After a household is in the potential adopter state, it triggers a yearly event where it calculates the affordability of each adoption action (technology adoption). For each adoption action, the model calculates the *Affordability Index* considering the technologies adopted before. If the index is less than the user-defined affordability threshold, the household makes the decision to adopt that technology. If it exceeds the affordability threshold, that means the adoption of technology is not affordable and thus the agent will remain as a potential adopter. The algorithm for this process is described in Figure 2. Different organizations such as California Department of Public Health, US Environmental Protection Agency, and United Nations Development Programs have reported various measures of affordability threshold that range between 1%-3%.

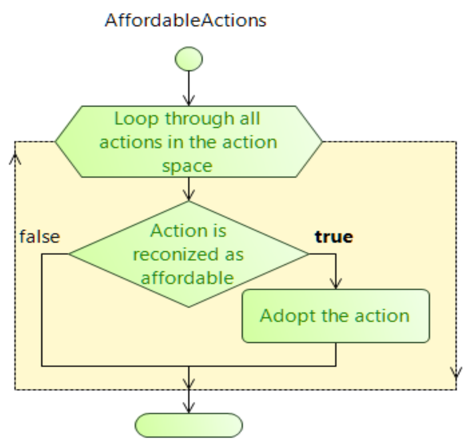

Figure 2: Action chart for transition between potential adopter and adopter

In the affordability measurement process, water price regime is incorporated into the model as an input parameter. Three different water pricing structures were assessed: *flat price, fixed charge,* and *block tariffs*. Table 2 outlines how the three strategies were implemented into the ABM framework.

Table 2: Input parameters for water price strategies (Cahill 2011)

Strategy	Attribute	Input Price
Flat Price	Volume Use Charge	$0.0044 per gallon
Fixed Charge	Regardless of Volume Use	$25.24 per month
Block Tariffs (Volumetric Pricing)	First Block: Demand: 0-172 gall/household/day	$0.0036 per gallon
	Second Block: Demand: 172-393 gall/household/day	$0.0043 per gallon
	Third Block: Demand: >393 gall/household/day	$0.0052 per gallon

Equations 1 and 2 make up the *Potential Utility* and *Affordability Index*, which define the adoption state of each household agent (i.e. non-adopter, potential adopter, and adopter). There is another phenomenon that can lead a household agent to transition from the non-adopter state to the potential adopter state and that is social network influence from other agents. Household agents can have a connection to each other; based on the theory of *Peer Effect,* through this connection between non-adopter and adopter households, non-adopter agents may communicate with adopter agents and thus get influenced by them into making decisions regarding the adoption of new technology (Friedkin, 2001). The model considers and implements five structures of social networks: *random, distance-based, ring lattice, small-world* and *scale-free* networks. Table 3 specifies more about how each structure of social network works.

Table 3: Structures, attributes and parameters for the implemented social networks

Network Type	Description	Parameter	Parameter Value
Random	Assigns each agent a random number of connections within the given average.	Average number of connections per agent (N)	N= 0-10
Distance-based	If the distance between two agents is less than the given maximum connection range (the maximum distance in meters between agents for there to be a connection), then both agents are connected.	Maximum connection ranges (R)	R= 0-500
Ring Lattice	Agents are connected according to their closeness to each other while also forming a ring.	Average number of connections per agent (N)	N= 0-10
Small-World	Connections between agents are similar to the ring lattice, while also including some long-distance relationships. The neighbor link probability is the chance that two agents connected to the same neighbor, may also connect to each other (Porter 2012).	Average number of connections per agent (N); and Neighbor link probability (P)	N= 0-10; P= 0-1
Scale-Free	Some agents are very social (or hubs) and may have lots of connections, while others prefer to be loners or have very few connections.	Number of hubs (M)	M= 1-10

Once the model has established a network according to the given parameters, it proceeds to simulate the social influence between connected agents. Every simulated year, the model checks all the non-adopter agents who have connections with adopter agents. Given a user-defined *likelihood of influence*, if the non-adopter agent is connected to an adopter agent, there is a chance that the non-adopter will transition into the potential adopter state. For every connection that the non-adopter agent has with an adopter agent the function randomTrue(p) is used, given the likelihood of influence “p”, can return either True or False. If there is at least one instance when the transition is True, the agent transitions to the potential adopter state. The way randomTrue( ) works is that it first creates a random number uniformly distributed in the interval [0, 1). If the value created is less than the given likelihood number “p”, then the result is true, else the result is false. For example, if the non-adopter agent is connected to three adopter agents, and the likelihood of influence (p) is 10%, the model calculates randomTrue(0.1) for three times. If in at least one of those calculations is less than 0.1, the result was true, then the agent transitions to potential adopter.

In this model, an agent was able to adopt six main types of water conservation technology shown in Table 4. This table shows the cost information and the potential rebate that the Miami-Dade Utility offers for each of these technologies, which will be incorporated as an input parameter into the model.

Table 4: Cost and potential rebate of tested water conservation technologies

Technology	**Cost**	**Rebate**	**Category**	***Technology***	**Cost**	**Rebate**	**Category**
Bathroom faucet	$15	$15	Inexpensive	*Toilet*	$420	$50	Expensive
Kitchen faucet	$15	$15	Inexpensive	*Washing machine*	$670	$150	Expensive
Shower head	$100	$25	Inexpensive	*Dishwasher*	$500	$50	Expensive

The user of the model can define whether or not the rebates will apply. The rebates can be important to the technology cost as well, since Affordability Index of household agents can be affected by rebates in the model. Income growth and household size growth were the last attribute input parameters for the model. All of these inputs will generate a number of outputs, which demonstrate the basis of the type and timing of technology adoption by household agents. The model outputs include the percentage distribution of all of the adopter states, the overall water demand reduction, and the different types of technology adopted over the twenty-year predetermined time period.

3 MODEL IMPLEMENTATION

Anylogic 7.0 was utilized to create the computational agent-based model. This model incorporates only one class of agent, which is the household. Data from the City of Miami Beach was used in the implementation of this ABM. The City of Miami Beach has more than ten thousand residential water consumers. To reduce the computational complexity of the model and improve its efficiency, a sample of 280 households that statistically represents the demographic distribution of the population (with 95% confidence interval) was selected and modeled. All 280 agents will start out as non-adopters; and, depending on different influences, will transition to potential adopter or adopter. The population of household agents taken from the City of Miami Beach are separated into three zip codes. The model then runs using Census data from these three zip codes, as well as individual household water use data provided by the Miami-Dade Utility. The census data includes information regarding median household income, education, average home ownership and average household size (Figure 3).

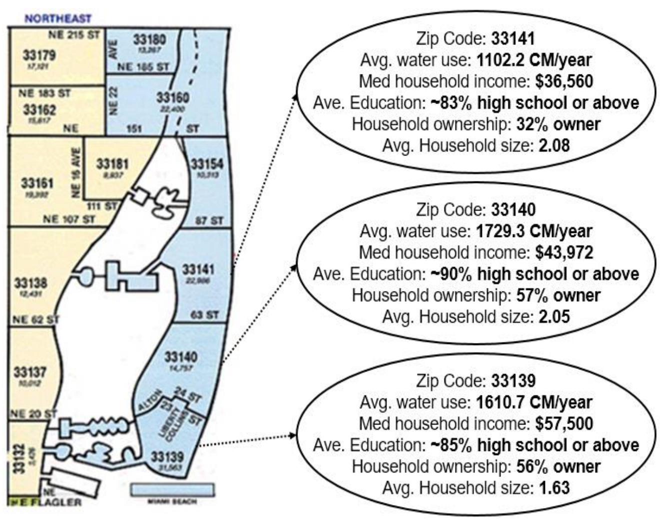

Figure 3: Demographic trends and average water consumption of the zip codes used in the model

Since some of the data provided by the census are only average values, a triangular average distribution was used to assign each household a random value. A uniform distribution was also used to assign the head resident age, garden size, and house size in square feet. Values such as head gender and home age are randomly assigned following no distribution. Moreover, data related to a household's source of water such as the number of showerheads, toilets and faucets come from a custom distribution.

The model input parameters include: water price, rebate status, income growth, household size growth, adoption utility threshold, affordability threshold, type of social network, and likelihood of influence. After twenty years, the model stops and provides the distribution of non-adopter, potential adopter, and adopter, as well as the number of actions adopted by the households. Figure 4 depicts the class diagram of the computational ABM and summarizes the information regarding the attributes and functions implemented.

were used to formulate results. The first was scenario analysis, where different animation components from the model are directly compared. Secondly, a trend analysis was conducted. Trend analysis allows for juxtaposing multiple scenarios. For each scenario, one hundred runs of Monte-Carlo experiments were implemented to determine the mean value of each output parameter. The trend analysis was used for visualizing how many households began adopting, as well as which technology they adopted. In order to accurately compare scenarios equally across the analyses, a base case (Table 6) was created to act as a reference point that every other scenario is compared to.

Table 6. Base case scenario parameters

Parameter	***Value***	**Parameter**	***Value***
Water Price Strategy	*Flat Price*	Income Growth	*+1 %*
Rebate Status	*With Rebate*	Household Size Growth	*+1 %*
Likelihood of Adoption	*10 %*	Utility Threshold	*30,000*
Social Network Type	*Small-World (N=1, P=0.1)*	Affordability Threshold	*1.5 %*

The model animation component of the base case over a 20-year analysis horizon is shown in Figure 5. This animation visually and graphically displays the outputs from the base case inputs. It shows the households' state distribution, which reflects the adoption state of all of the agents; the households' adopted actions display how many of each technology was adopted; the map, which geographically shows where the 280 households are located in Miami Beach as well as how they are socially connected to each other (based on a small-world network structure); total adopters, which displays the number of people who adopted; and the overall demand reduction, which shows how much water will be saved (per day) at the end of the analysis horizon.

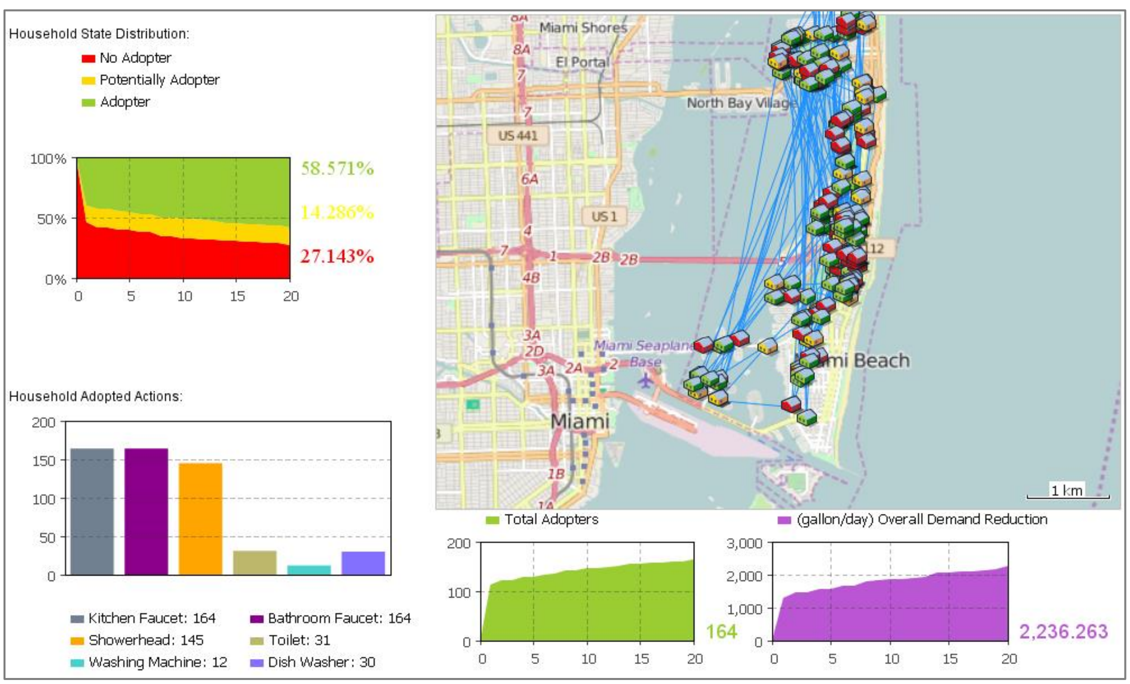

Figure 5: Base case animation from the model

In this base case scenario, 27.1% of households after 20 years remain non-adopters, and 58.6% become adopters that are mostly located in the south of the city where the communities are affluent. Among those who did adopt, kitchen, and bathroom faucets were the most common technologies adopted, while the expensive technologies—toilet, washing machine, and dishwasher—were adopted less frequently. A total of 164 household adopted one or more water conservation technologies, and through adoption of these technologies, the overall water demand is reduced by 2,236 gallons per day, which means around 2% reduction in the average overall daily water demand of the case study.

Various scenarios composed of different combinations of input parameters were simulated, reflecting changes in water price strategy, rebate status, income growth, social network structure, and affordability threshold. Figure 6 shows the number of each technology adopted under different scenarios of water pricing and rebate strategy (while other parameters remained unchanged compared to the base case scenario). It can be observed that inexpensive technologies (i.e., kitchen and bathroom faucets and showerhead) were mostly adopted when the fixed charge strategy was implemented for water pricing. However, for the expensive technology adoption, the impact of water pricing strategy is insignificant. Also, the rebate allocation was more effective along with the volumetric pricing strategies rather than the fixed charge strategy especially in the adoption of expensive technologies.

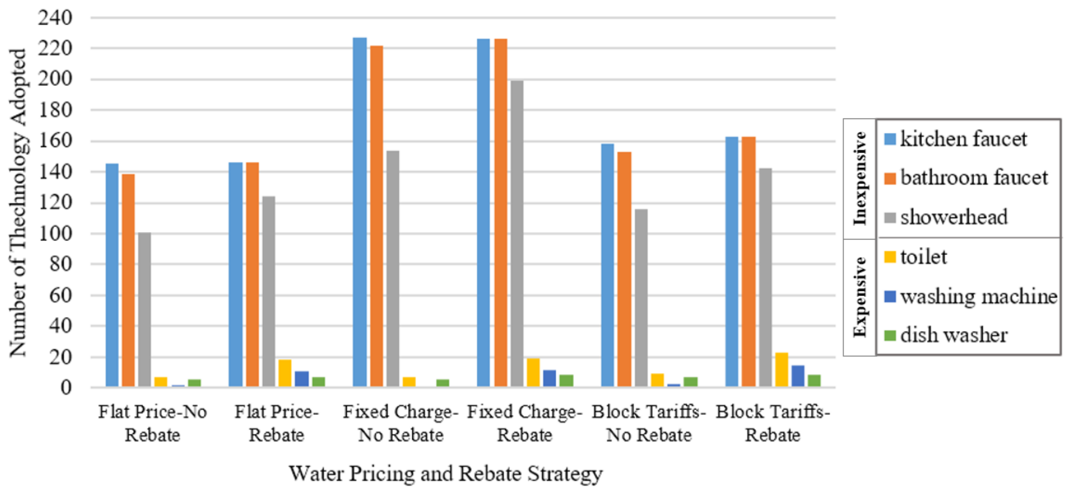

Figure 6: Impact of water pricing and rebate strategy

Figure 7 demonstrates the sensitivity of technology adoption to affordability threshold of households. For all water price strategies and rebate status, as affordability threshold increase, there was a logarithmic and exponential increase in adoption of inexpensive and expensive technologies, respectively. This finding means that adoption of expensive technologies is more sensitive than inexpensive ones to the affordability threshold.

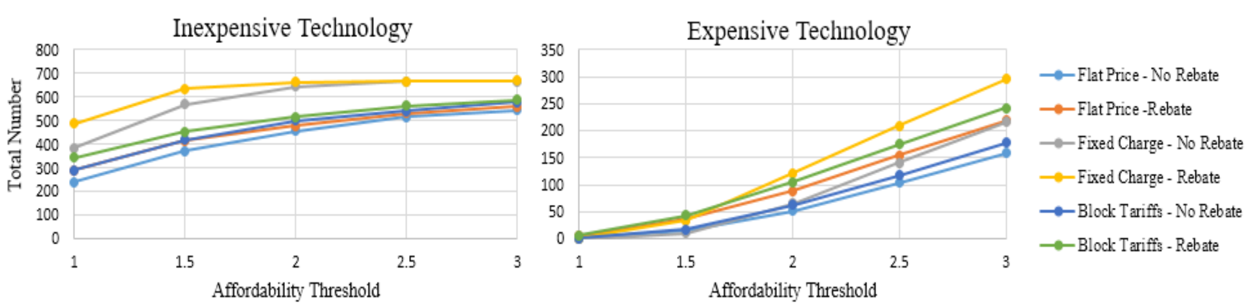

Figure 7: Modeling trends on number of technology adopted and affordability threshold

Finally, the five implemented social network structures were tested under the base case scenario and the results are documented in Figure 8. The results show that, among different social network structures, scale-free structure can lead to a less number of non-adopters in the community. For instance, it leads 10% more adoptions compared to the random social network structure, which is statistically significant.

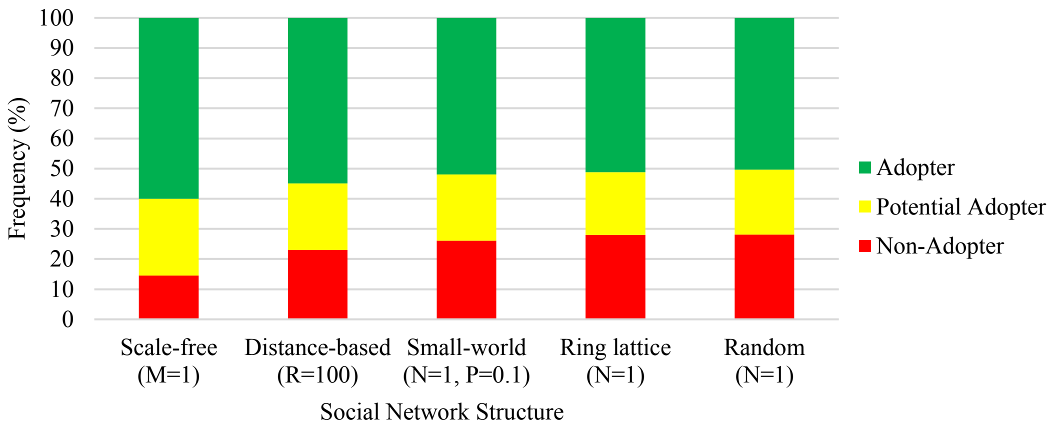

Figure 8: Influence of social network structure on adoption state distribution

6 CONCLUDING REMARKS

This study presented a theoretical agent-based simulation framework to capture the complex adaptive mechanisms influencing the household decisions in adoption of water conservation technology. The results of the study showed that to what extent many demographic characteristics, household attributes, social network interactions, and external water policies affect a household's willingness to adopt water conservation technology simultaneously. Hence, the findings of this study will help municipalities and water agencies to better understand the mechanisms affecting residential water conservation technology adoption and effectively implement strategies to increase the household adoption of water conservation technology—as a demand-side strategy— in order to build resilience against water scarcity. From a theoretical perspective, this study contributes to the growing field of urban science in the context of water management and sustainable planning.

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AUTHOR BIOGRAPHIES

KAMBIZ RASOULKHANI is a PhD student in the Zachry Department of Civil Engineering at Texas A&M University. He holds a Bachelor degree in Civil Engineering from Sharif University of Technology, Iran. His research focuses on sustainable and resilient infrastructure and complex systems modeling. His e-mail address is Kambiz.r@tamu.edu.

BRIANNE LOGASA is a Master's student at the Luskin School of Public Affairs at University of California, Los Angeles. She holds a Bachelor's degree in Urban Studies and Planning from University of California, San Diego. Her research focuses on sustainable approaches to community development and land use planning. Her email is blogasa@g.ucla.edu.

MARIA PRESA REYES is a PhD student at the Florida International University, in Miami, Florida. She holds a Master's degree in Computer Science from the same university. Her research focus is on multimedia data mining and visualization of disaster data. Her e-mail address is mpres029@cs.fiu.edu.

ALI MOSTAFAVI is an Assistant Professor in the Zachry Department of Civil Engineering at Texas A&M University. He holds a Ph.D. in Civil Engineering and a Master of Science in Industrial Administration at Purdue University. His research focuses on a system-of-systems paradigm that bridges the boundaries between complex systems science, network theory, and civil infrastructure systems to address sustainability and resilience challenges. His e-mail address is amostafavi@civil.tamu.edu.