Water Resour Manage (2018) 32:2033–2059
https://doi.org/10.1007/s11269-018-1916-6

An Agent-based Modeling Framework for Assessing the Public Health Protection of Water Advisories

M. Ehsan Shafiee[1] · Emily Zechman Berglund[1] · Michael K. Lindell[2]

Received: 24 January 2017 / Accepted: 22 January 2018 /
Published online: 2 February 2018

Abstract In the event that pathogens or toxins are introduced to a water distribution system, a utility manager may identify a threat through water quality data or alerts from public health officials. The utility manager may issue water advisories to warn consumers to reduce water use activities. As consumers react and change water demands, dynamic feedbacks among the community, utility managers, and the engineering infrastructure can create unexpected public health consequences and network hydraulics. A Complex Adaptive System (CAS)-based methodology is developed to couple an engineering model of a water distribution system with agent-based models (ABM) of consumers, public health officials, and utility managers to simulate feedback among management decisions, system hydraulics, and public behavior. A utility manager and a public health official are represented as agents, who respond to the event using a set of rules and equations that are based on a statistical analysis of a set of recorded water events. Consumers are represented as agents who update their water activities based on exposure to the contaminant and warnings from a utility agent and family members. A model of consumer compliance is developed using results from two surveys that report data to characterize consumer perceptions toward information sources during a water contamination event. The ABM framework is applied for an illustrative mid-sized virtual city to quantify the significance of interactions and advisories on public health consequences.

✉ M. Ehsan Shafiee
mshafie@ncsu.edu

Emily Zechman Berglund
emily_berglund@ncsu.edu

Michael K. Lindell
mlindell@archone.tamu.edu

1 Department of Civil, Construction, and Environmental Engineering, North Carolina State University, Raleigh, NC 27695, USA

2 Hazard Reduction and Recovery Center, Texas A&M University, College Station, TX 77840, USA

Keywords Water distribution network · Contamination · Complex adaptive system · Agent-based modeling · News media · Broadcast warning · Water notification · Risk perception

1 Introduction

Water distribution infrastructure networks are vulnerable to contaminants that may be introduced to a pipe network through intentional actions or accidental events. Intentional events, in which chemicals are injected at exposed access points, are rare, and accidental contamination through leaks, chemical spills, and seasonal changes in water quality are more common. Consequences associated with contamination events for large municipalities may be severe. For large systems, a contaminant that is introduced to a water source can be transported via an extensive pipe network through sprawling metropolitan areas and delivered to a population, causing widespread public health consequences (Geldreich 1991; Kroll 2006). The U.S. Environmental Protection Agency (EPA) encourages municipalities and water utilities to develop plans for threat management and provides guidance through the Response Protocol Toolbox, which defines approaches for simulating water contamination events, hardening networks, and preparing response plans (United State Environment Protection Agency 2004a, b, c, d, e, f). To reduce the public health impacts of an event, utility managers can implement hydraulic operations, such as flushing hydrants and manipulating valves to move or isolate a contaminant plume. Utility managers can also initiate water advisories to limit consumption of contaminated water, rather than control hydraulics, by encouraging customers to suspend contact end uses of water for a short duration. Television, radio, telephone, and short message systems can be used to disseminate water notices to consumers (Rodríguez et al. 2007).

Threat management activities should test alternative response plans for their effectiveness in protecting public health. For example, hydraulic response plans can be evaluated using water distribution system simulation models, and optimization methods have been developed and applied to identify effective strategies for opening hydrants to flush a contaminant (Reis et al. 1997; Alfonso et al. 2010). Evaluating the effectiveness of water advisories, however, poses challenges beyond simulating the water distribution network and requires knowledge about social and technical interactions during a water contamination event. As demonstrated by Woo and Kim (2003), the water distribution contamination event is a sociotechnical system, in which interactions between a social system and an engineering system have significant impacts on outcomes. Consumers, utility managers, and public health officials exchange information in an event, and these interactions influence the degree to which consumers reduce their consumption of contaminated water. Water customers perceive and comply with water notices based on the characteristics of the water notice and *a priori* knowledge and beliefs about water (Lindell and Perry 2004; Rundblad 2008), and their actions can impact the outcomes of a public health event and the performance of water advisories. The hydraulics of the pipe network may be altered due to changes in expected water demands, which increases the complexity and dynamics of a contamination event, and causes the potential emerging public health consequences to become unpredictable, when the interactions among the involved actors are not explicitly considered. Water distribution system models do not include automatic simulation capabilities to include these interactions and behaviors and, as a result, may be limited in simulating the effectiveness of water advisories.

An agent-based modeling (ABM) approach was developed and demonstrated for simulating the interactions of consumers and the water network in a contamination event (Zechman 2011; Ehsan Shafiee and Zechman 2013). The ABM approach represents the event as a Complex Adaptive System (CAS) (Holland 1995; Miller and Page 2007), in which interacting components influence emergent system properties through dynamic feedback loops. Consumers are represented as agents, and the ABM is coupled with a water distribution system model to calculate changes in flows within the network, due to the actions and reactions of consumers. The work presented here contributes a new dimension to simulation of water contamination events, based on informed modeling of both consumer and community officials to mimic complex behaviors during water events. The ABM approach is extended to include new rules and actions to simulate consumer agents, which receive warnings and comply with messages, and water utilities and public health agents, which detect events and issue water advisories. Models for the behaviors of utility managers, public health officials, and customers are developed through the analysis of recorded events and surveys that were conducted to assess consumer response to water notices. Simulation of consumer compliance and the decision-making of community officials provides a pathway for applying the ABM to evaluate public health protection achieved through water advisories. The framework is tested by simulating realistic contamination scenarios for a virtual city and water supply system. Results about the dynamics of warning consumers through the news media provide insight that can be used to develop response plans.

2 Sociotechnical Dynamics of a Water Distribution Contamination Event

In a contamination event, consumers, public health officials, and utility managers interact with one another and with engineered infrastructure (Fig. 1). The contamination event proceeds in three phases (Bristow and Brumbelow 2006). The first phase is *threat identification*. Consumers drink contaminated water, become exposed to a critical dose, experience symptoms, and visit public health facilities. Public health officials may notice an unusual number of patients seeking attention and alert public officials or utility managers to the threat of a potential event. Utility managers may also receive an alert through sensors that detect unusual water quality in a pipe network. The second phase is *threat verification*. Utility managers obtain additional information, such as water quality samples, to verify an event. While utility managers verify the event, consumers become aware of an event through word-of-mouth and symptomatic responses. As consumers reduce their water use, they may create a shift in flow directions and volumes in the network. This shift in contaminant movement may create difficulties in the verification of events. After the threat is verified, the third phase is *threat warning*. Utility managers issue water notices and alerts to warn consumers. As consumers use the news media, they receive warnings about the event and reduce a fraction of their water uses, further influencing movement of the contaminant plume. These interactions among consumers, utility managers, public officials, and a water network create a complex and dynamic environment. This CAS is modeled using an ABM approach, described below.

3 Agent-based Modeling Framework

This research develops a sociotechnical approach to integrate infrastructure modeling and behavioral data through an ABM framework that simulates consumers, utility managers,

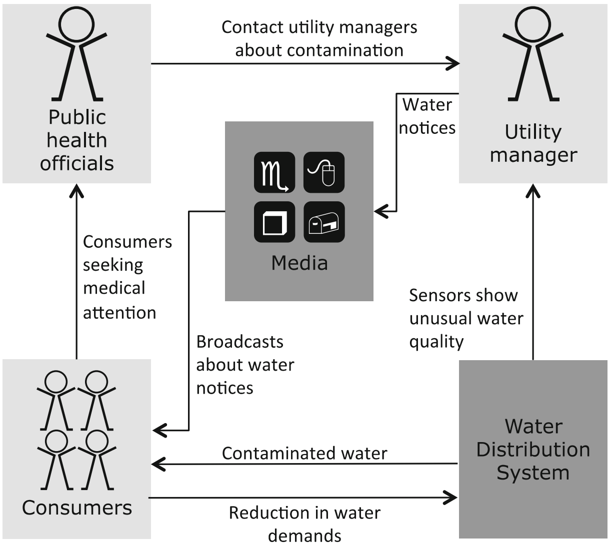

Fig. 1 Actors (light gray boxes) and engineered infrastructure (dark gray box) interact in a sociotechnical water distribution contamination event. Arrows show information that is passed and actions that are exerted between components

and public health officials as agents that interact with water distribution infrastructure. ABM is a modeling paradigm for studying a CAS by simulating actors as autonomous agents. Agent behavior is simulated by a set of rules that are applied to select actions, satisfy individual goals, and adapt to new environmental conditions (Miller and Page 2007; Railsback and Grimm 2012). The emergence of system-level properties can be assessed through modeling a collection of agents and their interactions. Previously conducted research in this area developed an ABM approach to simulate a sociotechnical contamination event system for a small water network (Zechman 2011; Ehsan Shafiee and Zechman 2013). The ABM framework was constructed to simulate heterogeneous consumer behaviors, including the volume and timing of daily water consumption; travel between residential and non-residential locations; exposure and symptomatic response to a contaminant; demand reduction in response to awareness; and communication with other consumers. Results demonstrated that hydraulics can be significantly altered when consumers change water demands. The research presented here extends the ABM framework to include interactions of consumer agents with a water utility manager agent and a public health agent. Social agents are modeled using AnyLogic (XJ-Technologies 2012), which is a platform for discrete-event and agent-based modeling. AnyLogic is tightly coupled with EPANET, which is software that performs extended period simulation of the water movement and water quality behavior within pressurized pipe networks (Rossman 2000). The components of the framework (Fig. 1) are described in the following subsections, and the data and modeling that were developed to encode new rules for agents are described in Sections 3.1.1–3.3.

Consumer, utility manager, and public health official agents are there social agents in this study. Each agent is explained below.

3.1 Consumer Agents

Consumer agents are created to model individual residents of a community. A consumer agent is assigned parameters and rules to represent attributes and behaviors. Parameters (which do not change during a simulation) and state variables (which do change during a simulation) are summarized in Table 3 in Appendix C. The original development of the ABM approach was described in detail by Ehsan Shafiee and Zechman (2013). The research included the development of modeling for consumer behaviors, including the volume of water ingested daily per person, based on weight, age, and gender; the timing for five daily ingestion events; the pattern of movement for each consumer during a day as it travels to non-residential nodes; exposure to a contaminant; and the volume of reduction in water demand. The rules are explained in detail in Ehsan Shafiee and Zechman (2013). This study develops additional behaviors for consumers, receipt of and compliance with advisories and warnings, which are described in detail in Section 3.1.1.

3.1.1 Probabilistic Approach to Model Compliance with Water Advisories

Three data sets are used to develop behavioral rules for consumer agents to represent their response to water contamination advisories. Rogers and Sorensen (1991) reports results of a time use study conducted for Any City, which is an unnamed U.S. city. The study reports the time of day that respondents engage in a set of activities, and the survey data are used in this framework to characterize the agent behavioral rules for sleeping. Lindell and his colleagues (Lindell et al. 2010, 2011) report the results of two surveys that were conducted to assess media use and individual response to water contamination advisories. The College Station sample comprised 48 undergraduates in the Psychology Department Subject Pool and the Boston sample comprised 110 respondents from the ZIP codes in which water contamination advisories were issued. College Station residents answered questions about their intention to use water in the event that a hurricane would disrupt the provision of a clean water supply. Boston residents answered questions about their actual responses to boil water notices, which were issued when a water main ruptured on May 1, 2010 (Pantic et al. 2011). We regard these samples as providing illustrative data, not definitive data. The data they provide are more realistic than arbitrary assumptions we might have made in the absence of these data. American Time Use Survey published the data for sleeping and watching TV, which is quite similar to the results of the surveys (American Time Use Survey 2014). The behavioral rules for receiving messages and complying with advisories are developed using these datasets, described as follows.

3.1.1.1 Receiving Messages

Consumers receive a water notice when they interact with the news media. The timing for using television and radio can be simulated using the three sets of survey data described in the previous section. Rogers and Sorensen (1991) reports the percentage of the population that is expected to be awake at each hour of the day (Fig. 2a). Results of the surveys conducted in Any City, College Station, and Boston report the percentage of the population that uses radio and television at each hour (Figs. 2b and c, respectively). At each time step, consumer agents are flagged as awake, using radio, and using television, based on these probabilities. When an agent is awake and interacts with a news media channel that is simultaneously broadcasting a water contamination advisory, that agent is flagged as alerted to

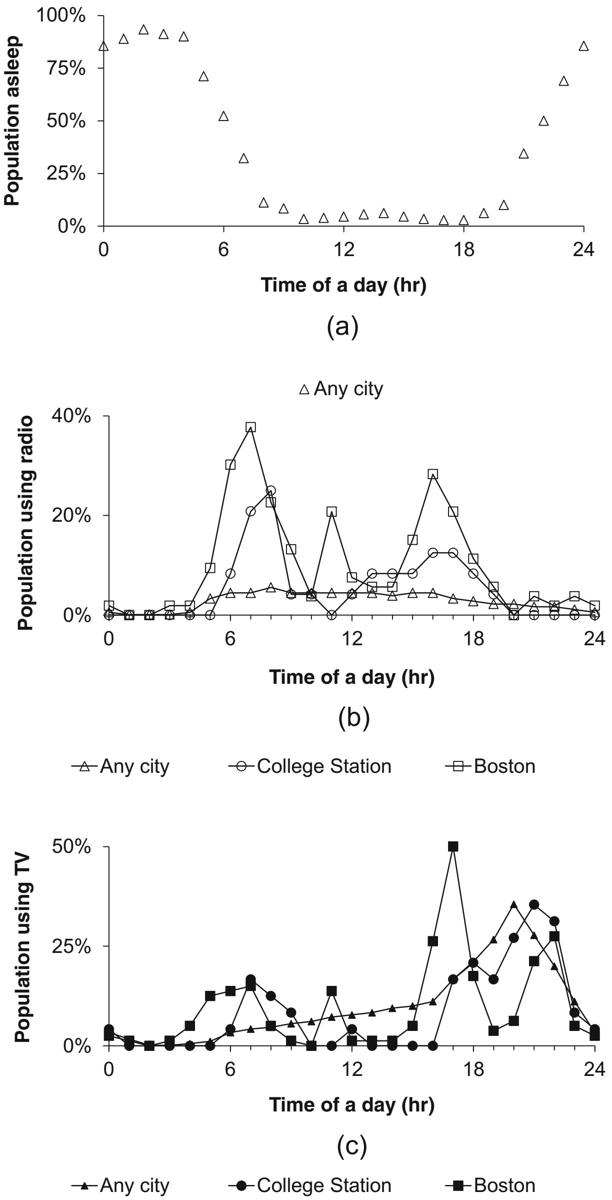

Fig. 2 Daily distribution of **a** population asleep, **b** population using radio, and **c** population using television. Reported for Any City (Rogers and Sorensen 1991), College Station (Lindell et al. 2010), and Boston (Lindell et al. 2011). References (Lindell et al. 2010, 2011) are not published at the time of this manuscript

the event. The distribution of the population using radio and television is similar for College Station and Boston data sets, whereas Any City shows less use of media during the day. Any City data represents behavior of the population in the mid-1980's, and the new datasets show shifts in the use of the news media in 2010.

Once a consumer agent is alerted, the agent is modeled to communicate with peers within its community. The community is modeled for each agent using a modified small world model (Watts 1999). Details of building the communication model are given by Ehsan Shafiee and Zechman (2013).

3.1.1.2 Compliance with Water Advisories

Consumers that receive a warning message choose to comply with or disregard the message based on their perception of the source of information, or the *stakeholder* (Lindell et al. 2010). Recipients perceive the expertise, trustworthiness, and protection responsibility of a stakeholder and select a decision based on these perceptions. Each agent is assigned values for perceived stakeholder source characteristics, based on survey data. A probability distribution function is used to determine whether or not the agent complies, based on values for perceived stakeholder source characteristics. The probability distribution function (1) is created using a probability distribution table that was generated using survey responses (Appendix A). Three positive probability distributions, the Uniform, Exponential, and Poisson probability functions, are used to approximate the likelihood of compliance, based on the values for E, R, and T. The three probability distributions are selected as options because the input multivariate can be represented as a discrete number from one to five in increments of 1.0. The uniform probability distribution can be characterized as the mean and the standard deviation of this function depend on the upper and lower bound of the function. The standard deviation of an Exponential distribution function is quantifiable if the mean is known. The standard deviation of Poisson distribution function is equal to its mean, which is known for the dataset used here. For other distribution functions, the standard deviation is unknown, which creates difficulties in characterizing these functions. Equation 1 is used to calculate P_C, which is the likelihood that a consumer complies with a water advisory or message.

$$P_C(c) = P_{C|E,R,T}(c \mid e, r, t), \tag{1}$$

where $P_C(c)$ is the probability distribution of compliance. The variables C, E, R, and T represent compliance, expertise, protection responsibility, and trustworthiness, respectively. The lower case letters e, r, and t indicate the value of each variable, which takes an integer value from one to five. The value of $P_{(C|E,R,T)}(c \mid e, r, t)$ is the conditional probability of compliance.

To make a decision to comply, each agent is randomly assigned, with uniform probability, one of the three conditional probability distributions for $P_{(C|E,R,T)}(c \mid e, r, t)$, which is used to calculate values for the probability of compliance, $P_{C,u}(c)$, for responding to a utility manager, and $P_{C,f}(c)$, to a family member. Random assignment of a conditional probability distribution represents the difference among individuals in perceiving and responding to warnings from stakeholders. If a consumer agent receives a warning through television or radio, the value of $P_{C,u}(c)$ for that consumer is compared to a random number to determine whether or not the agent complies. For an agent that receives a message through word-of-mouth, the value of $P_{C,f}(c)$ for that consumer is compared to a random number to determine compliance. When an agent chooses to comply, it reduces its water uses and communicates with other agents, based on the rules for those behaviors (described in Section 3.1).

3.2 Utility Manager Agent

Utility managers are modeled as agents that receive an alert, spend time to verify the threat, and issue water notices. A set of recorded water events in which authorities warned consumers is used to develop rules for utility manager behaviors (Hrudey and Hrudey 2004) (Table 6 in Appendix C). In these events, utility managers become aware through the reports of public health officials, utility personnel, or infrastructure warning systems (such as water quality sensors). After receiving an alert, utility managers typically ensure the validity of the threat through verification and, subsequently, write and issue a water notice. These steps delay the response of a utility manager and may take several days.

Rules are developed here to describe the behavior of utility managers in disseminating water advisories, based on a set of 29 recorded water events in which authorities warned consumers (Hrudey and Hrudey 2004) (Tables 4 and 6 in Appendix C). The 29 events are selected from a set of 69 events that occurred between 1970 and 2002. The 29 events were selected because data about the decisions of stakeholders were reported; the amount of contaminant that was in the water supply was significant; and a substantial risk to public health was introduced in a short period of time. It is assumed that these events are from the same population of events.

A statistical inference approach (Ang and Tang 2007) uses data about historic events to construct a probability function of the response time that a utility manager takes to issue a water advisory, as shown in Eq. 2. The non-exceedance technique is used to reconstruct a probability distribution, which is the approach used by Bristow and Brumbelow (2006) in analyzing this data set.

$$P_U(t_a) = 1 - \exp(-0.649t_a), \tag{2}$$

where $P_U(t_a)$ is the likelihood that a utility managers confirms the water event at time t_a, and t_a is the time in days that passes after an alert is received about a potential water event. The average response time of a utility manager to a warning message is 1.54 days. The Chi-Square test for goodness-of-fit is 0.103, which is smaller than 5.99 and indicates that the exponential distribution accurately models the behavior of utility managers at the 0.05 significance level.

The utility manager agent is modeled to broadcast a water notice that is issued when a contaminant is verified and remains in effect for the rest of simulation, representing the time that the contaminant is removed from the system.

3.3 Public Health Official Agent

Public health officials receive consumer complaints about waterborne illnesses and inform utility officers about potential threats to a water distribution system. The time of identification is the time at which a public health officer recognizes that drinking water is the source of public health impacts and alerts a utility manager about a water contamination event. Public health officials recognize waterborne illnesses from an unusual number of consumers seeking medical attention, and an increasing number of complaints increases the likelihood that threat will be identified. These two factors affect the time of identification, shown in the historical data. To estimate the time of identification, the total probability of recognizing a waterborne event is computed by multiplying two independent probability distribution functions: (1) the probability that a public health official identifies a water contamination event based on the number of consumers seeking medical attention, $P_{N_m}(t_c)$; and (2) the probability that a public health official identifies a water event based on the time that passes after the first consumer is diagnosed at a medical facility, $P_t(t_c)$. In reality, a water event is recognized based on the number of individuals who seek medical attention, rather than the portion of population that experiences symptoms. Therefore, the percentage of the population that experiences symptoms is not used in modeling the response of the public health official. Information for reported water contamination events (Table 6 in Appendix C) includes data that describe the percentage of the population that experienced symptoms during the event and the percentage of the population that sought medical attention at the time of identification. It is assumed that the two distributions are statistically independent, because the correlation between the number of consumers at medical services and the time that has passed after the first consumer sought medical attention (fourth and fifth columns in Table 6 in Appendix C) is -0.105, which is not significantly different from zero ($t_{27} = 0.29$). The derivation of the $P_{N_m}(t_c)$ and $P_t(t_c)$ is explained in Appendix B.

At each time step after the first consumer agent is diagnosed at a medical facility, the public health official agent determines if an event is identified as a water contamination incident by calculating the product of $P_t(t_c)$ and $P_{N_m}(t_c)$ and comparing this value to a random number between 0.0 and 1.0, generated using a uniform distribution. The likelihood of identification increases with time. The overview of rules for the public heath official agent is summarized in Table 5 in Appendix C.

3.4 Hydraulic and Water Quality Simulation Model

Hydraulic and water quality conditions in the water infrastructure system are modeled using EPANET (Rossman 2000), which is coupled with the AnyLogic modeling system. Input files for EPANET specify the layout, specifications, and demands of a water distribution piping system. Consumer demands are aggregated at nodes, which are junctions at intersecting pipes. EPANET calculates the flow volumes, flow directions, and water quality in the pipe network. The simulation proceeds at discrete time steps for hydraulic calculations in EPANET. At each time step, water quality information is passed from EPANET to the agents. As consumers reduce their water use, changes in demands are communicated to EPANET, and the hydraulic conditions for successive time steps are calculated by EPANET. This simulation establishes the feedback loop between the consumers and the water distribution system.

An ensemble of water quality sensors is installed in the water network to detect contamination. Sensors are simulated as perfect sensors, without error in concentration values, and detect contaminant concentrations exceeding an identified threshold.

4 Illustrative Case Study: Virtual City of Mesopolis and Modeling Scenarios

The ABM framework is applied to simulate public response to water contamination events in the city of Mesopolis, which is a virtual city that was developed for water contamination threat management research (Please refer to Fig. 6 in Ehsan Shafiee and Zechman (2013)). Mesopolis is modeled with realistic land uses, including residential, commercial, and industrial, in addition to a naval base, an airport, and a university (Fig. 3). In total, the population is approximately 150,000 consumers. Water is withdrawn from the river at a location 13 miles south of the city and pumped through a main pipe to the southern edge of Mesopolis, where the pipe branches to deliver water to an East Water Treatment Plant (WTP) and a West WTP. The West WTP provides the majority of the water demand for the western portion of the city, which is separated from the eastern side by the river. The East WTP supplies water for the eastern side of the city, and, during peak demands, for the western side of the city. Four different demand patterns are specified – residential, commercial, industrial, and naval demands. Commercial nodes include churches, schools, grocery stores, and

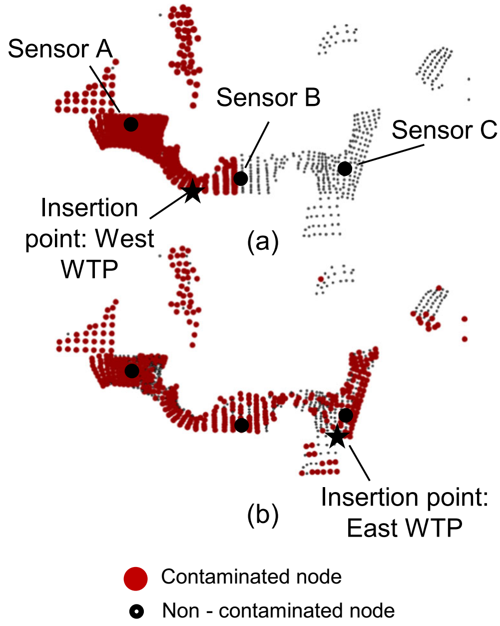

Fig. 3 Contaminated area for the **a** West and **b** East contamination events, simulated using the Base Model. Water quality sensors are shown as Sensors A, B, and C

malls. Demands at industrial nodes are typically constant through a 24-hour period, corresponding to three 8-hour shifts, while the demands at other nodes types increase during the day and reduce to nearly zero at night.

Four arsenic (e.g., as arsenic trioxide (EPA 2001)) contamination events, the West Short, West Long, East Short, and East Long, are created and compared for the contamination events (Table 1). Arsenic is a well-studied contaminant in the public health literature and is a proxy for representing the exposure pattern of a community to bacterial contaminants, such as *E. coli*. For each event, a load of 300 *kg* of arsenic is injected at a treatment plant (West or East) (Fig. 3), beginning at 12AM and continuing for six hours (Short) or 18 hours (Long) (Rasekh and Brumbelow 2014; 2015). Contamination events are simulated during the winter season, which corresponds to relatively low flows in the network (specified by a demand multiplier of 0.65 in the EPANET input file). The first model, the Base model, serves as a benchmark for successive models. For the Base model, consumer agents are simulated with behaviors, including mobility, word-of-mouth communication, probabilistic drinking water patterns, and demand reduction. The Base model is Model 5, as described in Ehsan Shafiee and Zechman (2013). Although word-of-mouth communication is included in the Base Model, official water advisories from water utility manager agents

Table 1 Modeling Scenarios

Model	Compliance with warnings from family members	Compliance with advisories
Base	Deterministic	N/A
Compliance 1 (C1)	Stochastic	N/A
Compliance 2 (C2)	Stochastic	Deterministic
Compliance 3 (C3)	Stochastic	Stochastic

are not simulated. Additionally, consumers respond deterministically (within one hour) to word-of-mouth communication. For the Compliance 1 (C1) Model, consumer agents comply probabilistically with warnings from family members, using the approach described in Section 3.1. The Compliance 2 (C2) Model simulates the compliance with water advisories at a rate of 100%, and consumer agents who receive warnings reduce their water uses immediately. Consumers respond probabilistically to family members. The Compliance 3 (C3) Model simulates probabilistic compliance with both warnings from family members and official water advisories.

Three sensors are simulated at main pipelines in the network. Numerous research studies have developed sensor placement methodologies to most effectively place sensors in a distribution network (e.g., see Ostfeld et al. (2008)); however, decisions about placing sensors for this study were made based on insight about the direction of water flows in the network. Sensors are activated by contaminant concentrations greater than 0.015 $\frac{mg}{L}$. For each of the four events, a sensor is activated within 10 hours after a contaminant enters the system. Sensor A is the activated sensor for the west events, and Sensor B and C are the activated sensors for the East Short and East Long events.

5 Results

The four models were executed for each contamination event for 30 random trials. The simulation period is eight days, including two days that serve as a warm-up period for the hydraulic model. During the warm-up period, the simulation runs to allow the network hydraulics to equilibrate, but no data are collected from the output. Each modeling scenario takes 15 minutes to execute on a 64-bit desktop computer with an Intel Core i7 processor and 8 GB RAM.

The number of exposed consumers is simulated for the four contamination events using the Base Model and C1 Model. Respectively for the Base Model and C1 Model, the number of exposed consumers is 30,353$\pm$121 and 39,798$\pm$134 in West Short Sc., 35,580$\pm$122 and 46,901$\pm$134 in the West Long Sc., 37,625$\pm$209 and 46,382$\pm$179 in the East Short Sc., and 46,169$\pm$154 and 59,204$\pm$231 in the East Long Sc. For each model and contaminant event, the simulation is executed 30 times with random starting seeds, and the results are reported as the average and standard deviation over the 30 trials. For the Base Model, West events generate a smaller number of exposed consumers than East events, because contaminant that is introduced at the East WTP spreads through almost the entire network, as shown in Fig. 3. Short events result in fewer exposed consumers than Long events. Though the concentration of contaminant in the water is high for Short events, the contaminant leaves the system through terminal nodes more quickly than for the Long events. On average, the number of exposed consumers increases by 28.6% when the C1 Model is used to simulate probabilistic responses to the warnings of family members.

5.1 Compliance with Water Advisories

The C2 and C3 Models are used to simulate the four events for 30 random trials. The number of exposed consumers has a relatively low variance for the Base Model and the C1 Model, but the predicted number of exposed consumers varies significantly for the C2 and C3 Models. This is because there is a wide variation in the response time of the utility manager, which significantly influences the total number of exposed consumers (Fig. 4). The response time reaches a critical time at which it is too late to issue advisories, and advisories

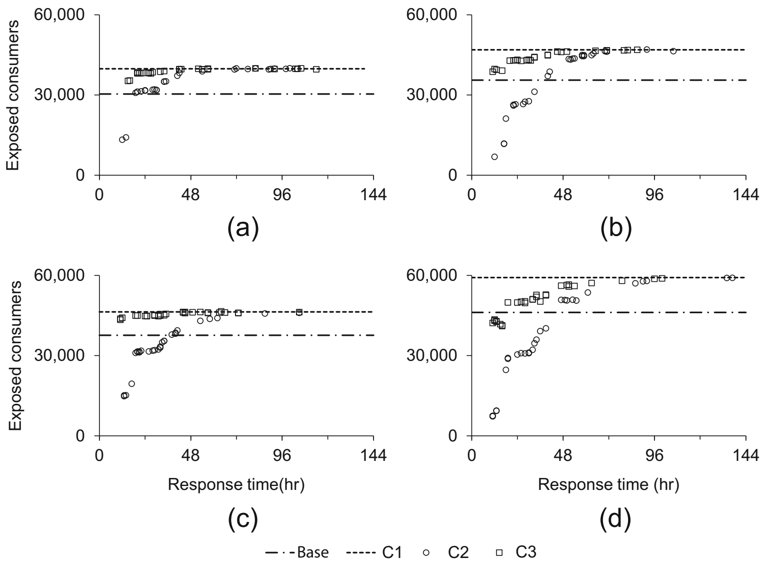

Fig. 4 Number of exposed consumers for utility manager response times **a** West Short, **b** West Long, **c** East Short, and **d** East Long Events. Results are shown for 30 random trials for each event and model. Results for the Base Model and C1 Model are not shown because they are independent of the utility manager's response time (*x*-axis)

that are issued are not effective. The critical response time is 46 hours for the West Short event, 96 hours for the West Long event, 102 hours for the East Short event, and 128 hours for the East Long event, simulated using the C3 Model. Therefore, when a contaminant is introduced to the network over a long duration, the critical response time is also long, as fewer consumers become exposed at each time step. Utility managers should take response actions as quickly as possible to increase the level of protection, because in short events, the rate of becoming exposed may be very high. Further research can simulate utility managers that are able to use event detection methods and source identification methods in a real-time manner to effectively select response actions.

The C3 Model predicts higher numbers of exposed consumers than predicted by the C2 Model because some consumers do not comply when simulated using the C3 model. The number of consumers who comply with official water advisories is significantly higher for the C2 Model (Fig. 5). For the C2 Model, the number of consumers who comply with official advisories decreases as the response time increases. If the event is verified by the utility manager quickly, many consumers are unaware of the event and can receive an official warning. As the event progresses, fewer consumers are influenced by official water advisories because they are already aware of the event by recognizing symptoms of exposure or by warnings from peers.

The range of exposure can vary widely for each event, depending upon consumer warning compliance, response time of the utility manager, and identification time of the public health official (Fig. 6). The lowest number of exposed consumers is predicted for cases in which utility managers respond immediately to sensor alerts, and consumers comply with advisories with a rate of 100%. All events activate a sensor, and the earliest time that a utility manager agent receives a sensor alert is 10 hours after the injection of contaminant. Results provide additional information about initiating water contamination warnings or hydraulic

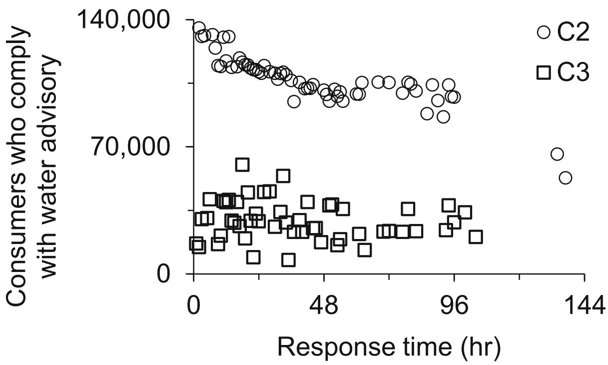

Fig. 5 Compliance with advisories, simulated using the C2 and C3 Models for the four contamination events. Response time, on the x-axis, shows the amount of time taken by utility managers to issue an advisory

operations when an event is detected and confirmed, based on the amount of time that has passed after the event was initiated. For example, during Short events, the use of the news media may not reduce the number of exposed consumers, as consumers ingest contaminant at high concentrations before they receive official advisories. For many events, the time that the event was initiated may be unknown, and existing computational methodologies that use sensor data can be applied to approximate the time of initiation (e.g., Zechman and Ranji Ranjithan 2009).

5.2 Comparison of Compliance Probability Distributions

The C3 Model uses a randomly selected probability distribution to simulate each consumer's compliance with official advisories and warnings from peers. Here, we simulate

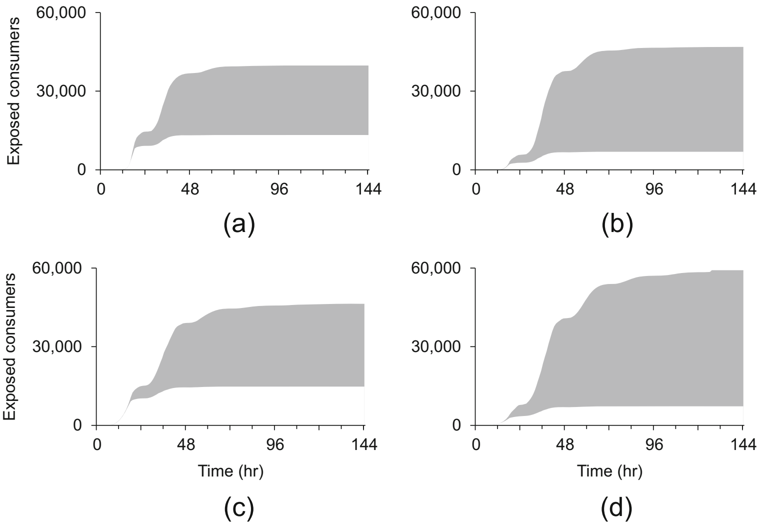

Fig. 6 Number of exposed consumers as an event progresses for **a** West Short, **b** West Long, **c** East Short, and **d** East Long events. Shaded area shows bounds of performance for 120 simulations, simulated using the Base, C1, C2, and C3 Models

compliance using one probability distribution for all consumers to test the sensitivity of modeling results (Fig. 7). Results (number of exposed consumers) are normalized by the C1 Model results to demonstrate the *reduction* in the number of exposed consumers as a result of water advisories. The three probability distributions predict similar numbers of consumers who comply, and differences between the predicted number of exposed consumers are slight. Probabilities of compliance are highest using the Exponential and Poisson distributions.

5.3 Comparison of College Station Survey and Boston Survey

The results presented above use joint probability distributions that were developed using the Boston data to simulate consumer compliance. Responses to survey questions vary between the two communities, Boston and College Station, and using the College Station data to characterize consumer agents may result in a different number of exposed consumers. When compliance is modeled using the joint probability distribution that was developed for the College Station data, the number of exposed consumers is noticeably lower in the first 48 hours of the event because respondents reported higher values, on average, for the perceived stakeholder properties (expertise, protection responsibility, and trustworthiness) of utility managers. Water advisories that are issued in College Station later in the evening have a noticeably stronger effect than water advisories that are issued in Boston later in the evening. As shown in the time use reports of the two communities, a higher percentage of residents in College Station use television later in the evening, which improves the effectiveness of broadcasts initiated after 10PM on the first day.

The likelihood of compliance with a water advisory for each community is calculated by summing the products of occurrence probability and the probability of compliance (using alternative compliance probability functions) across all cells in Table 2. The likelihood for compliance with water utility personnel is 70%, 51%, and 67% for College Station data and

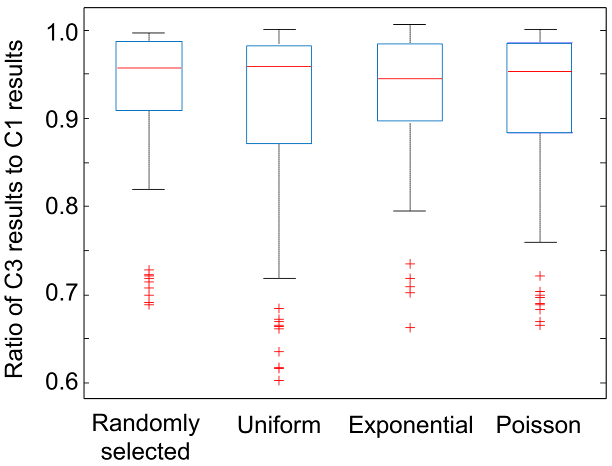

Fig. 7 Exposed consumers for all contamination events simulating using conditional probability distributions and the C3 Model. For the C3 Model, each consumer agent is randomly assigned the Uniform, Exponential, or Poisson distribution for modeling compliance, shown in the first column. The number of exposed consumers predicted by each model is normalized by C1 Model predictions

Table 2 The probability mass function, $P_{E,T,R}(e_i, t_i, r_i)$, for the perceived expertise, trustworthiness, and protection responsibility for a water utility personnel (first value per cell) and immediate family members (second value per cell) for College Station (C) and Boston (B)

		Survey	Protection Responsibility						
			1	2	3	4	5		
	1	C	0, **0.042**	0, 0	0, **0.021**	0, 0	0, 0	1	
		B	0, **0,010**	0, 0	**0.011**, 0	0, 0	0, 0		
	2	C	0, 0	0, 0	0, 0	0, **0.021**	0, 0		
		B	0, 0	0, 0	0, 0	**0.011**, 0	0, 0		
	3	C	0, 0	0, 0	0, 0	0, 0	0, 0		
		B	0, 0	0, 0	0, 0	0, 0	0, 0		
	4	C	0, 0	0, 0.021	0, 0	0, 0	0, 0		
		B	0, 0	0, 0	0, 0	**0.011**, **0.011**	0, 0		
	5	C	0, 0	0, **0.021**	0, 0	0, 0	0, **0.021**		
		B	0, 0	0, 0	0, 0	0, 0	**0.011**, 0		
	1	C	0, 0, **0.021**	0, 0	**0.021**, 0	0, 0	0, 0	2	
		B	0, **0.011**	0, 0	0, **0.021**	0, 0	0, **0.011**		
	2	C	0, **0.021**	0, **0.021**	0, 0	0, 0	0, **0.021**		
		B	0, **0.011**	**0.011**, **0.021**	**0.011**, 0	**0.011**, 0	**0.011**, 0		
	3	C	0, 0	**0.021**, **0.021**	**0.021**, **0.042**	0, 0	0, **0.021**		
		B	0, **0.021**	**0.011**, **0.021**	0, 0	**0.011**, **0.021**			
	4	C	0, 0	0, 0	0, **0.042**	0, **0.021**	0, **0.021**		
		B	0, **0.011**	0, 0	0, 0	0, **0.011**	0, 0		
	5	C	0, 0	0, 0	0, **0.042**	0, **0.011**	0, 0		
		B	0, **0.021**	0, 0	0, 0	0, 0	**0.011**, **0.021**		
Trustworthiness	1	C	0, 0	0, 0	0, 0	0, 0	0, 0	3	Expertise

Table 2 (continued)

	Survey	Protection Responsibility					
		1	2	3	4	5	
	B	0, **0.011**	0, 0	0, **0.021**	0, 0	**0.011**, 0	
2	C	0, 0	0, 0	0, **0.021**	**0.021**, 0	0, **0.021**	
	B	0, **0.011**	**0.011**, **0.011**	0, 0.021	0, 0	0, **0.011**	
3	C	0, 0	**0.021**, **0.021**	0, **0.021**	**0.021**, **0.125**	0, **0.083**	
	B	**0.011**, **0.03**	**0.011**, 0	**0.011**, 0.063	**0.054**, **0.032**	**0.021**, 0	
4	C	0, 0,	0, 0,	**0.021**, 0, 0	**0.021**, **0.021**		
	B	0, 0	0, **0.011**	**0.011**, **0.011**	**0.021**, 0	0.011, 0	
5	C	0, 0	0, 0	**0.021**, 0	0, **0.021**	**0.021**, **0.021**	
	B	0, 0	0, **0.011**	0, 0	**0.011**, **0.011**	**0.011**, **0.056**	
1	C	0, 0	0, 0	0, 0	0, 0	0, 0	4
	B	0, 0	0, **0.011**	0, 0	0, 0	0, **0.011**	
2	C	0, 0	0, 0	0, 0	0, 0	0, **0.021**	
	B	0, **0.011**	**0.021**, **0.011**	0, 0	**0.011**, 0	**0.011**, **0.021**	
3	C	0, 0	0, **0.021**	0, 0	**0.021**, 0	**0.021**, 0	
	B	0, 0	**0.011**, 0	0, 0	**0.065**, **0.011**	**0.021**, **0.011**	
4	C	0, 0	0, 0	0, **0.042**	**0.083**, **0.021**	**0.021**, 0	
	B	0, **0.011**	**0.011**, 0	**0.011**, **0.011**	**0.0130**, **0.063**	**0.043**, **0.043**	
5	C	0, 0	0, 0	0, 0	**0.063**, 0	**0.063**, 0	
	B	**0.011**, 0	0, **0.011**	0, 0	0, **0.042**	**0.021**, **0.053**	
1	C	0, 0	0, 0	0, 0	0, 0	0, 0	5
	B	0, 0	0, 0	0, 0	0, 0	0, 0	
2	C	0, 0	0, 0	0, 0	0, 0	0, 0	

Table 2 (continued)

	Survey	Protection Responsibility				
		1	2	3	4	5
	B	**0.011**, 0	0, 0	0, 0	0, 0	0, 0
3	C	0, 0	0, 0	0, 0	0, 0	**0.021**, 0
	B	0, 0	0, 0.011 40	0, 0	0, 0	**0.043**, **0.011**
4	C 0, 0	0, 0	0, 0	**0.042**, 0	**0.042**, 0	
	B	0, 0	0, 0	0, 0	**0.011**, 0	**0.054**, 0
5	C	0, 0	0, 0	0, 0	**0.042**, **0.042**	**0.375**, **0.021**
	B	0, 0	**0.021**, 0,	**0.011**, 0	**0.033**, 0	**0.141**, **0.126**

The discrete random variables, shown on the axes, are scores from one to five, based on scores that respondents assigned to stakeholders. Non-zero values are shown in bold.

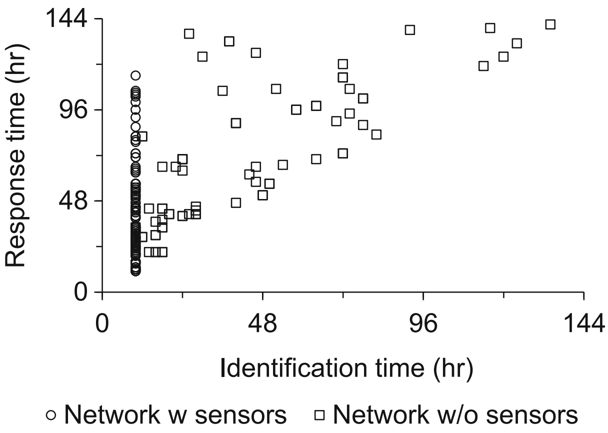

Fig. 8 Response time and identification time, predicted using the C3 Model, with and without sensors in the network. Results are shows for four contamination events

50%, 39%, and 52% for Boston data, for the Uniform, Exponential, and Poisson distributions respectively. The likelihood for compliance with family members is 28%, 24%, and 31% for College Station data and 40%, 30%, and 41% for Boston data, for the Uniform, Exponential, and Poisson distributions, respectively.

5.4 Response of the Public Health Official Agent

The utility manager agent is alerted to an event by either the public health official agent or an activated sensor. Sensors are activated relatively quickly after an event occurs and lead to a quick response by the utility manager agent. In realistic events, however, utility managers may not have access to a sensor network that can immediately detect the contaminant that is released in a network, so they may rely more heavily on public health officials. The four events are simulated for Mesopolis without the use of a water quality sensor network. Results demonstrate that the public health official agent recognizes the contamination events late in the event, and without sensors, the number of exposed consumers is close to the values predicted by the C1 model, which simulates the events without official advisories. The ratio of C3 results to C1 results is $0.98/pm0.01$ for the network without sensors and $0.96/pm$ 0.12 for the network with sensors. Figure 8 shows the response time of the utility manager agent and the identification time of the public health official agent for all four events, modeled for the network with sensors and without sensors. Sensors are activated after each event at time step 10, and the response time of the utility manager agent, measured from the time that the contaminant was introduced to the network, varies from 10 to 120 hours.

6 Conclusions

An ABM framework is developed here and evaluated using four contamination scenarios to predict the number of exposed consumers for a water distribution contamination event, based on water advisories that are broadcast by media to encourage consumers to stop using water. The ABM framework extends an existing model, and it includes a newly developed set of actions to represent consumer behaviors in using media and complying with water advisories. The model of consumer behavior is based on results of surveys that were conducted specifically to assess consumer compliance. Surveys were conducted in College Station, Texas, and Boston, Massachusetts, and data were collected to characterize respondents' perceptions of stakeholder characteristics – expertise, trustworthiness, and protection responsibility. This research also created models for the behaviors and actions of water utility managers and public health officials. Using a set of recorded data from historical events, probability distributions were created to characterize the response of public health officials and the time that a utility manager takes to confirm the existence of contaminant and disseminate water contamination advisories. Results show that during short events, or those events in which a contaminant enters a network over a small time window in high concentrations, the quick response of utility managers is important to protect more consumers, and using the news media as the only means to protect consumers may not provide high levels of public health protection. For long events, or those events in which contaminant enters the network over a longer period in low concentrations, utility managers can disseminate warnings within a wide time window to achieve similar levels of public health protection. To better protect consumers, especially in short events, additional response actions should be considered and planned, such as flushing contaminated water using hydrants (Ehsan Shafiee and Zechman 2012) and routing a fleet of emergency vehicles to warn those consumers who may not receive messages through the news media (Ehsan Shafiee 2013).

The modeling framework presented here integrates research and methodologies from social science and engineering infrastructure management to provide a holistic approach to assess water contamination events. Aspects of contamination events have been studied in depth by both the social science and engineering communities, and this research provides an approach to integrate these diverse bodies of knowledge. The sociotechnical approach can be applied to a real water distribution network and a community of heterogeneous consumers, and behavioral factors and the protective actions of consumers can be characterized by conducting surveys. Some data that has been collected describes behaviors for the U.S. population and can be applied broadly for U.S. municipalities.

Compliance with Ethical Standards

Conflict of interests Conflict of Interest - None

Appendix A: Perceiving Expertise, Trustworthiness, and Protection Responsibility of Stakeholders

In surveys that were conducted in College Station and Boston, as described above, respondents scored a set of stakeholders, including water utility personnel, public health personnel, emergency management personnel, elected officials, news media, personal physicians, and immediate family members, based on three perceived characteristics (Lindell et al. 2010, 2011). Respondents were asked to assign each stakeholder a score for expertise (E), protection responsibility (R), and trustworthiness (T), which are characteristics that influence compliance (Arlikatti et al. 2007), on a discrete scale of 1 to 5. A joint probability distribution was derived from the frequencies for unique combinations of the three characteristics in the survey dataset. For example, in the survey that was conducted in College Station, 19 out of 50 respondents judged water utility personnel to have a score of five for each perceived source characteristic (E, R, and T). The mass probabilities for the joint probability mass distribution are shown in Table 2 for the water utility personnel and immediate family members, based on the response of 48 residents in College Station and 110 residents in Boston. Joint probability distributions were constructed for the respondents' perceptions of other stakeholders listed above, but, for brevity, only the distributions developed for water utility personnel and family members are included in the modeling framework. Utility managers and family members were selected because they represent the likely extremes of expertise (utility managers should be relatively high, and family members should be relatively low). These two stakeholders do not differ significantly in trustworthiness and protection responsibility.

At the initialization of the simulation, each consumer agent is assigned values for E_u, R_u, T_u, E_f, R_f, and T_f, representing that agent's perception of the expertise, protection responsibility, and trustworthiness of the utility manager (u) and a family member (f). To create these values, a random number is generated to represent the occurrence of the joint probability of expertise, protection responsibility, and trustworthiness. Table 2 is used to assign a score from one to five for each attribute using the random number. To calculate the probability of $z = (e, r, t)$, the following equation is used: $P_Z(z) = \sum_{g(e_i, r_j, t_k) \leq z} P_{E,R,T}(e_i, r_j, t_k)$, where the mass probability distribution is denoted as $Z = g(E, R, T)$.

The survey conducted in College Station focused on perceptions of exposure paths, stakeholder characteristics, and alternative protective actions. Because the respondents could not be presumed to have experienced a water notice, they were not asked to report whether they had complied with any water contamination warning messages. As a result, the College Station data does not identify a relationship between consumer perceptions of stakeholder characteristics and the probability of compliance. The data from the Boston survey were analyzed to determine the correlation between perceived stakeholder characteristics and the likelihood of respondents in suspending use of tap water after receiving a water advisory. The analysis reveals that 91% of the respondents chose to use bottled water, boil water, or disinfect water using household liquid bleach instead of using untreated water after receiving a water advisory. The correlation between using at least one protective action and the expertise, protection responsibility, and trustworthiness of stakeholder is 0.07, 0.06, and 0.19 for a utility manager and 0.05, -0.03, 0.13 for a family member, respectively. Of these correlations, only the coefficient for trustworthiness of a utility manager was statistically significant at $p <= 0.05$. Correlation values show that recipients are more likely to comply with recommendations from utility managers than recommendations from family members.

Appendix B: Derivation of $P_{N_m}(t_c)$ and $P_t(t_c)$

A probability distribution is fitted with the data in Table 6 to calculate $P_{N_m}(t_c)$, which is the likelihood that the public health official identifies an event at time step (t_c). An exponential distribution is fit to the data in the third and fourth column of Table 6, using the following steps. The data in the fourth column is adjusted to represent the number of consumers at medical services, normalized by the number of consumers experiencing symptoms at the time of identification. The time of identification is measured in days after the first diagnosis is made at a medical facility, and the following probability distribution is fit to match the dataset:

$$P_{N_m}(t_c) = 1 - \exp(-7.9\frac{(N_m)_{t_c}}{(N_s)_{t_c}}), \tag{3}$$

where $(N_s)_{t_c}$ is the cumulative number of symptomatic consumers in a community at time t_c. $(N_m)_{t_c}$ is the cumulative number of exposed consumers at medical facilities and is calculated using the following equation:

$$(N_m)_{t_c} = (n_s)_{t_c} \times p_r + (N_m)_{t_{c-1}}, \tag{4}$$

where $(n_s)_{t_c}$ is the incremental number of consumers who become exposed between two time steps t_{c-1} and t_c. The time step when the first agent is diagnosed at a medical facility is modeled as the time step at which $(N_m)_{t_c}$ is non-zero. The variable p_r is the percentage of exposed consumers who seek medical attention at each time step and is calculated using an exponential distribution function, which is fit to the data in the third column of Table 6:

$$p_r = 1 - \exp(-0.126r), \tag{5}$$

where r is a random number between 0.0 and 1.0. The mean of p_r is 7.92%. The function and the data are shown in. The Chi-square test for goodness-of-fit is 5.86 and indicates that the function that is identified fits with data with a 0.05 significance level.

The time of identification also depends on the amount of time that has passed after the diagnosis of the first exposed consumer at a medical facility. A probabilistic approach was developed to calculate $P_t(t_c)$, the likelihood that a public health official recognizes a water contamination event at time t_c. An exponential distribution is fit to the data in the fifth column of Table 6 and $P_t(t_c)$ is calculated as:

$$P_t(t_c) = 1 - \exp(-0.293t_c), \tag{6}$$

Appendix C: Tables

Table 3 Consumer agent parameters, state variables, and behaviors

Parameter	Value
number of age groups	11
age range for each age group ($yrs.$) (The U.S. Census Bureau 2010)	{≤0.5, .5-.9, 1-3, 4-6, 7-10, 11-14, 15-19, 20-24, 25-54, 55-64, ≥65}

Table 3 (continued)

Parameter	Value
percentage of females among consumers (%) (The U.S. Census Bureau 2010)	50.6%
percentage of population, female by age group(%)(The U.S. Census Bureau 2010)	{0.8, 0.7, 4.9, 4.6, 6, 6, 7.4, 7.3, 44.6, 7.6, 10.1}
percentage of population, male by age group (%) (The U.S. Census Bureau 2010)	{0.7, 0.7, 4.3, 4.5, 5.3, 5.9, 6.6, 7.1, 42.6, 8.6, 13.7}
average weight, female by age group (kg)*(The U.S. Census Bureau 2010)	{6, 9, 14, 20, 31, 50, 61, 64, 69, 71, 67}
average weight, male by age group (kg)*(The U.S. Census Bureau 2010)	{6, 9, 14, 21, 32, 52, 73, 80, 85, 84, 80}
average volume of ingested water, female by age group ($\frac{ml}{day}$)* (US Environmental Protection Agency 2000)	{301, 394, 316, 394, 430, 525, 653, 911, 1023, 1117, 1108}
average volume of ingested water, male by age group ($\frac{ml}{day}$)* (US Environmental Protection Agency 2000)	{291, 325, 306, 419, 474, 665, 861, 1039, 1182, 1172, 1153}
peak time for ingestion of tap water, 5 events (Davis and Janke 2009) **(US Environmental Protection Agency 2000)	{8am, 10am, 12pm, 3pm, 6pm}
exposure threshold (White 1999)	$0.05 \frac{mg}{kg}$ of consumer agent's body weight
residential node (Johnson and Brumbelow 2008; Ehsan Shafiee and Zechman 2013)	*generated using mobility algorithm*
non-residential node(Johnson and Brumbelow 2008; Ehsan Shafiee and Zechman 2013)	*generated using mobility algorithm*
mode of working start time(Johnson and Brumbelow 2008; Ehsan Shafiee and Zechman 2013)	8 am
average working duration ($hrs.$)(Johnson and Brumbelow 2008; Ehsan Shafiee and Zechman 2013)	8
number of agents in communication network (Johnson and Brumbelow 2008; Ehsan Shafiee and Zechman 2013)	15 consumer agents
water demand reduction factor (%)(Ehsan Shafiee and Zechman 2013)	discrete value [3.5, 41.7]
Action	Status update
ingest $\frac{1}{5}$ of volume of tap water at 5 ingestion events	amount of ingested contaminant increases based on the contaminant concentration in the ingested water
travel between residential node & non-residential node	current node, at which a consumer agent ingests tap water or reduces water demand, is assigned
become exposed if the amount of ingested contaminant exceeds exposure threshold	consumer agents is considered as the exposed agent and starts to warn other consumers
determine the likelihood to seeking medical attention at medical services after exposure using Table 2	if present at a medical service, the number of consumers who recognized with waterborne illnesses increases
warn other consumers within its community	other consumers receive a water notice from a friend or a family

Table 3 (continued)

Parameter	Value
interact with the news media	receive a water notification from the utility manager if the warning has been issued by the utility manager agent in the previous time steps
Comply with the water warning using Section 3.1.1	consumer agent is considered as the warned agent
reduce water demand if consumer agents is warned or exposed	the node's water demand is updated based on the water demand reduction factor of consumer agents that are located at the node

* Use $x = -x_m \ln(1 - p)$, which is the inverse of the exponential distribution, to randomly quantify a value for each agent. p is a randomly generated value and x_m is the mean of parameter

** time-based distributions, representing the likelihood of ingesting water at a time of day based on the time of the previous ingestion event

Table 4 Parameters and actions and status update at each time step for utility manager agent

Parameter	Value
receive an alert	false/true
issue a water notice	false/true
Action	Status update
verify the likelihood of the threat using Eq. 2 if an alert is received from a warning sensor or the public health agent	issue a water notice
issue water notices	consumer agent receives a water notice when interacting with the news media

Table 5 Parameters and actions and status update at each time step for public health agent

Parameter	Value
waterborne illnesses	false/true
start time of first complaint	time step at which the first complaint is registered
Action	Status update
evaluate the probability of identifying a water event based on the number of consumers seeking medical attention using Eq. 5	P_r
evaluate the probability of identifying a water event based on the time that passes after the start time of first complaint using Eq. 3	P_{Nm}
evaluate the probability of identifying a water event	$P_{Nm} \times P_r$
send an alert to the utility manager agent	change the value of the waterborne illnesses parameter to true

Table 6 Characteristics of reported water events in affluent countries (Hrudey and Hrudey 2004) representing the response of utility managers and public health officials during a water event

Water Contamination Event	Response time (days that pass before an alert is received by a public official)	Consumers seeking medical attention (as % of consumers experiencing symptoms)	Consumers at medical services at time of identification (as % of consumers seeking medical attention)	Identification time (days that pass before first complaint is registered at medical facility)
Berlin, New Hampshire, USA, 1977	1	3.93	5.45	2
Grums, Sweden, 1980	1	11.05	84.16	2
Eagle-Vail, CO, USA, 1981	1	N/A	28.85	9
Drumheller, Alberta, Canada, 1983	5	44.20	1.89	2
Greenville, Florida, USA, 1983	2	1.27	18.50	10
Orangeville, Ontrario, Canada, 1985	4	23.65	24.56	4
Pittfiled, Massachusetts, USA, 1986	8	18.50	5.69	10
Penticton, B.C., Canada, 1986	N/A	11.68	2.21	1
Sunbury, Victoria, Australia, 1988	0	10.00	31.67	2
Cabool, MO, USA, 1989	1	N/A	4.12	3
Naas, Ireland, 1991	1	5.00	26.47	2
Uggelose, Denmark, 1991	0	N/A	N/A	3
Jackson County, OR, USA, 1992	0	0.29	0.20	N/A
Warrington, UK, 1992	1	N/A	21.28	1
Milwaukee, WI, USA, 1993	0.5	0.07	10.88	1
Gideon, MO, USA, 1993	1	4.77	N/A	1
Villege in Fife, Scotland, 1995	3	2.11	40.72	2
South Devon, UK, 1995	3	N/A	N/A	1

Table 6 (continued)

Water Contamination Event	Response time (days that pass before an alert is received by a public official)	Consumers seeking medical attention (as % of consumers experiencing symptoms)	Consumers at medical services at time of identification (as % of consumers seeking medical attention)	Identification time (days that pass before first complaint is registered at medical facility)
Cranbrook, B.C., Canada, 1996	2	1.45	N/A	1
Ogose Town, Japan, 1996	1	1.37	N/A	N/A
NW London, UK, 1997	N/A	N/A	9.28	N/A
Heinavesi, Finland, 1998	1	0.88	89.41	1
Brushy Creek, TX, USA, 1998	N/A	5.93	23.33	3
La Neuveville, Swiss, 1998	1	2.50	5.45	3
Clitherore, Lancashire, UK, 2000	1	N/A	15.52	N/A
Belfast, Ireland, 2000	0	N/A	9.38	N/A
North Battleford, Canada, 2001	1	4.90	N/A	2
Walkerton, Canada, 2000	1	12.17	5.36	2
Asikkala, Finland, 2001	1	0.52	1.55	14
Sample mean	**1.54**	**7.92**	**20.26**	**3.41**
Standard deviation	**1.73**	**10.45**	**23.80**	**3.54**

References

The U.S. Census Bureau (2010). People Data. Available at http://www.census.gov/people/

American Time Use Survey (2014) The U.S. department of labor

United State Environmental Protection Agency (2004a) Response protocol toolbox: Planning for and responding to drinking water contamination threats and incidents — module 1: Water utility planning guide. EPA report, pages EPA report 817–03–005. Environmental Protection Agency, Washington, D.C.

United State Environmental Protection Agency (2004b) Response protocol toolbox: Planning for and responding to drinking water contamination threats and incidents — module 2: Threat management guide. EPA report, pages EPA report 817–03–005. Environmental Protection Agency, Washington, D.C.

United State Environmental Protection Agency (2004c) Response protocol toolbox: Planning for and responding to drinking water contamination threats and incidents — module 3: Site characterization and sampling guide. EPA report, pages EPA report 817–03–005. Environmental Protection Agency, Washington, D.C.

United State Environmental Protection Agency (2004d) Response protocol toolbox: Planning for and responding to drinking water contamination threats and incidents — module 4: Analytical guide. EPA report, pages EPA report 817–03–005. Environmental Protection Agency, Washington, D.C.

United State Environmental Protection Agency (2004e) Response protocol toolbox: Planning for and responding to drinking water contamination threats and incidents — module 5: Public health response guide. EPA report, pages EPA report 817–03–005. Environmental Protection Agency, Washington, D.C.

United State Environmental Protection Agency (2004f) Response protocol toolbox: Planning for and responding to drinking water contamination threats and incidents — module 6: Remediation and recovery guide. EPA report, pages EPA report 817–03–006. Environmental Protection Agency, Washington, D.C.

Alfonso L, Jonoski A, Solomatine D (2010) Multiobjective optimization of operational responses for contaminant flushing in water distribution networks. J Water Resour Plan Manag 136(1):48–58

Ang AH, Tang WH (2007) Probability concepts in engineering emphasis on applications to civil and environmental engineering. Wiley, Reading

Arlikatti S, Lindell MK, Prater CS (2007) Perceived stakeholder role relationships and adoption of seismic hazard adjustments. Int J Mass Emergencies Disast 25(3):218–256

Bristow E, Brumbelow K (2006) Delay between sensing and response in water contamination events. J Infrastruct Syst 12(2):87–95

Davis MJ, Janke R (2009) Development of a probabilistic timing model for the ingestion of tap water. J Water Resour Plan Manag 135(5):397–405

EPA (2001) Fact sheet: Drinking water standard for arsenic. Environmental Protection Agency

Geldreich EE (1991) Microbial water quality concerns for water supply use. Environ Toxicol Water Qual 6(2):209–223

Holland J (1995) Hidden order: how adaptation builds complexity. Helix books, USA

Hrudey S, Hrudey E (2004) Safe Drinking Water. lessons from recent outbreaks in affluent nations international water association

Johnson G, Brumbelow K (2008) Developing mesopolis-a virtual city for research in water distribution system and interdependent infrastructures, available online at https://ceprofs.civil.tamu.edu/kbrumbelow/Mesopolis/index.html

Kroll D (2006) Security our water supply protecting a vulnerable resources. Pennwell Publishers

Lindell MK, Perry RW (2004) Communicating environmental risk in multiethnic communities. SAGA, Thousand Oaks

Lindell MK, Mumpower J, Wu H-C, Huang S-K (2010) Perceptions and expected responses to a water contamination emergency. College Station TX: Texas A&M University Hazard Reduction and Recovery Center

Lindell MK, Huang S-K, Prater CS (2011) Residents' responses to the may 1-4 2010 boston water contamination incident College Station TX: Texas A&M University Hazard Reduction and Recovery Center

Miller J, Page S (2007) Complex adaptive system. Princeton University Press, Princeton

Ostfeld A, Uber J, Salomons E, Berry J, Hart W, Phillips C, Watson J, Dorini G, Jonkergouw P, Kapelan Z, di Pierro F, Khu S, Savic D, Eliades D, Polycarpou M, Ghimire S, Barkdoll B, Gueli R, Huang J, McBean E, James W, Krause A, Leskovec J, Isovitsch S, Xu J, Guestrin C, VanBriesen J, Small M, Fischbeck P, Preis A, Propato M, Piller O, Trachtman G, Wu Z, Walski T (2008) The battle of the water sensor networks (bwsn): a design challenge for engineers and algorithms. J Water Resour Plan Manag 134(6):556–568

Pantic Z, Ballinger R, Bambei J (2011) MWRA MetroWest water supply tunnel shaft 5A pipe break pipe failure scenario report, available online at http://www.mwra.com/01news/2011/052511-mwra-report-final.pdf
Railsback SF, Grimm V (2012) Agent-based and individual-based modeling: a practical introduction. Princeton University Press, Princeton
Rasekh A, Brumbelow K (2014) Drinking water distribution systems contamination management to reduce public health impacts and system service interruptions. Environ Model Softw 51:12–25
Rasekh A, Brumbelow K (2015) A dynamic simulation–optimization model for adaptive management of urban water distribution system contamination threats. Appl Soft Comput 32:59–71. ISSN 1568-4946
Reis L, Porto R, Chaudhry F (1997) Optimal location of control valves in pipe networks by genetic algorithm. J Water Resour Plan Manag 123(6):317–326
Rodríguez H, Quarantelli EL, Dynes RR, Sorensen JH, Sorensen BV (2007) Community processes: warning and evacuation. In: Handbook of disaster research, handbooks of sociology and social research. Springer, New York, pp 183–199
Rogers G, Sorensen J (1991) Diffusion of emergency warning:comparing empirical and simulation results. In: Zerros C et al (eds) Risk Analysis Prospects and Opportunities. (1): 117–134
Rossman L (2000) Epanet user's manual. U.S. Environmental Protection Agency Risk Reduction Engineering Lab
Rundblad G (2008) The semantics and pragmatics of water notices and the impact on public health. J Water Health 6(1):77–86
Ehsan Shafiee M (2013) Integrating an Agent-Based Model with a Multi-Objective Evolutionary Algorithm to Warn Consumers in a Water Contamination Event Using Emergency Vehicles, chapter 251, pp 2550–2558. https://doi.org/10.1061/9780784412947.251
Ehsan Shafiee M, Zechman EM (2012) Integrating evolutionary computation and sociotechnical simulation for flushing contaminated water distribution systems. In: Proceedings of the 14th annual conference companion on Genetic and evolutionary computation, GECCO'12. ACM, New York, pp 315–322
Ehsan Shafiee M, Zechman EM (2013) An agent-based modeling framework for sociotechnical simulation of water distribution contamination events. J Hydroinf 15(3):862–880
US Environmental Protection Agency (2000) Estimated per capita water ingestion in the united states. U.S. Environmental Protection Agency -822-00-008, Office of Water, Washington, D.C.
Watts DJ (1999) Small worlds: the dynamics of networks between order and randomness. Princeton series in complexity. Princeton University Press, Princeton
White JW (1999) Hazards of short-term exposure to arsenic contaminated soil. Office of Environmental Health Assessment Services, Post Office Box 47846. ISSN 0232-9298
Woo DM, Kim J (2003) Sociotechnical systems, risk management, and public health: comparing the north battleford and walkerton outbreaks. Reliab Eng Syst Saf 80(3):253–269
XJ-Technologies (2012) Anylogic 6.7.1. Available at www.xjtek.com, Accessed in 2012
Zechman EM (2011) Agent-based modeling to simulate contamination events and evaluate threat management strategies in water distribution systems. Risk Anal 31(5):758–772. ISSN 1539-6924
Zechman EM, Ranji Ranjithan S (2009) Evolutionary computation-based methods for characterizing contaminant sources in a water distribution system. Water Resour Plan Manag 135(5):334–343