Investigating the micro-level dynamics of water reuse adoption by farmers and the impacts on local water resources using an agent-based model

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Abstract

Agricultural water reuse is gaining momentum to address freshwater scarcity worldwide. The main objective of this paper was to investigate the micro-level dynamics of water reuse adoption by farmers at the watershed scale. An agent-based model was developed to simulate agricultural water consumption and socio-hydrological dynamics. Using a case study in California, the developed model was tested, and the results showed that agricultural water reuse adoption by farmers is a gradual and time-consuming process. In addition, results also showed that agricultural water reuse could significantly decrease the water shortage (by 57.7%) and groundwater withdrawal (by 74.1%). Furthermore, our results suggest that recycled water price was the most influential factor in total recycled water consumption by farmers. Results also showed how possible freshwater shortage or groundwater withdrawal regulations could increase recycled water use by farmers. The developed model can significantly help assess how the current water reuse management practices and strategies would affect the sustainability of agricultural water resources.

Keywords

Water reuse; agent-based modelling; agricultural water management; recycled water for irrigation

Code availability

The WRAF (water reuse adoption by farmers) model presented in this paper and its complete description following the Overview, Design concepts, Details, and Decision-making (ODD) (Grimm et al., 2006) protocol can be found at https://www.comses.net/codebase-release/cc6d551e-cf0f-472e-a54b-28591cd39b4d/.

1. Introduction

Agriculture is the largest water-consuming sector worldwide, responsible for almost 70% of the world's total freshwater consumption (Suri et al., 2019). In the US, for example, in 2018, 231,474 farms (226,219 million m^2) were irrigated with 102,872 million m^3 of water (USDA-NASS, 2019). During this time frame, the primary sources of irrigation in the US were as follows: 1) groundwater from on-farm wells (146,496 million m^2 of land irrigated with 49.8% of the total irrigation water consumption); 2) on-farm surface water 25,495 million m^2 of land irrigated with 10% of the total irrigation water consumption); and 3) off-farm water from a variety of sources (64,345 million m^2 of land irrigated with 40.2% of the total irrigation water consumption) (USDA-NASS, 2019).

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As such, the agriculture sector is highly dependent on water availability (Mendelsohn & Dinar, 2003), and any water shortage diminishes the number of productive farms, irrigated areas, and crops, thus impacting food production. Therefore, access to adequate water resources is crucial to the future of global agriculture, food security, and the economy (Paul et al., 2020).

Solutions for addressing water scarcity can generally be categorized into two major groups: increasing water supply and decreasing demand. While there are several ways to increase water supply (e.g., water reuse, desalination, and water transfer), agricultural water reuse is one of the most prominent ones by introducing a reliable alternative water resource (Paul et al., 2020). Using treated wastewater for irrigation is the dominant water reuse application globally (Eslamian, 2016). Agricultural water reuse provides various benefits, such as reducing freshwater withdrawal, managing/recovering nutrients, decreasing pollutants discharge, avoiding groundwater pollution, closing the water cycle, and increasing water supply reliability (Shoushtarian & Negahban-Azar, 2020).

Although agricultural water reuse has excellent potential to alleviate global water scarcity, its challenges make it less likely to be chosen by water resources decision-makers than other alternative water supplies. Agricultural water reuse includes various challenges such as water quality concerns, social acceptance, technical feasibility, socio-economic factors, regulatory considerations, and potential conflicts between stakeholders (Shoushtarian & Negahban-Azar, 2020). Generally, agricultural water reuse challenges can be categorized into seven categories: human health, environmental health, technical, social, legal, and socio-economic (Shoushtarian & Negahban-Azar, 2020). Therefore, it is necessary for water resources decision-makers to consider multiple agricultural water reuse challenges to plan and manage safe agricultural water reuse practices worldwide.

Planning and managing agricultural water reuse projects without paying adequate attention to different water system components, their complex interactions, and the exogenous factors affecting them can result in various ramifications. Socio-economic factors are among the most critical factors for successful agricultural water reuse projects, potentially turning the project into a failure if not appropriately addressed (Lazarova & Bahri, 2005; Asano et al., 2007; Sheikh et al., 2018). It is also necessary to investigate the dynamics of coupled human-environment systems in agricultural water reuse projects. The micro-scale dynamics of these projects are of paramount importance for decision-makers to successfully identify and implement best management practices. For example, policies set at the local level (e.g., irrigation district) can alter the micro-dynamics of agricultural water reuse adoption, resulting in changing the macro-scale dynamics of water resources systems at the watershed scale (e.g., groundwater over-drafting caused by the increase in using groundwater).

Agent-based modeling (ABM) is one of the methods which has been used to study complex systems (e.g., coupled human-environment systems) (Elsawah et al., 2015; Filatova et al., 2013; Huber et al., 2018; Janssen and Ostrom, 2006). Although this method is relatively new, it is becoming a prominent way to analyze, model, and simulate socio-hydrological complex systems in recent years (Akhbari and Grigg, 2013). Comparing agent-based and other modeling paradigms, the advantages of this method are as follows: 1) this method uses a bottom-up approach which enables us to capture the emergent phenomena in the system being studied; 2) it is an efficient way to study the socio-economic and socio-demographic factors geospatially using its natural environment; 3) it provides the opportunity for including elements of randomness in models; and 4) it develops a platform to create agents that are autonomous, adaptive, and have unlimited numbers of impacting parameters and rules (Bert et al., 2015; Bithell and Brasington, 2009; Crooks et al., 2018; Groeneveld et al., 2017; Crooks and Castle 2012; Kelly et al., 2013).

Various agent-based models have been developed to study water resources management and socio-hydrological systems. For example, Nikolic et al. (2015) integrated ABM with three other analytical tools (geographic information system, system dynamics, and hydrologic simulation) to develop a decision support system for integrated water resources management of the Upper Thames River watershed (Ontario, Canada). In another study, Tillman et al. (2001) explored municipal water supply stakeholders' decision-making processes to test various management scenarios for developing adaptive planning and management strategies using ABM. Wise and Crooks (2012) studied local social and institutional structures in the physical water systems in northern New Mexico to investigate traditional farming sustainability. Rasoulkhani et al. (2018) developed an agent-based model to explore the dynamics in water conservation technology adoption of residential users, using Miami Beach, Florida, as the case study. In another example, Kandiah et al. (2019a) used an ABM framework to study urban water reuse adoption by consumers and infrastructure expansion (the Town of Cary, North Carolina).

Moreover, Kock (2008) developed a socio-hydrological agent-based model to study how increasing water resources management institutional capacity would decrease conflict levels in the USA and Spain. In another study, Pouladi et al. (2019) proposed a socio-hydrological ABM framework to study the performance of complex water resources systems to restore Urmia Lake (Iran). A socio-hydrological ABM framework was developed by Mashhadi Ali et al. (2017) for simulating urban water supply and demand with different climate change scenarios, studying Raleigh, North Carolina, as a case study. In another example, Farhadi et al. (2016) developed a socio-hydrological ABM framework to find the best policy mechanisms for allocating groundwater to users in Daryan Aquifer, Fars Province, Iran. Pope and Gimblett (2015) used a coupled model (agent-based and Bayesian) to simulate the complex interactions of decision-makers (water demand) and environmental conditions in the Rio Sonora watershed, Mexico. A socio-hydrological ABM framework was created by Akhbari and Grigg (2013) to simulate the conflicts between parties in the San Joaquin (California) watershed and find the best solutions scenarios for water resources management in this watershed.

The development of agent-based models for water resources management can help to improve understanding on how how water demand and supply interact with the hydrologic cycle over time and space. For instance, agent-based models can help determine water conservation's main incentives in a watershed by simulating different water users' responses (i.e., urban users) under different management scenarios (Rasoulkhani et al., 2018). However, it is evident that as the main step toward further development of such models, we need to gain an understanding of how the current water management operates in the watersheds and how stakeholders may impact the system. For example, it is necessary to capture the complex and adaptive dynamics of socio-hydrological systems inherent in sustainable water resources management when alternative water sources (e.g., recycled water) are introduced at the watershed scale (Kandiah et al., 2019b). We would argue that this is of paramount importance for water resource managers, especially when it comes to managing agricultural water reuse projects sustainably due to the complexities involved in these projects. However, to the best of our knowledge, very limited studies have investigated the adaptive and complex dynamics of socio-hydrological systems inherent in agricultural water reuse projects, especially regarding capturing the dynamics of agricultural water reuse adoption by farmers and its impacts on local water resources. There has also been very limited research on quantifying the potentials of agricultural water reuse projects in addressing water shortage and groundwater over-drafting problems so far.

Therefore, this study attempts to fill these gaps by investigating the micro-level dynamics of agricultural water reuse adoption by farmers and its impacts on local water resources. It further explores how agricultural water reuse adoption, as a community-wide behavior, emerges from interactions, relationships, and dependencies between farmers and the local water resources, as the water supply system shifts from having only conventional water sources to a mix of conventional and alternative water sources. This study further explores the most critical parameters (e.g., the unit price of recycled water) when it comes to the sustainability of agricultural water reuse projects and local water resources to beneficially help water resource managers make better-informed decisions for managing these projects. In summary, this study's main objective is to fill this gap in the literature by developing an agent-based model for simulating the socio-hydrologic dynamics of agricultural water reuse projects to identify the best planning and management practices for these projects. In the remainder of this paper, Section 2 introduces our study area and methodology, Section 3 presents our results, Section 4 discusses the results of this study and its limitations, and Section 5 summarizes the paper and suggests areas for further study.

2. Methodology

2.1 Study area

The Del Puerto Water District (DPWD) in Central Valley, California, was selected as the study area (Figure 1). DPWD provides irrigation water for approximately 182.1 million m^2 of agricultural land in three counties: Stanislaus, San Joaquin, and Merced (RMC Water and Environment, 2013). DPWD's main water supply is provided through a contract with the United States Bureau of Reclamation (USBR). It delivers 172,946,231 m^3 per year of water from the Central Valley Project (CVP) (RMC Water and Environment, 2013). However, due to recent drought conditions and limitations on pumping from the San Joaquin Bay Delta, CVP allocation has not been completely provided for the DPWD (RMC Water and Environment, 2013). Since 1983, fallowing practices have increased in this area as alternative water resources in DPWD (e.g., groundwater and temporary transferred water) have been unreliable, unsustainable, and unaffordable (RMC Water and Environment, 2013). California State Water Resources Control Board adopted its Recycled Water Policy on January 22, 2013, and shortly after this, the North Valley Regional Recycled Water Program (NVRRWP) was started to address the DPWD's water shortage problem (RMC Water and Environment, 2013).

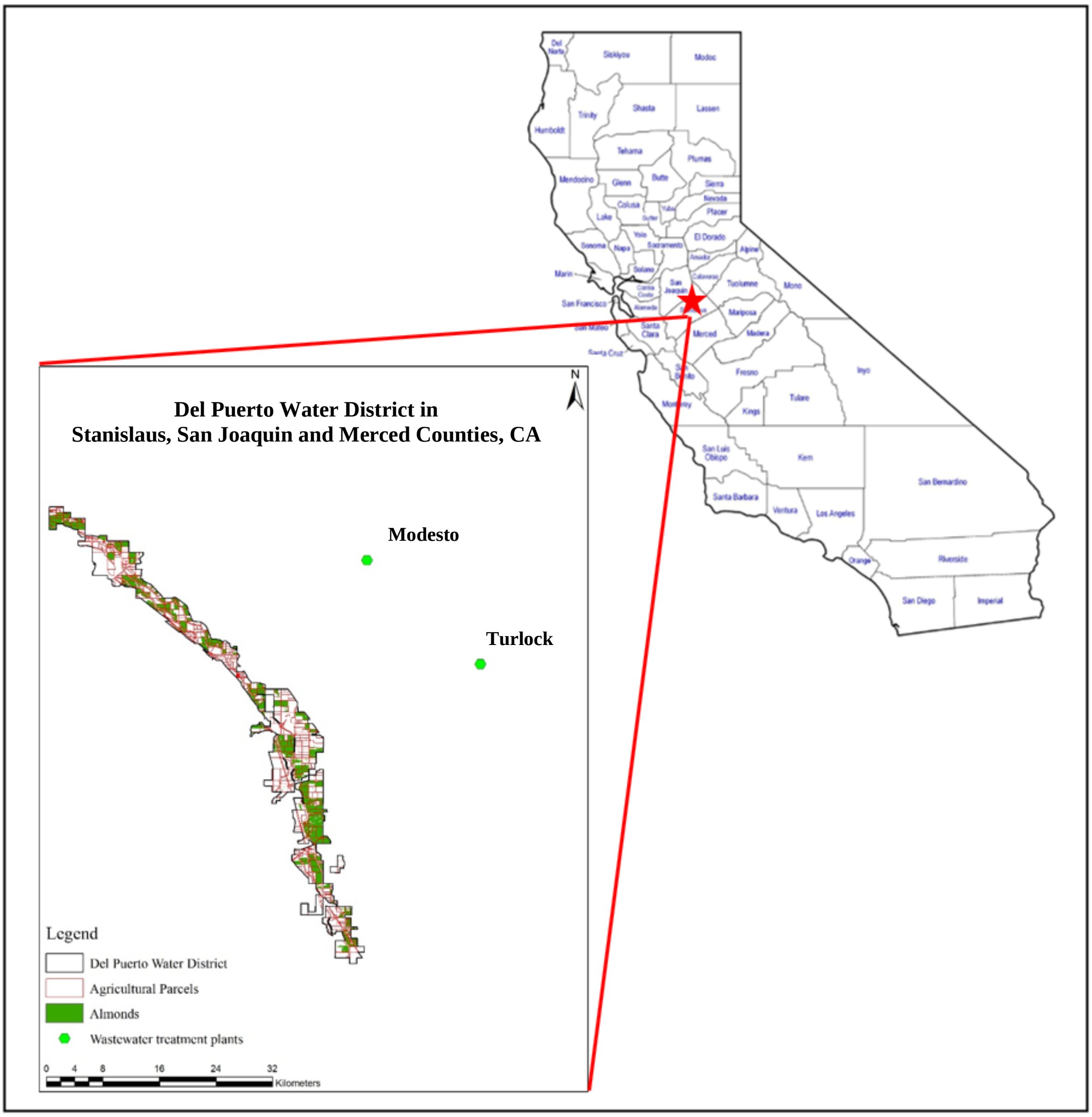


Figure 1: Map of this research's case study area (Del Puerto Water District, CA, USA)

In the NVRRWP, two treatment plants, one in Modesto and another in Turlock, are responsible for treated wastewater. These plants were planned to transfer the wastewater to the DPWD to supplement its water resources for agricultural irrigation in the region (RMC Water and Environment, 2013). Based on the NVRRWP feasibility study (RMC Water and Environment, 2013), the DPWD average water demand in the future (2045) will be 0.1 billion m^3 per year, while the expected future average supply (precipitation and CVP) will be between 34,537,440 and 60,440,520 m^3 per year. Therefore, DPWD is expected to have a water shortage of 49,339,200 to 74,008,800 m^3 per year. Furthermore, the feasibility study (RMC Water and Environment, 2013) also interviewed 12 farmers to assess their perceptions toward water reuse. Overall, these interviews showed that the farmers did not have an opposing perspective toward agricultural water reuse. However, the farmer's main concern was whether the DPWD could deliver recycled water at an affordable cost.

To successfully simulate the study area and explore water reuse adoption, farms, their characteristics (e.g., crop type, area, and water requirement), and existing infrastructure that provides the recycled water were needed. Therefore, the National Agricultural Statistics Service Cropland Data Layers (NASS-CDL) were used to identify and collect the study area land use and land cover data. This data were used to determine each farm's crop. The California State Geoportal website was also used to find and gather the farms' shapefiles to calculate their area. The United States Department of Agriculture (USDA) census of agriculture in 2017 and the NVRRWP feasibility study were used to determine crop's daily irrigation requirements. These data were needed for each farm to determine its water requirement (discussed further in Section 2.2.1).

Moreover, data on farmers' opinions on the use of recycled water, the location of wastewater treatment plants in the study area, and their discharge flow rate were needed. Survey results from Suri et al. (2019) were used to determine farmers' perceptions toward using recycled water, which will be described more in the following sections. It should be noted that the survey was conducted by Suri et al. (2019); we used the results of this study for developing the model presented in this paper (which we will detail more in Section 2.2). The US Environmental Protection Agency's (EPA) Enforcement and Compliance History Online database were also utilized to identify and collect the existing wastewater treatment plants' location and discharge flow rate (Table 1).

Table 1: Input data used for developing the agent-based model in this research.

Data	Source	Link
Land use and land cover data	National Agricultural Statistics Service Cropland Data Layers (NASS-CDL) with 30m resolution	https://nassgeodata.gmu.edu/CropScape/
Shapefiles of agricultural parcels	California State Geoportal	https://gis.data.ca.gov/
Survey data from farmers	U.S. farmers' opinions on the use of nontraditional water sources for agricultural activities (Suri et al., 2019).	Raw data were obtained from the authors.
Crop's irrigation requirements	1) The United States Department of Agriculture (USDA) census of agriculture (2017), 2) the NVRRWP feasibility study	1) https://www.nass.usda.gov/Publications/AgCensus/2017/index.php 2) RMC Water and Environment (2013)
Wastewater treatment plants' location and discharge flow rate	The United States Environmental Protection Agency's (EPA) Enforcement and Compliance History Online	https://echo.epa.gov/facilities/facility-search/results

2.2 ABM Framework

This section describes the agent-based model developed for simulating the dynamics of agricultural water reuse adoption by farmers (WRAF) and its effects on water resources in the study area (Figure 2a). It was developed as an exploratory tool for scenario analysis. The WRAF model simulates a virtual agricultural area where several autonomous farms operate. It also simulates these farms' water consumption dynamics. The developed model includes two types of agents: farmers and wastewater treatment plants. In general, farmer agents are the main water-consuming agents, and wastewater treatment plant agents are recycled water providers in the WRAF model. Dynamic simulation of agricultural water supply and demand in the area allows the user to observe the results of various irrigation water management scenarios, including the use of recycled water. The model also enables the user to apply multiple climate change scenarios, including normal, moderate drought, severe drought, and wet weather conditions. The model was developed using NetLogo 6.1.1 (Wilensky, 1999). The following sections describe the model structure and explain the agents in the model in more detail.

2.2.1 Agents

2.2.1.1 Farmers

Almond is the most dominant crop in the study area (Table 2) (RMC Water and Environment, 2013). Compared to other cultivated crops in the area, almond farms require most of the water supply for irrigation (RMC Water and Environment, 2013). The fact that almond growing requires a significant amount of water makes it vulnerable to water shortages. Almond trees stay in production for 25 years or more and require a constant water source during their lifetime. Furthermore, starting an almond orchard requires significant capital investment and is considered a high-value crop, producing high profits for farmers compared to other crops (RMC Water and Environment, 2013). Considering all these factors and the need to keep the model as simple as possible for the sake of parsimony, we only included the almond farmers as farmer agents (however, as we will discuss in Section 4, this could be an area of further work).

Table 2: Total irrigation demand and area under cultivation of crops grown in the study area (RMC Water and Environment, 2013)

Crop	Total irrigation demand (m^3/year) [%]	Area (Hectare) [%]
Almonds	6,663,382 [44.14%]	5,740 [43.61%]
Apricots	3,219,259 [21.33%]	1,019 [7.75%]
Other deciduous fruits and nuts	2,521,603 [16.70%]	480 [3.64%]
Cherries	970,749 [6.43%]	210 [1.59%]
Beans	632,775 [4.19%]	899 [6.83%]
Vineyard	593,057 [3.93%]	150 [1.14%]
Tomatoes	451,084 [2.99%]	1,575[11.97%]
Walnuts	38,855 [0.26%]	721 [5.48%]
Oats/barley	5,057 [0.03%]	1,000 [7.60%]
Alfalfa/mixed pasture	0.00 [0.00%]	672 [5.10%]
Vegetables	0.00 [0.00%]	370 [2.81%]
Melons	0.00 [0.00%]	161 [1.22%]
Grapefruit/lemons/oranges	0.00 [0.00%]	138 [1.05%]
Flowers, nursery	0.00 [0.00%]	27 [0.20%]
Total	15,095,822 [100.00%]	13,161 [100.00%]

Each almond farm is represented as an individual agent (i.e., farmer) in the model. Farm characteristics, including the farm area and crop type, were added to the model based on the available data (Table 1). It was assumed that farmers would irrigate their farms from available water resources during the irrigation season using the following assumptions (Figure 2b). First, based on equations (1) and (2), farmers calculate gross crop irrigation requirement (GCIR) (FAO, 2015) to determine the amount of water that they need for irrigation. Second, farmers determine if they have a water shortage based on a water mass balance, subtracting GCIR from their primary water supply shares. Those farmers with no water shortage continue their farming as usual. However, farmers with water shortages will look for alternative water sources to irrigate their farms. Then among the available alternative water resources, farmers will choose the cheapest one. The assumption is that farmers would buy the amount of water they need for irrigation if they can afford it.

This process repeats during the irrigation season daily. At the end of the farming season, farmers sell their crops (discussed further below). Alternative water sources included in the WRAF model were groundwater, transferred water, and recycled water (from wastewater treatment plants). Of note is that farmers take recycled water into account as an alternative water resource after adopting water reuse (accepting to use recycled water for irrigation). Water reuse adoption is determined using a sub-model, explained in the following.

$$ET_c = K_c \times ET_0 \tag{1}$$

$$Gross\ Crop\ Irrigation\ Requirement\ (GCIR) = \frac{ET_c - EP}{IE} \tag{2}$$

Where K_c is the crop coefficient, ET_0 is the evapotranspiration for the reference crop (mm/day), ET_c is the crop evapotranspiration (mm/day), *EP* is the effective precipitation (mm/day), and *IE* is the irrigation efficiency (FAO, 2015).

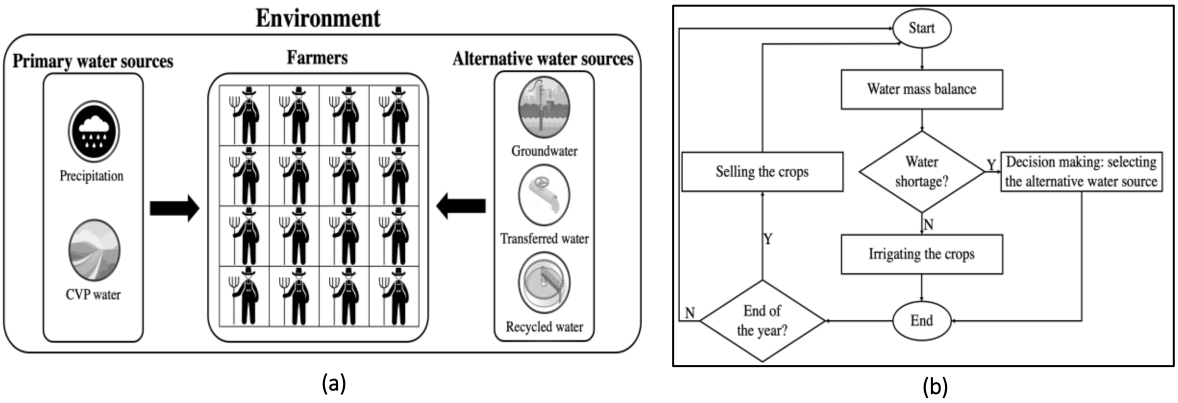


Figure 2: (a) WRAF framework; (b) Farmers' decision-making flowchart

There were 244 almond farmers in DPWD in 2018. Among these farms, 19%, 38%, and 43% of the almond farmers use sprinkler (irrigation efficiency (IE) = 80%), surface irrigation (IE = 75%), and drip irrigation (IE = 85%) technology, respectively (RMC Water and Environment, 2013). Farmers calculate their GCIR based on Table 3. It should be mentioned that daily GCIRs were considered constant during each month. So, farmers calculate their daily GCIRs by dividing monthly GCIRs (Table 3) by days of the month (28, 30, or 31 days).

USBR provided farmers with a maximum of 0.9 m^3/m^2 in each year for all the DPWD area. For scenario analysis, the user can change the available USBR water supply percentage between 0 and 100 percent. The starting age of almond trees for each farm was chosen randomly (33% of farms were between 0-8 years of age; 33% of farms were between 9-16 years of age; 34% of farms were between 17-25 years of age). It often takes three years from the day almond trees are planted till they can be harvested. In this model, almond farmers could sell their almonds from year three until year 25 based on equation (3). It was also assumed that another set of almond trees would again be planted after year 25 was finished.

Table 3: Monthly effective precipitation (EP) in DPWD and evapotranspiration (ET) of almond trees (adapted and modified from RMC Water and Environment, 2013).

Month	30-year EP, 80% of average (mm)	ET, Sprinkler (mm)	ET, Surface (mm)	ET, Drip (mm)
Jan.	51.82	43.69	43.69	42.67
Feb.	44.20	50.04	50.04	20.83
Mar.	40.64	66.80	69.60	30.73
Apr.	12.7	84.84	99.31	65.28
May.	0.00	163.07	168.66	147.83
Jun.	0.00	180.09	202.95	175.26
Jul.	0.00	189.23	219.20	187.96
Aug.	0.00	172.21	197.36	171.70
Sep.	0.00	122.17	136.39	117.36
Oct.	12.45	87.12	86.11	65.03
Nov.	24.89	38.35	39.62	23.37
Dec.	30.73	43.43	43.43	43.43

Based on the 2017 census of agriculture (USDA-NASS, 2019), it was assumed that almonds yield and price were 246.6 gr/m^2 and 6.61 × 10^{-3} \$/gr on average. The starting money (i.e., financial resources that each farmer owns) of each farm was determined according to its area (\$1.63 × farm size (m^2)) to make it simple. Selling their crops and paying for water supply were the only factors that increased and decreased farmers' money, respectively. Unit price of water resources were as follows (RMC Water and Environment, 2013; USDA-NASS, 2019): 1) CVP 0.0291-0.0486 \$/m^2; 2) Transferred Water 0.0778-0.3210 \$/m^2; 3) Groundwater 0.0778-0.1265 \$/m^2; and 4) Recycled Water 0.0486-0.1459 \$/m^2. The user can set CVP and recycled water unit prices, while transferred water and groundwater unit prices were randomly chosen within their range. It should be mentioned that the unit prices of CVP and recycled water remained constant during the simulations for simplification. Moreover, although transferred water and groundwater unit prices could also be dependent on various factors (e.g., climate), we decided to stochastically simulate them using the historical data from the study area for the sake of parsimony.

$$Money_{year=i+1} = Money_{year=i} + 1.63 \times \left(1 - \left(\frac{total\ days\ without\ water_{year=1}}{365}\right)\right) \times farm\ size \quad (3)$$

Where farm size was the area of the farm in m^2 unit. It should be mentioned that in the model, the groundwater and transferred water did not have any limitations in terms of the water volume that they could provide for farmers. However, according to the NVRRWP's feasibility study, groundwater is hard to find in the Southern part of the DPWD, and if found, its quality is poor (RMC Water and Environment, 2013). Therefore, it was assumed that only 20% of Southern farmers who choose groundwater as their alternative water source would find suitable water to irrigate their farms. The remaining Southern farmers who choose groundwater as their alternative source of water (80%) would experience water shortage. Also, if farmers want to use recycled water, but the amount of recycled water is not enough to supply all their irrigation requirements, they will use groundwater to supplement their water supply.

Water reuse adoption sub-model: Unlike the physical sciences, where the constituents act in a known pattern (under specific conditions), human behavior changes dynamically and adaptively based on each situation. Therefore, understanding human behavior over time and space has been challenging for researchers (Crooks et al., 2018). The challenges are 1) choosing a theory that is applicable for the study, 2) making the theory formal for use, and 3) establishing the casualties in theory (Crooks et al., 2018; Schlüter et al., 2017). Researchers have used two scientific approaches to model human behavior, including artificial intelligence and conceptual cognitive approaches. The most widely used methods in modeling human decision-making in ABM can be further divided into three groups: behavioral frameworks, mathematical approaches, and conceptual cognitive models (Crooks et al., 2018).

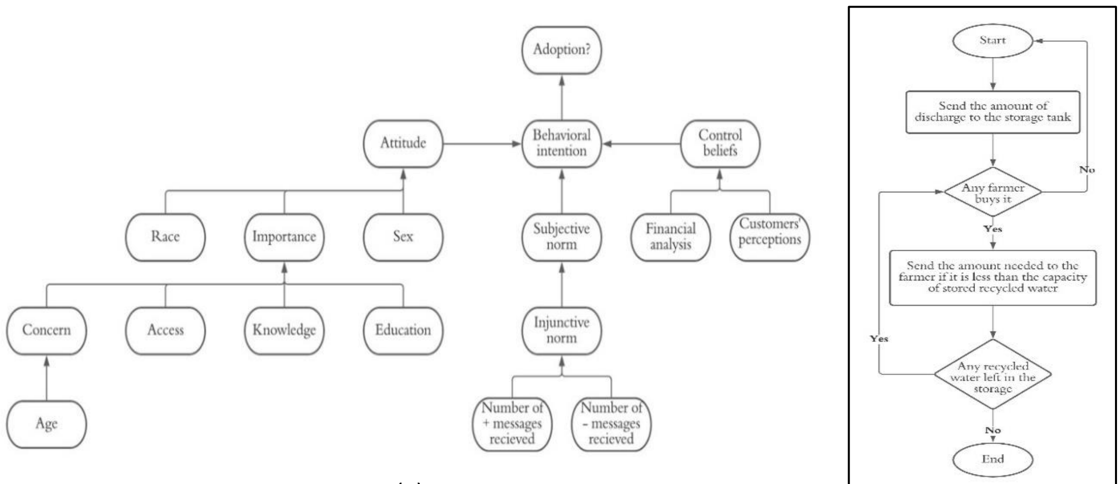
While many theories exist, we chose to use the Theory of Planned Behavior (TPB) (Ajzen, 1991) in this study because it provides a realistic decision-making framework and is widely used to explain and predict human behavior in various disciplines (Wang et al., 2019). The TPB describes how a person's behavioral intention can determine the probability of the implemented behavior (Ajzen, 1991). This theory claims that control beliefs, subjective norms, and attitudes influence behavioral intention, thus, affect the person's decisions (equation (4)) (Ajzen, 1991).

$$I \cong a \times AT + b \times SN + c \times PBC \quad (4)$$

Where *I* refers to intention, *a*, *b*, and *c* are empirical weights for the parameters, and *AT*, *SN*, and *PBC* refer to attitude, subjective norm, and perceived behavioral control, respectively. A person's attitude toward a behavior is how the person thinks and feels about the behavior and reflects his expectations and evaluations of the behavior (Ajzen, 1991). The subjective norm describes the support given by significant others, such as family, friends, and co-workers. It can be divided into two subsections, including injunctive norms, describing whether others encourage the behavior, and descriptive norms, describing whether others do the behavior as well or not (Ajzen, 1991). The perceived behavioral control illustrates the extent to which a person feels capable and has confidence in their ability to execute the desired behavior and can overcome the barriers and challenges of implementing the desired behavior (Ajzen, 1991). TPB was utilized in various studies to simulate human decision-making dynamics and their effects on water resources (Gilg and Barr, 2006; Koutiva and Makropoulos, 2016; Pouladi et al., 2019; Yazdanpanah et al., 2014).

At the start of each year, this sub-model determines the farmers who have already adopted water reuse. Water reuse adoption means that the farmer has accepted to consider recycled water as an alternative water supply for irrigation if it is available. If it is cheaper than other options, the farmer will use it for irrigation. This sub-model simulates the dynamics of farmers' water reuse adoption using cognitive mapping. The TPB and probabilistic models inspire the farmers' cognitive map. This framework enables researchers to evaluate the effects of farmers' personal attitudes, peer influence (other farmers), financial situation, and customers' perception toward buying products irrigated with recycled water on agricultural water reuse adoption.

This sub-model uses survey data collected by Suri et al. (2019), who surveyed farmers' perceptions toward agricultural water reuse in the Southwest and Mid-Atlantic, USA. Of note is that we only used the survey data collected from Southwest farmers. Suri et al. (2019) concluded that factors including age, water availability concern, knowledge about water reuse, access to recycled water, education level, being aware of the importance of water reuse, race, and gender were significantly associated with farmers' perceptions toward agricultural water reuse adoption (Figure 3a and Tables S1 and S2 in the Supplementary Material). Based on the data, probabilities of different levels of these parameters were calculated to be used in the sub-model (Tables S2, S3, S4 and S5 in the Supplementary Material). The sub-model uses these results to simulate the dynamics of farmers' attitudes toward water reuse, where their attitude at the end of this process could be either positive or negative. Farmers are linked to each other based on the "Preferential Attachment," the social network introduced by Barabási and Albert (1999) to determine the subjective norm. Farmers with a positive attitude toward water reuse send positive messages (the number of messages is randomly chosen between 1-5) to their peers and vice versa. Farmers sum up all the positive and negative messages that they receive. If this sum is positive, their subjective norm toward water reuse would be positive, and vice versa.



(a) (b)

Figure 3: (a) Water reuse adoption sub-model framework; (b) Wastewater treatment plants flowchart

The control belief component comprises two parts (Figure 3a). For the first part, which is financial analysis, farmers assess whether they can afford to pay for the recycled water next year. For this, based on their water shortage in the previous year, the unit price of recycled water, and their available money, farmers can determine whether recycled water is an appropriate option for them or not. The second part considers customers' perceptions based on literature as an exogenous factor. According to Fielding et al. (2019), the acceptance of products irrigated with recycled water ranges from 44% to 90% among customers. Therefore, the customers' perceptions were randomly chosen between 44% to 90%. Theoretically, the control belief component results could be positive or negative.

Finally, the behavioral intentions of the farmers are determined according to equation (4). This study assumed that these three factors equally affect farmers' decisions (a = b = c = 1). At the start of the model, farmers' behavioral intention is set to neutral. However, this sub-model determines those farmers whose behavioral intention changes to positive or negative at the beginning of each year. Farmers' behavioral intentions change to positive only if at least the results of two components (attitude, subjective norm, and control belief) are positive; otherwise, it changes to negative.

2.2.1.2 Wastewater treatment plants

Wastewater treatment plants is another group of agents in the model. These agents try to provide recycled water to farmers who select recycled water as their alternative water resource (Figure 3b). The location, volumetric rate of treated wastewater effluent, effluent water quality, and stored water volume of these agents are set at the start of the model according to each case. It was assumed that wastewater treatment plants in the WRAF model first serve farmers closer to their locations. There were two wastewater treatment plant agents in this study, named Modesto and Turlock. The user could set the average daily flow of treated wastewater effluent produced by these treatment plants. Each wastewater treatment plant first sent its effluent to storage ponds with a maximum of 6,167,400 m^3 storage (to store treated wastewater when there was no demand). Of note is Modesto treatment facility already has storage with a capacity of 6,167,400 m^3, and the Turlock treatment facility is planning storage soon. This study assumed that the recycled water was conveyed from these storage ponds to each farm's irrigation system using pipes. It should be mentioned that five recycled water delivery alternatives were studied in the NVRRWP feasibility study (RMC Water and Environment, 2013); the second alternative included the piping system used in this study. It was assumed that the piping system could deliver all the recycled water that farmers buy each day for simplification. Moreover, wastewater treatment plants collect the money from recycled water sales to farmers based on the unit price of recycled water (set by the user). Of note is that the actual expansion plans for Modesto and Turlock wastewater treatment plants were also considered in this study (Figure 4).

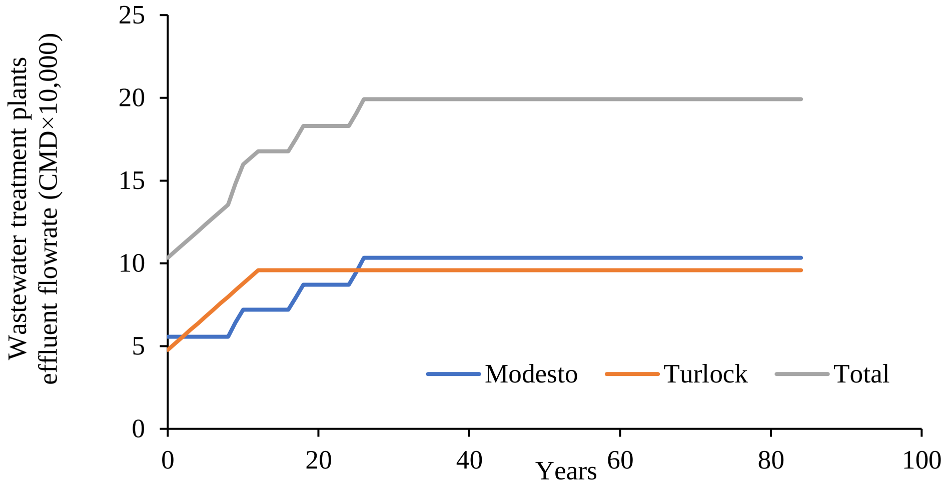


Figure 4: Flow rates of Modesto and Turlock wastewater treatment plants years after starting the agricultural water reuse project (adapted from RMC Water and Environment, 2013). CMD = Cubic Meters per Day.

2.2.2 Environment

Inspired by the AgriPoliS model (Happe et al., 2006), WRAF models the environment in a stylized manner. The environment is divided into several equally-sized cells similar to a chessboard, all of which are associated with attributes, including farm size and crop type. To input almond farms into the WRAF model, almond farms GIS maps were created using San Joaquin (San Joaquin County Geographic Information Systems, 2020), Stanislaus (Stanislaus County GIS Division, 2014), and Merced (Merced County GIS, 2019) counties land parcels and the 2018 crop data layer (U.S. Department of Agriculture, 2018) maps (Figure 1). According to NVRRWP's feasibility study (RMC Water and Environment, 2013), these farms were divided into three regions (Northern, Central, and Southern). This map was used as an input for the WRAF model, determining the farm area, region, and crop type.

2.3 Model verification, sensitivity analysis, and scenario experiments

Verification: The goal of verifying a model is to ensure that the implemented model matches its design (North and Macal, 2007; Patel et al., 2012). This was achieved through code walkthroughs and testing the input parameters to evaluate their effects on the model results. During the verification process, simulations were run for 84 years to simulate three consecutive cycles of growing almond trees in the DPWD. Several sub-model runs showed that 84 years was enough to capture the dynamics of diffusion of water reuse among the farmers.

Sensitivity analysis: In addition to verification, we also carried out an extensive sensitivity analysis. The main goal of sensitivity analysis is to identify independent variables that significantly influence the model's dependent variables (Happe et al., 2006). Emergent properties are inherent to agent-based models, making it difficult to easily investigate how agent-based models' assumptions and inner interactions influence the model behavior (Happe et al., 2006). Therefore, a formal sensitivity analysis was applied to the developed model to address these challenges in a structured way. To do so, the Design of Experiments (DOE) statistical techniques were used for the sensitivity analysis. These techniques enable researchers to study the details of the model's dynamics and evaluate different input parameters' influence on the output parameters. They also help study the simulation results using a common basis and help detect the potential problems in the model's logic (Happe et al., 2006; Kleijnen, 2005). DOE enables researchers to test a subset of all possible combinations of input parameters, called experimental design, reducing tests and saving time and money while effectively evaluating the effects on output parameters (Happe et al., 2006). However, it should be mentioned that the resulting meta-models of DOEs are very coarse and cannot fully capture the models' complex behavior (Happe et al., 2006).

In this study, as the screening step, seven factors were considered by the authors to assess their influence on the WRAF model (Table 4). The authors expected these factors to significantly influence the farmer's water consumption dynamics in this model. A fractional factorial design was utilized to design the screening experiments for investigating the factors' preliminary significance and their interactions (resolution: IV, fraction: 1/8). All the factors were evaluated at two levels, including low (-) and high (+) levels (Table S6 in the Supplementary Material). Four center points were also included in the design, estimating the experimental variance and checking the loss of linearity between the levels of the factors (the curvature test) (Martendal et al., 2007) (Table S6). All the other factors were kept constant during the experiments.

Table 4: Factors considered in the screening step of the study

	Factor- unit	Description	Range
A	Modesto (m^3)	The daily flow rate of the Modesto wastewater treatment plant discharge into its storage pond	55,646-189,271
B	Turlock (m^3)	The daily flow rate of the Turlock wastewater treatment plant discharge into its storage pond	47,696 -189,271
C	Primary-water-source (%)	The percentage of the contracted CVP water available for farmers for their irrigation each year	0-100
D	CVP-water-price ($/$m^2$)	The unit price of the contracted CVP water, which farmers have to pay upon using	$0.0291-$0.0486
E	Water-reuse-expenses ($/$m^2$)	The unit price of the recycled water that farmers have to pay upon using	$0.0486-$0.1459
F	Transferred-water	Availability of transferred water for farmers to use for their irrigation each year	Available (-1), not-available (+1)
G	Groundwater	Availability of groundwater for farmers to use for their irrigation each year	Available (-1), not-available (+1)

Farmers' total recycled water consumption was used as the response variable in this study. Sensitivity analysis simulations included 84 years, and the data were gathered at the end of each year. Some of the parts of the WRAF model were simulated stochastically, including farmers' irrigation method, location of farmers in each of the regions, unit prices of groundwater and transferred water, access to groundwater with decent quality for irrigation in the southern region, and farmers' age, sex, education, race, knowledge, access, concern, importance, attitude, and network. Therefore, all the 20 simulations (Table S6) were replicated ten times. The means of the results were used to form the meta-model, considering the stochasticity in the results. Ten replications were sufficient for the screening stage as the results were robust against the stochastic processes of the WRAF model. This robustness was illustrated using standard error bands in the simulation results section.

The linear regression models were fitted to data to determine the effects of factors and compare them, using the data from years 27, 55, and 84. These three years were selected because they were at the end of the three cycles of almond production. The regression models (second-order polynomial) were fitted to the data using the backward elimination method (alpha = 0.05). Significant factors and their effects were identified for each year using the linear regression model, analysis of variance, and Pareto charts (P ≤ 0.05).

Finally, six scenarios were defined using the factors and their effects that were found influential on the total recycled water consumption to test the screening stage results. Scenarios were designed to shed light on how the factors affect recycled water consumption dynamics, including changing between 3 levels (low, middle, and high levels) of one of the factors each time (Table 5). Other factors and parameters were fixed each time to decrease their variation effect on the response. All the simulations were replicated ten times and run for 84 years. Total recycled water consumption was evaluated during these simulation experiments as the response.

Table 5: Details of simulation experiments for testing the sensitivity analysis results in this study.

Term	Factor	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
E	Water-reuse-expenses ($/m³)	0.05, 0.10, 0.15	0.10	0.10	0.10	0.10	0.10
G	Groundwater	A[1]	A, NA[2]	A	A	A	A
BD	Turlock (m³) × CVP-water-price ($/m³)	118,483 × 0.04	118,483 × 0.04	47,696 × 0.03, 118,483 × 0.04, 189,271 × 0.05	118,483 × 0.04	47,696, 118,483, 189,271 × 0.04	118,483 × 0.04
A	Modesto (m³)	122,647	122,647	122,647	55,645, 122,647, 189,271	122,647	122,647
B	Turlock (m³)	118,483	118,483	47,696, 118,483, 189,271	118,483	47,696, 118,483, 189,270	118,483
C	Primary-water-source-%	50	50	50	50	50	0, 50, 100

[1] Available; [2] Not-available

Simulation experiments: After verifying that the WRAF model was working according to its design (verification) and identifying the influential factors (sensitivity analysis), the WRAF model was utilized for simulation experiments. Four scenarios were defined for the tests using the WRAF model (Table 6). The first scenario (I) was according to the NVRRWP plan. The second and third scenarios (II and III) were defined to simulate possible moderate and severe drought conditions in the DPWD, respectively. The fourth scenario (IV) was also set to simulate possible wet conditions in the DPWD.

Table 6: Specifications of the simulation experiments scenarios in this study.

Term	Factor	Scenario I (normal)	Scenario II (moderate drought)	Scenario III (severe drought)	Scenario IV (wet)
C	Primary-water-source (%)	35	20	5	100[1]
D	CVP-water-price ($/m³)	0.040	0.045	0.050	0.030
E	Water-reuse-expenses ($/CM)	0.09	0.10	0.11	0.08
F	Transferred-water	Available	Not-available	Not-available	Available
G	Groundwater	Available	Available	Not-available	Available

[1] There were several years that CVP could provide 100% to the DPWD's farmers in the past (i.e., 1995, 1998, and 2006).

Accordingly, all scenarios were simulated using the NVRRWP expansion planning regarding Modesto and Turlock's effluent flow rates (Figure 4). All the other factors were set according to the climatic conditions of the scenarios. Regarding the available CVP water supply percentage, 35%, 20%, 5%, and 100% were used for the normal, moderate drought, severe drought, and wet conditions scenarios, respectively (Table 6). The unit prices of CVP water and the unit prices of recycled water provided to the DPWD's farmers were reported under scenarios I, II, III, and IV in Table 6. It was assumed that the transferred water supply was not available to farmers in moderate and severe drought scenarios (Table 6). Groundwater was also not available as an irrigation source for farmers in the severe drought scenario (Table 6). All the simulations were repeated ten times and for 84 years of almond production.

3. Results

3.1 Verification and sensitivity analysis

Verification: The results of representative runs are depicted in Figure 5. Figures 5a and 5b illustrate the number of farmers based on their water sources in years one and 84, respectively. It was apparent that precipitation and CVP water resources were insufficient to ensure that all farmers get enough water to irrigate their almond orchards throughout the year, especially from May (day 121) through September (day 274). In this period, farmers had to supplement their irrigation with groundwater, transferred water, and/or recycled water. Results also showed that introducing recycled water in this area could decrease the number of farmers who use groundwater or transferred water for irrigation. During these months, the number of farmers with water shortages also decreased by using recycled water (Figure 5b). The volume of recycled water stored at the storage ponds is depicted in Figures 5c and 5d. As the number of farmers who use recycled water increases, the recycled water volume in these storage ponds decreases. After several years, this depletion even reaches a level that these ponds become empty at some point, as the wastewater treatment effluent could not recharge them fast enough relative to the demand. This implies that the two treatment plants could not completely satisfy the need for recycled water in the DPWD after several years since starting the agricultural water reuse project. For example, the total amounts of consumed recycled water in years two and 84 by DPWD farmers were also illustrated in Figure 5e and 5f, respectively. The results of these two figures were consistent with Figures 5a, 5b, 5c, and 5d. Comparing these two figures shows how, as time passed, the amount of recycled water supplied by the two storages was not enough to support all farmers who needed it in year 84.

Sensitivity analysis: The factors with a significant effect ($p \leq 0.05$) on total recycled water consumption were identified using the methodology described before (Table 7). The unit price of recycled water was the most influential factor, negatively affecting the total recycled water consumption. This clearly showed how recycled water pricing was important for this water reuse project. The higher the unit price of recycled water, the lower the total recycled water consumption. The second influential factor in the total recycled water consumption was groundwater availability. When the groundwater was available for irrigation, less recycled water was used by farmers to supplement their water sources. The third influential factor in the total recycled water consumption was the interaction of the Turlock wastewater treatment plant's effluent flow rate and the unit price of the CVP water. This result demonstrated that these two factors affected the total recycled water consumption only if they were changed simultaneously. Other factors that could significantly affect the total recycled water consumption were the Modesto wastewater treatment plant's effluent flow rate and the percentage of CVP water available to the DPWD's farmers (primary-water-source). The Modesto wastewater treatment plant's effluent flow rate positively influenced the total recycled water consumption. However, the "primary-water-source" factor negatively affected the total recycled water consumption.

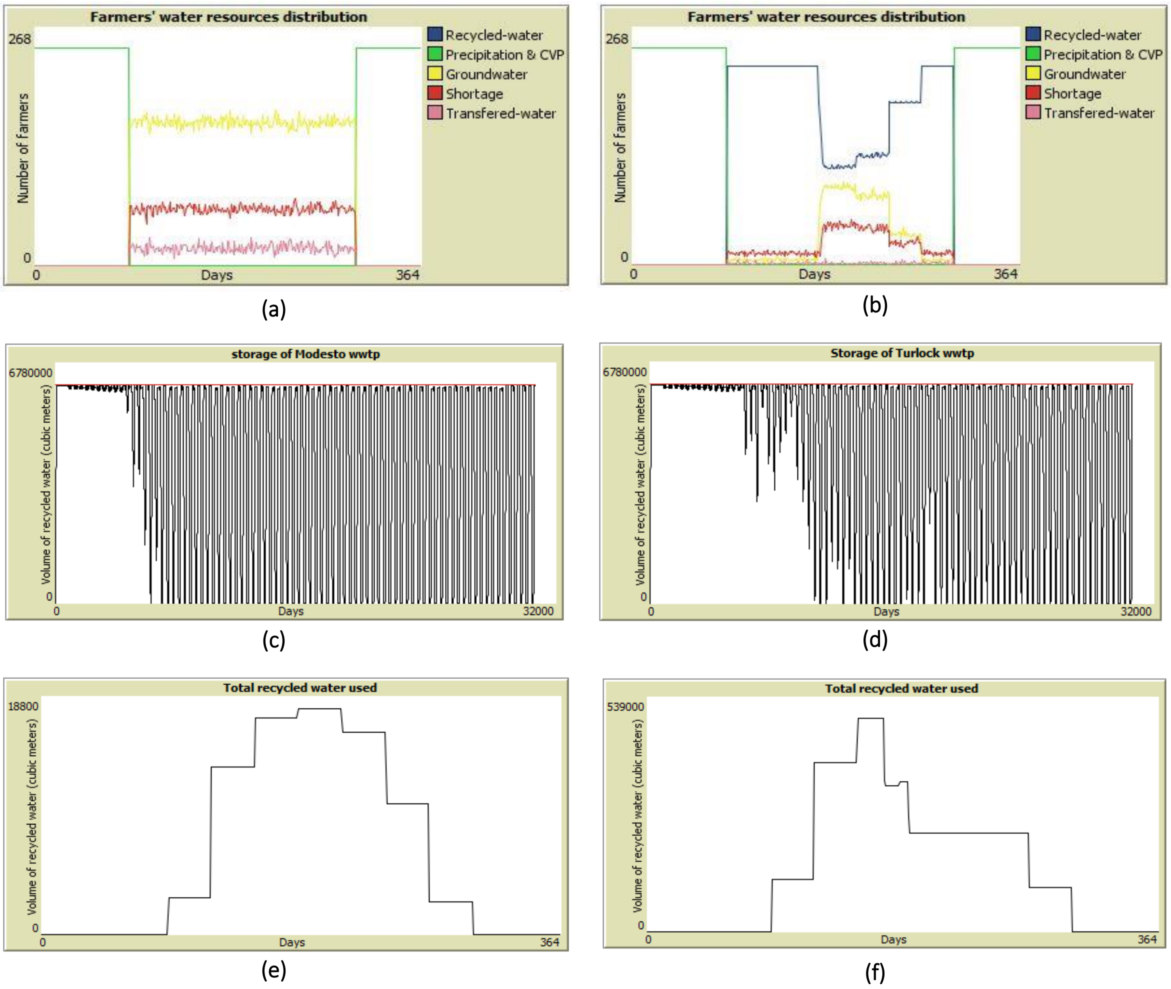


Figure 5: Representative simulation results: farmers' water resources distribution in year one (a) and year 84 (b); available recycled water in the storage ponds of Modesto (c) and Turlock (d) wastewater treatment plants; total recycled water used by farmers in year two (e) and year 84 (f).

Table 7: Significant factors effects (p ≤ 0.05). The responses are total recycled water consumption at the end of years 27, 55, and 84.

Term	Factor	Effect (t = 27)	Effect (t = 55)	Effect (t = 84)
E	Water-reuse-expenses	-237,846	-268,040	-274,850
G	Groundwater	203,309	233,185	235,435
BD	Turlock×CVP-water-price	194,785	218,543	231,266
A	Modesto	77,366	136,161	141,772
B	Turlock	82,166	120,055	134,656
C	Primary-water-source	-111,785	-125,721	-125,586
	R^2_{adj}	91.92%	93.68%	94.1%

Residual plots were used to check whether the regression model was adequate and met the analysis' assumptions (ordinary least squares assumptions) (Figure 6). The normal probability plot of the residuals approximately followed a straight line, confirming that the residuals were normally distributed (Figures 6b, 6d, and 6f). The versus fits plots of the residuals illustrated that the residuals fell randomly on both sides of 0, with no distinguishable patterns, confirming that the residuals were randomly distributed and had constant variance. As the versus order plots of the residuals demonstrated no trend or pattern, it was concluded that the residuals were not correlated. Histograms of the residuals were also used, showing some skewness in the distributions of the residuals.

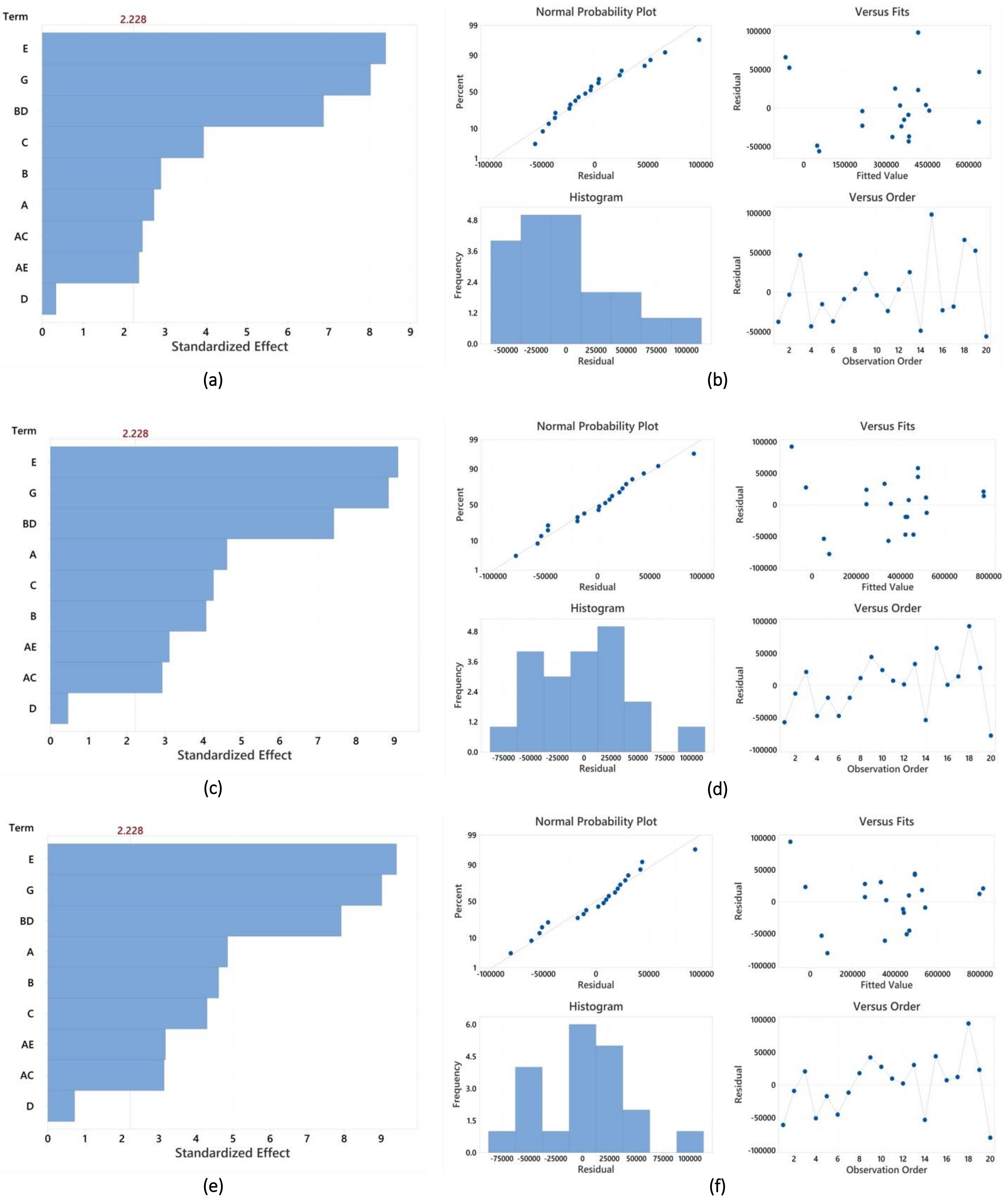


Figure 6: Pareto charts of standardized effects and residual plots in t = 27 [(a) and (b)], t = 55 [(c) and (d)], and t = 85 [(e) and (f)] for cumulative recycled water consumption as the response variable.

3.1.1 Results of testing the screening stage

The results of increasing the unit price of recycled water clearly showed how this increase could affect the water reuse project's future (Figure 7a) by decreasing the total recycled water consumption. These results are in accordance with the sensitivity analysis results presented above. The results also illustrated that the differences between total recycled water consumption increased as time went on and reached a plateau (Figure 7a). Also, the total recycled water consumption could be decreased to zero if the unit price of recycled water was not competitive with other alternative water resources (e.g., \$0.15 per m^3). Therefore, decision-makers need to pay extra attention to recycled water pricing, and in some cases, state or government incentives might be required. As the water reuse projects are costly, the decision-makers may tend to sell the recycled water as expensive as possible to compensate for these projects' high costs. However, if the recycled water is not priced right, it may lead to the project's failure.

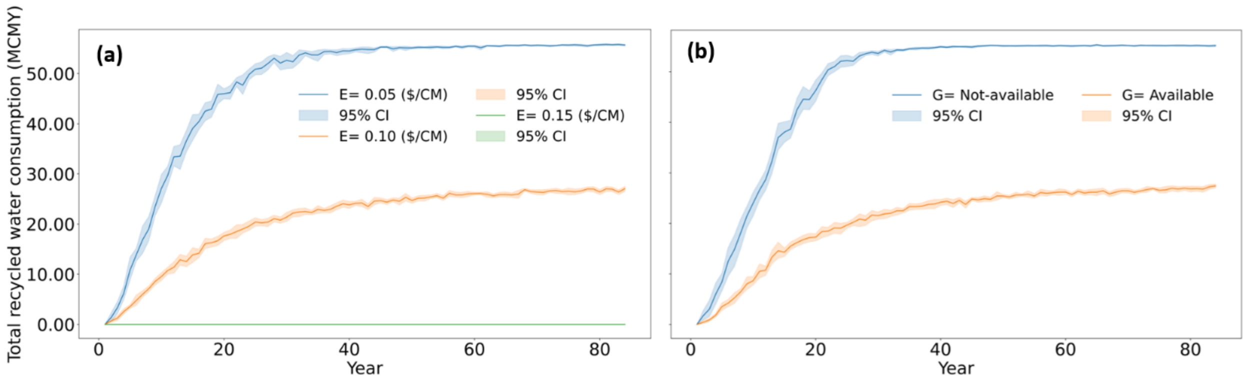


Figure 7: The effects of (a) E = the unit price of recycled water and (b) G = groundwater availability on the cumulative recycled water consumption (MCMY = Millions Cubic Meters per Year).

Furthermore, the results illustrated that groundwater availability significantly affected the total recycled water consumption (Table 7 and Figure 7b). Based on these results, when groundwater was not available for farmers to use, they used more recycled water than when the groundwater was available. This result confirmed that limitation on groundwater use by any means (e.g., drought or regulations) might result in increased use of recycled water by farmers for their irrigation purposes. The simulation results of the interaction of the Turlock wastewater treatment plant's effluent flow rate and the CVP water's unit price (BD), the Turlock and Modesto wastewater treatment plants' effluent flow rates (B and A) were not consistent with sensitivity analysis results (Figures 8a, 8b and 9a). The results demonstrated that these factors were not significantly influential on the total recycled water consumption. This inconsistency could be due to the fact that was mentioned before; the meta-model resulting from the screening stage of DOEs is coarse and cannot fully represent agent-based models' complex behavior (Happe et al., 2006). Simulation results confirmed the effects of available primary water sources on total recycled water consumption (Figure 9b). These results showed that their total recycled water consumption increased significantly by decreasing the availability of farmers' primary water source (CVP). This result also indicated that variations in the amount of water provided to farmers by the CVP due to climate change and local restrictions could affect the amount of recycled water farmers consumed to supplement their primary water source. Like groundwater, decision-makers must pay attention to the effects of this factor on the sustainability of agriculture and water resources in this area.

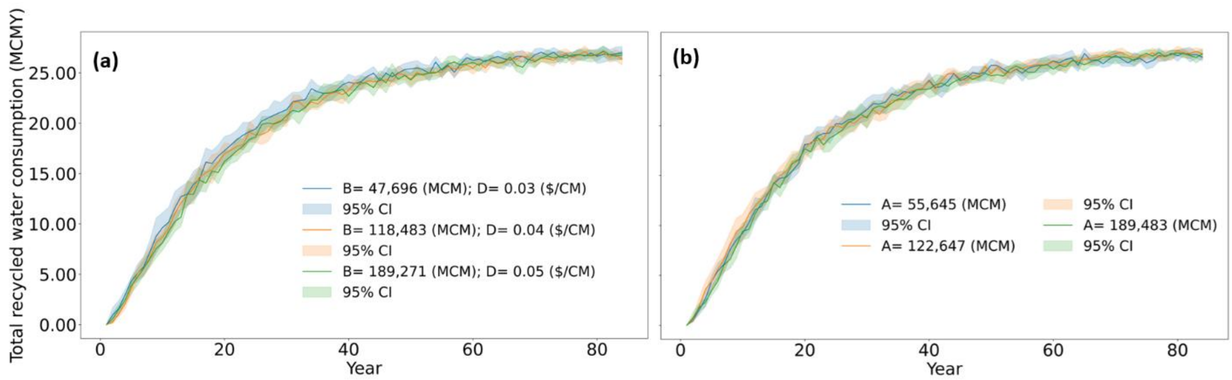


Figure 8: The effects of (a) BD = the interaction of Turlock effluent flowrate and the unit price of the CVP water and (b) A = the Modesto effluent flowrate on the cumulative recycled water consumption (MCMY = Millions Cubic Meters per Year).

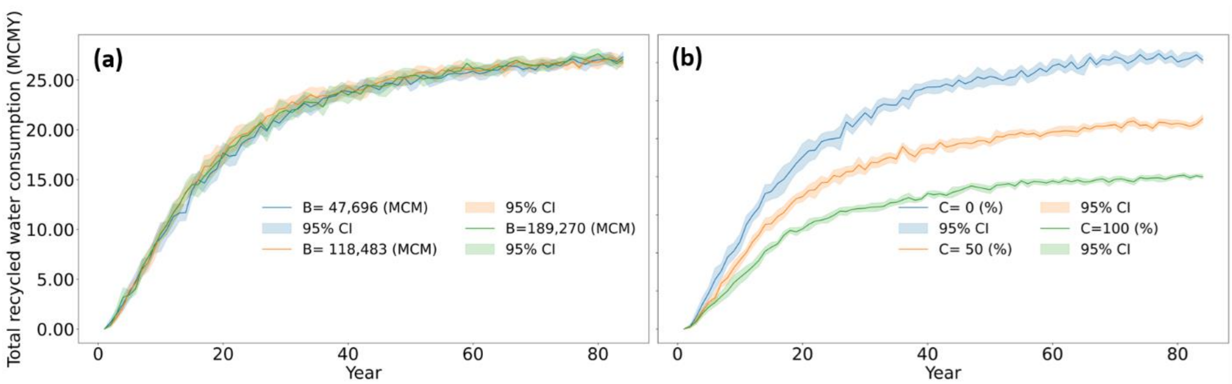


Figure 9: The effects of (a) B = the Turlock effluent flow rate and (b) C = the available percentage of the CVP water on the cumulative recycled water consumption (MCMY = Millions Cubic Meters per Year).

3.2 Simulation experiments results

The results illustrated that implementing agricultural water reuse in the DPWD could successfully increase the district's water sustainability. The total water shortage was decreased by 41%, 32%, 57.7%, and 32% in scenarios I, II, III, and IV, respectively. The greatest decline in total water shortage was under the third scenario (severe drought). Under this scenario, the total water shortage tumbled by 57.7% as the water reuse project started and reached a plateau in year 30. In other scenarios, the total water shortage had a gradual declining trend (Figure 10a). The results also demonstrated that agricultural water reuse in the DPWD could significantly decline farmers' total groundwater consumption (Figure 10b). In scenarios where the groundwater was available to farmers for their irrigation practices (I, II, and IV), the agricultural water reuse project reduced the total groundwater consumption by 54.7%, 38.2%, and 74.1%, respectively. The total groundwater consumption decreased gradually from 56,337,638 CMY to 25,501,312 CMY (30,836,429 CMY decrease), 66,367,901 CMY to 41,025,195 CMY (25,342,707 CMY decrease), and 37,822,253.58 CMY to 9,791,996 CMY (28,030,258 CMY decrease) over the 84 years of simulation under scenarios I, II, and IV, respectively.

The results further depicted that the total recycled water consumption had a rising trend in all scenarios (Figure 11a). The total recycled water consumption increased from zero CMY to 46,266,156 CMY, 34,734,190 CMY, 60,339,053 CMY, and 43,005,139 CMY under scenarios I, II, III, and IV over 84 years, respectively. However, the yearly recycled water consumption reached a plateau under the severe drought scenario (III), indicating that the recycled water production could not keep up with the demand after year 30. Total transferred water consumption results also showed that implementing agricultural water reuse in the DPWD could successfully decrease the transferred water consumption for irrigation by the DPWD's farmers in scenarios where it was available for use (I and IV). The transferred water consumption was decreased by 55% and 91% in these scenarios, respectively (Figure 11b). The trend of adopting recycled water by farmers was consistent with the Diffusion of Innovations Theory, which describes the pattern and speed at which new ideas, practices, or products spread through a population (Rogers et al., 2005) (Figure 12). These results further showed that water reuse adoption was a gradual process. The trends of scenarios I, II, and IV were almost similar; however, under scenario III, the trend was significantly different from others, with a more gradual increase in the number of farmers who adopted agricultural water reuse.

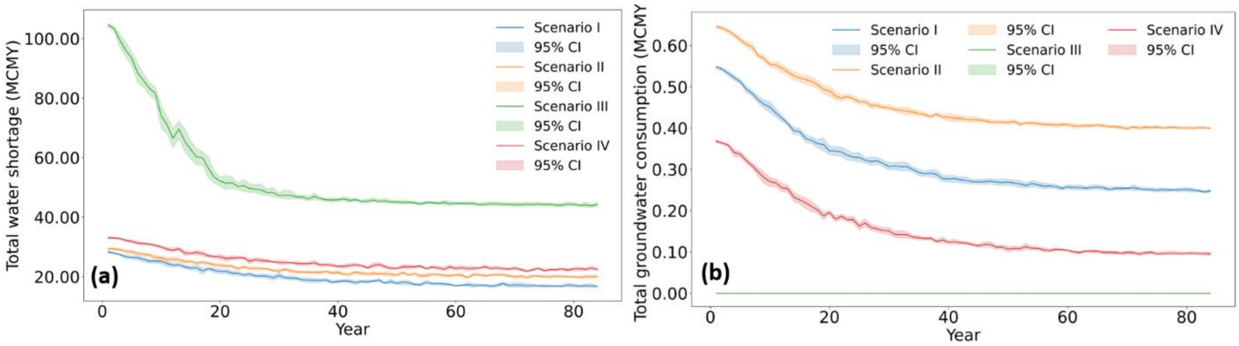


Figure 10: The results of the simulation experiments: (a) total water shortage and (b) total groundwater consumption.

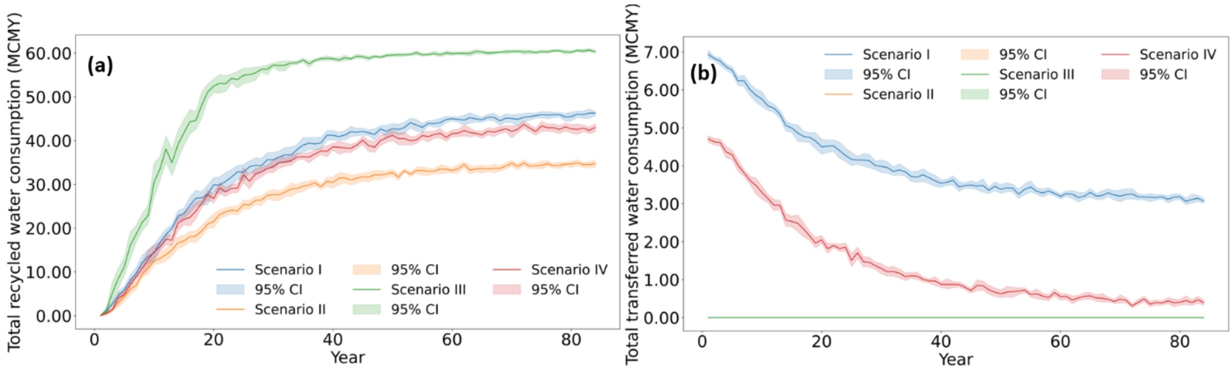


Figure 11: The results of the simulation experiments: (a) cumulative recycled water consumption and (b) cumulative transferred water consumption.

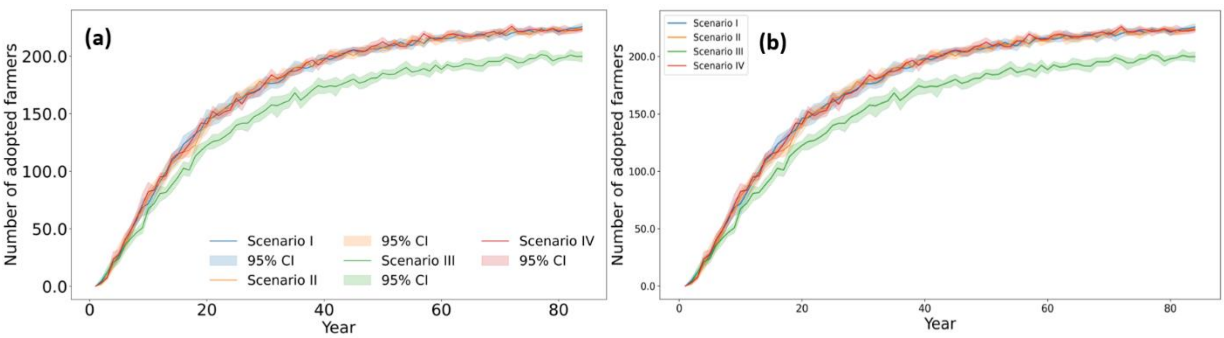


Figure 12: The results of the simulation experiments: number of farmers who adopted agricultural water reuse.

4. Discussion

As discussed in Section 1, the aim of this paper was to fill a gap with respect to micro-scale dynamics of agricultural water reuse adoption by farmers and its impacts on local water resources. In what follows, we will provide a discussion of the main findings of this paper before presenting model limitations and areas of further work. Through our systematic sensitivity analysis via fractional factorial experimental design, we were able to identify the most important parameters influencing the model output (i.e., total recycled water consumption). According to the literature, the financial aspects of water reuse projects are of the most important factors affecting these projects (Asano et al., 2007; Bixio et al., 2008; Lazarova & Bahri, 2005; Sheikh et al., 2018; Shoushtarian & Negahban-Azar, 2020). Similarly, the results of our sensitivity analysis identified the unit price of recycled water as the most important parameter affecting agricultural water reuse in the model which is the same as in the real world (e.g., Sheikh et al., 2018). It should also be noted that such sensitivity analysis is not the norm with agent-based models; many studies either neglect such sensitivity analysis or conduct it unsystematically (Borgonovo et al., 2022; Saltelli et al., 2019, 2020; Utomo et al., 2018).

The model was further used to analyze various water reuse scenarios using the most influential parameters determined by the sensitivity analysis (as described in Section 2.3). Results of the scenario analysis clearly show that recycled water consumption gradually rises with an increasing number of farmers adopting it. Furthermore, the model shows that as recycled water consumption increases, it alleviates the farmers' water shortage and could decrease groundwater over-drafting and the reliance on transferred water (Section 3). Such results suggest that recycled water as a water resource whose production does not rely on climatic conditions could also benefit farmers in this agricultural water district by providing a reliable water source for their crops. This is in accordance with agricultural water reuse literature (Asano et al., 2007; Bixio et al., 2008; Jeong & Adamowski, 2016; Lazarova & Bahri, 2005; Asano et al., 2007; Miller-Robbie et al., 2017; Nazari et al., 2012). Furthermore, this result from our models aligns with another study conducted to evaluate how water reuse can increase the robustness of a water system in the Netherlands (Pronk et al., 2021). Like our study, this study demonstrated that implementing agricultural water reuse could successfully substitute the amount of water extracted from the groundwater sources for agriculture, increasing the water system's robustness to future stresses on groundwater sources.

Now turning the discussion to limitations, one could argue that all models have their limitations, and our model is no exception. For example, as noted in Section 3, one of the assumptions made in this research was to keep the unit prices of CVP and recycled water constant during the simulation. Our rationale for this simplifying assumption was that there is currently no unified structure for pricing recycled water, and there is a huge gap in the literature regarding recycled water pricing (Abdelmoula et al., 2021; Clumpner, 2016; Gonzalez-Serrano et al., 2005; Hurlimann & McKay, 2007; Seguí-Amórtegui et al., 2005). For example, water utilities in California currently use various methods for setting recycled water prices, including base and tiered rates. This price depends on various factors (e.g., the type of water utility, the type of water user, and the water requirement volume) that increases the complexities of setting a price on recycled water. It also should be mentioned that the prices set by utilities can be changed year by year due to various factors such as the economy and environmental conditions (e.g., drought and water bodies contamination) (Clumpner, 2016). Therefore, in this study, the unit prices of CVP and recycled water remained constant for the sake of parsimony. Hence, this is one of the areas for further research. This is one of the reasons why we provide the data and code for the model so others can extend the model to include such investigations if they deem it appropriate. For example, one could change these unit prices exogenously by randomly sampling from a distribution (e.g., normal distribution) or simulate unit prices by developing a sub-model considering such things as the climatic (e.g., wet or drought conditions) and social (e.g., public acceptance of these water sources) factors as independent variables.

Another simplifying assumption we made is with respect to simulating the unit prices of transferred water and groundwater stochastically (Section 2.2.1.1). However, transferred water and groundwater costs can be impacted by various factors (e.g., climate, local governmental policies, and economy). For example, in case of any drought occurring in the study area, it is likely that the drought negatively impacts neighboring areas from which water is transferred to the study area. Therefore, the unit price of transferred water might increase due to this climatic factor. Groundwater unit prices can also be affected by drought as the available groundwater for farmers would decrease. On the other hand, suitable climatic conditions with ample rain can decrease transferred water and groundwater unit prices. The economy is another factor that can potentially indirectly impact these two water resources' unit prices. For example, increases in the cost of energy sources (e.g., gasoline and electricity) can significantly affect the costs associated with pumping water from other areas (i.e., the transferred water source) and aquifers (i.e., groundwater source) to the farms. However, including these factors in the model could significantly increase the complexities of the model presented here. Therefore, we decided not to include these in this study and leave them as suitable areas for further research.

Moreover, demographic parameters included in this model included farmers' age, race, sex, education, knowledge of recycled water, concern about water availability, the importance of recycled water, and access to recycled water. The assumption of considering these parameters constant during the simulations helped us decrease the complexities of the model. However these parameters can significantly change due to various reasons (e.g., farmers' migration and economy) during a long period. This is one of the interesting areas of further study for researchers interested in extending this study using the data and model provided. More survey studies can be done at different times to see the changes in these parameters and their effects on model results over time. Moreover, a sensitivity analysis can be conducted to investigate the most influential demographic parameters on farmers' perceptions toward agricultural water reuse and the model results. Following on from this point, a related area for further research would be to explore time-varying sensitivity analysis as such analysis could help illustrate the dynamics of parameters' importance on the model outputs. For example, Ghoreishi et al. (2021) showed how time-varying sensitivity analysis on an agent-based model led to new insights into how financial factors impact water conservation methods for crop production. However, we feel this is beyond the scope of the current paper, but it is one reason we provide the data and source code of the model available online.

5. Conclusion

The use of recycled water for agricultural irrigation is a potentially viable way to address water scarcity in many parts of the world. However, the complexities of the socio-hydrological systems of water reuse projects make it very difficult to successfully investigate the implementation of these systems. Furthermore, these projects' high costs of capital, operation, and maintenance add to the systems' complexity. Investigating the socio-hydrological dynamics of agricultural water reuse projects can provide insights into these complex systems. It enables the decision-makers to test various scenarios when they intend to promote water reuse and helps them select the best management practices.

In this study, an agent-based model was successfully developed and implemented for simulating the socio-hydrological dynamics of agricultural water reuse projects. We tested the model using the NVRRWP case study. The agent-based model evaluated the water consumption dynamics and how the adoption of recycled water use by farmers impacts the local water resources. The model demonstrated that agricultural water reuse could decrease total water shortage, groundwater over-drafting, and transferred water consumption if planned and managed correctly. The model, similar to the literature, suggests that decision-makers should pay special attention to the price-setting of recycled water, which was identified as the most influential factor in total recycled water consumption by farmers in the model. This study also showed how possible droughts or groundwater withdrawal regulations could increase recycled water use by farmers. The results also depicted that under possible drought scenarios in the future, agricultural water reuse could successfully address water supply challenges by decreasing farmers' water shortage by providing a reliable water resource for irrigation purposes.

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