Sustainable Cities and Society 130 (2025) 106517

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Assessing equitable access to safe and affordable water during COVID-19: Agent-based modeling for tap water avoidance behaviors

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ARTICLE INFO

Keywords:
Agent-based model
Equity
Water distribution systems
Water affordability

ABSTRACT

Water distribution systems (WDSs) should deliver safe and affordable water for communities, yet consumers are regularly exposed to tap water that violates federal guidelines for pathogens and chemicals. In response to reduced water quality, consumers may shift demands away from tap water to bottled water, increasing household water spending. Intra-system water quality fluctuates with changes in demands, a consequence observed during the COVID-19 pandemic. This research develops the COVID-19 social-distancing and tap water avoidance agent-based model (COST-ABM), which simulates water quality in a water distribution network and decisions to avoid tap water and purchase bottled water. COST-ABM is developed to assess equitable access to affordable water. Agents represent water consumers that decide to avoid tap water by purchasing bottled water for cooking, cleaning, and hygienic end uses, reducing demand from the system. The agent-based model is tightly coupled with a water distribution system model that calculates the spatiotemporal dynamics of water quality in a pipe network, which is used in agent decision-making. Equity is evaluated in a bottom-up approach using the cost of tap and bottled water as a percentage of household income, calculated at each household. The framework is applied for a virtual water distribution system, and results demonstrate economic inequities in water affordability. This research presents a framework to assess equity in a WDS based on tap water avoidance and water affordability and can be used to facilitate infrastructure management that provides equitable access to safe and affordable water.

1. Introduction

Access to safe and affordable water is essential to promote public health and economic development. Public water distribution systems (WDSs) serve 286 million people in the United States, yet in recent years, millions of people have been exposed to tap water that violates federal guidelines for pathogens, nitrates, arsenic, and harmful disinfection by-products (Allaire et al., 2018; Fedinick et al., 2019; Mueller & Gasteyer, 2021). Water stagnation and dead end pipes lead to the decay of residual chlorine, allowing microbes to flourish (Abokifa et al., 2016; Charisiadis et al., 2015; García-Ávila et al., 2021; Liu et al., 2017). Chemical constituents interact with hydraulic dynamics, leading to potential spikes in disinfection by-products and metal elements in pipe systems (Maheshwari et al., 2020; Martin et al., 2022). Contaminants in drinking water cause gastrointestinal illnesses, harm to nervous and reproductive systems, and chronic diseases (USEPA, 2024). The dynamics of the hydraulic system play an important role in the fate and transport of contaminants, directly affecting spatial variations in tap water quality. Large and unexpected changes in demand can exacerbate hotspots of poor water quality by causing changes in flow direction, velocity, and stagnation. The complex interaction between water demand changes and intra-system water quality disparities is largely unknown.

One example of documented system-wide demand changes was the COVID-19 pandemic. The COVID-19 pandemic changed many aspects of daily life for people around the world, including work schedules and the willingness to gather in groups or public settings, all with the goal of protecting personal health. By adopting social distancing behaviors, individuals spent more time at home and less time in public spaces including places of work and leisure. Changes in the spatio-temporal patterns of individuals drove changes in water demand (Cahill et al., 2022). The primary change observed in water demand was an increase in residential demand caused by working from home, worker hour reduction or layoff, and unemployment. Water utilities reported changes in water demand, changes in water quality, and necessary adjustments in chlorine dosing as a result of COVID-19 demand changes (Berglund et al., 2022; Spearing et al., 2021). Vizanko, Kadinski, Ostfeld et al.

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https://doi.org/10.1016/j.scs.2025.106517
Received 6 March 2025; Received in revised form 2 June 2025; Accepted 2 June 2025
Available online 17 June 2025

(2024) quantified the connection between COVID-19 social distancing and water demand using an ABM and found water quality degradation in residential locations near industrial locations without characterizing the ramifications of water quality degradation.

Intra-system changes in water quality can create inequities in access to clean and affordable water. Deterioration of tap water quality, manifested as taste, color, and odor, leads to tap water avoidance (Doria, 2006; Doria et al., 2009; Hamed et al., 2022; Levêque & Burns, 2017). In addition, households choose to avoid tap water in response to public reports of drinking water quality (Chatterjee et al., 2022; Ochoo et al., 2017; Pierce et al., 2019) and risk perceptions (Grupper et al., 2021; Hu et al., 2011; Johnstone & Serret, 2012; Levêque & Burns, 2017; Park et al., 2023; Pierce & Gonzalez, 2017; Weisner et al., 2020). Avoiding tap water significantly increases household spending on water because bottled water is, on average, 100 times more expensive than tap water (IBWA, 2021a; Teodoro, 2018). Low-income and minority households are vulnerable to water affordability concerns, as they are more likely to be exposed to contaminated tap water, less likely to trust tap water, and more likely to consume disproportionate amounts of bottled water (Balazs & Ray, 2014; Doria, 2010; Fedinick et al., 2019; Gorelick et al., 2011; Hanna-Attisha et al., 2016; Hobson et al., 2007; Hu et al., 2011; Huerta-Saenz et al., 2012; Javidi & Pierce, 2018; Pierce & Gonzalez, 2017; Regnier et al., 2015; Schaider et al., 2019; Scherzer et al., 2010; VanDerslice, 2011). Water equity has been evaluated based on access to affordable water, calculated as the cost of water as a percentage of median household income (Goddard et al., 2022). Water is considered affordable for the community when the ratio is below a predetermined threshold, such as 4.0 or 4.5% (Cardoso & Wichman, 2022; USEPA, 1984). Cardoso and Wichman (2022) adopted a value of 4.5% to represent the cost of water equivalent to working eight hours at minimum wage, and Teodoro (2018) used the disposable income for the lower quintile instead of the median household income to calculate the water affordability ratio. Karrenberg et al. (2024) modeled water affordability based on the cost of water as a percent of income. Other research studies applied the Gini index and Thiel Index to assess equity concerns in water affordability at city, county, and national scales (Babuna et al., 2020; Goddard et al., 2022; He et al., 2020; Malakar & Mishra, 2017; Malakar et al., 2018). A related study developed the water injustice model to assess access to safe water for counties in the U.S. by evaluating the number of households with incomplete household plumbing, community water systems that violate the Safe Drinking Water Act, and permit holders that do not comply with the Clean Water Act (Mueller & Gasteyer, 2021). Existing models evaluate equity at a community-level without accounting for the distribution of water quality within a WDS, uneven distribution of resources within a population of water consumers, and decisions to avoid tap water (Babuna et al., 2023; Karrenberg et al., 2024; Malakar & Mishra, 2017; Mueller & Gasteyer, 2021).

Inequities in water affordability can emerge due to the interplay between complex spatio-temporal hydraulic conditions and household-level decisions to avoid tap water. Large demand changes lead to fluctuations in flows and pipe velocities, which can exacerbate water stagnation in pipes and local water quality deterioration, leading to expensive tap water avoidance behaviors (Blokker et al., 2016; Machell & Boxall, 2012, 2014; USEPA, 2002). However, intra-system inequities within WDNs remain an unexplored area of research. An intersectional and sociotechnical approach is needed to study and simulate intra-system equity based on interactions among complex system actors and infrastructure in the context of drinking water quality, tap water avoidance, and affordability. A complex adaptive system (CAS) approach characterizes heterogeneous and interacting agents that generate dynamic feedback regimes and emergent system-level phenomena (Axelrod, 1997; Holland, 1996; Miller & Page, 2007). Agent-based modeling (ABM) simulates CASs by encoding agents with heterogeneous parameters and rules of behavior that facilitate interaction with other agents and the environment (Wilensky & Rand, 2015). ABMs are well suited to model intersectional equity by simulating interactions of heterogeneous actors and their unique experience of the environment (Liu et al., 2025; Williams et al., 2022), and ABMs have been applied to explore the adaptation of consumer water demands and the performance of urban water systems (Bakhtiari et al., 2020; Berglund et al., 2023; Vidal-Lamolla et al., 2024). An ABM approach was developed to simulate interactions among water consumers and a hydraulic network to assess contamination response (Kadinski, Berglund et al., 2022; Kadinski et al., 2022; Shafiee & Berglund, 2017; Shafiee et al., 2018; Shafiee & Zechman, 2013; Strickling et al., 2020; Zechman, 2011), premise plumbing (Burkhardt et al., 2023), and water reuse (Kandiah et al., 2016; Ramsey et al., 2020). Vizanko, Kadinski, Ostfeld et al. (2024) developed a tightly-coupled framework to explore water demand and water age changes caused by COVID-19 social distancing behaviors. The framework was applied to identify inequities in exposure to poor water quality that emerge due to stagnating water near industrial areas, but did not analyze how changes in water quality impact tap water avoidance and household water expenses. Another study used an ABM approach to simulate and assess inequities in affordable water caused by time of use tariffs, but did not explore agent interaction with a hydraulic network (Karrenberg et al., 2024). New modeling approaches are needed to quantify inequities that arise from complex interactions between human behaviors and hydraulics.

The goal of this research is to develop an ABM framework to capture the emergence of water equity as a community of consumers respond to the quality of drinking water provided by a WDS. This research presents the COVID-19 social-distancing and tap water avoidance agent-based model (COST-ABM), which extends an existing ABM framework that couples household-level water use decisions with a WDS model (Vizanko, Kadinski, Cummings et al., 2024). Agents represent households that transmit COVID-19 and make social distancing decisions, updating demands at residential, industrial, and commercial nodes. A WDS model is used to simulate water quality changes as changing demand patterns lead to stagnated water and increased water age. This research develops new modeling to simulate tap water avoidance decisions, and agents select to use bottled water to meet different end uses in response to high water age. Equity is assessed as water affordability for low and high income groups, based on the cost of tap and bottled water. COST-ABM is applied for a case study to demonstrate disparities in access to safe and affordable water. This work presents a framework to assess changes to the affordability of water based on changing water quality and tap water avoidance.

The manuscript is organized as follows. Section 2 describes the materials and methods used to develop COST-ABM. The illustrative case study and modeling scenarios are described in Section 3. Results of applying COST-ABM to the case study are shown in Section 4. Section 5 provides a discussion of the results in the context of previous related literature, and Section 6 summarizes the research with broad conclusions of this work. Data required to implement the COST-ABM framework is provided in the Supplemental Information.

2. COVID-19 social distancing and tap water avoidance agent-based model (COST-ABM)

COST-ABM was developed using an existing framework that incorporates a susceptible–exposed–infected–recovered (SEIR) COVID-19 transmission model, a social distancing model, and a hydraulic model (Vizanko, Kadinski, Cummings et al., 2024). This research adds a water equity model that simulates tap water avoidance in response to high water age. The ABM framework is updated to assess the total cost of water as the sum of the cost of tap and bottled water and reports the cost of water as the percent of income (Fig. 1). The water equity model is describe as a sub-model in the COST-ABM framework (Section 2.4). Households that buy bottled water use less tap water, further changing water flows and water quality in the WDS.

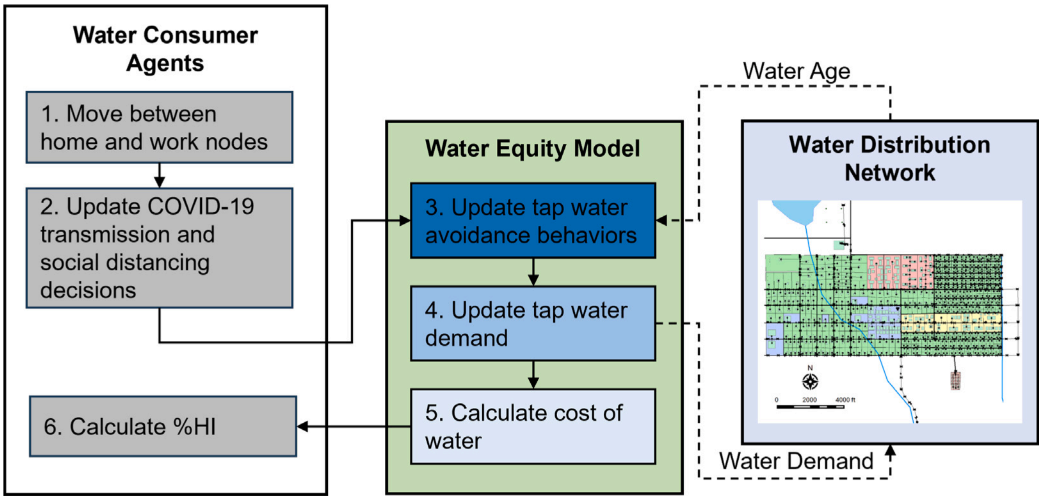

Fig. 1. COST-ABM integrates a new water equity model.

Table 1
Agent parameters are used to model tap water avoidance and water affordability. TWA: tap water avoidance.

Parameter	Symbol	Value
Water age	A_w	Hydraulic simulation
Decision to drink BW modifier	τ_d	130
Decision to cook with BW modifier	τ_c	140
Decision to use BW for hygiene modifier	τ_h	150
Threshold to use BW for [drinking, cooking, hygiene]	T_i	Eq. (1)
Decision to [drink, cook, hygiene] with BW (TWA)	D_i	[yes, no]
Tap water base rate	BR_w	\$15.55
Sewer base rate	BR_w	\$16.21
Tap water unit price	CR_w	\$0.000844/L
Sewer unit price	CR_s	\$0.000816/L
Bottled water unit price	CR_{bw}	\$0.325/L
Tap water demand	Q_{tw}	Eq. (7)
Bottled water demand	Q_{bw}	Eq. (6)
Drinking water demand reduction	QR_d	Eq. (3)
Cooking water demand reduction	QR_d	Eq. (4)
Hygiene water demand reduction	QR_h	Eq. (5)
BW cost	C_{bw}	Eq. (12)
TW cost	C_{tw}	Eq. (11)
Water cost	C_W	Eq. (8)
Household income	I_H	Section 2.3.2

COST-ABM developed in this research is described using the ODD+D protocol (Müller et al., 2013), which is an expansion of the ODD protocol (Grimm et al., 2006). The ODD+D protocol includes overview, design concepts, and details. A description of human decision-making is included in design concepts.

2.1. Overview

2.1.1. Purpose

The purpose of COST-ABM is to quantify the distribution of financial burden of water quality changes and tap water avoidance caused by social distancing during the COVID-19 pandemic.

2.1.2. Entities, state variables, and scales

An agent represents a person that consumes water at the node it occupies. Agents make decisions that affect tap and bottled water demand (Table 1). Agents update decisions to use bottled water based on the water age at the node they occupy. Agents are assigned COVID-19 threshold parameters (Table B.1) and state variables that are updated to reflect an agent's COVID-19 status, time spent in phases of COVID-19 disease, and decision-making (Table B.2).

The physical environment of the ABM is represented by a hydraulic network composed of nodes, pipes, pumps, tanks, and valves. Agents move between residential and non-residential nodes based on diurnal schedules. Social distancing changes movement patterns, leading to changes in the water demands exerted by agents and, therefore, in the hydraulic response of the system. A small-world network (SWN) (Watts & Strogatz, 1998) is used to simulate agent social interactions, connecting each agent with six other agents that pass information about their experience with COVID-19. Each simulation is run at hourly time steps for 6 months (180 days). Agent movement is updated every hourly time step, COVID-19 transmission information is updated every day, and tap water avoidance behaviors are updated every month.

2.1.3. Process overview and scheduling

Agents and households perform activities in hourly (Ht), daily (Dt), and monthly (Mt) steps (Vizanko, Kadinski, Ostfeld et al., 2024). At hourly time steps, agents move between residential and non-residential locations, update COVID-19 timing indicators (t_{exp}, t_{inf}, t_{sev}, and t_{symp}), transmit COVID-19, interact with media by updating mass media exposure (C_{med}) based on hourly probabilities (Table SI.2), and exert water demand at a network node. At daily time steps, agents update COVID-19 infection status state variables (S, S_{symp}, and S_{inf}), personal experience with COVID-19 state variable (C_{per}), and friends and family COVID-19 status state variable (C_{ff}). Agents also update decisions to adopt social distancing measures (work from home, dine out less, grocery shop less, and wear personal protective equipment (PPE)) using individual Bayesian Belief Network (BBN) models on a daily time step. At monthly time steps, households of agents calculate the cost of buying tap and bottled water at their home node (C_{tw} and C_{bw}, respectively), update decisions to use bottled water based on water age (D_i), and update the demand for tap and bottled water for their home node (Q_{tw} and Q_{bw}, respectively). For more information on the agent parameters and state variables, see Tables B.1 and B.2. Sub-models for the water equity model (actions that are taken at monthly steps) are presented in Section 2.4. Sub-models for hourly and daily steps are adapted from Vizanko, Kadinski, Ostfeld et al. (2024) and included in the Appendix (Appendix A).

2.2. Design concepts

2.2.1. Theoretical and empirical background

Adoption of TWA Behaviors: Organoleptics, or taste, odor, and color, of tap water is a primary reason individuals buy bottled water (Doria, 2010). Many water quality factors can impact the formation of taste, odor, and color compounds, and this framework uses water age to represent poor water quality. Three TWA behaviors are modeled, including drinking bottled water, cooking with bottled water, and using bottled water for teeth brushing. These actions were selected as the most probable actions to require bottled water as they include direct ingestion of water. Water age thresholds that drive TWA behaviors are based on research that demonstrated a reduction in total chlorine and an increase in heterotrophic plate count (HPC) values after water age reached values of 60–80 h (Machell & Boxall, 2014). Because HPC values are not directly linked to organoleptic values, conservative values of 130–150 h were selected for TWA decision thresholds. A threshold of 130 h was selected for drinking bottled water as the first TWA behavior that would be adopted, and a value of 150 h was selected for hygiene, based on the assumption that households would resist buying bottled water for teeth brushing until water quality had worsened further. COST-ABM does not model a connection between COVID-19 prevention measures and TWA behaviors. It is assumed that drinking, cooking and teeth brushing rates are unchanged when individuals practice social distancing behaviors.

COVID-19 Transmission: Disease transmission of COVID-19 is modeled using the formulation developed for Covasim, which is an ABM that provides mathematical relationships and parameter values for the COVID-19 SEIR model (Kerr et al., 2021). Susceptible agents have an age-progressive probability of becoming exposed when occupying the same node as a infected agents. Agents progress through the four stages of the SEIR model and cannot be reinfected.

Adoption of Prevention Measures: Agents adopt prevention measures using a decision-making model that is based on the Protection Motivation Theory. BBN models were developed to use variables that represent threat appraisal and coping appraisal with decisions to adopt social distancing behaviors (Vizanko, Kadinski, Cummings et al., 2024). BBNs were trained using responses to a survey administered across 11 countries in March and April 2020 for four social distancing behaviors, which are working from home, dining out less, shopping for groceries less, and wearing PPE (Figure SI.2, Figure SI.3, Figure SI.4, Figure SI.1). Variables that are used as input for BBN models are described in Table SI.3 and Table SI.4. Accuracy values for the four BBN models range from 66.5–95.2% and F_1 values range from 52.8–82.1% (Table SI.5).

Demand Changes: Demand changes at residential nodes are simulated based on analysis of water demands during the first week of the pandemic (Pesantez et al., 2022). Data were collected at approximately 20,000 accounts for a utility in California, and demands for March 2019 and March 2020 were compared to assess changes due to a stay-at-home order. Analysis demonstrated that demands during the pandemic were sustained throughout the day. The model represents the demand change based on agent decisions to work from home: if 50% of agents at a residential node work from home, the demand pattern is changed to a flattened demand curve adapted from data collected during the first week of the COVID-19 pandemic (Pesantez et al., 2022). This represents a higher volume of water use during working hours and a higher total volume of water consumed (Table SI.1).

2.2.2. Individual decision-making

Decisions to adopt social distancing behaviors are simulated using BBN models. Agents adopt social distancing behaviors based on the posterior probability of each BBN (Figures SI.1, SI.2, SI.3, and SI.4) updated with input state variables, including COVID-19 status (C_{per}), friends and family COVID-19 status (C_{ff}), and COVID-19 media exposure (C_{med}).

The decision to adopt individual TWA behaviors (drink bottled water, cook with bottled water, and use bottled water for hygiene) is selected when the water age exceeds a threshold based on the specific TWA behavior. Decisions to adopt TWA behaviors are made once per month and are irreversible. If the water age falls below the threshold for a TWA behavior after it has been adopted, the agent will not revert back to tap water consumption. The assumption that TWA behaviors are irreversible was chosen based on the relatively short simulation period of six months, and it is assumed that consumers would not revert back to tap water within six months of a poor water quality event.

2.2.3. Collectives

At initialization, agents are grouped into households that are used to form each agent's family network to represent a mindset on TWA behaviors that is shared within a household. All agents at a household share the same thresholds for TWA decision-making and select the same decision because the water age at each node is shared by all members of the household. Since TWA decision-making is shared by the household, tap and bottled water costs are also calculated at the household level.

2.2.4. Heterogeneity and stochasticity

Several agent parameters are assigned stochastically, which results in heterogeneity among agents. Water age thresholds, household income, BBN parameters, residential and non-residential nodes, and time thresholds for each COVID-19 stage are stochastically assigned. Agents use media including TV and radio with stochasticity (Table SI.2), which contributes to heterogeneity in the information that agents use about COVID-19 to make social distancing decisions.

2.2.5. Observation

Parameters that are recorded each month include the number of households drinking bottled water, number of households cooking with bottled water, number of households using bottled water for hygiene, demand for tap water for each household, demand for bottled water for each household, cost of tap water for each household, and the cost of bottled water for each household.

2.3. Details

2.3.1. Implementation details

COST-ABM is implemented in Python version 3.12 using the Mesa package for ABM coordination and the Water Network Took for Resiliency (WNTR) for hydraulic analysis (Klise et al., 2017). All simulations were run in parallel on a machine with a 2.10 GHz Intel Xeon Gold 6230 CPU with 40 cores and 128 GB of RAM.

2.3.2. Initialization

Nodes in the water network are initialized with average water age values from the base case scenario, and a warm-up period is run to ensure the water age at each node is at steady state. The warm-up period converges when the change in average water age is less than 0.001. Each simulation is initialized with 0.1% infected agents.

Time thresholds for each COVID-19 stage are drawn from log-normal distributions (Kerr et al., 2021) (Table B.1 and described by Vizanko, Kadinski, Ostfeld et al. (2024)). BBN parameters (Table SI.3) are assigned to each agent from the survey responses. To assign parameters to one agent, a survey response was selected randomly without replacement. Residential and non-residential nodes are randomly assigned to agents based on the capacity of consumer agents of each node.

Households are initialized with an income drawn from a gamma distribution. Households are initialized with a water age threshold for each TWA behavior using a β distribution with parameters $\alpha = 3$ and $\beta = 1$, which has a support of $[0, 1]$ and a mean value of 0.75. The threshold is initialized with a minimum value of 24 h and a maximum of τ_i (see Table 1). Using the average value from the β distribution of 0.75, the average water age threshold for TWA behaviors for drinking, cooking and hygiene are 121.5 h, 130 h, and 136.5 h, respectively.

$$T_i \sim Beta(3, 1) * \tau_i + 24 \tag{1}$$

2.3.3. Input data

Necessary input data include COVID-19 transition values, risk perception variables for BBN training, time of use for radio and TV, and hydraulic information (including pipes, pumps, tanks, valves and demands), in addition to demographics, tap water cost, and income parameters representative of a location of interest.

2.4. Sub-models: Water equity model

Equations that are newly implemented in this research as the water equity model are described as follows. Descriptions for the remaining steps that are adapted from previous research (Vizanko, Kadinski, Ostfeld et al., 2024) are provided in Appendix A.

The following steps are executed every 30 days within the water equity model. These calculations use data on agent mobility from the previous 30 days of simulation:

1. **Households update decisions to use bottled water based on water age.** Each household assesses the current water age at their home node, which is an output of the hydraulic simulation of the previous 30 days, and updates decisions to use bottled water for drinking, cooking, and hygiene (Eq. (2)).

$$D_i = \begin{cases} No, & \text{if } A_w \leq T_i \\ Yes, & \text{if } A_w > T_i \end{cases} \tag{2}$$

where D_i is the decision to adopt TWA i, which includes [drinking, cooking, hygiene], A_w is the water age at the household node, and T_i is the threshold for TWA i (Table 1).

2. **Households update tap and bottled water demand.** Unadjusted tap water demand, $Q_{tw,u}$, for each node is calculated as a function of the number of agents occupying each node and the hourly demand pattern. The unadjusted tap water demand is the nodal demand if no TWA behaviors were adopted. Households that adopt TWA behaviors, i.e., $D_i = yes$, reduce the demand at the their home node, reducing the tap water demand. Drinking water demand reduction is determined stochastically (Eq. (3)) (Crouch et al., 2021), cooking water demand is determined deterministically (Eq. (4)) (Gleick, 1996), and hygiene water demand is determined stochastically using a triangular function (Eq. (5)) (Crouch et al., 2021).

$$QR_d = \sum_{i=1}^{30} LN(2.0, 0.75) * N_{a,i} \tag{3}$$

$$QR_c = \sum_{i=1}^{30} 11.5 * N_{a,i} \tag{4}$$

$$QR_h = \sum_{i=1}^{30} 2 * TR(min = 0.25, max = 1.5, mode = 0.5) \tag{5}$$

where QR_d is the daily drinking water demand reduction (L), QR_c is the daily cooking water demand reduction (L), QR_h is the daily hygiene water demand reduction (L), and $N_{a,i}$ is the average number of agents at each node for day i. The reduction is calculated each day and aggregated monthly.

$$Q_{bw} = QR_d + QR_c + QR_h \tag{6}$$

The tap water demand is the unadjusted tap water demand less the bottled water demand (Eq. (7)).

$$Q_{tw} = Q_{tw,u} - Q_{bw} \tag{7}$$

3. **Households calculate the cost of buying water.** The cost of tap and bottled water is the summation of the two cost values (Eq. (8)).

$$C_W = C_{tw} + C_{bw} \tag{8}$$

where C_{tw} and C_{bw} are the cost of purchasing tap water and bottled water ($), respectively, and C_W is the total cost of water. The cost of purchasing tap water (Eq. (11)) has two components, a cost for supply (Eq. (9)) and a cost for sewer (Eq. (10)).

$$W = BR_w + \begin{cases} 0, & \text{if } Q_{tw} \leq 8,495L \\ Q_{tw} * CR_w, & \text{if } Q_{tw} > 8,495L \end{cases} \tag{9}$$

$$S = BR_s + Q_{tw} * CR_s \tag{10}$$

$$C_{tw} = W + S \tag{11}$$

where W is the cost for water supply, BR_w is the tap water base rate, Q_{tw} is the tap water demand, CR_w is the tap water unit price, S is the cost to sewer water, BR_s is the sewer base rate, and CR_s is the sewer unit rate.
The cost of bottled water for a household for a month is the product of the bottled water demand, Q_{bw}, and the bottled water unit price, CR_{bw} (Eq. (12)).

$$C_{bw} = Q_{bw} * CR_{bw} \tag{12}$$

3. Illustrative case study: Micropolis

The virtual water distribution network, Micropolis, is used to demonstrate the COST-ABM framework (Fig. 2). The infrastructure model for Micropolis was developed by Brumbelow et al. (2007), and agent-based models of the consumers in the population were developed by Zechman (2011) based on the demand data in the infrastructure model. This research develops another layer of data to describe the income for households in Micropolis, allowing new research in equity for under-resourced groups. This research models agent income using data from Clinton, North Carolina. Clinton was selected for this application because the population served by the municipal water provider in Clinton is 7000, similar to the size of Micropolis. Further, the Clinton water system has been in violation of the Safe Water Drinking Act twice in the last 10 years.

3.1. Water infrastructure modeling

Micropolis consists of 434 residential nodes, 15 commercial nodes, and 9 industrial nodes. Four of the 434 residential nodes are multi-family housing units with 10–200 households per node. Of the 15 commercial nodes, two are grocery stores and three are restaurants for which different demand patterns were created to better simulate these building types. Other nodes represent common commercial buildings such as banks, post offices, and schools. Demand values for individual

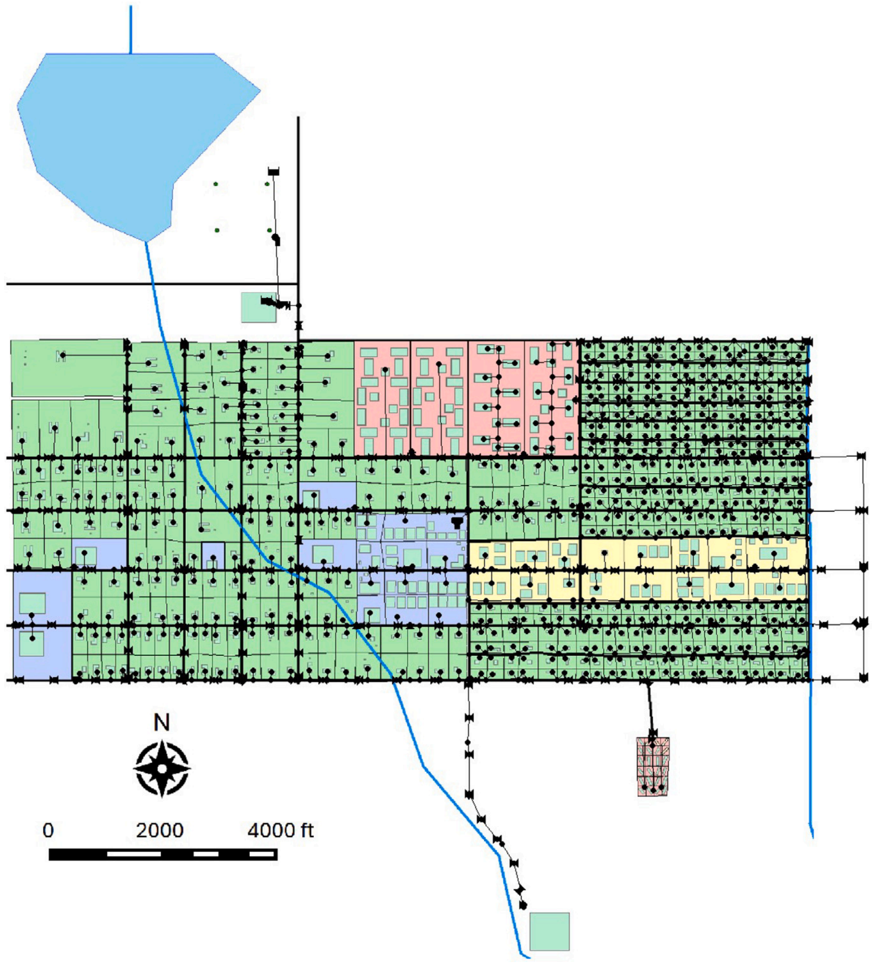

Fig. 2. Virtual city of Micropolis (Brumbelow et al., 2007). Single-family residential (green), multi-family residential (red), commercial (blue), and industrial (yellow) buildings shown with the hydraulic objects. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

commercial and industrial nodes were set during the development of Micropolis and reflect the heterogeneity in building demands (Brumbelow et al., 2007; Zechman, 2011). The total volume of water supplied in Micropolis is 4.54 ML/day. Industrial nodes are located along a central corridor to the east, and commercial nodes are grouped near the center of the city with three grouped to the west (Fig. 2). Micropolis is a complex WDS that when simulated with EPANET, provides rigorously calculated water age values.

The cost of bottled water is $0.325/L, an average established by the International Bottled Water Association (IBWA, 2021b). The cost of tap water is the sum of the tap water cost (Eq. (9)) and sewer cost (Eq. (10)), calculated using the 2023–2024 rate schedule from the city of Clinton, NC (Eq. (11)).

3.2. Population modeling

Micropolis serves a population of approximately 4600 people. Data to describe household income distributions were developed from median household income estimates from the 2022 American community survey (ACS) (Bureau, 2022) for the city of Clinton. Data table S1901 from the ACS was used to bootstrap gamma distribution parameters and is recreated in Table 2. A bootstrapped dataset was created by resampling 10,000 sets of 1000 income values. The percentage of households in each income bracket was multiplied by 100 and that number of uniformly distributed samples were drawn between the lower and upper bound of the income bracket (Table 2). The mean and variance from this bootstrapped data set were calculated and used to build a gamma distribution (Eq. (13)). The median income assigned from the gamma distribution was $38,089 and the 20th percentile income was $15,378. Corresponding values from the 2022 ACS for Clinton, NC were $38,880 and $15,000, respectively, validating income assignment using a gamma distribution calibrated with ACS data.

Table 2
Income data used to bootstrap gamma distribution parameters.

Income	Percentage of population
$0–$10,000	7.6%
$10,000–$15,000	11.9%
$15,000–$25,000	13.3%
$25,000–$35,000	14.6%
$35,000–$50,000	12.3%
$50,000–$75,000	14.3%
$75,000–$100,000	9.3%
$100,000–$150,000	11.1%
$150,000–$200,000	2.6%
$200,000+	3.0%

$$I \sim Gamma(a = 0.6697, b = 92,027.75) \tag{13}$$

3.3. Modeling scenarios

Four modeling scenarios are used to explore equity in Micropolis (Table 3). The Base scenario does not include prevention measures (PM) associated with social distancing or TWA behaviors. Other scenarios

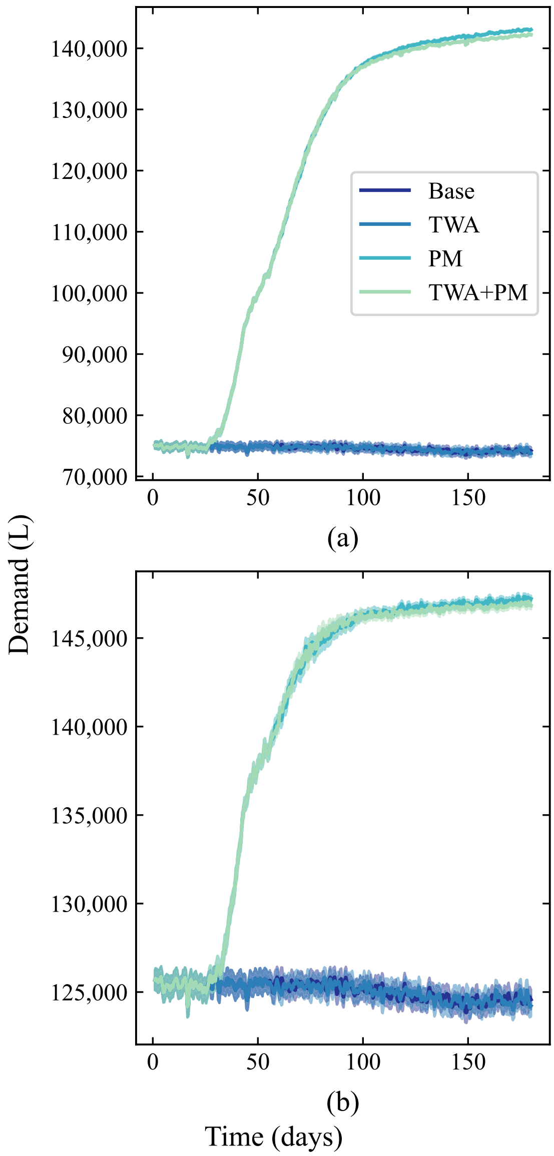

Fig. 3. Demand calculated for the *Base*, *TWA*, *PM*, and *TWA+PM* scenarios across (a) all nodes and (b) residential nodes. Solid lines represent the mean demand and the shaded regions represent the standard error for 30 simulations.

model PM and TWA behaviors. Sensitivity analysis is conducted using the TWA+PM scenario to test the influence of the change in industrial demands due to social distancing, as reported in Section 4.4. All scenarios were executed for 30 randomly generated seeds that were repeated between scenarios. The average runtime of each scenario was 3.25 h.

4. Results

4.1. Demand and water age

Four scenarios were simulated to explore changes in demand over the 180-day simulation period (Fig. 3). Demands for the Base case do not change over the simulation, reporting a 0.17% reduction in the average demand when comparing the first 30 days and the final 30 days. Similarly, TWA behaviors do not significantly change system-wide demand across the simulation, with a 0.013% increase in average demand between the first 30 and final 30 days for the TWA scenario. When social distancing is included in the simulation for the PM and TWA+PM Scenarios, there is a significant increase in demands (Fig. 3b). Agents adopt social distancing behaviors (working from home, dining out less, and grocery shopping less), causing residential demand to increase (Fig. 3a). The difference between the PM and TWA+PM scenarios is negligible, with a 0.17% reduction in demands for the TWA+PM scenario.

Table 3
Modeling scenarios.

Scenario	Prevention measure	Tap water avoidance
Base	N	N
TWA	N	Y
PM	Y	N
TWA+PM	Y	Y

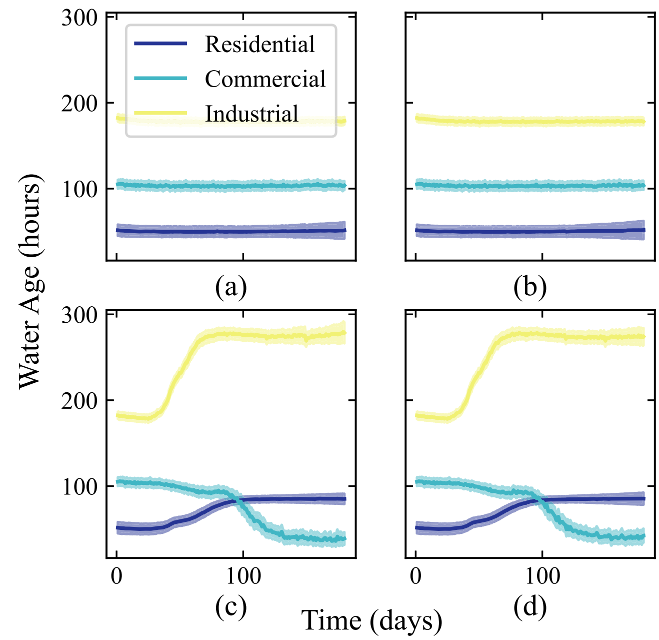

Fig. 4. Average water age at industrial, commercial, and residential nodes in the (a) *Base*, (b) *TWA*, (c) *PM*, and (d) *TWA+PM* scenarios. Solid lines represent the mean water age and the shaded regions represent the standard error for 30 simulations.

Water age is reported as a water quality metric for each of the four scenarios (Fig. 4). For the Base and TWA scenarios, water age does not change across the simulation (Fig. 4a, b). Only 6.6% of households exceeded the maximum TWA threshold of 150 h in the Base and TWA scenarios and 13.3% of households exceeded this threshold in the TWA+PM scenario (Figure SI.7). Because TWA behaviors do not significantly affect the volume of demand and flows, water quality is also not affected. In the PM and TWA+PM scenarios, residential water age increased as a result of the close spatial proximity of a significant proportion of residential nodes to industrial nodes. Industrial water age increased as agents adopted social distancing behaviors and industrial water demands decreased. Increasing residential water age also increased the number of households exceeding the threshold to adopt TWA behaviors (Figure SI.7). Commercial water age, on the other hand, increased because most commercial nodes are located in the center of the network, and velocities increased in the pipes supplying the commercial sector by 200% (red box in Figure SI.8).

4.2. Tap water avoidance

The percentage of households that bought bottled water for cooking and drinking increased when social distancing was implemented (Fig. 5). In the TWA scenario, the percentage of households buying bottled water for cooking or drinking is approximately 7.5% at the end of the 180 day simulation (Fig. 4a). Due to water quality deterioration under

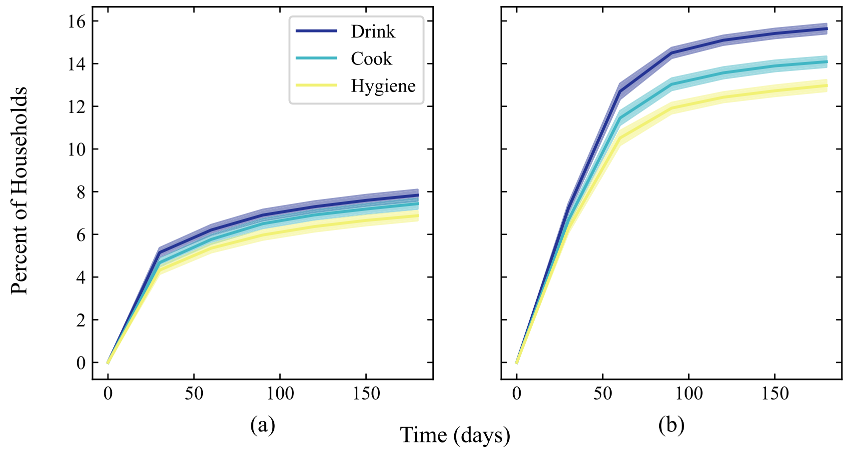

Fig. 5. Percentage of households that bought bottled water for drinking, cooking and hygiene (a) without social distancing (TWA) and (b) with social distancing (TWA+PM). Solid lines represent the mean percentage of households adopting each TWA and the shaded regions represent the standard error for 30 simulations.

the TWA+PM scenario associated with the water quality impacts of social distancing, the average percentage of households buying bottled water for drinking and cooking is 14% (Fig. 4b). Adoption of all three TWA behaviors increases in the TWA+PM scenario because water age across the residential nodes increased due to social distancing behaviors (Fig. 4). More households bought bottled water for drinking because the threshold for adoption was 130 h, which is lower than the thresholds for other water end uses, at 140 h for cooking and 150 h for hygiene.

4.3. Cost of water

The median cumulative cost of water, including tap water, sewer, and bottled water costs, for the base case is between \$200 and \$300 for 75% of households (Fig. 6). The cost of water increases marginally when TWA behaviors are included due to existing values for water age causing households to buy comparatively expensive bottled water. Social distancing increases the cost of water for households because households use more water at home, increasing household expenditure on water. The largest increase in the median cost of water occurs when agents social distance and avoid tap water (TWA+PM). The additive effect of increased water use at residential nodes (Fig. 3b) and increased bottled water buying behaviors due to water quality deterioration creates an increase in water cost for a significant proportion of households. The maximum household cost of water increased from \$400 in the Base scenario to nearly \$1000 in the TWA+PM scenario, a 150% increase over the six month simulation. Median water costs also increased, rising from \$220 in the based scenario to \$300 in the TWA+PM scenario. No difference is observed in the cost of water for low-income (lower 20th percentile, Fig. 6a) and high-income (upper 80th percentile, Fig. 6b) households.

The median cost of water as a percentage of income (%HI) for high-income households (Fig. 7b) was below 3% for all scenarios. More than 75% of high-income households had %HI less than 4.6%, a threshold that represents one 8-h work day spent on water services, showing nearly universal water affordability for high-income households. For low-income households, however, water is unaffordable for more than 50% of households in all scenarios. In the *Base* scenario, water services are unaffordable for half of the low-income households. In all other scenarios, the number of low-income households facing water unaffordability increases, and, in the *TWA+PM* scenario, nearly 75% of low-income households face water unaffordability.

For low-, and high-income households (Fig. 7a and b, respectively), prevention measures and tap water avoidance alone did not increase the %HI significantly. However, for low-income households, prevention measures and tap water avoidance combined to increase %HI to unaffordable levels. For nearly 75% of low-income households, the %HI exceeded one 8-h day of working at minimum wage (%HI = 4.6%), which is a commonly cited affordability threshold (Cardoso & Wichman, 2022). The emergent effect of increased demands due to the adoption of prevention measures and tap water avoidance due to poor water quality demonstrates the complex interactions among social phenomena.

4.4. Sensitivity analysis: Tap water avoidance for drinking, cooking, and hygiene end uses

The sensitivity of the results to tap water end use was tested through a set of simulations. For the simulations reported above, when agents choose to avoid tap water, they use bottled water for drinking, cooking, and hygiene. Sensitivity analysis tests results when agents use tap water for only one end use (drinking, cooking, or hygiene) and use bottled water for two other end uses. Water affordability is reported and compared with a simulation in which agents do not use tap water for any of the end uses, but use bottled water for each end use (shown as None in Fig. 8). The %HI for low-income households is not sensitive to changes in individual end uses (Fig. 8). The median value does not change when tap water is used for individual end uses. The only significant difference is a reduction in the maximum %HI observed when tap water is used for cooking. This is because the amount of water used for cooking is greater than the amount of water used for drinking and hygiene (Eqs. (3), (4), and (5)). When agents use tap water for cooking instead of buying bottled water, the cost of water decreases as well as the %HI.

4.5. Sensitivity analysis: Industrial water demand

The amount of demand that is exerted at industrial facilities may not be reduced when people are not present due to social distancing behaviors. For example, industries that are high water consumers, such as the beverage industry, may continue to exert high water demands when only a skeleton crew is present. Sensitivity analysis was conducted on the amount of demand at industrial nodes that is attributed to the presence of agents. This analysis tests degradation of water quality and the adoption of TWA behaviors when industrial water demands stay high during periods of social distancing. The percent of the demand that depends on the number of agents is varied in a set of five simulations (Fig. 9). Scenarios represent the percentage of industrial demand that is attributed to the number of agents at each node, and the remaining demand exerted at that facility remained constant. In the original ABM formulation (TWA+PM in Fig. 9), all of the demand attributed to an industrial node is dependent on the number of agents at that node at a given time step. Scenarios TWA+PM-N refer to scenarios where N% of

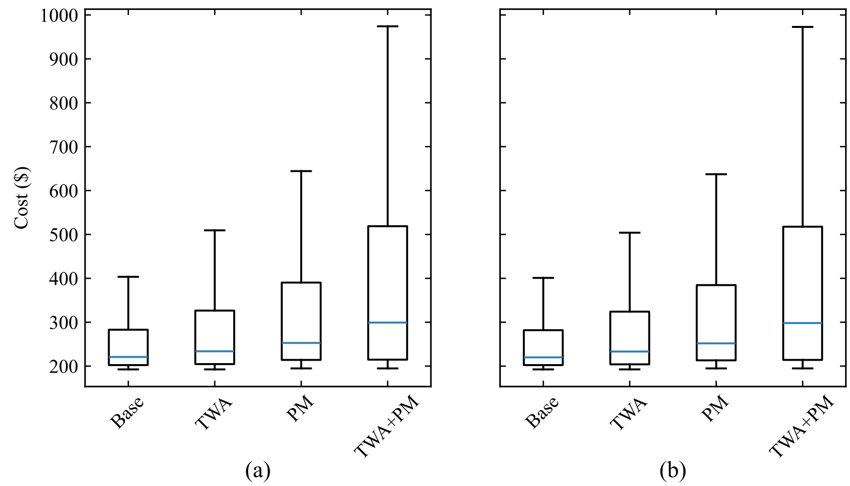

Fig. 6. The total cost of water over the 180-day simulation for (a) low-income (lower 20th percentile) and (b) high-income (upper 80th percentile) households.

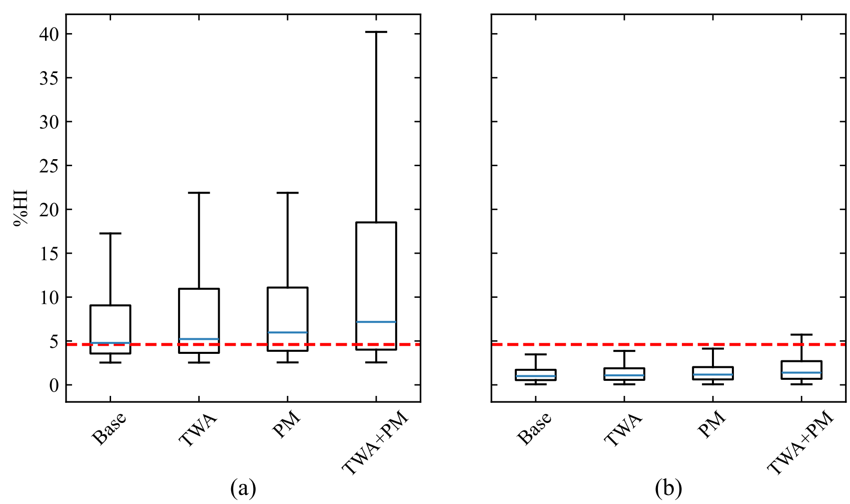

Fig. 7. Water affordability, %HI, for (a) low-income (lower 20th percentile) and (b) high-income households (upper 80th percentile). Red-dashed line represents 4.6% or the %HI where a household must spend one 8-h day's worth of income on water services.

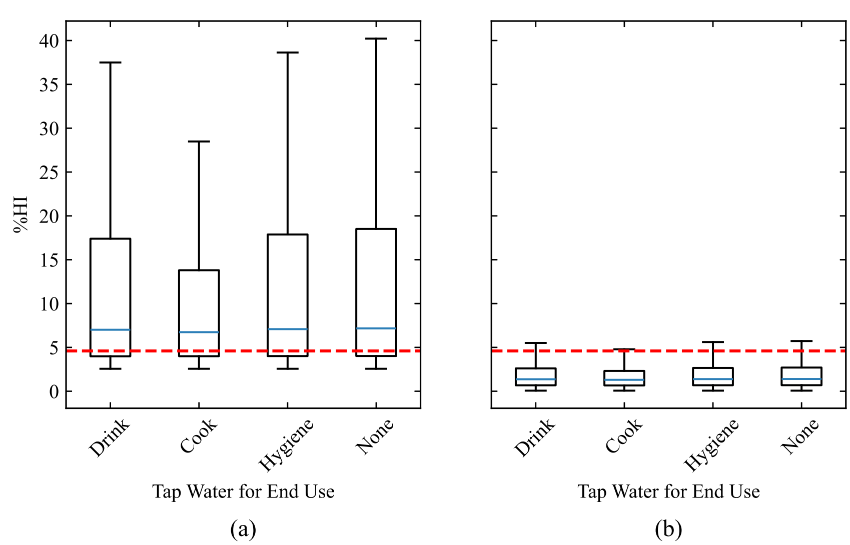

Fig. 8. Water affordability, %HI, for (a) low-income (lower 20th percentile) and (b) high-income households (upper 80th percentile) for scenarios when agents use tap water (do not use bottled water) for drinking, cooking, and hygiene. Red-dashed line represents 4.6% or the %HI where a household must spend one 8-h day's worth of income on water services.

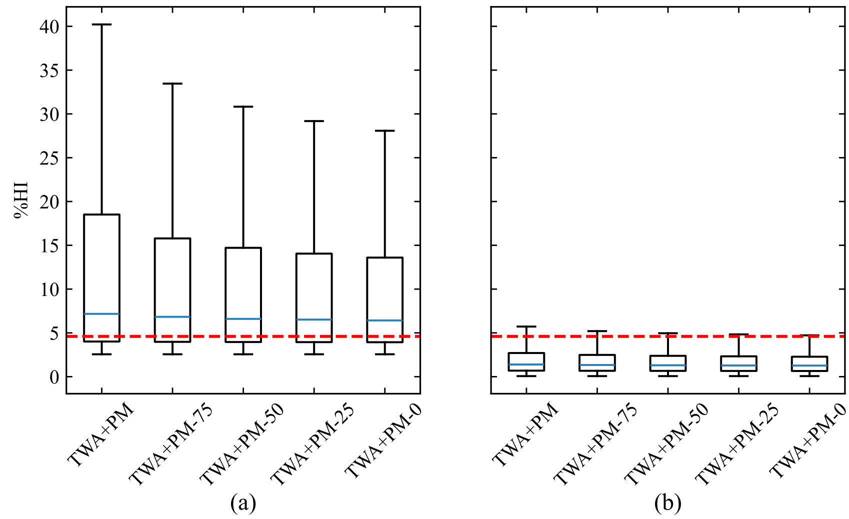

Fig. 9. Water affordability, %HI, for (a) low-income (lower 20th percentile) and (b) high-income households (upper 80th percentile). Scenarios represent the percentage of industrial demand that is attributed to the number of agents at industrial nodes. Red-dashed line represents 4.6% or the %HI where a household must spend one 8-h day's worth of income on water services.

industrial node demand is affected by the number of agents at the node. The TWA+PM-0 scenario represents industrial buildings with no or negligible demand associated with agent locations. As the percentage of industrial demand associated with agents is reduced, the total industrial demand increases. This increase in industrial demand decreased water age at surrounding residential nodes, reducing the %HI in the system. The median %HI for low-income households remained above the 4.6% affordability threshold for increasing volume of demands at industrial facilities, showing a weak sensitivity of %HI on industrial demand. These results imply that residential water age and %HI is not solely driven by increases in industrial water age, and that more complex spatial dynamics are occurring in the network.

5. Discussion

5.1. Assessing equitable access to affordable drinking water

The cost of water as a percentage of income (%HI) is used as the equity metric in this research and is calculated at each household using income and the total cost of tap and bottled water. This approach is similar to previous research (Cardoso & Wichman, 2022; Onda & Tewari, 2021; Teodoro, 2018; Teodoro & Saywitz, 2020), but includes the cost of bottled water and does not make an implicit assumption on per capita water use. Previous studies used a set per capita volume of 50 gallons per capita per day (GPCD) (Cardoso & Wichman, 2022; Onda & Tewari, 2021; Teodoro, 2018; Teodoro & Saywitz, 2020), whereas this research calculates water use for each household using a bottom-up approach based on end uses. The assumption of 50 GPCD represents water necessary to meet basic needs and may under-estimate %HI. Our approach provides a more realistic interpretation of household water expenditure beyond meeting basic needs, potentially providing a more realistic representation of water affordability for low-income households. Teodoro and Saywitz (2020) update previous work (Teodoro, 2018) and present a mean affordability ratio for households in the lower 20% by income, AR_{20}, of 12.42 for $n = 399$ water utilities. The AR_{20} metric is the ratio of the basic water service cost to disposable household income and better represents household-level affordability, compared with the utilities system-level financial capability (Davis & Teodoro, 2014). Although not directly comparable, the median %HI values for low-income households are reported here as 4.6%–7%, which are similar to the mean AR_{20} of 12.42. The median %HI values would increase if they are calculated using disposable income instead of total household income. Cardoso and Wichman (2022) reported that 8.4–14.2% of households exceed an affordability threshold of 4.5% at per capita volumes of 40–75 GPCD. In this research, 12.5% of households exceed a threshold of 4.5% in the Base scenario and 25.5% of households exceeded 4.5% in the TWA+PM scenario. The Base scenario falls within the range reported by Cardoso and Wichman (2022), but the TWA+PM scenario exceeds the range. The increased populations above the affordability threshold of 4.5% is likely caused by the higher demand volumes used in this research and the inclusion of bottled water buying in household water expenditure. To our knowledge, bottled water buying has not been included in previous studies, yet it represents an expenditure on water that is deemed necessary for many households (Doria, 2010).

Calculating %HI at each household provides new insight into how changes in the hydraulic system, such as poor water quality, impact the ability of low-income households to afford water services. ABMs are uniquely suited to address this concern by modeling individual households with diverse income values representative of the target population. COST-ABM, developed in this research, generates household level metrics attributable to spatially unique households that interact with the physical hydraulic network, which could provide greater depth to national and global water distribution equity studies (Cardoso & Wichman, 2022; Hutton, 2012; Teodoro, 2018).

5.1.1. Limitations

Because Micropolis is a virtual city, data that would geospatially locate income and ethnicity are not available. The spatial intersection of demographic characteristics with water quality hot spots could potentially lead to different equity impacts than predicted here. Spatial differences in income from inequitable practices such as redlining can lead to unpredicted spatial changes to affordability. New research is needed to apply COST-ABM for real-world cities, assess equity impacts, and validate the framework and modeling approaches using measured data. Other work has calculated the cost of water based on disposable income, and COST-ABM can be updated to use other affordability metrics in analysis (Teodoro, 2018).

5.2. Modeling tap water avoidance behaviors

Tap water avoidance behaviors are modeled in COST-ABM to represent that as water quality deteriorates, individuals choose to buy bottled water as an alternative to tap water. This research applies the assumption that water quality is linked to water age. Previous studies have made a qualitative connection between water age and water quality, reporting water quality degradation with increased water age (Blokker et al., 2016; Machell & Boxall, 2012, 2014; USEPA, 2002). This framework uses thresholds on water age to represent water quality degradation and trigger the adoption of tap water avoidance behaviors. Because there is a lack of research that has quantitatively linked water quality thresholds or water age thresholds with bottled water buying behaviors, thresholds were selected using conservative engineering judgment. COST-ABM is a novel modeling approach to connect water quality with tap water avoidance behaviors for drinking water systems.

5.2.1. Limitations

New research can model water quality explicitly to capture the fate and transport of specific drinking water constituents, such as the decay of chlorine and chloramine (Ricca et al., 2019), and their interaction with microbes. New research is needed to fully develop and demonstrate models using, for example a multi-species extension (MSX) for EPANET, that simulate spatial and temporal changes to water quality constituents in a water distribution system.

While research has demonstrated that organoleptic compound formation is associated with poor water quality (Doria et al., 2009; Font-Ribera et al., 2017), further research is needed to quantitatively link specific water quality parameters with organoleptic compounds and the formation of organoleptic compounds with tap water avoidance behaviors. Previous work has shown that individuals make the decision to buy bottled water based on many factors including not just organoleptics (taste, odor, and color), but also trust in the water utility and risk perceptions related water quality (Anadu & Harding, 2000; Doria, 2010; Saylor et al., 2011). These factors have been shown to vary considerably with demographic groups and affect the use of tap water (Balazs & Ray, 2014; Doria, 2010; Fedinick et al., 2019; Gorelick et al., 2011; Hanna-Attisha et al., 2016; Hobson et al., 2007; Hu et al., 2011; Huerta-Saenz et al., 2012; Javidi & Pierce, 2018; Pierce & Gonzalez, 2017; Regnier et al., 2015; Schaider et al., 2019; Scherzer et al., 2010; VanDerslice, 2011). Future work can also include risk perception modeling for different demographic groups and capture tap water avoidance behavior decision-making.

This research modeled demands and demand changes at buildings as a diurnal pattern, rather than the aggregation of end uses at fixtures by individuals sharing a home or non-residential building. Unique demand patterns and changes to demands during working-from-home periods may be captured by considering personal end uses, or water consumption at fixtures specific to each individual person. For example, seasonal demands associated with outdoor water use are not modeled in the formulation presented here. Demands can change drastically between seasons, with major peaks in summer time demands caused by outdoor water use, and working-from-home scenarios could result in more gardening and outdoor water use. For households that worked from home, appliances such as dishwashers and washing machines could be used during working hours and would contribute unevenly to water use profiles. This research assumed a change in demands when 50% of agents sharing a building work from home. Simulating personal end uses for agents would allow more descriptive simulation of demand changes. New data is needed to characterize personal end uses for individuals in a shared household during pandemic and post-pandemic periods (Vizanko et al., 2025) and relate personal beliefs around water uses and social distancing to changes in water demands (Berglund et al., 2025).

Other tap water avoidance behaviors can be included in future research. This research assumes that COVID-19 prevention measures do not influence tap water avoidance behaviors. Drinking, cooking and teeth brushing rates may be changed when individuals practice social distancing behaviors, and those reactions can be included in the agent behaviors. The model that was formulated here assumes that consumers do not use tap water for drinking, cooking, and hygiene once they have adopted tap water avoidance behaviors. New research is needed to explore how tap water avoidance behaviors are abandoned and to integrate those behaviors in COST-ABM. Park et al. (2023) reported higher intake of sugar-sweetened beverages when individuals perceive bottled water as safer than tap water. Park et al. (2023) also found that these perceptions are race and ethnicity dependent, affirming the need to address sociodemographic differences in future work. Other research can explore tap water avoidance behaviors that seek sugar-sweetened behaviors and assess the health effects of consuming or avoiding tap water.

5.3. Agent-based modeling to assess equitable access to affordable water

COST-ABM is a bottom-up framework that assesses water equity as the cost of water as a percent of income based on water quality and tap water avoidance behaviors. The dynamics that lead to inequities are evident in literature (Javidi & Pierce, 2018) but have not been directly measured and reported. Without research that reports individual household water quality sampling and tap water avoidance behaviors, COST-ABM is an important step in understanding and mitigating inequity in community water systems. COST-ABM is readily scalable to other hydraulic networks that represent real cities. The data required to apply COST-ABM to a new location include the cost of water, a hydraulic model of the pipe network, and income statistics, such as Table S1901 from the ACS.

Micropolis is a virtual application, but represents a hydraulically complex network with similarities to common practices seen in small towns, and some lessons that emerge in this research can apply generally. For example, Micropolis has a core of commercial and industrial nodes that represent centralized common spaces such as government buildings, restaurants, clinics, and schools, which reflects a common urban planning concept. In this application, commercial water age decreased despite a decrease in demand, which may be a common and generalizable phenomenon in cities built with a layout similar to Micropolis.

Previous work developed ABM approaches specifically for the virtual city of Micropolis to study contamination response (Kadinski, Berglund et al., 2022) and social distancing (Vizanko, Kadinski, Ostfeld et al., 2024). This research adds a new socioeconomic layer to Micropolis that incorporates both household incomes and tap and bottled water cost simulation. The population of Micropolis was modeled after a small, rural U.S. city that has a population with below average income and has experienced violations of the Safe Drinking Water Act. Enhancing the Micropolis dataset with household income and the cost of water allows new analysis of equitable outcomes that can be included across future applications of WDS infrastructure management. Future work can further enhance the sociodemographic layers with race and ethnicity. Enhancing these datasets facilitates new analysis of environmental justice in decision-making for water infrastructure management.

5.3.1. Limitations

Each simulation of COST-ABM was executed in parallel on a 40-core machine with an average runtime of 3.25 h. High computational requirements can pose a potential challenge for utilities in applying COST-ABM. The results presented here were executed over a 180-day timeline to capture changes in the transmission of COVID-19 and social distancing behaviors. Future work can reduce runtime by simulating a snapshot of social distancing and demand shifting behaviors to assess water quality and the cost of water at pre-determined points in a pandemic or unfolding hazard.

COST-ABM can be applied to explore the performance of infrastructure changes that are designed to improve water quality at hotspots through operational changes such as hydrant flushing or tank optimization. Capital projects, such as correcting oversized pipes, adding pipes in areas with stagnation concerns, or adding water sources can be assessed using COST-ABM. Policy changes can encourage tap water consumption through household water filtration system rebates, tap water education programs, and community engagement that builds trust between water utilities and the community, and these mechanisms can be implemented in COST-ABM.

6. Conclusion

This research presents COST-ABM, which quantifies the equity and affordability impacts of COVID-19 social distancing and tap water avoidance behaviors. COST-ABM incorporates COVID-19 social distancing behaviors that cause spatio-temporal changes in water quality. Household perceptions of water quality lead to decisions to adopt tap water avoidance behaviors that reduce tap water demand. The cost of water for each household is calculated including the cost of buying bottled water due to poor water quality. Spatio-temporal changes in water quality, driven by COVID-19 social distancing, caused bottled water buying behavior that increased the average household cost of water. The combination of COVID-19 social distancing behaviors and tap water avoidance behaviors led to an emergent reduction in household water affordability for an illustrative case study. These findings have not been established in other research studies to date, though the modeling framework is based on dynamics that have been described and documented in numerous research studies. Results demonstrate emergence of water equity, that is, the cost of water as a percentage of income, under scenarios that combine social distancing and tap water avoidance is not equal to the sum of impacts due to individual scenarios of social distancing and tap water avoidance alone. Increases in household water cost disproportionately led to a decrease in water affordability for low-income households.

COST-ABM is the first to assess equity in an ABM that tightly couples COVID-19 transmission, social distancing, and WDS hydraulic performance. The ABM measures equity using the cost of water as a percentage of household income that is calculated at each household, which offers increased specificity when assessing water affordability for low-income households. COST-ABM can be applied in future work to not only assess (in)equities in WDS, but develop management strategies to address inequities through policy and operational changes that will improve water affordability for all consumers.

CRediT authorship contribution statement

Brent Vizanko: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Shimon Komarovsky:** Writing – review & editing, Validation, Software, Methodology. **Avi Ostfeld:** Writing – review & editing, Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization. **Emily Zechman Berglund:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research was funded by the United States - Binational Science Foundation (BSF) and the Israeli Water Authority under project number 143990. We would also like to thank both the City of Lakewood and Dryhurst et al. (2020) for providing access to data that were critical to the development of the models presented in this research.

Appendix A. Process scheduling details

The following descriptions for Steps H1–H5 and D1–D5 are adapted from Vizanko, Kadinski, Ostfeld et al. (2024).

Step H1. Agents move between residential and non-residential nodes. Agents move between nodes based on predefined node capacities and node type requirements. Agents are assigned to move to and from non-residential nodes based on an hourly total capacity at each non-residential node.

Step H2. Agents update COVID-19 status indicators. Agents update COVID-19 status indicators, which represent the number of hours an agent spends in the exposed, infected, severe, and symptomatic stages (t_{exp}, t_{inf}, t_{sev}, and t_{symp}, respectively).

Step H3. Agents transmit COVID-19. Infected agents expose susceptible agents when they occupy the same node. When an infected agent moves to a new node, up to 10 susceptible agents at the new node are exposed based on the node's exposure rate (e_{res} for residential nodes e_{nr} for non-residential nodes in Table B.1).

Step H4. Agents update mass media exposure. Agents receive information from TV and radio based on probabilistic estimates that they use each form of media at each hour of the day (Rogers & Sorensen, 1991; Shafiee & Zechman, 2013) (Table SI.2). The mass media exposure (C_{med}) is a binary number that is changed from 0 to 1 once an agent receives information about COVID-19 at any time step, based on probabilistic behaviors to use radio and TV.

Step H5. Agents exert water demand. The hourly demand at each node is calculated based on the number of agents at each node, as follows.

$$Bd'_{t,N} = \frac{K_N}{K_{N,cap}} \times Bd_{t,N} \tag{A.1}$$

where $Bd'_{t,N}$ is the new demand for node N at time t, K_N is the number of agents at node N, $K_{N,cap}$ is the capacity of node N, and $Bd_{t,N}$ is the base demand.

The following steps are completed every 24 h:

Step D1. Agents update COVID-19 status. Agents update COVID-19 status state variables (S, S_{symp}, and S_{inf}) based on their progression through disease stages. Once the time in a stage exceeds an agent's threshold for that stage (e.g., $t_{exp} > \tau_{exp}$, Table B.1), the agent updates its COVID-19 status (e.g., $S = infected$).

Step D2. Agents update personal experience with COVID-19. Once an agent enters the infectious stage ($S = infected$), the agent updates the personal COVID-19 status (C_{per}) from "no" (value of 1), to "doctor confirmed and am still infected" (value of 9) (Vizanko, Kadinski, Ostfeld et al., 2024).

Step D3. Agents update friends and family COVID-19 status. An agent updates the friends and family COVID-19 status (C_{ff}) when peer agent enters the infectious stage. The value (C_{ff}) can increase up to 7 to represent the number of peers in an agent's network that are infected. A value of seven corresponds to survey responses that the person is "very much affected" by friends or family testing positive or dying from COVID-19 (Vizanko, Kadinski, Ostfeld et al., 2024).

Step D4. Agents update decision to adopt prevention measures. BBN models are applied to calculate the probability of adopting each prevention measures based on mass media exposure, personal COVID-19 status, and friends and family COVID-19 status (C_{med}, C_{ff}, and C_{per}, respectively). Prevention measures include working from home, dining out less, grocery shopping less, and wearing PPE and bottled water buying behaviors are drinking bottled water, cooking with bottled

Table B.1
Agent parameters are used to model exposure to COVID-19, communication, and mobility in the network. LN(x, y) represents a log-normal distribution with mean x and standard deviation y.

Parameter	Symbol	Value
Residential exposure rate	e_{res}	0.05[a]
Non-residential exposure rate	e_{nr}	0.01[a]
Probability of listening to radio	P_R	Table SI.2
Probability of watching TV	P_{TV}	Table SI.2
Work node	N_{work}	All industrial nodes
Home node	N_{home}	All residential nodes
Exposed stage threshold (days)	τ_{exp}	$\sim$LN$(4.5, 1.5)$[a]
Symptomatic stage thresholds (days)	τ_{symp}	$\sim$LN$(1.1, 0.9)$ (to severe stage)[a] $\sim$LN$(8.0, 2.0)$ (to recovered stage)[a]
Infected stage threshold (days)	τ_{inf}	$t_{symp} + t_{sev} + t_{crit}$
Severe stage thresholds (days)	τ_{sev}	$\sim$LN$(1.5, 2.0)$ (to critical stage)[a] $\sim$LN$(18.1, 6.3)$ (to recovered stage)[a]
Critical stage thresholds (days)	τ_{crit}	$\sim$LN$(10.7, 4.8)$ (to dead stage)[a] $\sim$LN$(18.1, 6.3)$ (to recovered stage)[a]

[a] Values reported by Kerr et al. (2021).

Table B.2
Agent state variables.

State variable	Symbol	Value
COVID-19 status	S	[susceptible, exposed, infected, recovered, dead]
Symptomatic status	S_{symp}	[Symptomatic, asymptomatic]
Infected status	S_{inf}	[mild, severe, critical]
Personal COVID-19 status (BBN input)	C_{per}	$\in [1, 9]$
Friends and family COVID-19 status (BBN input)	C_{ff}	$\in [1, 2, 3, 4, 5, 6, 7]$
Mass media exposure (BBN input)	C_{med}	$\in \{0, 1\}$
Time in exposed stage (days)	t_{exp}	
Time in symptomatic stage (days)	t_{symp}	
Time in infected stage (days)	t_{inf}	
Time in severe stage (days)	t_{sev}	
Time in critical stage (days)	t_{crit}	
WFH decision	D_{WFH}	[Not WFH, WFH]
Dine out less decision	D_{dine}	[Dine out, dine out less]
Grocery shop less decision	D_{shop}	[Grocery shop, grocery shop less]
PPE decision	D_{PPE}	[Wear PPE, not wear PPE]

water and using bottled water for hygiene. Refer to previous work for more information on prevention measures (Vizanko, Kadinski, Cummings et al., 2024; Vizanko, Kadinski, Ostfeld et al., 2024).

Step D5. Agents update demand patterns. Agents that select to work from home, dine out less, or grocery shop less update their demand patterns from a typical diurnal pattern to a pattern that expresses demands uniformly across daylight hours (standard and COVID-19 demand patterns in Table SI.1).

Appendix B. State variables and parameters

See Tables B.1 and B.2.

Appendix C. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.scs.2025.106517.

Data availability

All data, models, and code that support the findings of this study are available from the corresponding author upon reasonable request. The ABM is available through Zenodo.

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