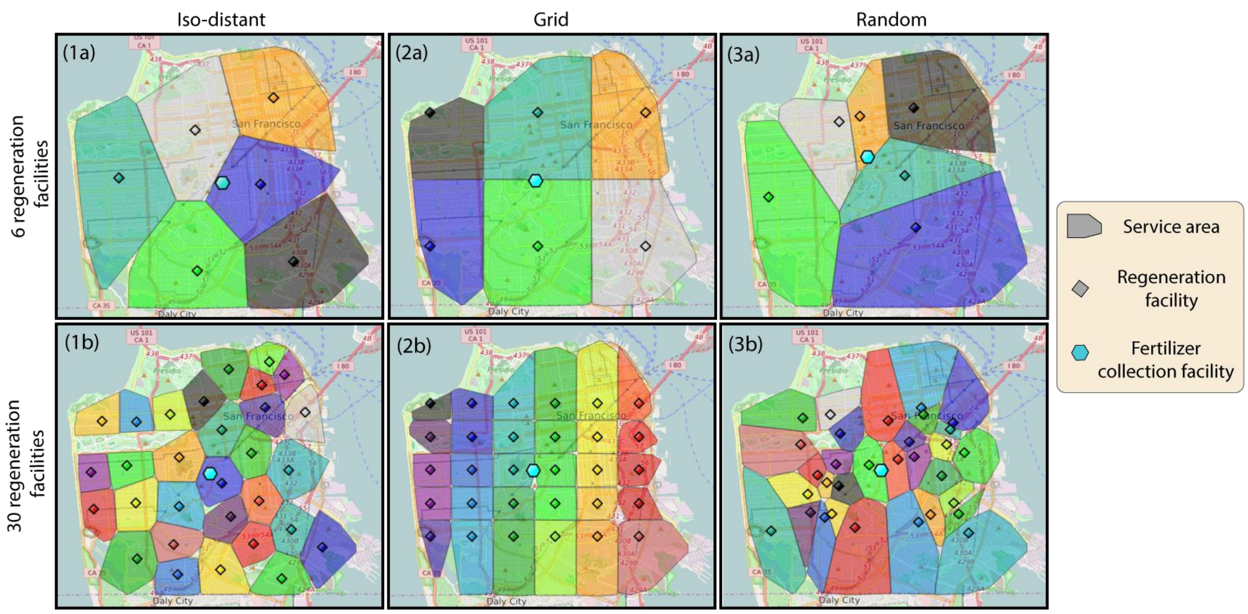


Figure 37: Locations for regeneration facilities and their corresponding service areas for (a) 6 regeneration facilities and (b) 30 regeneration facilities for the (1) iso-distant allocation scenario, (2) grid allocation scenario and (3) random allocation scenario.

5.2.6 Logistics Modeling

To perform the logistics modeling the building locations in San Francisco needed to be identified. SF Open data was used to acquire the building latitude and longitude information for all buildings in San Francisco, along with their footprint and number of floors. The building footprints were converted to point data using the polygon centroid as a target. A subset of the San Francisco buildings is shown in Figure 38a.[62] Population data was gathered from the Census Bureau in a block resolution as illustrated in Figure 38b.[121] By combining the previous datasets, the population of each block was allocated to the overlapping residential buildings equivalently to their area (Figure 38c).

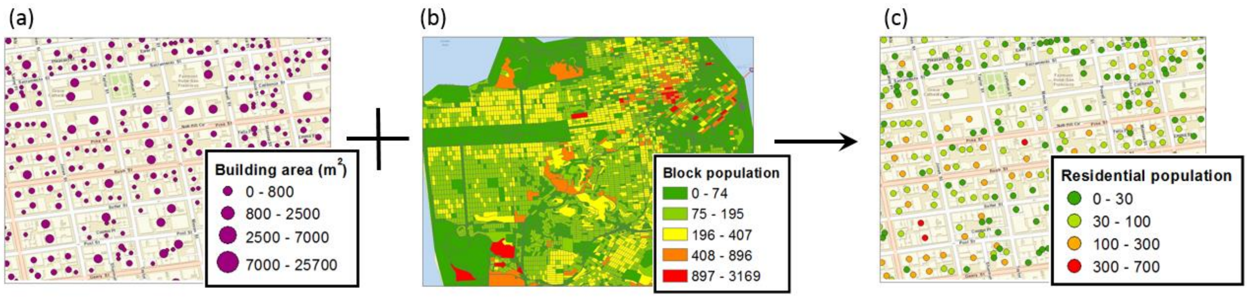


Figure 38: Population allocation to buildings

After the regeneration facilities were placed on the map (given the assumptions of each logistics scenario described in the main text), a building allocation had to occur where each building was allocated to its closest facility by using a clustering algorithm as illustrated in Figure 39a. Given the facility allocation a traveling distance was calculated using a Traveling Salesman Problem solution (Figure 39b).

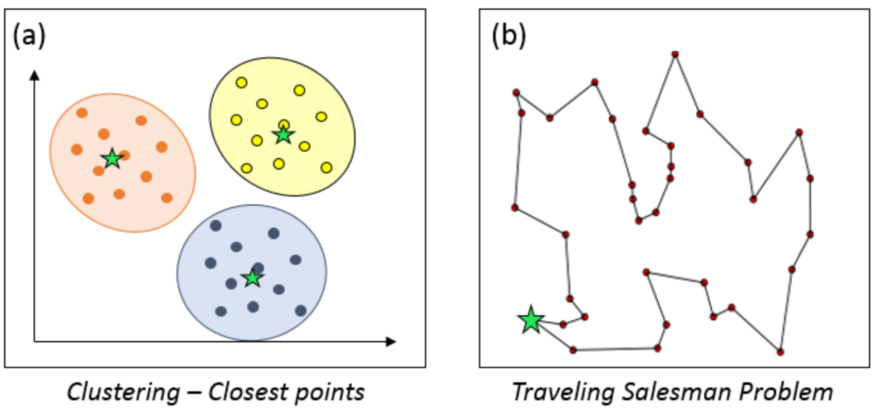


Figure 39: Facility allocation and transport distance

For the traveling salesman problem, an approximation method of using Euclidean distances between all buildings was used instead of the actual street network. This approximation error converges to zero with more buildings added to the analysis (such as in a dense urban area as San Francisco). The model performance and speed of computation gets significantly lower when the real network is taken into account as advanced spatial operations also need to occur, such as snapping buildings to the road network and complex network operations. The approximation error is not significant enough to justify the significant decrease in computational efficiency.

By applying the same methodology to all facilities, we could identify which buildings are served by each facility, how many people are served and the total distances the cartridges need to be transported for the collection system of each regeneration facility, illustrated in Figure 40. Different number of buildings can be allocated to each facility which will indicate the facility size and the required trucking (Figure 41).

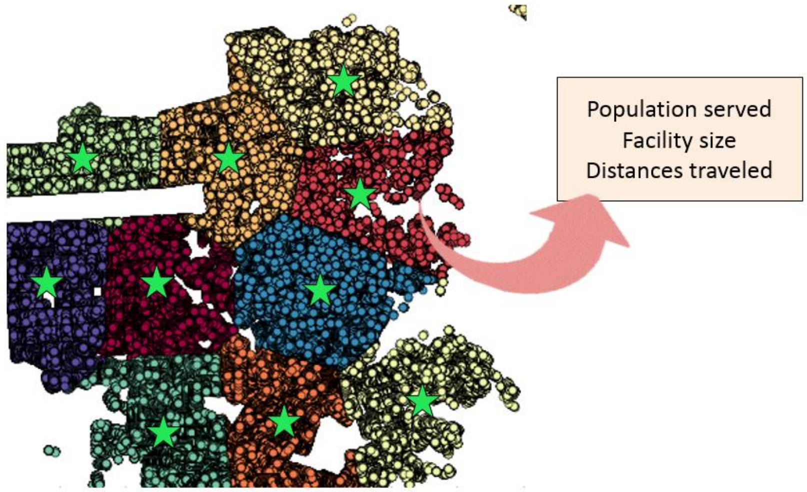


Figure 40: Illustration facility and building allocation for an example iso-distant scenario.

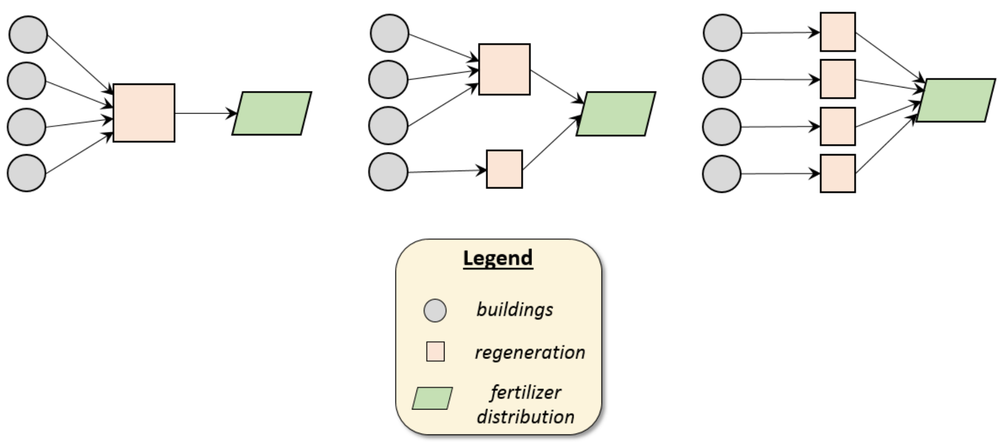


Figure 41: Different decentralization options for the regeneration facilities

5.2.7 Regenerant Comparison

Sulfuric acid was used in this model for the resin regeneration process. We considered using other regenerants as well and their corresponding performance for energy, GHG and cost (Figure 42). Sulfuric acid had the second lowest energy and GHG impact and a higher cost compared to the other regenerants. The acids are compared using the required amounts used based on the same molar concentrations for regenerating the same amount of resin (Table 3: Regenerant comparison). The amount of stock solution required was calculated based on commonly available stock concentrations and stoichiometric exchange. As an example, the amount of sulfuric acid required per gram resin was calculated as follows:

4.9 mmol NH_4^+-N/g resin* 1 mmol H^+/mmol NH4$^+$-N * 1 mmol H_2SO_4/2 mmol H^+ * 1 mL/18.21 mmol H_2SO_4= 0.135 mL 98% sulfuric acid solution/g resin.

Table 3: Regenerant comparison

Regenerant *	Volume of regenerant per mass of resin (mL/g)	Cost of regenerant (USD/L)
H_2SO_4 (98% stock solution)	0.135	0.50 [166]
HCl (65% stock solution)	0.402	0.28 [166]
HNO_3 (32% stock solution)	0.312	0.43 [166]
NaCl (17% stock solution)	0.797	0.02 [166]

** Values in parenthesis indicate commonly available stock concentrations*

Different acids have different impacts associated with their manufacturing which is illustrated in their embodied energy and GHG emissions and cost. The embodied energy and GHG emissions for the different acids were calculated using Gabi software.

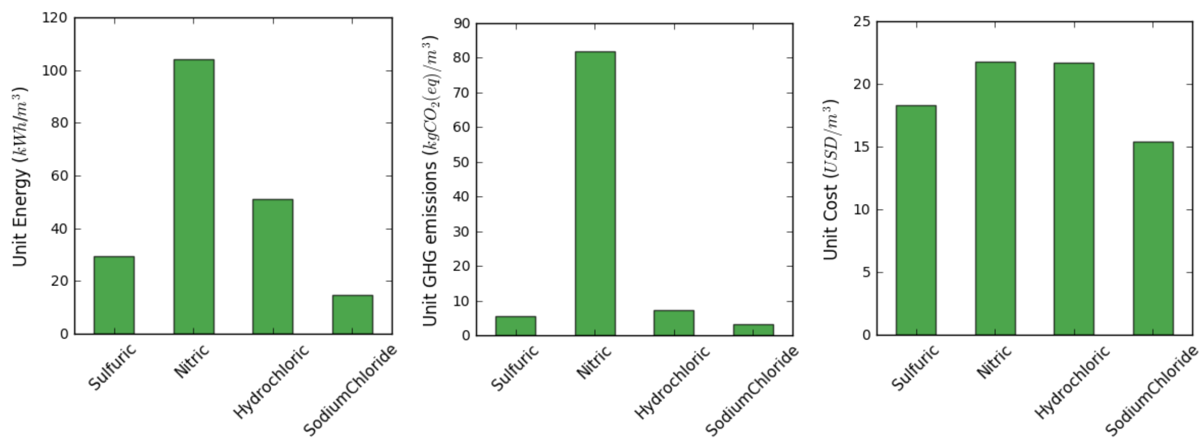


Figure 42: Regenerant performance comparison for energy, GHG and cost.

For sodium chloride, we estimated the increase in total dissolved solids (TDS) associated with sodium desorbing from regenerated resin as ammonium from urine adsorbed:

7.5 g N/L urine* 1 L urine/100 L wastewater * 1 mol N/14 g N* 1 mol Na^+/mol $NH4^+$-N * 23 g Na/mol Na * 1 g TDS/g Na * 1000 mg TDS/g TDS = 123 mg TDS/L.

According to Metcalf & Eddy 2007, TDS in untreated domestic wastewater ranges from 270-860 mg/L, with a medium strength wastewater containing approximately 500 mg/L TDS.[167] Adding 123 mg TDS/L is a 24.6% increase, which we rounded to 25%.

5.2.8 Commercial Facility space cost

For the purposes of this study we assumed that the space for regeneration facilities would be rented as commercial space in San Francisco. We assumed that facility area would be proportional to the number of cartridges regenerated and the amount of fertilizer stored. We calculated the area of each facility based on the number of cartridges regenerated per week, the volume of fertilizer produced and a fixed area of 20 m^2 as working space. The storage space for cartridges and fertilizer was estimated based on their total volume if they could be stacked at 2 m high.

For commercial space rent prices, we used actual data for San Francisco using Craigslist database[168]. We performed a regression analysis on the Craigslist data to derive a relationship between required commercial area to rent and the total renting price (Figure 43).

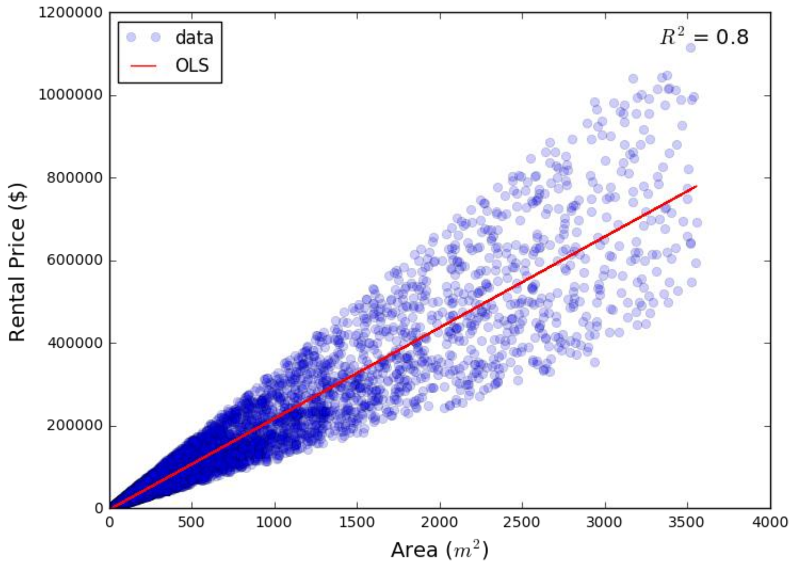


Figure 43: Regression analysis for cost prediction of facilities of different sizes

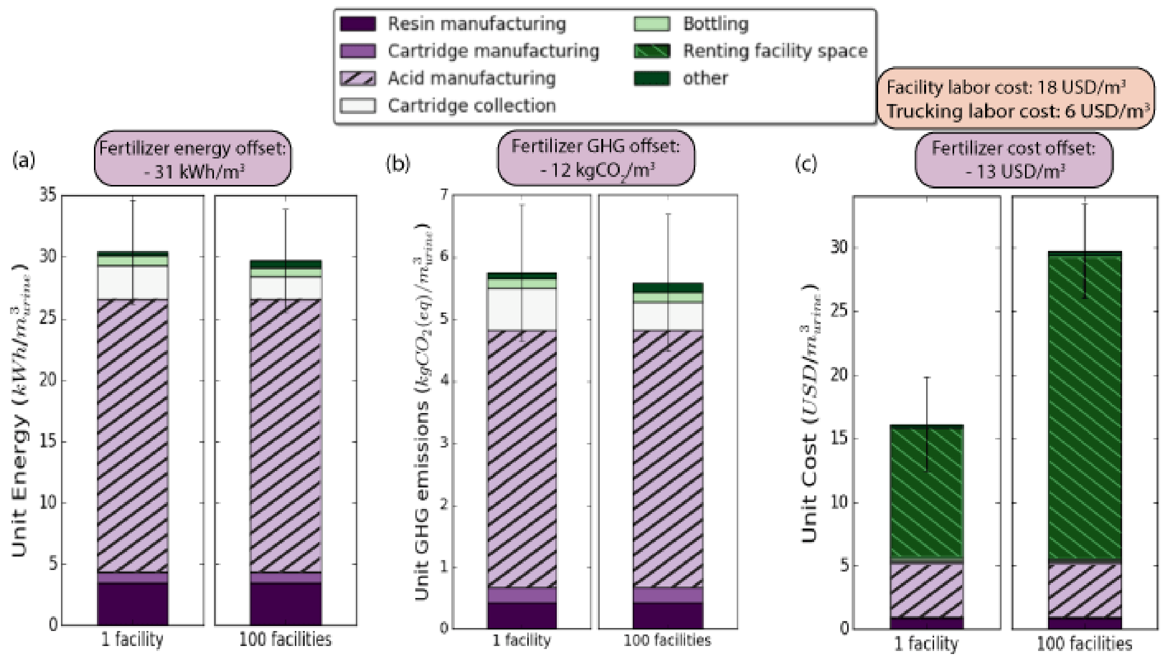
5.3 Results

5.3.1 Component Breakdown

For each logistics scenario in San Francisco we calculated the life-cycle energy, GHG emissions and cost for building-scale nitrogen recovery. We analyzed each scenario separately and for the entire range of number of regeneration facilities (1 to 100). The contribution of each process component is shown in Figure 44. For energy and GHG emissions, acid manufacturing was found to have the most significant impact (about 75%), followed by resin manufacturing and transportation impacts. The cost is mainly driven by the space rental cost for the regeneration facility (65 - 78% of total cost). This high contribution of facility space can be attributed to the site-specific location costs, as San Francisco is ranked the 3rd most expensive region in the real estate market in the United States.[169] Labor costs can increase the total cost from 70 - 160% depending on the number of regeneration facilities. The presented impacts also include traditional fertilizer offsets in the form of ammonium nitrate on a mass of nitrogen basis, as one kg of nitrogen from urine would offset the equivalent kg of nitrogen in the form of ammonium nitrate. Accounting for fertilizer offsets reduced energy intensity (100% reduction), GHG emissions (200% reduction) and cost (48-90% reduction, Figure 44).

Comparing the results for 1 versus 100 regeneration facilities (Figure 44), it is evident that there were slight diseconomies of scale for energy and GHG emissions, and large economies of scale for cost. Energy and GHG emissions were dominated by factors that are independent of scale, such as acid, resin, and cartridge manufacturing. Transportation impacts decreased by about 35% for 100 facilities versus 1 facility; however, the overall impact of transportation is minimal (Figure 44). It should be noted that we accounted for no fugitive GHG emissions from the urine or ion exchange column itself; however, this assumption needs to be confirmed under realistic use conditions, as biological transformation of ammonia could occur during urine storage. If this assumption is correct, it is an advantage over biological nutrient removal practices, which can potentially emit significant quantities of N_2O.[97,147]

To put the system performance in perspective, we compared the decentralized source separation to conventional nitrification-denitrification at a centralized plant (full description of values in Table S - 9). From performing a thorough literature review on nitrification-denitrification, we compiled several literature values, and calculated average unit energy values of 18 for aeration only (wastewater as carbon source) and 34 kWh/m$^3_{\mathrm{urine}}$ (aeration plus carbon substrate addition).[170–173] These values are similar to our results for source-separation, not including the fertilizer offset. We found average GHG emissions of 16 and 30 kg $CO_{2(eq)}$/m$^3_{\mathrm{urine}}$,[171,173] which are 2-5 times higher than for source-separation (not including fertilizer offset). It is possible that anammox processes, which are still under development, will prove to be more efficient than nitrification-denitrification; if so, these energy and GHG values could potentially decrease by a factor of two, primarily due to the lower aeration requirements.[172] However, direct N_2O emissions from anammox remain highly uncertain.[174–177] We found average direct costs for nitrification-denitrification reported to be 19 USD/m$^3_{\mathrm{urine}}$,[173,178,179] which is also similar to those estimated for source-separation.



*other includes: pump and equalization tank manufacturing, pump operation and all material transportation for infrastructure construction and transportation of bottled fertilizer to the distribution facility.

Figure 44: (a) Life-cycle energy, (b) life-cycle GHG emissions and (c) life-cycle costs if the entire city is served by 1 regeneration facility versus 100 regeneration facilities. Error bars represent +/- one standard deviation, based on the uncertainty analysis.

5.3.2 Effect of Decentralization

A closer look at economies and diseconomies of scale is provided in Figure 45. For energy and GHG emissions, we found lower impacts as the number of regeneration facilities increased, but the change was quite small (3 - 4%). The opposite occurred for cost, as the unit cost increased by about 87% as the number of regeneration facilities increased from 1 to 100. Interestingly, the effect of facility location was minimal, as we identified only small benefits from increasing the uniformity of facility distribution (comparing random versus iso-distant). This is a positive finding, indicating that under the high population density conditions represented by San Francisco, there are minimal benefits to optimizing the location of regeneration facilities, which would be difficult from a planning perspective.

The non-linear diseconomies of scale for energy and GHG emissions are due to the effect of transportation distances for cartridge collection (Figure 45a and b). The distances decrease exponentially with increasing facility number. Other non-linearity occurs from the pumping operation, because larger pumps can be used which are more efficient in their operation; however, as facility size increased, the overall effect was minimal (pumping is included in "other" in Figure 44). In terms of cost (Figure 45c), the major impact for the linear increase with respect to regeneration facility numbers is the cost of renting the facility. Smaller facilities tend to have a higher cost per square foot and more facilities need to be acquired, which drives the cost up.

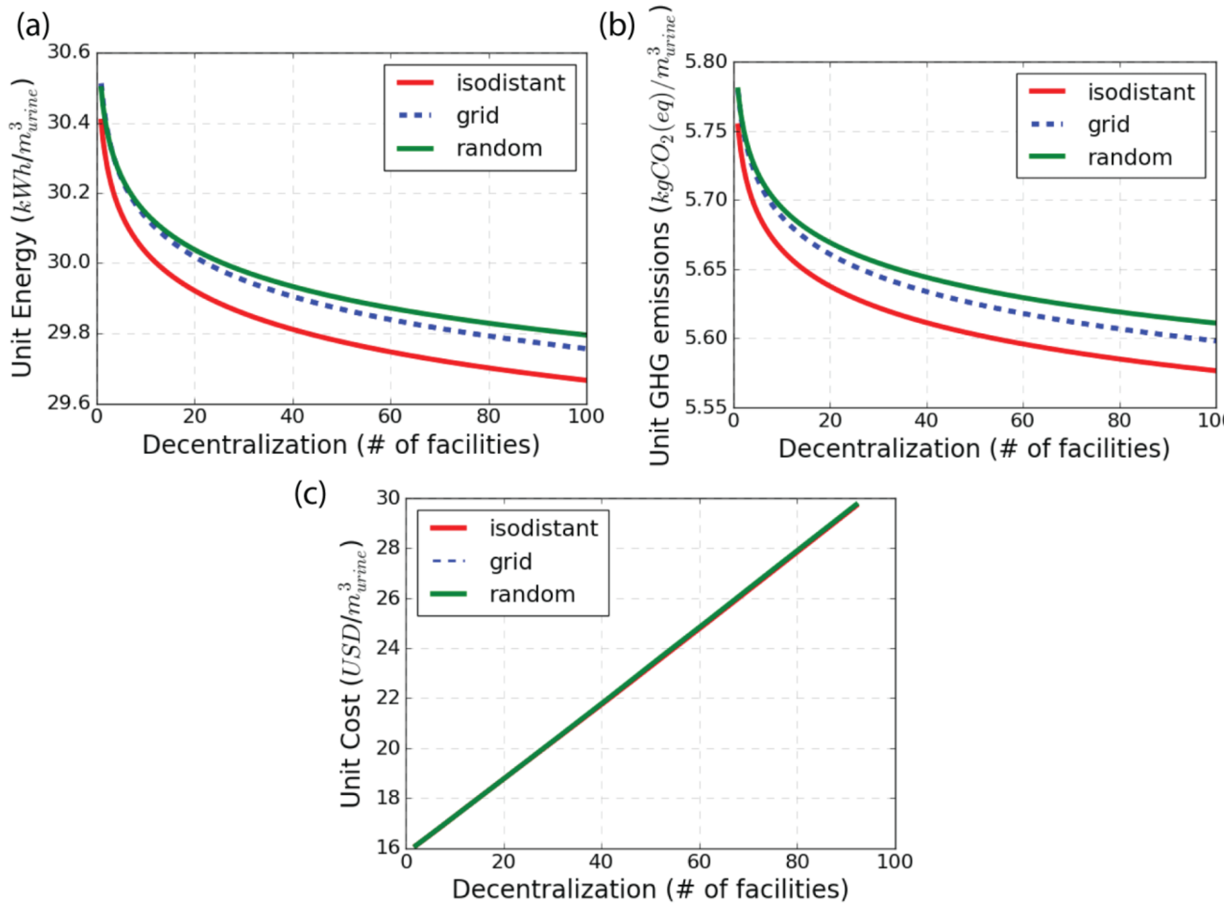


Figure 45: Economies/diseconomies of scale for life-cycle (a) unit energy and (b) unit GHG emissions and (c) unit costs for all 3 logistics scenarios

5.3.3 System Tradeoffs

As energy and GHG emissions decreased with the number of regeneration facilities, whereas costs increased, a globally optimal solution for all three parameters does not exist. However, we can identify tradeoffs for different levels of decentralization (Figure 46). The curve represents the frontier for which it is impossible to decrease one parameter without increasing the other, either energy and cost (Figure 46 a) or GHG and cost (Figure 46 b). By evaluating these frontiers, we can identify at which level of decentralization the marginal benefits of increasing cost to minimize energy intensity become insignificant and thus there is little benefit in continuing to increase the system cost.

Due to the shape of the curve for low levels of decentralization, more regeneration facilities increase the unit cost but enable the energy/GHG intensity to decrease at a higher rate. On the other hand, at high levels of decentralization the same increase in cost results in a lower unit decrease of the energy/GHG intensity. By increasing the number of facilities from 1 to 40 we identified the greatest energy (2% decrease) and GHG (3% decrease) benefits with a cost increase of 37%. Further increasing the facilities number to 100 only led to additional gains of 0.5% for energy and 0.7% for GHG with an added cost increase of 37%. In both cases, the changes in energy and GHG intensity are small and within the uncertainty of our analysis; thus, it is appropriate to make decisions on the number and location of regeneration facilities based on cost alone. However, we note that the influence of the level of decentralization on energy and GHGs could be larger if the acid and resin impacts are further reduced by future technology development. The analysis demonstrates how, depending on stakeholders' motivations and goals, Figure 46 can provide insight to the best local planning scenario by evaluating the tradeoffs between energy, GHG and cost based on weighted importance by decision makers.

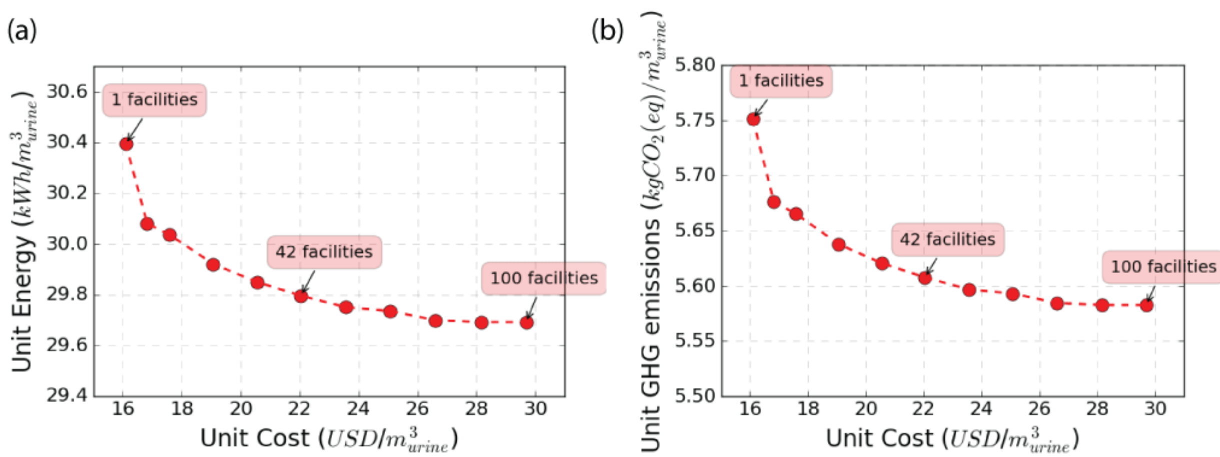


Figure 46: Tradeoff analysis for (a) energy - cost and (b) GHG-cost for different number of regeneration facilities.

5.3.4 Uncertainty

To estimate the uncertainty of the analysis we performed a Monte Carlo simulation to identify the margins of error due to the uncertainty in all the parameter values. We estimated the possible ranges of parameter values and ran 10,000 simulations to calculate the distribution of the results for energy, GHG emissions and cost, shown in Figure 47. The uncertainty of the model parameters was modeled as a uniform probability distribution. The results of the Monte Carlo simulation present a normal distribution of the probability density function of the potential results. We included the standard deviation as error bars in our analysis to show the potential uncertainty ranges (Figure 44).

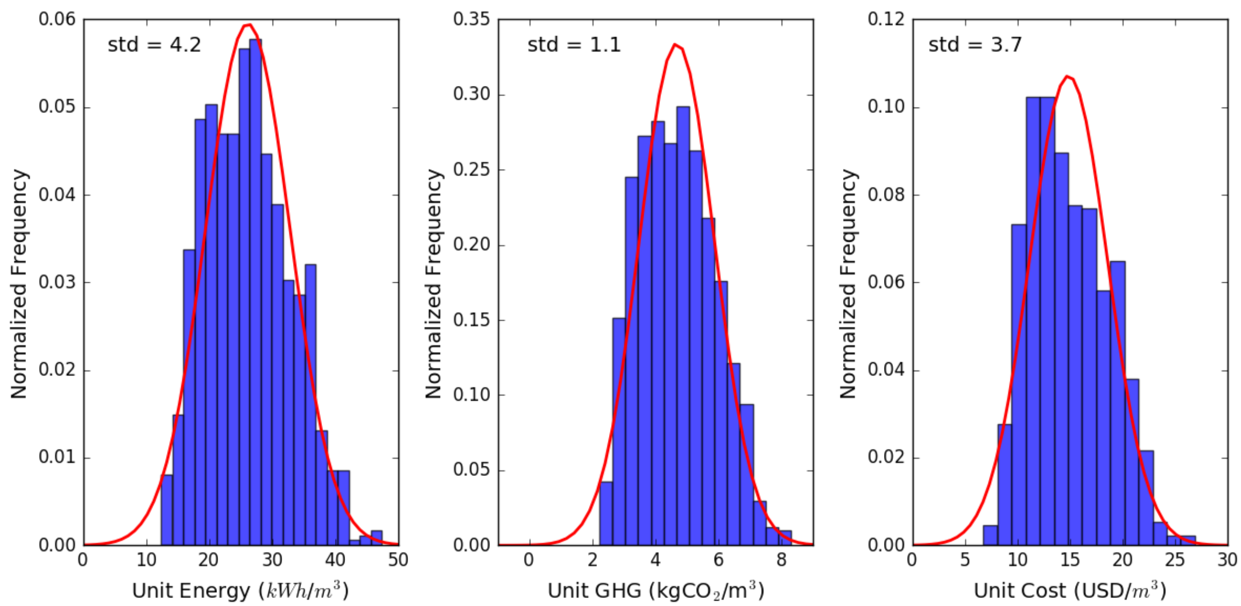


Figure 47: Uncertainty results of the Monte Carlo simulation (averaged across all decentralization scenarios)

Common factors between all metrics that affect the overall uncertainty are the urine production rate and the resin adsorption density. Urine production is highly uncertain and can be correlated with dietary habits and local conditions while the adsorption density had a high experimental uncertainty because it varied with urine composition, which differs among individuals and regions. Uncertainty in the acid manufacturing is an important aspect of the overall uncertainty which can be attributed to the limited information in the literature. Better estimation of the overall energy and GHG emissions occurring from the sulfuric acid production could limit the uncertainty range in these metrics significantly. As for cost, most of the uncertainty occurs due to the uncertain rental cost values. Table 4 presents the ranking of the most important parameters out of the 59 total parameters with respect to its contribution to the model variability. Each parameter was perturbed independently inside the bounds of its uncertainty ranges presented in Table S - 8 in the Appendix 3. Table 4 presents the relative impact of each parameter to the model output, which characterizes its economic and environmental importance. The higher the impact of the parameter on the output it demonstrates a larger influence on the model variability.

Table 4: Parameter contribution to variance

Parameter	Energy / GHG	Cost
Urine production	30 %	45 %
Sulfuric acid manufacturing	29 %	8.5 %
Adsorption density	27 %	23 %
Resin lifetime	5 %	4 %
Facility cost	-	30 %

5.4 Discussion

Adoption of new technologies requires a holistic assessment of their economic and environmental implications and careful planning during their implementation. For decentralized technologies, supply chain management impacts can be significant and should be modeled in detail. Although decisions are usually based on economic efficiency, pressing climate change issues have increased the importance of planning to minimize energy use and GHG emissions to meet GHG reduction targets, such as the California emissions target of 40% GHG emissions reduction relative to 1990 levels by 2030.[46] This work identified opportunities to minimize the economic and environmental impacts by seeking multi-objective optimal solutions and identifying the most important process steps that contribute to energy, GHG and system cost.

5.4.1 Optimization

The supply chain impacts of decentralized nitrogen management are spatially sensitive and can only be captured with detailed spatial modeling. As presented in this work, in dense urban settings such as San Francisco, the facility location did not have a significant impact on the economic and environmental metrics assessed as the different location scenarios only altered the results by ~1.5%. Another important finding was that the level of decentralization did not have a large impact on the energy intensity (up to 3% change) or GHG emissions (up 4% change), but had a large impact on cost (up to 45% change). Thus, in this specific case study, we learned that planning decisions based on cost are unlikely to significantly increase energy or GHG emissions; this is a very useful outcome for decision makers. The analysis approach we used demonstrates how optimal decisions can be made through multi-objective analysis to identify trade-offs.

Based on the contributions of each process step to key metrics (Figure 44), several opportunities for further optimization remain. For example, sulfuric acid manufacturing was a significant source of energy demand and GHG emissions; alternative regenerants could decrease the impacts of the household ion exchange process, especially a waste product from another industrial process. For comparison, we analyzed nitric acid, hydrochloric acid and sodium chloride to investigate their performance with respect to energy, GHG and cost. Only sodium chloride was found to have lower impacts; the reductions in unit energy, GHG emissions, and cost were found to be 50%, 40%, and 17%, compared to sulfuric acid, respectively (see Section 5.2.7). We estimate that the use of sodium chloride would increase the total dissolved solids (TDS) of municipal wastewater by around 25% (see Section 5.2.7). If the treated wastewater effluent is discharged to an estuary or ocean, the TDS increase may be acceptable. However, if the water is reused and the treatment train does not involve salt removal (e.g. reverse osmosis), the TDS increase is likely to be undesirable. The use of nitric acid appears attractive because the nitrate is more beneficial than sulfate in the fertilizer product; however, the life-cycle unit energy and GHG emissions for nitric acid are several times larger than sulfuric acid.

Operating trucks at full capacity is another consideration for optimization. Given our calculations, the truck collection system in this study was time constrained (assuming 8 h days) and not capacity constrained. This implies that trucks were not operating at full capacity; load-sharing with other industries could further reduce life-cycle impacts.[66] It is also important to point out that the reason that the facility location had minimal impact on the energy, GHG emissions and cost is because the collection management assumption was a TSP problem, with trucks following an optimal route to collect the cartridges. If the problem was set up such that every building transported its own cartridge to the regeneration facility, then the impact of facility location would have been much more significant.

5.4.2 Comparison with urine transport

The premise of utilizing ion exchange to concentrate nitrogen at toilets was to reduce the volume for trucking and storage of the urine itself. For comparison, we also evaluated collection of untreated urine for application as fertilizer to determine the impact on the metrics of interest (energy, GHG emissions, and cost). These scenarios have the benefit of avoiding any impacts due to the materials for concentrating the nitrogen but involves challenges for handling large volumes of urine both at the household level as well as the collection facility level.

In the first scenario, we assumed that urine from households was collected once a week and trucked to a centralized urine collection facility where it could be distributed to farmers. This scenario had minimal energy and GHG impacts but involved significant costs for renting a facility large enough to store a week's worth of urine before it gets collected for reuse (Figure 48a). The facilities needed to be large enough to store a week's worth of urine as it would be extremely optimistic to think that the urine would be so efficiently managed that it could be transported to the farmers right away. In the second scenario, we evaluated collecting the urine daily from households, which would require the same volume as the resin cartridges and not burden the households with storing large amounts of urine. The transportation impacts of this scenario are significantly larger for all metrics assessed (Figure 48b).

Although urine collection would involve minimal processing and would not have significant material impacts, the challenge presented is the storage and transportation of the large volume of urine for the same mass of nitrogen. With ion exchange, the nitrogen from the urine produced in one week is captured in a single cartridge, which results in a volume reduction of approximately 88%. As a result, the volume of material that needs to be transported is reduced, as well as the frequency of collection. In addition, the cost for renting a facility large enough to store a week's worth of urine is significantly larger. Because storing a week's worth of urine at the building level before collection may be socially untenable, we also modeled a scenario in which the urine is collected every day. In this scenario, the transportation impacts were significantly larger than the overall impacts of ion exchange (Figure 48). Our analysis did not consider the impacts of trucking the fertilizer product or urine from the central facility in the city to the farms where it would actually be used. If this distance is significant, the impacts from trucking urine would be much greater than the fertilizer product.

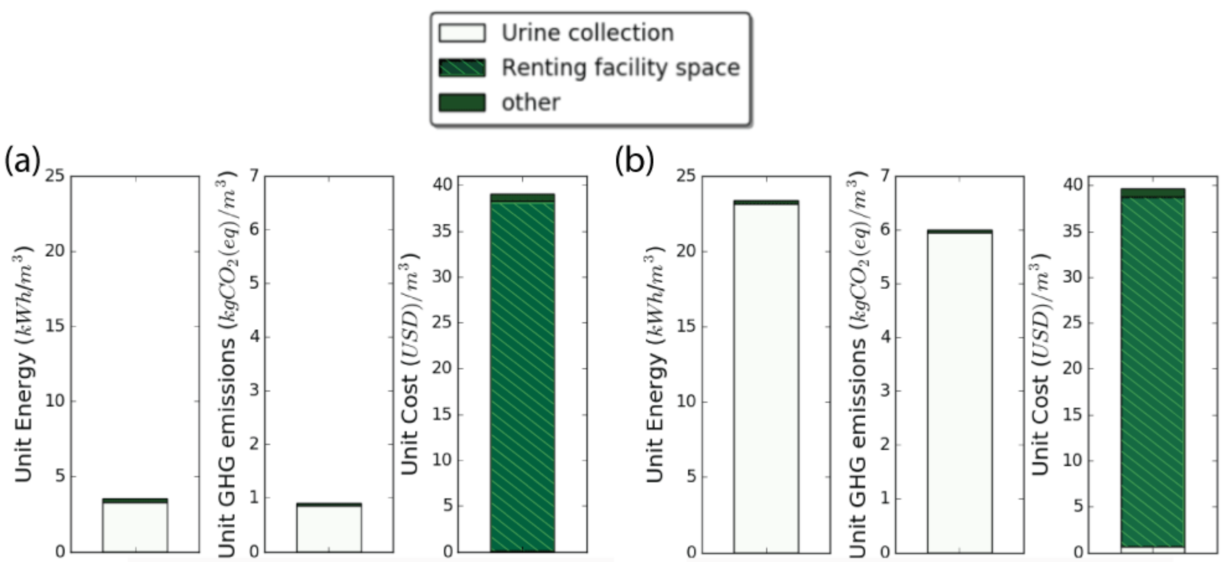


Figure 48: Urine collection scenario – (a) Once a week (b) Everyday

5.4.3 Further Research

In addition to demonstrating the promise of household ion exchange for nitrogen recovery from urine, the environmental and economic assessment in this study has spurred additional fundamental research questions. Given the dominant influence of acid and resin manufacturing on all performance metrics, more research is needed to reduce the uncertainty associated with these steps. It needs to be confirmed that stoichiometric exchange is possible, as well as the number of times the resin can be regenerated without losing adsorption capacity. Also, new technological approaches should be explored that could improve performance beyond the ranges evaluated in our analysis. For example, as mentioned above, perhaps an acidic waste stream from another process could be utilized for regeneration. Alternative technologies that would not require a chemical regenerant at all could be explored, such as electrically regenerated ion exchange. We also assumed that urea hydrolysis could occur to an appreciable extent within one day of storage in an equalization tank. Although this rate of conversion of urea to ammonium has been observed in several real-world systems, more research is needed to identify approaches that consistently achieve rapid urea hydrolysis in urine diversion systems.

Another source of uncertainty in the GHG emissions that was not addressed is the potential for biological nitrification facilitated by the high ammonium concentrations on the adsorbent, especially with a storage period of one week between collection and regeneration. Incomplete nitrification or denitrification could lead to emissions of N_2O and loss of the ammonia product. This biological mechanism has been observed and optimized for removal of nitrogen from wastewater using zeolite columns;[180] further research is needed to determine if it spontaneously occurs under the conditions outlined in this study. Based on the inhibition of nitrification due to high total ammonia concentrations in urine,[181] and the weekly regeneration with strong acid, we do not expect significant biological nitrification in the cartridges. Other potential questions for future work include the fate of other urine constituents during ion exchange (e.g., trace organic contaminants, metals) and the effects of urine-derived fertilizers on plant growth.

More research is needed to investigate the feasibility of decentralized nitrogen management in high-rise buildings. This study assumed that the nitrogen recovery technology would be implemented at the toilet level. However, in a multi-story building it may make more sense to collect urine in the basement of each building, with a single large ion exchange column and onsite regeneration. Although this configuration would reduce transportation impacts, it raises other challenges, including extra premise piping for the source-separated urine and more decentralized monitoring and management to provide all the required inputs for the recovery process at the building level. This approach also has practical challenges, such as passive ammonia stripping in pipes with intermittent flows.[182]

Although outside of the scope of this work, social acceptance is key for the successful introduction of a new management system like that proposed herein. People may be unwilling or unable to correctly remove and install replacement cartridges. Alternatively, using trained personnel to perform this task would require them to enter peoples' homes to collect the cartridges, which would raise privacy concerns. These are only a few examples of the complex issue of social acceptance that need to be investigated now that we have identified that nitrogen recovery via household ion exchange is a promising alternative to centralized nitrogen management.

We used San Francisco as a case study because different options for reducing nutrient discharges from wastewater are currently being evaluated there, and because we could find the data required for characterizing the household ion exchange process (e.g. population density, building locations, geospatial data). The results are broadly relevant to other similar urban settings. Alternatively, the analysis can be conducted for other locations using site-specific data on population density and distribution, rental costs, urine volumes, and composition. The modeling approach could also be used to explore other scenarios, such as higher or lower adoption rates than the 50% assumed for this study (40-80% in the uncertainty analysis). Future work could adapt our analysis to non-sewered areas, such as individual septic tanks facing effluent nitrogen limits or urban slums that rely on container-based sanitation. Also, the last-mile logistics modeling and use of geospatial data could be adapted to model the life-cycle impacts for other decentralized nutrient recovery technologies, implementation schemes, and for the collection and treatment of septage or fecal sludge.

This work adds to the growing literature on resource recovery from wastewater and the potential for source-separation and decentralized approaches to improve the sustainability of wastewater management. While there is still much uncertainty surrounding the technical and social feasibility of the approach presented herein, our results suggest that further development is warranted. The findings can be used to encourage consideration of alternate strategies by policymakers and wastewater agencies responding to stricter nitrogen effluent controls.

Chapter 6.

Conclusions

6.1 Summary of Outcomes

The goal of this study was to adopt a systems approach when assessing non-potable water reuse and nitrogen recovery and to propose generalizable frameworks for decision-making support. The central hypothesis guiding this research was that context and scale impact the economic and environmental sustainability of water and wastewater systems and optimal decisions should be based on advanced spatial planning to holistically assess the implementation potential. Previous research focused on technology development and site-specific assessments of one possible scale. This research examined the optimal system scale and applied advanced spatial modeling and life-cycle assessment to provide a methodology for assessing the economic and environmental implications of resource recovery, focused on water reuse and nitrogen recovery. Understanding the site-specific characteristics and identifying the infrastructure impacts of a specific setting is of high importance and significantly increases the accuracy of the assessments rather than using average values that do not apply to the actual conditions.

Chapter 3 explored the difference between centralized and decentralized non-potable water reuse, from a life-cycle perspective. It identified the critical parameters that affect the energy intensity and GHG emissions of both types of reuse. Decentralized and centralized options were explored for the same context area and various options were assessed to identify at which locations decentralized systems would achieve environmental advantages over centralized alternatives. This chapter illustrates the significance of the water distribution effects and highlights the importance of detailed modeling of the site specific spatial conditions on the environmental metrics. Treatment operational energy was found to have the largest environmental footprint in decentralized systems but is also characterized by huge economies of scale (modeled after MBRs). This illustrates the importance of investing effort in increasing the energy efficiency of these systems to make small scale treatment systems competitive. Technologies that are energy efficient in their operation in decentralized systems can push the industry to more decentralized approaches that promote the use of local sources and decrease the conveyance requirements. Piping and pumping infrastructure have lower environmental impacts than the treatment operation but can become significant in centralized infrastructure options where the wastewater treatment plant is located miles from the point of demand and with steep inclines.

Chapter 4 introduced a deeper dive into decentralization for non-potable water reuse with a strong focus on system scale. The goal of this chapter was to increase the resolution of water reuse implementation down to the building scale. It assessed the economic and environmental impacts of decentralized water reuse by identifying the tradeoffs between various levels of connected buildings. The framework developed in this chapter was based on a heuristic modeling using geospatial algorithms to determine the optimal degree of decentralization. A decision support tool was developed to assess and visualize alternative non-potable water reuse system designs considering topography, economies of scale and building size. This chapter highlights the significance of site-specific modeling and the impact of location specific characteristics. Decentralized water reuse is highly sensitive to local characteristics and its impacts can only be realistically assessed if high resolution local data are used. Building characteristics such as number of floors and population can significantly affect the impacts of water reuse infrastructure. By developing a high-resolution assessment tool, the location specific optimal decentralization scale could be identified.

Chapter 5 addresses the practice of resource recovery, specifically for nitrogen. As nitrogen standards for discharge of wastewater effluent into aquatic bodies are becoming more stringent, treatment plants are required to reduce effluent nitrogen concentrations. This chapter assessed, from a life-cycle perspective, an innovative decentralized approach to nitrogen recovery: ion exchange of source-separated urine. To provide insight into how this decentralized technology would be implemented, the traditional economic and environmental assessment approach was enhanced by combining spatial analysis, system-scale evaluation and detailed last-mile logistics modeling. This work illustrated that in dense urban areas the facility location is not an important parameter and does significantly affect the system performance. The level of decentralization of the nitrogen recovery system also did not have a significant effect on the environmental impacts. However, it was an important parameter of the economic cost, as cost increased with increases in decentralization because of the added rental costs for the facility spaces. This work highlighted the importance of identifying the tradeoffs between technology requirements and system logistics, to minimize economic and environmental impacts.

6.2 Research Contributions

Leveraging the current trend of data-driven development, water and wastewater utilities are becoming better at measuring, estimating and predicting water demands and patterns. This is a significant first step to reaching a closed-loop management system, where resources can be reused in an efficient and effective way through improved estimation and planning tools. This research contributes towards a practical implementation of water reuse and nitrogen recovery by developing frameworks and tools for effectively assessing these options in real-world settings. The main contributions of this work include:

- *Identifying the parameters that affect the economic and environmental impacts of water reuse and nitrogen recovery*. This is an important contribution towards the academic and professional world as it identifies the key factors that should be taken into consideration when investigating different options. It also educates future research by highlighting the parameters that should be investigated in depth to increase the efficiency of the systems.

- *Quantifying economies of scale for non-potable water reuse treatment*. This research quantified the operating performance of MBR technology for water reuse systems which enables the understanding of the effect of scale in practical implementations. It identified the non-linear relationship between system scale and treatment energy consumption which affects the overall economic and environmental impacts of water reuse systems. This information is rarely collected and published. By quantifying its importance through this research, maybe others will be motivated to collect this data and push the entire sector towards more energy efficient approaches.

- *Quantifying site-specific factors for water distribution in non-potable water reuse*. Water reuse is highly influenced by spatial and topographical characteristics of an area. This research managed to develop a framework for quantifying the impact of topography, population density and building characteristics to accurately assess the impacts of water reuse implementation. It showed the importance of combining advanced spatial modeling in holistically assessing the economic and environmental impacts of water reuse given a specific setting rather than using average values that most likely do not apply to the conditions in question.

- *Designing generalizable frameworks and models for decision support.* This research designed and developed generalizable methods for assessing the tradeoffs between the treatment scale and distribution effects. The frameworks and models developed are agnostic to a specific setting but can be applied anywhere to assess the location specific parameters and identify optimal implementation strategies. This is critical to ensure applicability of the described methods and to enable scenario development and consistent assessment approaches.

- *Integrating technical, economic and environmental assessment of water reuse and nitrogen recovery.* The work presented here characterizes the economic and environmental impacts associated with water reuse and decentralized nitrogen management. These quantitative assessments enable decision makers to realize the holistic effects of implementation of these strategies. By identifying the percent contributions of each parameter to the overall impact, it provides academics and technologists with an insight on the aspects that should be researched more in-depth to achieve better overall efficiencies.

- *Assessing technology diffusion for nitrogen recovery.* A major contribution of this research is unpacking the real-world issues that influence implementation and developing methods for assessing the impacts of a full-scale technology. It starts from understanding the theory behind a technology and then extending this knowledge to understand the implementation impacts. Such information can then be used to think through the real-world implementation challenges. This concerns translating laboratory results from lab-scale technologies to field applications and modeling of the logistics that are required in an implemented system. Unfortunately, building the technology is insufficient, a more holistic assessment way on how it would be implemented and managed in a real-world situation. This research tries to combine operations research methods and logistics to understand the impacts of a system management and assess the economic and environmental issues more comprehensively.

The specific applications that are presented in this research in Chapter 3 and 4 for water reuse and Chapter 5 for nitrogen recovery serve as a "proof-of-concept." Similar analyses are possible, and the assessment frameworks developed are readily implementable with the appropriate data available. But most importantly the work shows that these examples are developed based on a general framework which is agnostic to the specific conditions modeled and can be implemented in various settings. It is the hope of the author that data-driven development and planning support tools for optimal implementation will continue to be studied and adopted in practice.

6.3 Future Work

While this research made a lot of progress in exploring the importance of data driven development in planning and decision-making, there are aspects that need further research and more modeling techniques to be explored.

This researched focused on developing algorithmic models for scenario development to assess the impacts of decentralization for the water/wastewater industry. Centralized infrastructure, though perceived as more reliable and with benefits of economies of scale, presents barriers for some applications such as non-potable water reuse and source separation as large scale dual-distribution systems can be costly and disruptive to implement in dense urban areas.[92] Decentralized infrastructure allows for a flexible, incremental approach for system expansion with uncertain growth patterns. Although important, these societal impacts were not considered in comparing the two systems. There are several metrics that are hard to quantify but could benefit decentralized infrastructure ranging from community engagement to societal, behavioral and aesthetical. On the other hand, even though decentralized systems could potentially be proven economical and environmentally beneficial, there are societal impacts that might provide friction in their implementation. Social acceptance is a major issue in integrating decentralized systems into people's lives and a barrier that needs to be overcome. Identifying ways to include these unquantifiable metrics into the assessment could potentially tip the cost-benefit scale towards different planning alternatives.

More research is required in the technology side. There exist large potential for new innovations to enable lower energy requirements or even be energy positive.[82,93] Although research on lab and pilot scale systems is promising, more work is needed to characterize how the technologies performance once integrated into complete treatment trains and deployed in actual installations. Tracking and releasing measured performance data for a wide variety of technologies and scales will be crucial in developing and improving future systems. Understanding the parameters behind treatment scale performance and how to accurately assess the same technology in different scales is critical to optimal planning. Increasing treatment energy and resource efficiency as well as optimizing the system's operating scale could improve the performance of decentralized systems.

Uncertainty in these types of analysis is a critical part. More research is needed to reduce uncertainties in the analysis, particularly related to treatment process energy use at various scales- and how it may change over time with advances in treatment technology and direct GHG emissions. Empirical performance data on how wastewater reuse technologies perform in full scale implementations are rare and difficult to find. Especially focusing on decentralized systems, where the systems' scale is small, performance metrics are even more dispersed in the literature. The results of this study are based on several assumptions for the treatment performance that could be improved if monitoring data were available for actual installations of small-scale treatment technologies.

On a similar note, this research made considerable progress in identifying important parameters in the economic and environmental assessment of different systems. This knowledge needs to be disseminated and applied towards educating future research on which areas are low hanging fruit for increased performance. By focusing on the aspects of the system that contribute the most to energy, GHG emissions or cost, more efficient and effective technologies can be developed to serve the purpose of decentralized systems.

An interesting extension to this work would be to investigate the connections between urban form and water reuse systems design performance. This research focused on assessing the current urban form and the distribution system that would be required to serve it. However, we can imagine a future where the urban form could inform future research directions of the energy use of water supply.[183] Changing the urban form and developing different distribution network configurations could potentially increase the attractiveness of water reuse systems and lead to more sustainable cities. A future assessment could examine the links between the population distribution, street network design and water reuse systems and identify options that would benefit the overall system performance.

Finally, this research focused on quantifying decentralized systems performance on several metrics, namely economic cost, energy intensity and GHG emissions. Integrating different metrics and understanding their interconnections and interactions can be extremely valuable to optimal decision-making. Multiparameter assessments multicriterial decision making should be prioritized. An example could be using marginal abatement curves. Using the GHG savings one can produce GHG marginal abatement curves, which can be used to make comparisons between different options and technologies. GHG marginal abatement curves plot the marginal unit cost of producing output against the system's ability to abate GHGs. When ranked based on cost, these curves can show which strategies offer low hanging fruit for saving GHG emissions in the most cost-effective way. This analysis can provide an extra dimension to this research and help assess the different alternatives in a systematic way.

References

(1) Roy, S. B.; Chen, L.; Girvetz, E. H.; Maurer, E. P.; Mills, W. B.; Grieb, T. M. Projecting Water Withdrawal and Supply for Future Decades in the U.S. under Climate Change Scenarios. *Environ. Sci. Technol.* **2012**, *46* (5), 2545–2556.

(2) U.S.EPA. *Energy Efficiency in Water and Wastewater Facilities*; Washigton, DC, 2014.

(3) California Air Resources Board. *California Greenhouse Gas Emission Inventory: 2000-2012*; 2014.

(4) California Public Utilities Commission. *Embedded Energy in Water Studies Study 1: Statewide and Regional Water-Energy Relationship*; Sacramento, CA, 2010.

(5) Office of Governor. *EXECUTIVE ORDER S-03-05*; Sacramento, CA, 2005.

(6) State of California. *California Water Action Plan*; Sacramento, CA, 2016.

(7) Horvath, A. .; Stokes, R. J. *Life-Cycle Energy Assessment of Alternative Water Supply Systems in California: Extensions and Refinements*; 2011.

(8) Natural Resources Defence Council. *The Untapped Potential of California's Water Supply: Efficiency, Reuse, and Stormwater*; 2014.

(9) Guo, T.; Englehardt, J.; Wu, T. Review of Cost versus Scale: Water and Wastewater Treatment and Reuse Processes. *Water Sci. Technol.* **2014**, *69* (2), 223.

(10) Newman, J.; Dandy, G.; Maier, H. Multiobjective Optimization of Cluster Scale Urban Water Systems Investigating Alternative Water Sources and Level of Decentralization. *Water Resour. Res.* **2014**, No. 1, 7206–7230.

(11) NASA. Socioeconomic data and applications center http://sedac.ciesin.columbia.edu/theme/population?main.html&2 (accessed Jan 1, 2017).

(12) United Nations. *World Urbanization Prospects: The 2014 Revision*; New York, 2014.

(13) Major, D. C.; Omojola, A.; Dettinger, M.; Hanson, R. T.; Sanchez-Rodriguez, R. *Climate Change, Water, and Wastewater in Cities*, Climate Ch.; Rosenzweig, C. ., Solecki, D. W. ., Hammer, S. A. ., Mehrotra, S., Eds.; Cambridge University Press: Cambridge, UK, 2011.

(14) Rygaard, M.; Binning, P. J.; Albrechtsen, H.-J. Increasing Urban Water Self-Sufficiency: New Era, New Challenges. *J. Environ. Manage.* **2011**, *92* (1), 185–194.

(15) State Water Resources Control Board. *Policy for Water Quality Control for Recycled Water (Recycled Water Policy)*; Sacramento, CA, 2013.

(16) Cornejo, P. K. Environmental Sustainability of Wastewater Treatment Plants Integrated with Resource Recovery: The Impact of Context and Scale, University of South Florida, 2015.

(17) Intergovernmental Panel on Climate Change (IPCC). *Summary for Policymakers*; Cambridge, United Kingdom and New York, NY, USA., 2014.

(18) Makropoulos, C. K.; Butler, D. Distributed Water Infrastructure for Sustainable Communities. *Water Resour. Manag.* **2010**, *24* (11), 2795–2816.

(19) Goldstein, R.; Smith, W. *Water and Sustainability (Volume 4): U.S. Electricity Consumption for Water Supply and Treatment - The Next Half Century*; Technical Report No. 1006787, 2002.

(20) Department of Water Resources. Water-Energy Nexus: State Water Project http://www.water.ca.gov/climatechange/WaterEnergyNexusSWP.cfm (accessed Jan 1, 2017).

(21) Johnson Foundation at Wingspread. *Optimizing the Structure and Scale of Urban Water Infrastructure: Integrating Distributed Systems*; The Johnson Foundation at Wingspread: Racine, WI, 2014.

(22) Gikas, P.; Tchobanoglous, G. The Role of Satellite and Decentralized Strategies in Water Resources Management. *J. Environ. Manage.* **2009**, *90* (1), 144–152.

(23) San Francisco Water Power Sewer. *San Francisco's Non-Potable Water Program*; City and County of San Francisco, 2015.

(24) San Francisco Public Utilities Commission. *BLUEPRINT for Onsite Water Systems*; San Francisco, CA, 2014.

(25) Smith, S. V; Hollibaugh, J. T. Water, Salt, and Nutrient Exchanges in San Francisco Bay. *Limnol. Oceanogr.* **2006**, *51* (1), 504–517.

(26) Harris-Lovett, S. Water Infrastructure in the Face of Uncertainty: An Integrative Approach to Nitrogen Management in the San Francisco Bay Estuary, University of California, Berkeley: Berkeley, CA, 2013.

(27) Galloway, J. N.; Winiwarter, W.; Leip, A.; Leach, A. M.; Bleeker, A.; Erisman, J. W. Nitrogen Footprints: Past, Present and Future. *Environ. Res. Lett.* **2014**, *9* (11), 115003.

(28) Jönsson et al. Composition of Urine , Faeces , Greywater and Biowaste. *Urban Water ,Chalmers Univ. Technol.* **2005**, *6* (June, 2005, Gothenburg), 21–32.

(29) Larsen, T. A.; Udert, K. M.; Lienert, J. *Source Separation and Decentralization for Wastewater Management*; IWA Publishing, 2013.

(30) McKee, L.; Sutula, M.; Gilbreath, A.; Beagle, J.; Gluchowski, D.; Hunt, J. Numeric Nutrient Endpoint Development for San Francisco Bay Estuary: Literature Review and Data Gap Analysis. *South. Calif. Coast. Water Res. Proj.* **2011**, *Research R* (644).

(31) Tarpeh, W. A.; Udert, K. M.; Nelson, K. L. Comparing Ion Exchange Adsorbents for Nitrogen Recovery from Source-Separated Urine. *Environ. Sci. Technol.* **2017**, *51* (4), 2373–2381.

(32) Finkbeiner, M.; Inaba, A.; Tan, R.; Christiansen, K.; Klüppel, H.-J. The New International Standards for Life Cycle Assessment: ISO 14040 and ISO 14044. *Int. J. Life Cycle Assess.* **2006**, *11* (2), 80–85.

(33) Norris, G. a. Integrating Life Cycle Cost Analysis and LCA. *Int. J. Life Cycle Assess.* **2001**, *6* (2), 118–120.

(34) Stokes, J. R.; Horvath, A. Supply-Chain Environmental Effects of Wastewater Utilities. *Environ. Res. Lett.* **2010**, *5* (1), 14015.

(35) Hendrickson, T. P.; Horvath, A. A Perspective on Cost-Effectiveness of Greenhouse Gas Reduction Solutions in Water Distribution Systems. *Environ. Res. Lett.* **2014**, *9* (2), 24017.

(36) Piratla, K. R.; Ariaratnam, S. T.; Cohen, A. Estimation of CO2 Emissions from the Life Cycle of a Potable Water Pipeline Project. *J. Manag. Eng.* **2012**, *28* (1), 22–30.

(37) Du, F.; Woods, G.; Kang, D. Life Cycle Analysis for Water and Wastewater Pipe Materials. *J. Environ. Eng.* **2012**, No. May, 703–711.

(38) Lundie, S.; Peters, G. M.; Beavis, P. C. Life Cycle Assessment for Sustainable Metropolitan Water Systems Planning. *Environ. Sci. Technol.* **2004**, *38* (13), 3465–3473.

(39) Stokes, J.; Horvath, A. Life-Cycle Assessment of Urban Water Provision: Tool and Case Study in California. *J. Infrastruct. Syst.* **2011**, No. December, 395–408.

(40) Friedrich, E. Life-Cycle Assessment as an Environmental Management Tool in the Production of Potable Water. *Water Sci. Technol.* **2002**, *46* (9), 29–36.

(41) Vigon, B. *Life Cycle Assessment: Inventory Guidelines and Principles*; US Environmental Protection Agency: Cincinnati, Ohio, 1993.

(42) Hendrickson, C.; Horvath, A.; Joshi, S.; Lave, L. Economic Input-Output Models for Environmental Life-Cycle Assessment. *Environ. Sci. Technol.* **1998**, *32* (7).

(43) Suh, S. Critical Review System Boundary Selection in Life-Cycle Inventories Using Hybrid Approaches. *Environ. Sci. Technol.* **2004**, *38* (3), 657–664.

(44) Ye, X.; Konduri, K.; Pendyala, R. M.; Sana, B.; Waddel, P. A Methodology to Match Distributions of Both Household and Person Attributes in the Generation of Synthetic Populations. *88th Annu. Meet. Transp. Res. Board* **2011**, *9600* (206), 1–25.

(45) Boulware, B. *Alternative Water Sources and Wastewater Management*; McGraw Hill Professional: New York, 2012.

(46) Legislative Counsel Bureau. *SB-32 California Global Warming Solutions Act of 2006: Emissions Limit.*; Legislative Counsel Bureau: Sacramento, California, 2016.

(47) National Research Council. *Water Reuse : Expanding the Nation's Water Supply Through Reuse of Municipal Wastewater Understanding the Risks*; National Academy of Sciences: Washington, DC, 2011.

(48) Woods, G.; Kang, D. Centralized versus Decentralized Wastewater Reclamation in the Houghton Area of Tucson, Arizona. *J. Water Resour. Plan. Manag.* **2012**, *139* (3), 313–324.

(49) Cornejo, P. K.; Zhang, Q.; Mihelcic, J. R. How Does Scale of Implementation Impact the Environmental Sustainability of Wastewater Treatment Integrated with Resource Recovery? *Environ. Sci. Technol.* **2016**, *50* (13), 6680–6689.

(50) Stillwell, A.; Twomey, K.; Osborne, R.; Greene, D.; Pedersen, D.; Webber, M. An Integrated Energy, Carbon, Water, and Economic Analysis of Reclaimed Water Use in Urban Settings: A Case Study of Austin, Texas. *J. Water Reuse Desalin.* **2011**, *1* (4), 208–223.

(51) Daigger, G. T. Evolving Urban Water and Residuals Management Paradigms: Water Reclamation and Reuse, Decentralization, and Resource Recovery. *Water Environ. Res.* **2009**, *81* (8), 809–823.

(52) Hering, J. G.; Waite, T. D.; Luthy, R. G.; Drewes, J. E.; Sedlak, D. L. A Changing Framework for Urban Water Systems. *Environ. Sci. Technol.* **2013**, *47* (19), 10721–10726.

(53) Bichai, F.; Ryan, H.; Fitzgerald, C.; Williams, K.; Abdelmoteleb, A.; Brotchie, R.; Komatsu, R. Understanding the Role of Alternative Water Supply in an Urban Water Security Strategy: An Analytical Framework for Decision-Making. *Urban Water J.* **2015**, *12* (3), 175–189.

(54) Eggimann, S.; Truffer, B.; Maurer, M. To Connect or Not to Connect? Modelling the Optimal Degree of Centralisation for Wastewater Infrastructures. *Water Res.* **2015**, *84*, 218–231.

(55) Lee, E. J.; Criddle, C. S.; Bobel, P.; Freyberg, D. L. Assessing the Scale of Resource Recovery for Centralized and Satellite Wastewater Treatment. *Environ. Sci. Technol.* **2013**, *47*, 10762–10770.

(56) Guo, T.; Englehardt, J. D. Principles for Scaling of Distributed Direct Potable Water Reuse Systems: A Modeling Study. *Water Res.* **2015**, *75*, 146–163.

(57) Bisinella de Faria, A. B.; Spérandio, M.; Ahmadi, A.; Tiruta-Barna, L. Evaluation of New Alternatives in Wastewater Treatment Plants Based on Dynamic Modelling and Life Cycle Assessment (DM-LCA). *Water Res.* **2015**, *84*, 99–111.

(58) Shehabi, A.; Stokes, J. R.; Horvath, A. Energy and Air Emission Implications of a Decentralized Wastewater System. *Environ. Res. Lett.* **2012**, *7* (2), 24007.

(59) Baresel, C.; Dahlgren, L.; Almemark, M.; Lazic, A. Municipal Wastewater Reclamation for Non Potable Reuse - Environmental Assessments Based on Pilot -Plant Tudies and System Modelling. *Water Sci. Technol.* **2015**, *72* (9), 1635–1643.

(60) Hendrickson, T. P.; Nguyen, M. T.; Sukardi, M.; Miot, A.; Horvath, A.; Nelson, K. L. Life-Cycle Energy Use and Greenhouse Gas Emissions of a Building-Scale Wastewater Treatment and Nonpotable Reuse System. *Environ. Sci. Technol.* **2015**, *49* (17), 10303–10311.

(61) City and County of San Francisco. *Ordinance*; Board of Supervisors: San Francisco, 2015.

(62) City and County of San Francisco. SF Open Data https://data.sfgov.org/ (accessed May 1, 2015).

(63) Wu, W.; Simpson, A. R.; Maier, H. R. Accounting for Greenhouse Gas Emissions in Multiobjective Genetic Algorithm Optimization of Water Distribution Systems. *J. water Resour. Plan. Manag.* **2009**, *136* (2), 146–155.

(64) RSMeans. *RSMeans Building Construction Cost Data*, 71st Ed.; LLC Construction Publishers & Consultants: Norwell, MA, 2013.

(65) EIO-LCA. Carnegie Mellon University Green Design Institute http://www.eiolca.net.

(66) Taptich, M. N.; Horvath, A. Bias of Averages in Life-Cycle Footprinting of Infrastructure: Truck and Bus Case Studies. *Environ. Sci. Technol.* **2014**, *44* (22), 13045–13052.

(67) Crites, R.; Tchobanoglous, G. *Small and Decentralized Wastewater Management Systems*; McGraw-Hill, 1998.

(68) Memon, F. a.; Zheng, Z.; Butler, D.; Shirley-Smith, C.; Lui, S.; Makropoulos, C.; Avery, L. Life Cycle Impact Assessment of Greywater Recycling Technologies for New Developments. *Environ. Monit. Assess.* **2007**, *129* (1–3), 27–35.

(69) World Steel Association. *Life Cycle Assessment Methodology Report*; 2011.

(70) Metcalf&Eddy. *Water Reuse Issues, Technologies and Applications*, 4th editio.; McGraw-Hill: New York, NY, 2007.

(71) Liu, S.; Konstantopoulou, F.; Papageorgiou, G. Gikas, P. Optimal Planning of Water and Wastewater Management Infrastructure for Insular Areas: The Role of Water Reuse. *Water Sci. Technol. Water Supply* **2015**, *15* (4), 701.

(72) U.S.EPA. EGRID. *U.S. Environmental Protection Agency*. Washigton, DC 2014, p Version 1.0, 9th .

(73) Nazaroff, W.; Alvarez-Cohen, L. *Environmental Engineering Science*, 6th ed.; Wiley: New York, 2001.

(74) Lee, A. K.; Lewis, D. M.; Ashman, P. J. Energy Requirements and Economic Analysis of a Full-Scale Microbial Flocculation System for Microalgal Harvesting. *Chem. Eng. Res. Des.* **2010**, *88* (8), 988–996.

(75) City & County of San Francisco. *2030 Sewer System Master Plan: Task 100, Technical Memorandum No. 102 - Wastewater Flow & Load Projections*; 2009.

(76) San Francisco Public Utilities Commission. *2010 Urban Water Management Plan for the City and County of San Francisco*; San Francisco, CA, 2011.

(77) Fletcher, H.; Mackley, T.; Judd, S. The Cost of a Package Plant Membrane Bioreactor. *Water Res.* **2007**, *41* (12), 2627–2635.

(78) Englehardt, J. D.; Wu, T.; Tchobanoglous, G. Urban Net-Zero Water Treatment and Mineralization: Experiments, Modeling and Design. *Water Res.* **2013**, *47* (13), 4680–4691.

(79) Prieto, A. L.; Vuono, D.; Holloway, R.; Benecke, J.; Henkel, J.; Cath, T. Y.; Reid, T.; Johnson, L.; Drewes, J. E.; 1NSF; A. L. Prieto; D. Vuono; R. Holloway; J. Benecke; J. Henkel; T. Y. Cath; T. Reid; L. Johnson; J. E. Drewes. Decentralized Wastewater Treatment for Distributed Water Reclamation and Reuse: The Good, the Bad, and the Ugly— Experience from a Case Study. *Nov. Solut. to Water Pollut.* **2014**, *1123*, 251–266.

(80) Judd, S.; Judd, C. *The MBR Book: Principles and Applications of Membrane Bioreactors in Water and Wastewater Treatment*; Elsevier, 2008.

(81) Ortiz, M.; Raluy, R. G.; Serra, L. Life Cycle Assessment of Water Treatment Technologies: Wastewater and Water-Reuse in a Small Town. *Desalination* **2007**, *204* (May 2006), 121–131.

(82) Smith, A. L.; Stadler, L. B.; Cao, L.; Love, N. G.; Raskin, L.; Skerlos, S. J. Navigating Wastewater Energy Recovery Strategies: A Life Cycle Comparison of Anaerobic Membrane Bioreactor and Conventional Treatment Systems with Anaerobic Digestion. *Environ. Sci. Technol.* **2014**, *48* (10), 5972–5981.

(83) Parker, D. S. Introduction of New Process Technology into the Wastewater Treatment Sector. *Water Environ. Res.* **2011**, *83* (6), 483–497.

(84) Intergovernmental Panel on Climate Change (IPCC). *2006 IPCC Guidelines for National Greenhouse Gas Inventories.*; 2006.

(85) Foley, J.; de Haas, D.; Yuan, Z.; Lant, P. Nitrous Oxide Generation in Full-Scale Biological Nutrient Removal Wastewater Treatment Plants. *Water Res.* **2010**, *44* (3), 831–844.

(86) Open Street Map. San Francisco Road Network http://www.openstreetmap.org/ (accessed Feb 10, 2015).

(87) San Francisco Public Utilities Commission Wastewater Enterprise. *Operators Manual*; 2016.

(88) Stokes, J. R. Water-Energy Sustainability Tool (WEST) http://west.berkeley.edu (accessed Nov 5, 2015).

(89) American Legal Publishing Corporation. San Francisco Environment Code http://www.amlegal.com/ (accessed Feb 1, 2016).

(90) Washington State Water Reuse Workgroup. *Pipeline Separation Design and Installation Reference Guide*; 2006.

(91) Buer, T.; Cumin, J. MBR Module Design and Operation. *Desalination* **2010**, *250* (3), 1073–1077.

(92) Leverenz, H. L.; Tchobanoglous, G.; Asano, T. Direct Potable Reuse: A Future Imperative. *J. Water Reuse Desalin.* **2011**, *1* (1), 2.

(93) McCarty, P. L.; Bae, J.; Kim, J. Domestic Wastewater Treatment as a Net Energy Producer - Can This Be Achieved? *Environ. Sci. Technol.* **2011**, *45* (17), 7100–7106.

(94) Bae, J.; Shin, C.; Lee, E.; Kim, J.; McCarty, P. L. Anaerobic Treatment of Low-Strength Wastewater: A Comparison between Single and Staged Anaerobic Fluidized Bed Membrane Bioreactors. *Bioresour. Technol.* **2014**, *165* (C), 75–80.

(95) Shin, C.; McCarty, P. L.; Kim, J.; Bae, J. Pilot-Scale Temperate-Climate Treatment of Domestic Wastewater with a Staged Anaerobic Fluidized Membrane Bioreactor (SAF-MBR). *Bioresour. Technol.* **2014**, *159*, 95–103.

(96) Law, Y.; Ye, L.; Pan, Y.; Yuan, Z. Nitrous Oxide Emissions from Wastewater Treatment Processes. *Philos. Trans. R. Soc. Lond. B. Biol. Sci.* **2012**, *367* (1593), 1265–1277.

(97) Ahn, J. H.; Kim, S.; Park, H.; Rahm, B.; Pagilla, K.; Chandran, K. N2O Emissions from Activated Sludge Processes, 2008-2009: Results of a National Monitoring Survey in the United States. *Environ. Sci. Technol.* **2010**, *44* (12), 4505–4511.

(98) U.S. Environmental Protection Agency (EPA). *Global Anthropogenic Non-CO2 Greenhouse Gas Emissions : 1990 - 2030*; Washington, DC, 2012.

(99) Mannina, G.; Ekama, G.; Caniani, D.; Cosenza, A.; Esposito, G.; Gori, R.; Garrido-Baserba, M.; Rosso, D.; Olsson, G. Greenhouse Gases from Wastewater Treatment — A Review of Modelling Tools. *Sci. Total Environ.* **2016**, *551*, 254–270.

(100) Perez-Garcia, O.; Chandran, K.; Villas-Boas, S. G.; Singhal, N. Assessment of Nitric Oxide (NO) Redox Reactions Contribution to Nitrous Oxide (N2O) Formation during Nitrification Using a Multispecies Metabolic Network Model. *Biotechnol. Bioeng.* **2015**, *113* (5), 1124–1136.

(101) Mannina, G.; Cosenza, A.; Gori, R.; Garrido-baserbac, M.; Sobhani, R.; Rosso, D. Greenhouse Gas Emissions from Wastewater Treatment Plants on a Plantwide Scale : Sensitivity and Uncertainty Analysis. *J. Environ. Eng.* **2012**, *142* (6).

(102) Cornejo, P. K.; Zhang, Q.; Mihelcic, J. R. How Does Scale of Implementation Impact the Environmental Sustainability of Wastewater Treatment Integrated with Resource Recovery? *Environ. Sci. Technol.* **2016**, *50* (13), 6680–6689.

(103) Lundin, M.; Bengtsson, M. Life Cycle Assessment of Wastewater Systems: Influence of System Boundaries and Scale on Calculated Environmental Loads. *Environ. Sci. Technol.* **2000**, *34* (1), 180.

(104) Kavvada, O.; Horvath, A.; Stokes-Draut, J. R.; Hendrickson, T. P.; Eisenstein, W. A.; Nelson, K. L. Assessing Location and Scale of Urban Non-Potable Water Reuse Systems for Life-Cycle Energy Consumption and Greenhouse Gas Emissions. *Environ. Sci. Technol.* **2016**, acs.est.6b02386.

(105) Marlow, D. R.; Moglia, M.; Cook, S.; Beale, D. J.; Land, C.; Road, G. Towards Sustainable Urban Water Management : A Critical Reassessment. *Water Res.* **2013**, *47* (20), 7150–7161.

(106) Maurer, M.; Rothenberger, O.; Larsen, T. A. Decentralised Wastewater Treatment Technologies from a National Perspective: At What Cost Are They Competitive? *Water Sci. Technol. Water Supply* **2005**, *5* (6), 145–154.

(107) Libralato, G.; Volpi Ghirardini, A.; Avezzù, F. To Centralise or to Decentralise: An

Overview of the Most Recent Trends in Wastewater Treatment Management. *J. Environ. Manage.* **2012**, *94* (1), 61–68.

(108) Poustie, M. S.; Deletic, A.; Brown, R. R.; Wong, T.; de Haan, F. J.; Skinner, R. Sustainable Urban Water Futures in Developing Countries: The Centralised, Decentralised or Hybrid Dilemma. *Urban Water J.* **2015**, *12* (7), 543–558.

(109) Eggimann, S.; Mutzner, L.; Wani, O.; Schneider, Y. M.; Spuhler, D.; Moy de Vitry, M.; Beutler, P.; Maurer, M. The Potential of Knowing More: A Review of Data-Driven Urban Water Management. *Environ. Sci. Technol.* **2017**, *51* (5), 2538–2553.

(110) Eggimann, S.; Truffer, B.; Maurer, M. Economies of Density for on-Site Waste Water Treatment. *Water Res.* **2016**, *101*, 476–489.

(111) Hernandez-Sancho, F.; Molinos-Senante, M.; Sala-Garrido, R. Cost Modelling for Wastewater Treatment Processes. *Desalination* **2011**, *268* (1–3), 1–5.

(112) Iglesias, R.; Simón, P.; Moragas, L.; Arce, A.; Rodriguez-Roda, I. Cost Comparison of Full-Scale Water Reclamation Technologies with an Emphasis on Membrane Bioreactors. *Water Sci. Technol.* **2017**, *75* (11), 2562–2570.

(113) Blumensaat, F.; Wolfram, M.; Krebs, P. Sewer Model Development under Minimum Data Requirements. *Environ. Earth Sci.* **2012**, *65* (5), 1427–1437.

(114) Nielsen, S.; Moller, B. GIS Based Analysis of Future District Heating Potential in Denmark. *Energy* **2013**, *57*, 458–468.

(115) Hasik, V.; Anderson, N. E.; Collinge, W. O.; Thiel, C. L.; Khanna, V.; Wirick, J.; Piacentini, R.; Landis, A. E.; Bilec, M. M. Evaluating the Life Cycle Environmental Benefits and Trade-Offs of Water Reuse Systems for Net-Zero Buildings. *Environ. Sci. Technol.* **2017**, *51* (3), 1110–1119.

(116) Bradshaw, J. L.; Luthy, R. G. Modeling and Optimization of Recycled Water Systems to Augment Urban Groundwater Recharge through Underutilized Stormwater Spreading Basins. *Environ. Sci. Technol.* **2017**, *51*, 11809–1181.

(117) Zvoleff, A.; Kocaman, A. S.; Huh, W. T.; Modi, V. The Impact of Geography on Energy Infrastructure Costs. *Energy Policy* **2009**, *37* (10), 4066–4078.

(118) Kocaman, A. S.; Huh, W. T.; Modi, V. Initial Layout of Power Distribution Systems for Rural Electrification: A Heuristic Algorithm for Multilevel Network Design. *Appl. Energy* **2012**, *96*, 302–315.

(119) Cormen, H. T. *Introduction to Algorithms*; Press, M., Ed.; Cambridge, 2009.

(120) Garey, M. R.; Johnson, D. S. *Computers and Intractability*; wh freeman: New York, 2002.

(121) US Census Bureau. Tiger Products https://www.census.gov/geo/maps-data/data/tiger.html (accessed May 6, 2015).

(122) ESRI. ESRI Business Analyst. 2016.

(123) Kavvada, O.; Tarpeh, W. A.; Horvath, A.; Nelson, K. L. Life-Cycle Cost and Environmental Assessment of Decentralized Nitrogen Recovery Using Ion Exchange from Source-Separated Urine through Spatial Modeling. *Environ. Sci. Technol.* **2017**, *51(21), 12061-12071.*

(124) Intergovernmental Panel on Climate Change (IPCC). *Summary for Policymakers. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*; Cambridge University Press: Cambridge, United Kingdom and New York, NY, USA, 2014.

(125) The World Bank. CO2 Emissions per capita https://data.worldbank.org/indicator (accessed Jan 1, 2017).

(126) Department of Water Resources. Water-Energy Nexus http://www.water.ca.gov/climatechange/WaterEnergyStatewide.cfm (accessed Jan 1, 2017).

(127) San Francisco Public Utilities Commission. *Water Resources Division- Annual Report Fiscal Year 2013-2014*; San Francisco, CA, 2014.

(128) Sapkota, M.; Arora, M.; Malano, H.; Moglia, M.; Sharma, A.; George, B.; Pamminger, F. An Overview of Hybrid Water Supply Systems in the Context of Urban Water Management: Challenges and Opportunities. *Water* **2014**, *7* (1), 153–174.

(129) Kemp, W. M.; Boynton, W. R.; Adolf, J. E.; Boesch, D. F.; Boicourt, W. C.; Brush, G.; Cornwell, J. C.; Fisher, T. R.; Glibert, P. M.; Hagy, J. D.; Harding, L. W.; Houde, E. D.; Kimmel, D. G.; Miller, W. D.; Newell, R. I. E.; Roman, M. R.; Smith, E. M.; Stevenson, J. C. Eutrophication of Chesapeake Bay: Historical Trends and Ecological Interactions. *Mar. Ecol. Prog. Ser.* **2005**, *303*, 1–29.

(130) Yun, S.; Gray, D.; Falk, M.; Neethling, J.; Musabyimana, M.; Graham, D.; Dang, J.; Collison, R.; Roa, A. Sidestream Treatment Study for San Francisco Bay Dischargers: A Coordinated Regional Approach to Managing Nutrients. In *Proceedings of the Water Environment Federation*; 2016; pp 4913–4941.

(131) Aissa-Grouz, N.; Garnier, J.; Billen, G.; Mercier, B.; Martinez, A. The Response of River Nitrification to Changes in Wastewater Treatment (The Case of the Lower Seine River Downstream from Paris). *Ann. Limnol. - Int. J. Limnol.* **2015**, *51* (4), 351–364.

(132) Novick, E.; Senn, D. Quantifying External Nutrient Loads to San Francisco Bay. In *State of the San Francisco Estuary Conference*; 2013; p 16000.

(133) Ahn, Y. H. Sustainable Nitrogen Elimination Biotechnologies: A Review. *Process Biochem.* **2006**, *41* (8), 1709–1721.

(134) Oakley, S. M.; Gold, A. J.; Oczkowski, A. J. Nitrogen Control through Decentralized Wastewater Treatment: Process Performance and Alternative Management Strategies. *Ecol. Eng.* **2010**, *36* (11), 1520–1531.

(135) McCray, J. E.; Kirkland, S. L.; Siegrist, R. L.; Thyne, G. D. Model Parameters for Simulating Fate and Transport of on-Site Wastewater Nutrients. *Groundwater* **2005**, *43* (4), 628–639.

(136) Baum, R.; Luh, J.; Bartram, J. Sanitation: A Global Estimate of Sewerage Connections without Treatment and the Resulting Impact on MDG Progress. *Environ. Sci. Technol.* **2013**, *47* (4), 1994–2000.

(137) Başakçilardan-Kabakci, S.; İpekoğlu, A. N.; Talinli, I. Recovery of Ammonia from Human Urine by Stripping and Absorption. *Environ. Eng. Sci.* **2007**, *24* (5), 615–624.

(138) Pronk, W.; Biebow, M.; Boller, M. Electrodialysis for Recovering Salts from a Urine Solution Containing Micropollutants. *Environ. Sci. Technol.* **2006**, *40* (7), 2414–2420.

(139) Udert, K. M.; Wächter, M. Complete Nutrient Recovery from Source-Separated Urine by Nitrification and Distillation. *Water Res.* **2012**, *46* (2), 453–464.

(140) Van Dongen, U.; Jetten, M. S. M.; Van Loosdrecht, M. C. M. The SHARONff-Anammoxff Process for Treatment of Ammonium Rich Wastewater. *Water Sci. Technol.* **2001**, *44* (1),

153–160.

(141) Scherson, Y. D.; Wells, G. F.; Woo, S.-G.; Lee, J.; Park, J.; Cantwell, B. J.; Criddle, C. S. Nitrogen Removal with Energy Recovery through N2O Decomposition. *Energy Environ. Sci.* **2013**, *6* (1), 241.

(142) Lind, B.; Ban, Z.; Byden, S. Nutrient Recovery from Human Urine by Struvite Crystallization with Ammonia Adsorption on Zeolite and Wollastonite. *Bioresour. Technol.* **2000**, *73*, 169–174.

(143) Landry, K. A.; Boyer, T. H. Life Cycle Assessment and Costing of Urine Source Separation : Focus on Nonsteroidal Anti-Inflammatory Drug Removal. *Water Res.* **2016**, *105*, 487–495.

(144) Tervahauta, T.; Hoang, T.; Hernández, L.; Zeeman, G.; Buisman, C. Prospects of Source-Separation-Based Sanitation Concepts: A Model-Based Study. *Water* **2013**, *5* (3), 1006–1035.

(145) Remy, C.; Jekel, M. Sustainable Wastewater Management: Life Cycle Assessment of Conventional and Source-Separating Urban Sanitation Systems. *Water Sci. Technol.* **2008**, *58* (8), 1555–1562.

(146) Oldenburg, M.; Peter-Fröhlich, A.; Pawlowski, L.; Bonhomme, A. EU Demonstration Project for Separate Discharge and Treatment of Urine, Faeces and Greywater - Part I: Results. *Water Sci. Technol.* **2007**, *56* (5), 239–249.

(147) Law, Y.; Ye, L.; Pan, Y.; Yuan, Z. Nitrous Oxide Emissions from Wastewater Treatment Processes. *Philos. Trans. R. Soc. Lond. B. Biol. Sci.* **2012**, *367* (1593), 1265–1277.

(148) Drangert, J. O. Fighting the Urine Blindness to Provide More Sanitation Options. *Water SA* **1998**, *24* (2), 157–164.

(149) Macharis, C.; Melo, S. *City Distribution and Urban Freight Transport: Multiple Perspectives*; Macharis, C., Melo, S., Eds.; Edward Elgar Publishing, 2011.

(150) Corbett, J.; Hawker, J. S.; James, W. J. *Transport Model with Cargo Flow Analysis*; 2010.

(151) Jenkins, B.; Parker, N.; Tittmann, P.; Hart, Q.; Cunningham, J.; Lay, M. *Western Governors ' Association : Strategic Development of Bioenergy in the Western States. Task 3: Spatial Analysis and Supply Curve Development*; 2008.

(152) Yeh, A. G.-O.; Chow, M. H. An Integrated GIS and Location-Allocation Approach to Public Facilities planning—An Example of Open Space Planning. *Comput. Environ. Urban Syst.* **1996**, *20* (4), 339–350.

(153) Kaylen, M.; Van Dyne, D. L.; Choi, Y. S.; Blase, M. Economic Feasibility of Producing Ethanol from Lignocellulosic Feedstocks. *Bioresour. Technol.* **2000**, *72* (1), 19–32.

(154) Sathre, R.; Scown, C. D.; Kavvada, O.; Hendrickson, T. P. Energy and Climate Effects of Second-Life Use of Electric Vehicle Batteries in California through 2050. *J. Power Sources* **2015**, *288*, 82–91.

(155) Hendrickson, T. P.; Kavvada, O.; Shah, N.; Sathre, R.; D Scown, C. Life-Cycle Implications and Supply Chain Logistics of Electric Vehicle Battery Recycling in California. *Environ. Res. Lett.* **2015**, *10* (1), 14011.

(156) Pedescoll, A.; Samsó, R.; Romero, E.; Puigagut, J.; García, J. Reliability, Repeatability and Accuracy of the Falling Head Method for Hydraulic Conductivity Measurements under Laboratory Conditions. *Ecol. Eng.* **2011**, *37* (5), 754–757.

(157) Hendrickson, C. T.; Lave, L. B.; Matthews, H. S. *Environmental Life Cycle Assessment of Goods and Services: An Input-Output Approach.*; Resources for the Future, 2006.

(158) Bureau of Labor Statistics. Wage data by area and occupation https://www.bls.gov/bls/blswage.htm (accessed Jan 1, 2017).

(159) Rose, C.; Parker, A.; Jefferson, B.; Cartmell, E. The Characterization of Feces and Urine: A Review of the Literature to Inform Advanced Treatment Technology. *Crit. Rev. Environ. Sci. Technol.* **2015**, *45* (17), 1827–1879.

(160) US Census Bureau. Fact Finder https://factfinder.census.gov/faces/nav/jsf/pages/ community˙facts.xhtml (accessed Jan 1, 2016).

(161) Wilsenach, J. a; Van Loosdrecht, M. C. M. Effects of Separate Urine Collection on Advanced Nutrient Removal Processes. *Environ. Sci. Technol.* **2004**, *38* (4), 1208–1215.

(162) Ekama, G. A.; Wilsenach, J. A.; Chen, G. H. Saline Sewage Treatment and Source Separation of Urine for More Sustainable Urban Water Management. *Water Sci. Technol.* **2011**, *64* (6), 1307–1316.

(163) Jimenez, J.; Bott, C.; Love, N.; Bratby, J. Source Separation of Urine as an Alternative Solution to Nutrient Management in Biological Nutrient Removal Treatment Plants. *Water Environ. Res.* **2015**, *87* (12), 2120–2129.

(164) United States Census Bureau. Census 2010 Summary File www.cenus.gov (accessed Jan 7, 2017).

(165) San Francisco Bay Regional Water Quality Control Board. *Waste Discharge Requirements for Nutrients from Municipal Wastewater Discharges to San Francisco Bay*; San Francisco Bay Regional Water Quality Control Board: San Francisco, CA, 2014.

(166) Alibaba.com. Products https://www.alibaba.com (accessed May 11, 2016).

(167) Metcalf, E.; Asano, T.; Burton, F.; Leverenz, H.; Tsuchihashi, R.; Tchobanoglous, G. *Water Reuse: Issues, Technologies, and Applications*; McGraw Hill: New York, 2007.

(168) Craigslist.com. Office/ commercial https://sfbay.craigslist.org/ (accessed Jan 1, 2017).

(169) Boeing, G.; Waddell, P. New Insights into Rental Housing Markets across the United States : Web Scraping and Analyzing Craigslist Rental Listings. *J. Plan. Educ. Res.* **2016**, 0739456X16664789.

(170) Mulder, A. The Quest for Sustainable Nitrogen Removal Technologies. *Water Sci. Technol.* **2003**, *48* (1), 67–75.

(171) Corominas, L.; Foley, J.; Guest, J. S.; Hospido, A.; Larsen, H. F.; Morera, S.; Shaw, A. Life Cycle Assessment Applied to Wastewater Treatment: State of the Art. *Water Res.* **2013**, *47* (15), 5480–5492.

(172) Maurer, M.; Schwegler, P.; Larsen, T. A. Nutrients in Urine: Energetic Aspects of Removal and Recovery. *Water Sci. Technol.* **2003**, *48* (1), 37–46.

(173) Falk, M. W.; Reardon, D. J.; Neethling, J. B.; Clark, D. L.; Pramanik, A. Striking the Balance between Nutrient Removal, Greenhouse Gas Emissions, Receiving Water Quality, and Costs. *Water Environ. Res.* **2013**, *85* (12), 2307–2316.

(174) Kampschreur, M. J.; Poldermans, R.; Kleerebezem, R.; Van Der Star, W. R. L.; Haarhuis, R.; Abma, W. R.; Jetten, M. S. M.; Van Loosdrecht, M. C. M. Emission of Nitrous Oxide and Nitric Oxide from a Full-Scale Single-Stage Nitritation-Anammox Reactor. *Water Sci. Technol.* **2009**, *60* (12), 3211–3217.

(175) Law, Y.; Lant, P.; Yuan, Z. The Effect of pH on N2O Production under Aerobic Conditions in a Partial Nitritation System. *Water Res.* **2011**, *45* (18), 5934–5944.

(176) Ali, M.; Rathnayake, R. M. L. D.; Zhang, L.; Ishii, S.; Kindaichi, T.; Satoh, H.; Toyoda, S.; Yoshida, N.; Okabe, S. Source Identification of Nitrous Oxide Emission Pathways from a Single-Stage Nitritation-Anammox Granular Reactor. *Water Res.* **2016**, *102*, 147–157.

(177) Hauck, M.; Maalcke-Luesken, F. A.; Jetten, M. S. M.; Huijbregts, M. A. J. Removing Nitrogen from Wastewater with Side Stream Anammox: What Are the Trade-Offs between Environmental Impacts? *Resour. Conserv. Recycl.* **2016**, *107*, 212–219.

(178) U.S. Environmental Protection Agency (EPA). *Biological Nutrient Removal Processes and Costs*; 2007.

(179) Fux, C.; Siegrist, H. Nitrogen Removal from Sludge Digester Liquids by Nitrification/denitrification or Partial Nitritation/anammox: Environmental and Economical Considerations. *Water Sci. Technol.* **2003**, *50* (10), 19–26.

(180) Almutairi, A.; Weatherley, L. R. Intensification of Ammonia Removal from Waste Water in Biologically Active Zeolitic Ion Exchange Columns. *J. Environ. Manage.* **2015**, *160*, 128–138.

(181) Aponte-Morales, Veronica; Tong, Shuang; Ergas, S.; Ergas, S. J. Nitrogen Removal from Anaerobically Digested Swine Waste Centrate Using a Laboratory-Scale Chabazite-Sequencing Batch Reactor. *Environ. Eng. Sci.* **2016**, *33* (5), 324–332.

(182) Udert, K. M.; Larsen, T. A.; Biebow, M.; Gujer, W. Urea Hydrolysis and Precipitation Dynamics in a Urine-Collecting System. *Water Res.* **2003**, *37* (11), 2571–2582.

(183) Wong, H. G.; Speight, V. L.; Filion, Y. R. Impact of Urban Form on Energy Use in Water Distribution Systems at the Neighbourhood Level. *Procedia Eng.* **2015**, *119* (1), 1049–1058.

(184) Verrecht, B.; Maere, T.; Benedetti, L.; Nopens, I.; Judd, S. Model-Based Energy Optimisation of a Small-Scale Decentralised Membrane Bioreactor for Urban Reuse. *Water Res.* **2010**, *44* (14), 4047–4056.

(185) Filion, Y. R.; MacLean, H. L.; Karney, B. W. Life-Cycle Energy Analysis of a Water Distribution System. *J. Infrastruct. Syst.* **2004**, *10*, 120–130.

(186) Alibaba.com. Bar Screen Filter for Watewater Treatment Plants http://www.alibaba.com/ (accessed Jan 1, 2016).

(187) Gabi. Gabi Software. 2003.

(188) Freshwater Systems. Sanitron 220C http://www.freshwatersystems.com/p-- -4526-- -sanitron-- -s50c-- -20-- -gpm-- -ultraviolet-- -water-- -purifier.aspx (accessed Jan 1, 2016).

(189) Ecoinvent database. Ecoinvent Database. 2013.

(190) Alibaba.com. Anthracite Filtering Media for Water Treatment http://www.alibaba.com/product-detail/0-8-1-6mm-F-C˙60183530156.html?spm=a2700.7724838.30.1.BuIWbv&s=p (accessed Jan 1, 2015).

(191) San Francisco Public Utilities Commission. Water Resources Division. *Annual Report Fiscal Year 2013-2014*; San Francisco, CA, 2014.

(192) Kavvada, O.; Horvath, A.; Stokes-Draut, J. R.; Hendrickson, T. P.; Eisenstein, W. A.; Nelson, K. L. Assessing Location and Scale of Urban Nonpotable Water Reuse Systems for Life-Cycle Energy Consumption and Greenhouse Gas Emissions. *Environ. Sci. Technol.* **2016**, *50* (24), 13184–13194.

(193) US Energy Information Administration. Independent Statistics and Analysis http://www.eia.gov/environment/ (accessed Jan 1, 2016).

(194) Dow Chemical Company. *Liquid Separations DOWEX Ion Exchange Resin DOWEX MAC-3 Engineering Information July 2003 DOWEX MAC-3 Weak Acid Cation Exchange Resin*; 2003.

(195) US Census Bureau. Families and Living Arrangements https://www.census.gov/hhes/families/data/cps2015AVG.html (accessed Jan 1, 2017).

(196) Piratla, K. R. Investigation of Sustainable and Resilient Design Alternatives for Water Distribution Networks. *Urban Water J.* **2015**, No. June, 1–14.

(197) Sigma-Aldrich. Product Results http://www.sigmaaldrich.com/united-states.html (accessed May 12, 2016).

(198) The Samuel Roberts Noble Foundation. Summer Nitrogen Sources - Which Is Best? https://www.noble.org/news/publications/ag-news-and-views/2012/june/summer-nitrogen-sources---which-is-best/ (accessed Jan 1, 2017).

(199) Corominas, L.; Larsen, H. F.; Flores-alsina, X.; Vanrolleghem, P. A. Including Life Cycle Assessment for Decision-Making in Controlling Wastewater Nutrient Removal Systems. *J. Environ. Manage.* **2013**, *128*, 759–767.

(200) Larsen, T. A.; Udert, K. M.; Lienert, J. *Wastewater Treatment: Source Separation and Decentralisation*; International Water Association, 2013.

Appendix 1: Centralized vs Decentralized Water Reuse

Table S - 1: HDPE Pipe Parameters

Size (mm)	Weight (kg/m)[35]	Cost ($ 2012/m)[35]	Embodied energy (mj/kg)[35]	Excavation volume (m^3/m)[37,90]
25	6.8	8.28	25.31	0.19
50	7.6	9.21	25.31	0.22
100	9.5	11.54	25.31	0.30
160	11.9	14.45	25.31	0.41
200	15	18.1	25.31	0.49
350	39.5	47.69	25.31	0.86
375	43.5	52.5	25.31	0.9
450	65.3	78.55	25.31	1.17

Table S - 2: Pump Parameters

Size (hp)	Cost ($ 2012)[64]	Embodied energy (mj)[65]	Ghg emissions ($kgco_{2(eq)}$)[65]	Weight (kg)[39]
0.1	183.3	1215.6	80.6	14
0.15	237.7	1576.7	104.5	14
0.2	276.3	1832.8	121.5	14
0.25	751.0	4980.9	330.3	14
0.3	881.0	5842.8	387.5	14
0.35	1010.9	6704.8	444.6	14
0.4	1090.2	7231.1	479.5	14
0.45	1169.6	7757.4	514.4	14
0.5	1248.9	8283.7	549.3	14
1	2009.1	13325.7	883.7	14
2	2300	15255.5	1011.6	22.5
3	2300	15255.5	1011.6	25
4	2300	15255.5	1011.6	30.4
5	2300	15255.5	1011.6	35

6	2875	19069.3	1264.5	45
7	3220	21357.7	1416.3	45
8	3450	22883.2	1517.5	63.5
9	4140	27459.8	1820.9	63.5
10	4830	32036.5	2124.4	77
20	5405	35850.35	2377.4	77
30	6325	41952.5	2782.0	94
40	6555	43478.1	2883.2	120
50	9315	61784.7	4097.1	143
60	9890	65598.5	4350.1	164
70	6440	42715.3	2832.6	183
80	11500	76277.3	5058.2	210
90	12592.5	83523.7	5538.7	210
100	13685	90770.0	6019.3	230
150	21505	142638.6	9458.8	250
200	21620	143401.4	9509.4	318
250	22195	147215.3	9762.3	378
300	22425	148740.8	9863.5	400

Table S - 3: MBR Operational performance data

Scale (m^3/day)	Energy (kWh/m^3)	Type	Reference
1.2	4.9	Multi-tube sidestream MBR (pumped)	77
1.9	6.2	Vacuum MBR with anoxic and aerated zones	78
4	4.9	Multi-tube sidestream MBR (pumped)	77
10	7.2	Multi-tube sidestream MBR (pumped)	77
20	7.2	Pumped MBR with 0.5mm screen	77
20	4	Anoxic and aerobic submerged MBR	184
27	5	Hollow fiber ultrafiltration MBR.	79
40	7.2	Multi-tube sidestream MBR (pumped)	77
100	3	Pumped and airlift MBR	80
100	1.4	Vacuum rotating time MBR system.	80
113	1.3	Vacuum rotating time MBR system.	80
600	2.9	Aerobic MBR	80
610	1.1	Anoxic and aerobic MBR	80
1700	0.64	Anoxic and aerobic MBR	80
3500	0.72	Anoxic and aerobic MBR	80
5670	0.66	Anoxic and aerobic MBR	80

Table S - 4: Steel Sheet Parameters [69]

Type	Density (kg/m^3)	Length (m)	Height (m)	Thickness (m)	Volume (m^3)	Mass (kg)	Area (m^2)
STEEL SHEET	7850	1.2	3.1	0.0064	0.02	186.9	3.72

Table S - 5: Model Parameters

	Parameter	Units	Typical value	Uncertainty range	Probability type	Data source
GENERAL PARAMETERS	*design volume*	*m^3/person-day*	*0.2*	*0.1-0.4*	*triangular*	[75]
	slope	%	estimated	+/- 10%	uniform	Estimated. Elevation contours. [62]
	population density	#/km^2	estimated	+/- 10%	uniform	Census data. [62]
	infrastructure lifetime	years	50	+/- 30%	triangular	[36,185]
	treatment infrastructure lifetime	years	25	+/- 30%	triangular	[34]
	reinforced concrete energy	MJ/m^3	2869	+/- 20%	uniform	WEST tool [39,88]
	reinforced concrete GHG	$kgCO_{2(eq)}/m^3$	270.8	+/- 20%	uniform	WEST tool [39,88]
	steel energy	MJ/kg	17.5	+/- 20%	uniform	[69]
	steel GHG	$kgCO_{2(eq)}$/kg	1.3	+/- -20%	uniform	[69]
	transport energy	MJ/ton-mile	8.16	+/- 20%	uniform	[66]
	transport GHG	$kgCO_{2(eq)}$/ton-mile	0.656	0.16-2.9	uniform	[66]
	material transport	miles	50	20-80	triangular	Estimated for San Francisco
	electricity emission factor	$kgCO_{2(eq)}$/kWh	0.4	+/- 30%	uniform	[72]
	SFPUC Electricity emission factor	$kgCO_{2(eq)}$/kWh	0.083	+/- 30%	uniform	[60]

	Parameter	*Units*	*Typical value*	*Uncertainty range*	*Probability type*	*Data source*
CONVEYANCE PARAMETERS	distance from centralized	m	estimated	+/- 10%	uniform	Estimated (Dijkstra's algorithm)
	piping density	m/km^2	8000	4000-15,000	triangular	Estimated: Assumed grid with 80x80 m residential blocks
	pipe diameter	mm	evaluated	+/- 1 size	uniform	Estimated based on volume
	excavation energy	MJ/m^3	153	+/- 20%	uniform	dimensions:[63,90]; energy: [10]
	excavation GHG	$kgCO_{2(eq)}/m^3$	12	+/- 20%	uniform	[10]
	pipe construction energy	MJ/m	estimated	+/- 20%	uniform	[36]
	pipe construction GHG	$kgCO_{2(eq)}/m$	estimated	+/- 20%	uniform	[35]
	pipe maintenance energy	MJ/m	estimated	+/- 10%	uniform	[35]
	pump operating time fraction	-	0.8			[71]
	pump power	hp	evaluated	+/- 1 size	uniform	Estimated based on volume and head
	pump efficiency	-	estimated	+/- 10%	uniform	[10]
	pump motor efficiency	-	0.95	0.80-1	normal	[63]
	pump construction energy	MJ/pump	estimated	+/- 20%	uniform	cost: [64]; energy: [65]
	reuse water storage size (concrete)	days	3	2-10	uniform	[55]

	Parameter	*Units*	*Typical value*	*Uncertainty range*	*Probability type*	*Data source*
TREATMENT PARAMETERS	screen filter (SF) manufacturing energy	MJ/unit	23,800	+/- 10%	uniform	cost:[186], energy: [65]
	SF manufacturing GHG	$kgCO_{2(eq)}$/unit	1,632	+/- 10%	uniform	cost:[186], GHG: [65]
	SF operational energy	kWh/m3	0.008	0.001-0.0013	uniform	[67]
	grinder pump usage	h/day	0.2	0.1-2	triangular	[60]
	grinder pump hp	hp	1.5	0.5-2	triangular	[67]
	grit chamber retention time (concrete)	s	60	45-90	uniform	[67]
	equalization tank retention time (concrete)	h	6	3-12	uniform	[67]
	MBR membrane lifetime	y	10	+/- 20%	uniform	[70]
	MBR capital energy	MJ/m^3	estimated	+/- 50%	triangular	materials: [68], energy: [65,187]
	MBR manufacturing GHG	$kgCO_{2(eq)}/m^3$	estimated	+/- 50%	triangular	materials: [68], energy: [65,187]
	MBR operational GHG	$kgCO_{2(eq)}/m^3$	estimated	+/- 50%	triangular	Electricity mix: [60,72]
	MBR operational energy	MJ/m^3	estimated	+/- 50%	triangular	Regression
	UV lifetime	y	3	2-5	triangular	[70]
	UV capital energy	MJ/W	34	+/- 20%	triangular	cost:[188], energy: [65]
	UV capital GHG	$kgCO_{2(eq)}$/W	2.2	+/- 20%	triangular	cost:[188], GHG: [65]
	UV rating	W/m^3-day	9.5	8-12	triangular	[60]
	UV usage	h/day	12	8-20	triangular	[60]
	chlorine mass added (HOCl)	mg/L	10	6-20	uniform	[67]
	chlorine concrete tank retention time	min	60	30-120	uniform	[70]
	chlorine energy (HOCl)	MJ/kg	30	+/- 20%	uniform	[187]
	chlorine GHG (HOCl)	$kgCO_{2(eq)}$/kg	0.74	+/- 20%	uniform	[189]

	centr. treatment capital energy	MJ/m^3	0.5	+/- 30%	uniform	[60]
	centr. treatment operational energy	MJ/m^3	2.4	+/- 30%	uniform	[60]
	centr. treatment operational GHG	kgCO$_{2(eq)}$/m^3	0.06	+/- 30%	uniform	[60]
	centr. treatment capital GHG	kgCO$_{2(eq)}$/m^3	0.07	+/- 30%	uniform	[60]
	coagulation time	s	1	0.5-5	uniform	[67]
	flocculation time	min	20	10-30	uniform	[67]
	flocculation energy	kWh/m^3	0.05	+/- 20%	uniform	[74]
	alum mass added	mg/L	150	25-225	uniform	[70]
	alum energy	MJ/kg	0.91	+/- 20%	uniform	[187]
	alum GHG	kgCO$_{2(eq)}$/kg	0.07	+/- 20%	uniform	[187]
	rapid sand filtration (RSF) rate	L/m^2-min	150	80-240	uniform	[70]
	RSF sand depth	mm	600	500-750	uniform	[70]
	RSF anthracite depth	mm	750	600-900	uniform	[70]
	RSF sand energy	MJ/kg	0.147	+/- 20%	uniform	cost: [64]; energy: [65]
	RSF anthracite energy	MJ/kg	0.231	+/- 20%	uniform	cost:[190]; energy: [65]
	RSF operational energy	kWh/m^3	0.05	0.03-0.08	uniform	[67]
	RSF sand GHG	kgCO$_{2(eq)}$/kg	0.0104	+/- 20%	uniform	cost: [64]; GHG: [65]
	RSF anthracite GHG	kgCO$_{2(eq)}$/kg	0.06	+/- 20%	uniform	cost:[190]; GHG: [65]
	sludge mass	kg/m^3 water	0.1	+/- 20%	uniform	[67]
	fraction of sludge to landfill	-	0.5	0-1	triangular	[34]
	miles to disposal (sludge)	miles	30	10-50	triangular	[34]
	landfill GHG	kgCO$_{2(eq)}$/kg sludge	0.04	+/- 30%	triangular	[34]

Appendix 2: Decentralized Optimization of Water Reuse

Table S - 6: *Model Parameters*

Parameter	Units	Value	Reference
Residential water demand	m^3/person-day	0.19	[191]
Commercial water demand	m^3/person-day	0.12	[191]
NPR water demand percentage (residential)	%	0.5	[23]
NPR water demand percentage (commercial)	%	0.95	[23]
infrastructure lifetime	years	50	
treatment infrastructure lifetime	years	25	
Piping embodied energy	MJ/m	240	[35]
Piping cost	USD/m	1500	[116]
In-building piping length	m/m^2	0.05	[115]
MBR treatment embodied energy	kWh/ m^3	0.3	[192]
MBR treatment embodied GHG	$kgCO_{2(eq)}$/ m^3	0.06	[192]
Electricity cost	USD/kWh	0.12	[193]
electricity emission factor	$kgCO_{2(eq)}$/kWh	0.4	[7]
SFPUC Electricity emission factor	$kgCO_{2(eq)}$/kWh	0.083	[60]

Appendix 3: Nitrogen Recovery

Urea hydrolysis: $(NH_2)_2CO + 3\,H_2O \rightarrow 2NH_4^+ + HCO_3^- + OH^-$ [eq. S - 1]

Ion-exchange: $2(NH_4^+ + \equiv H^+ \rightarrow\ \equiv NH_4^+ + H^+)$ [eq. S - 2]

Nitrification: $NH_4^+ + O_2 + CO_2 \rightarrow\ NO_3^- + (CH_2O)_B + 2H^+$ [eq. S - 3]

Denitrification: $2NO_3^- + C_6H_{12}O_2 + H^+ \rightarrow N_2 + 3(CH_2O)_B + 3CO_2 + H_2O$ [eq. S - 4]

Table S - 7: Component material selection

Parameter	Material
Ion − exchange resin	Dow Max 3 [194]
Cartridge	Fiberglass cylinder [143]
Urine flow equalization tank	HDPE [143]
Fertilizer bottling	Plastic bottle
Collection and distribution trucks	Class 4 conventional van [66]

Table S - 8: Model Parameters

Parameter	Units	Value	Uncertainty Range	Reference
Percent served	%	50	40-80	this study
Household size	people/household	2.54	2.53 - 4	[195]
Number of cartridges	Cartridges/ household	1.5	+/- 20%	estimated
Nitrogen in urine	gN/L	7.5	4 - 9	[159]
Urine density	kg/L	1		
Nitrogen molar mass	g/mol	14.0067		
Urine production	L/person-day	1.42	0.6 - 2.6	[159]
Resin density	g/L	750		[194]
Resin cost	$/kg	2	+/- 20%	[166]

Parameter	Units	Value	Uncertainty Range	Reference
Resin hydraulic conductivity	m/s	0.00253	+/- 20%	experimental
Resin lifetime	years	5	+/- 20%	estimated
Adsorption density	mmolN/g resin	4.9	3.5 - 5.2	[31]
Cartridge diameter	cm	12	+/- 20%	experimental
Fiberglass cost	$/m3	1,955	+/- 20%	[143]
Fiberglass density	kg/L	1.5	+/- 10%	
Time between cartridge regeneration	days	7	6 - 8	estimated
Time for regeneration	h/day	1.5	1.16 - 1.83	experimental
Flow equalization retention time	days	1	+/- 20%	estimated
Plastic embodied energy	MJ/$	14.8	+/- 20%	"Piping manufacturing" [65]
Plastic embodied GHG	$kgCO_2$/$	0.904	+/- 20%	"Piping manufacturing" [65]
Plastic cost	$/m3	300	+/- 20%	[166]
Plastic density	kg/m3	20	+/- 20%	
Plastic lifetime	years	50	+/- 20%	[185,196]
Transportation GHG	$kgCO_2$/ton-km	0. 85	+/- 20%	[66]
Diesel carbon content	kg CO_2/gal	10		[193]
Diesel energy content	MJ/kg fuel	46.8		[193]
Diesel cost	$/gal	2.3	+/- 20%	[193]

Parameter	Units	Value	Uncertainty Range	Reference
Truck embodied energy	MJ/$	0.89	+/- 20%	"Light truck and vehicle manufacturing" [65]
Truck embodied GHG	$kgCO_2$/$	0.06	+/- 20%	"Light truck and vehicle manufacturing" [65]
Electricity GHG emissions	$kgCO_2$/kWh	0.083	+/- 20%	[60]
Electricity cost	$/kWh	0.1	+/- 20%	[193]
Pump lifetime	years	10	+/- 20%	[34]
Pump motor efficiency	%	95	+/- 20%	[63]
Pump manufacturing	MJ/unit	Estimated based on size	+/- 20%	Pump and pumping equipment manufacturing[65]
Sulfuric acid cost	$/kg	0.27	+/- 20%	[166]
Sulfuric acid density	g/L	1840	+/- 10%	[197]
Sulfuric acid volume	L(acid)/L(resin)	0.1	+/- 20%	experimental
Nitric acid cost	$/kg	0.287	+/- 20%	[166]
Nitric acid density	g/L	1510	+/- 10%	[197]
Nitric acid volume	L(acid)/L(resin)	0.23	+/- 20%	experimental
Hydrochloric acid cost	$/kg	0.285	+/- 20%	[166]
Hydrochloric acid density	g/L	1003	+/- 10%	[197]
Hydrochloric acid volume	L(acid)/L(resin)	0.3	+/- 20%	experimental
Sodium Chloride cost	$/kg	0.06	+/- 20%	[166]

Parameter	Units	Value	Uncertainty Range	Reference
Ammonium nitrate cost	$/kgN	1.7	+/- 20%	[198]
Fertilizer collection frequency	times/week	1	+/- 20%	estimated
Facility space lifetime	years	50	+/- 20%	estimated
Facility rental cost	$/year	based on size	based on size	See Figure 43
Cartridge per facility employee	Cartridge / hour	30	+/- 20%	estimated
Labor cost (truck driver)	$ / hour	16.4	+/- 20%	[158]
Labor cost (chemist at facility)	$ / hour	37.4	+/- 20%	[158]

Table S - 9*: Nitrification/Denitrification metrics*

Metric	Value	Reference	Mean value
Energy (aeration only)	2.3 (kWh/kgN)	[170]	18.3 (kWh/m³ urine)
	3.9 (kWh/kgN)	[199]	
	4 (kWh/kgN)	[172*]	
	1.6 (kWh/kgN)	[173]	
Energy (aeration + substrate)	9.4 (kWh/kgN)	[172*]	34.4 (kWh/m³ urine)
	2.9 (kWh/kgN)	[173]	
Cost	5.35 (USD/kgN)	[173]	19 (USD/m³ urine)
	1.07 (USD/kgN)	[178#]	

	3.21- 4.28 (USD/kgN)	179	
GHG (direct + aeration)	4.2 ($kgCO_2$/kgN)	171Ξ	16 ($kgCO_2/m^3$ urine)
	3 ($kgCO_2$/kgN)	173	
GHG (direct + aeration + substrate addition)	8.8 ($kgCO_2$/kgN)	199Ξ	30 ($kgCO_2/m^3$ urine)
	5 ($kgCO_2$/kgN)	173	

**Includes conversion from primary energy to electricity using 0.31 conversion efficiency*

Ξ Life-cycle assessment values

 # Calculated from median nitrification/denitrification upgrade cost and wastewater loading rate for WWTPs in Chesapeake Bay region ($787/(gal ww/day)). Converted to USD/kg N assuming 27 mg/L N removed and 30 year lifetime.

Calculations for nitrification/denitrification are shown below:

Mass nitrogen removed in conventional nitrification/denitrification: 75% [170]

Urine in wastewater: 1% [200]

Nitrogen in urine: 7.5 gN/L_{urine}

Nitrogen removed per volume wastewater treated (ww): $75\frac{gN_{influent}}{m^3_{ww}} \times 0.75\frac{gN_{removed}}{gN_{influent}} = 56\frac{gN_{removed}}{m^3_{ww}}$

Nitrogen removed per volume wastewater treated (ww)[171]:

$$49.7\frac{gN_{influent}}{m^3_{ww}} - 13.2\frac{gN_{influent}}{m^3_{ww}} = 36.5\frac{gN_{removed}}{m^3_{ww}}$$

Energy

Energy (aeration only – average [170,172,173,199]): $2.9\frac{kWh}{kgN} \times 0.056\frac{kgN}{m^3_{ww}} \times 100\frac{m^3_{ww}}{m^3_{urine}} = 14.6\frac{kWh}{m^3_{urine}}$

Energy (aeration only): $\frac{\left(14.6\frac{kWh}{m^3_{urine}} + 22\frac{kWh}{m^3_{urine}}\right)}{2} = \mathbf{18.3\frac{kWh}{m^3_{urine}}}$

Energy (aeration + substrate): $6.2\frac{kWh}{kgN} \times 0.056\frac{kgN}{m^3_{ww}} \times 100\frac{m^3_{ww}}{m^3_{urine}} = \mathbf{34.4\frac{kWh}{m^3_{urine}}}$

Cost: $3.4\frac{USD}{kgN} \times 0.056\frac{kgN}{m^3_{ww}} \times 100\frac{m^3_{ww}}{m^3_{urine}} = \mathbf{19\frac{USD}{m^3_{urine}}}$

<u>GHG emissions</u>

Direct +aeration emissions [173]: $3\,\frac{kg\ CO_2}{kgN} \times 0.056\,\frac{kgN}{m^3_{ww}} \times 100\,\frac{m^3_{ww}}{m^3_{urine}} = 16.8\,\frac{kg\ CO_2}{m^3_{urine}}$

Direct +aeration emissions [171]: $0.15\,\frac{kg\ CO_2}{m^3_{ww}} \times 100\,\frac{m^3_{ww}}{m^3_{urine}} = 15\,\frac{kg\ CO_2}{m^3_{urine}}$

Direct +aeration emissions: $\frac{\left(16.8\frac{kg\ CO_2}{m^3_{urine}}+15\frac{kg\ CO_2}{m^3_{urine}}\right)}{2} = \mathbf{16\,\frac{kg\ CO_2}{m^3_{urine}}}$

Direct + aeration + substrate emissions [173]: $5\,\frac{kg\ CO_2}{kgN} \times 0.056\,\frac{kgN}{m^3_{ww}} \times 100\,\frac{m^3_{ww}}{m^3_{urine}} = 28\,\frac{kg\ CO_2}{m^3_{urine}}$

Direct + aeration + substrate emissions [171]: $0.32\,\frac{kg\ CO_2}{m^3_{ww}} \times 100\,\frac{m^3_{ww}}{m^3_{urine}} = 32\,\frac{kg\ CO_2}{m^3_{urine}}$

Direct +aeration emissions+substrate emissions: $\frac{\left(28\frac{kg\ CO_2}{m^3_{urine}}+32\frac{kg\ CO_2}{m^3_{urine}}\right)}{2} = \mathbf{30\,\frac{kg\ CO_2}{m^3_{urine}}}$