Spatial optimization for decentralized non-potable water reuse

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Abstract

Decentralization has the potential to reduce the scale of the piped distribution network needed to enable non-potable water reuse (NPR) in urban areas by producing recycled water closer to its point of use. However, tradeoffs exist between the economies of scale of treatment facilities and the size of the conveyance infrastructure, including energy for upgradient distribution of recycled water. To adequately capture the impacts from distribution pipes and pumping requirements, site-specific conditions must be accounted for. In this study, a generalized framework (a heuristic modeling approach using geospatial algorithms) is developed that estimates the financial cost, the energy use, and the greenhouse gas emissions associated with NPR (for toilet flushing) as a function of scale of treatment and conveyance networks with the goal of determining the optimal degree of decentralization. A decision-support platform is developed to assess and visualize NPR system designs considering topography, economies of scale, and building size. The platform can be used for scenario development to explore the optimal system size based on the layout of current or new buildings. The model also promotes technology innovation by facilitating the systems-level comparison of options to lower costs, improve energy efficiency, and lower greenhouse gas emissions.

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 [1]. Wastewater is a sustainable water source that can contribute to conserving significant fresh water sources if treated to an appropriate standard and reused. 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 [2, 3]. 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 in terms of energy consumption and cost per unit of water treated [2, 4]. However, by implementing water reuse, a tradeoff occurs: in a centralized system non-potable reuse requires delivering the recycled water back to where demand exists, which may require substantial piping and upgradient conveyance [5, 6]. Decentralized water reuse, on the other hand, produces recycled water close to its point of use [7, 8]. 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 [9–11]. The optimal degree of decentralization can range...
from a single household to a cluster of buildings or an entire neighborhood. This work aims to add to the 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, and/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 [12, 13]. 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 [14].

Previous research has focused on the optimal scale for just wastewater collection, which confirmed and quantified the expected result that the optimal scale of centralization decreases with topographic complexity and more disperse population distribution [15]. 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 [16].

Treatment technology selection, which is influenced by regulations on water quality, is an important aspect of assessing decentralized systems. The performance of different technologies may scale differently, which researchers have tried to characterize with respect to cost [17–19], energy intensity [5], and GHG emissions [5, 19]. This characterization is especially useful in decentralized systems whose performance is highly sensitive to system size.

Resource recovery has been getting increased attention [20]. For example, a multivariable analysis was recently conducted to understand the effect of location on recovery potential and economic cost, pointing out the need for hybrid solutions [21]. 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 [22]. 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, generalizable 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.

The objective of this study was to develop a generalizable model to identify the optimal decentralization scale for NPR for toilet-flushing with respect to energy intensity, GHG emissions, and economic cost. The model assesses the impacts of water conveyance based on local conditions, detailed spatial analysis, and the impacts of treatment performance using economies-of-scale curves [17]. We incorporate the algorithmic model into a web-based decision-support platform that allows users to explore the impact of local conditions (topography and population density) under different scenarios. To illustrate uses of the platform, we apply it to a real-world case study to quantify how system scale changes the impacts of decentralized NPR based on local conditions. We also use it to model a city-wide implementation plan for NPR under a constrained GHG emissions scenario.

Methods

The algorithmic process developed for this research aims to identify the optimal NPR system scale (number of people served) that minimizes economic and environmental metrics (economic cost, energy intensity, or GHG emissions) by considering the relevant site-specific conditions. It is based on network design assumptions to collect wastewater, treat it, and deliver the recycled water to buildings for toilet flushing. The algorithm is divided into two main components: (1) the impact module, and (2) the spatial expansion module. The impact module considers the impacts of treatment (economies-of-scale of the treatment technology) and conveyance (piping and pumping for collection and distribution) by calculating the requirements to serve all buildings in the cluster. 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 section. The objective function of the algorithmic process (equation 1) is the minimization of the metric of interest, and is solved numerically to identify the system scale that minimizes the treatment and conveyance requirements (figure 1)

$$\text{Min } C(Q_{\text{WWTP}} , L, Q_{\text{PUMP}} , H)$$  \hspace{1cm} (1)
where $C$ is the metric of interest (energy intensity, GHG emissions, economic cost), $Q_{WWTP}$ is the flow rate to the decentralized wastewater treatment plant (WWTP), $L$ is the conveyance piping length, $Q_{PUMP}$ is the flow rate of recycled water that is pumped, and $H$ is the pumping head. In this work $Q_{WWTP}$ and $Q_{PUMP}$ are considered equal, but they could be different if the entire treated volume is not reused.

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 [23], a realistic assumption for an urban mixed-use setting (equation 2). 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.

$$Q_{NPR} = 0.5Q_{WW}$$ (2)

**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 identifies the impacts for collecting the wastewater, treating it, 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 conveyance of the specific scale is calculated.

**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 (people in residential and commercial buildings to be served) and calculates the manufacturing and operating requirements for the treatment unit for that scale. The impacts are based on published data describing wastewater treatment (we assumed a membrane bioreactor, MBR) capital and operation requirements at different scales and are expressed by polynomial equations for economic costs and energy intensity (equations S1-S5 in the SI) [5, 24].

The GHG emissions for the operation and manufacturing are estimated based on the technology selection and energy performance curve (equation S5 in the SI) (assuming all energy use is in the form of electricity) as calculated by the authors in previous work [5]. The user can define the location-specific electricity mix to account for the local conditions. No direct GHG emissions from the treatment process are accounted for due to the scarcity of data, but the user can change this input if information is available.

**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 buildings’ demographic and size characteristics to estimate the amount of piping and pumping that would be required to deliver water to the bathrooms. The pumping needs for water conveyance between buildings are estimated based on the pumping head, using the ground elevation of the building with the treatment technology (assumed to be in the building with the lowest elevation, such that wastewater collection occurs by gravity flow) and enough pressure to deliver water to the top floor of each building in the cluster (SI–section 3).

The in-between building piping lengths 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 [15, 25, 26]. The wastewater collection piping was not explicitly modeled or optimized. It was, however, included in the analysis based on the assumption that the wastewater collected could serve double the number of people for NPR uses (NPR is 50% of the total water use (equation 2)), thus the sewer collection pipes would be half the length of the NPR pipes.

The in-building piping is calculated based on the area of the building and the number of floors. The average piping length per building area was approximated based on measurements of an existing typical building with water reuse infrastructure [27]. The piping costs are calculated as directly related to the piping length and diameter (SI–section 3) for economic cost [28], energy intensity and GHG emissions [29], and are reported in table S-1 in the supplementary information (SI) available at stacks.iop.org/ERL/13/064001/mmedia. Piping costs include only material costs; note that installation costs may be significant and could be substantially higher for retrofits compared to new construction.

**Spatial 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 2. The system expansion part is solved using a heuristic approach (iterative searching inside the solution space) 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 [30, 31]. 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 ($Q^*$ in figure 1). A detailed description of the algorithmic process is described in the SI (section 3).

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 [32], 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 would exceed the restrictions of computational intensity [33]. 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 3).

### Web-based decision-support platform

We developed a web-based platform that allows the user to select the location of interest and run the algorithm to estimate the optimal system scale at the point of interest. A snapshot of the developed web-based platform is shown in figure 3. The platform allows the user to have flexibility to input different treatment technology criteria and electricity mixes, as they can be important determinants of the optimal scale in a given location. 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.

### Case study

To test the algorithm under varying system conditions and show the benefits of the optimization
Figure 3. Web-based platform snapshot highlighting the inputs and outputs of the model. The darker colored dots result from overlapping buildings.
framework with real-world data, we applied it to the case of San Francisco, a medium-sized US city (865,000 citizens) with high population density (6700 people km$^{-2}$) that is an innovation leader in decentralized urban water reuse due to policies and incentives implemented to promote alternative water supplies [5]. 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. The data sources and spatial analysis specific to San Francisco are documented in the SI (SI–section 1) along with the specific parameter values (table S-1).

**Results**

**Location analysis**

We used the web-based platform to explore the effect of location and population distribution on the optimal decentralization scale. An automated script iteratively assessed different locations on the map and stored the results of the optimal scale. 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. This means that 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 smoothing of the local conditions (using a nearest neighbor interpolation) and eliminated errors based on extreme and outlier building characteristics.

The location-specific results for running the analysis in the 850 points are presented in figure 4. For each metric, we identified the optimal system scale for minimizing 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.

As the results presented in figure 4 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 economies of scale. In low population density areas where the buildings are more spread out, and significant pumping and piping needs are required to serve more buildings, the optimal system scales are smaller and the corresponding impacts are larger.

Figure 5 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 5(a), 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 (rightmost point). After that point, the energy increases with system scale (these points are not shown in the results as the optimal point has been identified). The shape of the curve provides valuable insight on the actual range of optimal scales. If some variance was 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. 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.

Figure 5(b) 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 (Location B; 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 (Location D). From figure 5(b) 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 can be found in the SI in figure S-3 and figure S-4.

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) [13]. 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 would reduce the difference in unit cost for small versus larger systems and have the potential to make smaller systems more viable financially.

Treatment selection analysis
One of the largest contributors to energy, GHG, and cost metrics of decentralized reuse is treatment technology, which is influenced by policies and regulations that determine appropriate treatment levels for reuse. Cities, regions, and countries can have different standards on the appropriate treatment level, water quality, and allowed uses of recycled water. Such differences could lead to different treatment technologies being selected, and large differences in the resulting cost, energy, and GHG impacts.

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 6 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 6(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 figures 6(a) and (b). From the differences in figures 6(a) and (b), we can identify that the more prominent the economies of scale in treatment are, the larger the preferred systems would be.

Optimization analysis
To illustrate another potential application of the web-based platform, we performed a spatial optimization to identify the areas for implementing water reuse under an emissions budget. To meet the climate

Figure 6. Assessing the optimal scale under different treatment options.
goals of staying below a 2 °C increase, it has been estimated that the maximum GHG emissions allowance would be 1 kgC/person-day [34]. As a reference, the GHG emissions for California in 2013 were about 7 kgC/person-day [35]. 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 [36]. 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 [23]. This allocation ends up allowing 180 gCO$_2$/person-day ($1$ [kgC/person-day] $\times 10\% \times 50\% \times 44$ [gCO$_2$/mol]/12 [gC/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 achieve maximum savings 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 maximum number of people that occupy that cell. To perform the optimization, we chose a grid cell size of 1000 × 800 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 in the SI (section 7).

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 7. 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 7 illustrates the areas that should be targeted. The optimization identifies the areas where water reuse can be implemented most efficiently with respect to GHG emissions under the current conditions. It does not take into account redevelopment strategies as that data was not available. The selected areas, according to the algorithm, have the potential to save the maximum amount of water with the minimum GHG emission requirements.

The gross water consumption in San Francisco is about 238 000 m$^3$ day$^{-3}$ (63 million gallons per day (MGD)), of which 155 000 m$^3$ day$^{-3}$ (41 MGD) are residential uses and 83 000 m$^3$ day$^{-3}$ (22 MGD) are commercial/municipal water uses [37]. 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 [23]. Given these assumptions, the total non-potable water used in San Francisco is roughly 102 000 m$^3$ day$^{-3}$ (27 MGD) [38]. 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$^{-3}$, equal to about 56% of the total daily non-potable water use of San Francisco while remaining under the GHG emissions budget.

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 percent increase in total saved water with respect to percent increase in per-capita GHG emissions allowance is shown in figure 8. 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. 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%, emitting 450 gCO$_2$/person-day.

**Discussion**

This research aims to address the challenges of implementing decentralized NPR systems efficiently with respect to energy, GHG emissions, and cost. Decentralization is an intuitive approach for implementing NPR and to address the ‘purple pipe dilemma’ [39], but because of the economies of scale in treatment, it is not trivial to estimate the implications of system size. A generalized algorithm that considers the specific local conditions 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 transferable to other locations and treatment technologies. 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. 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 and the conventional water supply. 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 alternative water sources to meet toilet flushing and irrigation demand) [40]. 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.

An important aspect of the model is that it is based on multiple decision metrics that allow decision makers to understand the tradeoffs and make optimal decisions based on their priorities, not just economic efficiency. While energy, GHG, and cost may not always be the principal drivers for decision making, it is important to consider these effects in planning and policies. Environmental performance and pressing climate change issues should influence behavior in optimal planning, especially in places like California where GHG reduction targets have been set [41]. To capture the complexity of sustainable water management, holistic consideration based on multiple criteria are required to make optimal infrastructure decisions. Our platform, by allowing exploration of various metrics, can potentially be expanded to perform multicriteria analysis by assigning importance weights to the different metrics assessed. 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 bears that cost (utilities, developers, etc.) and how that cost would compare to the overall costs of a project.

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 can lead to increased uncertainty in the model as the treatment requirement is a large contributor to energy use, GHG emissions, and costs. As currently modeled, the model highly penalizes small systems due to lack of available data. This research seeks to drive innovation in decentralized treatment technologies and increase awareness of 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. Moreover, the generalizable nature
of the tool and its applicability to various locations increases the uncertainty of the algorithm as it relies on data that can be gathered for almost all urban areas and is not limited by specific water consumption and distribution network data. 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 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 proposed 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.

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 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.

Webtool

The webtool can be accessed free of charge at: https://water-reuse-map.herokuapp.com/. Citation to this article is required for use of the tool in other projects.

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