ABSTRACT

RAMSEY, ELIZABETH VIRGINIA. Coupling Agent-Based Modeling and a Genetic Algorithm to Simulate Adoption of Dual-Flush Toilets Using Household Survey Data (Under the direction of Dr. Emily Z. Berglund).

The spread of individual water conservation behaviors within a population can have large cumulative impacts on overall water demand. Agent-based models (ABMs), in which agents represent individual actors and update their behaviors over time in response to their environment and each other, have been applied to model the adoption of water conservation behavior. Existing ABM approaches are parameterized based on cumulative water demand data and use assumptions about household-level adoption behaviors. This research uses real world survey data on water conservation technology adoption to develop an ABM of residential water use. An ABM is developed to simulate adoption of dual-flush toilets based on interactions among population members and drought. This research couples an ABM with a noisy genetic algorithm (NGA) to parameterize the residential water use ABM using a real world household survey data on conservation behavior adoption. The ABM is applied to Jaipur, India as a case study, using household survey data collected in 2015 in Jaipur on dual-flush toilet installation trends as a measure of the adoption of water conservation behavior. The accuracy of the ABM is highly sensitive to the frequency of the agents' updating behavior, which drives adoption. The ABM is applied for population change projections and varying frequency of drought. Projections forecast significant water savings of nearly 2.3 billion liters of water per year due to the adoption of dual-flush toilets, as compared to static demand projections.

Coupling Agent-Based Modeling and a Genetic Algorithm to Simulate Adoption of Dual-Flush Toilets Using Household Survey Data

by
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DEDICATION

To Dr. Berglund, for all of your guidance and support. Thank you for your outstanding mentorship and leadership, and for encouraging me when I needed it the most.

To my mom and dad, who have supported me through every wild career decision and encouraged me to continue pursuing my education.

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BIOGRAPHY

Liz Ramsey was born and raised in Statesville, NC. She obtained her B.A. in Peace, War, and Defense at the University of North Carolina at Chapel Hill, and her M.S. in Strategic Intelligence at the National Intelligence University. She worked for the Department of Defense (DoD) for five years as a South Asia analyst, where she became passionate about water resource management as a national and international security concern. She left her position with DoD and enrolled in second M.S. program to pursue that passion full time.

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CHAPTER 1: INTRODUCTION

In rapidly growing cities around the world, a fundamental challenge facing water resource managers is ensuring adequate potable water supply in the future while simultaneously limiting cost (Chikozho and Kujinga 2017; Jamieson 1986). When considering infrastructure development, water resource planners have often based water demand projection models on population growth rates and assumed per capita consumption rates because of their ease of use (United States Geological Survey 2002). However, water systems are complex adaptive systems, in which the interactions and decisions of individual actors can contribute to system-level dynamics in unforeseen ways (Berglund 2015). For example, the adoption of water conservation technology by a few individuals can create feedback loops in which social interactions may actively encourage the adoption of water conservation technology among neighbors, and tipping points emerge at which water conservation technology is universally adopted (Young 1996). These individual dynamics have a broad impact on overall water demand, given that a decline in per capita indoor residential water demand has been attributed to the adoption of water-efficient appliances (DeOreo and Mayer 2012; Willis et al. 2009). A model of the dynamics of water conservation technology diffusion could thus help provide more accurate predictions of cumulative water demand, and potentially reduce the expense of building unnecessary capacity.

Agent-based models (ABMs), in which agents represent individual actors and autonomously update their behaviors over time in response to their environment and each other, can provide more insight into the role social dynamics play on adoption of conservation behavior (Edwards et al. 2005; Srbljinovic and Skunca 2003). ABMs have been applied to a variety of systems to explore emerging dynamics, which include diffusion of innovation (Kiesling et al. 2012), land-use decisions (Parker et al. 2003), agricultural water use (Berger et al. 2007), and coupled human and environmental systems (An 2012). ABMs have been widely used to model water supply systems (Ali et al. 2017; Berglund 2015; Chu et al. 2009; Giacomoni and Berglund 2015; Kanta and Zechman 2014; Srinivasan et al. 2010; Tillman et al. 1999, 2005) and residential water demand (Klassert et al. 2015; Linkola et al. 2013; Yuan and Wei 2014). ABMs have also been applied to model the adoption of water conservation behavior, and most of the existing models have been parameterized based on cumulative water demand data and assumptions about household-level adoption behaviors (Athanasiadis and Mitkas 2005; Edwards et al. 2005; Galán et al. 2009; Koutiva and Makropoulos 2016; López-Paredes et al. 2005). A proprietary survey was conducted and used to calibrate a model of water conservation technology adoption trends based on lifestyles (Schwarz and Ernst 2009). The survey questions used are not freely available, limiting the replicability of their methodology.

This paper presents a methodology for using real world data on water conservation technology adoption to model water demands more accurately. The framework presented here is based on a sociotechnical modeling approach used by Edwards, Ferrand, Goreaud & Huet (2005) and Galán, Lopez-Paredes, and del Olmo (2009) to model the spread of water conservation behavior. Their framework simulates the diffusion of a binary water conservation status throughout a social network. Agents examine the status of all neighboring agents and calculate the utility of keeping and changing their water conservation status, based on the ratio of all neighboring agents exhibiting each conservation status and an exogenous term that represents external pressures to adopt conversation behavior. Agents then compare utilities and update their status to the one with the highest utility. This research applies their framework to a set of data collected about the adoption of dual-flush toilets. The existing framework is extended to improve the ABM accuracy to match adoption data by introducing a drought module, delay in

behavior updates, communication function that limits agents' awareness of their neighbors' behaviors, and population change. This research applies a noisy genetic algorithm (GA) to parameterize the ABM using data on conservation behavior adoption. The ABM is applied to Jaipur, India as a case study, using household survey data collected in 2015 in Jaipur, India on dual-flush toilet installation trends as a concrete measure of the adoption of water conservation behavior. The ABM produces a conservative estimate of water savings of nearly 2.3 billion liters of water per year as compared to static per capita demand projections alone.

CHAPTER 2: BACKGROUND

Models that address variability in water demands among consumers have been widely explored for several decades, using an assortment of variables to account for variations in residential demand. Early models assumed pricing was the primary driver of changes in water demand (Gibbs 1978; Young 1973). Agthe and Billings (1980) introduced one of the first dynamic econometric models of residential water demand which incorporated past water consumption levels and household incomes as variables. Models that attempted to capture the impact water policies had on water consumption emerged later. Renwick and Archibald (1998) present an econometric water demand model to evaluate the extent to which water pricing and policy instruments such as water pricing or rebates may have on consumption in two cities in California, and find that household demand was responsive to price changes, but that wealthier households were significantly less price responsive than poorer households. Fan et al. (2013) used a survey conducted in Wei River Basin, China, to develop a model of water consumption based on ownership of a solar water heater, household income, vegetable garden area, household head age, family size. Zhang and Brown (2005) developed a model of urban residential water use in Beijing and Tianjin based on socioeconomic backgrounds, appliances, water use habits, and water perception (knowledge of shortages and education/public info campaigns). Choudhary, Sharma, & Kumar (2012) presented an econometric demand model based on wealth indicators and household size.

Econometric and regression models are not dynamic and do not capture the influence of social norms and interactions between community members, which have been empirically shown to influence individual behavior. In a study in Zhangye City, China, Chang (2013) explored subjective norms, defined as the perceived social pressure to engage in or refrain from a behavior, which were found to have a significant influence on water conservation behavior. McKenzie-Mohr and Smith (McKenzie-Mohr and Smith 1999) demonstrated in a study at University of California Santa Cruz that witnessing another individual engaging in conservation behavior increases the likelihood of participants momentarily mimicking the behavior.

ABM has been an effective methodology to bridge that gap and represent the process of communication and its effects on the adoption of water conservation technology and reduction of water demands. Koutiva and Makropoulos (2016) developed the Urban Water Agents' Behavior model, which simulates the change in water consumption behavior over time using water pricing as a variable within the agents' utility function. Athanasiadis & Mitkas (2005) developed a model of the spread of conservation behavior through a population, the Distributed Agents for Water Simulation, which combined a conventional price based model with a social network model.

Innovation diffusion has been more widely studied in the fields of economics and marketing. Kiesling et al. (2012) and Perez (2015) provide a synopsis of the variety of approaches for modeling innovation diffusion. Earlier models of diffusion innovation simulated overarching adoption trends, but provided little insight into the drivers of innovation adoption or predictive capabilities (Bass 1969; Valente 1996). ABMs provide a way to explore how network structure and individual behaviors and beliefs can impact adoption trends (Garcia 2005). Some studies have used ABMs to explore the impacts of social network structure and influence on adoption of innovation (Abrahamson and Rosenkopf 1997; Midgley et al. 1992). Delre, Jager, Bijmolt, and Janssen (2010) found that networks with high levels of social influence reduce the likelihood of an innovation being adopted by the majority of the market, and Choi, Kim, and Lee (2010) found that innovation diffusion is more likely to fail in random networks than in highly-clustered networks, such as the small-world network model. Modeling innovation diffusion by incorporating utility functions has not been widely explored (Kiesling et al. 2012). Two notable exceptions are models by Choi et al. (2010) and Young (1996), who both explored the spread of behavior among agents within a network using utility functions based on internal and external pressures.

Models of the spread of environmental behaviors and technology are also limited. Some, such as Weisbuch, Gutowitz, and Duchateau-Nguyen (1996), model the spread of environmentally-friendly behaviors based on information contagion. Others, such as Jager (2006), explore theories about the influence of social psychology on adoption of eco-innovations. Edwards et al. (2005) expanded on Young's model of innovation diffusion to incorporate adoption of environmentally conscientious behaviors.

Linkola, Andrews, & Schuetze's ABM (2013) of residential water demand featured agents that updated end-use behaviors based on their environment and an internal decision-making process. Schwarz and Ernst (2009) designed an agent-based model that simulated the diffusion of water-saving shower heads, toilets, and rain-harvesting systems and applied it to southern Germany based on individual characteristics, communication, innovation characteristics, and decision-making. Galan et al. (2009) coupled models of technological diffusion, behavioral diffusion, and urban residential movement dynamics, which was an expansion of the Edwards et al. (2005) model, itself an adaptation of Young's sociologic diffusion model (1996) for environmental behavior. Koutiva and Makropoulos (2017) developed an ABM exploring "social impact theory" influence on water conservation attitudes.

While using real world data to validate water conservation diffusion models is common, parameterization approaches are often limited. Edwards et al. (2005) uses pre-defined parameters without explaining their origins because of the exploratory nature of their model, and Galan et al.

(2009) uses these same parameters in their model. Schwarz and Ernst (2009) provide an explanation of their parameterization approach, but used a proprietary Sinus-Milieus data collection, which limits its utility for other applications. Koutiva (2017) parameterized their model using a Latin hypercube sampling process to match aggregated water consumption data.

This research explores the use of genetic algorithms (GA) to parameterize an ABM. GAs have been used to find optimal solutions to a wide variety of problems within water resources including pipe placement (Savic and Walters 1997), water reuse networks in industry (Halim et al. 2015), reservoir rules (Suiadee and Tingsanchali 2007), watershed management (Arabi et al. 2006), and groundwater remediation (Mirghani et al. 2009). Within diffusion of innovation literature, GAs have been applied to parameterize Bass diffusion models for LCD screen diffusion (Savic et al. 2006) and notebook shipping problems (Wang et al. 2013) but have not been applied to water conservation technology diffusion ABMs.

CHAPTER 3: METHODS AND MATERIALS

This research develops an ABM to simulate the adoption of dual-flush toilets. A survey was developed and conducted to collect data about adoption rates of dual-flush toilets. The ABM was developed to simulate the influence of communication within a social network and the occurrence of dual-flush toilet adoption decisions, and a population growth module is included in the simulation. A GA is coupled with the ABM to identify parameter values to minimize error between model outputs and survey results (Figure 1). This chapter is organized as follows: first, the survey data collection methodology is discussed; second, the ABM structure is presented; third, a new drought module is described; next, the population growth module is presented; and finally, the parameterization of the model with the GA is described.

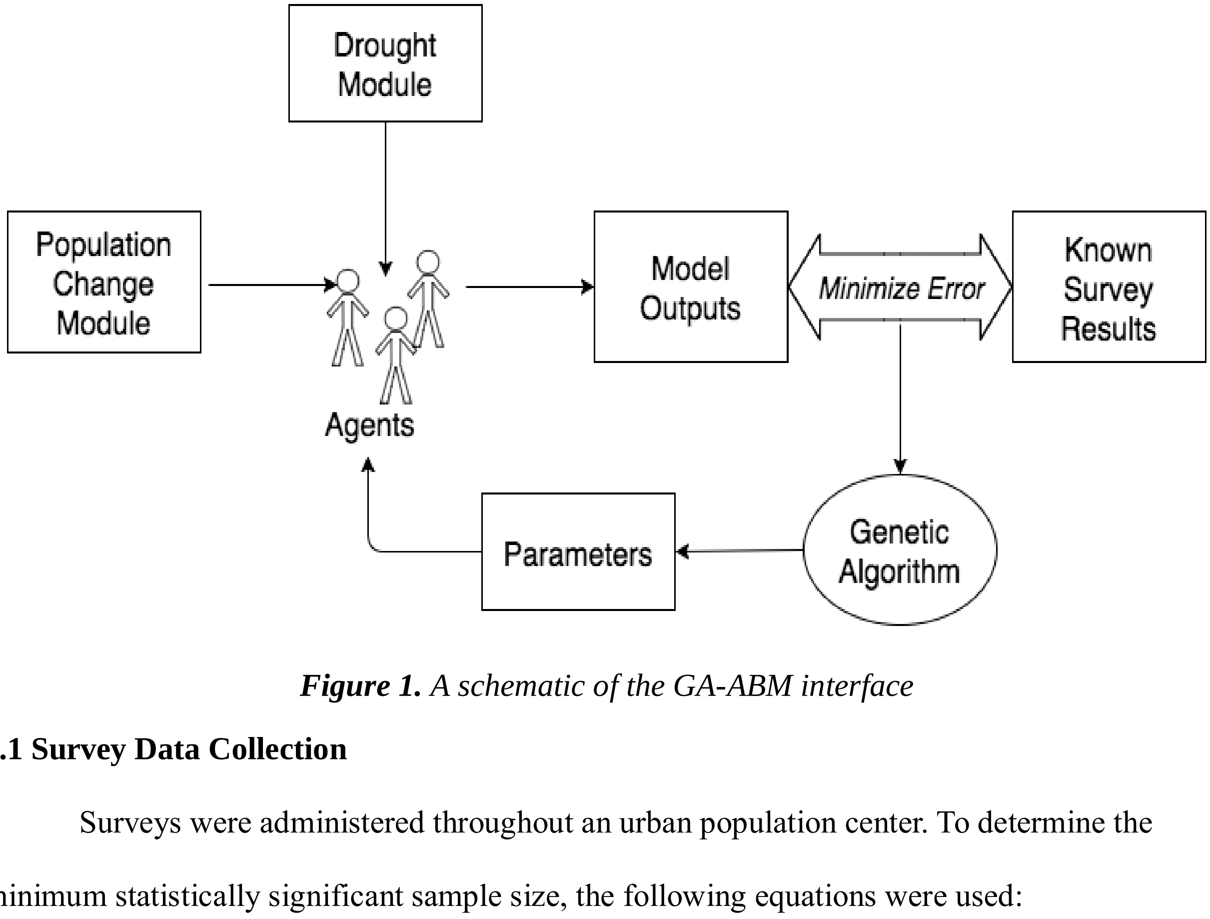

Figure 1. *A schematic of the GA-ABM interface*

3.1 Survey Data Collection

Surveys were administered throughout an urban population center. To determine the minimum statistically significant sample size, the following equations were used:

$$S = Z^2 \frac{p(1-p)}{C^2} \tag{3.1}$$

$$S_{adjusted} = \frac{S}{1+\frac{S-1}{P}} \tag{3.2}$$

where S is the sample size, Z is the z-score, p is the estimated value of the proportion of population needed to be surveyed ($p = 0.5$ is most conservative assumption and is used when the proportion is unknown), C is the confidence level, $S_{adjusted}$ is the adjusted sample size, P is the population size.

Neighborhoods were selected for this study based on their water supply's original source (groundwater or surface water) and to ensure the widest geographic coverage around the city. Once neighborhoods were identified, survey administrators selected streets and homes from those neighborhoods at random. Surveys were conducted on weekends to ensure better representation of working citizens. If the occupant of a home was not available or declined to take the survey, the next house was selected. For a thorough description of the survey methodology and analysis of results, see Ramsey, Berglund, & Goyal (2017).

Identifying water-conservation behaviors is inherently difficult because many personal water-consumption behaviors are unverifiable within a simple written survey, such as turning off the tap when washing dishes. Consequently, this study explored the installation of dual-flush toilets as a concrete measure of conservation behavior adoption. The two survey questions used to parameterize this study based on dual-flush toilet installation:

1.) How many of each toilet do you have?
    a.) Dual-Flush
    b.) Single-Flush
    c.) Pour-Flush
    d.) Other/don't know
2.) If you have dual-flush toilets, what year did you install them?

The responses to these questions were used to derive the expected number of *WC* agents at every twelfth time step as follows:

$$\frac{n_{WC,t}}{n_{respondents}} \times N_t = N_{expected\ WC,t} \tag{3.3}$$

where $n_{WC,t}$ is the total number of survey respondents who had adopted dual-flush toilets by time step t, $n_{respondents}$ is the total number of survey respondents, N_t is the total number of agents interacting in the model at time t, and $N_{expected\ WC,\ t}$ is the number of expected *WC* agents at time step *t* based on survey data.

3.2 ABM Framework

The framework presented here is an extension of the behavior diffusion ABM developed by Young (1996) and expanded by Edwards et al. (2005) and Galán et al (2009).

Their framework models the diffusion of water conservation technology throughout a network of agents. Agents are programmed as either adopters or non-adopters, and at each time step they examine the adoption status of all of their neighbors and then compute the utility of updating versus maintaining their adoption status. Agents then update their status based on the highest utility. This research extends the model to include time delays in decision making and a separate communication function that limits agents' awareness of their neighbors' behaviors. It also incorporates drought and population growth modules and a Watts-Strogatz small world network structure. The ABM is programmed in MASON, a Java-based discrete-event multi-agent simulation library (Luke 2004) and presented in accordance with the ODD (Overview, Design concepts, and Details) protocol introduced by Railsback and Grimm as a standardized method of describing an ABM (Railsback and Grimm 2012). In the Overview section, the model *purpose*, *entities*, *state variables*, temporal *scales*, and *process overview* and *scheduling* are introduced. Next, in the Design section, the *basic principles* of the model, *emergence*, *adaptation*, *learning,* and *objectives*, *sensing*, *interaction*, *stochasticity*, and *observation* capabilities within the model are discussed. In the Details section, the state of the model at *initialization* and *inputs* to the model are described.

3.2.1 Overview

The *purpose* of the model is to simulate the spread of residential water conservation behavior over time within a population and to evaluate the potential impacts it may have on water demand. The *entities* in the model are agents, which each represent 100 households (to reduce computational complexity). The agents have several *state variables*, which distinguish entities from each other or trace how the entity changes over time. These include a binary consumption behavior of either Water Conserver (*WC*) or Non-Water Conserver (*NWC)*; a weight for susceptibility to extrinsic pressures other than drought, e_{OTHER}; a weight for importance assigned to drought occurrence, $e_{DROUGHT}$; a frequency of communication with neighbors, $f_{COMMUNICATE}$; and a frequency of updating utility function, f_{UPDATE}. A full list of the state variables can be found in Table 1. The model's temporal *scale* is a monthly time step.

Table 1. *ABM state variables*

State Variable		**Description**
Consumption Behavior	*WC / NWC*	Binary water consumption behavior, either Water Conserver or Non-Water Conserver
Household Size	HH_{size}	Number of people living at household, used to calculate total water consumption
Total Water Consumption	T	Amount of water used by household agent on a monthly basis
Known-Status Neighbors	*<KSN>*	List of identities of neighbor agents with which the agent has communicated
Exogenous Term - Drought	$e_{DROUGHT}$	Value in utility function; represents importance agent attributes to drought
Exogenous Term – Other External Pressure	e_{OTHER}	Value in utility function; represents importance agent attributes to environmental pressures other than drought
Frequency of Communication with Neighbors	$f_{COMMUNICATE}$	Average number of time steps skipped between communicating with neighbor agents ($f_{COMMUNICATE} = 0$ means it communicates with neighbor agents at every time step, $f_{COMMUNICATE} = 12$ means agents communicate with neighbor agents every 12 time steps on average)
Frequency of Updating Utility Function	f_{UPDATE}	Average number of time steps skipped between utility function updates ($f_{UPDATE} = 0$ means it communicates with neighbor agents at every time step, $f_{UPDATE} = 120$ means agents communicate with neighbor agents every 120 time steps on average)
Time Step Born	t_{born}	Time step at which agent is introduced and allowed to interact with other agents and make decisions

The *process overview and scheduling* of the model, which are repeated at each time step, are outlined below.

Step 1:

The model calls the population module and determines how many agents have a t_{born} at the current time step, and then introduces them into the population. Once introduced, agents are allowed to interact and update their own behaviors.

This population module adds to the Edwards model, which keeps population static. Galan's model includes population growth, but the social network structures differ between this approach and Galan's model, which results in a difference in the way agents are introduced.

Step 2:

The model calls the drought module to determine if the previous year was a drought and sets the dummy drought variable, *d*, to 1 or 0 if the previous year was a drought or was not a drought, respectively. This module is a new extension of the Edwards model.

Step 3:

Each agent determines whether it communicates with a neighbor at the current time step as follows:

```
IF $x \leq 1/f_{COMMUNICATE}$ THEN:
    FOR all neighbors of current agent:
        Select a random agent from neighbors
        IF selected neighbor agent $t_{born} \leq t$ THEN:
            IF selected neighbor agent is not in <KSN>THEN:
                Add neighbor agent to <KSN>
                Add self to neighbor agent <KSN>
```

```
        Exit loop
```

where x is a randomly selected number in the interval [0,1). Agents are allowed to communicate only with agents that have a t_{born} less than or equal to than the current model time step. It the selected agent has a higher t_{born}, (i.e. it has not been introduced yet), then it is discarded and the agent iterates through neighbor agents randomly until either an agent with a lower t_{born} is found or all neighbors have been discarded, at which point the next agent starts Step 3. The ability of agents to decide when to communicate with other agents and the limited scope of their awareness of their neighbors' behaviors is an adaptation of the Edwards model.

Step 4:

Each agent determines whether it updates its utility functions at the current time step. For a given agent, A, $v_A(WC \rightarrow WC)$ is the utility of maintaining *WC* behavior, $v_A(WC \rightarrow NWC)$ is the utility of switching from *WC* to *NWC* behavior, $v_A(NWC \rightarrow WC)$ is the utility of switching from *NWC* to *WC* behavior, and $v_A(NWC \rightarrow NWC)$ is the utility of maintaining *NWC* behavior. The agent computes if it should update its utility functions and, if so, calculates them as follows:

```
IF WC:
    IF $x \leq 1/f_{UPDATE}$ THEN:
        $v_A(WC \rightarrow WC) = a \cdot V(A, WC) + e_{OTHER} + d \cdot e_{DROUGHT}$    (3.4)
        $v_A(WC \rightarrow NWC) = b \cdot V(A, NWC)$    (3.5)
ELSE:
    IF $x \leq 1/f_{UPDATE}$ THEN:
        $v_A(NWC \rightarrow WC) = a' \cdot V(A, WC) + e_{OTHER} + d \cdot e_{DROUGHT}$    (3.6)
        $v_A(NWC \rightarrow NWC) = b' \cdot V(A, NWC)$    (3.7)
```

where x is a randomly selected number from the interval (0,1], a and a' are the weights used to evaluate conservation behavior when Agent A is a WC or WNC, respectively; b and b' are the weights used to evaluate non-conservation behavior when Agent A is a WC or NWC, respectively; $V(A, WC)$ is the ratio of *WC*s within their Known Status Neighbor list, <KSN>, to total number of neighbors; $v(A, NWC)$ is is the ratio of *NWC*s within <KSN> and assumed *NWC* neighbors to the total number of neighbors, and *d* is a dummy variable (*d* = 1 if previous year was a drought year, *d* = 0 otherwise). Agents assume that any agent with which they have not communicated exhibits a *NWC* behavior when calculating these ratios.

This approach builds on the Edwards and Galan models by designating two separate exogenous terms $e_{DROUGHT}$ and e_{OTHER}, to represent a change in external pressures due to climatological changes. The approach also separates the communication function from the utility update function and implements a delay in both functions to represent the delays involved in deciding to adopt dual-flush toilets, due to their expense and the effort required to install them.

Step 5:

To allow for some stochasticity in the model, the agent calculates a probability function based on the utility function and updates its behavior with probability *P*. $P(WC\rightarrow WC)$ and $P(\mathrm{N}WC\rightarrow NWC)$ are the probabilities of maintaining current *WC* or *NWC* behavior, respectively. $P(WC\rightarrow NWC)$ and $P(\mathrm{N}WC\rightarrow WC)$ are the probabilities of switching behaviors, either from *WC* to *NWC* or *NWC* to *WC*, respectively. The probability functions are as follows:

IF *WC* THEN:

$$P(WC\rightarrow WC) = \frac{e^{\beta\cdot v_A(WC\rightarrow WC)}}{e^{\beta\cdot v_A(WC\rightarrow WC)}+e^{\beta\cdot v_A(WC\rightarrow NWC)}} \tag{3.8}$$

$$P(WC\rightarrow NWC) = \frac{e^{\beta\cdot v_A(WC\rightarrow NWC)}}{e^{\beta\cdot v_A(WC\rightarrow WC)}+e^{\beta\cdot v_A(WC\rightarrow NWC)}} \tag{3.9}$$

ELSE:

$$P(\mathrm{N}WC \rightarrow WC) = \frac{e^{\beta \cdot v_A(NWC \rightarrow WC)}}{e^{\beta \cdot v_A(NWC \rightarrow WC)} + e^{\beta \cdot v_A(NWC \rightarrow NWC)}} \qquad (3.10)$$

$$P(NWC \rightarrow NWC) = \frac{e^{\beta \cdot v_A(NWC \rightarrow NWC)}}{e^{\beta \cdot v_A(NWC \rightarrow WC)} + e^{\beta \cdot v_A(NWC \rightarrow NWC)}} \qquad (3.11)$$

where ß is a measure of the randomness of Agent *A*’s decision-making process. If ß = 1, the process is completely stochastic, and if ß = 100, the process is largely deterministic.

Step 6:

The model aggregates data about the number of *WC* agents, total monthly water consumption (*T*), the number of total agents, and the ratio of all *WC* agents to the total number of agents. *T* is calculated as follows:

$$T = \sum_{i=0}^{m_{NWC}} HHsize_i \cdot D + \sum_{j=0}^{n_{WC}} HHsize_j (D - ws) \qquad (3.12)$$

where m_{NWC} and n_{WC} are the number of *WC* and *NWC* agents at time step *t*, respectively, *D* is the expected monthly demand used by water resource managers, and *ws* is the expected monthly water savings generated from water conservation behavior adoption.

3.2.2 Design

Basic Principles: The model is an adaptation of the innovation diffusion model, which is often used to simulate the adoption of technology within a population. This design incorporates population growth and an element of timing in decision making and communication about technology to allow for a closer approximation to reality.

Emergence: The interactions between water consumer agents drive the emergence of conservation technology adoption.

Adaptation, learning and objectives: The water consumer agents have rules of adaptation based on utility functions. The utility functions are designed to meet the agents’ objectives of adhering to social norms and responding to external pressures, but they do not optimize any objective functions. Agents do not learn from other agents or the environment.

Sensing: The consumer agents sense the behaviors of members of their social networks with whom they have communicated at each time step after communication.

Interaction: Consumer agents are all connected via a Watts-Strogatz small world network, using the GraphStream library (Balev et al. 2015). Agents store identities of known-status neighbors and then check their status every time they recalculate their utility functions and reevaluate their behavior. This network structure was added to the Edwards model.

Stochasticity: Stochasticity occurs in the model due to several factors: the decision to update behavior based on a probability function, the connections between agents, the timing of communication and updating of the utility function, and the order of agents selected to communicate.

Observation: Results of the model are observed as the number of agents exhibiting *WC* behavior, the number of agents introduced, the ratio of *WC* to total number of agents, assumed water consumption, and assumed water savings. Results are collected at the end of each time step, after all agents have completed their interactions.

3.2.3 Details

The model creates an entire population of agents equal to the maximum number of agents for the scenario at *initialization.* All agents are assigned a conservation behavior of *NWC*, and a household size drawn from a Poisson distribution with an average value taken from census data. If the household size drawn is <1, then another household size is drawn. Agents are also assigned a frequency of communicating with other agents, $f_{COMMUNICATE}$, and a frequency of updating their utility functions, f_{UPDATE}, drawn from Poisson distributions with an average of $f_{communicate}$ and f_{update}, respectively. The values for $f_{communicate}$ and f_{update} are determined by the GA. If $f_{COMMUNICATE} < 0$ or $f_{UPDATE} < 0$, then another value is drawn. All agents are also given the exogenous term values $e_{DROUGHT}$ and e_{OTHER}, drawn from a normal distribution with standard deviations of 0.1 and an average of $e_{drought}$ and e_{other}, respectively, which are also determined by the GA.

All agents are added as nodes to a Watts-Strogatz small world network (Figure 2). A small world network consists of a ring of n nodes, each of which is connected to its k nearest neighbors in the ring, and each of those nodes is rewired to another random node with a probability of $ß_{rewire}$. Each agent is assigned a time step, t_{born}, at which it is allowed to begin interacting with other agents and making behavior decisions.

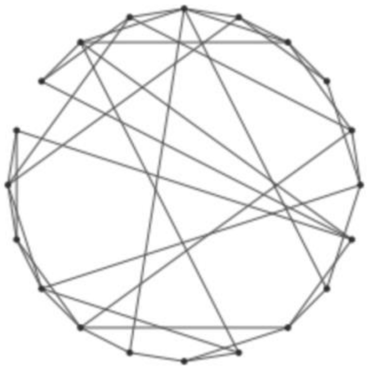

Figure 2. *Watts-Strogatz small world network structure*

The ABM reads in *inputs* from a precipitation sub-model every year (every twelfth time step), and inputs from a population growth projection every month (each time step), which is used to set t_{born} for each agent. If, for example, a total population of 100 agents is created and 10 agents are to be introduced at each time step, 10 agents would be assigned a $t_{born} = 0$, 10 agents would be assigned $t_{born} = 1$, and so on. The agents with $t_{born} = 1$ only interact or update their behaviors when $t_{born} \geq 1$.

3.3 Population Growth Module

The population growth module uses linear interpolation to derive population increase or decrease from census data, and then calculates the corresponding number of agents. The number of agents at each time step is determined by:

$$n_t = \frac{p_t}{hh \cdot 100} \tag{3.13}$$

where n_t is the number of agents with $t_{born} \geq t$ at time step t, p_t is the population at time t, and hh is the average household size. p_t is divided by 100 to reduce computational complexity.

3.4 Drought Module

When called at each time step representing the beginning of a new year (every twelfth time step), the drought module determines if the previous year was a drought year by the following equation:

```
IF $t/12 = 1$ THEN:
    IF $\sum_{i=1}^{i=12} p_{t-i} \leq 0.75 p_{avg}$ THEN:
        $d = 1$
    ELSE:
        $d = 0$
```

where $p_{t=i}$ is precipitation at time step t - i, p_{avg} is the long-term average precipitation, and d is the dummy variable for drought used in the agents' utility functions.

3.5 Parameterization with Genetic Algorithm

The ABM was parameterized using a GA which is implemented in Java and has been applied to solve a range of environmental and water resources planning and simulation problems (Zechman and Ranjithan 2004). A GA generates a population of solutions and applies heuristic rules at each generation to converge to an optimal or near-optimal solution. A solution is an array of decision variables that can have binary, real, or integer values. After each generation of solutions is created, the best performing solutions are selected for crossover, in which decision values from the best performing solutions are combined to produce another generation of solutions. Mutation is also applied, which makes random changes to existing solutions. This approach uses a noisy GA, which is a GA that uses an average of fitness function values in order to operate in a noisy or uncertain environment (Miller and Goldberg 1996).

A solution is represented as an array of six real-valued parameters. The GA is applied to identify ABM parameters over a range of potential values (Table 2). The decision variable b^{rep} is transformed to the parameter b in the ABM using Eqn. 3.14 to enforce that b is less than or equal to a.

$$b = b^{rep} \times a \tag{3.14}$$

The parameters corresponding to the weights attributed to the same behaviors, a *and* b', and opposite behaviors, a' and b, are set equal to each other (Eqn. 3.15 and 3.16), as was done in the Galan and Edwards models.

$$a = b' \tag{3.15}$$

$$b = a' \tag{3.16}$$

Each solution is simulated for five random realizations, and the average standard error of the regression, S, between the model outputs and the survey data is reported as the objective function, which is minimized. S is used to represent error because it can be used to determine error in non-linear models, and S is given in the same units as the model output, which is the total number of adopting agents (Frost 2014).

Table 2. *Parameter ranges for the ABM set by the GA*

Parameter	**Allowable Value Range**
a	0 – 1
b^{rep}	0 – 1
e_{other}	0 – 1
$e_{drought}$	0 – 1
$f_{communicate}$	0 – 36
f_{update}	12 - 180

CHAPTER 4: CASE STUDY—THE CITY OF JAIPUR

Jaipur is the capital and largest city in the state of Rajasthan in northwest India. It was selected as a case study because it is both severely water stressed and growing rapidly, with an annual growth rate of 5.3%. Jaipur's population in 2011 was approximately 3.1 million, more than triple its population in 1981 (Office of the Registrar General & Census Commissioner 2011). Projections of Jaipur's population growth vary widely; the Jaipur Development Authority (JDA), which is charged with planning for Jaipur's development, projects the population will grow to 6.5 million by 2025. Alternatively, the most aggressive projections from the Global Cities Institute (GCI), which are based on the United Nations World Urbanization Prospects, project the population will reach only 4.3 million by 2025, but hit 11.0 million by 2100. For this model, the JDA projections for 2025 and the GCI projections for 2050 to 2100 are combined (see Figure 3). This approach creates a lower growth rate for the time period between 2025 to 2050 than that of the GCI projections, but allows consistency with city plans.

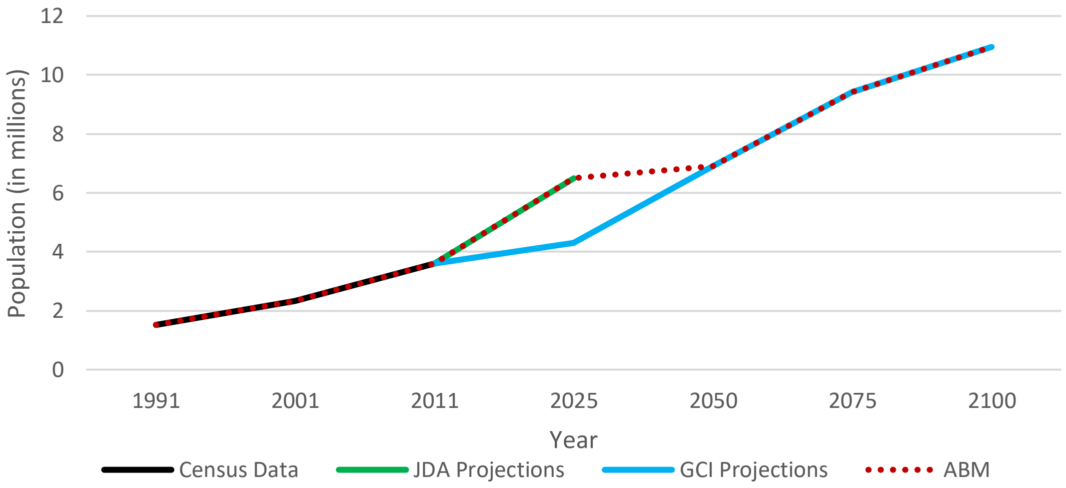

Figure 3. *Population data and projections for Jaipur City, 1991-2100*

Figure 4. *Location of Jaipur, India*

The Public Health Engineering Department- Rajasthan (PHED) provides water to most of Jaipur's citizens. PHED draws water from the Bisalpur Reservoir and from 1897 wells distributed throughout the city (Public Health Engineering Department 2011). The Bisalpur Reservoir, which became operational in 2009, lies on the Banas River, a seasonal river that often does not flow during the dry season. Previously, Jaipur's water supply came from Ramgarh Lake, which was created in the 1890s, but dried up in the late 1990s due to mismanagement and excessive upstream diversions (Bhandari et al. 2012). Jaipur relied solely on groundwater to meet its water demands during the interim between 1999 and 2009. According to a government audit, Bisalpur Reservoir has only 40% dependability; that is, only 40% of the designed capacity of the dam (317.2 million m^3) can be expected to be continuously available under drought conditions (Accountant General 2010). Consequently, PHED still relies heavily on groundwater to meet Jaipur's water demands, particularly when monsoon rains are low. Estimates show that the population is currently withdrawing water at 200% of the annual groundwater recharge rate, and in some areas of Jaipur District the groundwater table has dropped by over 25 meters since 2001 ("Jaipur: Groundwater table sinks 25 metres in 10 yrs" 2015).

Water supply is intermittent, and the majority of residents have access to running water for less than two hours per day. Many residents cope with this intermittency by storing water in tanks to use throughout the day. Select neighborhoods have been receiving 24-hour water supply in 2011 as part of a pilot project. A small percentage of residents do not use PHED-supplied water, relying instead on private wells. Wealthier residents often have both a PHED water connection and a private well, which they use when PHED-supplied water does not meet household demands.

The climate in Jaipur is semi-arid. Jaipur receives an annual average of 600.1 mm of rain a year, 88.5% of which falls during the monsoon season (Government of Rajasthan 2016), defined by the Indian Meteorological Department as June 1 to September 30. On average, Jaipur experiences a drought (less than 75% of the long term average rainfall, or 450.1 mm) at least once every five years (Disaster Management and Relief Department 2016).

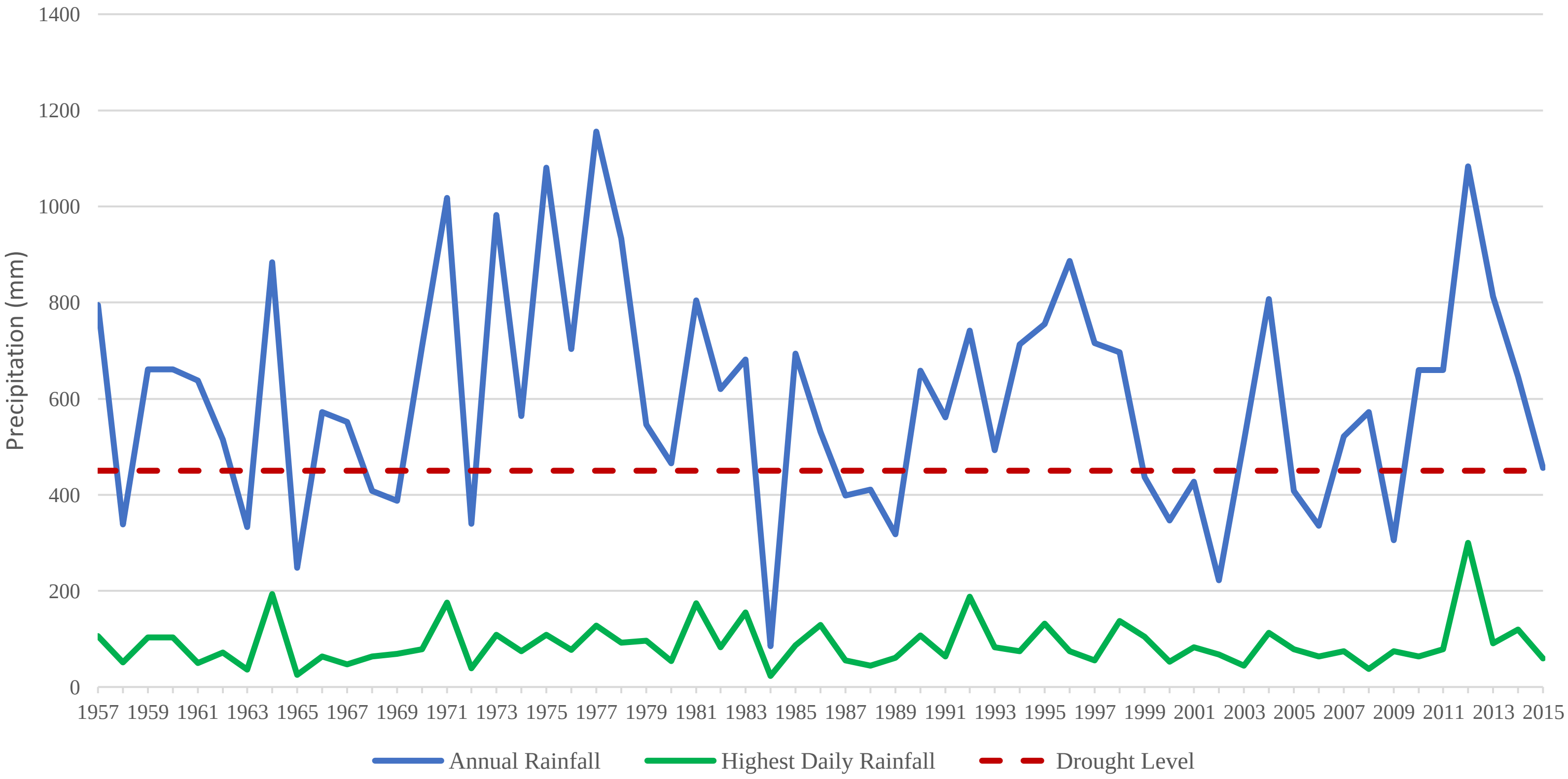

Figure 5. *Precipitation in Jaipur City (1957-2015)*

CHAPTER 5: RESULTS

5.1 Survey Results

A household survey was conducted on 248 households within Jaipur, India in 2015 (Figure 6). Responses on the year of installation of dual-flush toilets are shown in Figure 7. Responses in which participants did not know the date of installation were not included in the parameterization process. Because the model measures the installation of dual-flush toilets, a decision that is irreversible for the life of the technology, once agents adopt *WC* behavior, they do not update their utility function again.

The average assumed water savings, *ws*, per person are calculated as follows:

$$ws = 5.1 \times (6.06 - 4.54) = 7.75\ lpcd \tag{5.1}$$

based on dual flush toilet data (Table 3).

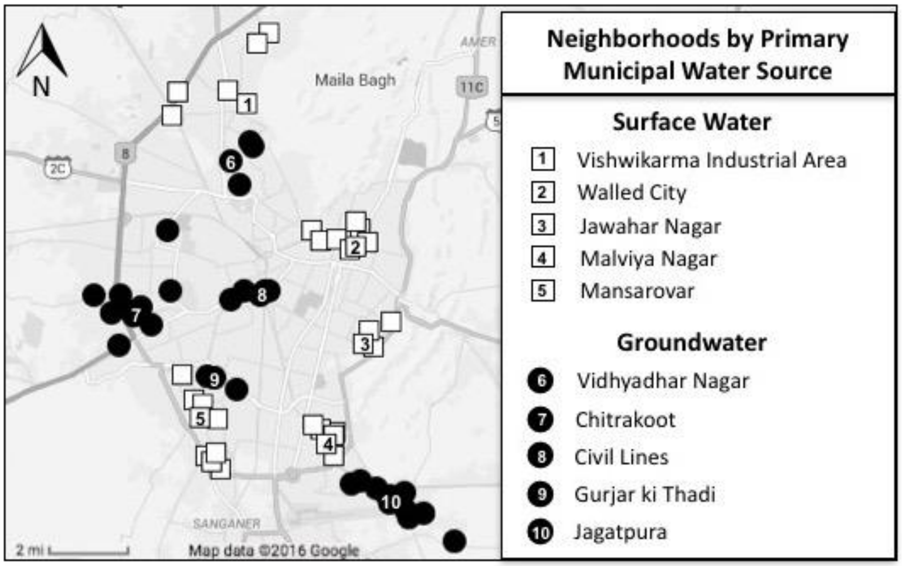

Figure 6. *Household survey locations in Jaipur, India* (Ramsey et al., 2017)

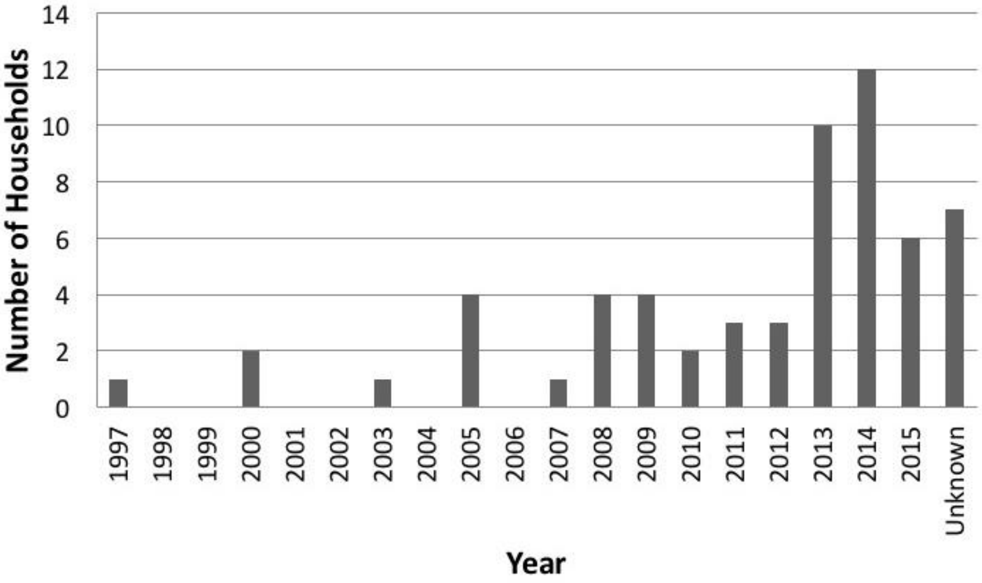

Figure 7. *Number of households adopting dual-flush toilets in Jaipur City, India by year*

Table 3. *Water demand data* (Jaipur Development Authority 2011; McMordie-Stoughton et al. 2005; Vickers 2001)

Per Capita Demand	200 liters/person/day
Dual Flush Toilet Water Consumption	4.54 liters/flush
Regular Flush Toilet Water Consumption	6.06 liters/flush
Average Number of Flushes	5.1 flush/person/day

5.2 Initialization of the ABM

For parameterization, the model is initiated in January 1997 and ends at December 2015. Using linear interpolation from census data, the population size at January 1997 is assumed to be 2.04 million, and 4.31 million at December 2015 (Office of the Registrar General & Census Commissioner 2011). 8280 agents are initialized for the duration of the model, with 3,922 given a $t_{born} = 0$.

Agents are assigned a household size from a Poisson distribution with an average size of 5.2, which is the average urban household size in Jaipur (Office of the Registrar General & Census Commissioner 2011), with a maximum size of 20 and a minimum of 1.

The Watts-Strogatz small world network is given an average number of connections of k=48, and an average rewiring probability ß = 0.25, based on a social network study conducted in southern India (Shakya et al. 2014).

5.3. Genetic Algorithm Performance

The GA was run for five independent trials to parameterize the ABM using algorithmic settings shown in Table 4. The results of the GA trials are listed in Table 5, ordered from best to worst performance. The best set of parameters generated by the GA has a standard error of S = 574.403. The fitness convergence (as measured by S) of each of the five optimal parameter sets for each generation is shown in Figure 8. The GA identifies a good solution early in the search and makes minor improvements throughout the rest of the search. Each GA trial takes an average of 12.8 hours to complete with the settings given in Table 4.

The GA was re-run for a single trial with a population of 1000 and five generations to assess whether increasing the number of chromosomes allows a better exploration of the problem space. While this approach generated marginal improvement in the model fitness, the returns for the added computational time required (35.8 hours vs 12.8 hours per trial) are of negligible benefit, and the settings shown in Table 4 were used to conduct experiments and generate results.

Table 4. *GA settings and values*

GA Setting	**Value**
Crossover Rate	0.80
Mutation Rate	0.01
Generations	100
Population	100

Table 5. *Parameters generated by GA for independent trials*

GA Trial #	a	b	e_{other}	$e_{drought}$	$f_{communicate}$	f_{update}	Standard Error of the Regression	Number of Runs to Convergence
1	0.803	0.333	0.516	0.129	2	141	574.403	9887
2	0.955	0.310	0.725	0.112	7	154	576.073	9913
3	0.784	0.378	0.544	0.098	5	171	582.474	9892
4	0.449	0.192	0.276	0.042	10	148	592.994	9882
5	0.642	0.229	0.048	0.393	2	112	597.640	9907

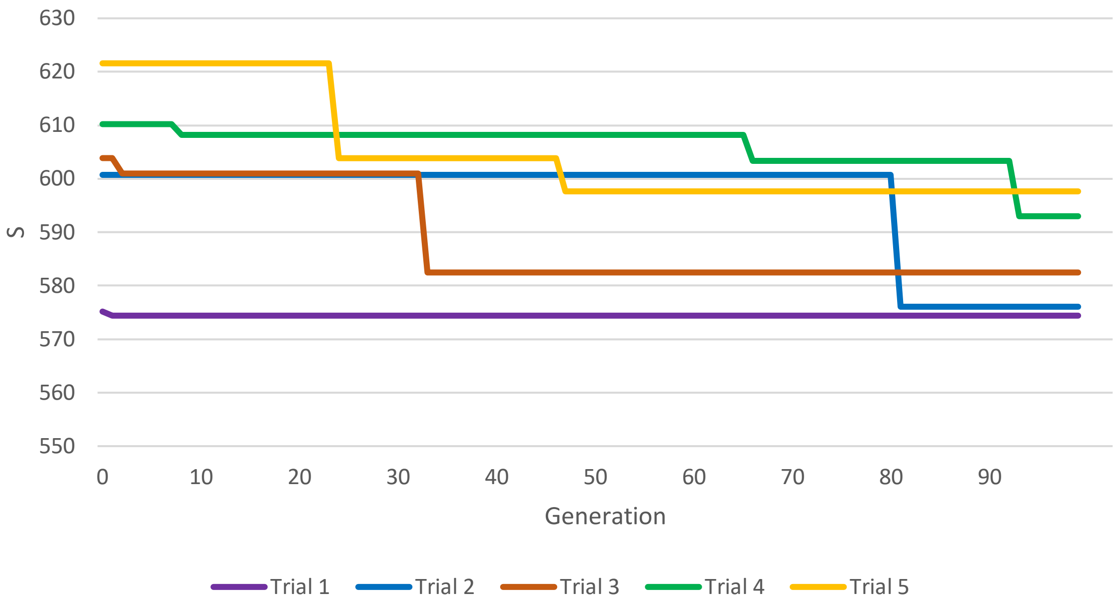

Figure 8. *Fitness of parameter sets generated by GA, as measured by S*

The ABM was executed for 30 random simulations using each of the GA-generated parameter sets to assess stochasticity in the model's performance. The average results from these trials are presented alongside the household survey in Figure 9 as a number of raw agents and in Figure 10 as a percentage of the total number of agents. The model performs well at the beginning of each of the runs, but fails to keep pace with the real world reported adoption rate that increased around 2013, suggesting that another driver of adoption behavior exists which is not represented by social pressures, external pressure, and responses to drought. One possible driver could be an increase in water awareness following the failure of Jaipur's former surface water source, Ramgarh Lake, to refill even during heavy monsoons in 2012 (Singh 2012).

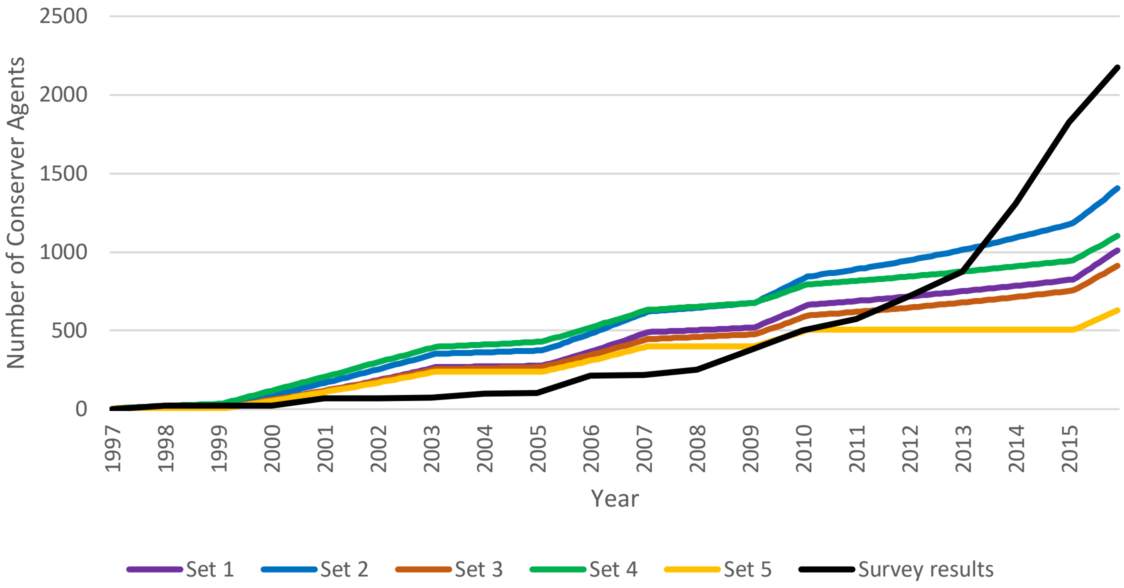

Figure 9. *Average number of conserver agents for 30 simulations of parameter sets 1-5*

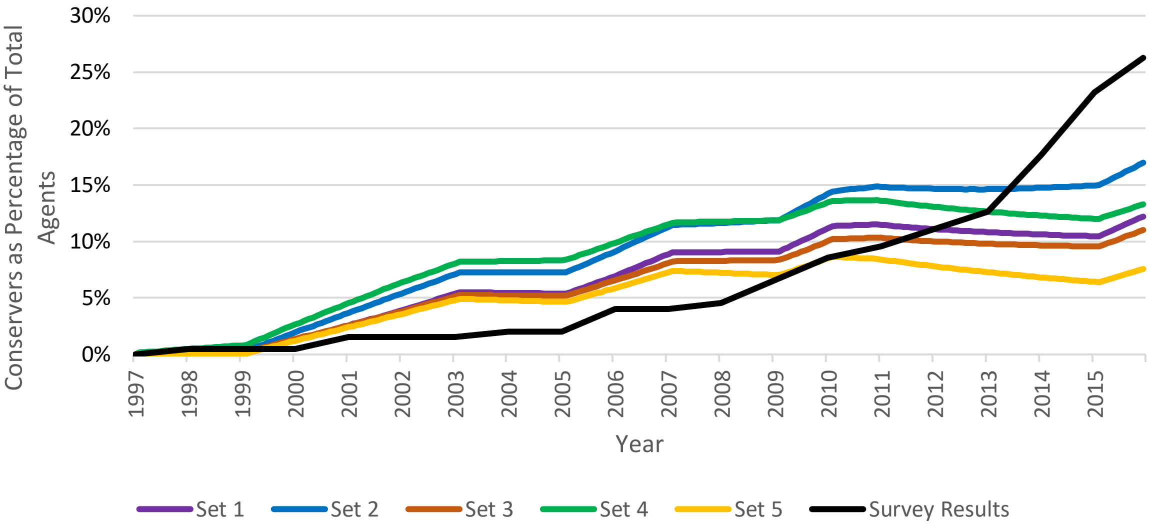

Figure 10. *Average percentage of population as water conservers for 30 simulations of parameter sets 1-5*

The relationship between the model's fitness and the six variables parameterized by the GA (a, b, $e_{drought}$, e_{other}, f_{update}, and $f_{communicate}$) as found for Trial 1 were explored to identify the ranges of parameters with the best performance and to analyze potential drivers behind the GA's behavior. The S values for each permutation within the GA are plotted against each of the variables in Figures 11-16. The ranges of the GA-generated parameters with the best solutions ($S < 1000$) are given in Table 6.

Table 6. *Ranges of parameters for the best solutions generated by GA Trial 1*

Parameter	Range
a	0.400-1.000
b	0.172-0.578
e_{other}	0.067-0.613
$e_{drought}$	0.018-0.501
$f_{communicate}$	1-36
f_{update}	12-179

The best performing values for a, the weight given to agents exhibiting the same behavior as the agent updating its utility function, are greater than 0.400 (Figure 11). The best performing values for b, the weight given to agents exhibiting the opposite behavior, are less than 0.578 (Figure 12). The best performing range for $a - b$ was determined to be between 0.109 and 0.531. The best performing values of e_{other} range from 0.067 to 0.613, and the best performing values of $e_{drought}$ range from 0.018 to 0.501. The best performing range for the sum of e_{other} and $e_{drought}$ is between 0.308 and 0.742 (Figures 13 and 14, respectively). The best performing range for $e_{other} - e_{drought}$ is -0.419 to 0.484, indicating that the model is not limited by which parameter is larger. The best performing values of $f_{communicate}$ range across the GA constraints of 1 to 36; the values thus do not appear to impact the model performance significantly (Figure 15).

Similarly, the best f_{update} values fall along the GA constraint range, from 12 to 179. As seen in Figure 16, a clear relationship between f_{update} and the range of S values (S_{range}) exists, and can be expressed by the equation

$$S_{range} = 0.0618f_{update}^{2} - 28.695f_{update} + 4992.5 \tag{5.1}$$

with an R^2=0.919. This relationship shows that the permutations within the GA all have a lower range of error as f_{update} increases. The minimum value for S_{range} = 1661.582, occurs when when f_{update} = 232.160 (19.3 years). This is due to the dominance of the f_{update} parameter as it increases. When f_{update} is low, the agents update their utility functions and behaviors more often. Consequently, they are more likely to adopt *WC* behavior early in the model, which yields a higher *S* value when compared to the slower real world adoption rate. As f_{update} increases, regardless of the other parameters, the slower adoption rate reduces the error of the model. There are, however, some permutations with a low f_{update} that have a relatively low error, indicating that while f_{update} dominates the model, the other parameters continue to play a contributing role in determining the performance of the model.

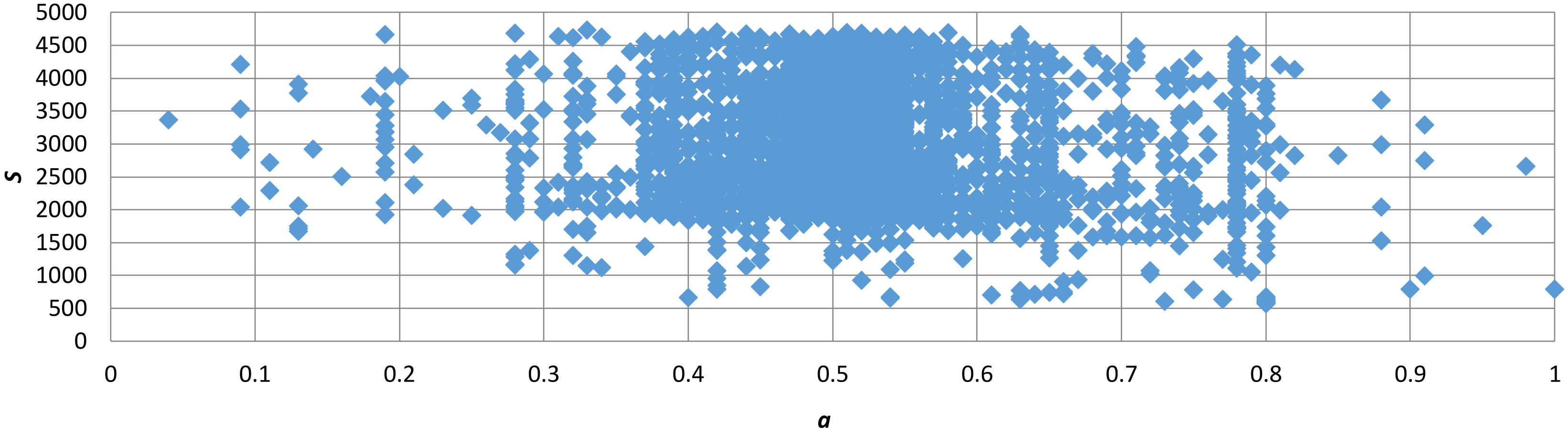

Figure 11. *Relationship between a and S for each chromosome in GA Trial 1*

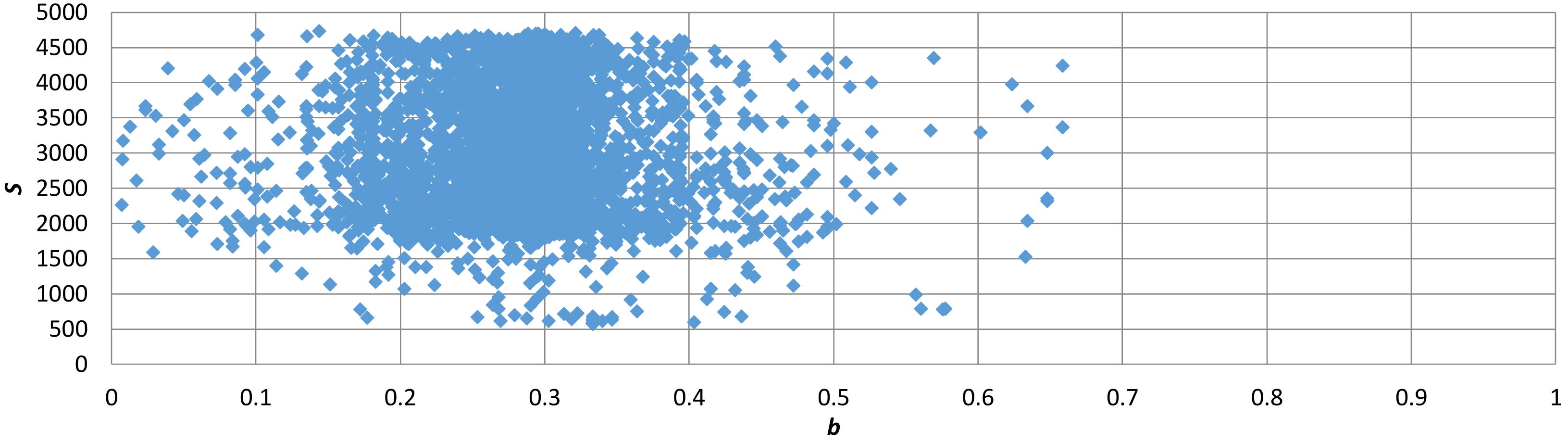

Figure 12. *Relationship between b and S for each chromosome in GA Trial 1*

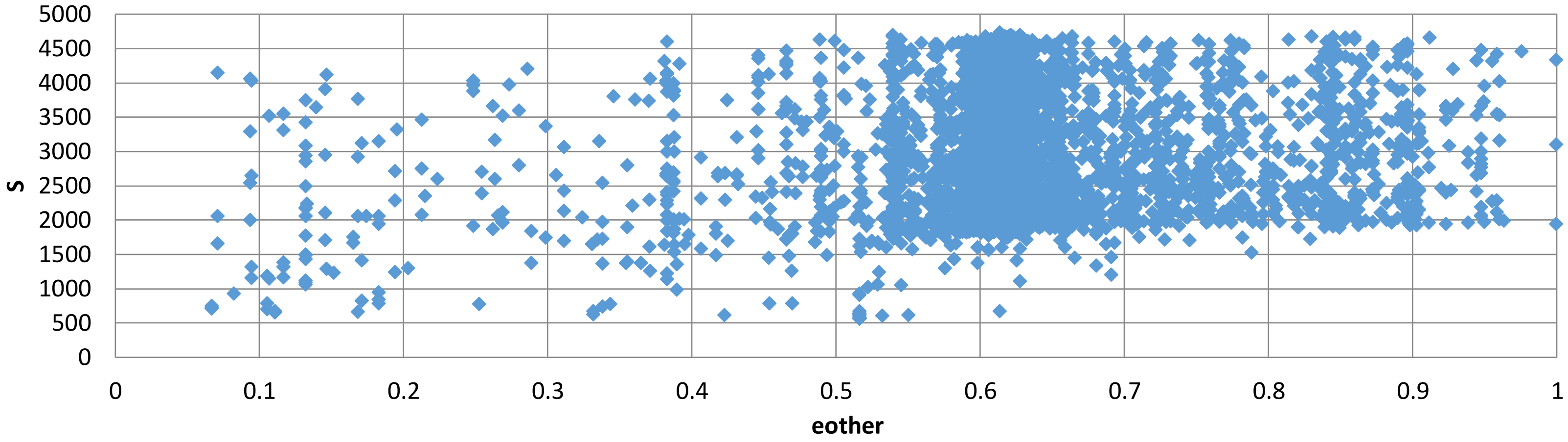

Figure 13. *Relationship between e_{other} and S for each chromosome in GA Trial 1*

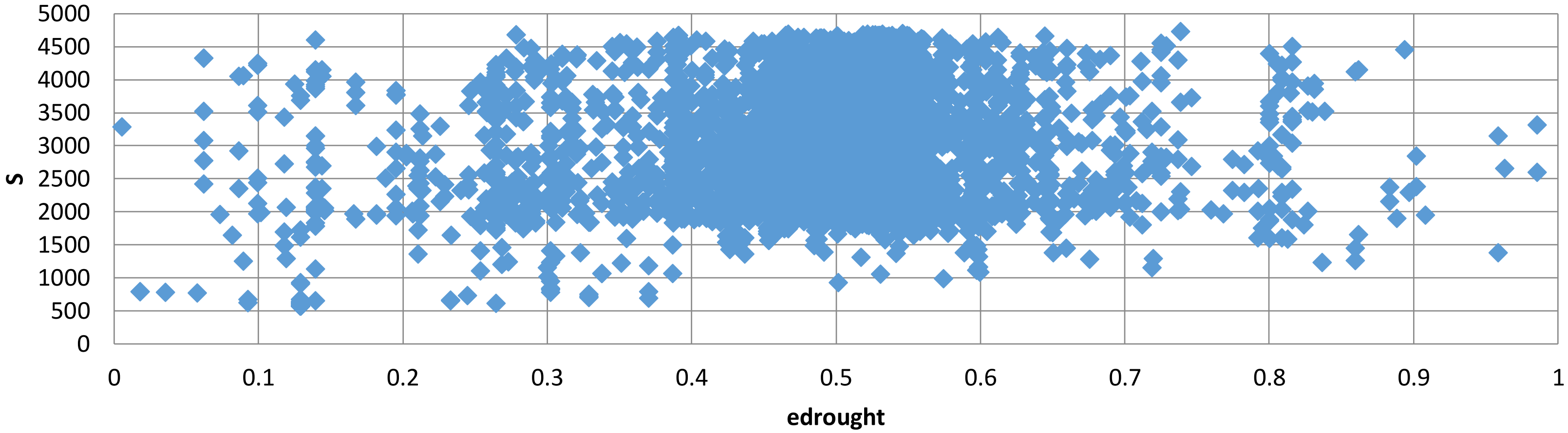

Figure 14. *Relationship between $e_{drought}$ and S for each chromosome in GA Trial 1*

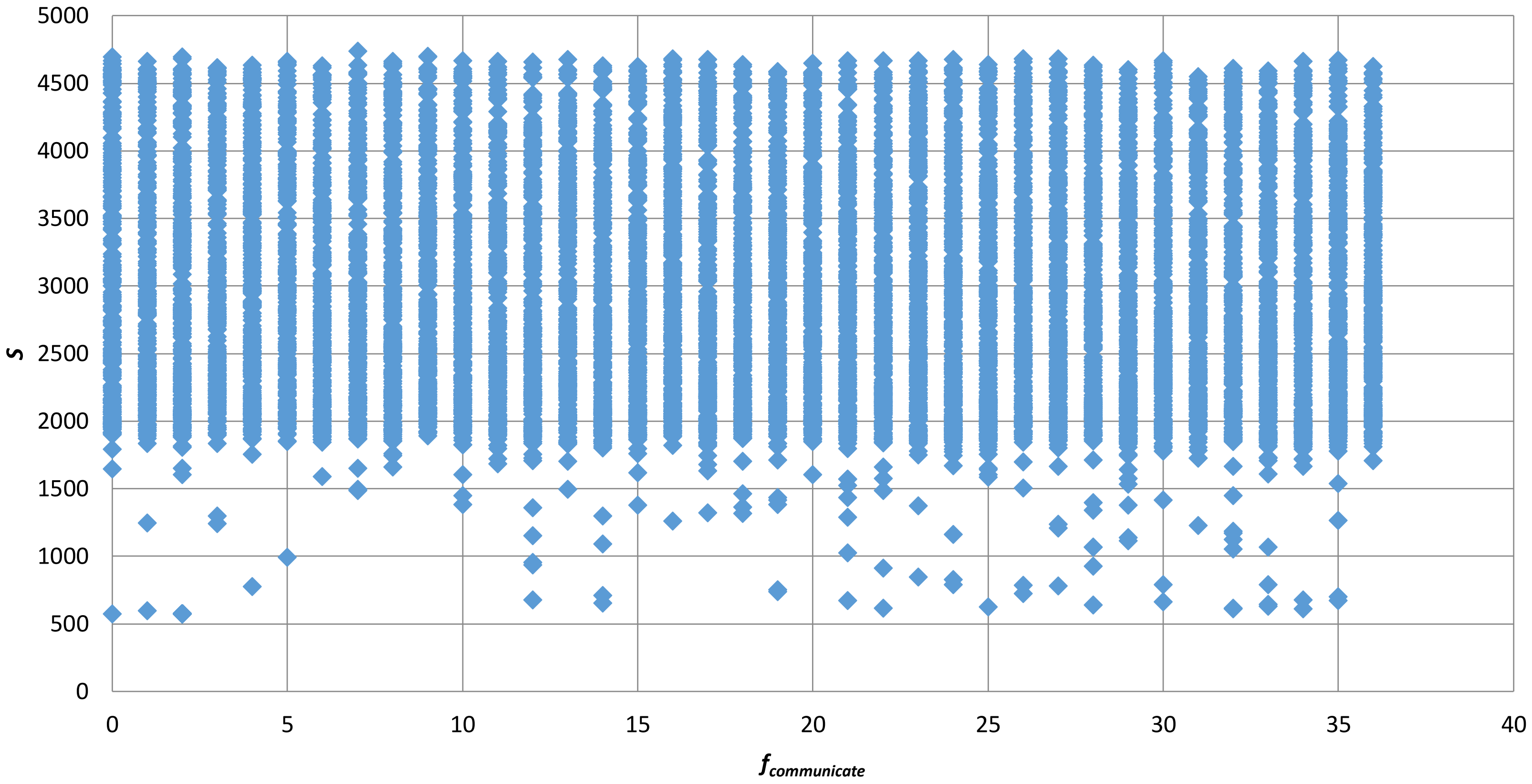

Figure 15. *Relationship between $f_{communicate}$ and S for each chromosome in GA Trial 1*

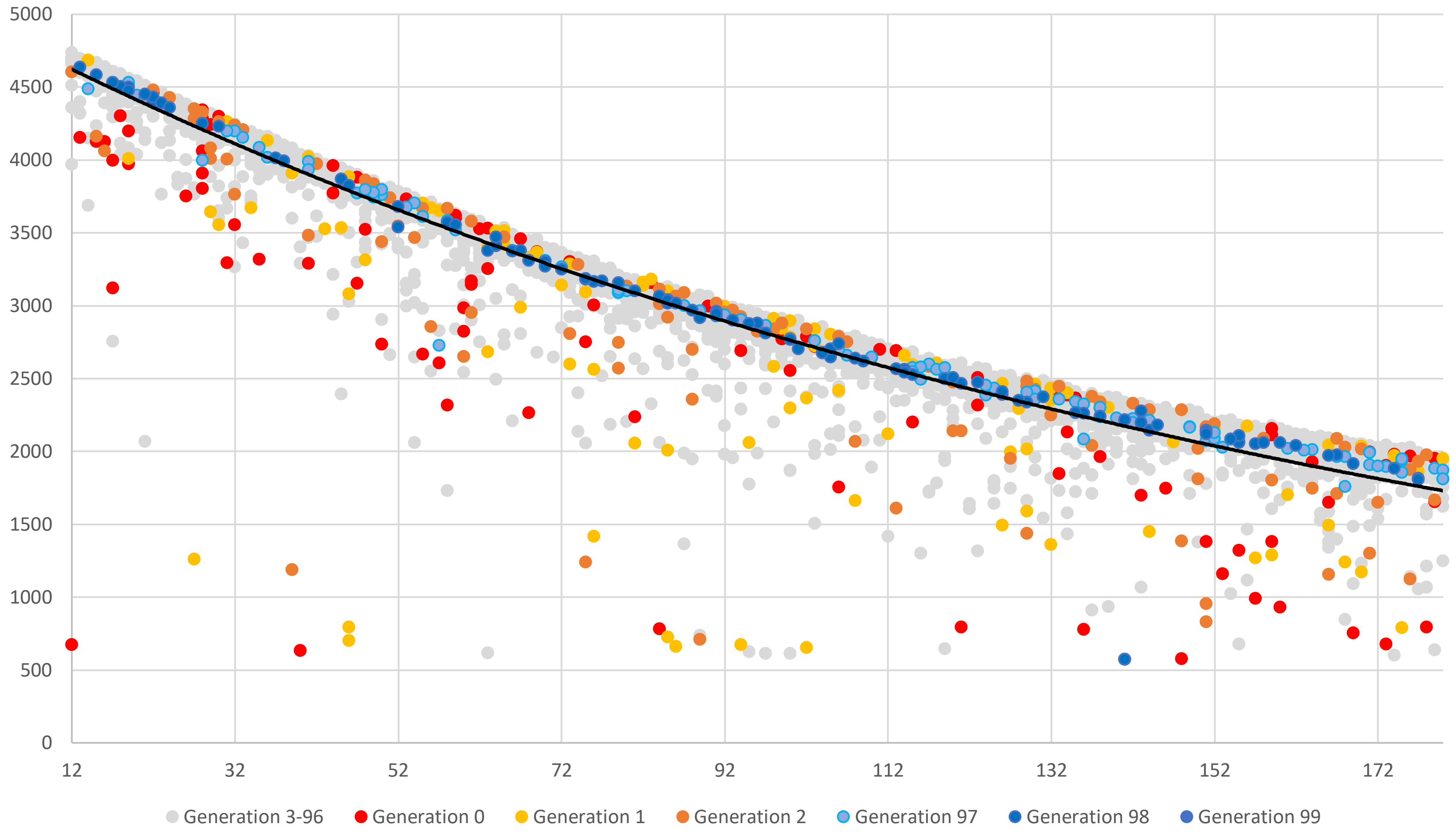

Figure 16. *Relationship between f_{update} and S for each chromosome in GA Trial 1, by select generation number*

5.4 Simulation Using Parameter Set 1

Using the highest performing set of parameters (Set 1), adoption rates were projected to 2100. Droughts are modeled using the historical record up to the year 2015 and are generated randomly starting in 2016, assuming a rate of drought occurrence consistent with the current rate (29.3%). Thirty simulations were run, and the average number and range of *WC* adopters at each time step are presented in Figure 17. The number of total agents is included in the graph for reference. The different model simulations generate a range in the number of adopters beginning in 2015, when the random drought generation module starts, indicating that the order in which droughts occur within the model plays a role in adoption rates. The maximum range reaches 3815 agents (29.0% of total agents at that time step) in February 2042. The model never reaches 100% adoption because new agents are introduced to the model as *NWC* agents, preventing universal adoption.

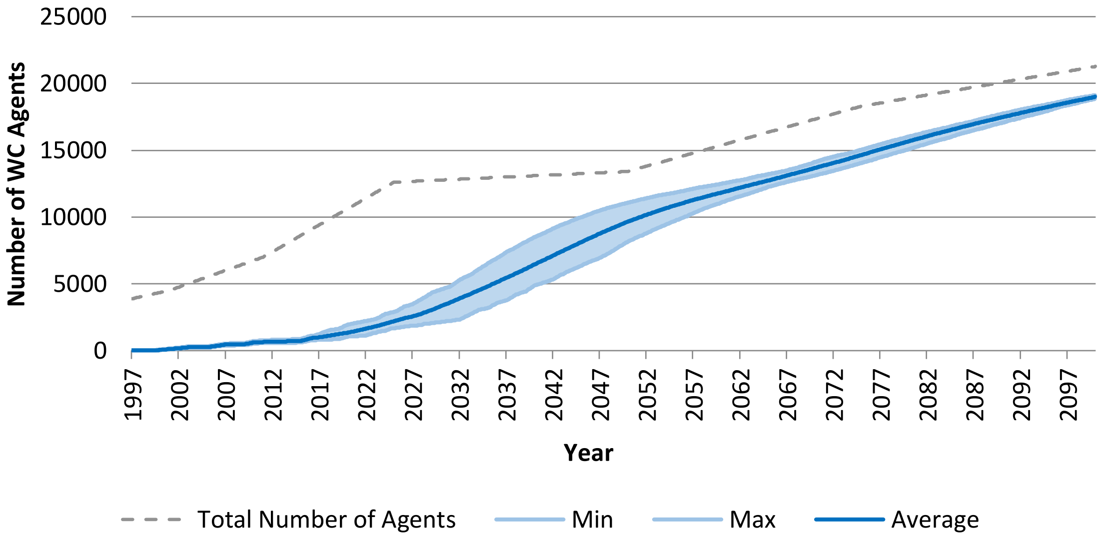

Figure 17. *Range of performance for WC behavior adoption projection, 1997-2100*

A comparison between the average monthly projected water demand for Jaipur City from the model and projected water demand based on static per capita demand is shown in Figure 18, and the difference between the two is shown in Figure 19. According to the model, water savings generated by adoption of *WC* behaviors will reach 2.3 billion liters of water per month will by 2100, or roughly 3.5% of static per capita demand.

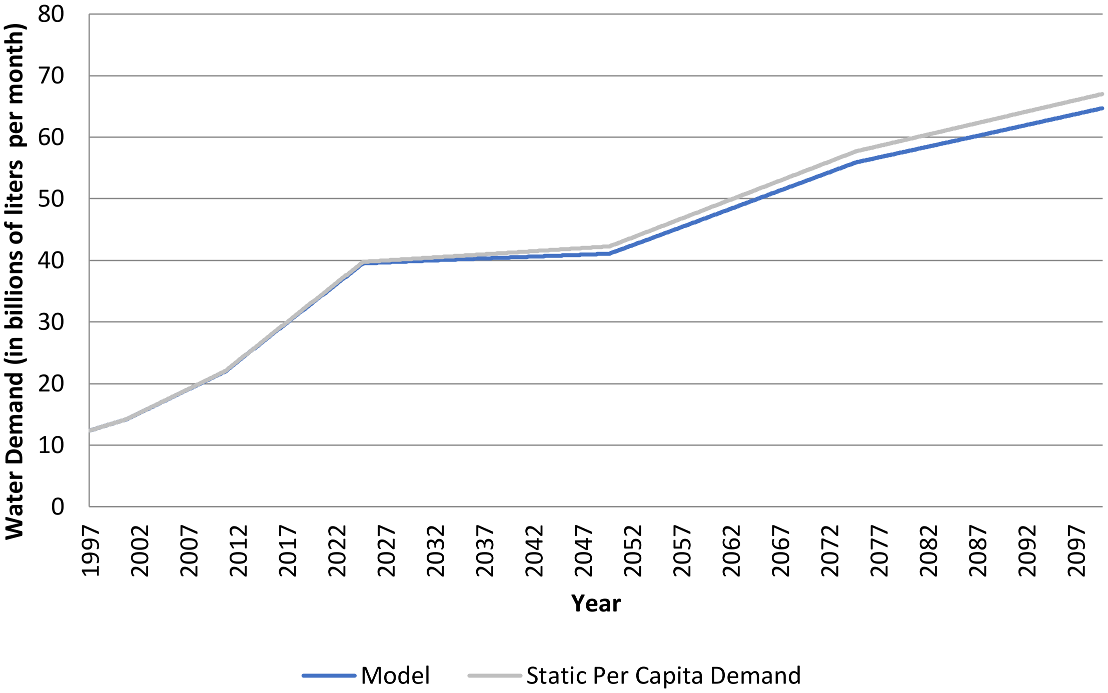

Figure 18. *Monthly projected water demand for Jaipur City*

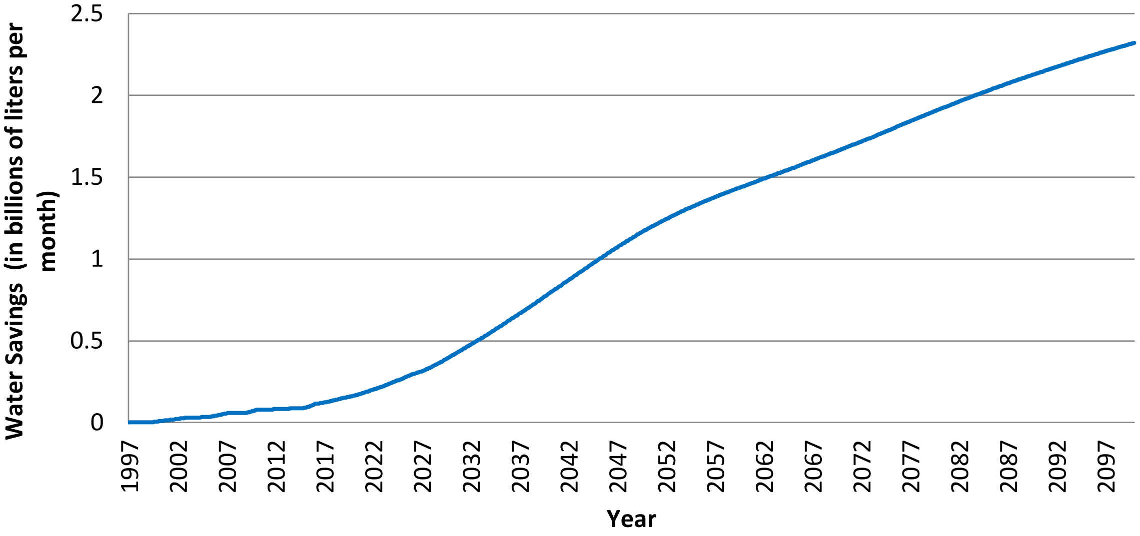

Figure 19. *Difference in water demand between model and static per capita demand*

In Figure 20, the results from the 30 simulations run with Parameter Set 1 with the highest and lowest number of adopters as well as the average performance are presented. The greatest difference between the best and worst performing simulations occurs at February 2043, with a difference of 2207 *WC* behavior adopter agents (16.7% of the total number of introduced agents). By October 2095, the difference between the best and the worst performance reaches <2% of the total number of agents. Thus, while there is significant stochasticity within the middle of the simulation, the performance is similar at the end.

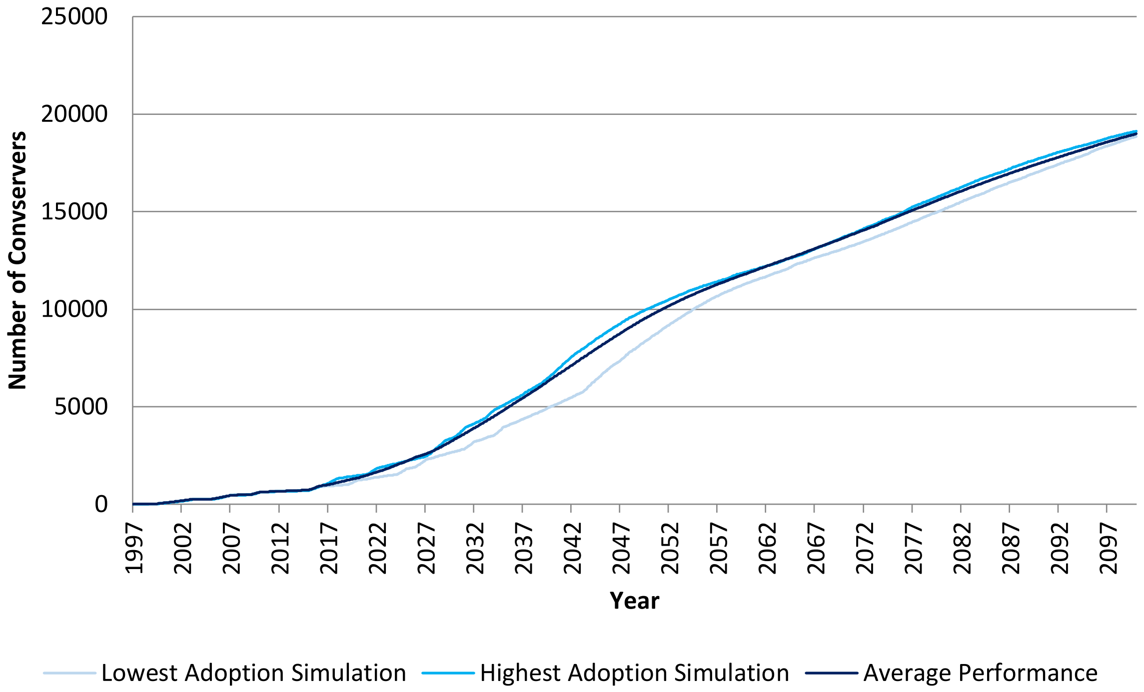

Figure 20. *Adoption of WC behavior--best, worst, and average performances*

Figure 21 shows the *rate* of adoption in agents/month for the three simulations shown in Figure 20 (lowest adoption, highest adoption, and average performance). The population growth *rate* is also shown, in new agents/month. The population growth rate between 2025 and 2050 drops as a result of the combination of the JDA and GCI population projections (as shown in Figure 3). Visualizing the rate of adoption and rate of population change, rather than cumulative values alone, provides another set of insights into the performance of the model.

At the beginning of the model, adoption rates are driven predominantly by the statically programmed drought conditions (denoted by red bands). When drought conditions are not present early in the model, adoption rates are close to zero. As more agents adopt *WC* behavior, the rate of adoption increases towards the middle of the simulation, and the primary driver of this spread becomes the social pressure from neighboring agents. Although the population growth rate drops between 2025 and 2050, the rate of adoption continues to increase as many of the newly introduced *NWC* agents begin to adopt *WC* behavior. The rate of change curve shown in Figure 21 demonstrates the characteristics that lead to a typical S-shape curve, as expected for technology adoption diffusion. Toward the end of the projected period, the rate of adoption does not return to zero, but it is approximately equal to the rate of population change.

The best performing simulation has a maximum adoption rate of 52 agents per month, which it achieves at two time steps: May 2040 and February 2041. The average of all simulations reaches its peak at 32.03 agents/month in September 2039, and the poorest performing simulation reaches its peak of 48 agents/month in May 2044. While the rates between the best and the worst performers are close in magnitude, the four-year delay could result in higher aggregate water use. The earlier high adoption rates in the best performing simulation are likely due to the order of drought occurrence generated by the drought module. During the top-performing simulation, the drought module generated consecutive droughts from 2015 to 2017, which caused more agents to adopt at the beginning of the model and pushed the model towards a critical number of adopters at an earlier time step.

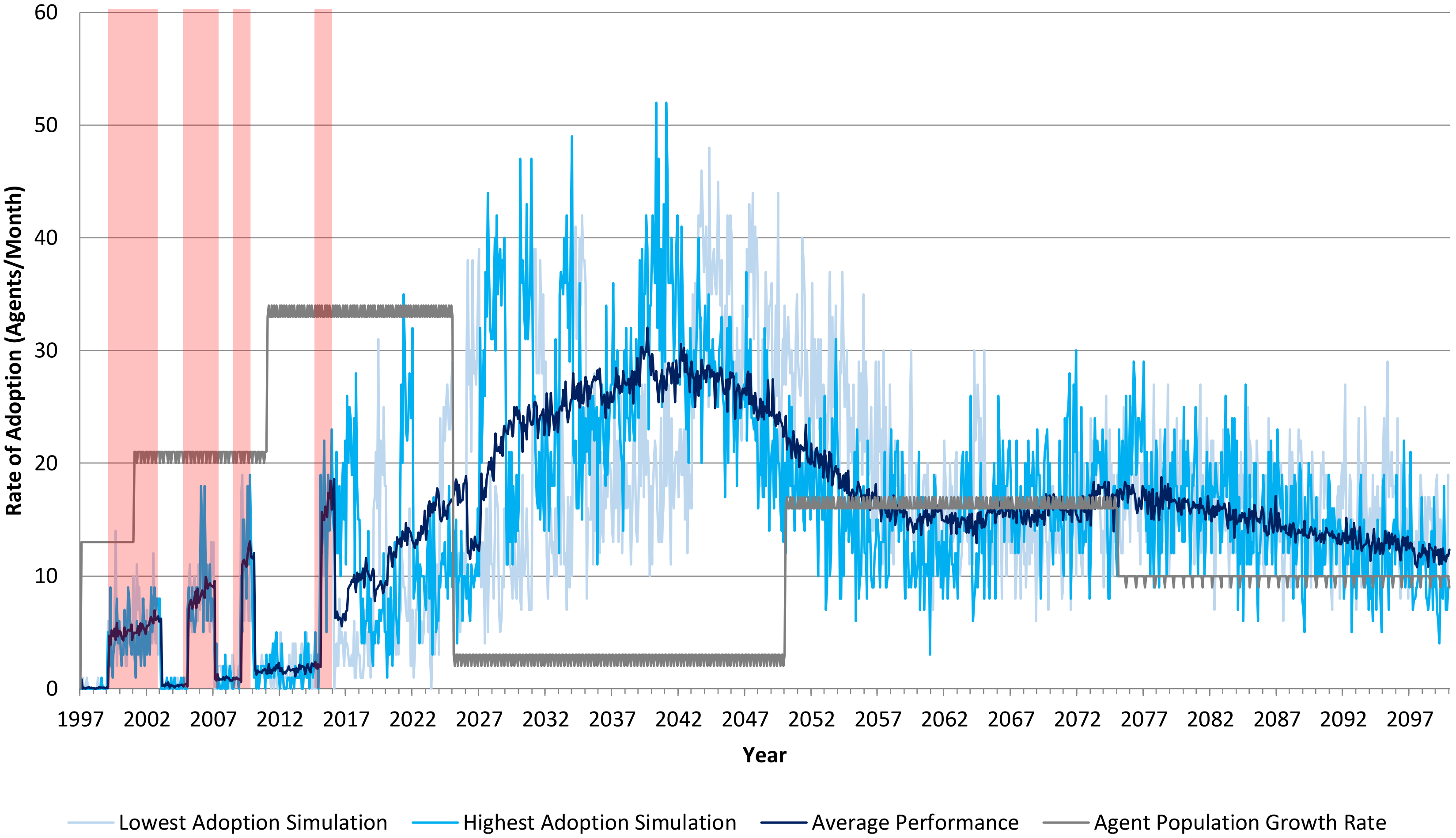

Figure 21. *Rate of WC behavior adoption, 1997-2100*

5.5 Simulation Using Various Drought Scenarios

The model was run for four drought scenarios: Dry (58.6% annual likelihood of drought, double the current drought rate), Very Dry (87.9% annual likelihood of drought, triple the current drought rate), Perpetual Drought (a drought occurs for the entire duration of the model), and Wet (no drought occurs for the duration of the model). The Perpetual Drought and Wet scenarios are climatologically improbable, but are used here to explore the sensitivity of the model to changes in drought frequency. Each scenario was modeled using the ABM for 30 random simulations and the average results are presented alongside the Stationary Climate scenario (presented in Section 5.5) in Figure 22.

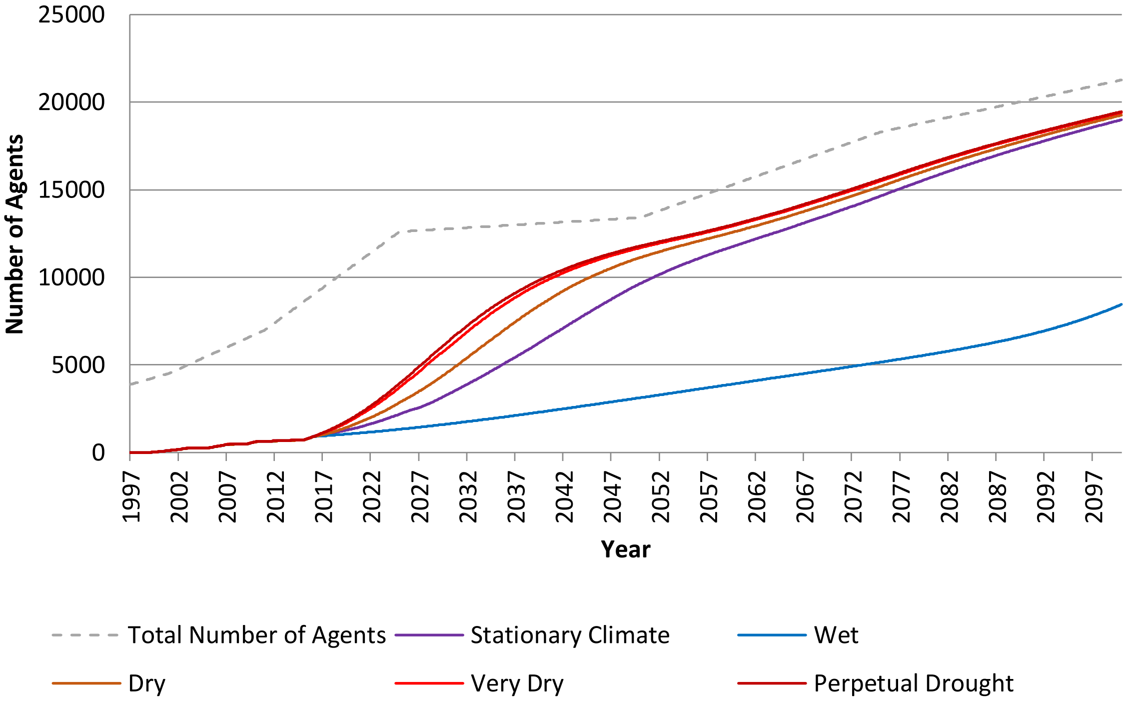

Figure 22. *WC behavior adoption under varying drought scenarios*

For the Dry, Very Dry, and Perpetual Drought scenarios, adoption rates are higher than the Stationary Climate scenario. The maximum differences in *WC* adoption numbers are given in Table 7. The maximum difference between the Stationary Climate and the Perpetual Drought scenario occurs eight time steps earlier in the model than the Very Dry scenario, but there is only a 2.0% difference in agents adopting *WC* behavior. The small difference between the two is likely due to the already high drought occurrence within the Very Dry scenario. The maximum difference between the Wet scenario and the Stationary Climate scenario is greater than 50% of the population, or number of agents that exist, at that time step, and occurs close to the end of the simulation. This demonstrates that the presence of the drought module is a key driver of the *WC* adoption behavior in the model. Again, the model never achieves 100% adoption even in the Perpetual Drought scenario because of the continued introduction of *NWC* agents into the model to simulate population change.

Table 7*. Maximum difference in WC adoption between drought scenarios and Stationary Climate scenario and time step of occurrence*

Scenario	Maximum Difference/ Percentage of Total Agents	Time Step of Occurrence
Dry	2133.8 (16.3%)	February 2041
Very Dry	3416.1 (26.2%)	October 2037
Perpetual Drought	3669.3 (28.2%)	February 2037
Wet	-10848.2 (-53.0%)	April 2093

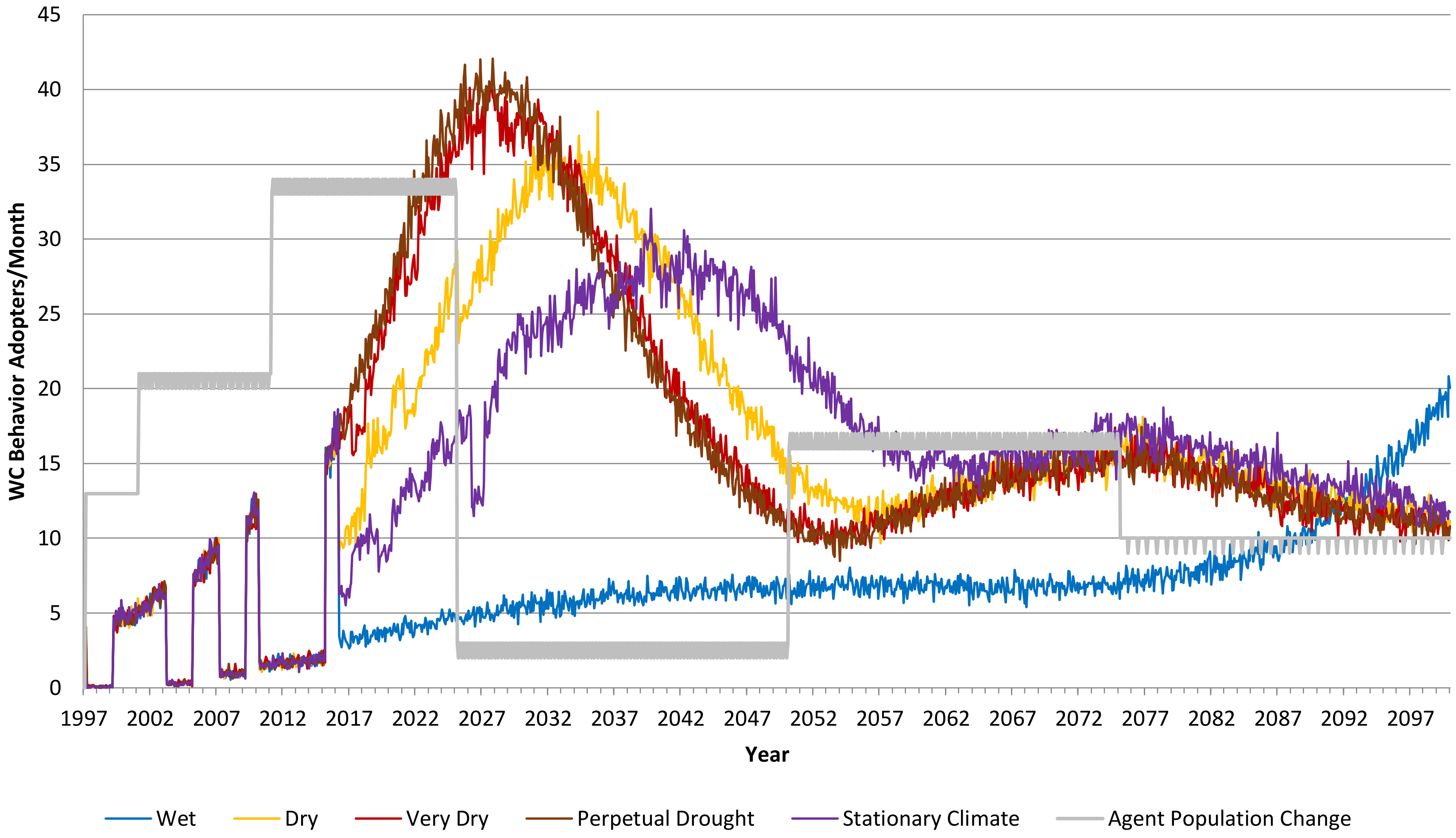

Figure 23. *WC behavior adoption rate under varying drought scenarios*

Table 8. *Maximum rate of WC behavior adoption in drought scenarios and time step of occurrence*

Scenario	Maximum Rate (Agents/Month)	Time Step of Occurrence
Dry	38.5	September 2035
Very Dry	40.4	August 2027
Perpetual Drought	42.1	October 2027
Wet	20.8	November 2099
Stationary Climate	32.0	September 2039

The rates of *WC* behavior adoption (shown in Figure 23) diverge immediately as the drought scenarios begin in 2015, and converge to less than one agent/month rate difference in September 2064 in the model for the three driest scenarios. The maximum adoption rates for the scenarios and the Stationary Climate Scenario are presented in Table 8. The three dry scenario adoption rates are all within <4 agents/month of each other. However, the time scale varies between the scenarios. The Perpetual Drought scenario maximum adoption rate occurred two time steps after the Very Dry scenario maximum adoption rate was achieved. In contrast, the maximum rate for the Dry scenario occurred 97 time steps later than the Very Dry scenario. This indicates that a threshold exists beyond which an increase in drought frequency has minimal impact on the adoption rate's magnitude or timing.

WC behavior adoption continues in the Wet scenario due to the presence of social pressure, but it is outpaced by the rate of population change. The maximum adoption rate is achieved two time steps before the end of the simulation; it is likely that a higher rate would be obtained after 2100 if the simulation had continued, as social pressure begins to dominate agent utility functions. The performance of the model during the Wet scenario indicates that $e_{drought}$ is a catalyst for earlier adoption, but adoption rates will eventually increase even in its absence.

5.6 Sensitivity Analysis

The sensitivity of two of the three new parameters introduced to the model, f_{update} and $e_{drought}$, were tested because their values were shown to have an impact on the overall performance of the model (Section 5.3). The sensitivity of $f_{communicate}$ was not tested because it had minimal influence on the model.

5.6.1 Sensitivity of f_{update} parameter

Using the Stationary Climate scenario for Parameter Set 1, the sensitivity of the model to the f_{update} parameter was tested. The value of f_{update} was decreased incrementally by 12 time steps (starting at the original value of $f_{update} = 141$) for the duration of the model to approximate a shorter deliberation time for installation of *WC* technology. A shorter deliberation time could represent the introduction of a rebate program or other financial incentive for adopting water-efficient technology. The simulation was run for 30 random simulations, keeping all other parameters consistent.

The number of adopters with changing of f_{update} values are presented in Figure 24, and the rates of adoption are shown in Figure 25. A decrease in the f_{update} value generates an increase in the number of *WC* agents early in the model, which allows the adoption rates to increase at an earlier time step than higher f_{update} values. The numbers of adopters for the various f_{update} values eventually converge to within less than one agent/month difference by March 2063. The maximum differences between the number of *WC* agents and the original Trial 1 f_{update} value are shown in Table 9, and the maximum rates of adoption are shown in Table 10.

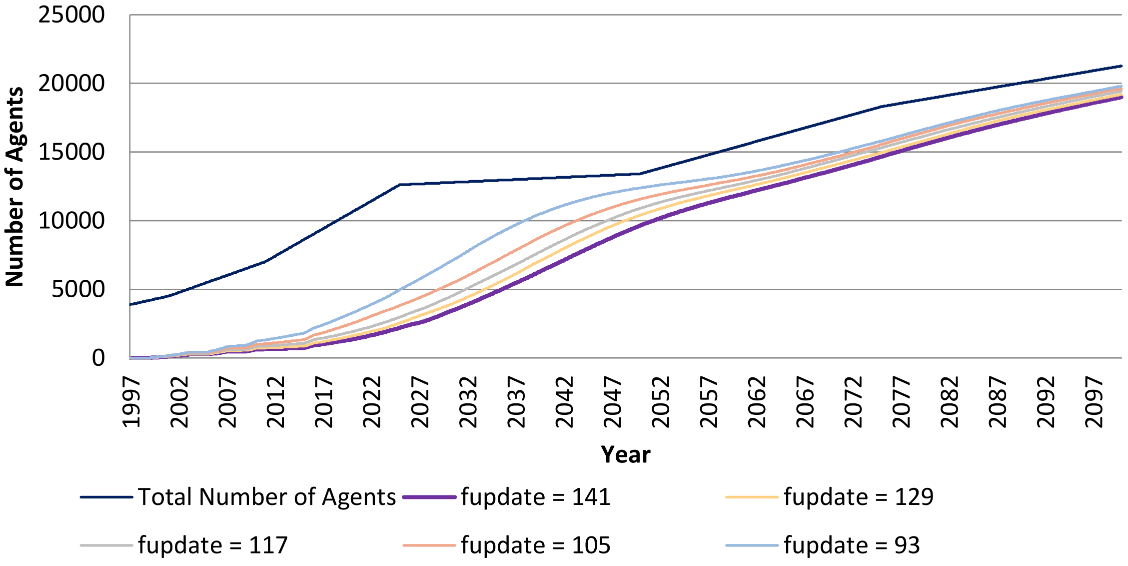

Figure 24. *WC behavior adoption with decreasing f_{update} values*

Table 9. *Maximum difference in WC behavior adoption between f_{update} value and Stationary Climate scenario and time step of occurrence*

f_{update} Value	Maximum Difference	Percentage of Total Agents	Time Step of Occurrence
129	862.0	6.51% 6.49%	September 2045 November 2045
117	1473.1	11.16% 11.15%	April 2043 August 2043
105	2495.6	19.01%	March 2041
93	4248.6	32.63%	October 2037

Table 10. *Maximum rate of WC behavior adoption for f_{update} values and time step of occurrence*

f_{update} Value	Maximum Rate (Agents/Month)	Time Step of Occurrence
141 (Stationary Climate)	32.0	September 2039
129	33.7	June 2038
117	32.4	July 2036
105	34.7	June 2035
93	38.4	March 2032

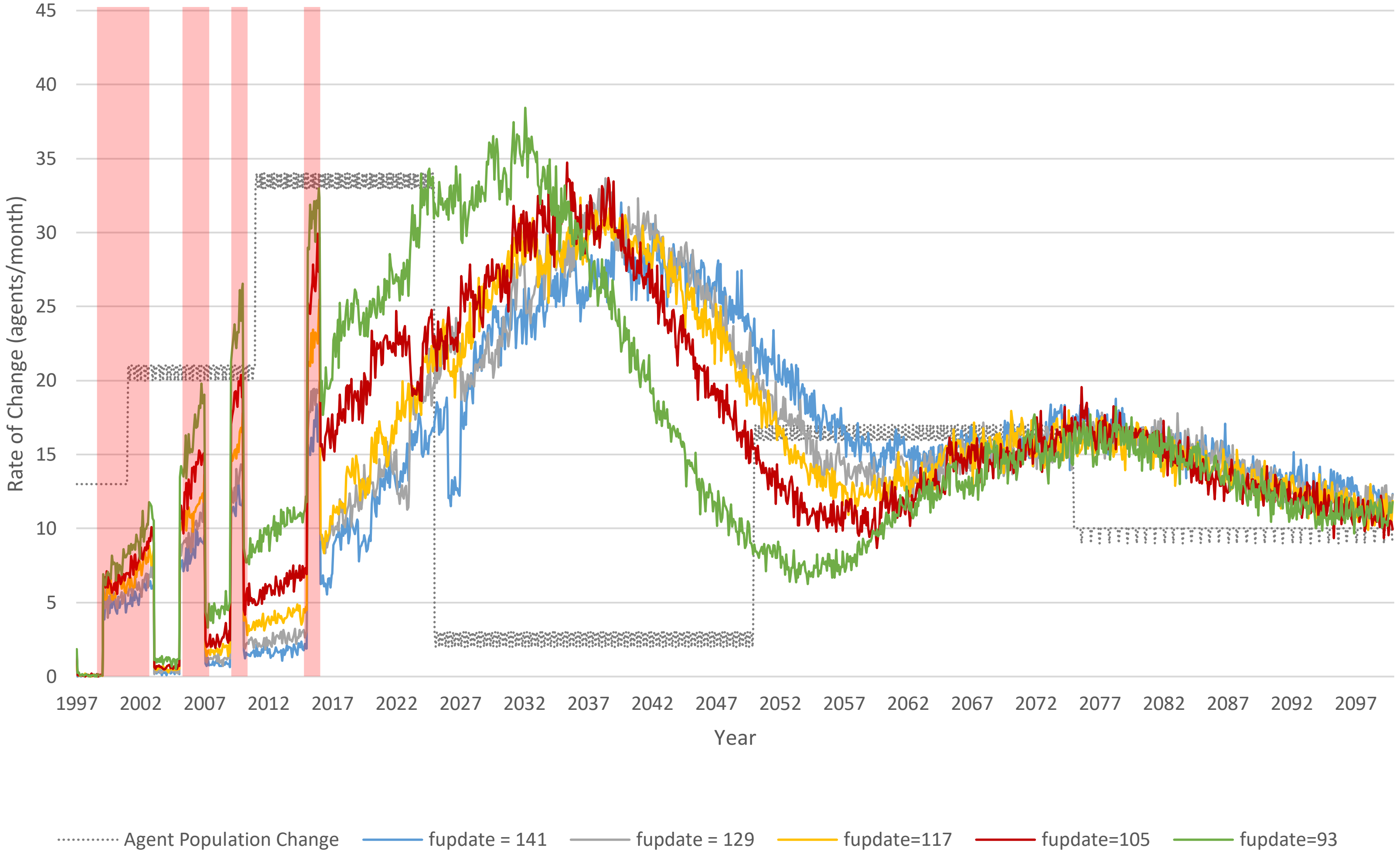

Figure 25. *Monthly rate of WC behavior adoption for f_{update} values*

5.6.2 Sensitivity of $e_{drought}$ parameter

Using the Stationary Climate scenario for Parameter Set 1, the sensitivity of the model to the $e_{drought}$ parameter was tested next. The value of $e_{drought}$ was increased incrementally by 0.05 (starting at the original value of $e_{drought} = 0.129$). This change could represent an external incentive to reduce water consumption, such as a fine for overuse or increased water prices. The simulation was run for 30 random simulations, keeping all other parameters consistent. The number of adopters are presented Figure 26 and the rates of adoption are shown in Figure 27.

An increase in the $e_{drought}$ value generates an increase in the number of *WC* agents early in the model, which allows the adoption rates to increase at an earlier time step. The maximum differences between the number of *WC* agents and the original Trial 1 f_{update} value are shown in Table 11. However, it does not increase the maximum adoption rate significantly, and in some instances slightly reduces it (Table 12).

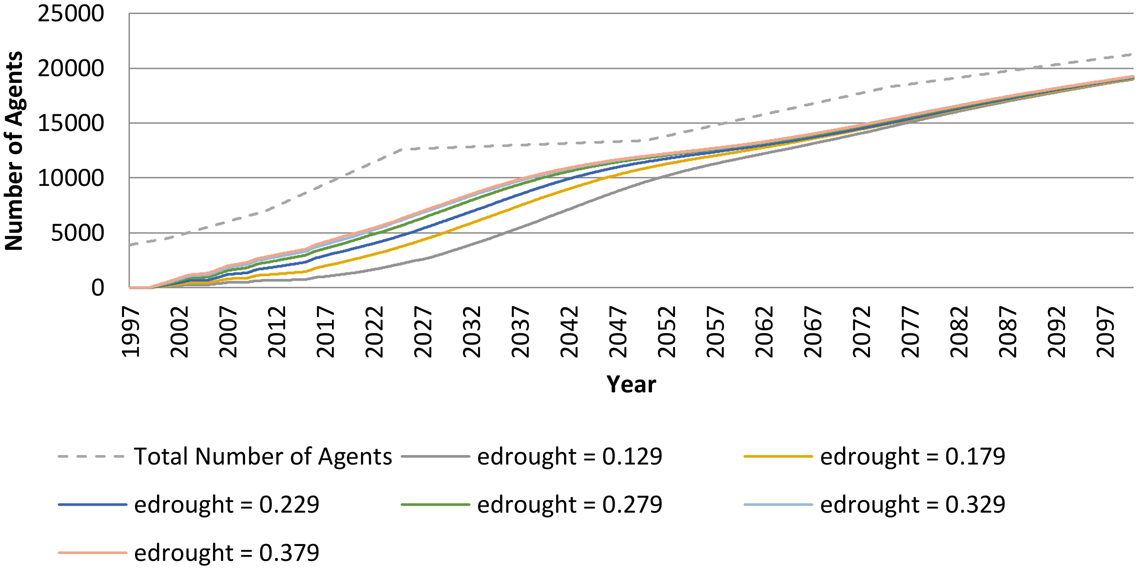

Figure 26. *Number of conservers with varying $e_{drought}$ terms*

***Table 11**. Maximum difference in WCs adoption between $e_{drought}$ values and Stationary Climate scenario and time step of occurrence*

$e_{drought}$ value	Maximum Difference	Percentage of Total Agents	Time Step of Occurrence
0.129 (Stationary Climate)	2022.1	15.5%	March 2037
0.179	3056.0	23.6%	July 2035
0.229	4054.8	31.5%	February 2033
0.329	4456.5	34.6%	January 2033
0.379	4618.8	35.9%	December 2032

***Table 12.** Maximum rate of WC behavior adoption for various $e_{drought}$ values and time step of occurrence*

$e_{drought}$ value	Maximum Rate (Agents/Month)	Time Step of Occurrence
0.129 (Stationary Climate)	32.0	September 2039
0.179	29.8	March 2036
0.229	32.8	September 2015
0.279	32.0	July 2015
0.329	35.6	December 2015
0.379	35.0	January 2016

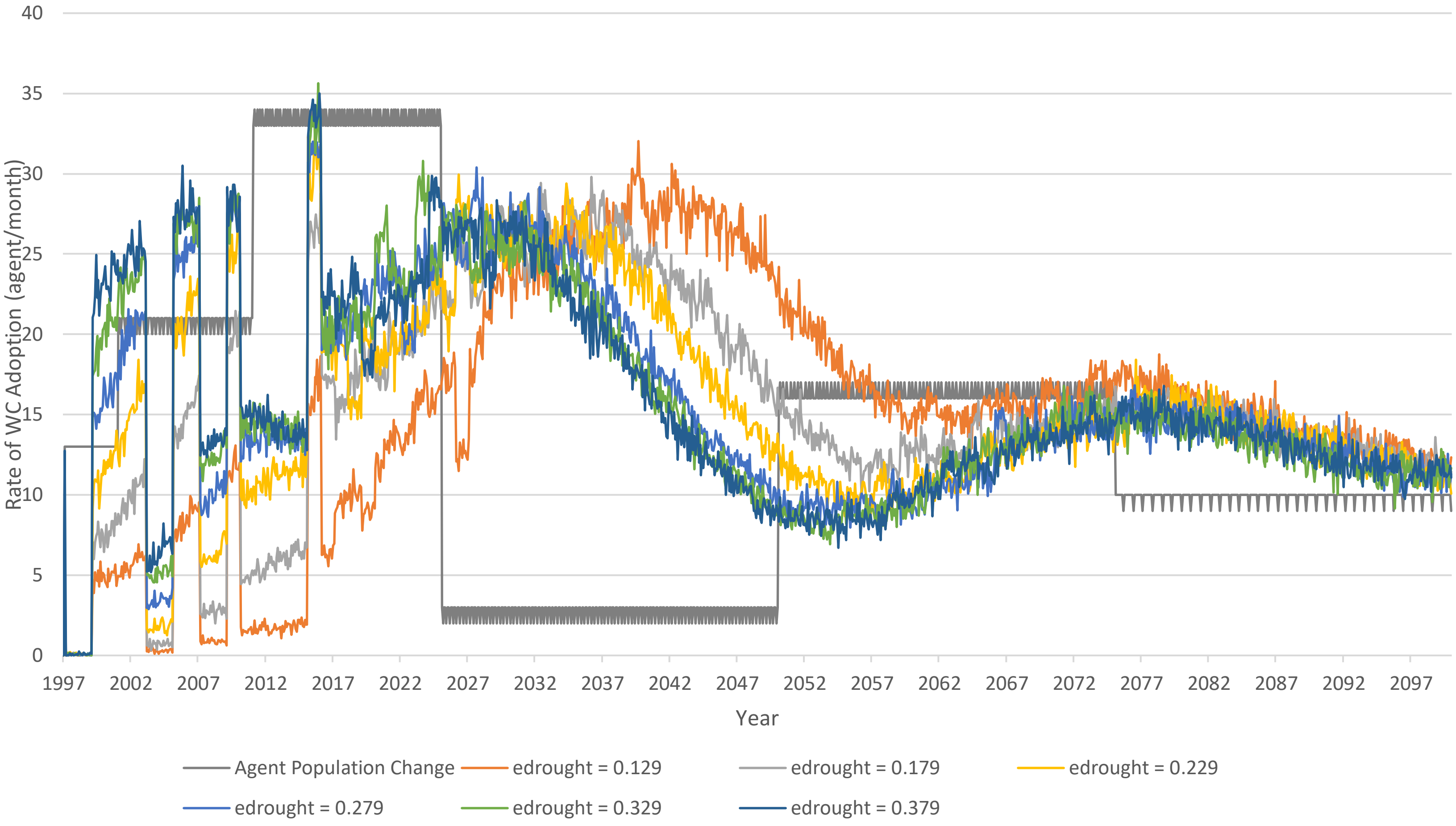

Figure 27. *Rate of WC behavior adoption with varying* $e_{drought}$ *values*

CHAPTER 6: CONCLUSIONS

This research demonstrates an approach to using a GA and real world survey data to parameterize a water conservation behavior diffusion ABM, and then applies that ABM to the City of Jaipur, India. The GA identifies solutions to parameterize the model in early generations. The ABM that is identified produces a conservative estimate of the spread of water conservation behavior adoption, and shows a significant reduction in demand as compared to static per capita demand projections.

The ABM projects monthly water savings of nearly 2.3 billion liters of water per month by the end of the model. Adoption rates peak earlier in the model when agents update their behavior more quickly in the model and when droughts occur more frequently. Adoption rates also peak very early in the model when $e_{drought}$ is increased, but a threshold exists at which a greater value for $e_{drought}$ does not correspond with a greater increase in adoption rates. Adoption rates are also impacted by the order in which droughts occur; multiple consecutive years of drought early in the model force adoption rates higher than more evenly distributed droughts. When agents update their behavior more quickly in the model, adoption rates peak earlier in the model. Adoption rates also peak earlier in the model when the $e_{drought}$ is increased, but a threshold exists at which a greater value for $e_{drought}$ does not correspond with a greater increase in adoption rates. Adoption rates are also impacted by the order in which droughts occur; multiple consecutive years of drought early in the model force adoption rates higher than more evenly distributed droughts.

The GA finds solutions through multiple generations that perform marginally better than the first solutions generated. A more extensive exploration of the problem space was attempted by using a larger population of chromosomes. While this approach marginally increased the accuracy of the model (a reduction in error of 11.2 agents across the entire model), it increased the computation time by 280%. The performance of the GA is likely due to the inherent stochasticity of the model as well as the dominance of the model by the f_{update} parameter. During calibration, the range of f_{update} values was set between 12 and 180. Examination of the performance of every solution generated by the GA shows that the range of error decreases as f_{update} increases. The smallest range of error in the model exists when $f_{update} = 232.138$ (19.3 years). Having a smaller range of error means that the worst performing solutions for the largest f_{update} values perform better than the worst performing solutions for the smallest f_{update} values. However, a smaller range of error does not necessarily imply that the best performing solutions for larger f_{update} values will be better than those for smaller f_{update} values, as evidenced by the wide range of f_{update} values for the optimal results. Testing the GA performance with a static f_{update} value may increase coverage of the problem landscape and could result in a smaller error, and is an area for future research.

The performance of the GA was also likely constrained by the variables used within the ABM. The survey data shows a spike in adoption rates in 2013, which is unaccounted for within the model. The discrepancy between the model and adoption rates could be due to several reasons. One potential cause could be an increase in public awareness of their water use. In 2012, Ramgarh Lake (the former surface water source for Jaipur) remained completely dry despite high monsoon rains, a story featured in the media (Singh 2012), and by 2013 reported rates of dual-flush toilet installation were significantly higher. Another potential source of error could be the reliance on survey participants’ memory of installation dates. A third exogenous term or universal forced utility update in 2012 could be explored in further research as a way to improve the fit of the data.

The ABM has limitations that should be addressed in further research. First, the Watts-Strogatz small world network structure may have a detrimental impact on performance for scenario projections because of the large discrepancy in population from 1997 to 2100. The network requires that all agents that will be introduced in the model be created at initialization due to the computational complexity of expanding the network at each time step. For Jaipur, the network had a maximum population of 8,280 agents, but the number increases by 257% percent to 21,268 agents for the 2100 projection. The impacts this change has on the parameterization has not been tested and is another area for further research.

Another limitation is the assumed omnipotence of agents once they have communicated with another agent, which is an artifact of the Young model approach in which ratios are calculated instantaneously. The model presented here assumes that once an agent has communicated with another agent, it keeps track of the other agent’s behavior for the rest of the model. For example, Agent A communicates with B at time step 1, when B has *NWC* behavior. However, if B updates to *WC* behavior at time step 1000, Agent A immediately knows that B has updated its behavior and uses that information in its utility function. A more appropriate way to code the model could be to allow agents to hold a limited number of communicated agents’ behaviors in memory.

The model presented here can be used to aid in water resource planning and to anticipate potential impacts of a water conservation policy such as a rebate program or media campaign. The GA-ABM approach can be applied to new case studies where survey data is easily attainable and could be extended to evaluate the adoption of other water conservation technologies, such as low-flow showerheads, or behaviors, such as reduced lawn-watering. This research provides a methodology for parameterizing a water conservation ABM with real world data and expands the modeling framework used by Edwards and Galan by introducing a Watts-Strogatz small world network structure, a limited scope of awareness of other agents' behaviors, and delays in agent decision-making.

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