ABSTRACT

Title of Dissertation: SUSTAINABLE WATER RESOURCES MANAGEMENT THROUGH AGRICULTURAL WATER REUSE: APPLICATION OF A DECISION SUPPORT SYSTEM

Farshid Shoushtarian, Doctor of Philosophy, 2022

Dissertation directed by: Assistant Professor, Dr. Masoud Negahban-Azar, Environmental Science and Technology Department

The water crisis caused by climate change, population growth, high urbanization rate, lifestyle changes, and industrialization has decreased global access to safe freshwater resources. As the primary food-producing and the largest water-consuming sector, agriculture heavily depends on water availability. Incorporating alternative water supplies (e.g., water reuse) can reduce freshwater demands, addressing water crisis consequences. Water reuse generally includes recycling treated effluent (known as recycled water) from wastewater treatment plants for different applications (e.g., agricultural irrigation). This alternative water resource can reliably and sustainably increase the resiliency of agriculture to water shortage. However, the complexities inherent in water resources management and the challenges associated with water reuse make planning and managing agricultural water reuse practices demanding. Agricultural water reuse projects include many interrelated/ interconnected components, including the human (e.g., farmers) and technical (e.g., engineering and natural infrastructures) components. The abilities of existing models are limited in simulating these components' complex and adaptive behaviors. It is necessary to utilize tools capable of capturing these complexities and adaptations to plan and manage agricultural water reuse practices sustainably.

The main research question of this dissertation was: How to capture the complex and adaptive dynamics of socio-hydrological systems inherent in sustainable water resources management when alternative water sources are introduced in the water supply system? The primary focus of the dissertation was to develop a dynamic decision support system that can successfully simulate the complexities and adaptations inherent in agricultural water reuse practices. It aims at increasing the existing knowledge regarding agricultural water reuse planning and management and help water resource decision-makers make sustainable and better-informed decisions in agricultural water reuse practices. To accomplish this goal, first, the literature was thoroughly reviewed to identify, collect, and analyze the data related to agricultural water reuse (e.g., current agricultural water reuse regulations and guidelines). Second, two models were developed using a "bottom-up" approach to study two agricultural water reuse practices in the Southwest (CA) and

Mid-Atlantic (MD-DE) regions. These two models were used to further study the dynamics of agricultural water reuse adoption by farmers and their impacts on local water resources.

The results showed that the regulations and guidelines were mainly human health centered, insufficient regarding some potentially dangerous pollutants such as emerging constituents, and with large discrepancies when compared with each other. In addition, some important water quality parameters, such as pathogens, heavy metals, and salinity, were only included in a few of the regulations and guidelines investigated in this study. Finally, specific treatment processes were only mentioned in some of the regulations and guidelines, with high levels of discrepancy. Moreover, 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%) in CA. The results also showed that climate change and recycled water storage capacity and unit price were among the top factors with significant influence on agricultural water reuse practice studied in this dissertation. This study demonstrated the importance of conducting time-varying sensitivity analysis for complex simulation models. Furthermore, results demonstrated that implementing agricultural water reuse could decrease farmers' water shortage, groundwater consumption, and surface water consumption (by almost 19.5 %) in MD. This dissertation's results can help decision-makers effectively take advantage of agricultural water reuse projects and other alternative water resources to plan and manage water resources sustainably.

SUSTAINABLE WATER RESOURCES MANAGEMENT THROUGH AGRICULTURAL WATER REUSE: APPLICATION OF A DECISION SUPPORT SYSTEM

by

Farshid Shoushtarian

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2022

Advisory Committee:
Assistant Professor Masoud Negahban-Azar, Chair
Professor Adel Shirmohammadi
Professor Andrew Crooks
Associate Professor Gary K. Felton
Professor Gregory B. Baecher

© Copyright by
Farshid Shoushtarian
2022

"Let's not muddy the water
A dove may be drinking water downstream
Or a finch washing her feathers at a distance thicket
Or a pitcher is being filled in a village
Let's not muddy the water
This water may run to a poplar's foot
To wash away the grief of a lonely heart
A dervish may be dipping dry bread in the water
A beautiful lady walked to the brink of the water
Let's not muddy the water
The beautiful face has been doubled
What refreshing water
What clean water
How friendly the folks at the upstream are
May their springs always gush
May their cows always be full of milk
I have not seen their village
God's footprints must lie at the foot of their huts
Moonlight enlightens the words there
Hedges are undoubtedly short in the upper village
The folks there know poppy well
Blue is blue there
All the village knows if a plant is flowering
what a village it must be
May the village be full of music
The folks upstream understand the water
They did not muddy the water
Let's not muddy the water, too."

By Sohrab Sepehri,
Iranian poet and painter,
1928-1980.

Dedication

I dedicate this dissertation to my lovely wife, parents, and sister, whose love and support have always warmed my heart.

Acknowledgments

I appreciate my advisor, Dr. Masoud Negahban-Azar, for all his help, support, and encouragement throughout these five years. I also thank my entire advisory committee, Dr. Andrew Crooks, Dr. Adel Shirmohammadi, Dr. Gary Felton, and Dr. Gregory Baecher, for their valuable advice and support.

I acknowledge the financial support from CONSERVE (A Center of Excellence at the Nexus of Sustainable Water Reuse, Food, and Health), United States Department of Agriculture (USDA), National Institute of Food and Agriculture (NIFA), University of Maryland Graduate School, Department of Environmental Science and Technology (ENST), and Maryland Department of Transportation-State Highway Administration (MDOT-SHA).

I also like to thank all my friends in the ENST department.

At last but not least, I would like to immensely thank my wife, parents, sister, family, and friends for their endless support and love.

Table of Contents

Dedication iii
Acknowledgments iv
Table of Contents v
List of Tables vii
List of Figures x
List of Abbreviations xiv
Chapter 1: Introduction 1
1.1. Background 1
1.2. Statement of the problem 2
1.3. Research plan 4
1.3.1. Research motivation 4
1.3.2. Research question and objective 4
1.3.3. Methodology 5
1.4. Dissertation outline 11
Chapter 2: Literature review 12
2.1. Water resources availability in the U.S. (Mid-Atlantic and Southwest regions). 12
2.2. Current water reuse regulations and guidelines 13
2.3. Public acceptance of recycled water and its effects on water reuse projects 14
2.4. Sustainable water resources management using DSSs 15
2.4.1. "Bottom-up" approach 16
Chapter 3: Worldwide regulations and guidelines for agricultural water reuse: A critical review 20
Abstract 20
3.1. Introduction 20
3.1.1. Water reuse history 23
3.1.2. Water reuse current status 24
3.2. Methodology 26
3.2.1. Definitions and terminologies 26
3.3. Results and discussion 28
3.3.1. Reference regulations and guidelines 35
3.3.2. Recycled water quality standards 44
3.4. Summary of findings 110
3.4.1. Constituents in reclaimed water 110
3.5. Conclusions 114
Chapter 4: Investigating the micro-level dynamics of water reuse adoption by farmers and the impacts on local water resources using an agent-based model 117
Abstract 117
4.1. Introduction 117
4.2. Methodology 120
4.2.1. Study area 120
4.2.2. ABM framework 122
4.2.3. Model verification, sensitivity analysis, and scenario experiments 132

4.3. Results 136
4.3.1. Verification and sensitivity analysis 136
4.3.2. Results of testing the screening stage 142
4.3.3. Simulation experiments results 147
4.4. Discussion 151
4.5. Conclusion 153
Chapter 5: Sustainable water resources management through agricultural water reuse in Maryland; Application of agent-based modeling 155
Abstract 155
5.1. Introduction 155
5.2. Methodology 159
5.2.1. Study area 159
5.2.2. Framework 160
5.2.2.1. Environment 161
5.2.2.2. Agents (farmers): 162
5.2.2.3. Agents (WWTP) 169
5.2.3. Methods 169
5.3. Results and discussions 174
5.3.1. Results of UA-SA 175
5.3.2. Results of simulation experiments and model validation 183
5.4. Conclusions 203
Chapter 6: Optimization of agent-based models: Application in planning and management of an agricultural water reuse project 205
Abstract 205
6.1. Introduction 205
6.2. Methodology 208
6.2.1. ABM 208
6.2.2. ABM optimization using RL 211
6.3. Results and discussions 217
6.3.1. Results of SA 217
6.3.2. Results of scenario analysis 234
6.4. Conclusions 253
Chapter 7: Summary and conclusions 255
Bibliography 260

List of Tables

Table 1. The data and their sources for developing agent-based models in this research. 10
Table 2. Benefits and challenges of agricultural water reuse (adapted from Lazarova and Bahri (2004)). 22
Table 3. The definition of standard, criteria, guideline, and regulation (Asano et al., 2007). 27
Table 4. Agricultural water reuse regulations or guidelines included in this study.... 28
Table 5. Health-based targets for recycled water use in agriculture (modified from (World Health Organization, 2006b)). 37
Table 6. Water quality for irrigation (adapted from (Wastewater Quality Guidelines for Agricultural Use, 1999)). 38
Table 7. EPA guideline for agricultural water reuse (adopted from (USEPA (US Environmental Protection Agency), 2012)). 40
Table 8. Water quality for irrigation in California's regulation (adapted from Title 22: California Water Recycling Criteria (California Legislative Information (Water Code))). 43
Table 9. The E.U. commission proposal for minimum recycled water quality in agriculture (adapted from (Didier, 2018)). 44
Table 10. Restrictive agricultural water reuse regulations and guidelines. 47
Table 11. Less restrictive agricultural water reuse regulations and guidelines. 58
Table 12. Descriptive statistical analysis of common pathogen indicators included in agricultural water reuse regulations and guidelines. 63
Table 13. Chemicals and trace elements thresholds in agricultural water reuse regulations and guidelines (numbers in parentheses show the threshold level of chemical constituents and trace elements). 65
Table 14. Salinity (EC and TDS) thresholds in agricultural water reuse regulations and guidelines. 72
Table 15. The SAR thresholds in the agricultural water reuse regulations and guidelines. 74
Table 16. Toxic ions (Chloride, Sodium, and Boron) thresholds in agricultural water reuse regulations and guidelines. 76
Table 17. Bicarbonate and carbonate thresholds in agricultural water reuse regulations and guidelines. 78
Table 18. Nutrients thresholds in agricultural water reuse regulations and guidelines. 80
Table 19. Residual Chlorine thresholds in agricultural water reuse regulations and guidelines. 82
Table 20. Turbidity thresholds in agricultural water reuse regulations and guidelines. 83
Table 21. TSS/SS thresholds in agricultural water reuse regulations and guidelines. 86
Table 22. $CBOD_5$ thresholds in agricultural water reuse regulations and guidelines. 92
Table 23. BOD_5 thresholds in agricultural water reuse regulations and guidelines. .. 93
Table 24. COD thresholds in agricultural water reuse regulations and guidelines..... 99

Table 25. Required treatment technologies in agricultural water reuse regulations and guidelines. 100
Table 26. Regulations and guidelines that indicated treatments. 109
Table 27. Some of the existing CECs in recycled water reported by literature (Anderson et al., 2010)..... 113
Table 28. Input data used for developing the agent-based model in this research. .. 122
Table 29. Total irrigation demand and area under cultivation of crops grown in the study area (RMC Water and Environment, 2013) 124
Table 30. Monthly effective precipitation in DPWD and evapotranspiration of almond trees (adapted and modified from (RMC Water and Environment, 2013)). 126
Table 31. Level of parameters used in the water reuse adoption sub-model (source: (Suri et al., 2019)) 129
Table 32. Demographics of agents (farmers in the Southwest, U.S.), based on (Suri et al., 2019). 129
Table 33. Discrete probabilities distributions used in determining agents' concerns about water reuse, based on (Suri et al., 2019). 130
Table 34. Discrete probabilities distributions used in determining agents' importance of water reuse, based on (Suri et al., 2019)..... 130
Table 35. Discrete probabilities distributions used in determining agents' attitude toward water reuse, based on (Suri et al., 2019). 131
Table 36. Design table for sensitivity analysis in this study (randomized). 135
Table 37. Factors considered in the screening step of the study..... 135
Table 38. Details of simulation experiments for testing the sensitivity analysis results in this study. 138
Table 39. Specifications of the simulation experiments scenarios in this study..... 138
Table 40. Significant factors effects ($P \leq 0.05$). The responses are total recycled water consumption at the end of years 27, 55, and 84. 142
Table 42. Weather conditions in Maryland based on IPCC (Gutiérrez et al., 2021) and corresponding irrigation need coefficients assumed in this study. 164
Table 43. Maryland Daily temperature and precipitation projections (2021-2040) based on IPCC-CORDEX-North America (Gutiérrez et al., 2021)..... 164
Table 44. Maryland Daily temperature and precipitation projections (2041-2060) based on IPCC-CORDEX-North America (Gutiérrez et al., 2021)..... 164
Table 45. Maryland Daily temperature and precipitation projections (2061-2100) based on IPCC-CORDEX-North America (Gutiérrez et al., 2021)..... 165
Table 46. Demographics of agents, based on Suri et al., (2019). 167
Table 47. Discrete probabilities distributions used in determining agents' concerns about water reuse, based on Suri et al., (2019). 168
Table 48. Discrete probabilities distributions used in determining agents' importance of water reuse, based on Suri et al., (2019)..... 168
Table 49. Discrete probabilities distributions used in determining agents' attitude toward water reuse, based on Suri et al., (2019). 169
Table 50. Factors considered in the sensitivity analysis. 172
Table 51. Specifications of the simulation experiments scenarios in this study..... 174
Table 52. Results of correlation analysis between model factors using Spearman's method..... 179

Table 53. Distributions of the farmers' SI components without agricultural water reuse under scenario I 187
Table 54. Distributions of the farmers' SI components with agricultural water reuse under scenario I 188
Table 55. Distributions of the farmers' SI components without agricultural water reuse under scenario II 192
Table 56. Distributions of the farmers' SI components with agricultural water reuse under scenario II 192
Table 57. Distributions of the farmers' SI components without agricultural water reuse under scenario III 196
Table 58. Distributions of the farmers' SI components with agricultural water reuse under scenario III 197
Table 59. Distributions of the farmers' SI components without agricultural water reuse under scenario IV 201
Table 60. Distributions of the farmers' SI components with agricultural water reuse under scenario IV 201
Table 61. Farmers' attributes used in this ABM for this study 209
Table 62. WWTP's attributes used in this ABM for this study 210
Table 63. Inputs of the ABM used in this study 210
Table 64. The manager's S in this study 214
Table 65. Specifications of the SA experiments in this study. 215
Table 66. Specifications of the simulation experiments scenarios in this study 217

List of Figures

Figure 1. Schematic representation of this study's framework. 6
Figure 2. Agricultural water quality parameters. 45
Figure 3. Required pH ranges in agricultural water reuse regulations and guidelines 71
Figure 4. Salinity thresholds in agricultural water reuse regulations and guidelines: (a) EC and (b) TDS. 73
Figure 5. Required SAR ranges in agricultural water reuse regulations and guidelines. 75
Figure 6. Comparison of the TDS and selected TSS thresholds, required in agricultural water reuse regulations and guidelines which included both of TDS and TSS thresholds. 91
Figure 7. The number of regulations and guidelines which indicated different indicator microorganisms..... 111
Figure 8. The number of regulations and guidelines which included different agronomic parameters. 112
Figure 9. The number of regulations and guidelines which used different physico-chemical parameters..... 113
Figure 10. Map of this research's case study (Del Puerto Water District, CA, USA) 123
Figure 11. (a) WRAF framework; (b) Farmers' decision-making flowchart..... 125
Figure 12. (a) Water reuse adoption sub-model framework; (b) Wastewater treatment plants flowchart) 133
Figure 13. 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). 134
Figure 14. Representative simulation results: (a) and (b) farmers' water resources distribution in years one and 84, respectively; (c) and (d) available recycled water in the storage ponds of the two wastewater treatment plants; (e) and (f) total recycled water used by farmers in year two and 84, respectively. 141
Figure 15. 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. 143
Figure 16. 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; the 95% confidence intervals were calculated using bootstrap resampling method)..... 145
Figure 17. 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; the 95% confidence intervals were calculated using bootstrap resampling method). 146
Figure 18. 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; the 95% confidence intervals were calculated using bootstrap resampling method)..... 147

Figure 19: The results of the simulation experiments: (a) total water shortage and (b) total groundwater consumption (MCMY = Millions Cubic Meters per Year; the 95% confidence intervals were calculated using bootstrap resampling method)..... 149
Figure 20: The results of the simulation experiments: (a) cumulative recycled water consumption and (b) cumulative transferred water consumption (MCMY = Millions Cubic Meters per Year; the 95% confidence intervals were calculated using bootstrap resampling method). 150
Figure 21: The results of the simulation experiments: number of farmers who adopted agricultural water reuse (the 95% confidence intervals were calculated using bootstrap resampling method)..... 151
Figure 22. The Easton WWTP and its surrounding agricultural farms (in Talbot County, MD) within a 15 km radius investigated in this study. 160
Figure 23. (a) The stylized environment of the ABM developed in this study, (b) Farmers' daily activities algorithm..... 161
Figure 24. Line (a), quantile-quantile (b), and kernel density estimation plots of the U.S. inflation rate from 1990 to 2020. 175
Figure 25. Uncertainties observed in the model outputs (a) total yearly water shortage, (b) total yearly groundwater consumption, (c) total yearly surface water consumption, (d) total yearly recycled water consumption, (e) the cumulative number of farmers who adopted agricultural water reuse, and (f) mean of farmers' SI. 179
Figure 26. Time-varying SA results using the moment-independent method (delta) for various model outputs (a) total water shortage, (b) total groundwater consumption, (c) total surface water consumption, (d) total recycled water consumption, (e) the cumulative number of farmers who adopted agricultural water reuse, and (f) mean of farmers' SI. 183
Figure 27. Simulation experiments results under the scenario I (a) total yearly water shortage, (b) total yearly groundwater consumption, (c) total yearly surface water consumption, (d) total yearly recycled water consumption, (e) cumulative adoption curve of agricultural water reuse adoption by farmers, and (f) yearly mean of farmers' SI (MCMY = Millions Cubic Meters per Year; the 95% confidence intervals were calculated using bootstrap resampling method)..... 187
Figure 28. Simulation experiments results under scenario II (a) total yearly water shortage, (b) total yearly groundwater consumption, (c) total yearly surface water consumption, and (d) total yearly recycled water consumption, (e) cumulative adoption curve of agricultural water reuse adoption by farmers, and (f) yearly mean of farmers' SI (MCMY = Millions Cubic Meters per Year; the 95% confidence intervals were calculated using bootstrap resampling method). 191
Figure 29. Simulation experiments results under scenario III (a) total yearly water shortage, (b) total yearly groundwater consumption, (c) total yearly surface water consumption, and (d) total yearly recycled water consumption, (e) cumulative adoption curve of agricultural water reuse adoption by farmers, and (f) yearly mean of farmers' S (MCMY = Millions Cubic Meters per Year; the 95% confidence intervals were calculated using bootstrap resampling method). 196
Figure 30. Simulation experiments results under scenario IV (a) total yearly water shortage, (b) total yearly groundwater consumption, (c) total yearly surface water consumption, and (d) total yearly recycled water consumption, (e) cumulative

adoption curve of agricultural water reuse adoption by farmers, and (f) yearly mean of farmers' SI (MCMY = Millions Cubic Meters per Year; the 95% confidence intervals were calculated using bootstrap resampling method). 200
Figure 31. RL schematic process (Sutton & Barto, 2018) 211
Figure 32. Results of SA for parameter θ; (a) ε × θ, (b) the manager agent's reward, (c) the unit price of recycled water ($/TCM), and (d) WWTP's storage capacity (MCM); $WSI = 50$, $WSH = 50$, $WGW = 50$, $WRU = 50$, $WRP = 50$, $WST = 50$, θ = 0.995, 0.997, 0.999, ε = 0.9, $\gamma = 0.5$, and $\alpha = 0.5$ (the 95% confidence intervals were calculated using bootstrap resampling method). 219
Figure 33. Results of SA for parameter ε; (a) ε × θ, (b) the manager agent's reward, (c) the unit price of recycled water ($/TCM), and (d) WWTP's storage capacity (MCM); $WSI = 50$, $WSH = 50$, $WGW = 50$, $WRU = 50$, $WRP = 50$, $WST = 50$, θ = 0.997, ε = 0.1, 0.5, 0.9, $\gamma = 0.5$, and $\alpha = 0.5$ (the 95% confidence intervals were calculated using bootstrap resampling method). 222
Figure 34. Results of SA for parameters α and γ, (a) and (d) the unit price of recycled water ($/TCM); (b) and (e) WWTP's storage capacity (MCM); (c) and (f) the manager agent's reward; $WSI = 50$, $WSH = 50$, $WGW = 50$, $WRU = 50$, $WRP = 50$, $WST = 50$, θ = 0.997, ε = 0.5, $\gamma = 0.1, 0.5, 0.9$, and $\alpha = 0.1, 0.5, 0.9$ (the 95% confidence intervals were calculated using bootstrap resampling method). 225
Figure 35. Results of SA for parameters WGW, WRU and WRP, (a), (d), and (g) the unit price of recycled water ($/TCM); (b), (e), and (h) WWTP's storage capacity (MCM); (c), (f), and (i) the manager agent's reward; $WSI = 1$, $WGW = 1, 50, 100$, $WRU = 1, 50, 100$, $WRP = 1, 50, 100$, $WST = 1$, θ = 0.997, ε = 0.5, $\gamma = 0.5$ and $\alpha = 0.5$ (the 95% confidence intervals were calculated using bootstrap resampling method). 231
Figure 36. Results of SA for parameters WSI and WST, (a), (d) the unit price of recycled water ($/CM), (b) and (e) WWTP's storage capacity (MCM), (c) and (f) the manager agent's reward; $WSI = 0, 50, 100$, $WSH = 50$, $WGW = 50$, $WRU = 50$, $WRP = 50$, $WST = 0, 50, 100$, θ = 0.997, ε = 0.2, $\gamma = 0.5$, and $\alpha = 0.5$ (the 95% confidence intervals were calculated using bootstrap resampling method). 234
Figure 37. Results of scenario analysis (I), (a) the unit price of recycled water ($/CM), (b) WWTP's storage capacity (MCM), (c) the manager agent's reward, (d) total yearly groundwater consumption (cumulative), (e) mean of farmers' SI, and (f) the number of recycled water users (the 95% confidence intervals were calculated using bootstrap resampling method). 239
Figure 38. Results of scenario analysis (II), (a) the unit price of recycled water ($/CM), (b) WWTP's storage capacity (MCM), (c) the manager agent's reward, (d) total yearly groundwater consumption, (e) mean of farmers' SI, and (f) the number of recycled water users (the 95% confidence intervals were calculated using bootstrap resampling method). 244
Figure 39. Results of scenario analysis (III), (a) the unit price of recycled water ($/CM), (b) WWTP's storage capacity (MCM), (c) the manager agent's reward, (d) total yearly groundwater consumption, (e) mean of farmers' SI, and (f) the number of recycled water users (the 95% confidence intervals were calculated using bootstrap resampling method). 249

Figure 40. Results of scenario analysis (IV), (a) the unit price of recycled water ($/CM), (b) WWTP's storage capacity (MCM), (c) the manager agent's reward, (d) total yearly groundwater consumption, (e) mean of farmers' SI, and (f) the number of recycled water users (the 95% confidence intervals were calculated using bootstrap resampling method). 252

List of Abbreviations

ABM	Agent-based modeling
AGWR	Australian guidelines for water recycling
BMP	Best management practices
BOD	Biological oxygen demand
CA	California
CBOD	Carbonaceous biological oxygen demand
CVP	Central Valley Project
CFU	Colony forming units
CM	Cubic meters
COD	Chemical oxygen demand
CEC	Contaminant of emerging concern
CVP	Central valley project
DALY	Disability-adjusted life year
DOE	Design of experiments
DPWD	Del Puerto water district
DSS	Decision support system
EPA	Environmental protection agency
FAO	Food and agriculture organization of the United Nations
FSMA	Food safety modernization act
GCIR	Gross crop irrigation requirement
IPCC	Intergovernmental Panel on Climate Change
ISO	International organization for standardization

Km	kilometer
MD	Maryland
MDE	Maryland department of environment
Mg/l	Milligrams per liter
MCMY	million cubic meters per year
ML	milliliter
MCDA	Multi-criteria decision analysis
NASS-CDL	National agricultural statistics service cropland data layers
NVRRWP	North valley regional recycled water program
NTU	Nephelometric turbidity unit
OFAT/OAT	One factor at a time/ one at a time
ODD	Overview, design concepts, details, and decision-making
P.E.	Population equivalent
PPY	Person per year
QMRA	Quantitative microbial risk assessment
RCP	Representative concentration pathway
RSM	Response surface methodology
RL	Reinforcement learning
RT	Retention time
SA	Sensitivity analysis
SAR	Sodium adsorption ration
TCM	Thousand cubic meters
TCMY	Thousand cubic meters per year

TDS	Total dissolved solids
TPB	Theory of planned behavior
TSS	Total suspended solids
UA	Uncertainty analysis
USAID	United States agency for international development
USBR	United States bureau of reclamation
US	United States
USDA	United States department of agriculture
WHO	World health organization
WWTP	Wastewater treatment plant

Chapter 1: Introduction

1.1. Background

Humans' access to safe freshwater resources has been decreased due to climate change, industrialization, urbanization, inefficient use of available water, and population growth (Eslamian, 2016; Shoushtarian & Negahban-Azar, 2020; Zhang et al., 2020). In 2007, almost one-fifth of the world's population (1.2 billion people) lived in physical water scarcity (United Nations, 2007). The United Nations also estimated that five hundred million people were going to live in physical water scarcity as well (United Nations, 2007). Approximately 1.6 billion other people do not have access to infrastructure to beneficially extract water from rivers and aquifers worldwide (United Nations, 2007). Based on existing climate change scenarios, about half of the world's population will suffer from living in high water stress areas by 2030 (UN-WWAP, 2012). The water shortage is expected to negatively impact the environment, human health, economy, industries, political relationships, and energy/ food production (Eslamian, 2016).

Agriculture is the largest water-consuming sector, responsible for almost 70% of the world's total freshwater consumption (Suri et al., 2019). In the U.S., for example, in 2018, 231,474 farms (22.6 million hectares) were irrigated with 102.9 billion cubic meters of water (USDA-NASS, 2019). The primary sources of irrigation in the U.S. are as follows: 1) groundwater from on-farm wells (13.6 million hectares of land irrigated with 51.2 billion cubic meters of water), 2) on-farm surface water (2.6 million hectares of land irrigated with 10.2 billion cubic meters of water), and 3) off-farm water from a variety of sources (6.4 million hectares of land irrigated with 41.5 billion cubic meters of water) (USDA-NASS, 2019). This sector also produced $388.5 billion in agricultural products in 2017 (USDA-NASS, 2019). The implications of water shortage in the agriculture sector are significant, as this sector is highly dependent on water availability (Mendelsohn & Dinar, 2003). Water shortage diminishes the number of productive farms, irrigated areas and crops, and food production. Therefore, access to safe 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 be categorized into two major groups: increasing water supply and decreasing water demand. The methods which augment the water supply may include water reuse (Jeong & Adamowski, 2016), seawater/ brackish water desalination (Dawoud, 2005), rainwater harvesting (Kahinda et al., 2007), and water conveyance from other locations (Shrestha et al., 2011). The solutions that decrease water demand may include various demand mitigation strategies, such as using modern irrigation technologies with high efficiencies to decrease water consumption in agriculture (Perry et al., 2009).

Water reuse generally includes recycling treated effluent (known as recycled water) from wastewater treatment plants for different applications (e.g., urban use,

agricultural irrigation, groundwater recharge, and impoundments) (Shoushtarian & Negahban-Azar, 2020). It is important to note that water reuse applications may vary in different countries and depend on several factors, such as levels of treatment, the conditions of water resources, environmental status, and public acceptance (USEPA (US Environmental Protection Agency), 2012).

Agricultural water reuse is the most dominant water reuse application in the world (Eslamian, 2016). It is one of the most prominent methods of increasing the water supply for agriculture by introducing a reliable and sustainable alternative water resource (Paul et al., 2020). Currently, in agricultural water reuse, 91% of the recycled water is utilized for crop and pasture irrigation, and the rest (9%) is used in the cleaning of piggeries and drinking water for livestock and dairy productions (Eslamian, 2016). Agricultural water reuse provides various benefits, including declining freshwater withdrawal, managing and recovering nutrients, and increasing water supply reliability (Shoushtarian & Negahban-Azar, 2020). Despite its benefits, agricultural water reuse has its challenges, including recycled water quality, social acceptance, and conflicts between different stakeholders (Shoushtarian & Negahban-Azar, 2020). Readers are encouraged to read the author's publication (Chapter 3) for a complete list of agricultural water reuse benefits and challenges (Shoushtarian & Negahban-Azar, 2020). Nevertheless, existing scientific knowledge and practical experience can lower the risks associated with agricultural water reuse by informing sound planning and effective irrigation management with recycled water (Lazarova & Bahri, 2004).

1.2. Statement of the problem

Although agricultural water reuse has great potential to alleviate global water scarcity, the challenges associated with it make it less likely to be chosen by water resources decision-makers than other alternative water supplies. These challenges can be categorized into seven categories: human health, environmental health, technical, social, legal, and socio-economic (Shoushtarian & Negahban-Azar, 2020).

Human and environmental health are two of the most important measures to be taken into account. Agricultural water reuse regulations and guidelines set recycled water quality thresholds to ensure these projects do not harm human and environmental health. Decision-makers need to pay special attention to the existing regulations and guidelines in their decision-making process (e.g., Food Safety Modernization Act (FSMA), 1998). They need to evaluate the reliability of these regulations and guidelines for ensuring human and environmental health. These regulations and guidelines must be set by cutting-edge scientific methods and without any gaps or shortcomings. They also need to be updated regularly to keep up with the emerging contaminants (e.g., pharmaceuticals and personal care products).

The complex adaptive system of water resources requires exclusive attention to being managed successfully. Planning and managing agricultural water reuse projects

without paying attention to these systems' components, their complex interactions, and exogenous factors affecting them can result in various ramifications for water resources management projects. Consequently, these ramifications can further harm the human, economy, and environment (e.g., food insecurity, groundwater over drafting, and economic hardship for farmers and their workers). For example, socio-economic factors are among the most critical factors for successful agricultural water reuse projects with the potential to turn the project into a failure if not appropriately evaluated.

It is also necessary to investigate the dynamics of human-environment systems in agricultural water reuse management projects (Jeong & Adamowski, 2016). These projects' macro and micro-scale dynamics are of paramount importance for decision-makers to identify best management practices successfully (Jeong & Adamowski, 2016). For example, policies set at the local level (e.g., irrigation district) can alter the micro-dynamics of agricultural water reuse adoption, resulting in altering the macro-scale dynamics of water resources systems at the watershed scale (e.g., groundwater over-drafting caused by the increase in using groundwater instead of recycled water for irrigation). On the other hand, policies set at the macro scale (e.g., river basin) can significantly alter the micro-scale dynamics of agricultural water reuse adoption.

Therefore, it is necessary to consider multiple agricultural water reuse challenges to plan and manage safe agricultural water reuse practices worldwide. However, this is a very demanding issue for water resources decision-makers. Moreover, the complexities inherent in water resources planning and management make the planning and managing agricultural water reuse practices more challenging.

Many researchers have acknowledged the advantages of using decision support systems (DSSs) for making equitable, efficient, and sustainable decisions in water resources management (Al-Jawad et al., 2019; Isaeva et al., 2019; Johnson, 1986; Khan et al., 2020; Sarband et al., 2020). However, DSSs that focus on one aspect of water resource management challenges cannot successfully help decision-makers make effective decisions. Thus, it is necessary to develop DSSs that can capture the complexities and adaptive processes involved in projects that include agricultural water reuse as a water supply alternative.

The DSS need to capture water reuse adoption dynamics and their impact on water resources (Kandiah et al., 2019). Various socio-economic, technical, and public health parameters may significantly affect these adoption processes, including public acceptance, recycled water pricing, social networks, and water supply and demand policies. DSSs that incorporate these factors and their interactions in their frameworks would be beneficial tools for decision-makers. Using these DSSs, decision-makers will be able to make better-informed decisions in river basins, watersheds, states, counties, or irrigation districts. However, available DSSs in the literature are not sufficient for decision-makers to use in their decision-making processes beneficially. Therefore, some of the questions that should be answered to fill some of the existing knowledge gaps are:

1. Where is agricultural water reuse allowed? If allowed, what are the codes of safe agricultural water reuse practices?
2. How do farmers adopt agricultural water reuse practices?
3. How should decision-makers plan and manage agricultural water reuse projects considering the complex and adaptive behavior of different stakeholders toward agricultural water reuse?
4. What are the best management practices for exploiting agricultural water reuse projects?
5. To what extent do agricultural water reuse practices increase water supply reliability and resiliency to water shortages, and decrease excessive groundwater withdrawal?

1.3. Research plan

1.3.1. Research motivation

Various measures are necessary to be taken into account by water resources decision-makers to sustainably promote, plan, and manage safe agricultural water reuse projects. However, evaluating water resources complex systems by simultaneously considering multiple criteria and factors to make the optimum decisions is not easy, especially considering the uncertainties inherent in these complex systems (e.g., climate change and water demand uncertainties). As mentioned before, a DSS is a useful tool for helping water resources decision-makers in the process mentioned. The DSS should be designed and implemented in a way that enables it to capture the complex adaptive system of agricultural water reuse practices along with other water supply/ demand practices successfully.

Therefore, the overall goal of this research was to develop a DSS capable of helping water resources decision-makers sustainably promote, plan, and manage safe and sound agricultural water reuse projects to increase water supply reliability, resiliency toward water shortage, and vulnerability to future stresses (e.g., climate change). Such a DSS will be of paramount importance for decision-makers, especially in the future, when climate change and population growth effects are exacerbated. The details of the procedures needed to design and develop the DSS mentioned above will be described in the following sections.

1.3.2. Research question and objective

In this dissertation, the main research question was: How to capture the complex and adaptive dynamics of socio-hydrological systems inherent in sustainable water resources management when alternative water sources are introduced into the water supply system? In other words, the main goals of this research were to investigate the dynamics of introducing an alternative water source (e.g., reclaimed wastewater), and

to simulate the complete feedback loop between farmers' behavior, policy-makers' decisions, and the water resources in a coupled socio-hydrological system.

The main objective of this research was to explore how water reuse adoption, as a community-wide behavior, emerges as a result of interactions, relationships, and dependencies between individuals and the environment, as the water supply systems shift from having only conventional water sources to a mix of conventional and alternative water sources. Various farm-level factors were tested to investigate how farmers choose their alternative water sources, such as recycled wastewater. The parameters specific to adopting agricultural water reuse were also evaluated to investigate further how farmers were likely to use recycled water for their irrigation practices.

Local water resources managers need to know about water reuse projects' dynamics if they want to incorporate recycled water as an alternative source into the water supply portfolio. It is vital to acquire insight into their customers' reactions to water reuse projects and the impacts of their behavior on local water resources, and vice versa. They also need these insights for planning the required infrastructure and their future expansions. These insights enable water resources decision-makers to manage water reuse projects effectively. For example, the decision-makers can use these insights to adopt policies that can maximize the number of recycled water customers and earn the most potential revenue to compensate for capital, operation, and maintenance expenses of water supply projects. These better-informed policies also help decision-makers address freshwater scarcity and groundwater over-drafting at local and regional levels.

Furthermore, various water resources management scenarios, including several water supply portfolios, were simulated under various challenges (e.g., climate change). This objective also helped evaluate local water supply's reliability, the resiliency of the human-water system toward water scarcity, and the water supply system's vulnerability to future challenges. According to (Hashimoto et al., 1982), the reliability of a system determines the likelihood that the system fails; resiliency of a system determines the speed at which the system recovers from a failure; the vulnerability of a system determines the severity of the system failure consequences. Therefore, this study used these concepts and corresponding indexes suggested by the literature to assess how agricultural water reuse projects can affect the reliability, resiliency, and vulnerability of water resources systems at the local scales. Decision-makers can get valuable insights by simulating various water resources management scenarios. This will enable them to identify a portfolio of the best management practices for addressing future challenges (e.g., climate change)

1.3.3. Methodology

In general, the proposed research framework includes two stages (Figure 1). The first stage addresses the safety of agricultural water reuse practices by investigating existing regulations and guidelines globally, specifically in various states of the U.S.

This stage will focus more on the acceptable recycled water quality for irrigation based on different crops grown in each state. This stage will determine the crops that can be irrigated by recycled water, based on the wastewater treatment facilities' effluent quality.

The next stage benefits from a "bottom-up" approach for exploring how farmers' agricultural water reuse adoption emerges. Insights from this stage can help decision-makers find the best micro-level management strategies for promoting, planning, and managing agricultural water reuse practices. Overall, the proposed DSS can be useful for water resources decision-makers at different levels (e.g., irrigation district, watershed, and county) to manage water resources sustainably. Some of the great features of this DSS that make it useful for water resource decision-makers are as follows:

- Various criteria (human health, social, economic, environmental, and technical) will be considered for developing and implementing this DSS,
- This DSS investigates the introduction of recycled water into the portfolio of available alternative water resources for agricultural purposes,
- This DSS's versatility makes it applicable for studying various water resources systems with different conditions (e.g., climate, land use-land cover, and socio-economic status).

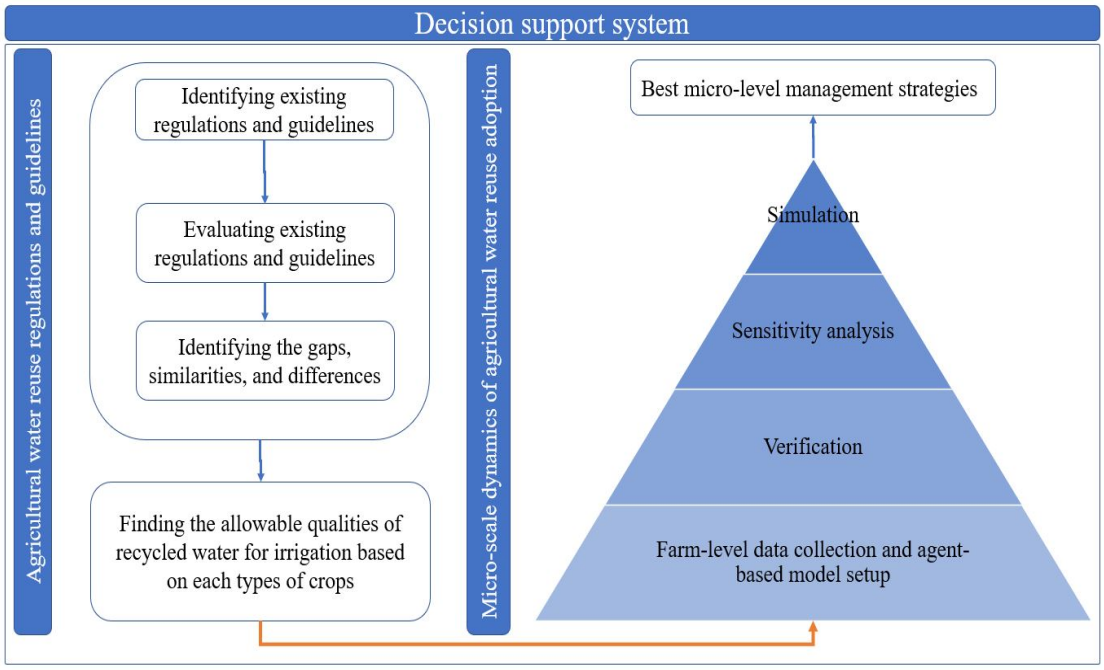


Figure 1. Schematic representation of this study's framework.

1.3.3.1 Study areas

The study areas of this research included the states of CA and MD. This enabled the author to apply this research to two different areas with different conditions (i.e., semi-arid vs. humid regions). Due to its climatic conditions and the growing water demand in the Southwest region, CA has been dealing with water scarcity for a long time, which will be exacerbated even more in the future. Therefore, the results of this research can be put into practice in this state. CA is one of the pioneering places in water reuse practices globally.

Moreover, the Mid-Atlantic region is one of the regions experiencing groundwater level decline in many parts of the region due to over withdrawal, climate change, and population growth. Therefore, this research could help decision-makers in MD alleviate the pressure on limited fresh groundwater sources. The MD Department of Environment (MDE) has also begun reinvigorating and promoting water reuse in this state by starting an initiative (MDE's Water Reuse Initiative) in 2017 (Maryland Department of Environment, 2017), so MDE can use the results of this research for promoting safe and proper agricultural water reuse in MD effectively.

Two agricultural water reuse projects in the states mentioned above were selected to implement agent-based models. The first site was an agricultural water reuse project in the Del Puerto Water District (DPWD), Central Valley, CA, United States (Southwest region). This project, named North Valley Regional Recycled Water Program (NVRRWP), was considered a solution for the DPWD water shortage problem caused by the recent drought conditions and limitations on pumping from the San Joaquin-Bay Delta (*North Valley Regional Recycled Water Program*, 2013). DPWD provides irrigation water for approximately 18,210.9 hectares of agricultural land in California's three counties (Stanislaus, San Joaquin, and Merced) (RMC Water and Environment, 2013). DPWD's primary water resource is provided through a contract with the United States Bureau of Reclamation (USBR), delivering 172.9 million cubic meters per year (MCMY) of the Central Valley Project (CVP) water to the DPWD (RMC Water and Environment, 2013). However, due to these problems, 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 (groundwater and temporary transferred water) have been unreliable, unsustainable, and unaffordable (RMC Water and Environment, 2013).

The second site was located at Easton city, Talbot County, MD (Mid-Atlantic region). This site was located at the Choptank River watershed. According to Dong et al. (Dong et al., 2019), this watershed has been experiencing severe groundwater level declines for the past decade due to groundwater withdrawals in this watershed as it is the primary source of water in this watershed. (Paul et al., 2020) identified this site as a suitable site for implementing agricultural water reuse practices using geospatial multi-criteria decision analysis. The criteria used in this study included the type of crops grown in each area, the distance from farm to wastewater treatment plants, the

drought index (PDSI) of each area, amount of groundwater withdrawal, and freshwater consumption in agriculture (Paul et al., 2020). Moreover, the Easton wastewater treatment plant is one of the major wastewater treatment facilities in MD, with an average of 12.1 thousand cubic meters per day effluent. Therefore, this site was selected in the Mid-Atlantic region as one of the sites with the potentials for practicing safe and proper agricultural water reuse.

1.3.3.2. Research tasks

The following tasks were performed to accomplish the research objective mentioned above. The following sections explain the methodologies used to perform each task.

Task 1: Investigating the existing agricultural water reuse regulations and guidelines.
Task 2: Collecting micro-level data and developing agent-based models.
Task 3: Conducting model verification and sensitivity analysis.
Task 4: Simulating an agricultural water reuse project under various scenarios.

1.3.3.2.1 Task 1: Investigating the existing agricultural water reuse regulations and guidelines.

The Google Scholar search engine was used as the first step to compile a complete worldwide agricultural water reuse regulations and guidelines database. In this step, keywords including "water reuse", "water reclamation", "water recycling", "wastewater reuse", "wastewater recycling", "recycled water", "reclaimed water", "agriculture", "regulation", "guideline", "standard", and "criteria" were used. Peer-reviewed journal articles related to agricultural water reuse regulations and guidelines were compiled and reviewed. In the second step, based on the results obtained from the first step, study cases were identified (e.g., countries, international organizations, and state agencies that have issued/ established agricultural water reuse regulations or guidelines). In the third step, the organizations' official website (e.g., state agencies, ministries, governmental institutes) were investigated. Official representatives at organizations/agencies were contacted if needed to ensure that the obtained regulations and guidelines were the latest version.

All the regulations and guidelines were thoroughly analyzed to find their similarities, differences, gaps, and strategies behind issuing/ establishing those regulations and guidelines. The criteria that were used include the necessary water qualities, treatment processes, and approaches. For evaluating the necessary water qualities, the parameters were categorized into three categories, including human-health parameters (pathogens and chemicals), agronomic parameters (salinity, toxic ions, Sodium adsorption ratio, trace elements, pH, Bicarbonate and Carbonate, nutrients, and free Chlorine), and Physico-chemical parameters (turbidity, total suspended solids and total dissolved solids, biochemical Oxygen demand, carbonaceous biochemical Oxygen demand, and chemical Oxygen demand). Regulations and guidelines were compared based on each of these parameters. Scientific literature was then reviewed to find the best ranges of these parameters and the consequences of not meeting them.

Finally, all the regulations and guidelines were categorized based on the allowable water quality thresholds for irrigating different crop types. This task's results can help determine which type of crops can be irrigated by the existing recycled water in the study areas (according to the recycled water quality).

1.3.3.2.2. Task 2: Collecting micro-level data and developing agent-based models.

In this section, the procedures for developing agent-based models are explained. The sources for collecting the micro-level data are summarized in Table 1. Two agent-based models were developed to study the micro-scale dynamics of agricultural water reuse adoption by farmers in the Mid-Atlantic and Southwest regions of the U.S. These models were developed using Netlogo 6.1.1 (Wilensky, 1999). These models built a virtual agricultural area in which several autonomous farms operate. Specifically, these models simulated the water consumption dynamics of these farms. Empirical data were used to set up available water resources and farms in the region. Using the model, the user was able to simulate different water resources management scenarios in the area. These models included two types of agents, including farmers and wastewater treatment plants. In general, farmer agents were the main water consuming agents, and wastewater treatment plant agents were alternative water resource (recycled water) providers in the models.

1.3.3.2.3. Task 3: Conducting model verification and sensitivity analysis.

Verification: The verification of a model includes ensuring that the implemented model matches its design (North & Macal, 2007; Patel et al., 2012). Therefore, the models' input parameters were varied to evaluate their effects on the model results. In particular, two model verification methods were used, including code testing and expected outcome alignment (Crooks et al., 2018). The uncertainty test (extreme tests method) was also implemented for verification of these models.

Sensitivity analysis: "*The goal of sensitivity analysis is to determine which input variables within a set of input variables in the model have important effects on the output* (Happe et al., 2006)." Emergent properties are inherent in ABM, making it difficult to quickly investigate how agent-based models' assumptions and inner interactions influence the model behavior (Happe et al., 2006). Therefore, formal sensitivity analyses were applied to these models for addressing these challenges in a structured way. Design of Experiments (DOE) statistical techniques was used as the means for this aim by Minitab® 19 statistical software. These techniques enable researchers to study the details of a model's dynamics, evaluate the influence of different input parameters on the output parameters, study the simulation results using a common basis, and help detect the problems in the logic of the model (Happe et al., 2006; Kleijnen, 2005). DOE also 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).

In engineering fields, input parameters that influence the output parameter are called "factors", and the output parameters are called "responses" in the DOEs. Three major steps are followed in DOEs, including 1) screening, 2) response surface methodology, and 3) model validation (Wass, 2010). The screening stage tends to find the factors that have a statistically significant influence on the response. Response surface methodology tries to find the optimal results space using the previous stage's influential factors. The model validation step tends to confirm the model at the end. These steps were conducted for the sensitivity analyses of the agent-based models.

Table 1. The data and their sources for developing agent-based models 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	1) The Maryland Department of Planning, 2) Maryland's GIS Data Catalog, 3) California State Geoportal	1)https://planning.maryland.gov/Pages/OurProducts/DownloadFiles.aspx 2) https://data.imap.maryland.gov/ 3)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).	The authors of this manuscript (our colleagues in the CONSERVE center) provided the data.
Crops irrigation requirements	1) The United States Department of Agriculture (USDA) census of agriculture (2017), 2) the University of Maryland Extension, 3) the NVRRWP feasibility study	1)https://www.nass.usda.gov/Publications/AgCensus/2017/index.php 2)https://extension.umd.edu/learn/publications/estimating-irrigation-water-requirements-optimize-crop-growth 3)(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

1.3.3.2.4. Task 4: Simulating the agricultural water reuse project under various scenarios.

After verifying that the models worked according to their design (verification) and influential factors on the models' desired responses were found (sensitivity analysis), the models were utilized for simulation experiments. Multiple scenarios were defined to evaluate the "what if" scenarios. These scenarios included various climate and management scenarios.

1.4. Dissertation outline

In Chapter 2, a brief literature review on water resources availability in the U.S. (Southwest and Mid-Atlantic regions), current water reuse regulations and guidelines, public acceptance of water reuse and its effects on water reuse practices, and applications of DSSs for sustainable water resources management is presented. While Chapter 3 critically reviews worldwide agricultural water reuse regulations and guidelines regarding recycled water quality and necessary treatment processes. This chapter identifies the gaps and discrepancies existing in current regulations and guidelines and proposes areas for addressing the gaps. In Chapter 4, the framework proposed and agent-based model developed in this dissertation to study the micro-scale dynamics of agricultural water reuse practices using a case study in CA were described.

Moreover, Chapter 5 demonstrates the results of developing another agent-based model using the framework proposed in this dissertation to study sustainable planning and management of agricultural water reuse practices in the Eastern Shore of MD, especially under climate change scenarios. This chapter further shows the application of time-varying moment independent sensitivity analysis suitable for complex adaptive systems (e.g., human-water systems). While in Chapter 6, the results of using reinforcement learning techniques for simulation-based multi-objective optimization of agricultural water reuse practices using the agent-based model developed in this dissertation was demonstrated. At the end, Chapter 7 summarizes the findings of this research study and presents the conclusion and directions for future research.

Chapter 2: Literature review

2.1. Water resources availability in the U.S. (Mid-Atlantic and Southwest regions).

The availability of the U.S. water resources in the present and projected future varies widely (Suri et al., 2019). Studies predict that precipitation will be higher than the present in several parts of the U.S. (e.g., the northern regions) due to climate change, while other parts of the U.S. will experience lower precipitations than the present. Researchers also predict that temperature will increase all over the U.S., increasing evaporation. In some areas, the increase in evaporation will negate the precipitation increase, decreasing streamflow (e.g., in parts of the Colorado River Basin). Moreover, research predict that climate change will increase hydrologic extremes, resulting in more intense and prolonged droughts in some parts of the U.S. (Brown et al., 2019).

In the Mid-Atlantic region of the U.S., the weather highly varies seasonally (Horton et al., 2014). This region has hot and often humid summers and cold winters (Horton et al., 2014; Suri et al., 2019). Year-round precipitation is typical in this region; however, the occurrence of massive precipitation events has increased drastically (by more than 70%) in recent years (Horton et al., 2014). The risk of more intense and frequent precipitation events and seasonal droughts are also expected to rise in this region (Horton et al., 2014). Despite the precipitation, aquifers are experiencing several challenges in this region, including declining water tables, salt-water intrusion, and low water quality. From 2002 to 2016, this region experienced an overall decline in groundwater level (0.06 m/year, 95% CI: 0.03, 0.09), while the changes varied by physiographic region (Dong et al., 2019). The Coastal Plain physiographic region was dominated by declining groundwater wells (48%) and had the most significant groundwater level declines (0.23 m/year, 95% CI: 0.19, 0.26) (Dong et al., 2019).

In the hottest and driest region of the U.S (Southwest), precipitation events are projected to fluctuate with increasing and decreasing patterns across this region (Suri et al., 2019). However, temperature projections indicate significantly hotter temperatures, resulting in more frequent, more intense, and longer-lasting droughts than in the past in this region (Suri et al., 2019). Famiglietti et al., (2011) estimated that the Central Valley (located in the Southwest region) experienced net groundwater depletion of about 20 km^3 during 2003–2010. Xiao et al., (2017) also estimated cumulative groundwater storage change for the Central Valley and found a depletion rate of 7.2 ± 1.0 km^3/year from April 2006 to March 2010, and 11.2 ± 1.3 km^3/year for the 2012–2016 drought. Other studies support similar findings that the Southwest groundwater has declined at least in the past 50 years, with the most accelerated decline over the last decade (Alam et al., 2019).

Comparing these two regions' recent precipitation and drought status, one can infer that the Southwest region is experiencing severe water shortages that will be worsen in some areas in the future. However, the Mid-Atlantic region is experiencing some water supply changes that will be worse according to future climate change projections. For instance, between 2016-2018, the Mid-Atlantic region received 940 mm/year of precipitation, while the Southwest region received 320 mm/year. In this period, the Mid-Atlantic region experienced normal drought conditions (based on the Palmer Drought Severity Index); however, the Southwest experienced normal to moderate drought conditions (Suri et al., 2019).

2.2. Current water reuse regulations and guidelines

One of the necessities for the safe application of recycled water is to ensure that it has the desired quality and poses no harm to human health and the environment (Khan, 2018). Starting with the state of California in 1918, countries around the world alongside international organizations (e.g., World Health Organization (WHO) and Food and Agriculture Organization of the United Nations (FAO)) have started to establish their water reuse regulations and guidelines to ensure safe water reuse practices (Angelakis & Gikas, 2014). In general, countries and organizations have taken different approaches to establish regulations and guidelines (Brissaud, 2008). For instance, some countries like Canada, Australia, and many states in the U.S. have issued more restrictive regulations, while others have chosen to take less restrictive approaches to develop water reuse regulations and guidelines which will be discussed thoroughly in Chapter 3 (Shoushtarian & Negahban-Azar, 2020). It is important to note that there is no federal regulation or guideline for agricultural water reuse in the U.S (USEPA (US Environmental Protection Agency), 2012). It is up to each state to establish its regulation or guideline (USEPA (US Environmental Protection Agency), 2012).

When compared in more detail, it becomes apparent that current agricultural water reuse regulations and guidelines vary significantly (Eslamian, 2016). For instance, some regulations and guidelines do not consider necessary biological and microbial quality parameters, and some do not consider necessary physico-chemical parameters. Furthermore, even in regulations and guidelines that consider the same parameters, those threshold levels vary significantly. As water reuse in agriculture is becoming popular for addressing water scarcity, the disparity in regulations and guidelines may create challenges at both regional and global levels (Brissaud, 2008). At the regional level, the absence of unified, or at least relatively similar, water reuse regulations and guidelines may result in uncertainty among stakeholders (e.g., farmers, consumers, and policy-makers), thereby slowing down the promotion of water reuse in agriculture. The U.S. is an excellent example in this respect.

In the U.S., 42 states have regulations or guidelines for nonfood crops/ processed food crops, and 28 states have regulations or guidelines for food crop irrigation (USEPA (US Environmental Protection Agency), 2012). Eight states do not have any regulations or guidelines for agricultural water reuse (USEPA (US Environmental

Protection Agency), 2012). When looked at in more detail, the water quality parameters and the threshold levels in those regulations and guidelines are different. This matter may create uncertainty among stakeholders and may increase the risks related to public acceptance, thereby slowing down the implementation of agricultural water reuse (Eslamian, 2016). Additionally, agricultural commodities are being exported/ imported all around the world. As a result, the difference in regulations and guidelines between the countries of origin and the end-use countries may pose significant obstacles in food safety, market acceptability, and import/ export relationships.

So far, there have been few studies that evaluate some of these regulations and guidelines (Alfarra, 2010; Angelakis et al., 1999; Asano et al., 2007a; Brissaud, 2008; Jeong et al., 2016; Jiménez & Asano, 2008; Lazarova & Bahri, 2004; Raso, 2013; Schaefer et al., 2004). However, there has been no study investigating and comparing the existing agricultural water reuse regulations and guidelines in the U.S. and worldwide.

2.3. Public acceptance of recycled water and its effects on water reuse projects

One of the most vital challenges that the planning and management of water reuse projects face is public acceptance. Despite all the benefits of water reuse and its successful applications worldwide, public acceptance is still one of the most critical barriers to planning and managing water reuse projects (Fielding et al., 2019a). There were cases that, due to the public opposition to the water reuse projects, resulted in the demise of those projects (e.g., the cases of Toowoomba, Australia; Maroochy, Australia; Caloundra, Australia; San Diego, United States; San Gabriel Valley, United States; and Dublin, CA, United States) (Fielding et al., 2019b; Po et al., 2003). Some projects (e.g., CA's Bay Area Water Recycling Program and City of Los Angeles Department of Water and Power's East Valley Water Reclamation Project, United States) had to be redesigned entirely or were delayed due to public opposition (Po et al., 2003). Negative perceptions toward recycled water can negatively influence consumers' decision-making when buying products irrigated with recycled water (Savchenko et al., 2018, 2019).

Therefore, one question arises; why do people oppose the application of recycled water despite its benefits? According to the literature, the following factors may play a role in answering this question: 1) disgust or "yuck factor", 2) perceptions of risk associated with using recycled water, 3) the specific uses of recycled water, 4) the sources of water to be recycled, 5) the issue of choice, 6) trust and knowledge, 7) attitudes toward the environment, 8) environmental justice issues, 9) the cost of recycled water, and 10) socio-demographic factors (Po et al., 2003). These factors have been investigated by researchers so far.

Farmers' perceptions toward using recycled water for their irrigation practices are of paramount importance in agricultural water reuse projects. Research that investigated

this issue can be categorized into two categories: first, those research that investigated the factors that influenced farmers to utilize recycled water in their irrigations; and second, those research that investigated the perceptions of farmers toward agricultural water reuse (Carr et al., 2011).

Water shortage was a significant driver of Greek farmers' willingness to adopt agricultural water reuse (Menegaki et al., 2007). According to (Menegaki et al., 2009), Greek farmers' willingness to use recycled water in their irrigation increased when it was called "recycled water" rather than "treated wastewater". Some studies in the Middle East showed that religion is not a limiting factor in using recycled water in agriculture in this area (Abu-Madi, 2004; Al Khateeb, 2001). (Sheidaei et al., 2016) found that a complex set of factors, including knowledge and closeness to recycled water canals, significantly affected perceived risks of agricultural water reuse among Iranian farmers. (Suri et al., 2019) investigated U.S. farmers' opinions on using nontraditional water sources (e.g., recycled water) for agricultural purposes. They surveyed 269 and 477 farmers in the Mid-Atlantic and Southwest regions of the U.S., respectively. This study showed that factors, including age, water availability concern, knowledge of recycled water, access to recycled water, education, race, the importance of recycled water, and gender influenced the farmers' willingness to use nontraditional water sources in both regions (Suri et al., 2019).

Existing knowledge and experience and future research can shed further light on public behavior regarding recycled water. The results can be used to better plan and manage water reuse projects while considering the public as an intrinsic part of water reuse projects with significant impacts on their efficiency and even plausibility.

2.4. Sustainable water resources management using DSSs

Sustainable water resources management is a complex and demanding issue. It involves multiple factors such as socio-economic and environmental impacts and several natural and human-disturbing parameters (e.g., human activities and hydrologic/ hydraulic conditions) (Weng et al., 2010). Moreover, uncertainties inherent in human activities (e.g., water demands) and exogenous hydrologic inflows in the future add to the difficulties of planning and managing these systems (Weng et al., 2010). Decision-makers need to assess various management options using multiple decision criteria (e.g., environmental, social, and economic factors) to make impartial, efficient, and sustainable decisions (Bromley, 2005). Multi-criteria decision analysis (MCDA) provides a systematic procedure, enabling decision-makers to choose the most desirable alternative among the available alternatives based on various scenarios (Weng et al., 2010). However, decision-makers need tools, techniques, and models to aid them throughout this process (Bromley, 2005).

Many researchers have acknowledged the advantages of using DSSs to help decision-makers make equitable, efficient, and sustainable decisions in water resources management (Al-Jawad et al., 2019; Isaeva et al., 2019; Johnson, 1986; Khan et al., 2020; Sarband et al., 2020). Studying complex systems is difficult due to the various

interactions, relationships, and dependencies between their components (Mitchell, 2006). Models and DSSs usually can take two overarching approaches, including "top-down" and "bottom-up" approaches, to shed light on how complex systems work and simulate them. "Top-down" approaches try to formulate an overview of the system; however, "bottom-up" approaches investigate the system constituents' underlying linkages (Pouladi et al., 2019). Different stakeholders can use "bottom-up" approaches to evaluate their options for water resources management. Watershed-scale regulations and plans can also be assessed according to existing natural and human-made infrastructure characteristics using "top-down" approaches (Van Emmerik et al., 2014).

Water resources complex systems have been studied using "top-down" (Kuil et al., 2016; Pande & Savenije, 2016; Van Emmerik et al., 2014) and "bottom-up" approaches (Al-Amin et al., 2018; Koutiva & Makropoulos, 2016a; Lu et al., 2018; Troy et al., 2015). A comprehensive assessment can benefit from both approaches for thoroughly shedding light on the complex adaptive system under evaluation.

2.4.1. "Bottom-up" approach

Despite the success of the "top-down" approaches in studying complex systems, they cannot capture the dynamics of different micro-level processes of complex systems (e.g., farmers' decision-making dynamics) (Pouladi et al., 2019). On the other hand, "bottom-up" approaches are built based on the sub-systems' underlying linkages, enabling researchers to capture the micro-level dynamics, including emergent phenomena (Pouladi et al., 2019; Sabzian et al., 2019). Various "bottom-up" methods are available, including cellular automata, microsimulation, discrete event models, and agent-based modeling (ABM) (Crooks et al., 2018).

2.4.2.1. ABM

ABM is one of the computational methods for simulating complex systems, using its constituents' perspective (i.e., the "bottom-up" approach) (Bonabeau, 2002; Grimm & Railsback, 2005). "*ABMs are highly effective in explaining how complex patterns emerge from micro-level rules during a period of time*" (Sabzian et al., 2019). According to Axelrod (1997), ABM is the "*third way of doing science*" compared to the other two contemporary ways, including deduction and induction. In deduction, conclusions are made by reducing a set of specified premises, while induction means concluding based on observing from empirical data patterns. In ABM, rules (explicit assumptions) are used to build the model; then, the model will generate simulated data. The data will be analyzed through quantitative and qualitative methods to conclude (Achorn, 2004). Complexity theory and network science form the basis of ABM (Sabzian et al., 2019). As a process model, an agent-based model shows the generation of complex emergence resulting from simple rules (based on complexity theory) (Sabzian et al., 2019). As a pattern model, an agent-based model is utilized to study the generation of patterns resulting from agents' interactions over time (based on network science) (Sabzian et al., 2019).

2.4.2.1.1. Components of agent-based models

Generally, agent-based models are consisting of three main components, including agents, an environment, and interactions (Berglund, 2015; Macal & North, 2010), which will be explained further in this section.

Agents: Agents in agent-based models are autonomous entities defined by their attributes and actions (Berglund, 2015; Sabzian et al., 2019). Based on their attributes, agents can do activities that can affect their or other agents' attributes or the environment (Sabzian et al., 2019). Based on (Crooks et al., 2018), agents' key characteristics are as follows: 1) Autonomy: agents act based on an independent decision-making process which means that they are not controlled by an external or a centralized control, 2) Heterogeneity: agent-based models can include various kinds of entities (agents) with different attributes and actions, 3) Active: agents are designed to achieve some goals in the model ("goal-directed"); agents may or may not be informed about their environment and other agents around them ("reactive or perceptive"); agents may have unbounded information and analytical ability (rational choice models) or be rationally bounded in their decision-making processes; agents can either interact with their environment and other agents based on their spatial location or communicate through their networks; agents can move in the environment ("mobility"), 4) Learning and adaptation: based on their information, past interactions and connections with other agents or their environment, and their memory, agents can learn and adapt to new circumstances, adjusting their actions.

Environment: "*The environment is composed of all conditions surrounding the agents as they interact within the model.*" (Sabzian et al., 2019). It provides agents with resources and information (Berglund, 2015). The environment can be categorized into three categories: spatial environment, networked environment, and mixed environment (Sabzian et al., 2019). A discrete environment comprises many discrete points, building agent-based models' spatial environment (Sabzian et al., 2019; Wilensky & Rand, 2015). Connections between agents can be a networked environment where agents and connections between them are nodes and links, respectively (Sabzian et al., 2019; Wilensky & Rand, 2015). Mixed environments enable modelers to simulate the spatial and networked environment simultaneously [68].

Interactions: Interactions define the agents' and the environment's rules of behavior. These include agent-agent/ self, agent-environment, environment-environment/ self, and environment-agent interactions (Sabzian et al., 2019). These interactions are based on the attributes and rules of behavior of interacting entities (agents or environment); these attributes can be changed due to the interactions.

2.4.2.1.2. Benefits of ABM

Comparing agent-based and other modeling paradigms, the advantages of this method are as follows: 1) this method uses the "bottom-up" approach, which enables us to capture the emergent phenomena, 2) this method is an efficient way to include the geographical and social sciences in models using its natural environment, 3) this method provides the opportunity for including elements of randomness in models, 4) this method develops a platform to create agents that are autonomous, adaptive, and have unlimited numbers of parameters and rules (Crooks et al., 2018; Heppenstall et al., 2012).

2.4.2.1.3. History of ABM

Early developments of the ABM concept go back to the early 1940s with John Von Neumann's machine and the 1970s John Conway's Game of Life. In the 1940s, John Von Neumann used the cellular automata environment for designing a self-reproducing machine using simple instructions (von Neumann, 1966). John Conway's Game of Life consisted of a grid of cells. Some predefined rules determined the life, death, and multiplication of the cells. The patterns that cells formed during the game were based on the initial conditions (Wolfram, 2002). Thomas Schelling's segregation model was one of the first social ABMs in 1971, studying housing segregation patterns (Schelling, 1971).

Starting in the 1970s, other researchers tried to use ABM, including Robert Axelrod's Prisoner's Dilemma model, Craig Reynolds' flocking model, and John Holland and John H. Miller's paper "*Artificial Adaptive Agents in Economic Theory*" (Axelrod, 1997; Holland & Miller, 1991). In the 1980s, the rise of rapid computers, computer science progresses, and the advent of object-oriented programming helped different modeling platforms to emerge in the upcoming years including, StarLogo (1990), NetLogo and Swarm (the 1990s), AnyLogic and RePast (2000), Mason (2003), and GAMA (2007) (An, 2012; Grignard et al., 2013; Taillandier et al., 2019). These platforms have played a significant role in the rise of ABM so far.

2.4.2.1.4. Applications of ABM in water resources management studies

Although ABM does not date back long ago, it has been an efficient way to analyze, model, and simulate water resources complex systems (Akhbari & Grigg, 2013). In water resources management studies, "*agent-based models vary in scope, water system of interest, management questions, and degree of interaction across social and physical systems*" (Berglund, 2015).

Early uses of ABM concepts for water resources management date back to 1995. (Geldof, 1995) used ABM for groundwater policy development for the Amsterdam municipality. In 1999, ABM was used for revealing the dynamics among the stakeholders of water supply systems and their effects on the ecological, technical,

and socio-economic environment (D. Tillman et al., 1999). Barreteau and Bousquet (2000) used ABM to study the existing social network effects on Senegal River Valley irrigated systems in 2000. In 2016, Farhadi et al. (2016) developed an agent-based model framework for finding the best policy mechanisms to allocate groundwater to users in the Daryan Aquifer, Fars Province, Iran. Ali et al. (2017) developed an ABM framework for simulating urban water supply and demand with different climate change scenarios, using Raleigh, North Carolina, as a case study in 2017. Rasoulkhani et al. (2018) developed an agent-based model to explore the dynamics of how residential users adopt water conservation technology using the City of Miami Beach as the case study in 2018. In 2019, (Kandiah et al., 2019b) used an ABM framework to study urban water reuse adoption by consumers and infrastructure expansion using the Town of Cary, North Carolina, as a case study.

Chapter 3: Worldwide regulations and guidelines for agricultural water reuse: A critical review[1]

Abstract

Water reuse is gaining momentum as a beneficial practice to address the water crisis, especially in the agricultural sector as the largest water consumer worldwide. With recent advancements in wastewater treatment technologies, it is possible to produce almost any water quality. However, the main human and environmental concerns are still to determine what constituents must be removed and to what extent. The main objectives of this study were to compile, evaluate, and compare the current agricultural water reuse regulations and guidelines worldwide, and identify the gaps. In total, 70 regulations and guidelines, including the Environmental Protection Agency (EPA), International Organization for Standardization (ISO), Food and Agriculture Organization of the United Nations (FAO), World Health Organization (WHO), the United States (state by state), European Commission, Canada (all provinces), Australia, Mexico, Iran, Egypt, Tunisia, Jordan, Palestine, Oman, China, Kuwait, Israel, Saudi Arabia, France, Cyprus, Spain, Greece, Portugal, and Italy were investigated in this study. These regulations and guidelines were examined to compile a comprehensive database, including all the water quality monitoring parameters and necessary treatment processes.

In summary, results showed that the regulations and guidelines were mainly human-health centered, insufficient regarding some of the potentially dangerous pollutants such as emerging constituents, and with significant discrepancies when compared with each other. In addition, some of the critical water quality parameters, such as pathogens, heavy metals, and salinity, were only included in a small group of regulations and guidelines investigated in this study. Finally, specific treatment processes were only mentioned in some of the regulations and guidelines, with high discrepancy levels.

3.1. Introduction

Climate change, industrialization, high rate of urbanization, and population growth are among the main reasons that have made many countries, especially in the arid and semi-arid areas, suffer from the water crisis (Eslamian, 2016). For instance, water scarcity in Australia has caused population losses in north-eastern, south-eastern, and western rural areas. These areas have experienced further unemployment, a lack of success in local businesses, and a downtrend in irrigation (Hogan & Young, 2013). Countries in the Middle East, Central Asia, and some parts of Southeast Asia have

[1] This chapter was published in the Journal of Water.
Shoushtarian, F.; Negahban-Azar, M. Worldwide Regulations and Guidelines for Agricultural Water Reuse: A Critical Review. *Water* **2020**, *12*, 971. https://doi.org/10.3390/w12040971

been struggling with water-related issues. It is anticipated that these struggles may result in conflicts over shared water resources in these regions (IISS (The International Institute for Strategic Studies), 1999).

Considering the adverse consequences of the water crisis, countries around the world have been trying to increasingly cope with this problem by implementing sustainable water management plans and looking for alternative water supply sources (Eslamian, 2016). Water conservation, water reuse, and desalination of seawater and brackish groundwater are among those strategies that have been tried to address the water crisis (Eslamian, 2016). In recent years, more and more countries are considering water reuse as an alternative water supply to supplement freshwater sources (Asano et al., 2007b; Eslamian, 2016; Lazarova & Bahri, 2004). Water reuse decreases the pressure on the freshwater resources, reduces the pollution discharged to water bodies, and can be a reliable source compared to other water resources directly dependent on rainfall (Eslamian, 2016). Due to these advantages and along with the recent developments in wastewater treatment technologies, scientists reported that the worldwide volume of recycled water in the 2010–2015 period increased from 33.7 (million m^3/d) to 54.5 (million m^3/d).

Generally, the application of recycled water can be divided into seven categories, including urban reuse, agricultural reuse, impoundments, environmental reuse, industrial reuse, groundwater recharge/ non-potable reuse, and potable reuse (USEPA (US Environmental Protection Agency), 2012). Of note is that water reuse applications are different in various countries and depend on several factors such as levels of treatment, the conditions of water resources, environmental status, and public willingness (USEPA (US Environmental Protection Agency), 2012). Agricultural water reuse, by far, is the most dominant application of water reuse in the world (Eslamian, 2016). In total, 91% of the recycled water in this section is allocated for crops and pastures irrigation, including the growing of fruit, tree nut, vegetables, cotton, and grain farming (Eslamian, 2016). The residual 9% is dedicated to cleaning piggeries and drinking water for stock and dairy (Eslamian, 2016).

Agricultural water reuse has multiple advantages, such as reducing pressure on freshwater sources (Jaramillo & Restrepo, 2017; Rahman et al., 2016), nutrients management and recovery (Hanjra et al., 2015; Miller-Robbie et al., 2017), and higher reliability due to constant yield (Chen et al., 2012; Rahman et al., 2016). However, wastewater needs to be adequately treated for agricultural irrigation due to potential health risks, especially for food crop irrigation (Khan, 2018). Other major limiting factors in agricultural water reuse include technical feasibility (e.g., treatment technologies and management), economic factors (e.g., water distribution cost), social factors (e.g., social acceptance and consumer response), and regulatory considerations (e.g., lack of regulations or guidelines) (Bixio et al., 2008; Urkiaga et al., 2008).

Of note is that while the focus of this study was agricultural water reuse, there might be some other challenges in the future related to water reuse in general (such as developing methods of coupling advanced wastewater treatment with seawater

desalination facilities; developing efficient methods of risk assessment for water reuse practices; establishing regulations and guidelines which ensure promoting and regulating water reuse practices) (Angelakis et al., 2018). A list of benefits and constraints of water reuse in agriculture is provided in Table 2. It should be noted that not every water reuse project will result in all these benefits immediately, nor will it face all these challenges at the same time (Lazarova & Bahri, 2004).

Table 2. Benefits and challenges of agricultural water reuse (adapted from Lazarova and Bahri (2004)).

Benefits	**Challenges**
Sustainable development: - Increasing food production (Angelakis et al., 2018). - Improving aquatic life/ fish production (Qadir et al., 2007). - Sustainable development of dry regions (Angelakis et al., 2018).	Technical issues: - Operation/ maintenance reliability (Easa et al., 1995). - Increasing water system complexity (Alderson et al., 2015). - Proper design of treatment processes (Zarghami & Akbariyeh, 2012). - Water reuse infrastructure resilience (Zhu & McBean, 2007). - Available knowledge/ expertise/ experience (Scott et al., 2012).
Water conservation: - Closing water cycle (Almasri & McNeill, 2009). - More efficient water use (Vergine et al., 2017). - Saving high-quality water (Alkhamisi et al., 2011).	Social concerns: - Unequal development. - Social acceptance (Sakellariou-Makrantonaki et al., 2003; Zozaya et al., 2018). - Consumer response/ crop marketability (Suri et al., 2019). - Conflicts between different stakeholders. - Socioeconomic/ cropping patterns change (Maloupa et al., 1999).
Water supply: - Reliable/ secure/ drought-proof water source (Eslamian, 2016). - Alternative/ efficient/ independent water supply (Eslamian, 2016).	Future challenges: - Developing methods of coupling advanced wastewater treatment with seawater desalination facilities (Mahesh et al., 2015). - Developing efficient risk assessment methods (Mahesh et al., 2015). - Establishing regulations and guidelines that promote and regulate water reuse practices (Mahesh et al., 2015).
Health benefits: - Improving public health (Hanjra et al., 2012). - Improving health/ environmental justice (Eslamian, 2016; Lazarova & Bahri, 2004).	Health concerns: - Microbial/ chemical pollution (Falkenberg et al., 2018). - The health of farmers/ workers/ consumers (Falkenberg et al., 2018). - Inadvertent exposure/ unreliable operation (Falkenberg et al., 2018).

Table 1 (continued). Benefits and challenges of agricultural water reuse (adapted from Lazarova and Bahri (2004)).

Benefits	**Challenges**
Environmental benefits: - Linking rural-urban areas (Capodaglio, 2017). - Reducing pollutants discharge (Hanjra et al., 2012). - Avoiding groundwater pollution (Hanjra et al., 2012). - Avoiding new water supply impacts (Chu et al., 2004). - Effective use of wastewater nutrients (Hanjra et al., 2012). - Improving the recreational value of waterways (Nazari et al., 2012). - Alternative to wastewater permit restrictions (Massey, 1983).	Environmental concerns: - Polluting soils (Hanjra et al., 2012). - Endangering wildlife (Fatta-Kassinos et al., 2011). - Polluting water bodies (Gallegos et al., 1999). - Greenhouse gas emissions (Matos et al., 2014). - Negative effects on crops/ food (Alarcón & Pedrero, 2009).
Legal benefits: - Policy awareness (Drechsel et al., 2008). - Compatible with treatment regulations (Quist-Jensen et al., 2015).	Legal issues: - Water rights. - Lack of reuse regulations/ guidelines (Angelakis et al., 1999).
Economic benefits: - Avoiding development costs (Okun, 1997). - Increasing land/ property value (Anwar et al., 2010). - Increasing tourism activities in dry regions (Borboudaki et al., 2005). - Additional revenue from recycled water sales (Rao et al., 2015). - Secondary revenue for customers/ industries (Rao et al., 2015). - Reducing/ eliminating commercial fertilizers (H. Marecos do Monte et al., 1989). - Lowering water treatment costs for downstream (Hanjra et al., 2012).	Economic challenges: - Water pricing. - Demand variations. - Vulnerability to market change (Rao et al., 2015). - Difficult revenue and cost recovery (Rao et al., 2015). - Large storage capacity requirement (Afshar & Mariño, 1989). - Cost of water reuse infrastructure/ operation and maintenance (Rao et al., 2015). - Need for a well-adapted economic approach (Rao et al., 2015).

3.1.1. Water reuse history

Humans have practiced water reuse for a very long time, sometimes not in an appropriate way. During the Bronze age, 3200–1100 BC, ancient civilizations used domestic wastewater to irrigate their crops (Angelakis & Gikas, 2014). Ancient Greeks conveyed their domestic wastewater to a storage chamber using a sewer system in public latrines (Jaramillo & Restrepo, 2017). Greeks and Romans also used wastewater in agricultural irrigation, preparing fertilizer for crops and orchards (Tzanakakis et al., 2007). During early modern history (1550–1700), direct use of wastewater in agriculture was being applied in Germany, Scotland, and England (Jaramillo & Restrepo, 2017). Beginning in the 19th century, irrigation with wastewater gained more popularity in some European and U.S. cities like Paris,

London, and Boston (Jaramillo & Restrepo, 2017). At about the same time, the first wastewater irrigation in agriculture happened in Australia (Tzanakakis et al., 2014; Tzanakakis et al., 2007).

However, conveying and discharging the untreated wastewater in urban fields caused epidemics of waterborne diseases, such as cholera and typhoid fever (Jaramillo & Restrepo, 2017). Unsafe wastewater application in urban and agricultural areas, industrialization, and urbanization resulted in unhealthy situations for societies in the 19th century (Jaramillo & Restrepo, 2017). To address the existing problems, some practical efforts were as follows: (1) establishing Great Britain's Public Health Act, (2) holding a lot of sanitary conferences on sanitation and demography, (3) the constitution of the International Office of Public Hygiene, and (4) constructing underground sewage systems (Jaramillo & Restrepo, 2017).

3.1.2. Water reuse current status

FAO (Food and Agriculture Organization of the United Nations) has estimated that 3.928×10^{12} m^3 of freshwater was withdrawn from existing water sources in 2010. In total, 11% of the total water withdrawal in the world was municipal water demand, of which 3% was consumed, and 8% was discharged as municipal wastewater (WWAP (United Nations World Water Assessment Programme), 2017). There were 2.75×10^6 million m^2 of land consisting of irrigated agriculture worldwide, of which about 15% (4×10^5 million m^2) could be irrigated by municipal wastewater (WWAP (United Nations World Water Assessment Programme), 2017). Moreover, 32% of the worldwide water withdrawal was discharged as agricultural wastewater and drainage (WWAP (United Nations World Water Assessment Programme), 2017). The majority of wastewater recycled in agriculture is municipal wastewater. However, these results show the need to change the focus of water reuse policies and plans from municipal wastewater management to sustainable management of municipal and agricultural (drainage and return flow) wastewater (Eslamian, 2016). Furthermore, approximately 5×10^4 to 2×10^5 million m^2 of the irrigated land is irrigated by raw and diluted wastewater, with the most considerable portion being in China (WWAP (United Nations World Water Assessment Programme), 2017). This includes 2–7% of the world's total irrigated area. Accordingly, there is great potential for implementing planned and safe water reuse in agriculture.

While irrigation with recycled water is recognized as an alternative source to reduce the pressure on freshwater sources, the ultimate goal is the safe implementation of water reuse practices (Eslamian, 2016). One of the necessities for the safe application of recycled water is to ensure that it has the desired quality and poses no harm to human health and the environment (Khan, 2018). Started by the state of California in 1918, countries around the world, alongside international organizations (e.g., World Health Organization (WHO) and FAO), have started to establish their water reuse regulations and guidelines to ensure safe water reuse practices (Angelakis & Gikas, 2014). Countries and organizations have generally taken different approaches to establish regulations and guidelines (Brissaud, 2008). For instance, some countries

like Canada, Australia, and many states in the U.S. have issued more restrictive regulations, while others have chosen to take less restrictive approaches to develop water reuse regulations and guidelines. Of note is that there is no federal regulation or guideline for agricultural water reuse in the U.S. (USEPA (US Environmental Protection Agency), 2012). It is up to the states to establish their own regulations or guidelines (USEPA (US Environmental Protection Agency), 2012).

When compared in more detail, it becomes apparent that current agricultural water reuse regulations and guidelines vary significantly (Eslamian, 2016). For instance, some of the regulations and guidelines do not consider some of the biological and microbial quality parameters, and some others do not consider some of the physico-chemical parameters. Furthermore, even in regulations and guidelines that do consider the same parameters, the threshold levels for those parameters vary significantly. As water reuse in agriculture is becoming popular as a beneficial approach to addressing water scarcity, the disparity in regulations and guidelines may become a source of problems at both regional and global levels (Brissaud, 2008). At the regional level, the absence of unified or at least relatively similar water reuse regulations and guidelines may result in uncertainty among stakeholders (e.g., farmers, consumers, and policymakers), thereby slowing down the promotion of water reuse in agriculture.

The U.S. is an excellent example in that respect. In the U.S., 42 and 28 states have regulations or guidelines for nonfood crop/ processed food crop and food crop irrigation, respectively (USEPA (US Environmental Protection Agency), 2012). Eight states do not have any regulations or guidelines for agricultural water reuse. The water quality parameters and the threshold levels in those regulations and guidelines are different when looked at in more detail. This may create uncertainty among stakeholders and increase the risk of public acceptance, thereby slowing down the implementation of agricultural water reuse (Eslamian, 2016). In addition, agriculture has a global market, and agricultural commodities are being imported/ exported worldwide. As a result, the difference in regulations and guidelines between the countries of origin and the end-use countries may pose significant obstacles to food safety, market acceptability, and import/ export relationships.

To date, there are very few studies that investigate and compare the existing agricultural water reuse regulations and guidelines in the U.S. and worldwide. The main objectives of this research were to compile and compare the existing agricultural water reuse regulations and guidelines around the world and identify the gaps in those regulations and guidelines. To achieve this goal, the most up to date regulations and guidelines were issued by national and international organizations (e.g., Environmental Protection Agency (EPA), International Organization for Standardization (ISO), FAO, WHO, European Commission), and by pioneering countries in water reuse (e.g., U.S., Canada, Mexico, Iran, Egypt, Tunisia, Jordan, Israel, Oman, China, Kuwait, Saudi Arabia, Australia, France, Greece, Portugal, Cyprus, Spain, and Italy) were obtained and investigated in this study. In addition, the water quality criteria in those regulations and guidelines were compared, and the

major differences between those criteria were identified. Results from this study identified the discrepancies in the current regulations and guidelines. They also highlighted the challenging areas that need to be addressed to promote agricultural water reuse with respect to the existing regulations and guidelines.

3.2. Methodology

To compile a complete worldwide agricultural water reuse regulations and guidelines database, the Google Scholar search engine was used as the first step of this study. In this step, keywords including "water reuse," "water reclamation," "water recycling," "wastewater reuse," "wastewater recycling," "recycled water," "reclaimed water," "agriculture," "regulation," "guideline," "standard," and "criteria" were used. Peer-reviewed journal articles related to agricultural water reuse regulations and guidelines were compiled and reviewed.

In the second step, study cases were identified based on the results obtained from the first step (e.g., countries, international organizations, and state agencies that have issued/ established agricultural water reuse regulations or guidelines). In the third step, the official website of the organizations (e.g., state agencies, ministries, and governmental institutes) were investigated. Moreover, official representatives at organizations/ agencies were contacted if needed to ensure that the obtained regulations and guidelines were the latest version. In total, 70 agricultural water reuse regulations and guidelines were gathered for this study. These regulations and guidelines were thoroughly analyzed and compared in this study.

3.2.1. Definitions and terminologies

Technical: The use of treated wastewater for beneficial purposes is generally called water reuse (Asano et al., 2007). However, different terminologies have been used in various water reuse regulations and guidelines, such as water reuse, water recycling, water purification, reclaimed water, recycled water, reused water, repurified water, NEWater, and more. To clarify, in this manuscript, water reuse refers to the treatment or processing of wastewater and then the application of the treated wastewater in agriculture. In addition, recycled or reclaimed water refers to the treated wastewater used for different applications. Of note is that "recycled" and "reclaimed" water have been used in this manuscript interchangeably.

Legal: Like scientific and technical terminologies, different legal terminologies have been used for water reuse regulations. While the main focus of this manuscript was technical and scientific aspects of agricultural water reuse, it is helpful to clarify these legal terminologies, which are commonly used in the reference documents (Table 3).

Table 3. The definition of standard, criteria, guideline, and regulation (Asano et al., 2007).

Term	Definition	Comments
Standard	A rule, principle, or measure established by an authority.	Standards are usually quite rigid, official, or quasi-legal. As standards may be written using safety factors, they can be potentially unfair, inequitable, or ignore scientific knowledge. Standards typically include qualitative restrictions in terms of numerical limits.
Criteria	As the basis for standards, criteria are developed based on available data and scientific opinion. It is expected that technical and economic feasibility are not considered in the developing criteria.	Effective criteria have the potential to be evaluated quantitatively through suitable analytical procedures. Criteria include qualitative restrictions (these restrictions can be numerical limits and narrative statements).
Guideline	Best practices that are used prior to the development of standards or regulations.	Usually, guidelines are voluntary, advisory, and non-enforceable. These guidelines can be used in water reuse permits to become enforceable requirements.
Regulation	When a state legislature or a water pollution control agency officially adopts a standard, criteria, or guideline.	Enforceable and mandatory by governmental agencies, water reuse regulations include treatment requirements, cross-connection controls, signage, and setback distances.
Act	Passed by Congress, state legislatures, or Parliament, depending on each country's type of government, acts set out the broad/ policy principles.	

3.3. Results and discussion

Seventy regulations, guidelines, standards, criteria, and acts were included in this study (Table 4). The State of California in the U.S. was the first to issue a specific regulation for agricultural water reuse in 1918. After 48 years, the following regulation was issued by the state of Iowa in the U.S. in 1966, followed by Mexico's standard in 1971. WHO is the first international organization that issued a guideline for agricultural water reuse in 1973. As illustrated in Table 4, among the 70 investigated documents, there were 30 regulations, 29 guidelines, six standards, four criteria, and only one act. It was found that most of these regulations and guidelines were issued after 1973, and most of them were issued after 1998. Starting from the 1970s and 1980s, international organizations, including WHO, FAO, and the World Bank, tried to effectively notify countries and organizations around the world of the importance of safe water reuse practices, resulting in the propagation of establishing water reuse regulations and guidelines (Eslamian, 2016).

Table 4. Agricultural water reuse regulations or guidelines included in this study.

#	Year[1]	Country (state)	Current edition	Type
1	1918	US (California)	Title 22: California Water Recycling Criteria (California Code of Regulations, 1918), Water Code-division 7- article 7 (California Legislative Information (Water Code), 1918).	Regulation
2	1966	US (Iowa)	567 IAC Chapter 62: Effluent and Pretreatment Standards: Other Effluent Limits or Prohibitions (NPDES Rules, 1966).	Regulation
3	1971	Mexico	Standard NOM-001-ECOL-1996 (Peasey et al., 2000; Wastewater Reuse for Agricultural Irrigation and Its Impact on Health).	Standard
4	1973	WHO	WHO guideline for the safe use of wastewater, excreta, and greywater- volume II- wastewater use in agriculture (World Health Organization, 2006b).	Guideline
5	1975	US (Alabama)	Alabama Environmental Regulations and Laws-division 6- volume 3- reclaimed water reuse program (Alabama Environmental Regulations and Laws, 1975).	Guideline

Table 3 (continued). Agricultural water reuse regulations or guidelines included in this study.

#	Year[1]	Country (state)	Current edition	Type
6	1976	US (South Carolina)	Regulation 61-9, Water Pollution Control Permits (Water Regulations & Standards: Water Pollution Control Permits, 1976).	Regulation
7	1977	Italy	National Inter Ministry Committee for the Protection of Waters from Pollution (Barbagallo et al., 2001).	Regulation
8	1980	EPA[2]	Guidelines for water reuse (USEPA (US Environmental Protection Agency), 2012).	Guideline
9	1981	US (Arizona)	Arizona administrative code, title 18, chapters 9 and 11 (Arizona Administrative Code, 1981).	Regulation
10	1985	US (Delaware)	Regulations governing the design, installation, and operation of On-site wastewater treatment and disposal systems (7101 Regulations Governing the Design, Installation and Operation of On-Site Wastewater Treatment and Disposal Systems, 1985).	Regulation
11		US (Wisconsin)	Chapter NR 206- land disposal of municipal and domestic wastewaters (Wisconsin Legislature: Chapter NR 206-land disposal of municipal and domestic wastewaters, 1985).	Regulation
12	1987	FAO[2]	Wastewater quality guidelines for agricultural use (Wastewater Quality Guidelines for Agricultural Use, 1987).	Guideline
13	1989	US (North Dakota)	Chapter 33-16-01- North Dakota pollutant discharge elimination system (North Dakota Administrative Code- Title 33, 1989).	Guideline
14		Tunisia	Tunisian standards NT 106-03 (Bahri, 2001; Marzougui et al., 2018).	Standard

Table 3 (continued). Agricultural water reuse regulations or guidelines included in this study.

#	Year[1]	Country (state)	Current edition	Type
15	1990	US (Oregon)	Department of environmental quality-Chapter 340-Division 53-Graywater reuse and disposal systems (Oregon Secretary of State- Department of Environmental Quality, 1990).	Regulation
16	1991	US (Florida)	Reuse of reclaimed water and land application (Florida Administrative Rules- Rule Chapter 62-610, 1991).	Regulation
17		France	water reuse criteria for agricultural and landscape irrigation in France (Paranychianakis et al., 2015).	Criteria
18		US (South Dakota)	Recommended Design Criteria Manual - Wastewater Collection and Treatment Facilities (Plans and Specifications - South Dakota Department of Environment and Natural Resources, 1991).	Guideline
19	1992	US (Washington)	Chapter 90.46 RCW (Washington State Legislature- Chapter 90.46, 1992).	Guideline
20	1993	Oman	Ministerial decision no. 145 of 1993, issuing the regulations on wastewater reuse and discharge (Ministerial Decision No. 145 of 1993 Issuing the Regulations on Wastewater Reuse and Discharge., 1993).	Regulation
21	1995	US (Illinois)	Title 35: environmental protection-Subtitle c: water pollution-Chapter ii: environmental protection agency- Part 372 Illinois design standards for slow rate land application of treated wastewater (Illinois Design Standards for Slow Rate Land Application of Treated Wastewater, 1995).	Regulation

Table 3 (continued). Agricultural water reuse regulations or guidelines included in this study.

#	Year[1]	Country (state)	Current edition	Type
22		US (Montana)	DEQ 2 - design standards for wastewater facilities (Montana Department of Environmental Quality, 1995).	Regulation
23	1996	CA (Atlantic Canada)	Atlantic Canada wastewater guidelines manual (Atlantic Canada Wastewater Guidelines Manual | Government of Prince Edward Island, 1996).	Guideline
24	1997	US (Texas)	Chapter 210-use of reclaimed water (Texas Administrative Code, 1997).	Regulation
25	1998	US (Indiana)	Article 6.1 - land application of biosolid, industrial waste product, and pollutant- bearing water (Indiana Administrative Code, 1998).	Regulation
26	1999	AU (Australian Capital Territory)	ACT- wastewater reuse for irrigation (Power, 2010).	Guideline
27		CA (British Columbia)	Chapter 10- use of reclaimed water (B.C. Irrigation Management Guide - Province of British Columbia, 1999).	Regulation
28		Israel	Israeli guideline for wastewater reuse (Aharoni & Cikurel, 2006; Becker, 2011; Inbar, 2007)	Guideline
29	2000	CA (Alberta)	Guidelines for municipal wastewater irrigation (Guidelines for Municipal Wastewater Irrigation, 2000).	Guideline/ Act[1]
30		US (Colorado)	Regulation 84: reclaimed water control regulation (Water Quality Control Commission Regulations-Colorado Department of Public Health and Environment, 2000).	Regulation
31		Greece	(Angelakis et al., 2000; Ilias et al., 2014)	Criteria
32		Saudi Arabia	(Al-Jasser, 2011)	Regulation
33	2001	Kuwait	Standards of the Kuwait Environment Public Authority (KEPA) (Abusam & Shahalam, 2013).	Standard

Table 3 (continued). Agricultural water reuse regulations or guidelines included in this study.

#	Year[1]	Country (state)	Current edition	Type
34	2002	China	GB20922-2007 (Lyu et al., 2016).	Standard
35		US (Hawaii)	Volume 1: recycled water facilities (State of Hawaii, Department of Health-Wastewater Branch, 2002).	Guideline
36		Jordan	Jordanian standard (JS: 893/2002) (World Health Organization, 2006a).	Standard
37		US (Maryland)	Guidelines for use of class iv reclaimed water (Maryland Department of Environment-Wastewater Permits- Guidelines for Use of Reclaimed Water, 2002).	Guideline
38		AU (Tasmania)	Environmental guidelines for the use of recycled water in Tasmania (Power, 2010)	Guideline
39	2003	AU (New South Wales)	The guidelines for sewerage systems: use of reclaimed water (ARMCANZ-ANZECC-NHMRC 2000) (Power, 2010).	Guideline
40		Palestine	(Mimi & Abu Madi, 2009)	Regulation
41		AU (Victoria)	The guidelines for environmental management: use of reclaimed water, guidelines for environmental management: dual pipe water recycling schemes - health and environmental risk management (Power, 2010).	Guideline
42	2004	CA (Saskatchewan)	Treated municipal wastewater irrigation guidelines-EPB 235 (Water Security Agency, 2014).	Guideline
43	2005	Cyprus	Cyprus regulation K.D.269/2005 (USEPA (US Environmental Protection Agency), 2012).	Regulation
44		Egypt	(Abdel-Shafy & Mansour, 2013)	Regulation
45		US (New Jersey)	Reclaimed water for beneficial reuse (Technical Manuals and Guidance Documents, 2005)	Guideline
46		Spain	Spanish regulations for water reuse-royal decree 1620/2007 of 7 December (Spanish Regulations for Water Reuse- Royal Decree 1620/2007 of 7 December, 2005).	Regulation

Table 3 (continued). Agricultural water reuse regulations or guidelines included in this study.

#	Year[1]	Country (state)	Current edition	Type
47	2006	AU (AGWR)	The Australian guidelines for water recycling: augmentation of drinking water supplies (Australian Guidelines for Water Recycling, 2006).	Guideline
48		Portugal	Portuguese standard NP 4434 (M. H. F. Marecos do Monte, 2007).	Criteria
49	2007	US (Ohio)	3745-42-13 Land application systems (Ohio Laws and Rules, 2007).	Guideline
50	2008	US (Idaho)	Rules for the reclamation and reuse of municipal and industrial wastewater (Idaho Department of Environmental Quality, 2008).	Regulation
51		AU (Queensland)	The water quality guidelines for recycled water schemes (DNRW 2008c) (Power, 2010).	Guideline
52		US (Virginia)	Chapter 740. Water reclamation and reuse regulation (Virginia Administrative Code, 2008).	Regulation
53	2009	US (Massachusetts)	314 CMR 20: Reclaimed water permit program and standards (314 CMR 20: Reclaimed Water Permit Program and Standards, 2009).	Regulation
54		AU (Western Australia)	Guidelines for the use of recycled water in western Australia (WA DoH 2009) (Power, 2010).	Guideline
55	2010	Iran	Criteria for using recycled water (In Farsi) (Iran Ministry of Energy-Guidelines for Wastewater Reuse, 2010).	Criteria
56		ISO[2]	Guidelines for treated wastewater use for irrigation projects (ISO 16075-2:2015 - Guidelines for Treated Wastewater Use for Irrigation Projects, 2015).	Standard
57		US (Minnesota)	Municipal wastewater reuse (Minnesota Pollution Control Agency, 2010).	Guideline
58	2011	US (Kansas)	Kansas EPA 503 land application of septage – updated (Kansas EPA 503 Land Application of Septage, 2011).	Guideline

Table 3 (continued). Agricultural water reuse regulations or guidelines included in this study.

#	Year[1]	Country (state)	Current edition	Type
59		US (North Carolina)	Subchapter 02U – reclaimed water (North Carolina Office of Administrative Hearings, 2011).	Regulation
60	2012	US (Georgia)	Guidelines for slow-rate land treatment of wastewater (Wastewater Technical & Environmental Review Guidance and Forms, 2012).	Guideline
61		US (Pennsylvania)	Reuse of treated wastewater guidance manual 385-2188-002 (Point and Nonpoint Source Management, 2012).	Guideline
62		US (Rhode Island)	Guidance for wastewater reuse projects (WWTF - Operations & Maintenance- Rhode Island - Department of Environmental Management, 2012).	Guideline
63		US (Wyoming)	Department of environmental quality, water quality, chapter 21: reuse of treated water (Wyoming Administration Rules, 2012).	Regulation
64	2013	US (New Mexico)	Title 20, chapter 7, part 3 (Liquid Waste Disposal and Treatment, 2013).	Guideline
65		US (Utah)	Title R317. Environmental quality, water quality (Utah Administrative Code- R317. Environmental Quality, Water Quality, 2013).	Regulation
66	2014	AU (Northern Territory)	Guidelines for wastewater works design approval of recycled water systems (Power, 2010).	Guideline
67	2015	US (Oklahoma)	Title 252., chapter 656. Water pollution control facility construction standards (Rules and Regulations - Oklahoma Department of Environmental Quality, 2015).	Regulation
68	2016	US (Nevada)	Use of reclaimed water (Chapter 445a - Water Controls, 2016).	Regulation

Table 3 (continued). Agricultural water reuse regulations or guidelines included in this study.

#	Year[1]	Country (state)	Current edition	Type
69	2017	European Commission	Minimum quality requirements for water reuse in agricultural irrigation and aquifer recharge (Minimum Quality Requirements for Water Reuse in Agricultural Irrigation and Aquifer Recharge - Towards a Water Reuse Regulatory Instrument at EU Level Réédition, 2017).	Guideline
70		US (Nebraska)	Title 119, chapter 12 (Nebraska Administrative Code- Nebraska Department of Environmental Quality, 2017).	Regulation

[1] The dates indicate when the documents were established/ issued for the first time.

3.3.1. Reference regulations and guidelines

This section discusses the pioneer agricultural water reuse regulations and guidelines that have been the source of inspiration and adoption for many states, countries, and organizations. They include WHO, EPA, FAO, Australian Guideline for Water Recycling (AGWR) guidelines, ISO standard, California, and European Commission regulations.

WHO guideline: WHO issued three guidelines for water reuse in 1973, 1989, and 2006. The first document was published in 1973, entitled "*Reuse of effluents: methods of wastewater treatment and health safeguards*," which became one of the main references for other international standards. The main goals of this document were to protect public health and to guide the safe application of wastewater and excreta in agriculture and aquaculture. However, the document had a minimal health risk approach and lacked epidemiological studies (Jaramillo & Restrepo, 2017). Later, the WHO updated its prior guideline in 1989 by implementing a complete epidemiological studies analysis. In this version, entitled "*Health guidelines for the use of wastewater in agriculture and aquaculture*," WHO focused on the microbiological quality of the recycled water for irrigation. Also, risk assessment and necessary information to determine the societies' tolerable risks were included. This guideline lacked any information about surveillance guidelines (Jaramillo & Restrepo, 2017).

WHO's final guideline was published in 2006, entitled "*Safe use of wastewater, excreta and greywater*," to contribute to forming governmental guidelines, standards, and regulations relating to wastewater management for each country regarding its specific situation. There were significant improvements regarding risk assessment in this guideline, including microbiological analysis based on the information gathered

from present pathogens and health risk management; estimations were made based on person per year (PPY) and disability-adjusted life year (DALY) (Jaramillo & Restrepo, 2017).

This risk-based guideline mainly focused on microbial health risks, but it also contained recommended maximum tolerable soil concentrations for various organic and inorganic pollutants assessed by QMRA (Quantitative Microbial Risk Assessment) and epidemiological evidence. The DALYs were used in this guideline to compare the results of a disease from one exposure pathway to another pathway. WHO indicated the determination of DALYs as follows: "*DALYs are calculated by adding the years of life lost to premature death to the years lived with a disability*," accounting for acute and chronic health effects (World Health Organization, 2006b). A water-borne disease burden of 10^{-6} DALYs per person per year was determined as the tolerable risk by WHO (World Health Organization, 2006b).

Critics claim that this is not the most appropriate value, especially in low-income countries (Mara et al., 2010). In this guideline (volume 2, section 4.5), it was mentioned that the appropriate value was less than 10^{-4} or 10^{-5} DALY (loss) per person per year, which Mara et al. supported less than 10^{-4} DALY to be used for water reuse in agriculture (Mara et al., 2010). Moreover, this guideline defined two exposure scenarios for agricultural irrigation, including unrestricted irrigation and restricted irrigation, suggesting the required log pathogen reductions for each of them (*Table 5*). Regarding the physico-chemical quality of the water, WHO refered to the FAO's requirements for irrigation practices. Of note was that WHO guideline required no specific type of treatment for the restrictions mentioned above.

FAO guideline: FAO issued two guidelines for water reuse in 1987 and 1999. In the latest version, FAO divided the application of recycled water in agriculture into three categories, including (A) Irrigation of crops likely to be eaten uncooked, sports fields and public parks, (B) Irrigation of cereal crops, industrial crops, fodder crops, pasture, and trees, and (C) localized irrigation of crops in category B if exposure of workers and the public does not occur (Wastewater Quality Guidelines for Agricultural Use). Moreover, FAO drafted some requirements for interpretation of water quality for irrigation (Table 6), including three degrees of restriction, including severe, slight to moderate, and none, on the use of recycled water based on its quality. Also, threshold levels of trace elements for crop production were introduced by FAO in its last guideline in 1999 (Wastewater Quality Guidelines for Agricultural Use, 1999).

In terms of microbial parameters, FAO followed a moderate approach, similar to WHO, considering epidemiological evidence. FAO recommended stabilization ponds, category A and B, and at least primary sedimentation, category C. In unrestricted category, A, FAO recommended stricter limitations for fruit trees as Fecal Coliforms < 200/100 ml. For physico-chemical parameters, the FAO guideline has been the leading guideline to which the standards, criteria, guidelines, and regulations of other organizations, countries, and state agencies have referred.

Table 5. Health-based targets for recycled water use in agriculture (modified from (World Health Organization, 2006b)*).*

Exposure scenario	Health-based target (DALY per person per year)	E. coli (cfu/100ml)	Log_{10} pathogen reduction needed [a]	Number of helminth eggs per liter
Unrestricted irrigation				
Leaf crops (e.g., lettuce)	$\leq 10^{-6}$[a]	$\leq 10^4$	6	≤ 1[b, c]
		$\leq 10^3$	7	≤ 1[b, c]
Root crops (e.g., onion)		$\leq 10^5$	5	Not recommended [d]
		$\leq 10^3$	7	≤ 1[c]
High growing crops (drip)				
Low-growing crops (drip)				
Restricted irrigation				
Highly mechanized	$\leq 10^{-6}$[a]	$\leq 10^5$	3	≤ 1[b, c]
Labor intensive		$\leq 10^4$	4	≤ 1[b, c]

[a] Rotavirus reduction. The health-based target can be achieved, for unrestricted and localized irrigation, by a 6-7 log unit pathogen reduction (obtained by a combination of wastewater treatment and other health protection measures, including an estimated 3-4 log unit pathogen reduction as a result of the natural die-off rate of pathogens under field conditions and the removal of pathogens from irrigated crops by normal domestic washing and rinsing); for restricted irrigation, it is achieved by a 2-3 log unit pathogen reduction.

[b] when children under 15 are exposed, additional health protection measures should be used (e.g., treatment to ≤ 0.1 egg per liter, protective equipment such as gloves or shoes/boots or chemotherapy).

[c] An arithmetic mean should be determined throughout the irrigation season. The mean value of ≤ 1 egg per liter should be obtained for at least 90% of samples to allow for the occasional high-value sample (i.e., with > 10 eggs per liter). With some wastewater treatment processes (e.g., waste stabilization ponds), the hydraulic retention time can be used as a surrogate to assure compliance with ≤ 1 egg per liter.

[d] No crops to be picked up from the soil.

Table 6. Water quality for irrigation (adapted from (Wastewater Quality Guidelines for Agricultural Use, 1999)*).*

Potential irrigation problem	Units	Degree of restriction on use		
		None	Slight to moderate	Severe
Salinity				
EC^1_w	dS/m	< 0.7	0.7-3.0	> 3.0
or TDS[2]	mg/l	< 450	450-2000	> 2000
Infiltration				
SAR = 0-3 and EC_w		> 0.7	0.7-0.2	< 0.2
3-6		> 1.2	1.2-0.3	< 0.3
6-12		> 1.9	1.9-0.5	< 0.5
12-20		> 2.9	2.9-1.3	< 1.3
20-40		> 5.0	5.0-2.9	< 2.9
Specific ion toxicity				
Sodium (Na)				
Surface irrigation	SAR	< 3	3-9	> 9
Sprinkler irrigation	me/l	< 3	> 3	
Chloride (Cl^-)				
Surface irrigation	me/l	< 4	4-10	> 10
Sprinkler irrigation	m^3/l	< 3	> 3	
Boron (B)	mg/l	< 0.7	0.7-3.0	> 3.0
Miscellaneous effects				
Nitrogen (NO_3-N)	mg/l	< 5	5-30	> 30
Bicarbonate (HCO_3)	me/l	< 1.5	1.5-8.5	> 8.5
pH	Normal range 6.5-8			

[1] Electric conductivity

[2] Total dissolved solids

EPA guideline: EPA developed four guidelines for water reuse in 1980, 1992, 2004, and 2012. The first guideline was issued as a technical research report in 1980. Later in 1992, the EPA updated the first version by including toxicity in crops irrigated with wastewater (Jaramillo & Restrepo, 2017). This version was provided for project planners and state regulatory officials to develop water reuse systems in different states. EPA included two new scopes in its updated guideline in 2004, consisting of "indirect potable reuse" and "industrial reuse." New treatment and disinfection technologies, concerning pathogens and emerging chemicals, information about economics, research actions, funding alternatives, and data sources were also elaborated on in the 2004 edition (Jaramillo & Restrepo, 2017).

The EPA along with the United States Agency for International Development (USAID) issued an updated version of the 2004 EPA guideline in 2012 (Table 7). The ultimate goal of this guideline was to make the water reuse process easy to implement based on global databases. In addition, EPA and USAID included the progress made in wastewater treatment technologies, regional variations of water reuse, best management practices (BMPs) in communities' involvement, case studies of water

reuse around the world, and the development of safe and sustainable water reuse. In this guideline, the EPA suggested some requirements for each water reuse category mentioned in the guideline (Jaramillo & Restrepo, 2017).

The EPA divided agricultural water reuse into two categories: water reuse for food crops and water reuse for processed food crops/ nonfood crops irrigation. This guideline also provided suggestions for the required treatments, recycled water quality, recycled water monitoring, setback distances, and chemical constituents' limits (USEPA (US Environmental Protection Agency), 2012). Secondary treatment, filtration, and disinfection were the required treatments for food crops; secondary treatment and disinfection were the required treatments for processed food crops/ nonfood crops, which were the most common treatments in existing regulations and guidelines. Furthermore, the EPA used a very high-demanding approach for its microbial requirements, resulting in a restrictive guideline for microbial water quality. Moreover, EPA recommended FAO's water quality criteria for irrigation.

AGWR guideline: As a national guideline, the supply and use of recycled water in Australia have been regulated through the *Australian Guideline for Water Recycling: Managing Health and Environmental Risks (AGWR)*. This guideline was issued by Australia's Environment Protection and Heritage Council and the Natural Resource Management Ministerial Council in 2006. The aim was to address the water crisis resulting from widespread droughts and population growth in Australia (NRMMC, 2006). In order to manage the risks to humans and the environment, the guideline focused on two situations, namely, the effluent of a centralized wastewater treatment plant and recycled water from greywater recycling. The guideline helps to identify major health risks and recommends preventive practices to lower those risks to an acceptable level (NRMMC, 2006).

Regarding human health, AGWR focused on microbial risks addressed using DALYs. The tolerable risks in AGWR, like WHO 2006 guideline, was 10^{-6} DALYs per person per year. Reference pathogens, including Campylobacter for bacteria, rotavirus and adenovirus for viruses, and Cryptosporidium parvum for protozoa and helminths, are used for risk identification (NRMMC, 2006). Also, two categories of intended and unintended use are included in the exposure consideration. Moreover, maximum risk, the risk with no preventive practices, residual risk, and remaining risk with the presence of preventive practices were considered for risk characterization in AGWR. For environmental risks, instead of DALYs and health-based targets, environmental values related to the impacts on specific endpoints in the environment were used (e.g., native tree species and specific grasses). Eighteen environmental hazards were identified by AGWR, including Boron, Cadmium, Chlorine disinfection residuals, hydraulic loading (water), Nitrogen, Phosphorus, salinity, Chloride and Sodium, Ammonia, Aluminum, Arsenic, Copper, Lead, Mercury, Nickel, and Surfactants (NRMMC, 2006).

Table 7. EPA guideline for agricultural water reuse (adopted from (USEPA (US Environmental Protection Agency), 2012)*).*

Requirements	Agricultural water reuse category	
	Food crops: crops that are consumed raw by humans.	**Processed food crops:** crops that are processed before human consumption.
Treatment	- Secondary[1] - Filtration[2] - Disinfection[3]	- Secondary - Filtration - Disinfection
Recycled water quality	- pH = 6.0-9.0 - $BOD_5 \leq 10$ mg/l - Turbidity ≤ 2 NTU - Fecal Coliforms = 0/100 ml[4,5,6] -Cl_2 residual ≤ 1 mg/l[7]	- pH = 6.0-9.0 - $BOD_5 \leq 30$ mg/l - Total suspended solids ≤ 2 NTU - Fecal Coliforms ≤ 200/100 ml[4,5,6] -Cl_2 residual ≤ 1 mg/l[7]
Recycled water monitoring	- pH [weekly] - BOD_5 [weekly] - Turbidity [continuous] - Fecal Coliform [daily] - Cl_2 residual [continuous]	- pH [weekly] - BOD_5 [weekly] - Total suspended solids [continuous] - Fecal Coliform [daily] - Cl_2 residual [continuous]
Setback distances	- 50 ft (15 m) to potable water supply wells - 100 ft (30 m) when located in porous media	- 300 ft (90 m) to potable water supply wells - 100 ft (30 m) to areas accessible to the public (if spray irrigation)

[1] Secondary treatment process includes activated sludge processes, trickling filters, rotating biological contractors, and may stabilization pond systems. Secondary treatment should produce effluent in which both the BOD and SS do not exceed 30 mg/l.

[2] Filtration means; the passing of wastewater through natural undisturbed soils or filter media such as sand or anthracite; or the passing of wastewater through microfilters or other membrane processes.

[3] Disinfection means the destruction, inactivation, or removal of pathogenic microorganisms by chemical, physical, or biological means. Disinfection may be accomplished by chlorination, ozonation, other chemical disinfectants, UV, membrane processes, or other processes.

[4] Unless otherwise noted, recommended coliform limits are median values determined from the bacteriological results of the last seven days for which analyses have been completed. Either the membrane filter or fermentation tube technique may be used.

[5]The number of fecal coliform organisms should not exceed 800/100 ml in any sample.

[6] Some stabilization pond systems may meet this coliform limit without disinfection.

[7] This recommendation applies only when chlorine is used as the primary disinfectant. The total chlorine residual should be met after a minimum actual modal contact time of at least 90 minutes unless a lesser contact time has been demonstrated to provide indicator organism and pathogen reduction equivalent to those suggested in these guidelines. In no case should the actual contact time be less than 30 minutes.

California's regulation: As mentioned before, California's regulation (the first version) was the first water reuse regulation worldwide issued in 1918 by the California Department of Health Services. As a pioneer in water reuse regulations, California's regulation has been the basis for many other state agencies as well as other countries and international organizations. This regulation has been considered a very comprehensive and restrictive regulation as it covers a wide range of water quality parameters and other requirements in terms of crops and irrigation types (Table 8). Like the EPA guideline, California's regulation required a high level of disinfection and total coliform inactivation of < 2.2 (total coliform/100 ml). Although this regulation is one of the most developed regulations in terms of water quality monitoring, treatment train design, and operation, it lacks any requirement for irrigation rates or storage requirements (Lazarova & Bahri, 2004).

Since its first edition establishment, California's agricultural water reuse regulation has been continuously studied and revised. The terms "reclaimed water" and "water reuse" in earlier versions of the regulation were changed to "recycled water" and "water recycling" in more recent versions, respectively. Also, oxidized wastewater, undisinfected secondary treated wastewater, was chosen as the requirement for industrial crops (Lazarova & Bahri, 2004). Moreover, turbidity requirements for high-level recycled water uses were added. Of note is that this regulation required no other physico-chemical water quality parameter.

ISO standard: The first ISO standard for water reuse was issued in 2010 based on a request from Israel for water reuse in agriculture, titled PC 253 (ISO 16075-2:2015 - Guidelines for Treated Wastewater Use for Irrigation Projects, 2015). The following ISO standard for water reuse was proposed by Japan to be established along with Israel and China, titled TC 282, in 2015. WHO guideline (2006), Australian national water reuse regulations (2006), Israeli regulations for agricultural irrigation (1978, 1999, and 2005), and California Code of Regulations (Title 22, division 4, chapter 3, water recycling criteria (2000)) were used as the references to establish The ISO standard (ISO 16075-2:2015 - Guidelines for Treated Wastewater Use for Irrigation Projects, 2015).

ISO standard consisted of three sections: 1) Treated wastewater use for irrigation, 2) Treated wastewater use in urban areas, and 3) Risk and performance evaluation of water reuse systems. In the first section, ISO introduced five categories of water quality for water reuse applications for irrigation, A: Very high-quality treated wastewater, B: High quality treated wastewater, C: Good quality treated wastewater, D: Medium quality treated wastewater, and E: Extensively treated wastewater (ISO 16075-2:2015 - Guidelines for Treated Wastewater Use for Irrigation Projects, 2015). As required treatments, combinations of secondary treatment, filtration, and disinfection were used in this guideline, depending on the water quality (ISO 16075-2:2015 - Guidelines for Treated Wastewater Use for Irrigation Projects, 2015).

Although disinfection was needed for A, B, and C categories, there were no residual Chlorine requirements in this guideline. The microbial approach in this standard was

close to the restrictive approach, but it also included the intestinal nematodes. For higher quality water, A and B, the low concentrations of thermo-tolerant coliforms were considered adequate to ensure the water is suitable for unrestricted and restricted food crops irrigation. Irrigation of nonfood, industrial, and seeded crops, C, D, and E, were regulated by thermo-tolerant coliforms and intestinal nematode restrictions. For physico-chemical qualities, ISO included BOD_5 and TSS restrictions, while turbidity was used only for category A recycled water (ISO 16075-2:2015 - Guidelines for Treated Wastewater Use for Irrigation Projects, 2015).

European Commission regulation: A proposal has been put forward by the European Commission to establish a European regulation for agricultural water reuse since May 2018 (Didier, 2018). The proposal's goals were to encourage the application of recycled water and to help address the water crisis in Europe (Didier, 2018). As an EU-wide project, it was estimated that the project could decrease the water stress in Europe by 5% by increasing the application of recycled water from 1.7 billion m^3 to 6.6 billion m^3, annually (Didier, 2018).

The references used to establish the proposal included a commission impact assessment for the 2012 Blueprint communication (Proposal for a Regulation of the European Parliament and of the Council on Minium Requirements for Water Reuse, 2012), a study on guidelines, needs, and barriers related to water reuse (Alcalde Sanza & Gawlik, 2014), a 2017 report on minimum quality requirements for wastewater reuse (JRC, 2017), a 2017 hydro-economic analysis (Pistocchi et al., 2018), a 2013 report on wastewater reuse in the EU (Raso, 2013), a 2015 report on optimizing water reuse in the EU (Knox et al., 2015), a 2016 report on EU-level instruments on water reuse (*EU Level Instrument on Water Reuse-Final Report EU-Level Instruments on Water Reuse Final Report to Support the Commission's Impact Assessment*, 2016), and a 2017 report on the patterns of unplanned water reuse (Drewes et al., 2017).

The proposal required the operators of water reuse practices to comply with minimum recycled water quality requirements summarized in Table 9. Moreover, the proposal required the operators to establish a risk management plan to ensure addressing the potential additional dangers (Didier, 2018). The Committee on Environment, Public Health, and Food Safety (ENVI) was the responsible committee for this proposal in the European Parliament.

Table 8. Water quality for irrigation in California's regulation (adapted from Title 22: California Water Recycling Criteria (California Legislative Information (Water Code))*).*

Irrigation type	Disinfected tertiary recycled water	Disinfected secondary 2.2 recycled water	Disinfected secondary 23 recycled water	Undisinfected secondary recycled water
Food crops where recycled water contacts the edible portion of the crop, including all root crops	✓	✗	✗	✗
Parks and playgrounds	✓	✗	✗	✗
School grounds	✓	✗	✗	✗
Residential landscaping	✓	✗	✗	✗
Unrestricted-access golf courses	✓	✗	✗	✗
Any other irrigation uses not specifically prohibited by other provisions of the California Code of Regulations	✓	✗	✗	✗
Food crops, surface-irrigated, above-ground edible portion, not contacted by recycled water	✓	✓	✗	✗
Cemeteries	✓	✓	✓	✗
Freeway landscaping	✓	✓	✓	✗
Restricted-access golf courses	✓	✓	✓	✗
Ornamental nursery stock and sod farms with unrestricted public access	✓	✓	✓	✗
Pasture for milk animals for human consumption	✓	✓	✓	✗
Nonedible vegetation with access control to prevent use as a park, playground, or school grounds	✓	✓	✓	✗
Orchards with no contact between edible portions and recycled water	✓	✓	✓	✓
Vineyards with no contact between edible portions and recycled Water	✓	✓	✓	✓
Non-food-bearing trees, including Christmas trees not irrigated less than 14 days before harvest	✓	✓	✓	✓
Fodder and fiber crops and pasture for animals not producing milk for human consumption	✓	✓	✓	✓
Seed crops not eaten by humans	✓	✓	✓	✓
Food crops undergoing commercial pathogen-destroying processing before consumption by humans	✓	✓	✓	✓
Ornamental nursery stock, sod farms not irrigated less than 14 days before harvest	✓	✓	✓	✓

✓ Allowed, ✗ Not allowed.

Table 9. The E.U. commission proposal for minimum recycled water quality in agriculture (adapted from (Didier, 2018)*).*

	A	**B**	**C**	**D**
Crop category	Root crops consumed raw; food crops, where the edible part is in direct contact with reclaimed water; other food crops	Food crops consumed raw, where the edible part is produced above ground and is not in direct contact with recycled water; processed food crops; non-food crops, including crops to feed milk- or meat-producing animal		Industrial, energy, and seed crops
Irrigation method	All methods	All methods	Drip irrigation only	All methods
Treatment	Secondary, tertiary and advanced treatment	Secondary and tertiary treatment	Secondary and tertiary treatment	Secondary and tertiary treatment
E. Coli (cfu/100 ml)	≤ 10	≤ 100	≤ 1,000	≤ 10,000
BOD_5 (mg/l)	≤ 10	25	25	25
TSS (mg/l)	≤ 10	35	35	35
Turbidity (NTU)	≤ 5	NS[1]	NS	NS
Other	Legionella spp.: < 1,000 cfu/l where there is a risk of aerosolization in greenhouses. Intestinal nematodes (Helminth eggs): ≤1 egg/l for irrigation of pastures or forage			

[1] Not specified.

3.3.2. Recycled water quality standards

In most cases, agricultural water reuse regulations and guidelines include three categories of water quality, treatment processes, and irrigation technologies (Angelakis et al., 1999). Recycled water quality can be categorized into three groups including human-health parameters, agronomic parameters, and physico-chemical parameters, each of which consists of many specific water quality parameters (Lazarova & Bahri, 2004) (Figure 2).

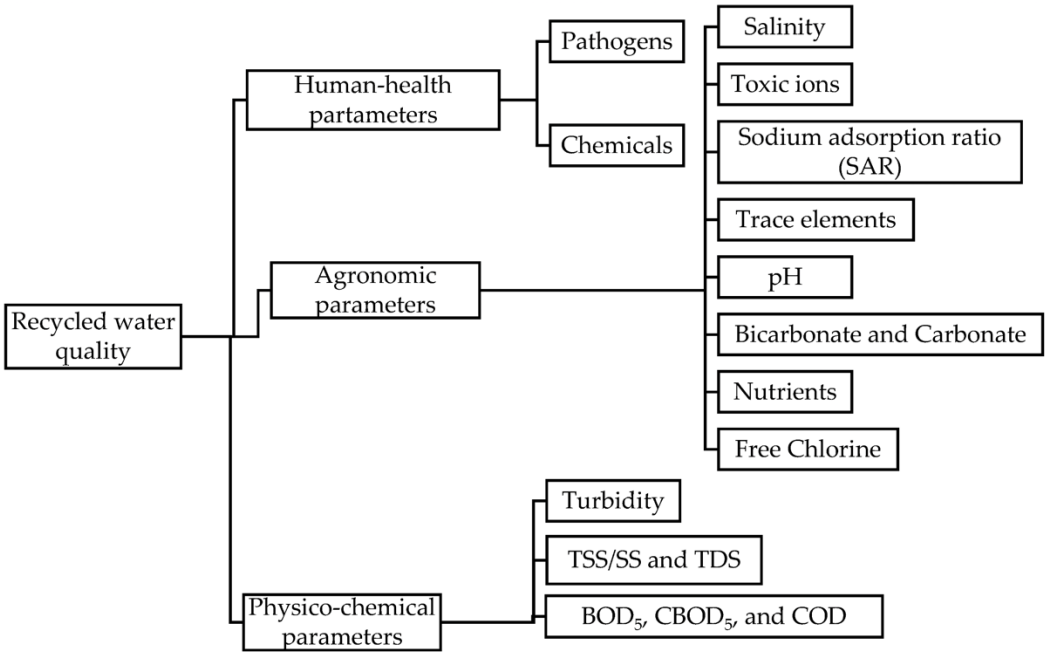


Figure 2. Agricultural water quality parameters.

3.3.2.1. Human-health parameters

Human-health parameters are of prominent importance in safe agricultural water reuse practices. The health of farmers, workers, consumers, and people who live in the close vicinity of farms must be considered for safe agricultural water reuse practices. This issue has been addressed mainly by including microbial and chemical water quality parameters related to human health.

I) Pathogens: The presence of pathogens is the main health concern when recycled water is used for irrigation. Scientists and experts have concluded that it is not practical to monitor the existence of all the pathogens in recycled water. Therefore, the indicator organism concept has been used to monitor the pathogens in a more practical manner (Lazarova & Bahri, 2004). There are many waterborne pathogens and their microbiological indicators, which have been included in the regulations and guidelines. In general, there are two major approaches to microbial water quality including “no fecal indicator bacteria” and “no real risk of infection”.

No Fecal Indicator Bacteria in the Water: In this approach, the assumption is that it is not viable to monitor all the pathogenic microorganisms (Blumenthal et al., 2000). Therefore, coliforms are considered as substitute parameters. Fecal coliforms are the most common bacteria of thermo-tolerant coliforms. Additionally, E. coli is the most common fecal indicator bacterium used by different organizations and countries. Under this approach, no detectable fecal indicator is required using fecal indicator as the microbial indicator. The advantage of this approach is that there is no need to monitor all the pathogenic microorganisms. On the other hand, the disadvantage of this approach is that it is so strict and costly even though there is no need to monitor all pathogenic microorganisms (Blumenthal et al., 2000).

Shuval et al. (1997) argued that using this approach would increase cost per case of disease averted. They estimated that the cost of using no detectable fecal coliform/100 mL was near US $330 million more than using 1000 fecal coliform/100 mL per each case of an infectious disease (i.e., hepatitis A) prevented (Shuval et al., 1997). As the level of endemic enteric diseases in developed counties are low, this higher cost may be justified. However, other countries with high levels of endemic enteric diseases which usually are transmitted through low levels of sanitation and hygiene may not justify this higher cost (Blumenthal et al., 2000). Of note is in most cases, the state of California's regulation has been widely used as the benchmark regulation under this approach by other organizations and agencies. In this study, we call regulations and guidelines which used this approach "restrictive".

From the Epidemiological Point of View; no Real Risk of Infection: According to this approach, epidemiological evidence must be used to issue any microbial quality requirement (Blumenthal et al., 2000). The advantage of using this method is that the risk assessment process is done by studying the infection between exposed people to the recycled water. In this method, people exposed to different recycled water qualities would be studied to determine what level of recycled water quality results in no more excess infection cases in the study population. On the other hand, this approach is only valid for the specific time and place that the risk assessment has been conducted. Therefore, to use the results in regulations and guidelines, they must be extrapolated, which requires making some assumptions about the changes to the variables, making it less precise.

Additionally, conducting epidemiological studies are not always easy, especially in developing countries. For example, there are critics about insufficiency of these studies and existence of some groups of people who have been immunized to many enteric infections. In addition, there may be a lack of health risk assessment methodologies which were used before for these types of studies (Blumenthal et al., 2000). The other disadvantage of this method is that epidemiological studies do not consider the secondary transmission (Blumenthal et al., 2000). Of note is in most cases, the WHO guideline has been considered as the benchmark guideline under this approach by other organizations and agencies. In this study, we call regulations and guidelines which used this approach "less restrictive".

Among the regulations and guidelines that were evaluated for this study, there were 49 documents that were considered restrictive, and 15 documents that were less restrictive (Table 10 and Table 11). The microbial quality parameters in restrictive agricultural water reuse regulations and guidelines were Fecal Coliforms (25 documents), E. coli (21 documents), Total Coliforms (7 documents), Intestinal Nematodes (6 documents), Thermo-tolerant Coliforms (5 documents), Enterococci (2 documents), Somatic Coliphages (2 documents), Clostridium Perfringens (1 document), and F-RNA Bacteriophages (1 document). In general, the threshold limits for food crops irrigation and unrestricted public access categories had lower limits compared to processed food crops/ non-food crops irrigation and restricted public access categories.

When compared, regulations and guidelines established by different organizations and agencies sometimes had different threshold levels for the same parameters (Table 10). The comparison also showed a considerable level of discrepancy among the restrictive regulations and guidelines with respect to microbial water quality (Table 10). It was apparent that restrictive regulations or guidelines have been adopted by developed countries in the world due to their costs and high-tech requirements. It was estimated that restrictive regulations and guidelines cost an additional $3–30 million per prevented enteric disease (Shuval et al., 1997).

Table 10. Restrictive agricultural water reuse regulations and guidelines.

Reuse Categories	**Required Microbial Quality (cfu/100 ml) [Monitoring]**
EPA (2012)	
Food crops	Fecal coliforms [daily] - 0 (median of last 7 days) - 14 (max)
Processed food crops/ non-food crops	Fecal coliforms [daily] - 200 (median of last 7 days) - 800 (max)
ISO (2015)	
A: very high-quality treated wastewater; unrestricted urban irrigation and agricultural irrigation of food crops consumed raw	Thermo-tolerant coliforms - 10 - 100 (max)
B: high quality treated wastewater; restricted urban irrigation and agricultural irrigation of processed food crops	Thermo-tolerant coliforms - 200 - 1000 (max)
C: good quality treated wastewater; agricultural irrigation of non-food crops	Thermo-tolerant coliforms - 1000 - 10,000 (max) Intestinal nematodes - 1 egg/l (average)
D: medium quality treated wastewater; restricted irrigation of industrial and seeded crops	Intestinal nematodes - 1 egg/l (ave) - 5 egg/l (max)
E: extensively treated wastewater; restricted irrigation of industrial and seeded crops	Intestinal nematodes - 1 egg/l (ave) - 5 egg/l (max)
British Columbia	
Restricted	Fecal coliform [weekly] - 200
Unrestricted	Fecal coliform [daily] - 2.2

Table 10 (continued). Restrictive agricultural water reuse regulations and guidelines.

Reuse Categories	Required Microbial Quality (cfu/100 ml) [Monitoring]
Alabama	
	- E. Coli [daily] - 18 (median of the last 7 results) - 34 (max)
Atlantic Canada	
Restricted	E. Coli [2/month] - 200 (only golf courses and parks)
Unrestricted	E. Coli [2/month] - 2 (only golf courses and parks)
Saskatchewan	
Food crops	Fecal Coliform or E. Coli [1/Week] - 2.2 (Median) - 23 (Max)
Non-food crops	Fecal Coliform or E. Coli [1/Month] - 1,000
Arizona	
Food crops	Fecal Coliform [Daily] - 0 (4 of the last 7 daily samples) - 23 (Max)
Processed food crops/ non-food crops	Fecal Coliform [Daily] - 1,000 (4 of the last 7 daily samples) - 4,000 (Max)
California	
Food crops	Total Coliform Bacteria [Daily] - 2.2 (Last 7 Days) - 23 (One Sample in Any 30-Day Period) - 240 (Max)
Colorado	
Processed food crops/ non-food crops	E. Coli - 126 (Monthly Geometric Mean) - 235 (Max)
Delaware	
All types	Fecal Coliform [2/Month] - 20
Florida	
Food crops	Fecal Coliforms - 0 (75% Samples) - 25 (Max)
Processed food crops/ non-food crops	Fecal Coliforms - 200 (Ave) - 800 (Max)

Table 10 (continued). Restrictive agricultural water reuse regulations and guidelines.

Reuse Categories	Required Microbial Quality (cfu/100 ml) [Monitoring]
Georgia	
Processed food crops/ non-food crops	- Fecal Coliform [Daily] - 23 (Monthly Geometric Mean) - 46 (Weekly Geometric Mean) - 100 (Max)
Hawaii	
Food crops	R-1: Fecal Coliform [Daily] - 2.2 (Last 7 Days) - 23 (More Than 1 Sample in any 30-Day Period) - 200 (Max) R-2: Fecal Coliform [Daily] - 23 (Last 7 Days) - 200 (More Than One Sample in Any 30-Day Period)
Idaho	
Food crops	B: Total Coliform [Daily] - 2.2 (Median) - 23 (Max) C: Total Coliform [Weekly] - 23 (Median) - 230 (Max)
Processed food crops/ non-food crops	C: Total Coliform [Weekly] - 23 (Median) - 230 (Max) D: Total Coliform [Monthly] - 230 (Median) - 2300 (Max)
Indiana	
Food crops	Fecal Coliform [Daily] - 0 (Median Value) - 14 (Max)
Processed food crops/ non-food crops	Fecal Coliform [Daily] - 200 (Median Value) - 800 (Max)

Table 10 (continued). Restrictive agricultural water reuse regulations and guidelines.

Reuse Categories	Required Microbial Quality (cfu/100 ml) [Monitoring]
Kansas	
Restricted	E. Coli [2/Month] - 160
Unrestricted	E. Coli [2/Month] - 20
Maryland	
Class i (restricted access)	Fecal Coliform - 200 (Monthly Geometric Mean)
Class ii (restricted access)	Fecal Coliform - 3 (Monthly Geometric Mean)
Class iii[1] (restricted access)	Fecal Coliform - 2.2 (Monthly Geometric Mean)
Massachusetts	
A: food crops, unrestricted	Fecal Coliform - 0 (Median, Continuous 7-Day Sampling) - 14 (Max)
B: pasture for milking animals, unprocessed food crops (no contact with the edible part of crop), restricted	Fecal Coliform - 14 (Median, Continuous 7-Day Sampling) - 100 (Max)
C: orchard and vineyard (no contact with the edible part of crop), processed food crops	Fecal Coliform - 200 (Median)
Minnesota	
Food crops	Total Coliform - 2.2
Processed food crops/ non-food crops	Fecal Coliform - 200
Montana	
All types	Total Coliforms [Weekly] - 2.2 (Last 7 Days) - 23 (Max)
Nevada	
Processed food crops/ non-food crops	Fecal Coliform - 200 (30-Day Geometric Mean) - 400 (Max)

Table 10 (continued). Restrictive agricultural water reuse regulations and guidelines.

Reuse Categories	Required Microbial Quality (cfu/100 ml) [Monitoring]
New Jersey	
Food crops	Fecal Coliform - 2.2 (7-Day Median) - 14 (Max)
Processed food crops/ non-food crops	Fecal Coliform - 200 (Monthly Geometric Mean) - 400 (Weekly Geometric Mean)
North Carolina	
All types	E. Coli or Fecal Coliform - 14 (Monthly Geometric Mean) - 25 (Max)
North Dakota	
Processed food crops/ non-food crops	E. Coli [Weekly] - 126 (Max)
Ohio	
Processed food crops/ non-food crops	Fecal Coliform [3/Week] - 1,000 E. Coli [3/Week] - 126
Oklahoma	
Processed food crops/ non-food crops	Fecal Coliform [3/Week] - 200 (Monthly Geometric Mean) - 400 (Max)
Oregon	
Food crops	Total Coliform - 2.2 (Last 7 Days) - 23 (Max)
Processed food crops/ non-food crops	Total Coliform - 23 (Last 7 Days) - 240 (Any 2 Consecutive Samples)
Pennsylvania	
Food crops	Fecal Coliform [2/week] - 2.2 (Monthly Average) - 23 (Max)
Processed food crops/ non-food crops	Fecal Coliform [Weekly] - 200 (Monthly Average) - 800 (Max)
Rhode Island	
Processed food crops/ non-food crops	Fecal Coliform - 23

Table 10 (continued). Restrictive agricultural water reuse regulations and guidelines.

Reuse Categories	Required Microbial Quality (cfu/100 ml) [Monitoring]
Texas	
Food crops	Fecal Coliform or E. Coli [2/Week] - 20 (30-Day Geometric Mean) - 75 (Max) Enterococci [2/Week] - 4 (30-Day Geometric Mean) - 9 (Max)
Processed food crops/ non-food crops	Fecal Coliform or E. Coli [Weekly] - 200 (30-Day Geometric Mean) - 800 (Max) Enterococci [Weekly] - 35 (30-Day Geometric Mean) - 89 (Max)
Utah	
Food crops	E. Coli - 0 (Daily Grab Samples) - 9 (Max)
Processed food crops/ non-food crops	E. Coli - 126 (Weekly Median) - 500 (Max)
Virginia	
Food crops	Fecal Coliform - 14 (Monthly Geometric Mean); Cat[2]> 49/100 ml E. Coli - 11 (Monthly Geometric Mean); Cat > 35/100 ml Enterococci - 11 (Monthly Geometric Mean); Cat > 24/100 ml
Processed food crops/ non-food crops	Fecal Coliform - 200 (Monthly Geometric Mean); Cat> 800/100 ml E. Coli - 126 (Monthly Geometric Mean); Cat > 235/100 ml Enterococci - 35 (Monthly Geometric Mean); Cat > 104/100 ml

Table 10 (continued). Restrictive agricultural water reuse regulations and guidelines.

Reuse Categories	Required Microbial Quality (cfu/100 ml) [Monitoring]
Washington	
Food crops	Total Coliform [Daily] - 2.2 (Median of Last 7 Days) - 23 (Max)
Processed food crops/ non-food crops	Total Coliform [Daily] - 23 (Median of Last 7 Days) - 240 (Max)
Cyprus	
Agglomerations > 2000 p.e[3]	E. Coli [1/15 Days] - 5 Intestinal Nematodes - 0
Agglomerations < 2000 p.e all crops	Fecal Coliforms - 5 (80% Of Samples Per Month (Min. Number of Samples=5)) - 15 (Max) Intestinal Nematodes - 0
Agglomerations < 2000 p.e unlimited access and vegetables eaten cooked (potatoes, beetroots, colocasia)	Fecal Coliforms - 50 (80% Of Samples Per Month (Min. Number of Samples=5)) - 100 (Max) Intestinal Nematodes - 0
Agglomerations < 2000 p.e limited access and crops for human consumption	Fecal Coliforms - 1,000 (80% Of Samples Per Month (Min. Number of Samples=5)) - 5,000 (Max) Intestinal Nematodes - 0
Agglomerations < 2000 p.e fodder crops	Fecal Coliforms - 1,000 (80% Of Samples Per Month (Min. Number of Samples=5)) - 5,000 (Max) Intestinal Nematodes - 0
Italy	
NS	E. Coli - 10

Table 10 (continued). Restrictive agricultural water reuse regulations and guidelines.

Reuse Categories	Required Microbial Quality (cfu/100 ml) [Monitoring]
Greece	
Restricted irrigation, fodder and industrial crops, pastures, trees (except fruit trees), if fruits are not in contact with the soil, seed crops and crops whose products are processed before consumption. Sprinkler irrigation is not allowed	E. Coli [Weekly] - 200 (Median)
Unrestricted irrigation: all crops including all irrigation methods	E. Coli [4/Week] - 5 (80% Samples) - 50 (95% Samples)
European Commission	
A:	E. Coli [Weekly] - 10 (90% of The Samples) Intestinal Nematodes [2/Month] - 1 Egg/l
B:	E. Coli [Weekly] - 100 Intestinal Nematodes [2/Month] 1 Egg/l
C:	E. Coli [2/Month] - 1,000 Intestinal Nematodes [2/Month] 1 Egg/l
D:	E. Coli [2/Month] - 10,000 Intestinal Nematodes [2/Month] 1 Egg/l
Israel	
NS	Fecal Coliforms - 10
Jordan	
A: cooked vegetables, parks, playgrounds roadsides in the city	E. Coli or Fecal Coliform - 100 Intestinal Nematodes 1 Egg/l
B: fruit trees, landscaped roadsides of highways	E. Coli or Fecal Coliform - 1,000
C: industrial crops, forest trees	NS
D: cut flowers	E. Coli or Fecal Coliform - 1.1

Table 10 (continued). Restrictive agricultural water reuse regulations and guidelines.

Reuse Categories	Required Microbial Quality (cfu/100 ml) [Monitoring]
Kuwait	
NS	Total Coliforms - 400 Fecal Coliforms - 20
Saudi Arabia	
Restricted	Thermo-Tolerant Coliform - 1,000 Intestinal Nematodes - 1
Unrestricted	Thermo-Tolerant Coliform - 2.2 Intestinal Nematodes - 1
Act (Australia)	
Pasture and fodder for grazing animals (except pigs)	Thermo-Tolerant Coliforms [Weekly] - 1,000 (Median)
Silviculture, turf, and non-food crops	Thermo-Tolerant Coliforms [Monthly] - 10,000 (Median)
Food crops in direct contact with water e.g., Sprays	Thermo-Tolerant Coliforms [Weekly] - 10 (Median)
Food crops not in direct contact with water (e.g., Flood or furrow) or which will be sold to consumers cooked or processed	Thermo-Tolerant Coliforms [Weekly] - 1,000 (Median)
NSW (Australia)	
Food production, raw human food crops in direct contact with effluent e.g., Via sprays, irrigation of salad vegetables	Thermo-Tolerant Coliforms [Weekly] - 10 (Median) Intestinal Nematodes - 1 egg/l
Food production, raw human food crops not in direct contact with effluent (edible product separated from contact with effluent, e.g., Use of trickle irrigation) or crops sold to consumers cooked or processed.	Thermo-Tolerant Coliforms [Weekly] - 1,000 (Median)
Food production, pasture, and fodder (for grazing animals except pigs and dairy animals, i.e., Cattle, sheep, and goats)	Thermo-Tolerant Coliforms [Weekly] - 1,000 (Median)
Food production, pasture, and fodder for dairy animals (with withholding period).	Thermo-Tolerant Coliforms [Weekly] - 1,000 (Median)

Table 10 (continued). Restrictive agricultural water reuse regulations and guidelines.

Reuse Categories	Required Microbial Quality (cfu/100 ml) [Monitoring]
Food production, pasture, and fodder for dairy animals (without withholding period). Drinking water (all stock except pigs). Wash-down water for dairies	Thermo-Tolerant Coliforms [Weekly] - 100 (Median)
Non-food crops, silviculture, turf, and cotton, etc.	Thermo-Tolerant Coliforms [Weekly] - 10,000 (Median)
NT (Australia)	
A+: (high level of human contact) commercial food crops consumed raw or unprocessed (e.g., Salad crops)	E. Coli [Weekly] - 1
B: (medium level human contact) commercial food crops	E. Coli [Weekly] - 100
C: (low level of human contact) commercial food crops	E. Coli [Weekly] - 1,000
D: (very low level of human contact) non-food crops (trees, turf, woodlots, flowers)	E. Coli [Annually] - 10,000
QLD (Australia)	
(Minimally processed food crops) a+:	Clostridium Perfringens [Weekly] - 1 (95%) E. Coli [Weekly] - 1 (95%) F-Rna Bacteriophages [Weekly] - 1 (95%) Somatic Coliphages - 1 (95%)
(Minimally processed food crops) a:	E. Coli [Weekly] - 10 (95%)
(Minimally processed food crops) b:	E. Coli [Weekly] - 100 (95%)
(Minimally processed food crops) c:	E. Coli [Weekly] - 1000 (95%)
(Minimally processed food crops) d:	E. Coli [Weekly] - 10,000 (95%)
TAS (Australia)	
A: direct contact of reclaimed water with crops consumed raw	Thermo-Tolerant Coliforms [Daily] - 10 (Median)
B: crops for human consumption	Thermo-Tolerant Coliforms [Weekly] - 1,000 (Median)
C: non-human food chain	Thermo-Tolerant Coliforms [Weekly] - 10,000 (Median)

Table 10 (continued). Restrictive agricultural water reuse regulations and guidelines.

Reuse Categories	Required Microbial Quality (cfu/100 ml) [Monitoring]
VIC (Australia)	
A: commercial food crops consumed raw or unprocessed	E. Coli - 1
B: dairy cattle grazing	E. Coli - 100
C: human food crops/processed, grazing, fodder for livestock	E. Coli - 1,000
D: non-food crops including instant turf, woodlots, flowers	E. Coli - 10,000
WA (Australia)	
(High level of human contact) commercial food crops consumed raw or unprocessed (e.g., Salad crops)	E. Coli [Weekly] - 1 Coliphages [Weekly] - 1 Clostridia [Weekly] - 1
(Low level of human contact) non-edible crops	E. Coli [Weekly] - 1,000
D: (extra low level of human contact) non-food crops (subsurface reticulation)	E. Coli [6 monthly] - 10,000
AGWR (Australia)	
Commercial food crops consumed raw or unprocessed	E. Coli - 1
Commercial food crops	E. Coli - 100
Commercial food crops	E. Coli - 1,000
Non-food crops- trees, turf, woodlots, flowers	E. Coli - 10,000

[1] Irrigation of Class III effluent on fruit and vegetables not commercially processed, including crops eaten raw, is prohibited. Irrigation of Class III effluent on bare soil is prohibited except for providing adequate moisture for seed germination in the seeding area. The irrigation area shall be planted with healthy vegetation cover. Irrigation on high water table or saturated soils which cause persistent surface runoff and ponding is prohibited.
[2] Corrective active threshold
[3] Population equivalent.

Fifteen documents were gathered under less restrictive regulations and guidelines (Table 11). The indicator parameters in these regulations and guidelines included Fecal Coliforms (11 documents), Intestinal Nematodes (6 documents), E. coli (3 documents), Total Coliforms (2 documents), and Enterococci (1 document). Like restrictive regulations and guidelines, the threshold limits for food crops irrigation and unrestricted public access categories had lower values than processed food crops/

non-food crops and restricted public access categories. In addition, threshold levels for same parameters were sometimes very different, when regulations and guidelines are compared with each other (Table 11).

Table 11. Less restrictive agricultural water reuse regulations and guidelines.

Reuse Categories	Required Microbial Quality (cfu/100 ml) [Monitoring]
FAO	
A: irrigation of crops likely to be eaten uncooked, sports field, public parks	Fecal Coliforms - 1000 (Geometric Mean) Fecal Coliforms - 200 (In Case of Fruit Trees, Geometric Mean) Intestinal Nematodes - 1 egg/L (Arithmetic Mean)
B: irrigation of cereal crops, industrial crops, fodder crops, pasture, and trees	Intestinal Nematodes - 1 egg/L (Arithmetic Mean)
C: localized irrigation of crops in category b if exposure of workers and the public does not occur	NS
WHO	
Restricted	E. Coli - 10,000 (Labor) - 100,000 (Highly Mechanized) Intestinal Nematodes - 1 egg/L
Unrestricted (Drip Irrigated)	E. Coli - 1,000 (Low-Growing) - 100,000 (High-Growing) Intestinal Nematodes - 1 egg/L
Unrestricted	E. Coli - 1,000 (Root Crops) - 10,000 (Leaf Crops) Intestinal Nematodes - 1 egg/L
Alberta	
Restricted	Total Coliform [Weekly or Daily] - 1,000 (Geometric Mean) Fecal Coliform [Weekly or Daily] - 200 (Geometric Mean)
Unrestricted	Total Coliform [Weekly or Daily] - 1,000 (Geometric Mean) Fecal Coliform [Weekly or Daily] - 200 (Geometric Mean)

Table 11 (continued). Less restrictive agricultural water reuse regulations and guidelines.

Reuse Categories	Required Microbial Quality (cfu/100 ml) [Monitoring]
Nebraska	
Unrestricted	Fecal Coliform - 200 (30-Day Geometric Mean) - 400 (No More Than 10% Samples)
South Dakota	
Food Crops	Total Coliform - 200 (Geometric Mean)
Wyoming	
Food Crops	Fecal Coliform - 200
Processed Food Crops/ Non-Food Crops	Fecal Coliform - 1,000
Mexico	
Restricted	Fecal Coliforms - 2,000 (Daily Average) - 1,000 (Monthly Average)
Unrestricted	Fecal Coliforms - 2,000 (Daily Average) - 1,000 (Monthly Average)
France	
A: unrestricted irrigation of all crops including these accessed by the public	Enterococci [Weekly] - ≥ 4 Logs E. Coli [Weekly] - 250
B: all crops except those consumed raw or green areas with public access	Enterococci [1/15 Days] - ≥ 3 Logs E. Coli [1/15 Days] - 10,000
C: other ornamental crops, shrubs, cereals; horticultural crops drip irrigated, forests with controlled access	Enterococci [Monthly] - ≥ 2 Logs E. Coli [Monthly] - 100,000
D: forests with no access	Enterococci - ≥ 2 Logs

Table 11 (continued). Less restrictive agricultural water reuse regulations and guidelines.

Reuse Categories	Required Microbial Quality (cfu/100 ml) [Monitoring]
Spain	
2.1	E. Coli [Weekly] - 100 Intestinal Nematodes - 1 egg/10L
2.2: quality 2.2 A) irrigation of crops for human consumption using application methods that do not prevent direct contact of reclaimed with edible parts of the plants, which are not eaten raw but after an industrial treatment process. B) irrigation of pastureland for milk- or meat-producing animals. C) aquaculture.	E. Coli [Weekly] - 1000 Intestinal Nematodes - 1 egg/10L
2.3: A) localized irrigation of tree crops whereby reclaimed water is not allowed to come into contact with fruit for human consumption. B) irrigation of ornamental flowers, nurseries and greenhouses whereby reclaimed water does not come into contact with the crops. C) irrigation of industrial non-food crops, nurseries, silo fodder, cereals and oilseeds.	E. Coli [Weekly] - 10,000 Intestinal Nematodes - 1 egg/10L
Iran	
A: irrigation of crops likely to be eaten uncooked, sports field, public parks	Fecal Coliforms - 1000 (Geometric Mean) Intestinal Nematodes - 1 (Arithmetic Mean)
B: irrigation of cereal crops, industrial crops, fodder crops, pasture, and trees	Intestinal Nematodes - 1 (Arithmetic Mean)
C: localized irrigation of crops in category b if exposure of workers and the public does not occur	NS

Table 11 (continued). Less restrictive agricultural water reuse regulations and guidelines.

Reuse Categories	Required Microbial Quality (cfu/100 ml) [Monitoring]
Egypt	
A: plants and trees grown for greenery at touristic villages and hotels and inside residential areas at the new cities	Fecal Coliforms - 1,000
B: fodder/feed crops, trees producing fruits with epicarp trees used for green belts around cities and afforestation of highways or roads nursery plants roses & cut flowers fiber crops mulberry for the production of silk	Fecal Coliforms - 5,000
C: industrial oil crops wood trees	NS
China	
Fiber crops	Fecal Coliforms - 40,000 Intestinal Nematodes - 2
Dry field corn oil crops	Fecal Coliforms - 40,000 Intestinal Nematodes - 2
Paddy field grain	Fecal Coliforms - 20,000 Intestinal Nematodes - 2
Vegetable	Fecal Coliforms - 20,000 Intestinal Nematodes - 2
Palestine	
A: High quality	Fecal Coliforms [1 sample/2 days] - 200
B: Good quality	Fecal Coliforms [1 sample/2 days] - 1,000
C: Medium quality	Fecal Coliforms [1 sample/2 days] - 1,000
D: Low quality	Fecal Coliform [1 sample/2 days] - 1,000

Table 11 (continued). Less restrictive agricultural water reuse regulations and guidelines.

Reuse Categories	Required Microbial Quality (cfu/100 ml) [Monitoring]
Portugal	
A: vegetables consumed raw	Fecal Coliforms - 100
B: public parks, and gardens, sport lawns, forests with public access	Fecal Coliforms - 200
C: vegetables to be cooked, forage crops, vineyards, orchards	Fecal Coliforms - 1,000
D: cereals (except rice), vegetables for industrial process, crops for textile industry, crops for oil extraction, forest, and lawns in places of restricted or controlled public access	Fecal Coliforms - 10,000
Oman	
A: vegetables likely to be eaten raw, fruit likely to be eaten raw and within 2 weeks of any irrigation	Fecal Coliform - 200 Intestinal Nematodes - 1 Egg/l
B: vegetables to be cooked or processed, fruit if no irrigation within 2 weeks of cropping, fodder, cereal, seed crops, pasture no public access	Fecal Coliform - 1,000 Intestinal Nematodes 1 Egg/l

By comparing the required microbial quality thresholds, one can simply notice large discrepancies among the existing regulations and guidelines. Of note is that none of the less restrictive regulations and guidelines used thermo-tolerant Coliforms in their documents. To have a better idea of these thresholds, common pathogen indicators were analyzed using descriptive statistical analysis (Table 12). Fecal Coliform was used more than the other indicators in the regulations and guidelines (Table 12). E. Coli thresholds had the largest range, 100,000, among the indicators. Additionally, the most frequent threshold of Fecal Coliform, E. Coli, Total Coliform, Thermo-Tolerant Coliform, Intestinal Nematodes, Enterococci, Coliphages, Clostridia, and F-RNA Bacteriophages were 200, 1000, 23, 1000, 1, 35, 1, 1, and 1, respectively (Table 12).

Table 12. Descriptive statistical analysis of common pathogen indicators included in agricultural water reuse regulations and guidelines.

Microbial indicator (cfu/100ml)	Number of documents	Total number of indications	Mean	Standard error	Median	Mode	Minimum	Maximum
Fecal Coliform	36	100	1810.62	627.08	200	200	0[1]	40,000[2]
E. Coli	24	69	6017.74	2465.17	126	1000	0[3]	100,000[4]
Total Coliform	9	22	284.18	113.92	23	23	2.2[5]	2,300[6]
Thermo-tolerant Coliform	5	20	2417.61	875.33	1000	1000	2.2[7]	10,000[8]
Intestinal nematodes (egg/l)	12	33	0.97	0.09	1	1	0[9]	2[10]
Enterococci	3	10[11]	30.5	12.92	23	35	4[12]	89[13]
Coliphages	2	2	1	0	1	1	1[14]	1
Clostridia	2	2	1	0	1	1	1[15]	1
F-Rna Bacteriophages	1	1	1	0	1	1	1[16]	1

[1] EPA, Arizona, Florida, Indiana, and Massachusetts
[2] China
[3] Utah
[4] WHO and France
[5] California, Minnesota, Montana, Oregon, and Washington
[6] Idaho
[7] Saudi Arabia
[8] ISO, ACT, NSW and TAS
[9] Cyprus
[10] China
[11] Four of the Enterococci thresholds, issued by France, are in terms of log reduction, excluded from the statistical analysis.
[12] Texas
[13] Texas
[14] QLD and WA
[15] QLD and WA
[16] QLD

One of the main human health concerns related to water reuse is parasitic intestinal infections (Adegoke et al., 2018). Verbyla et al. (2016) showed that the consumption of lettuce irrigated with river water contaminated with fecal contamination resulted in an estimated median health burden representing 37% of Bolivia's overall diarrheal disease burden. However, irrigation with filtered riverbank resulted in an estimated health burden of only 1.1% of this overall diarrheal disease burden. Median concentrations of different contaminants in the river water were as follows: 3.2×10^8 adenovirus copies/L, 6.4×10^7 pepper mild mottle virus copies/L, 1.8×10^7 E. Coli cfu/L, 1.4×10^7 human-specific HF183 Bacteroides copies/L, 3.6×10^6 human rotavirus group A copies/L, 1.1×10^5 Coliphage pfu/L, 530 Giardia cysts/L, and 4.0 Cryptosporidium oocysts/L (Verbyla et al., 2016). The following contaminants were detected in the filtered riverbank (lower median concentrations): 1.1×10^5 adenovirus copies/L, 7.7×10^4 pepper mild mottle virus copies/L, 3.0×10^3 E. coli cfu/L, 4.5×10^1 human-specific HF183 Bacteroides copies/L, 5.9×10^2 Coliphage pfu/L, 2.0 Giardia cysts/L, and 0.04 Cryptosporidium oocysts/L (Verbyla et al., 2016).

Based on Table 11 and the study by Verbyla et al. (2016), it was apparent that the microbial parameters and their thresholds in the existing regulations and guidelines were not adequate to make sure agricultural water reuse practices were safe for human health. For example, the E. Coli threshold set by WHO and France is 100,000 cfu/100mL; however other studies showed that irrigation by water with an E. Coli concentration of 18,000 cfu/mL caused an estimated median health burden that represented 37% of Bolivia's overall diarrheal disease burden (Verbyla et al., 2016).

It has also been reported that the most significant health risk in developing countries is the high concentration of nematode eggs (>1 Egg/L) when water reuse is practiced using spray irrigation technology, especially in the case of vegetables eaten raw by children (Lazarova & Bahri, 2004). Among the regulations and guidelines that were evaluated in this study, only 12 documents included intestinal nematodes, including ISO, Cyprus, E.U., Saudi Arabia, Tunisia, and NSW, from the restrictive group, and FAO, WHO, Spain, Iran, China, and Oman from the less restrictive group (Table 10 and Table 11).

II) Chemicals: Another human health concern related to recycled water use is potential contamination of crops and groundwater by chemical constituents that may be present in water. These chemicals may include heavy metals, pharmaceuticals, personal care products, and compounds which exert endocrine disruption properties such as hormones or other chemicals including PCBs, Octilphenol, and Nonilphenol (Lazarova & Bahri, 2004). These hazardous chemicals are of great concern for human health especially in heavily polluted industrial wastewater (Lazarova & Bahri, 2004). On the other hand, there is still a huge data gap in terms of characterization and treatment of these chemicals which their concentrations are very low in concerning waters.

Only a few agricultural water reuse regulations and guidelines included the chemical constituents in their documents (Table 13). Despite the potential negative

consequences of these chemical constituents, only 17 regulations and/or guidelines included some of these chemical parameters (Table 13). Among the studied regulations and guidelines, Italy, China, Oman, and AGWR included the highest number of chemical constituents in their documents (32, 22, 21, and 20 chemical parameters respectively, Table 13).

Table 13. Chemicals and trace elements thresholds in agricultural water reuse regulations and guidelines (numbers in parentheses show the threshold level of chemical constituents and trace elements).

Chemical/ trace element	Number of documents that included this parameter	Range (mg/l)	Regulation/ guideline (thresholds as mg/l)
Cadmium (Cd)	17	0.0001-0.2	EPA (0.01), FAO (0.01), WHO (0.01), British Columbia (0.05), Atlantic Canada (0.005), Cyprus (0.2), Italy (0.005), Greece (0.01), Israel (0.01), Jordan (0.01), Kuwait (0.01), Oman (0.01), Saudi Arabia (0.01), Tunisia (0.1), China (0.01), ACT (0.01), AGWR (0.0001-0.005)
Chromium (Cr)	17	0.001-0.15	EPA (0.1), FAO (0.1), WHO (0.1), British Columbia (hexavalent:0.008), Atlantic Canada (hexavalent:0.008, trivalent:0.005), Cyprus (0.1), Italy (0.1), Greece (0.1), Israel (0.1), Jordan (0.1), Kuwait (0.15), Oman (0.05), Saudi Arabia (0.1), Tunisia (0.1), China (0.1), ACT (0.1), AGWR (0.001-0.021)
Nickel (Ni)	17	0.002-0.2	EPA (0.2), FAO (0.2), WHO (0.2), British Columbia (0.2), Atlantic Canada (0.2), Cyprus (0.2), Italy (0.2), Greece (0.02), Israel (0.2), Jordan (0.2), Kuwait (0.2), Oman (0.1), Saudi Arabia (0.2), Tunisia (0.2), China (0.1), ACT (0.2), AGWR (0.002-0.02)

Table 13 (continued). Chemicals and trace elements thresholds in agricultural water reuse regulations and guidelines (numbers in parentheses show the threshold level of chemical constituents and trace elements).

Chemical/ trace element	Number of documents that included this parameter	Range (mg/l)	Regulation/ guideline (thresholds as mg/l)
Iron (Fe)	16	0.3-4.7	EPA (5), FAO (5), WHO (5), British Columbia (5), Atlantic Canada (5), Italy (2), Greece (3), Israel (2), Jordan (5), Kuwait (5), Oman (food crops:1, non-food crops:5), Saudi Arabia (2), Tunisia (0.5), China (1.5), ACT (1), AGWR (0.03-4.725)
Arsenic (As)	16	0.004-0.1	EPA (0.1), FAO (0.1), WHO (0.1), British Columbia (0.1), Atlantic Canada (0.1), Italy (0.02), Greece (0.1), Israel (0.1), Jordan (0.1), Kuwait (0.1), Oman (0.1), Saudi Arabia (0.1), Tunisia (0.1), China (0.05), ACT (0.1), AGWR (0.004)
Copper (Cu)	16	0.002-1	EPA (0.2), FAO (0.2), WHO (0.2), Atlantic Canada (0.2-1), Cyprus (0.1), Italy (1), Greece (0.2), Israel (0.2), Jordan (0.2), Kuwait (0.2), Oman (food crops:0.05, non-food crops:0.1), Saudi Arabia (0.4), Tunisia (0.5), China (1), ACT (0.2), AGWR (0.002-0.091)
Lead (Pb)	16	0.001-5	EPA (5), FAO (5), British Columbia (0.2), Atlantic Canada (0.2), Cyprus (0.15), Italy (0.1), Greece (0.1), Israel (0.1), Jordan (0.2), Kuwait (0.5), Oman (food crops:0.1, non-food crops:0.2), Saudi Arabia (0.1), Tunisia (1), China (0.2), ACT (0.2), AGWR (0.001-0.02)

Table 13 (continued). Chemicals and trace elements thresholds in agricultural water reuse regulations and guidelines (numbers in parentheses show the threshold level of chemical constituents and trace elements).

Chemical/ trace element	Number of documents that included this parameter	Range (mg/l)	Regulation/ guideline (thresholds as mg/l)
Cobalt (Co)	15	0.004-1	EPA (0.05), FAO (0.05), WHO (0.05), British Columbia (0.05), Atlantic Canada (0.05), Italy (0.05), Greece (0.05), Israel (0.05), Kuwait (0.2), Oman (0.05), Saudi Arabia (0.05), Tunisia (0.1), China (1), ACT (0.05), AGWR (0.004-0.013)
Zinc (Zn)	15	0.5-5	EPA (2), FAO (2), WHO (2), Atlantic Canada (1-5), Cyprus (1), Italy (0.5), Greece (2), Israel (2), Kuwait (2), Oman (5), Saudi Arabia (2), Tunisia (5), China (2), ACT (2), AGWR (0.049-0.11)
Aluminum (Al)	14	0.011-5	EPA (5), FAO (5), WHO (5), British Columbia (5), Atlantic Canada (5), Italy (1), Greece (5), Israel (5), Jordan (5), Kuwait (5), Oman (5), Saudi Arabia (5), ACT (5), AGWR (0.011-0.665)
Manganese (Mn)	14	0.019-0.5	EPA (0.2), FAO (0.2), WHO (0.2), British Columbia (0.2), Atlantic Canada (0.2), Italy (0.2), Greece (0.2), Israel (0.2), Kuwait (0.2), Oman (food crops:0.1, non-food crops:0.5), Saudi Arabia (0.2), China (0.3), ACT (0.2), AGWR (0.019-0.069)
Beryllium (Be)	13	0.002-2	EPA (0.1), FAO (0.1), WHO (0.1), British Columbia (0.1), Atlantic Canada (0.1), Italy (10), Greece (0.1), Israel (0.1), Kuwait (2), Oman (food crops:0.1, non-food crops:0.3), Saudi Arabia (0.1), China (0.002), ACT (0.1)

Table 13 (continued). Chemicals and trace elements thresholds in agricultural water reuse regulations and guidelines (numbers in parentheses show the threshold level of chemical constituents and trace elements).

Chemical/ trace element	Number of documents that included this parameter	Range (mg/l)	Regulation/ guideline (thresholds as mg/l)
Selenium (Se)	12	0.02-0.05	EPA (0.02), FAO (0.02), WHO (0.02), Atlantic Canada (0.02-0.05), Italy (0.01), Greece (0.02), Israel (0.02), Oman (0.02), Saudi Arabia (0.02), Tunisia (0.05), China (0.02), ACT (0.02)
Lithium (Li)	11	0.07-2.5	EPA (2.5), FAO (2.5), WHO (2.5), British Columbia (2.5), Atlantic Canada (2.5), Greece (2.5), Israel (2.5), Jordan (2, citrus:0.075), Oman (0.07), Saudi Arabia (0.07), ACT (2.5)
Molybdenum (Mo)	11	0.001-0.05	EPA (0.01), FAO (0.01), WHO (0.01), Atlantic Canada (0.01-0.05), Greece (0.1), Israel (0.01), Oman (food crops: 0.01, non-food crops: 0.05), Saudi Arabia (0.01), China (0.5), ACT (0.01), AGWR (0.001-0.021)
Vanadium (V)	11	0.1	EPA (0.1), FAO (0.1), WHO (0.1), British Columbia (0.1), Atlantic Canada (0.1), Italy (0.1), Greece (0.1), Israel (0.1), Oman (0.1), Saudi Arabia (0.1), China (0.1)
Mercury (Hg)	11	0.0001-0.2	Cyprus (0.005), Italy (0.001), Greece (0.002), Israel (0.002), Jordan (0.02), Kuwait (0.002), Oman (0.001), Saudi Arabia (0.001), Tunisia (0.001), China (0.001), AGWR (0.0001-0.002)
Total phenol	5	0.0005-1	Italy (0.1), Kuwait (1), Oman (food crops:0.001, non-food crops:0.002), Saudi Arabia (0.002), AGWR (0.0005-0.007)

Table 13 (continued). Chemicals and trace elements thresholds in agricultural water reuse regulations and guidelines (numbers in parentheses show the threshold level of chemical constituents and trace elements).

Chemical/ trace element	Number of documents that included this parameter	Range (mg/l)	Regulation/ guideline (thresholds as mg/l)
Copernicium (Cn)	3	0.05-0.1	Italy (0.05), Oman (food crops:0.05, non-food crops:0.1), Saudi Arabia (0.05)
Silver (Ag)	3	0.0001-0.5	Oman (0.01), Saudi Arabia (0.5), AGWR (0.0001-0.005)
Magnesium (Mg)	3	0.5-150	Oman (150), Tunisia (0.5), AGWR (6-40)
Uranium (U)	2	0.01	British Columbia (0.01), Atlantic Canada (0.01)
Benzene	2	0.01-2.5	Italy (0.01), China (2.5)
Cyanide (Cn)	2	0.001-0.5	China (0.5), AGWR (0.001)
Calcium (Ca)	1	10-74.00	AGWR (10-74)
Tin (Sn)	1	3	Italy (3)
Titanium (Ti)	1	0.001	Italy (0.001)
Pentachlorophenol	1	0.003	Italy (0.003)
Total aldehydes	1	0.5	Italy (0.5)
Tetrachloroethylene	1	0.01	Italy (0.01)
Total Chlorinated solvents	1	0.04	Italy (0.04)
Total trihalomethanes	1	0.03	Italy (0.03)
Total aromatic solvents	1	0.001	Italy (0.001)
Benzo(a)pyrene	1	0.00001	Italy (10^{-5})
Total organic Nitrogen solvents	1	0.01	Italy (0.01)
Total surfactants	1	0.2-0.5	Italy (0.5), AGWR (anionic:0.2)
Chlorinated biocides	1	0.0001	Italy (0.0001)
Phosphorated pesticides	1	0.00001	Italy (0.00001)
Other pesticides	1	0.05	Italy (0.05)
Volatile Phenol	1	1	China (1)

Table 13 (continued). Chemicals and trace elements thresholds in agricultural water reuse regulations and guidelines (numbers in parentheses show the threshold level of chemical constituents and trace elements).

Chemical/ trace element	Number of documents that included this parameter	Range (mg/l)	Regulation/ guideline (thresholds as mg/l)
Linear alkynate sulfunic	1	5	China (5)
Trichloracetic aldehyde	1	0.5	China (0.5)
Acrolein	1	0.5	China (0.5)
Methanol	1	1	China (1)
Barium (Ba)	1	0.001-0.0375	AGWR (0.001-0.0375)

3.3.2.2. Agronomic parameters

Agronomic parameters are of paramount importance in safe agricultural water reuse practices. Crops quality and yield, soil productivity, and ecological health must be considered in safe agricultural water reuse practices.

I) pH: As the indicator of water acidity and alkalinity, pH is one of the water quality parameters that can be easily measured and an indicator of the presence of toxic ions (Lazarova & Bahri, 2004; Wastewater Quality Guidelines for Agricultural Use). Although the normal pH range for safe irrigation is 6.5-8.4 (Wastewater Quality Guidelines for Agricultural Use), different pH ranges were used in the agricultural water reuse regulations and guidelines (Figure 3).

Recycled water outside the normal pH range might result in nutritional imbalance, which may alter the crops' growth and health, and facilitate the corrosion in pipelines, sprinklers, and control valves (Anugoolprasert et al., 2012; Kang et al., 2011; Lazarova & Bahri, 2004; Renan de Souza Santos et al., 2011; Ruan et al., 2007). Lower pH makes heavy metals move easier in the soil, contaminating crops and water bodies (Jeong et al., 2016). Out of 70 agricultural water reuse regulations and guidelines studied in this research, 34 documents included pH as one of their requirements. The most common ranges were 6-9 and 6.5-8.5 (Figure 3).

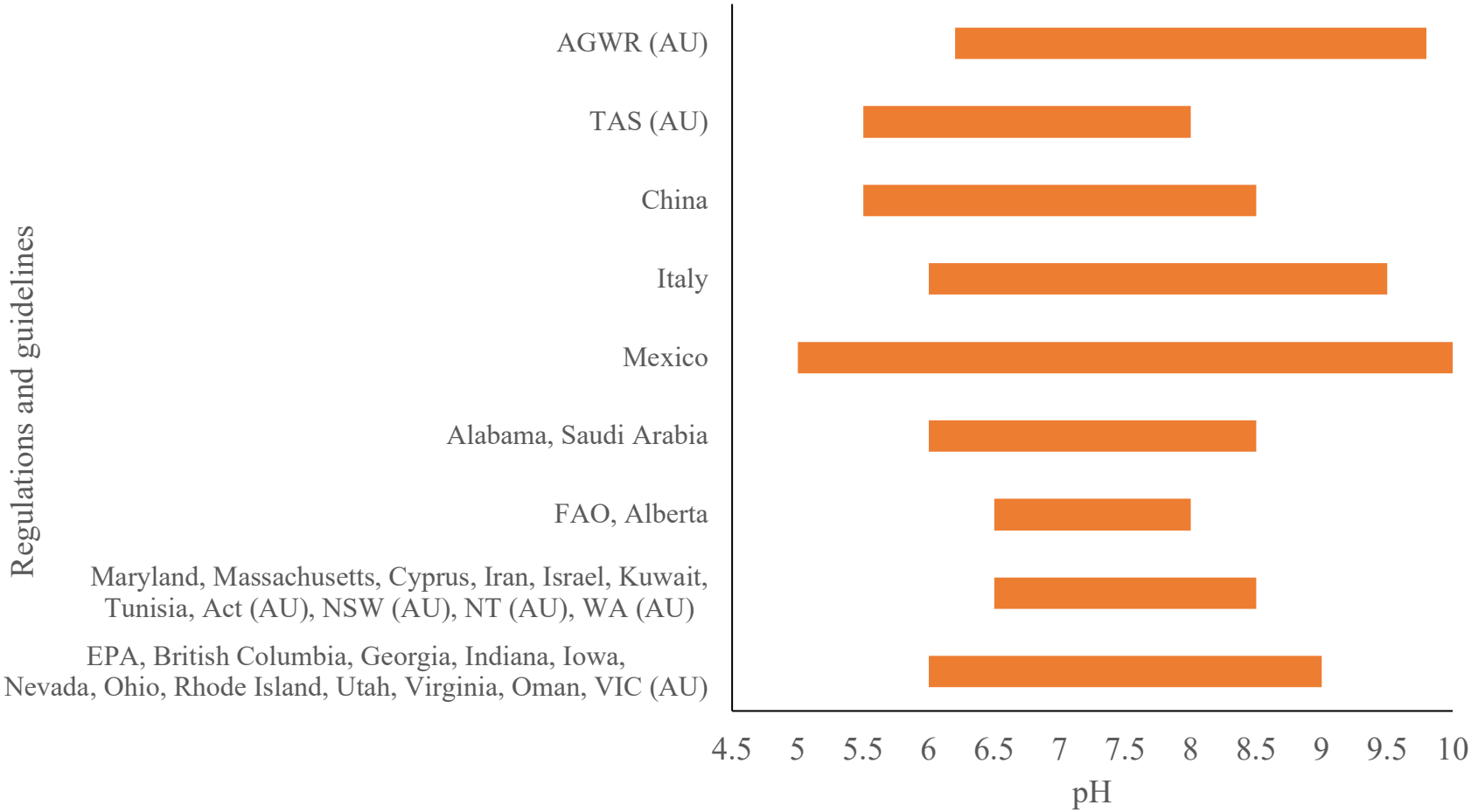


Figure 3. Required pH ranges in agricultural water reuse regulations and guidelines

II) Salinity: It's been reported that salinity is one of the most important recycled water quality parameters for agricultural water reuse practices. This is because the high concentration of dissolved salts increases the soil water pressure, requiring more energy from plants to take up water from the soil and also resulting in specific ion toxicity (Jeong et al., 2016; Lazarova & Bahri, 2004; McNeal, 1968; McNeal et al., 1968; McNeal & Coleman, 1966). The salinity of irrigation water often determines the salinity in the soil. Total dissolved solids (TDS (mg/l)) or electric conductivity (EC (dS/m)) are often used as indicators of salinity. While each of these parameters is important individually, there is an approximate correlation between TDS and EC, as shown by Equation (1) (Lazarova & Bahri, 2004).

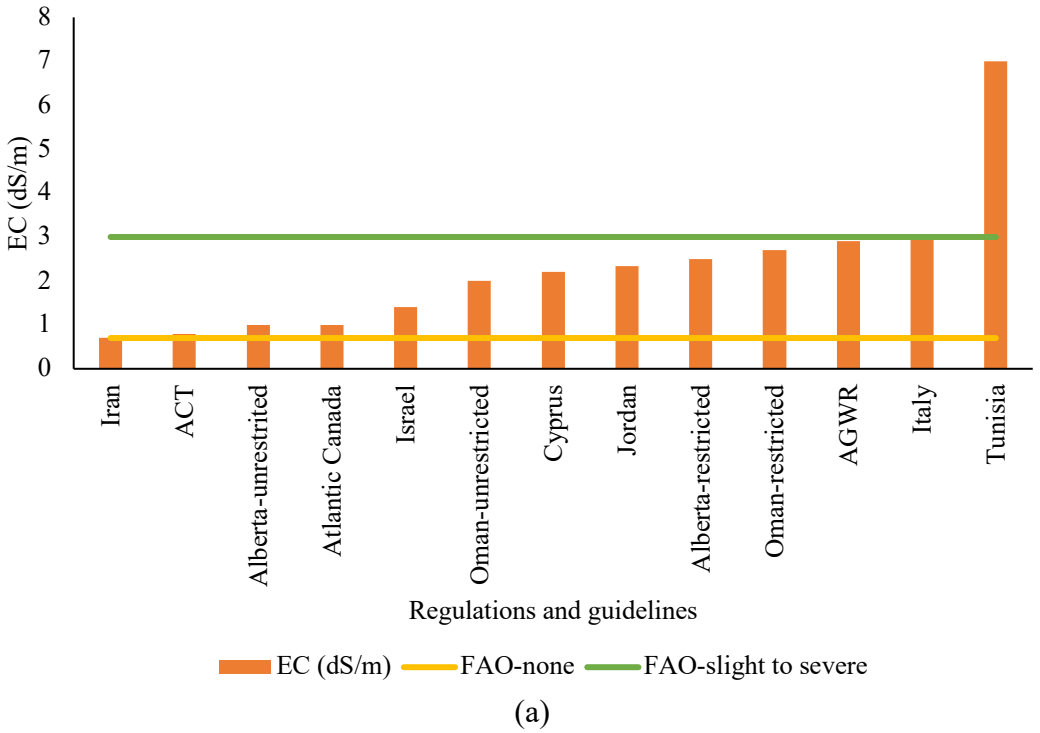
FAO's guideline included three categories for EC and TDS thresholds based on the water use restriction as none, slight to moderate, and severe negative impact (Table 14 and Figure 4). Only 13 and 10 regulations and guidelines (out of 70) included EC and TDS in their agricultural water reuse requirements, respectively (Table 14). FAO, Saskatchewan, Iran, Jordan, Oman, ACT, and AGWR regulations and guidelines included both EC and TDS thresholds in their documents. In addition, Kuwait, Saudi Arabia, and China only had TDS in their regulations and guidelines. Of note is that none of the U.S. states included EC and TDS thresholds in their agricultural water reuse regulations and guidelines.

$$TDS\ \left(\frac{mg}{l}\right) = EC\ \left(\frac{dS}{m}\right) \times 640 \quad (1)$$

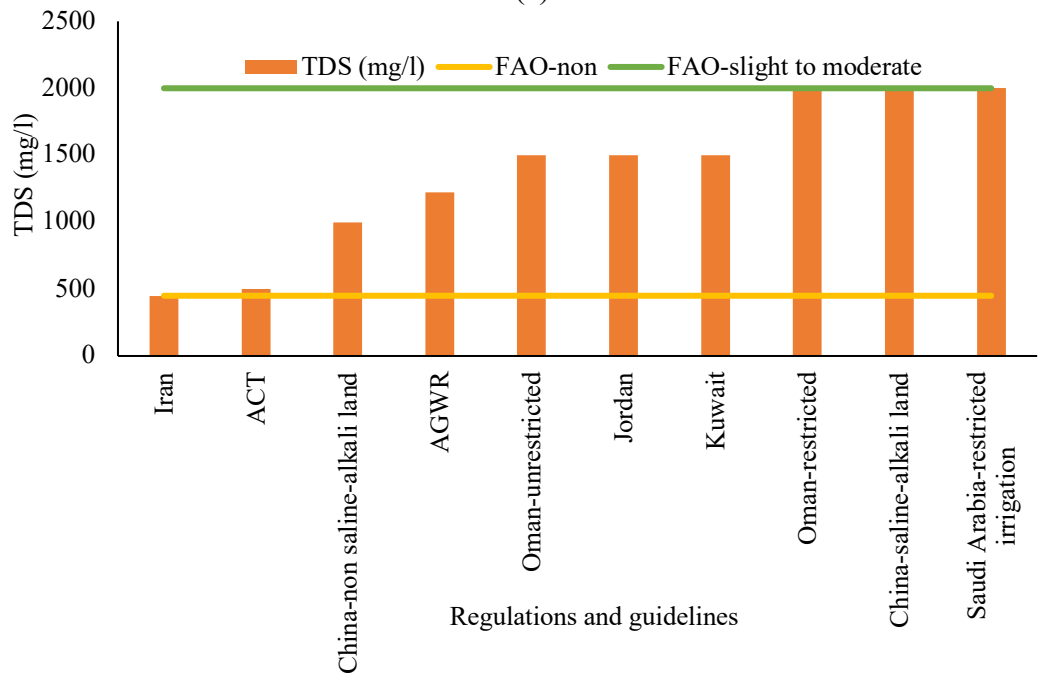
Table 14. Salinity (EC and TDS) thresholds in agricultural water reuse regulations and guidelines.

Regulation/guideline	EC (dS/m)	TDS (mg/l)
FAO and Saskatchewan	None: < 0.7	None: < 450
	Slight to moderate: 0.7-3.0	Slight to moderate: 450-2,000
	Severe: > 3	Severe: > 2,000
Alberta and Atlantic	Unrestricted: < 1.0	NS[1]
Canada	Restricted: 1.0-2.5	NS
	Unacceptable: > 2.5	NS
Oman	Restricted (public access): 2.7	Restricted (public access): 2,000
	Unrestricted (public access): 2.0	Unrestricted (public access): 1,500
China	NS	Saline-alkali land: 2,000
	NS	None saline-alkali land: 1,000
Cyprus	2.2	NS
Italy	3	NS
Iran	0.7	450
Israel	1.4	NS
Jordan	2.34	1,500
Tunisia	7	NS
ACT	0.8	500
AGWR	0.2-2.9	145-1,224
Kuwait	NS	1,500
Saudi Arabia	NS	Restricted irrigation: 2,000

[1] Not specified.



(a)



(b)

Figure 4. Salinity thresholds in agricultural water reuse regulations and guidelines: (a) EC and (b) TDS.

III) Sodium Adsorption Ratio (SAR): Sodium is one of the essential ions in irrigation water which must be regulated for agricultural practices. Its presence in the exchangeable form in the soil causes harmful effects on the physical and chemical properties of the soil. Excessive amounts of Sodium result in particle dispersion and reduction of water and air infiltration into the soil (Lazarova & Bahri, 2004; McNeal, 1968; McNeal et al., 1968; McNeal & Coleman, 1966; Suarez et al., 2006). The most common Sodium indicator used in literature was the SAR index, calculated by Equation (2).

$$SAR = \frac{Na^{+}}{\sqrt{0.5(Ca^{2+} + Mg^{2+})}} \quad (2)$$

In this equation, SAR is the amount of Sodium adsorption ratio, Na, Ca, and Mg are the concentrations of Sodium, Calcium, and Magnesium in me/l, respectively. There were no states in the U.S. with SAR thresholds in their regulations or guidelines. In Canada, the provinces of Alberta, Atlantic Canada, and Saskatchewan included SAR thresholds for restricted and unrestricted agricultural water reuse practices (Table 15 and Figure 5). In Iran's guideline, the SAR threshold was set as 3 when the EC < 0.7 dS/m, which was its required EC threshold. Also, Iran included other SAR thresholds when EC > 0.7 dS/m. Moreover, the highest SAR thresholds were issued by Italy and Oman. In total, 7 out of 70 regulations and guidelines investigated in this study had SAR in their requirements.

Table 15. The SAR thresholds in the agricultural water reuse regulations and guidelines.

Organizations /Countries /States	**SAR**	**Organizations /Countries /States**	**SAR**
Alberta	4-9, restricted use when EC > 1.0 dS/m < 4, unrestricted use	Italy	10
		Iran	< 3, EC < 0.7 3-6, EC > 1.2 6-12, EC > 1.9 12-20, EC > 2.9 20-40, EC > 5
Atlantic Canada	4-9, restricted use < 4, unrestricted use	Israel	5
		Oman	10
Saskatchewan	< 3, no restriction 3-9, slight to moderate restriction > 9, severe restriction	ACT	6
		AGWR	3-12.2

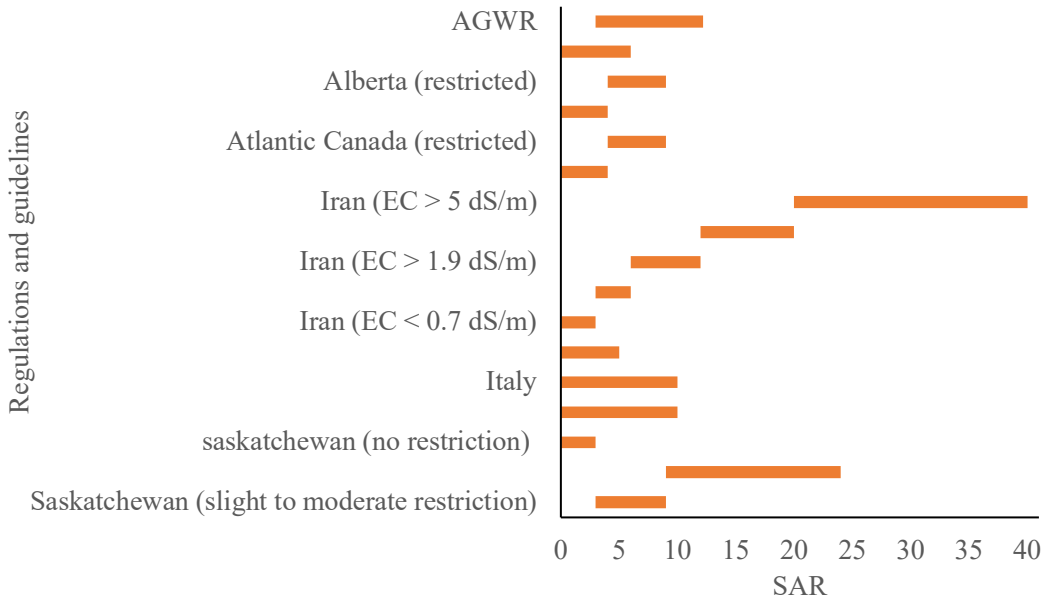


Figure 5. Required SAR ranges in agricultural water reuse regulations and guidelines.

IV) Ions: Chloride, Sodium, and Boron: Resulting in crop growth and yield reduction, morphology changes, and death, the presence of toxic ions can be detrimental to crops if their concentrations are more than the desired levels (Edelstein et al., 2005). Despite this potential negative impact, these ions are beneficial at relatively low concentrations. Among these ions, Sodium (Na), Chloride (Cl^-), and Boron (B) are of great significance. These ions affect the crop, which can be either direct by interference with the metabolic processes or indirect by influencing other nutrients (Lazarova & Bahri, 2004). Roots and leaves are the main parts of crops by which Sodium and Chloride can be absorbed. Usually, when leaves absorb the ion, it increases the rate of absorption, which results in toxic ion accumulation and can be the primary toxicity source (Ayers & Westcot, 1985).

Due to the extensive use of perborate as a bleaching agent, residential wastewater often contains a considerable amount of Boron. While one mg/l of Boron is essential for crop growth, if its concentration reaches two mg/l or more, most of the crops will suffer from Boron toxicity (Lazarova & Bahri, 2004). Atlantic Canada and Israel issued the highest and lowest thresholds for Boron as 6.5 and 0.4 mg/l, respectively. Even though Boron concentrations of more than two mg/l can result in toxic crops, Tunisia and Atlantic Canada have set their Boron thresholds as 3 and 6.5 mg/l, respectively. Excess Chloride can result in acute physiological dysfunctions. A salty taste is another result of more than desired amounts of Chloride, which affects the crop market negatively (Geilfus, 2018). The lowest chloride thresholds have been issued by Iran and Saudi Arabia, 100 mg/l, and the highest one has been issued by

Tunisia, 2000 mg/l (Table 16). Also, only Delaware included Chloride in its regulation among the U.S. states.

Extra Sodium increases osmotic stress and can kill crop cells (Munns, 2002). For Sodium, just six documents out of 70 investigated documents included Sodium among their water quality parameters. The lowest thresholds were issued by FAO, and Iran as 69 and 70 mg/l, respectively, and the highest were issued by AGWR as 312 mg/l and by Oman for non-food crops as 300 mg/l. None of the U.S. states included Sodium thresholds in their regulations and guidelines.

Table 16. Toxic ions (Chloride, Sodium, and Boron) thresholds in agricultural water reuse regulations and guidelines.

Organization / Country/ State	Chloride (Cl^-), mg/l	Sodium (Na^+), mg/l	Boron (B), mg/l
EPA			0.75
FAO	surface irrigation: < 142 (unrestricted use) 142 < Cl < 355 (restricted use) sprinkler irrigation: < 3 m^3/l (unrestricted use) 3 < m^3/l (restricted use)	surface irrigation: < 3 SAR (unrestricted use) 3 < Na < 9 SAR (restricted use) sprinkler irrigation: < 69 (unrestricted use) 69 < (restricted use)	< 0.7 (unrestricted) 0.7 < B < 3 mg/l (restricted)
Atlantic Canada			0.5-6.5
Delaware	250		
Cyprus	300		1
Italy	250		1
Greece			2
Iran	100	70	0.7
Israel	250	150	0.4
Kuwait			2
Oman	650 (food crops) 650 (non-food crops)	200 (food crops) 300 (non-food crops)	0.5 (food crops) 1 (non-food crops)
Saudi Arabia	100		0.5
Tunisia	2000		3
China	350		1
AGWR	340	62<Na<312	0.009-0.480

V) Trace elements: As mentioned before, trace elements (such as lead, cadmium, and mercury) exist in low concentrations in wastewater but are hardly included in routine irrigation water analysis. Industrial and urban wastewater may contain considerable amount of trace elements and may result in accumulating of these compounds in soil and plants, reducing crop growth and polluting groundwater (Hussain et al., 2013; Jiang et al., 2014; Lazarova & Bahri, 2004). Trace elements accumulation in soils depends on their chemical form, consisting exchangeable, sorbed, organic-bound, carbonate, and sulfide. The uptake of these elements by plants mostly depends on rhizosphere environment, plant root system features, and soil characteristics. The soil pH has the most effect on the plant's uptake. Toxicities caused by trace elements have been mostly reported in acidic soils (Lazarova & Bahri, 2004).

The threshold levels indicated by agricultural water reuse regulations and guidelines were issued using limited research by different agencies which made these thresholds relatively restrictive (Table 13). Therefore, if the suggested threshold is not met, it does not mean that it will always result in phytotoxicity. Trace elements thresholds were issued to help practice a safe and sustainable agriculture, but as these elements are used extensively nowadays, these thresholds need to be updated regularly. Also, more regulations and guidelines should include trace elements. Currently, at the best case, only 17 out of 70 investigated documents include trace elements. Of note is the discrepancies among the trace elements thresholds ranges in the documents. Cadmium (0.0001-0.2 mg/l), Arsenic (0.004-0.1 mg/l), Lead (0.001-0.5 mg/l), Copper (0.002-1 mg/l), and Mercury (0.0001-0.2) were some of the most frequent trace elements in current regulations and guidelines with 17, 16, 16, 16, and 11 number of mentions, respectively (Table 13).

VI) Bicarbonate and Carbonate: Bicarbonate and carbonate are among the essential ions for plant health. High concentrations of these ions in the recycled water for irrigation can cause different consequences (Alcántara et al., 1988; Alhendawi et al., 1997; Kosegarten et al., 1999; Shahabi et al., 2005). Irrigation of crops by recycled water, which has high bicarbonate and carbonate concentrations, using overhead sprinklers leaves white lime deposits on the leaves of the crops during hot irrigation days. These white deposits not only reduce crop sales due to their undesirable look but also result in clogging in the irrigation appurtenances, including spray nozzles and drip emitters (Lazarova & Bahri, 2004).

Another issue is increasing the SAR levels in the soil. If bicarbonate ions bond with chemical elements such as magnesium and calcium, resulting in its precipitation as magnesium carbonate or calcium carbonate, it will increase the soil SAR levels owing to dissolved calcium concentration decrease (Wastewater Quality Guidelines for Agricultural Use). Finally, a high bicarbonate concentration and carbonate may increase soil pH, influencing soil permeability (Shahabi et al., 2005; Wastewater Quality Guidelines for Agricultural Use). Despite the aforementioned consequences of bicarbonate and carbonate, they are mentioned in only three agricultural water

reuse regulations and guidelines that were investigated, including FAO, Iran, and Jordan (Table 17). Of note is only Iran included carbonate in its guideline.

Table 17. Bicarbonate and carbonate thresholds in agricultural water reuse regulations and guidelines.

Organization/ Country/state	Bicarbonate (mg/l)	Carbonate (mg/l)
FAO	91.5 (without restriction in use) 520 (with slight to moderate restrictions in use)	
Iran	90	3
Jordan	400	

VII) Nutrients and Micronutrients: Important nutrients and micronutrients for crop growth include Nitrogen (N), Phosphorus (P), Potassium (K), Zinc (Zn), and Sulfur (S). Although Nitrogen is the most important nutrient for crop growth, high concentrations of this nutrient may result in overstimulation of plant growth, lodging, poor crop quality, maturity postponement, and excessive foliar growth (Sainju et al., 2019; Thomidis et al., 2016; Wastewater Quality Guidelines for Agricultural Use). Also, as a long-term consequence of high Nitrogen concentration, stalks, stems, and branches of crops go weak, which makes the crop incapable of supporting the weight of vegetation in the case of winds and rain (Lazarova & Bahri, 2004). Moreover, the pasture irrigated with high Nitrogen levels may be an unsafe source for feeding the livestock.

Phosphorous is also essential for crop and livestock production. However, excess amounts of Phosphorous can increase the rate of eutrophication. EPA identified eutrophication as the major problem of surface waters in the U.S. This phenomenon decreases available water sources for different applications and drops dissolved Oxygen and sunlight in water which puts aquatic health in danger. Groundwater contamination and eutrophication in coastal areas are among other consequences of high concentrations of nutrients (Sharpley & Beegle, 2001). Potassium can stimulate algae and bacteria growth, clogging the irrigation system (Shatanawi & Fayyad, 1996). High concentrations of Zinc can cause phytotoxicity, including hindering crops and their roots' growth, chlorosis, decreasing crop productivity, and killing leaf tips (Rout & Das, 2009).

Comparing all the nutrients (Table 18), it was apparent that Zinc, Boron, and Nitrogen have gained more attention than other nutrients in existing agricultural water reuse regulations and guidelines. Zinc and Boron were discussed in previous sections. Total Nitrogen and Nitrate were mentioned more than other Nitrogen forms (Table 18). The typical concentrations of total Nitrogen, Nitrate, Ammonium, and total Phosphorus were 20-85 mg/l, 0-30 mg/l, 5-40 mg/l, and 4-15 mg/l, respectively (Lazarova & Bahri, 2004). Regarding total Nitrogen, Jordan almost set its threshold near the typical concentration of total Nitrogen in wastewater; however other regulations and guidelines required lower levels of total Nitrogen. Oman and FAO,

for restricted irrigation, required almost the same or higher concentrations of Nitrate, but the other regulations and guidelines set relatively lower Nitrate levels for irrigation by recycled water.

For Ammonium, all existing regulations and guidelines require lower Ammonium levels than its typical concentration in wastewater. Phosphorus thresholds in the existing regulations and guidelines were also much lower than the average levels in wastewater. Phosphate was mentioned more than total Phosphorous in the studied documents. Comparing countries that issued Phosphate or Phosphorous thresholds, of note was that developed countries (such as Canada, Israel, Australia, and Italy) were more restrictive than developing countries (such as Iran, Jordan, and Kuwait).

VIII) Free Chlorine: Chlorine is used in wastewater treatment plants to disinfect the effluent. Its quantity is usually determined so that there will be some free chlorine in the treated wastewater to ensure water is protected from recontamination by pathogens in the piping and storage system. The average amount of allowable free chlorine in recycled water for irrigation is one mg/l which does not impose any threat on crops, although some sensitive crops are affected by higher than 0.5 mg/l of free chlorine. If the concentration of free chlorine goes higher than the accepted level, severe crop damage will occur, including chlorosis, plant growth decrease, and leaf discoloration (Karaivazoglou et al., 2005; Schreuder & Brewer, 2001). Due to the free chlorine nature, high reactivity, and instability, if the recycled water is stored for a few hours before use, its excess free chlorine will dissipate (Lazarova & Bahri, 2004).

The most residual Chlorine threshold set in regulations and guidelines were one mg/l with 12 out of 25 regulations and guidelines and 0.5 mg/l with 6 out of 25 regulations and guidelines (Table 19). Moreover, China (1.5 mg/l) and two Australian guidelines, NT and WA (2 mg/l), required higher concentrations of 1 mg/l for residual Chlorine. Totally, 25 out of 70 regulations and guidelines required residual Chlorine monitoring as a part of their recycled water quality requirements.

Table 18. Nutrients thresholds in agricultural water reuse regulations and guidelines.

Organization /Country/ State	**Organic Nitrogen (mg/l)**	**Total Phosphorus (mg/l)**	**Total Nitrogen (mg/l)**	**Nitrate(NO_3^-) (mg/l)**	**Phosphate(PO_4^{-3}) (mg/l)**	**Ammonium (NH_4^+) (mg/l)**	**Ammonia (NH_3) (mg/l)**
FAO	-	-	-	5 (without restriction) 30 (with slight to moderate restrictions)	-	-	-
Alabama	-	-	-	10 (Nitrates+ Nitrites)	-	-	-
Saskatchewan	-	4 (food crops) 7 (non-food crops)	20 (food crops) 40 (non-food crops)	-	-	-	-
Massachusetts	-	-	10	-	-	-	-
Montana	-	-	5	-	-	-	-
New Jersey	-	-	10 (NO_3+NH_3)	-	-	-	-
North Carolina	-	-	-	-	-	-	4 (NH_3) (monthly average) 6 (NH_3) (maximum)
Ohio	-	-	10	-	-	-	-
Rhode Island	-	-	15	-	-	-	-
South Carolina	-	-	-	10	-	-	2 (NH_3)
Cyprus	-	-	-	15	10	-	-

Table 18 (continued). Nutrients thresholds in agricultural water reuse regulations and guidelines.

Organization /Country/ State	**Organic Nitrogen (mg/l)**	**Total Phosphorus (mg/l)**	**Total Nitrogen (mg/l)**	**Nitrate (NO_3^-) (mg/l)**	**Phosphate(PO_4^{-3}) (mg/l)**	**Ammonium (NH_4^+) (mg/l)**	**Ammonia (NH_3) (mg/l)**
Italy	-	-	-	15	2	2	-
Iran	-	-	-	-	50	5	-
Israel	-	5	25	-	-	20	-
Jordan	-	-	45 (unrestricted, food crops) 70 (fruit trees) 100 (industrial crops, forest trees) 70 (cut flowers)	6.8 (unrestricted, food crops) 10.4 (fruit trees) 16.1 (industrial crops, forest trees) 10.4 (cut flowers)	30 (all the categories)	-	-
Kuwait	-	-	35	-	30	15	-
Oman	5 (food crops) 10 (non-food crops)	-	-	50 (food crops) 50 (non-food crops)	-	5 (food crops) 10 (non-food crops)	-
Saudi Arabia	-	-	-	10 (unrestricted)	-	5 (unrestricted)	-
AGWR	-	12 (non-food crops)	39 (non-food crops)	-	-	34 (non-food crops)	-

Table 19. Residual Chlorine thresholds in agricultural water reuse regulations and guidelines.

Residual Chlorine (mg/l)	Number of regulations and guidelines	Organization/ Country/ State
2	2	NT (AU) and WA (AU)
1.5	1	China
1	12	NSW (AU), ACT (AU), Israel, Cyprus, Virginia, Utah, Pennsylvania, Ohio, New Jersey, Indiana, Idaho, and EPA
0.5	6	QLD (AU), Kuwait, Rhode Island, Hawaii, Florida, and Alabama
0.2	3	Saudi Arabia, Oklahoma, and Italy
0.1	1	Kansas

3.3.2.3. Physico-chemical parameters

I) Turbidity: Turbidity is among important parameters with both human health and agronomic significance. Disturbance to irrigation facilities, reduction in soil hydraulic conductivity, and polluting soil surface are among the potential negative impacts of excessive turbidity in recycled water (Ragusa et al., 1994; Vinten et al., 1983). One of the main reasons suspended solids are measured and controlled in recycled water is that germs can move along with soil particles by attaching to them. So, agencies considered turbidity, TSS, or SS in their agricultural water reuse regulations and guidelines as indicator parameters. In total, 27 out of 70 regulations and guidelines included turbidity as one of their requirements (Table 20).

There were five different methods of monitoring turbidity in the regulations and guidelines, including 24-hour average, more than 5% of the time in a 24-hour period, maximum of any time, maximum of any time in case of using membranes, and monthly average (Table 20). For the 24-hour average, 2 NTU was used in all the regulations and guidelines, EPA, ISO, Arizona, Hawaii, Idaho, Maryland, Massachusetts, Minnesota, Oregon, Utah, Virginia, Washington, and NSW. Regarding the second category, more than 5% of the time in a 24-hour period, 2 NTU was used by Australian states, NT, QLD, and WA, and 5 NTU was used by the U.S. states, Hawaii, Massachusetts, Oregon, and European Commission.

The next category, maximum of any time, was used more than the others by 27 regulations and guidelines. In this category, Pennsylvania required the highest threshold, and British Columbia, California, New Jersey, Rhode Island, Greece, and ACT required the lowest threshold for turbidity in agricultural water reuse practices. The last two categories were not used as the others. As two of the restrictive guidelines, Hawaii and EPA set 0.2 NTU for their turbidity threshold when membranes are used for treating the recycled water. The monthly average was only used by the state of Pennsylvania, 10 NTU.

Table 20. Turbidity thresholds in agricultural water reuse regulations and guidelines.

Reuse Categories	Turbidity (NTU) [Monitoring]
EPA	
1) Food crops	2 (24-h average) 5 (any time) 0.2 (any time, if membranes are used) [continuous]
ISO	
A: very high-quality treated wastewater; unrestricted urban irrigation and agricultural irrigation of food crops consumed raw	2 (average) 5 (max)
British Columbia	
Unrestricted	2 [continuous]
Arizona	
Food crops	2 (24-hour average) 5 (max) [continuous]
California	
Food crops	2 NTU [continuous]
Delaware	
All types	5 [continuous]
Georgia	
Processed Food Crops/ Non-Food Crops	3 [continuous]
Hawaii	
Food crops	2 (Media filtration) (24-hour average) 5 (Media filtration) (more than 5% of the time in a 24-hour period) 10 (Media filtration) (max) 0.2 (Membrane filtration) (more than 5% of the time in a 24-hour period) 0.5 (Media filtration) (max) [continuous]
Idaho	
Food crops	2 (arithmetic mean of all daily measurements) 5 (max) [continuous]
Maryland	
Class III (restricted access)	2 (daily average)
Massachusetts	
A	2 (24-hour average) 5 (more than 5% of the time within a 24-hour period) 10 (max)

Table 20 (continued). Turbidity thresholds in agricultural water reuse regulations and guidelines.

Reuse Categories	Turbidity (NTU) [Monitoring]
Minnesota	
Food Crops	2 (daily average)
New Jersey	
Food Crops	2
North Carolina	
All types	10
Oregon	
Food Crops	2 (before disinfection, within a 24-hour period) 5 (before disinfection, more than 5% of the time within a 24-hour period) 10 (max)
Pennsylvania	
Food Crops	10 (monthly average) 15 (max) [continuous]
Rhode Island	
Processed Food Crops/ Non-Food Crops	2
Texas	
Food Crops	3 [2/week]
Utah	
Food Crops	2 (daily arithmetic mean) 5 (max) [continuous]
Processed Food Crops/ Non-Food Crops	25 (daily arithmetic mean) 35 (weekly mean) [continuous]
Virginia	
Food Crops	2 (daily average of discrete measurements recorded over a 24-hour period); CAT > 5 NTU
Washington	
Food Crops	2 (monthly average) 5 (max) [continuous]
Processed Food Crops/ Non-Food Crops	2 (monthly average) 5 (max) [continuous]
Spain	
2.1	10 [1/week]
Greece	
Unrestricted irrigation: All crops including all irrigation methods	2
E.U.	
A:	5 (90% of the samples) 10 (max)

Table 20 (continued). Turbidity thresholds in agricultural water reuse regulations and guidelines.

Reuse Categories	Turbidity (NTU) [Monitoring]
Saudi Arabia	
Unrestricted	5
ACT (Australia)	
Food crops in direct contact with water e.g., sprays	2
NSW (Australia)	
Food production, Raw human food crops in direct contact with effluent e.g., via sprays, irrigation of salad vegetables	2 (24-hour mean) 5 (max) [continuous]
NT (Australia)	
A+: (high level of human contact) commercial food crops consumed raw or unprocessed (e.g., salad crops)	2 (95%) 5 (max) [continuous]
B: (medium level human contact) commercial food crops	5 (95%) [continuous]
QLD (Australia)	
(Minimally processed food crops) A+:	2 (95%)
WA (Australia)	
(High level of human contact) commercial food crops consumed raw or unprocessed (e.g., Salad crops)	2 (95%) 5 (max) [continuous]

II) TSS/SS and TS: The TS consists of total suspended solids (TSS) and TDS which can be separated by a filtration process. Solids that remain on the filter are suspended solids, and those that pass the filter are dissolved solids. According to WHO (World Health Organization, 2006c), TSS consists of various materials, namely industrial waste, decaying plants and animal matter, and silts. In contrast, TDS consists of dissolved organic matter and inorganic salts in water. As these two parameters are easily measured and can be used as indicators of recycled water quality, many organizations and agencies included them in their agricultural water reuse regulations and guidelines (Table 14 and Table 21). Of note is that the allowable concentrations of TDS in those regulations and guidelines, which included both TDS and TSS thresholds, were much higher than the permissible concentration of TSS for using recycled water in agriculture (Figure 6), preventing erosion, corrosion, and clogging in irrigation facilities, and damaging crops. Totally, TSS was mentioned in agricultural water reuse regulations and guidelines in 43 documents.

Table 21. TSS/SS thresholds in agricultural water reuse regulations and guidelines.

Reuse Categories	TSS (mg/l) [Monitoring]
EPA	
1) Food crops	5 0.5 (if membranes are used)
2) Process Food Crops & Non-food crops	30 [daily]
ISO	
A: very high-quality treated wastewater; unrestricted urban irrigation and agricultural irrigation of food crops consumed raw	5 (average) 10 (maximum)
B: high quality treated wastewater; restricted urban irrigation and agricultural irrigation of processed food crops	10 (average) 25 (maximum)
C: good quality treated wastewater; agricultural irrigation of non-food crops	30 (average) 50 (maximum)
D: medium quality treated wastewater; restricted irrigation of industrial and seeded crops	90 (average) 140 (maximum)
British Columbia	
Restricted	45 [daily]
Alberta	
Restricted	100 [2/year]
Unrestricted	100 [2/year]
Alabama	
	30 (monthly average) [weekly]
Colorado	
Processed Food Crops/ Non-Food Crops	30 [daily]
Delaware	
All types	10 [2/month]
Florida	
Food crops	5
Processed Food Crops/ Non-Food Crops	10
Georgia	
Processed Food Crops/ Non-Food Crops	5 [weekly]
Hawaii	
Food crops	10
Processed Food Crops/ Non-Food Crops	30 (monthly average of composite samples)
Indiana	
Food crops	5 (24-hour average) [daily]
Processed Food Crops/ Non-Food Crops	30 (24-hour average) [daily]
Iowa	
Processed Food Crops/ Non-Food Crops	30 (30-day average) 45 (7-day average)

Table 21 (continued). TSS/SS thresholds in agricultural water reuse regulations and guidelines.

Reuse Categories	TSS (mg/l) [Monitoring]
Maryland	
Class I (restricted access)	90 (monthly average)
Class II (restricted access)	10 (monthly average)
Massachusetts	
A	5
C	30
Nevada	
Processed Food Crops/ Non-Food Crops	30
New Jersey	
Food Crops	5
New Mexico	
All types (in case of food crops: just food trees and nut trees)	30
North Carolina	
All types	5 [monthly average] 10 [max]
North Dakota	
Processed Food Crops/ Non-Food Crops	45 (maximum) [daily]
Ohio	
Processed Food Crops/ Non-Food Crops	45 [2/week]
Pennsylvania	
Processed Food Crops/ Non-Food Crops	30 (average) 45 (maximum) [weekly]
Rhode Island	
Processed Food Crops/ Non-Food Crops	8
Virginia	
Processed Food Crops/ Non-Food Crops	30 (monthly average) 45 (maximum weekly average)
Washington	
Food Crops	30 (arithmetic mean of all samples collected during the month) [daily]
Processed Food Crops/ Non-Food Crops	30 (arithmetic mean of all samples collected during the month) [daily]

Table 21 (continued). TSS/SS thresholds in agricultural water reuse regulations and guidelines.

Reuse Categories	TSS (mg/l) [Monitoring]
Cyprus	
Agglomerations > 2000 p.e	10 [1/15 days]
Agglomerations < 2000 p.e all crops	10 (80% of samples per month (minimum number of samples=5))
Agglomerations < 2000 p.e unlimited access and vegetables eaten cooked(potatoes, beetroots, colocasia)	10 (80% of samples per month (minimum number of samples=5)) 15 (maximum)
Agglomerations < 2000 p.e limited access and Crops for human consumption	30 (80% of samples per month (minimum number of samples=5)) 45 (maximum)
Agglomerations < 2000 p.e fodder crops	30 (80% of samples per month (minimum number of samples=5)) 45 (maximum)
France	
A: unrestricted irrigation of all crops including these accessed by the public	15 [weekly]
Italy	
	10
Spain	
2.1	20 [weekly]
2.2: QUALITY 2.2 a) Irrigation of crops for human consumption using application methods that do not prevent direct contact of reclaimed with edible parts of the plants, which are not eaten raw but after an industrial treatment process. b) Irrigation of pastureland for milk- or meat-producing animals. c) Aquaculture.	35 [weekly]
2.3: a) Localized irrigation of tree crops whereby reclaimed water is not allowed to come into contact with fruit for human consumption. b) Irrigation of ornamental flowers, nurseries and greenhouses whereby reclaimed water does not come into contact with the crops. c) Irrigation of industrial non-food crops, nurseries, silo fodder, cereals and oilseeds.	35 [weekly]

Table 21 (continued). TSS/SS thresholds in agricultural water reuse regulations and guidelines.

Reuse Categories	TSS (mg/l) [Monitoring]
Greece	
Restricted irrigation: Areas where public access is not expected, fodder and industrial crops, pastures, trees (except fruit trees), if fruits are not in contact with the soil, seed crops and crops whose products are processed before consumption. Sprinkler irrigation is not allowed	35
Unrestricted irrigation: All crops including all irrigation methods	10 (80% samples)
E.U.	
A:	10 (90% samples) 20 (maximum)
B:	35
C:	35
D:	35
Iran	
A: Irrigation of crops likely to be eaten uncooked, sports field, public parks	40
B: Irrigation of cereal crops, industrial crops, fodder crops, pasture, and trees	40
C: Localized irrigation of crops in category B if exposure of workers and the public does not occur	40
Israel	
	10
Jordan	
A: cooked vegetables, parks, playgrounds roadsides in the city	50
B: fruit trees, landscaped roadsides of highways	200
C: industrial crops, forest trees	300
D: cut flowers	15
Kuwait	
	15
Oman	
A: vegetables likely to be eaten raw, fruit likely to be eaten raw and within 2 weeks of any irrigation	15
B: vegetables to be cooked or processed, fruit if no irrigation within 2 weeks of cropping fodder, cereal seed crops, pasture, no public access	30
Saudi Arabia	
Restricted	40
Unrestricted	10

Table 21 (continued). TSS/SS thresholds in agricultural water reuse regulations and guidelines.

Reuse Categories	TSS (mg/l) [Monitoring]
Egypt	
A: plants and trees grown for greenery at touristic villages and hotels and inside residential areas at the new cities	20
B: fodder/feed crops, trees producing fruits with epicarp, trees used for green belts around cities and afforestation of highways or roads, nursery plants, roses & cut flowers, fiber crops, mulberry for the production of silk	50
C: industrial oil crops, wood trees	250
Tunisia	
	30
China	
Fiber crops	100
Dry field corn oil crops	90
Paddy field grain	80
Vegetable	60
NSW (Australia)	
Food production, raw human food crops not in direct contact with effluent (edible product separated from contact with effluent, e.g., use of trickle irrigation) or crops sold to consumers cooked or processed.	30 [weekly]
Food production, pasture, and fodder (for grazing animals except pigs and dairy animals, i.e., cattle, sheep, and goats)	30 [weekly]
Food production, pasture, and fodder for dairy animals (with withholding period).	30 [weekly]
Food production, pasture, and fodder for dairy animals (without withholding period). Drinking water (all stock except pigs). Wash-down water for dairies.	30 [weekly]
Non-food crops, Silviculture, turf, and cotton, etc.	30 [weekly]
NT (Australia)	
A+: (high level of human contact) commercial food crops consumed raw or unprocessed (e.g., salad crops)	10 [weekly]
B: (medium level human contact) commercial food crops	30 [weekly]
C: (low level of human contact) commercial food crops	30 [weekly]

Table 21 (continued). TSS/SS thresholds in agricultural water reuse regulations and guidelines.

Reuse Categories	TSS (mg/l) [Monitoring]
VIC (Australia)	
B: dairy cattle grazing	30
C: human food crops/processed, grazing, fodder for livestock	30
D: non-food crops including instant turf, woodlots, flowers	30
WA (Australia)	
(High level of human contact) commercial food crops consumed raw or unprocessed (e.g., Salad crops)	10 [weekly]
(Low level of human contact) non-edible crops	30 [weekly]
AGWR (Australia)	
Commercial food crops	30

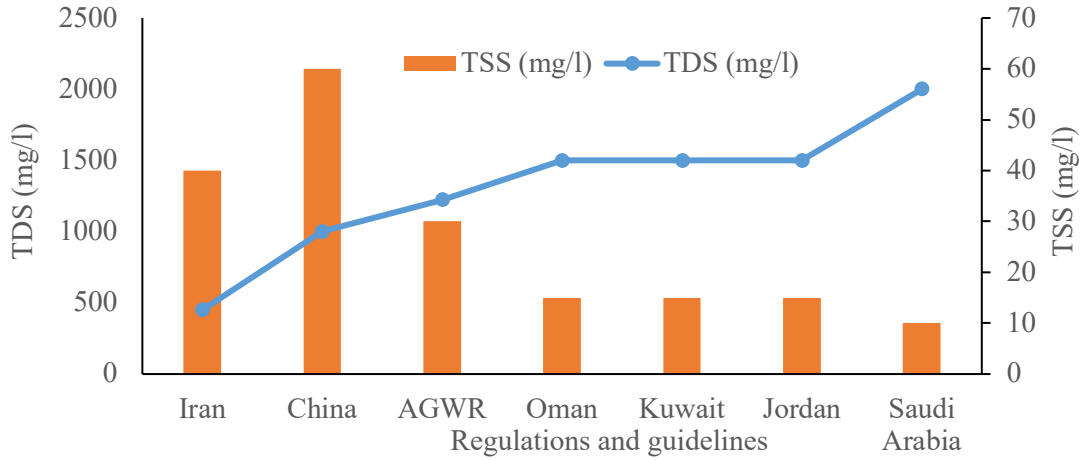


Figure 6. Comparison of the TDS and selected TSS thresholds, required in agricultural water reuse regulations and guidelines which included both of TDS and TSS thresholds.

III) BOD_5, $CBOD_5$, and COD: Biological oxygen demand (BOD), carbonaceous oxygen demand (CBOD), and chemical oxygen demand (COD) are different indicators of organic matter in water. Organic matter in the water may alter the water's color and odor, provide nutrients for microbial growth, and negatively impact the disinfection process (Jeong et al., 2016). To prevent these adverse effects, different organizations and agencies have included BOD_5, $CBOD_5$, and COD thresholds in their regulations and guidelines. In total, 7, 42, and 8 regulations and guidelines included $CBOD_5$, BOD_5, and COD in their requirements, respectively. The highest and lowest $CBOD_5$ thresholds were issued by Alberta (restricted and unrestricted public access) and Texas (food crops) as 100 and 5 mg/l, respectively

(Table 22). The highest BOD_5 thresholds was issued by Egypt (C: industrial oil crops and wood trees) as 400 mg/l (Table 23). The lowest BOD_5 threshold were issued by Texas (food crops), Hawaii (food crops), and Georgia (non-food crops/ processed food crops), and ISO (unrestricted/ food crops) as 5 mg/l. The highest and lowest COD thresholds were issued by Jordan (B: fruit trees, landscaped roadsides of highways and C: industrial crops, forest trees) China (vegetables) as 500 and 40 mg/l, respectively (Table 24).

Table 22. $CBOD_5$ thresholds in agricultural water reuse regulations and guidelines.

Reuse Categories	**$CBOD_5$ (mg/l)**
Alberta	
Restricted	100 [2/year]
Unrestricted	100 [2/year]
Alabama	
	10 (monthly average) [weekly]
Iowa	
Processed Food Crops/ Non-Food Crops	25 (30-day average) 40 (7-day average)
Ohio	
Processed Food Crops/ Non-Food Crops	40 [2/week]
Oklahoma	
Processed Food Crops/ Non-Food Crops	20 [weekly]
Texas	
Food Crops	5 [2/week]
Processed Food Crops/ Non-Food Crops	15 [weekly]
Virginia	
Food Crops	8 (monthly average)
Processed Food Crops/ Non-Food Crops	25 (monthly average) 40 (maximum weekly average)

Table 23. BOD_5 thresholds in agricultural water reuse regulations and guidelines.

Reuse Categories	BOD_5 (mg/l)
EPA	
1) Food crops	10 [weekly]
2) Process Food Crops/ Non-food crops	30 [weekly]
ISO	
A: very high-quality treated wastewater; unrestricted urban irrigation and agricultural irrigation of food crops consumed raw	5 (average) 10 (maximum)
B: high quality treated wastewater; restricted urban irrigation and agricultural irrigation of processed food crops	10 (average) 20 (maximum)
C: good quality treated wastewater; agricultural irrigation of non-food crops	20 (average) 35 (maximum)
D: medium quality treated wastewater; restricted irrigation of industrial and seeded crops	60 (average) 100 (maximum)
E: extensively treated wastewater; restricted irrigation of industrial and seeded crops	20 (average) 35 (maximum)
British Columbia	
Restricted	45 [weekly]
Unrestricted	10 [weekly]
Delaware	
All types	10 [2/month]
Georgia	
Processed Food Crops/ Non-Food Crops	5 [weekly]
Hawaii	
Food crops	5 (R-1) 10 (R-2)
Processed Food Crops/ Non-Food Crops	30 (monthly average of composite samples)
Indiana	
Food crops	10 [weekly]
Processed food crops/ non-food crops	30 [weekly]
Maryland	
Class I (restricted access)	70 (monthly average)
Class II (restricted access)	10 (monthly average)
Class III (restricted access)	10 (monthly average)
Massachusetts	
A	10
C	30
Nevada	
Processed Food Crops/ Non-Food Crops	30

Table 23 (continued). BOD_5 thresholds in agricultural water reuse regulations and guidelines.

Reuse Categories	BOD_5 (mg/l)
New Mexico	
All types (in case of food crops: just food trees and nut trees)	30
North Carolina	
All types	10 (monthly average) 15 (daily maximum)
North Dakota	
Processed Food Crops/ Non-Food Crops	30 (daily maximum) [1/14 days]
Oklahoma	
Processed Food Crops/ Non-Food Crops	20 [weekly]
Pennsylvania	
Food Crops	10 (monthly average) 20 (maximum) [weekly]
Processed Food Crops/ Non-Food Crops	30 (monthly average) 45 (maximum) [weekly]
Rhode Island	
Processed Food Crops/ Non-Food Crops	10
South Carolina	
Processed Food Crops/ Non-Food Crops	10
Texas	
Food Crops	5 [2/week]
Processed Food Crops/ Non-Food Crops	20 [1/week]
Utah	
Food Crops	10 (monthly arithmetic mean) [weekly]
Processed Food Crops/ Non-Food Crops	25 (monthly arithmetic mean) [weekly]
Virginia	
Food Crops	10 (monthly average)
Processed Food Crops/ Non-Food Crops	30 (monthly average) 45 (max weekly average)
Washington	
Food Crops	30 (monthly arithmetic mean) [weekly]
Processed Food Crops/ Non-Food Crops	30 (monthly arithmetic mean) [weekly]

Table 23 (continued). BOD_5 thresholds in agricultural water reuse regulations and guidelines.

Reuse Categories	BOD_5 (mg/l)
Wisconsin	
All types	50
Cyprus	
Agglomerations > 2000 p.e	10 [1/15 days]
Agglomerations < 2000 p.e all crops	10 (80% of samples per month (minimum number of samples=5))
Agglomerations < 2000 p.e unlimited access and vegetables eaten cooked (potatoes, beetroots, Colocasia)	10 (80% of samples per month (minimum number of samples=5)) 15 (maximum)
Agglomerations < 2000 p.e limited access and Crops for human consumption	20 (80% of samples per month (minimum number of samples=5)) 30 (maximum)
Agglomerations < 2000 p.e fodder crops	20 (80% of samples per month (minimum number of samples=5)) 30 (maximum)
Italy	
	20
Greece	
Restricted irrigation: Areas where public access is not expected, fodder and industrial crops, pastures, trees (except fruit trees), provided that fruits are not in contact with the soil, seed crops and crops whose products are processed before consumption. Sprinkler irrigation is not allowed	25
Unrestricted irrigation: All crops including all irrigation methods	10 (80% samples)
E.U.	
A:	10 (90% of the samples) 20 (maximum) [weekly]
B:	25
C:	25
D:	25

Table 23 (continued). BOD_5 thresholds in agricultural water reuse regulations and guidelines.

Reuse Categories	BOD_5 (mg/l)
Iran	
A: Irrigation of crops likely to be eaten uncooked, sports field, public parks	21
B: Irrigation of cereal crops, industrial crops, fodder crops, pasture, and trees	21
C: Localized irrigation of crops in category B if exposure of workers and the public does not occur	21
Israel	
	10
Jordan	
A: cooked vegetables, parks, playgrounds roadsides in the city	30
B: fruit trees, landscaped roadsides of highways	200
C: industrial crops, forest trees	300
D: cut flowers	30
Kuwait	
	20
Oman	
A: vegetables likely to be eaten raw fruit likely to be eaten raw and within 2 weeks of any irrigation	15
B: vegetables to be cooked or processed, fruit if no irrigation within 2 weeks of cropping, fodder, cereal seed crops, pasture, no public access	20
Saudi Arabia	
restricted	40
unrestricted	10
Egypt	
A: plants and trees grown for greenery at touristic villages and hotels and inside residential areas at the new cities	20
B: fodder/feed crops, trees producing fruits with epicarp, trees used for green belts around cities and afforestation of highways or roads, nursery plants, roses & cut flowers, fiber crops, mulberry for the production of silk	60
C: industrial oil crops, wood trees	400
Tunisia	
	30

Table 23 (continued). BOD_5 thresholds in agricultural water reuse regulations and guidelines.

Reuse Categories	BOD_5 (mg/l)
China	
fiber crops	100
dry field corn oil crops	80
paddy field grain	60
vegetable	40
ACT (Australia)	
Pasture and fodder for grazing animals (except pigs)	40 (kg/ha/day) [<3ML/year: initial and 6 monthly], [>3ML/year: initial and 3 monthly]
Silviculture, turf, and non-food crops	40 (kg/ha/day) [<3ML/year: initial and 6 monthly], [>3ML/year: initial and 3 monthly]
Food crops in direct contact with water e.g., sprays	40 (kg/ha/day) [<3ML/year: initial and 6 monthly], [>3ML/year: initial and 3 monthly]
Food crops not in direct contact with water (e.g., flood or furrow) or which will be sold to consumers cooked or processed	40 (kg/ha/day) [<3ML/year: initial and 6 monthly], [>3ML/year: initial and 3 monthly]
NSW (Australia)	
Food production, Raw human food crops not in direct contact with effluent (edible product separated from contact with effluent, e.g., use of trickle irrigation) or crops sold to consumers cooked or processed.	30 [weekly]
Non-food crops, Silviculture, turf, and cotton, etc.	30 [weekly]
NT (Australia)	
A+: (high level of human contact) commercial food crops consumed raw or unprocessed (e.g., salad crops)	10 [weekly]
B: (medium level human contact) commercial food crops	20 [weekly]
C: (low level of human contact) commercial food crops	20 [weekly]

Table 23 (continued). BOD_5 thresholds in agricultural water reuse regulations and guidelines.

Reuse Categories	BOD_5 (mg/l)
TAS (Australia)	
A: direct contact of reclaimed water with crops consumed raw	10 [weekly]
B: crops for human consumption	50 [weekly]
C: non-human food chain	80 [monthly]
VIC (Australia)	
B: dairy cattle grazing	20
C: human food crops/processed, grazing, fodder for livestock	20
D: non-food crops including instant turf, woodlots, flowers	20
WA (Australia)	
(High level of human contact) commercial food crops consumed raw or unprocessed (e.g., Salad crops)	10 [weekly]
(Low level of human contact) non-edible crops	20 [weekly]
AGWR (Australia)	
Commercial food crops	20

3.3.2.4. Treatment levels

As mentioned before, one of the main considerations of water reuse practices is ensuring that the recycled water is safe for reuse. Appropriate treatment technologies must be used to provide biologically and chemically safe water for use in agriculture. Accordingly, different agencies and organizations require various treatment technologies in their agricultural water reuse regulations and guidelines, considering recycled water quality, type of crops, irrigation methods, soil characteristics, and public access (Table 25 and Table 26).

Secondary treatment is the most frequent requirement mentioned in the regulations and guidelines. Of note was that 38 of 70 regulations and guidelines required disinfection as part of the treatment process. When compared, it was obvious that there was a large discrepancy in the required treatment methods in the regulations and guidelines. As different treatment methods can remove various contaminants from wastewater, it likely results in reclaimed water with significantly different water quality. Therefore, more investigation needs to be done in terms of required treatment methods in the regulations and guidelines by agencies.

Table 24. COD thresholds in agricultural water reuse regulations and guidelines.

Reuse Categories	COD (mg/l)
Cyprus	
agglomerations > 2000 p.e.	70 [1/15 days]
France	
A: unrestricted irrigation of all crops including these accessed by the public	60 [weekly]
Israel	
	100
Jordan	
A: cooked vegetables, parks, playgrounds roadsides in the city	100
B: fruit trees, landscaped roadsides of highways	500
C: industrial crops, forest trees	500
D: cut flowers	100
Kuwait	
	100
Oman	
A: vegetables likely to be eaten raw fruit likely to be eaten raw and within 2 weeks of any irrigation	150
B: vegetables to be cooked or processed, fruit if no irrigation within 2 weeks of cropping, fodder, cereal seed crops, pasture, no public access	200
Tunisia	
	90
China	
Fiber crops	200
Dry field corn oil crops	180
Paddy field grain	60
Vegetable	40

Table 25. Required treatment technologies in agricultural water reuse regulations and guidelines.

Organizations/ Countries/ States	Reuse categories	Treatment
EPA	Food crops	Secondary, filtration, disinfection
	Process Food Crops/ Non-food crops	Secondary, disinfection
FAO	A: Irrigation of crops likely to be eaten uncooked, sports field, public parks	A series of stabilization ponds or equivalent treatment
	B: Irrigation of cereal crops, industrial crops, fodder crops, pasture, and trees	Retention in stabilization ponds for 8-10 days or equivalent helminth and fecal coliform removal
	C: Localized irrigation of crops in category B if exposure of workers and the public does not occur	Pretreatment as required by the irrigation technology, but not less than primary sedimentation
ISO	A: Very high-quality treated wastewater; unrestricted urban irrigation and agricultural irrigation of food crops consumed raw	Secondary, contact filtration or membrane filtration and disinfection
	B: high quality treated wastewater; restricted urban irrigation and agricultural irrigation of processed food crops	Secondary, filtration and disinfection
	C: good quality treated wastewater; agricultural irrigation of non-food crops	Secondary and disinfection
	D: medium quality treated wastewater; restricted irrigation of industrial and seeded crops	Secondary or high-rate clarification with coagulation, flocculation
	E: extensively treated wastewater; restricted irrigation of industrial and seeded crops	Stabilization ponds and wetlands
British Columbia	Restricted	Secondary, disinfection
	Unrestricted	Secondary, chemical addition, filtration, disinfection, and emergency storage

Table 25 (Continued). Required treatment technologies in agricultural water reuse regulations and guidelines.

Organizations/ Countries/ States	Reuse categories	Treatment
Alberta	Restricted	A best practicable treatment approach, providing the required effluent quality (essentially secondary treatment with disinfection)
	Unrestricted	A best practicable treatment approach, providing the required effluent quality (essentially secondary treatment with disinfection)
Alabama		Secondary, disinfection
Atlantic Canada	Restricted	At least secondary with disinfection
	Unrestricted	At least secondary with disinfection
Saskatchewan	Food crops	Lagoons followed by a storage cell of holding at least 210-230 days of sewage flow or secondary treatment with adequate storage facilities, disinfection is required
	Non-food crops	Lagoons followed by a storage cell of holding at least 210-230 days of sewage flow or secondary treatment with adequate storage facilities
Arizona	Food crops	A: Secondary, filtration and disinfection
	Processed Food Crops/ Non-Food Crops	C: Secondary in a series of wastewater stabilization ponds, including aeration, with or without disinfection

Table 25 (Continued). Required treatment technologies in agricultural water reuse regulations and guidelines.

Organizations/ Countries/ States	Reuse categories	Treatment
California	Food crops	A disinfected tertiary recycled water: Filtration, disinfection
	Processed Food Crops/ Non-Food Crops	Undisinfected secondary recycled water: Oxidized wastewater
Colorado	Processed Food Crops/ Non-Food Crops	Category 1 & 2 & 3: Secondary treatment and disinfection
Florida	Food crops	Secondary treatment and high-level disinfection
	Processed Food Crops/ Non-Food Crops	Secondary treatment and basic level disinfection
Georgia	Processed Food Crops/ Non-Food Crops	Secondary treatment, filtration, and disinfection
Hawaii	Food crops	R-1: Oxidization, filtration, and disinfection R-2: Oxidization and disinfection
	Processed Food Crops/ Non-Food Crops	R-3: Oxidization
Idaho	Food crops	B: Oxidization, coagulation, clarification, and filtration C: Oxidization and disinfection
	Processed Food Crops/ Non-Food Crops	C: Oxidization and disinfection D: Oxidization and disinfection
Illinois	Processed Food Crops/ Non-Food Crops	A two-cell lagoon system or a mechanical secondary treatment facility

Table 25 (Continued). Required treatment technologies in agricultural water reuse regulations and guidelines.

Organizations/ Countries/ States	Reuse categories	Treatment
Indiana	Food crops	Secondary treatment: (A) activated sludge processes, (B) trickling filters, (C) rotating biological contactors, (D) stabilization pond systems or (E) other secondary treatment approved by the commissioner in the permit Domestic wastewater: (A) chlorination, (B) ozonation, (C) chemical disinfectants, (D) UV irradiation, (E) membrane processes or (F) other processes approved by the commissioner in the permit
	Processed Food Crops/ Non-Food Crops	Secondary treatment: (A) activated sludge processes, (B) trickling filters, (C) rotating biological contactors, (D) stabilization pond systems or (E) other secondary treatment approved by the commissioner in the permit Domestic wastewater: (A) chlorination, (B) ozonation, (C) chemical disinfectants, (D) UV irradiation, (E) membrane processes or (F) other processes approved by the commissioner in the permit
Iowa	Processed Food Crops/ Non-Food Crops	Secondary treatment

Table 25 (Continued). Required treatment technologies in agricultural water reuse regulations and guidelines.

Organizations/ Countries/ States	Reuse categories	Treatment
Minnesota	Food Crops	Disinfected tertiary: Secondary, filtration and disinfection
	Processed Food Crops/ Non-Food Crops	Disinfected secondary 200: Secondary and disinfection
Montana	All types	B-1: Oxidized, settled, and disinfected
Nebraska	Unrestricted	Disinfection
Nevada	Processed Food Crops/ Non-Food Crops	D: At least secondary treatment
New jersey	Food Crops	Secondary treatment and filtration
	Processed Food Crops/ Non-Food Crops	Secondary treatment
New Mexico	all types (in case of food crops: just food trees and nut trees)	Secondary treatment
North Carolina	All types	Tertiary treatment (filtration or equivalent)
North Dakota	Processed Food Crops/ Non-Food Crops	Secondary treatment or tertiary treatment
Oklahoma	Processed Food Crops/ Non-Food Crops	Secondary treatment, nutrient removal, and disinfection
Oregon	Food Crops	A: Oxidization, filtration, and disinfection
	Processed Food Crops/ Non-Food Crops	C: Oxidization and disinfection
Pennsylvania	Food Crops	B: Secondary treatment, filtration, and disinfection
	Processed Food Crops/ Non-Food Crops	C: Secondary treatment and disinfection
Utah	Food Crops	Type I: Filtration and disinfection
	Processed Food Crops/ Non-Food Crops	Type II: Disinfection
Virginia	Food Crops	Level 1: Secondary treatment, filtration, and high-level disinfection
	Processed Food Crops/ Non-Food Crops	Level 2: Secondary treatment and standard disinfection

Table 25 (Continued). Required treatment technologies in agricultural water reuse regulations and guidelines.

Organizations/ Countries/ States	Reuse categories	Treatment
Washington	Food Crops	Class A: Oxidization, coagulation, filtration, and disinfection
	Processed Food Crops/ Non-Food Crops	Class C: Oxidization and disinfection
Wyoming	Food Crops	Class B: Secondary treatment and disinfection
	Processed Food Crops/ Non-Food Crops	Class C: Primary treatment and disinfection
Cyprus	Agglomerations > 2000 (p.e)	NS
	Agglomerations < 2000 (p.e): all crops	Tertiary and disinfection
	Agglomerations < 2000 (p.e): unlimited access and vegetables eaten cooked (potatoes, beetroots, Colocasia)	Tertiary and disinfection
	Agglomerations < 2000 (p.e): limited access and Crops for human consumption	Secondary, disinfection and storage >7 days or tertiary and disinfection
	Agglomerations < 2000 (p.e): fodder crops	Secondary, disinfection and storage >7 days or tertiary and disinfection
Portugal	A: vegetables consumed raw	Secondary, filtration, and disinfection or tertiary, filtration, and disinfection
	B: public parks, and gardens, sport lawns, forests with public access	Secondary, filtration, and disinfection or tertiary, filtration, and disinfection
	C: vegetables to be cooked, forage crops, vineyards, orchards	Secondary, filtration, and disinfection or tertiary, filtration, and disinfection or waste stabilization ponds (≥ 3 ponds and RT ≥ 25 d)
	D: Cereals (except rice), vegetables for industrial process, crops for textile industry, crops for oil extraction, and forest and lawns	Secondary and maturation ponds (RT ≥10 d) or Secondary, filtration, and disinfection

Table 25 (Continued). Required treatment technologies in agricultural water reuse regulations and guidelines.

Organizations/ Countries/ States	Reuse categories	Treatment
Greece	Restricted irrigation: Areas where public access is not expected, fodder and industrial crops, pastures, trees (except fruit trees), provided that fruits are not in contact with the soil, seed crops and crops whose products are processed before consumption. Sprinkler irrigation is not allowed	Secondary treatment and disinfection
	Unrestricted irrigation: All crops including all irrigation methods	Secondary or higher and disinfection
E.U.	A:	Secondary treatment, filtration, and disinfection
	B:	Secondary treatment and disinfection
	C:	Secondary treatment and disinfection
	D:	Secondary treatment and disinfection
Egypt	A: plants and trees grown for greenery at touristic villages and hotels and inside residential areas at the new cities	Advanced or tertiary treatment that can be attained through upgrading the secondary treatment plants to include sand filtration, disinfection, and other processes.
	B: fodder/feed crops, trees producing fruits with epicarp, trees used for green belts around cities and afforestation of highways or roads, nursery plants, roses & cut flowers, fiber crops, mulberry for the production of silk	Secondary treatment
	C: industrial oil crops wood trees	Primary treatment that is limited to sand and oil removal basins and use of sedimentation basins.

Table 25 (Continued). Required treatment technologies in agricultural water reuse regulations and guidelines.

Organizations/ Countries/ States	Reuse categories	Treatment
China	Fiber crops	Primary treatment
	Dry field corn oil crops	Primary treatment
	Paddy field grain	Secondary treatment
	Vegetable	Secondary treatment
ACT	Pasture and fodder for grazing animals (except pigs)	Secondary, pathogen reduction by disinfection or detention in ponds or lagoons
	Silviculture, turf, and non-food crops	Secondary treatment
	Food crops in direct contact with water e.g., sprays	Secondary treatment, filtration, and pathogen reduction
	Food crops not in direct contact with water (e.g., flood or furrow) or which will be sold to consumers cooked or processed	Secondary treatment and pathogen reduction
NSW	Food production: Raw human food crops in direct contact with effluent	Tertiary treatment and pathogen reduction
	Food production: Raw human food crops not in direct contact with effluent (edible product separated from contact with effluent or crops sold to consumers cooked or processed.	Secondary treatment and pathogen reduction
	Food production: Pasture and fodder (for grazing animals except pigs and dairy animals)	Secondary treatment and pathogen reduction
	Food production: Pasture and fodder for dairy animals (with withholding period).	Secondary treatment and pathogen reduction
	Food production: Pasture and fodder for dairy animals (without withholding period), drinking water (all stock except pigs) and wash-down water for dairies	Secondary treatment and pathogen reduction
	Non-food crops: Silviculture, turf, and cotton, etc.	Secondary treatment and pathogen reduction

Table 25 (Continued). Required treatment technologies in agricultural water reuse regulations and guidelines.

Organizations/ Countries/ States	Reuse categories	Treatment
TAS	A: direct contact of reclaimed water with crops consumed raw	Advanced treatment
	B: crops for human consumption	Secondary with disinfection
	C: non-human food chain	Secondary treatment
VIC	A: commercial food crops consumed raw or unprocessed	Advanced treatment
	B: dairy cattle grazing	Secondary and pathogen reduction
	C: human food crops/processed, grazing, fodder for livestock	Secondary and pathogen reduction
	D: non-food crops including instant turf, woodlots, flowers	Secondary treatment
AGWR	Commercial food crops consumed raw or unprocessed	Advanced treatment to achieve total pathogen removal
	Commercial food crops	Secondary treatment with > 25 days lagoon detention and disinfection
	Commercial food crops	Secondary treatment or primary treatment with lagoon detention
	Non-food crops- trees, turf, woodlots, flowers	Secondary treatment or primary treatment with lagoon detention

Table 26. Regulations and guidelines that indicated treatments.

Description	Process	Regulations and guidelines
	Primary Treatment	
Eliminating suspended solids		Wyoming, Egypt, China, AGWR
	Sedimentation/ settlement	Montana, Egypt, and FAO
	Physico-chemical clarification: coagulation/ flocculation	ISO, Idaho, and Washington
	Secondary Treatment	
Removing Carbon and sometimes nutrients		EPA, ISO, British Columbia, Alberta, Alabama, Atlantic Canada, Saskatchewan, Arizona, California, Colorado, Florida, Georgia, Illinois, Indiana, Iowa, Minnesota, Nevada, New Jersey, New Mexico, North Dakota, Oklahoma, Pennsylvania, Virginia, Wyoming, Cyprus, Portugal, Greece, E.U., Egypt, China, ACT, NSW, TAS, VIC, AGWR.
	Wetland	ISO
	Lagoons	Saskatchewan, Illinois, ACT, AGWR.
	Oxidization	California, Hawaii, Idaho, Montana, Oregon, Washington
	Rotating biological contactors	Indiana
	Clarification	ISO and Idaho
	Stabilization ponds/ maturation ponds	FAO, ISO, Arizona, Indiana, Portugal
	Tertiary Treatment	
Effluent polishing		California, Minnesota, North Carolina, North Dakota, Cyprus, Portugal, Egypt, NSW.
	Filtration	EPA, ISO, British Columbia, Arizona, California, Georgia, Hawaii, Idaho, Minnesota, New Jersey, North Carolina, Oregon, Pennsylvania, Utah, Virginia, Washington, Portugal, E.U., Egypt, ACT.
	Disinfection	
Removing suspended particulate matter, viruses, and pathogens.		EPA, ISO, British Columbia, Alberta, Alabama, Atlantic Canada, Saskatchewan, Arizona, California, Colorado, Florida, Georgia, Indiana, Minnesota, Oklahoma, Pennsylvania, Virginia, Wyoming, Hawaii, Idaho, Montana, Nebraska, Oregon, Utah, Washington, Cyprus, Portugal, Greece, E.U., Egypt, ACT, TAS, AGWR.
	Chlorination	Indiana
	Ozonation	Indiana
	UV irradiation	Indiana
	Membrane processes	ISO, Indiana

3.4. Summary of findings

3.4.1. Constituents in reclaimed water

In general, the occurrence of constituents in reclaimed water is subject to treatment processes in wastewater treatment plants. Constituents in wastewater can be divided into three groups: conventional, nonconventional, and emerging. The constituents that have been the basis of the design of most conventional wastewater treatment plants are expected to be mostly removed during the treatment processes (e.g., TSS, BOD, Nitrate, Nitrite, Phosphorus, and Bacteria) (Metcalf and Eddy et al., 2007). There are also groups of constituents that may be removed or reduced using the advanced treatment processes (e.g., metals and TDS) (Metcalf and Eddy et al., 2007).

Finally, there are emerging constituents that are present in micro or nanogram/L, which may pose negative health and environmental concerns (Helmecke et al., 2020). These compounds sometimes cannot be removed effectively even with advanced treatment processes (Lazarova & Bahri, 2004). In what follows, the knowledge gaps related to microbial constituents, agronomic and physico-chemical properties, and emerging constituents of reclaimed water that are of concern in water reuse for agricultural irrigation were briefly discussed. In addition, the findings from the investigation of regulations and guidelines concerning each constituent group were summarized.

3.4.1.1. Microbial quality

As noted in section 4.3.2.1., in most of the regulations and guidelines, Total Coliforms, Fecal coliforms, and E. coli were used as the indicator microorganism to assess the microbial quality of the reclaimed water for irrigation. In the regulations and guidelines investigated in this study, Fecal Coliform, E. Coli, and Total Coliform were the most frequent indicator microorganisms with 36, 24, and 9 cases, respectively (Figure 7). However, indicator microorganisms do not represent all the existing pathogens in the recycled water. Regulations and guidelines need to consider that pathogens in recycled water are part of larger microbial communities (Kulkarni et al., 2018; Marcus et al., 2013). Kulkarni et al. claimed that microbial communities in recycled water could be affected by “wastewater treatment processes, operational parameters, organic and inorganic wastewater constituents, and water reuse site practices” (Kulkarni et al., 2018).

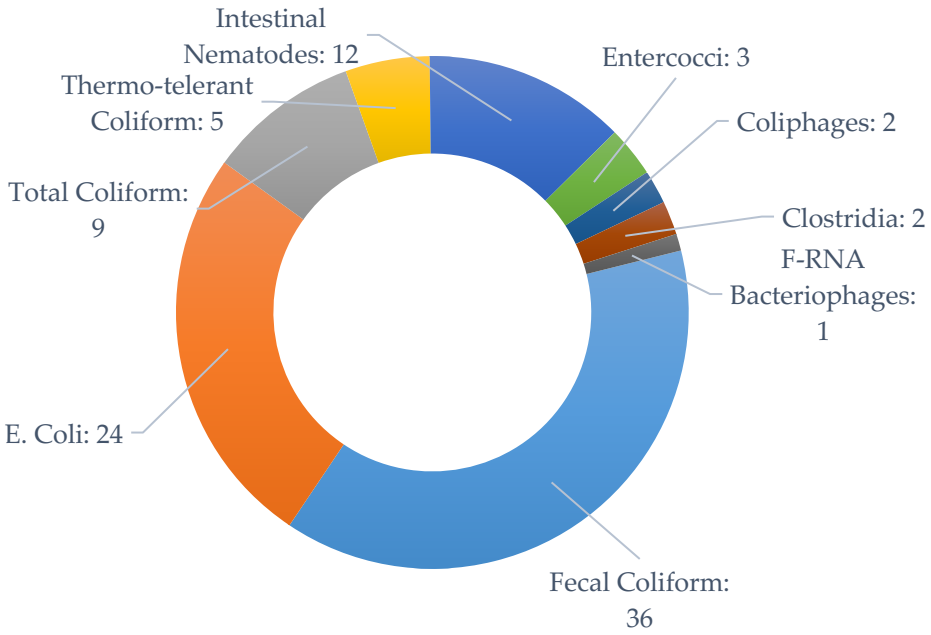


Figure 7. The number of regulations and guidelines which indicated different indicator microorganisms.

Another shortcoming of bacterial indicators is in predicting parasites and viruses, which can be more resistant to disinfection. In addition, the information derived from the microbiological analysis is not immediate and is not obtained continuously. These drawbacks have motivated the development of more preventive approaches, such as the Water Safety Plans proposed by the WHO (Figueras & Borrego, 2010). The recent advancement in detection methods, such as molecular markers and real-time monitoring techniques, necessitates modifying existing official detection methods in regulations and guidelines (Pachepsky et al., 2018; Tortorello, 2003). In summary, more information is still needed to assist regulatory agencies in improving or verifying the effectiveness of their criteria for microbial quality of recycled water, such as:

- Better selection of indicator organisms for estimation of microbial pathogens in reclaimed water
- Improvement in risk assessment methodologies to make it more useful during the regulation development
- Development of real-time biomonitoring methods
- Better verification of treatment effectiveness and reliability of removal of microbial pathogens during various treatment processes

3.4.1.2. Agronomic and physico-chemical parameters

The agronomic and physico-chemical parameters evaluated in this study comprise a complete list of the necessary parameters which can increase the safety of crops, soil, and in general agricultural water reuse practices. However, all the regulations and

guidelines investigated in this study did not use those parameters. For instance, pH (34), free Chlorine (25), and nutrients (21) were the most frequent parameters, respectively (Figure 8). TSS (43), BOD_5 (42), and turbidity (27) were the most frequent among physico-chemical parameters used in the studied regulations and guidelines (Figure 9). In addition, large discrepancies existed in the threshold levels, even in the regulations and guidelines that have included these parameters. This could not only threaten recycled water irrigation practices but also affect the farmers' tendency toward implementing water reuse.

Based on the results (sections 3.3.2.2. and 3.3.2.3), the main gap between agricultural water reuse regulations and guidelines regarding the agronomic and physico-chemical parameters was the absence of some critical parameters and the discrepancies among their existing thresholds. Due to the importance of agriculture and technological advancements, there is significant knowledge and expertise about these parameters, their measurement methods, and instruments. So, regulations and guidelines need to include all these parameters with similar thresholds. For instance, the potential negative impacts of low or high pH were clearly clarified in this paper according to the literature. Also, pH measurement is one of the easiest tests that can be done. However, only about half of the investigated regulations and guidelines (34 out of 70) have included pH as one of the water quality parameters.

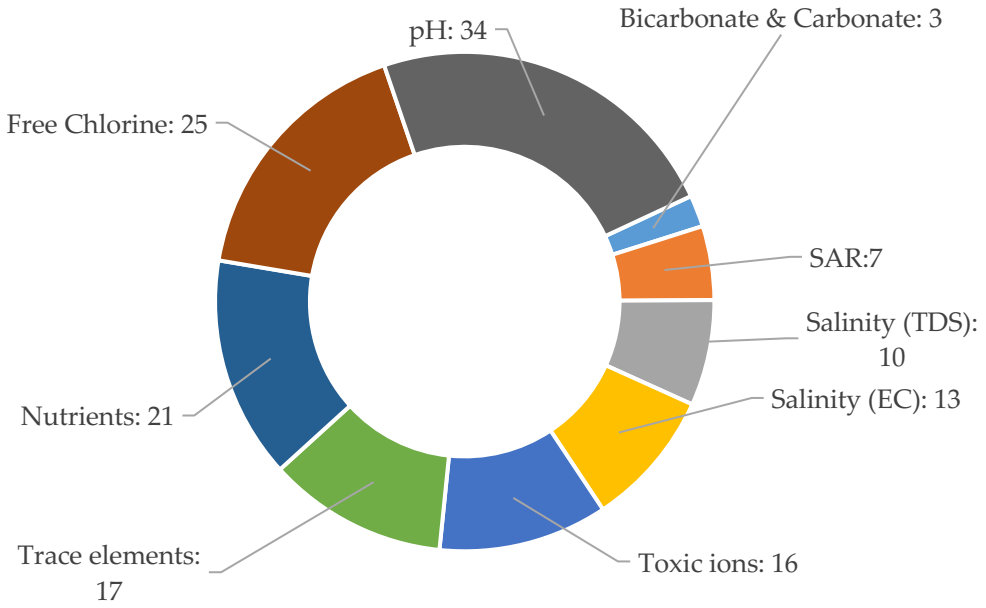


Figure 8. The number of regulations and guidelines which included different agronomic parameters.

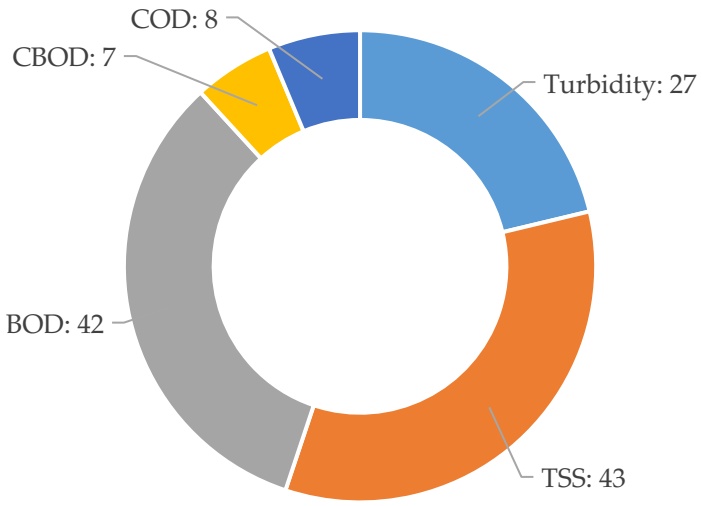


Figure 9. The number of regulations and guidelines which used different physico-chemical parameters.

3.4.1.3. Constituents of emerging concern

With the advancement of analytical instrumentation, it is now possible to measure a long list of trace constituents in the environment. Contaminants of emerging concern (CECs) include a wide range of trace constituents such as pharmaceuticals, personal care products, household products, drugs, flame retardants, etc. (Pennington et al., 2018). Many of these compounds are found in raw wastewater in considerable concentrations (Pennington et al., 2018). Conventional wastewater treatment technologies cannot remove many of these compounds during the treatment process because they are not designed to do so. In addition, many of these constituents are not included in the discharge regulations, thus, are not monitored by the wastewater treatment facilities. As a result, many of these CECs could be present in the treated wastewater (Table 27).

Table 27. Some of the existing CECs in recycled water reported by literature (Anderson et al., 2010).

CEC	**Concentration (ng/L)**
1,4-Dioxane	7,160
4,4-DDT	50
Acetaminophen	26
Atenolol	400
Azithromycin	650
Caffeine	25
Carbamazepine	200
Ibuprofen	160
Iopromide	2,600
Sucralose	40,000

Despite their potential negative effects on the ecological and public health (e.g., abnormalities in the reproductive systems of creatures, increasing the resistance of humans and animals to antibiotics, and changing the development processes of creatures), none of the regulations or guidelines has included CECs (Fent et al., 2006; Flaherty & Dodson, 2005; Kidd et al., 2007; Nash et al., 2004; Novo et al., 2013; Rizzo et al., 2013). It should be noted that there is an enormous variety of these compounds, which make their assessment a very challenging task. For instance, Huang et al. reported that there are approximately 7,700 pharmaceuticals that humans use, which may potentially end up in residential wastewater. In addition, these constituents have a wide range of physio-chemical properties and biodegradability (Huang et al., 2011). Agencies should consider several factors, including rates of consumption, the risk to human/ ecological health, physio-chemical properties, biodegradability, pharmacological class, and sustainability index, to include the CECs in the regulations and guidelines (Carballa et al., 2005; Removal of Pharmaceuticals and Personal Care Products - Results of the Poseidon Project). As a result, an enormous effort is still required to close the regulatory gaps with respect to emerging contaminants.

In a nutshell, this study highlighted some of the large discrepancies among current agricultural water reuse regulations and guidelines. (Brissaud, 2008) argued that the countries' rationale for setting up or adapting other regulations or guidelines is unclear. Most countries' rationale reflects a perception of a risk hierarchy (different among various countries) instead of using a scientifically based rationale (Brissaud, 2008). To address this challenge, (Brissaud, 2008) suggested that countries should base their agricultural regulations and guidelines on epidemiologic studies and quantitative microbiological health risk assessment. This will pave the way for countries to share their knowledge and experiences, find common policies, and determine the uncertainties of their regulations and guidelines, which will shed light on the needs for future scientific research (Brissaud, 2008). Moreover, these discrepancies might result from differences between countries' and states' approaches to their public health, economic, development, and education status, as well as their local climatic and geographical conditions.

3.5. Conclusions

With recent advancements in wastewater treatment technologies, it is possible to produce almost any water quality. However, the main human and environmental concerns are still to determine what constituents must be removed and to what extent. Different national and international organizations and agencies have issued regulations and guidelines to ensure safe water reuse practices. To do a comprehensive and comparative study of the existing water reuse regulations and guidelines, this study has evaluated the current status of existing regulations and guidelines for water reuse in agriculture throughout the world. In total, 83 cases were studied, among which 70 regulations and guidelines for agricultural water reuse were identified, and the latest versions of the documents were obtained. These regulations

and guidelines were collected from EPA, ISO, FAO, WHO, U.S. (statewide), European Commission, Canada (by provinces), Australia, Mexico, Iran, Egypt, Tunisia, Jordan, Israel, Oman, China, Kuwait, Saudi Arabia, France, Cyprus, Spain Greece, Portugal, and Italy. The main focus of this study was to evaluate, compare, and identify the gaps in the current agricultural water reuse regulations and guidelines.

Recycled water quality parameters were categorized into three major groups, including human-health parameters (pathogens and chemicals), agronomic parameters (salinity, toxic ions, SAR, trace elements, pH, Bicarbonate/Carbonate, nutrients, and free Chlorine), and physico-chemical parameters (turbidity, TSS, BOD_5, $CBOD_5$, and COD). Regulations and guidelines were categorized into two groups based on their microbiological requirements. Those which were high-cost/ low-risk, requiring zero detection of microbial indicators in recycled water, were named as "restrictive" regulations and guidelines, with California's regulation being their benchmark regulation. On the other hand, those which were low-cost/ high-risk, requiring no real risk of infection, were named as "less restrictive" regulations and guidelines, with WHO's guideline being their benchmark guideline.

Results showed that, to a larger extent, water reuse regulations and guidelines were mainly based on the control of conventional water quality parameters such as coliforms, BOD, turbidity, and TSS. Thus, most of the existing regulations and guidelines did not include emerging pathogens (such as salmonella and hepatitis), heavy metals, or contaminants of emerging concern. Pathogen thresholds were indicated by 64 out of 70 regulations and guidelines. The most frequent microbial indicator used by regulations and guidelines was Fecal Coliforms. Despite a wide range of chemicals and trace elements detected in treated wastewater, only a few have been regulated in agricultural water reuse regulations and guidelines. Among the long list of trace elements and chemicals, Chromium, Cadmium, and Nickel had the maximum number of indications, with inclusion in only 17 out of 70 regulations and guidelines investigated in this study. Considering the detrimental effects of chemicals and trace elements on human and environmental health, agricultural regulations and guidelines need to include more chemicals and trace elements in their requirements.

34 out of 70 regulations and guidelines included pH, most of which considered the 6.5-8 range to be the best pH range for agricultural water reuse practices. Although salinity, reported as EC and TDS thresholds, is the most important agronomic parameter, none of the U.S. states' regulations and guidelines included EC and TDS thresholds in their agricultural water reuse regulations and guidelines. SAR thresholds were included in only 7 out of 70 regulations and guidelines investigated in this study, none from U.S. states. Canadian provinces and Iran's guidelines contained the most comprehensive SAR thresholds compared with others. As the most frequently indicated nutrients in regulations and guidelines, Zinc, Boron, and total Nitrogen ranges in regulations and guidelines were in the severe restriction range of FAO's guideline. U.S. states mostly used turbidity, TSS, and BOD as water quality indicators in the regulations and guidelines (17, 19, and 19 documents, respectively).

Secondary treatment and tertiary treatment were the most frequent treatment processes required by different regulations and guidelines. In summary, the most frequent recycled water quality parameters required by the regulations and guidelines were as follows: 1) Pathogens; 2) TSS; 3) BOD_5; 4) pH; 5) Turbidity; 6) Chemicals/ trace elements; 7) Nutrients; 8) Free Chlorine; 9) EC; 10) TDS; 11) COD; 12) $CBOD_5$; 13) SAR and Bicarbonate/Carbonate.

To summarize, results showed that the regulations and guidelines were mainly human health centered, insufficient regarding some potentially dangerous pollutants such as emerging constituents, and with large discrepancies when compared with each other. In addition, some important water quality parameters, such as pathogens, heavy metals, and salinity, were only included in a few of the regulations and guidelines investigated in this study. Finally, specific treatment processes were only mentioned in some of the regulations and guidelines, with high levels of discrepancy. While agricultural water reuse can potentially give us the means to address the water crisis, the discrepancies in regulations and guidelines are one of the main barriers to successfully implementing water reuse practices. However, this does not mean that the practice of water reuse in agriculture should be construed as unsafe compared to other available water sources such as rivers, streams, and pond water. Instead, the focus should be on defining the acceptable level of risks by the regulatory agencies and endorsing by the public to promote water reuse as part of integrated water resources management. As to all types of water sources, special care is required to ensure recycled water quality matches crop needs, public health is protected, salinity is controlled, and both soil and groundwater conditions are kept sustainable.

Chapter 4: Investigating the micro-level dynamics of water reuse adoption by farmers and the impacts on local water resources using an agent-based model[2]

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 use 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.

4.1. 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 U.S., for example, in 2018, 231,474 farms (22.6 billion square meters) were irrigated with 102.9 billion cubic meters of water (USDA-NASS, 2019). During this time frame, the primary sources of irrigation in the U.S. were as follows: 1) groundwater from on-farm wells (13.6 million hectares of land irrigated with 49.8% of the total irrigation water consumption); 2) on-farm surface water 2.6 million hectares of land irrigated with 10% of the total irrigation water consumption); and 3) off-farm water from a variety of sources (6.4 million hectares of land irrigated with 40.2% of the total irrigation water consumption) (USDA-NASS, 2019). As such, the agriculture sector is highly dependent on water availability (Mendelsohn and 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).

[2] This chapter was submitted to the Journal of Socio-Environmental Systems Modelling (https://sesmo.org/)

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 and 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 and 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 and 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 systems' 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 and Bahri, 2005; Metcalf and Eddy 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; Heppenstall et al., 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 an 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 process to test various management scenarios for developing adaptive planning and management strategies using ABM. While 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 understand 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., 2019a). 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, no study has investigated the adaptive and complex dynamics of socio-hydrological systems inherent in agricultural water reuse projects. Nor does any study incorporate the various parameters and aspects involved in these projects (e.g., hydrologic, socio-demographic, and financial parameters), unlike this paper. Furthermore, no study has ever investigated the potential 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 (Chapter), Section 4.2 introduces our study area and methodology, Section 4.3 presents our results, Section 4.4 discusses the results of this study and its limitations, and Section 4.5 summarizes the paper and suggests areas for further study.

4.2. Methodology

4.2.1. Study area

The Del Puerto Water District (DPWD) in Central Valley, California, was selected as the study area (Figure 10). DPWD provides irrigation water for approximately 182.1 million square meters 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 172.9 million cubic meters 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).

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 cubic meters per year, while the expected future average supply (precipitation and CVP) will be between 34.5-60.4 million cubic meters per year. Therefore, DPWD is expected to have a water shortage of 49.3-74 million cubic meters 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. This data was 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. Each farm needed these data to determine its water requirement (discussed further in Section 4.2.2.1.).

Moreover, survey data of U.S. 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. The survey results 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 4.2.). The United States 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 28).

Table 28. 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

4.2.2. 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 11 (a)). 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 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. The 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://tinyurl.com/m6v2jd9e. We do this to allow others to replicate the results and adapt the model for their applications if they so desire.

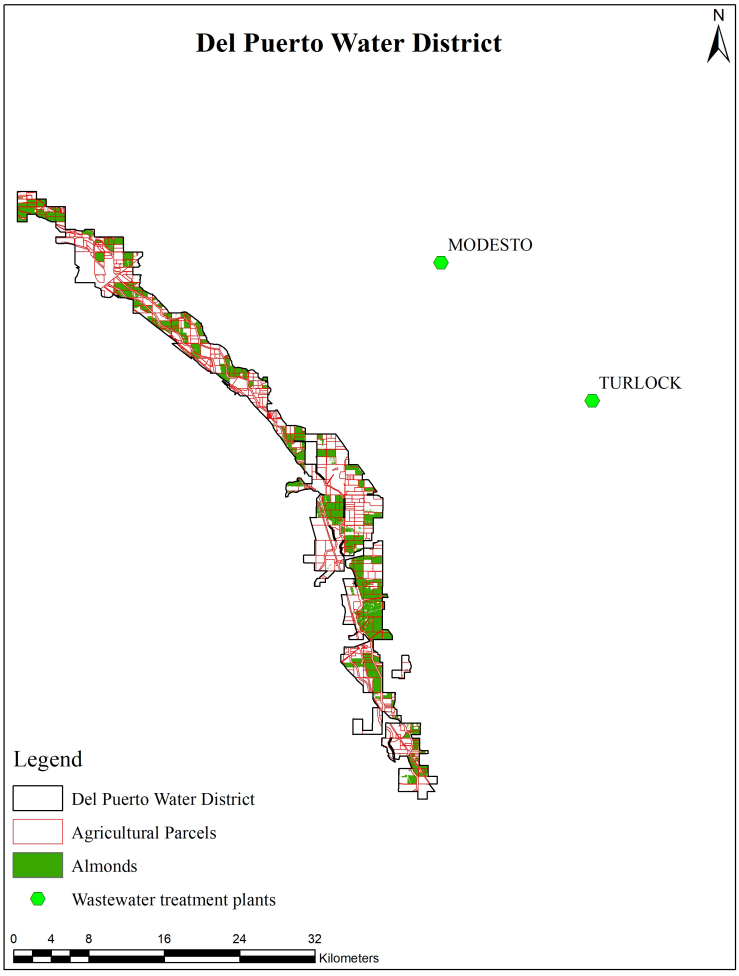


Figure 10. Map of this research's case study (Del Puerto Water District, CA, USA)

4.2.2.1. Agents

Farmers: Almond is the most dominant crop in the study area (Table 29) (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 4.4., this could be an area of further work).

Table 29. 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	6,663,382.00 [44.14%]	5,740.07 [43.61%]
Apricots	3,219,259.00 [21.33%]	1,019.40 [7.75%]
Other deciduous fruits and nuts	2,521,603.00 [16.70%]	479.55 [3.64%]
Cherries	970,749.00 [6.43%]	209.63 [1.59%]
Beans	632,775.00 [4.19%]	898.81 [6.83%]
Vineyard	593,057.00 [3.93%]	149.73 [1.14%]
Tomatoes	451,084.00 [2.99%]	1,575.04 [11.97%]
Walnuts	38,855.00 [0.26%]	721.15 [5.48%]
Oats/barley	5,057.00 [0.03%]	1,000.38 [7.60%]
Alfalfa/mixed pasture	0.00 [0.00%]	671.78 [5.10%]
Vegetables	0.00 [0.00%]	370.29 [2.81%]
Melons	0.00 [0.00%]	161.07 [1.22%]
Grapefruit/lemons/oranges	0.00 [0.00%]	137.59 [1.05%]
Flowers, nursery	0.00 [0.00%]	26.71 [0.20%]
Total	15,095,822.00 [100.00%]	13,161.20 [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 28). It was assumed that farmers would irrigate their farms from available water resources during the irrigation season using the following assumptions (Figure 11 (b)). First, based on equations (3) and (4), 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.

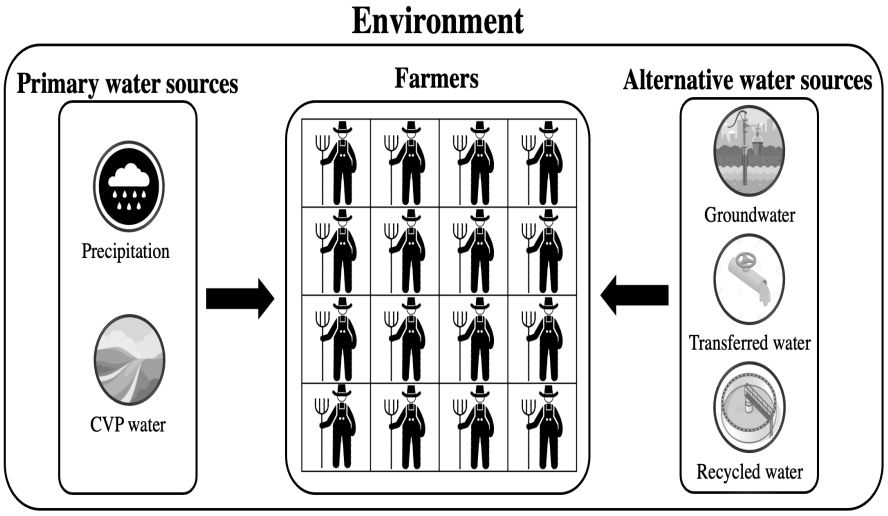
This process repeats during the irrigation season daily. At the end of the farming season, farmers sell their crops (discussed further below). Alternative water sources included in the WRAF model were groundwater, transferred water, and recycled water (from wastewater treatment plants). Of note is that 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.

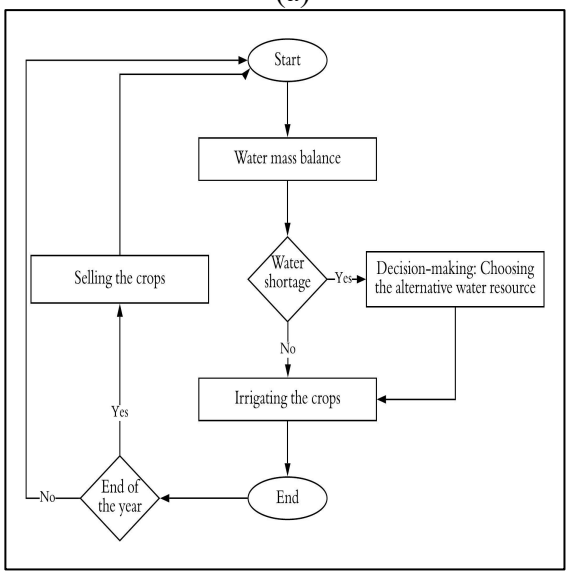
$$ET_c = K_c \times ET_0 \quad (3)$$

$$Gross\ Crop\ Irrigation\ Requirement\ (GCIR) = \frac{ET_c - EP}{IE} \quad (4)$$

Where *Kc* 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).



(a)



(b)

Figure 11. (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 30. It should be mentioned that daily GCIRs were considered constant during each month. So, farmers calculate their daily GCIRs by dividing monthly GCIRs (Table 30) by days of the month (28, 30, or 31 days).

USBR provided farmers with a maximum of 0.9 cubic meters per square meter in each year for all the DPWD area. Assuming even distribution of USBR water supply each year, each farmer in DPWD receives about 2.54×10^{-3} cubic meters per square meters per year (m^3/m^2.day). For scenario analysis, the user can change the available USBR water supply percentage between 0-100 percent from this 10.3 cubic meters per day. 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 (5). It was also assumed that another set of almond trees would again be planted after year 25 was finished.

Table 30. Monthly effective precipitation in DPWD and evapotranspiration 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/square meters 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 (square meters)) 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: 1) CVP: $2.91\text{-}4.86 \times 10^{-2}$ $/square meters, 2) transferred water: 7.78-

32.10×10^{-2} \$/square meters, 3) groundwater: $7.78\text{-}12.65 \times 10^{-2}$ \$/square meters, and 4) recycled water: $4.86\text{-}14.59 \times 10^{-2}$ \$/square meters (RMC Water and Environment, 2013; USDA-NASS, 2019). 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.

$$Money_{year=i+1} = Money_{year=i} + 1.63 \times \left(1 - \left(\frac{total\ days\ without\ water_{year=i+1}}{365}\right)\right) \times farm\ size \quad (5)$$

Where farm size was the area of the farm in square meter 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). 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, considering the fact mentioned above. 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, affecting the person's decisions (equation (6)) (Ajzen, 1991).

$$I \cong a \times AT + b \times SN + c \times PBC \quad (6)$$

Where I refers to intention, a, b, and c are empirical weights for the parameters, 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 sub sections, 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 the U.S. 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. They 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 12 (a), Table 31 and Table 32). Based on the data, probabilities of different levels of these parameters were calculated to be used in the sub-model (Tables 32, 33, 34, and 35). 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.

Table 31. Level of parameters used in the water reuse adoption sub-model (source: (Suri et al., 2019)*)*

Parameter	Age	Concern	Knowledge	Education	Race
Levels	18-29 30-49 50-69 70-89	Yes Somewhat No	Very Somewhat A little No	Doctorate Graduate degree Some college 4-year degree 2-year degree High school graduate Less than high school	American-Indian Asian Black/African-American Native American White Prefer-not-to-answer
Parameter	Sex	Importance	Attitude	Access	
Levels	Female Male	Very Moderately Not	Positive Negative	Yes I do not know No	

Table 32. Demographics of agents (farmers in the Southwest, U.S.), based on (Suri et al., 2019).

Parameter	**Age**	**Knowledge**
Levels (n (%))	18-29 (31.2) 30-49 (36.5) 50-69 (27.7) 70-89 (4.6)	Very (11.7) Somewhat (40.7) A little (36.9) No (10.7)
Parameter	**Sex**	**Access**
Levels (n (%))	Female (33.7) Male (66.3)	Yes (20.9) I do not know (18.1) No (61)
Parameter	**Education**	**Race**
Levels (n (%))	Doctorate (1.2) Graduate degree (17.8) Some college (24.7) 4-year degree (38.5) 2-year degree (8) High school graduate (8) Less than high school (1.2) Prefer not to answer (0.6)	American Indian / Alaskan Native (2.8) Asian (includes India and the Middle East) (4.5) Black/ African-American (3.4) White (73.4) Prefer not to answer (15.9)

Table 33. Discrete probabilities distributions used in determining agents' concerns about water reuse, based on (Suri et al., 2019).

Concern	Yes	No	Somewhat	Total
Age:18-29	60.4%	18.9%	20.7%	100%
Age:30-49	62.9%	11.3%	25.8%	100%
Age:50-69	83%	10.6%	6.4%	100%
Age:70-69	75%	25%	0%	100%

Table 34. Discrete probabilities distributions used in determining agents' importance of water reuse, based on (Suri et al., 2019).

Importance	Very important	Moderately important	Not important	Not answered	Total
Concern: Yes	51.2%	38.8%	10%	0%	100%
Concern: No	22.2%	48.1%	25.9%	3.8%	100%
Concern: Somewhat	40.6%	46.9%	12.5%	0%	100%
Knowledge: Very	32.4%	16.2%	5.4%	46%	100%
Knowledge: Somewhat	33.3%	21.7%	7%	38%	100%
Knowledge: A little	17.1%	24.8%	6.8%	51.3%	100%
Knowledge: No	17.6%	35.3%	11.8%	35.3%	100%
Access: Yes	70.3%	29.7%	0%	0%	100%
Access: No	39.8%	43.5%	16.7%	0%	100%
Access: I don't know	34.4%	53.1%	12.5%	0%	100%
Education: Less than high school	0%	100%	0%	0%	100%
Education: High school graduate	42.9%	35.7%	21.4%	0%	100%
Education: 2-year degree	57.1%	35.7%	7.2%	0%	100%
Education: 4-year degree	38.8%	44.8%	14.9%	1.5%	100%
Education: Some college	39.5%	53.5%	7%	0%	100%
Education: Graduate degree	61.3%	25.8%	12.9%	0%	100%
Education: Doctorate	100%	0%	0%	0%	100%
Education: Prefer not to answer	0%	0%	100%	0%	100%

The control belief Section comprises two parts (Figure 12 (a)). 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 section results could be positive or negative.

Table 35. Discrete probabilities distributions used in determining agents' attitude toward water reuse, based on (Suri et al., 2019).

Attitude	Yes	No	Not answered	Total
Importance: Very important	74.1%	4.9%	21%	100%
Importance: Moderately important	54.7%	13.3%	32%	100%
Importance: Not important	52.2%	13%	35%	100%
Race: American Indian / Alaskan Native	60%	40%	0%	100%
Race: Asian (includes India and Middle East)	62.5%	37.5%	0%	100%
Race: Black/ African-American	66.7%	16.7%	16.6%	100%
Race: White	65.1%	7.8%	27.1%	100%
Race: prefer not to answer	57.1%	3.6%	39.3%	100%
Sex: Female	56.1%	1.8%	42.1%	100%
Sex: Male	67%	13.4%	19.6%	100%

Finally, the behavioral intentions of the farmers are determined according to equation (6). 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 sections (attitude, subjective norm, and control belief) are positive; otherwise, it changes to negative.

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 12 (b)). 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 location. 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 cubic meters 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 cubic meters, 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 recycled water's unit price (set by the user). Of note is that the expansion plans for Modesto and Turlock wastewater treatment plants were also considered in this study (Figure 13).

4.2.2.2. 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 acreage 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 crop data layer (U.S. Department of Agriculture, 2018) maps (2018 crop pattern) (Figure 10). According to NVRRWP's feasibility study, 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.

4.2.3. Model verification, sensitivity analysis, and scenario experiments

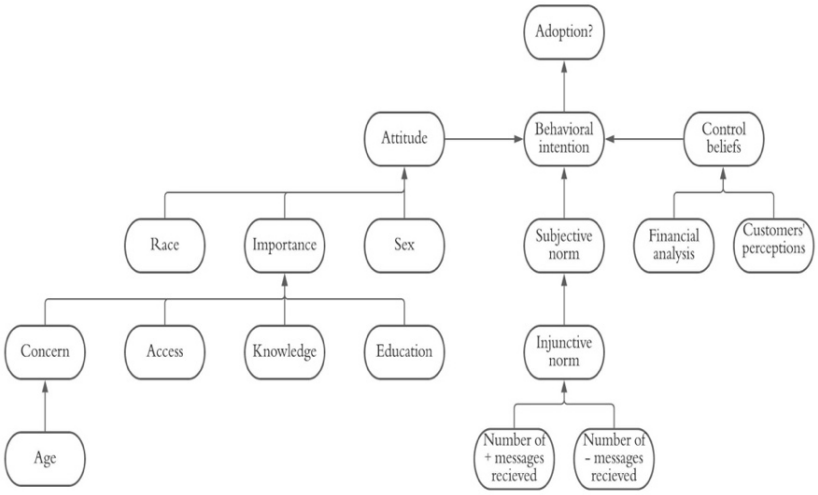
4.2.3.1. Verification

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.

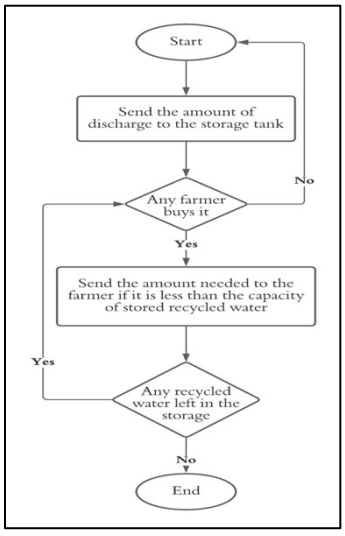
4.2.3.2. Sensitivity analysis:

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 using 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).



(a)



(b)

Figure 12. (a) Water reuse adoption sub-model framework; (b) Wastewater treatment plants flowchart)

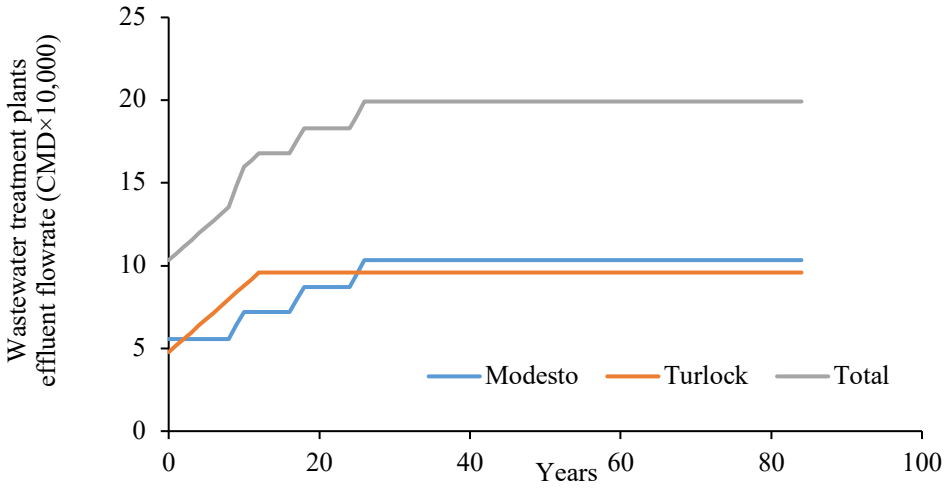


Figure 13. Flow rates of Modesto and Turlock wastewater treatment plants years after starting the agricultural water reuse project (adapted from (RMC Water and Environment, 2013)*; CMD: cubic meters per day).*

In engineering fields, input parameters that influence the output parameter are called "factors," the output parameters are called "responses" in the DOEs. DOE includes three major steps, including 1) screening, 2) response surface methodology, and 3) model validation (Wass, 2010). The screening stage tends to find the factors that have a statistically significant influence on the response. Response surface methodology tries to find the optimal results space using the previous stages influential factors. The model validation step tends to confirm the model at the end. Interested readers in simulation DOEs refer to Law et al. (2000) for further details about these methods.

In this study, as the screening step, seven factors were considered to find the influential factors of the WRAF model. 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 37). Four center points (0) 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 36). All the other factors were kept constant during the experiments.

Farmers' total recycled water consumption was used as the response 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 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.

Table 36. Design table for sensitivity analysis in this study (randomized).

Run	Blk	A	B	C	D	E	F	G
1	**1**	-	-	+	-	+	+	+
2	**1**	-	+	-	+	+	-	+
3	**1**	+	+	-	+	-	-	-
4	**1**	-	+	+	+	-	+	-
5	**1**	+	-	+	-	-	+	-
6	**1**	+	-	+	+	-	-	+
7	**1**	-	+	+	-	-	-	+
8	**1**	+	-	-	-	+	-	+
9	**1**	0	0	0	0	0	+	+
10	**1**	0	0	0	0	0	+	-

Run	Blk	A	B	C	D	E	F	G
11	1	+	+	+	+	+	+	+
12	1	-	-	-	+	-	+	+
13	1	-	-	-	-	-	-	-
14	1	-	+	-	-	+	+	-
15	1	0	0	0	0	0	-	+
16	1	0	0	0	0	0	-	-
17	1	+	+	-	-	-	+	+
18	1	-	-	+	+	+	-	-
19	1	+	+	+	-	+	-	-
20	1	+	-	-	+	+	+	-
Total		0	0	0	0	0	0	0

Table 37. Factors considered in the screening step of the study

	Factor- unit	Description	Range
A	Modesto (thousand cubic meters)	The daily flow rate of the Modesto wastewater treatment plant discharge into its storage pond	55.6-189.3
B	Turlock (thousand cubic meters)	The daily flow rate of the Turlock wastewater treatment plant discharge into its storage pond	47.7-189.3
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 ($/square-meters)	The unit price of the contracted CVP water, which farmers have to pay upon using	$2.91\text{-}4.86 \times 10^{-2}$
E	Water-reuse-expenses ($/square-meters)	The unit price of the recycled water that farmers have to pay upon using	$4.86\text{-}14.59 \times 10^{-2}$
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)

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 ($P \leq 0.05$).

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 38). 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.

4.2.3.3. 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 39). 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.

Accordingly, all scenarios were simulated using the NVRRWP expansion planning regarding Modesto and Turlock's effluent flow rates (Figure 13). 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 39). The unit prices of CVP water supplied to the DPWD's farmers were 0.040, 0.045, 0.05, and 0.03 ($/CM) in scenarios I, II, III, and IV, respectively (Table 39). The unit prices of recycled water provided to the DPWD's farmers were 0.09, 0.10, 0.11, and 0.08 ($/CM) in scenarios I, II, III, and IV, respectively (Table 39). It was assumed that the transferred water supply was not available to farmers in moderate and severe drought scenarios (Table 39). Groundwater was also not available as an irrigation source for farmers in the severe drought scenario (Table 39). All the simulations were repeated ten times and for 84 years of almond production.

4.3. Results

4.3.1. Verification and sensitivity analysis

4.3.1.1. Verification

The results of representative runs are depicted in Figure 14. Figure 14 (a and b) 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 14 (b)).

Table 38. 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 ($/cubic meters)	0.05, 0.10, 0.15	0.10	0.10	0.10	0.10	0.10
G	Groundwater	A[1]	A, NA[2]	A	A	A	A
BD	Turlock ($\times 10^{+3}$ cubic meters) × CVP-water-price ($/cubic meters)	118.5 × 0.04	118.5 × 0.04	47.7 × 0.03, 118.5 × 0.04, 189.3 × 0.05	118.5× 0.04	47.7, 118.5, 189.3 × 0.04	118.3 × 0.04
A	Modesto ($\times 10^{+3}$ cubic meters)	122.6	122.6	122.6	55.6, 122.6, 189.3	122.6	122.6
B	Turlock ($\times 10^{+3}$ cubic meters)	118.5	118.5	47.7, 118.5, 189.3	118.5	47.7, 118.5, 189.3	118,.5
C	Primary-water-source-%	50	50	50	50	50	0, 50, 100

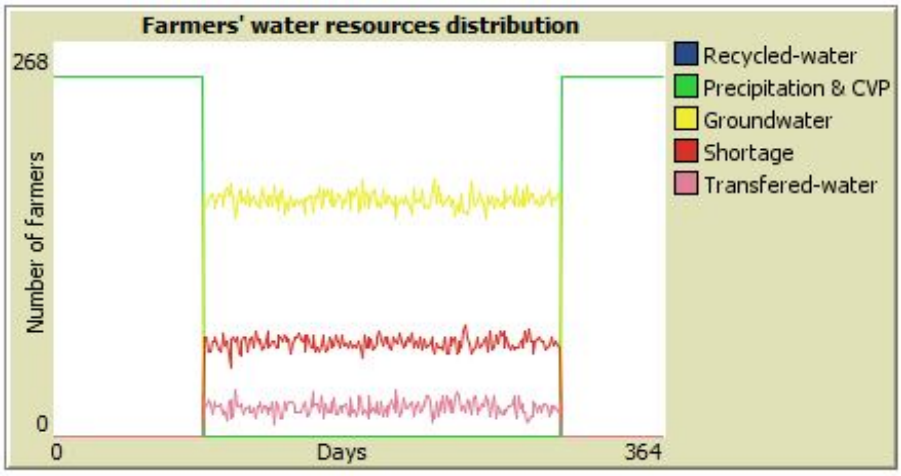
[1] Available; [2] Not-available

Table 39. Specifications of the simulation experiments scenarios in this study.

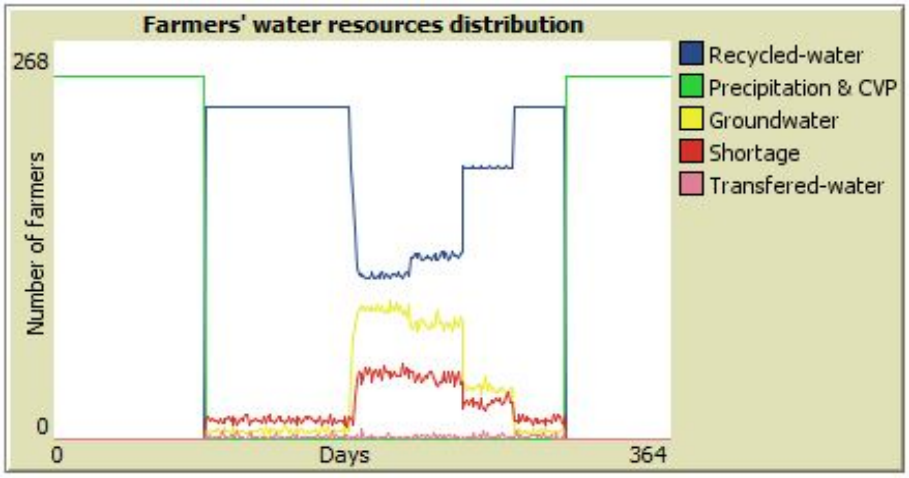
Term	Factor	Scenario I (normal)	Scenario II (moderate drought)	Scenario III (severe drought)	Scenario IV (wet)
C	Primary-water-source (%)	35	20	5	100[1]
D	CVP-water-price ($/CM)	0.040	0.045	0.050	0.030
E	Water-reuse-expenses ($/CM)	0.09	0.10	0.11	0.08
F	Transferred-water	Available	Not-available	Not-available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

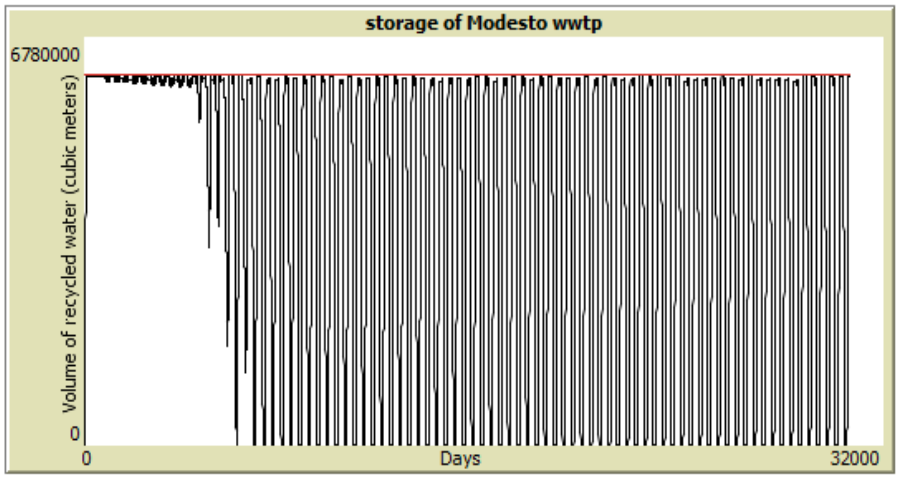
The volume of recycled water stored at the storage ponds is depicted in Figure 14 (c) and (d). As the number of farmers who use recycled water increases, the recycled water volume in these storage ponds decreases. After several years, this depletion even reaches a level that these ponds become empty 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 14 (e) and (f), respectively. The results of these two figures were consistent with Figure 14 (a), (b), (c), and (d). 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.



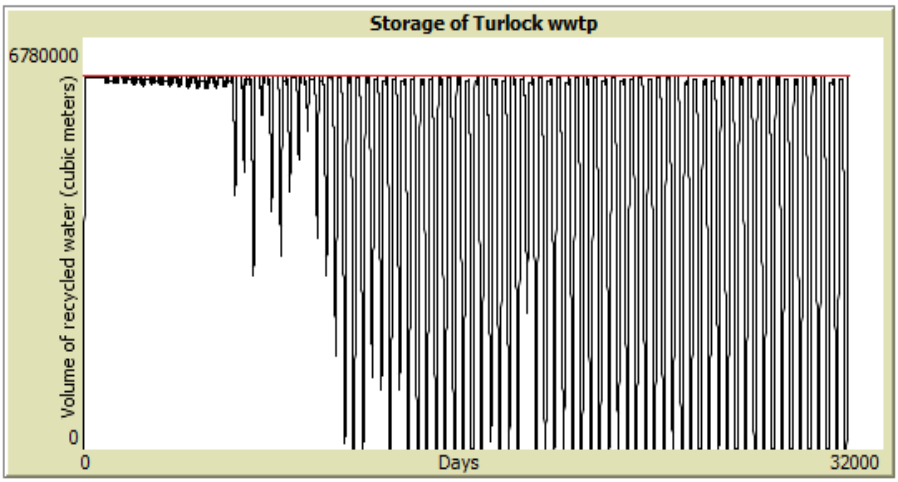
(a)



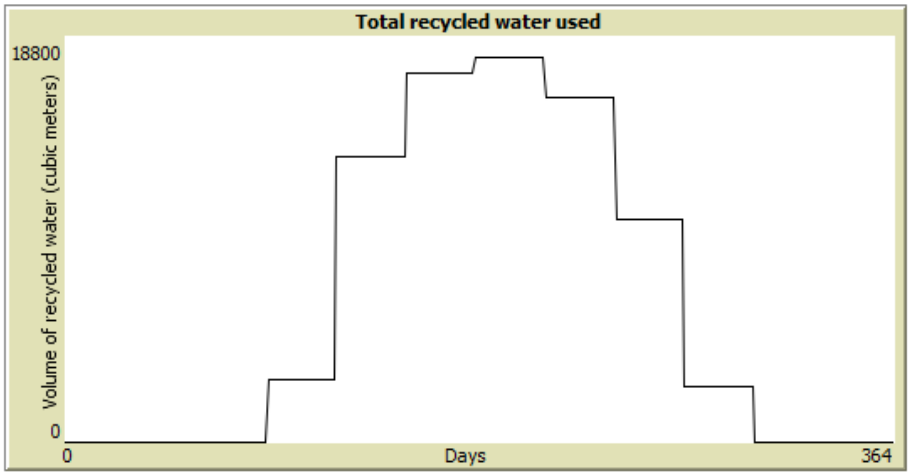
(b)


storage of Modesto wwtp
6780000
Volume of recycled water (cubic meters)
0
0
Days
32000

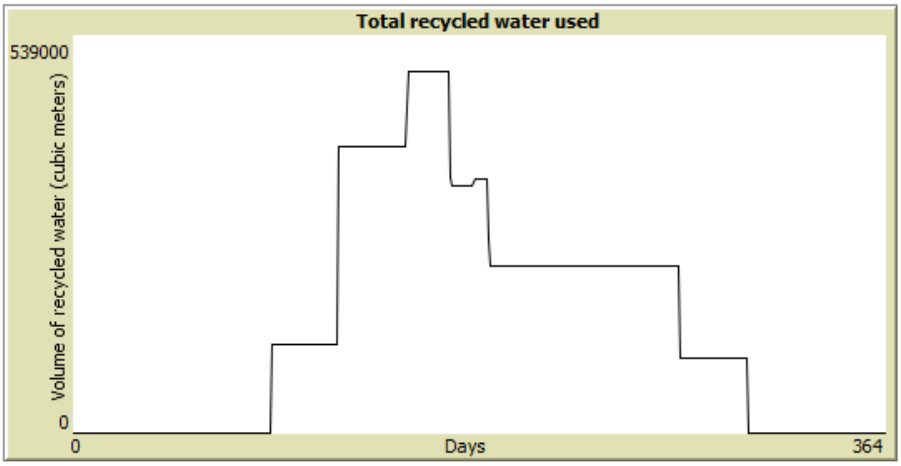
(c)


Storage of Turlock wwtp
6780000
Volume of recycled water (cubic meters)
0
0
Days
32000

(d)


Total recycled water used
18800
Volume of recycled water (cubic meters)
0
0
Days
364

(e)



(f)

Figure 14. Representative simulation results: (a) and (b) farmers' water resources distribution in years one and 84, respectively; (c) and (d) available recycled water in the storage ponds of the two wastewater treatment plants; (e) and (f) total recycled water used by farmers in year two and 84, respectively.

4.3.1.2. 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 40). 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.

Residual plots were used to check whether the regression model was adequate and met the analysis's assumptions (ordinary least squares assumptions) (Figure 15). The normal probability plot of the residuals approximately followed a straight line, confirming that the residuals were normally distributed (Figure 15 (b), (d), and (f)).

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.

Table 40. Significant factors effects ($P \leq 0.05$). 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-MGD×CVP-water-price	194,785	218,543	231,266
A	Modesto-MGD	77,366	136,161	141,772
B	Turlock-MGD	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%

4.3.2. 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 16 (a)) 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 16 (a)). 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 CM). 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.

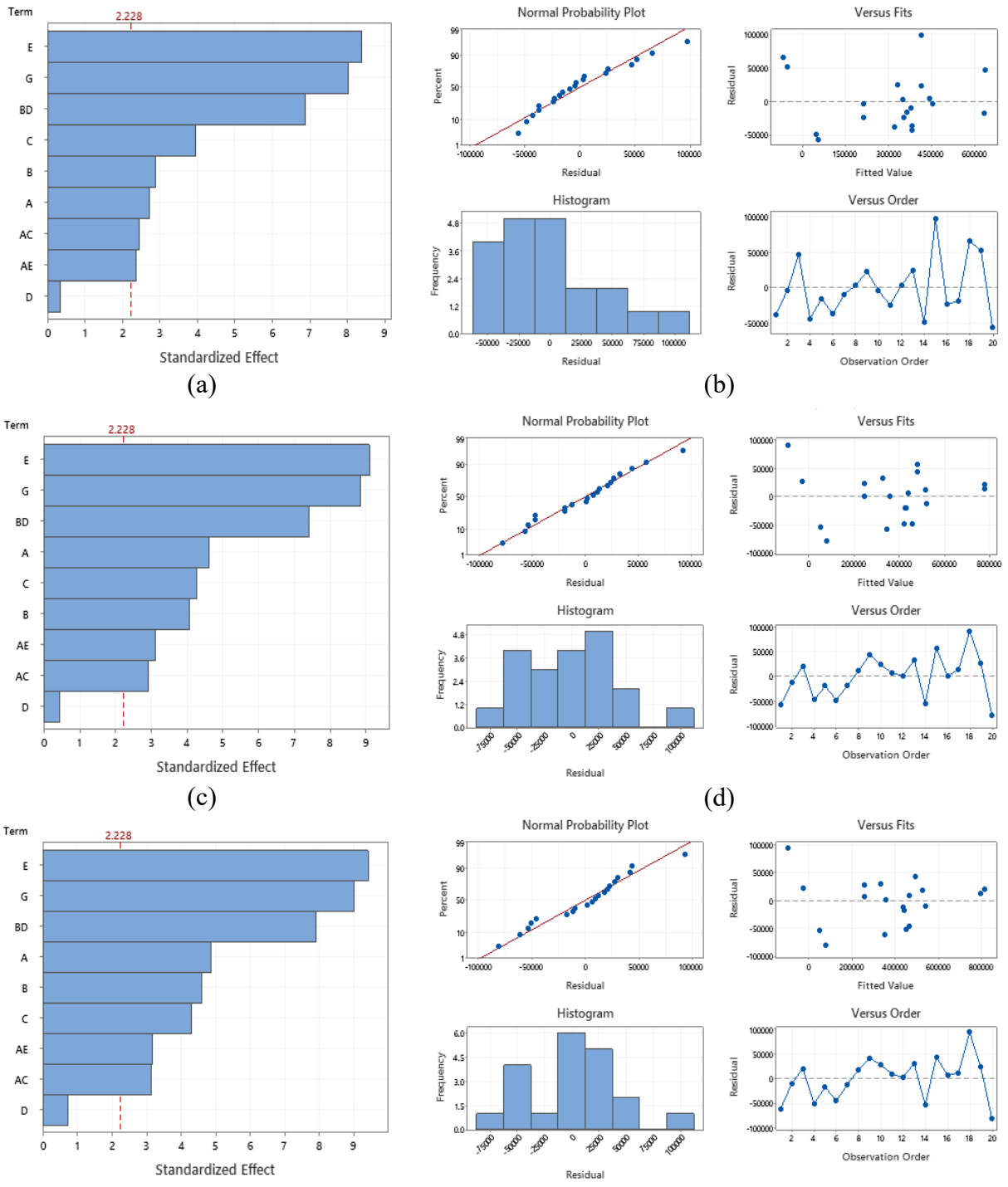
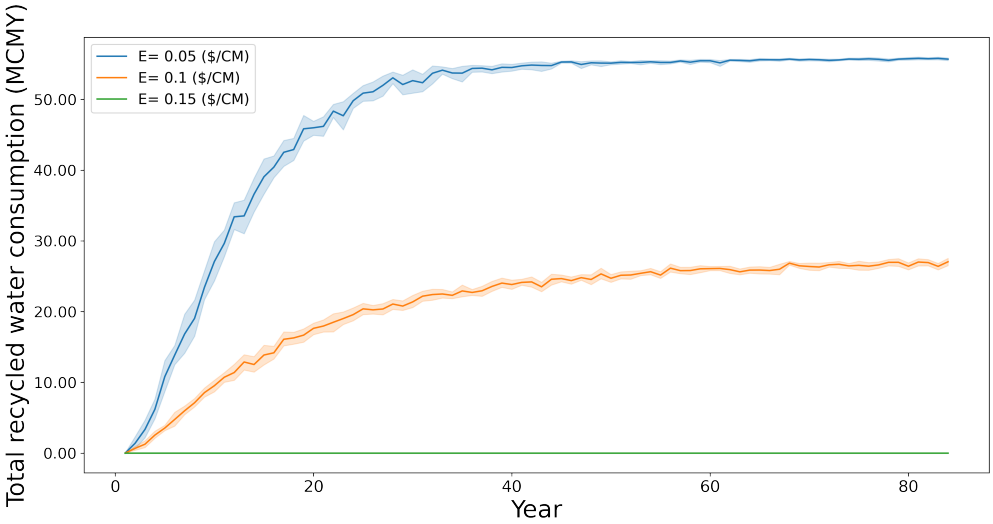


Figure 15. Pareto charts of standardized effects and residual plots in t = 27 ((a) and (b)), t = 55 ((c) and (d)), and t = 85 ((e) and (f)) for cumulative recycled water consumption as the response variable.

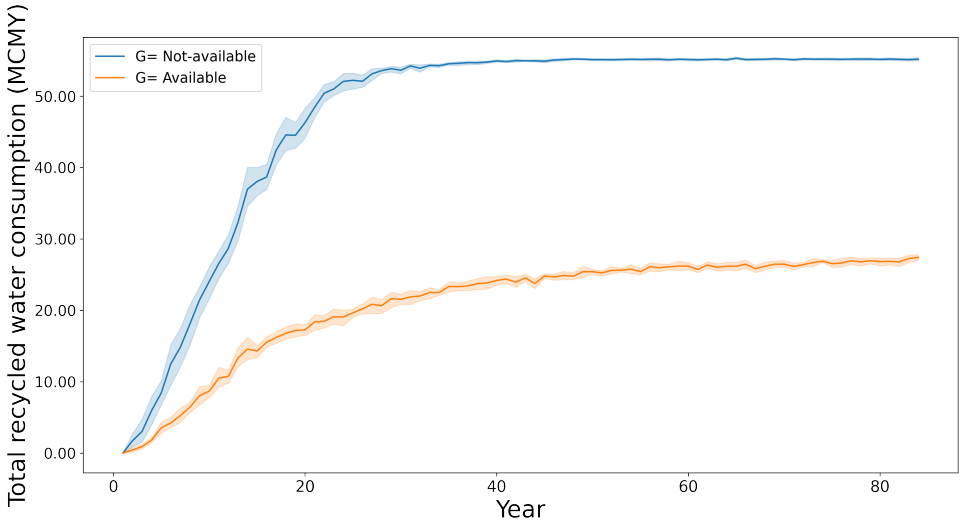
Furthermore, the results illustrated that groundwater availability significantly affected the total recycled water consumption (Table 40 and Figure 16(b)). Based on these results, when groundwater was not available for farmers to use, they used more

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 (Figure 17 (a and b) and Figure 18 (a)).

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 18 (b)). 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.

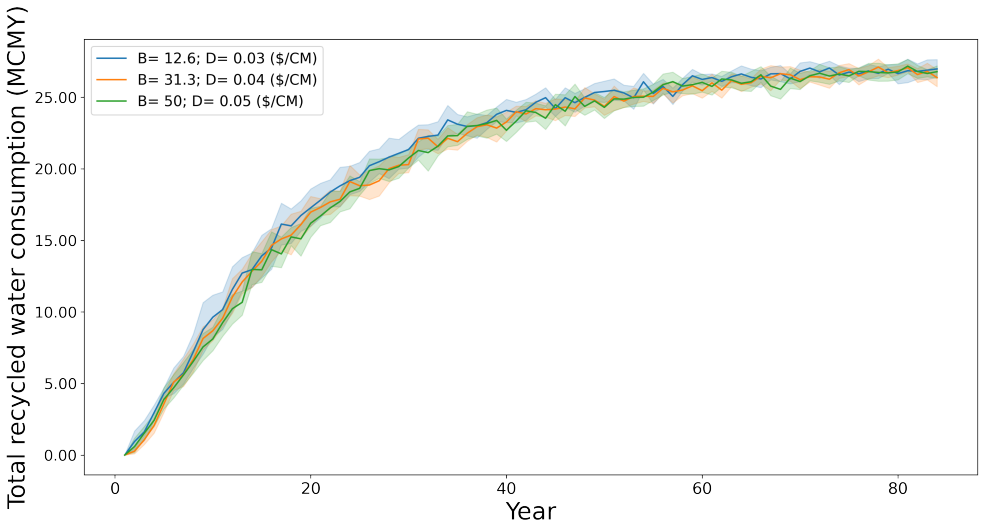


(a)

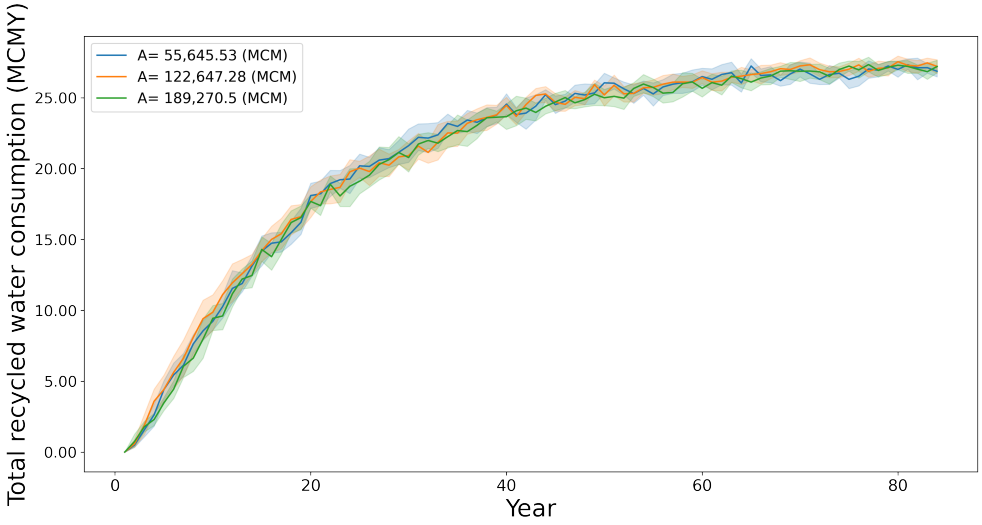


(b)

Figure 16. 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; the 95% confidence intervals were calculated using bootstrap resampling method).

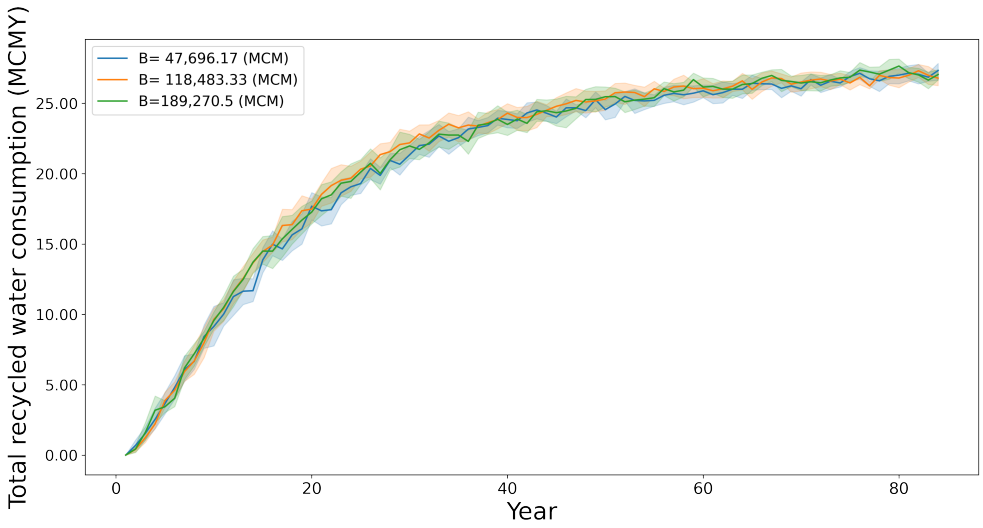


(a)

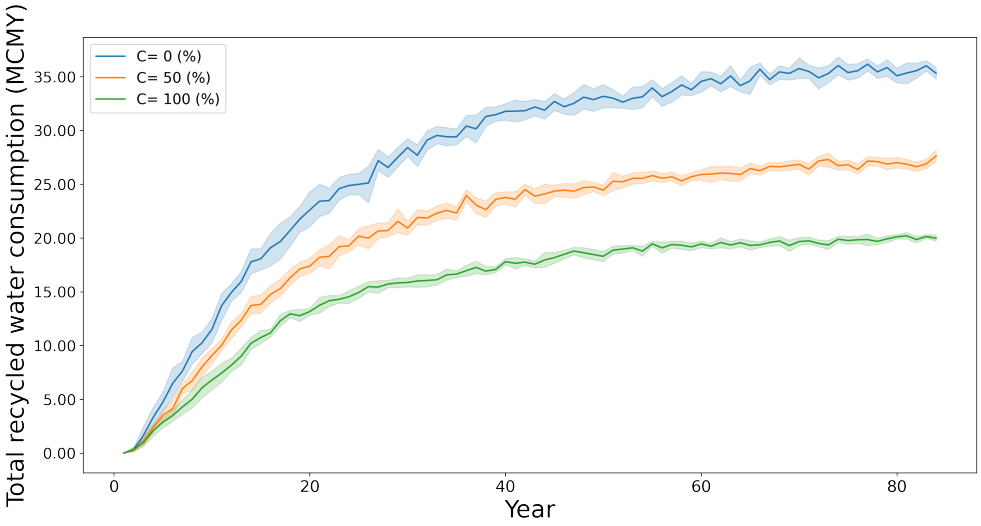


(b)

Figure 17. 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; the 95% confidence intervals were calculated using bootstrap resampling method).



(a)



(b)

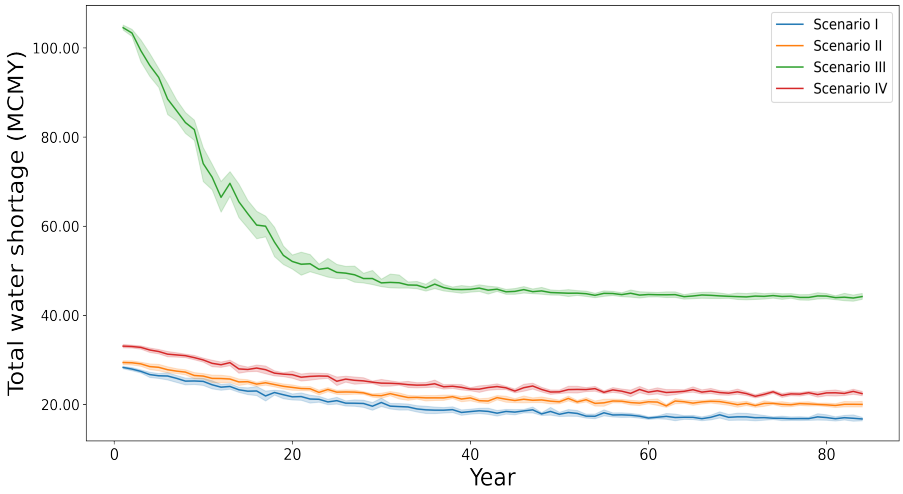
Figure 18. The effects of (a) B = the Turlock effluent flow rate and (b) C = the available percentage of the CVP water on the cumulative recycled water consumption (MCMY = Millions Cubic Meters per Year; the 95% confidence intervals were calculated using bootstrap resampling method).

4.3.3. Simulation experiments results

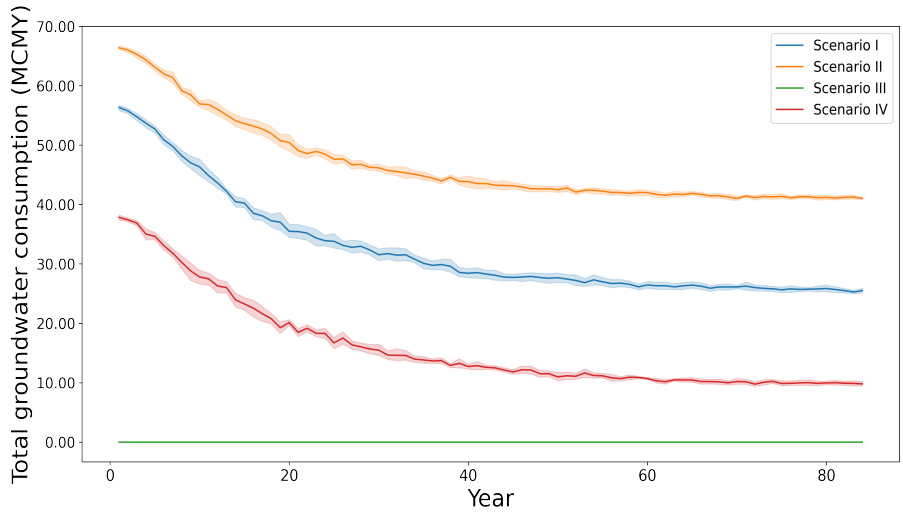
The results illustrated that implementing agricultural water reuse in the DPWD could successfully increase the district's water sustainability. The total water shortage was decreased by 41%, 32%, 57.7%, and 32% in scenarios I, II, III, and IV, respectively.

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 19 (a)). The results also demonstrated that agricultural water reuse in the DPWD could significantly decline farmers' total groundwater consumption (Figure 19 (b)). 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 56.3 MCMY to 25.5 MCMY (30.8 MCMY decrease), 66.4 MCMY to 41 MCMY (25.4 MCMY decrease), and 37.8 MCMY to 9.8 MCMY (28 MCMY 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 20 (a)). The total recycled water consumption increased from zero CMY to 46.3 MCMY, 34.7 MCMY, 60.3 MCMY, and 43 MCMY 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, 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 20 (b)). The trend of adopting recycled water by farmers was consistent with the Diffusion of Innovations Theory (Rogers et al., 2005) (Figure 21). 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.

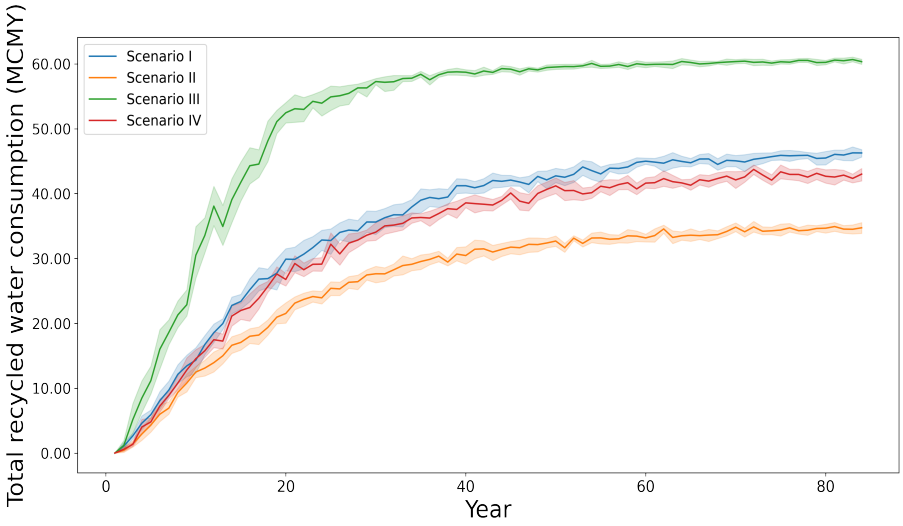


(a)

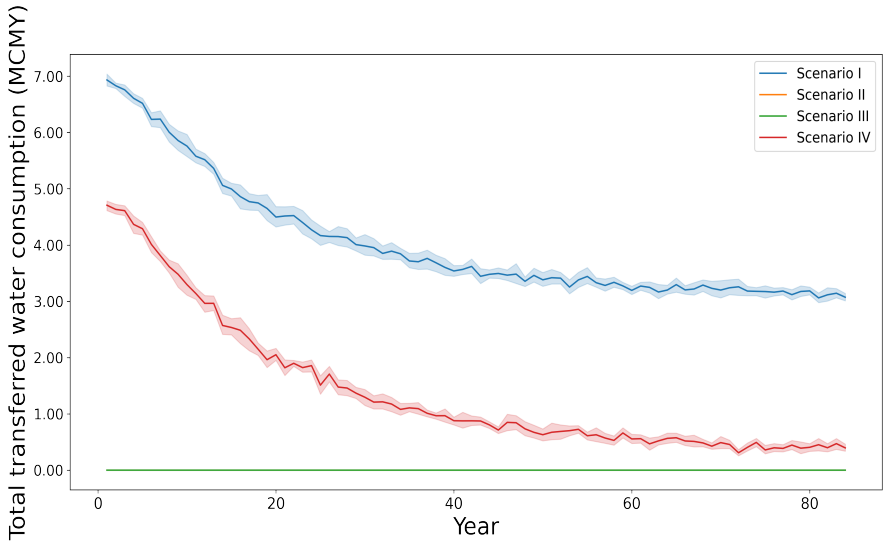


(b)

Figure 19: The results of the simulation experiments: (a) total water shortage and (b) total groundwater consumption (MCMY = Millions Cubic Meters per Year; the 95% confidence intervals were calculated using bootstrap resampling method).



(a)



(b)

Figure 20: The results of the simulation experiments: (a) cumulative recycled water consumption and (b) cumulative transferred water consumption (MCMY = Millions Cubic Meters per Year; the 95% confidence intervals were calculated using bootstrap resampling method).

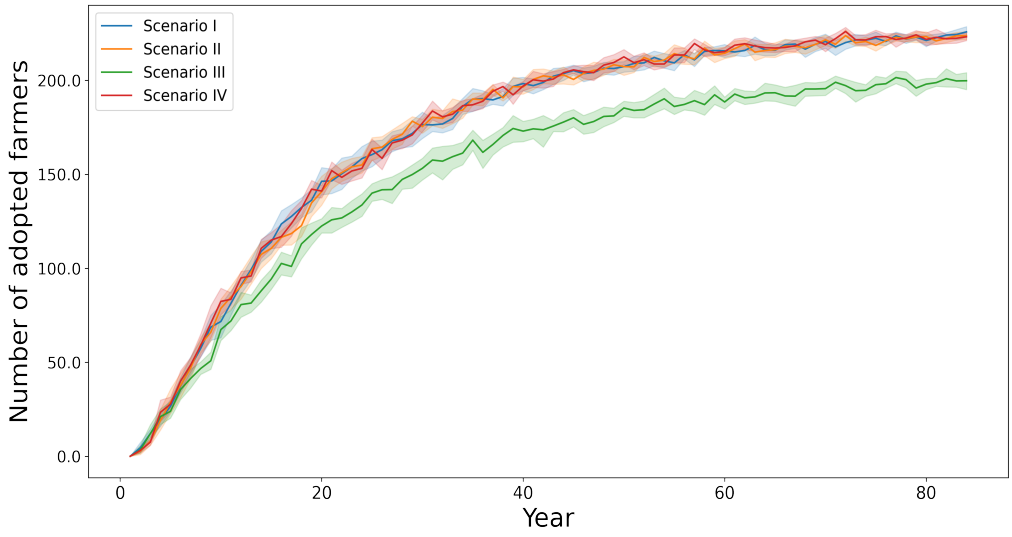


Figure 21: The results of the simulation experiments: number of farmers who adopted agricultural water reuse (the 95% confidence intervals were calculated using bootstrap resampling method).

4.4. 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 and Bahri, 2005; Sheikh et al., 2018; Shoushtarian and Negahban-Azar, 2020) Similarly, the results of our sensitivity analysis successfully 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 and Adamowski, 2016; Lazarova and Bahri, 2005; Metcalf and Eddy 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, Stofberg, van Dooren, 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 and 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. Therefore, 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 4.2.2.1.). 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 father 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.

4.5. 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. By integrating the DPWD's farmers'

perceptions toward agricultural water reuse in their decision-making regarding choosing their alternative water resources, the model captured the dynamics of farmers' water consumption for their irrigation practices. This model, therefore, demonstrated that agricultural water reuse could successfully 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.

Chapter 5: Sustainable water resources management through agricultural water reuse in Maryland; Application of agent-based modeling

Abstract

Climate change, population growth, and increasing water pollution are among the primary reasons for ever-increasing groundwater withdrawal, extensive groundwater level decline, and saltwater intrusion into the aquifers of the Mid-Atlantic (USA) region. One of the most sustainable and reliable methods for alleviating these challenges is agricultural water reuse. The main goal of this study was to investigate the dynamics of agricultural water reuse adoption by farmers and its impacts on local water resources in the Mid-Atlantic region. An agent-based model was developed using a case study in Easton, Maryland. A global uncertainty and sensitivity analysis was conducted to find the factors with the most significant influence on the model outputs. The model was also utilized for scenarios analysis under various climate change scenarios defined by the Intergovernmental Panel on Climate Change. The results showed that climate change and recycled water storage capacity and unit price were among the top factors with significant influence. This study demonstrated the importance of conducting time-varying sensitivity analysis for complex simulation models. Furthermore, results demonstrated that implementing agricultural water reuse could decrease farmers' water shortage, groundwater consumption, and surface water consumption (by almost 19.5 %). The agricultural water reuse was also able to increase farmers' water supply reliability, resiliency, and sustainability under various climate change scenarios.

5.1. Introduction

Water is one of the primary necessities of worldwide agriculture. The contribution of water to agriculture spans from completely rainfed to thoroughly irrigated agriculture (Rosegrant et al., 2009). Globally, agriculture uses around 70% of global freshwater withdrawals (Gleick et al., 2012). The productivity of this sector is intrinsically linked to available water (Aliyari et al., 2021). The dependency is so high that scientists often claim water supply availability must precede crop yield projections (Aliyari et al., 2021). Therefore, global food security is highly dependent on the availability of safe water resources. However, global water resources available for agriculture have been challenged by various factors. Some of these factors include: 1) population growth (Butler et al., 2017; Maja & Ayano, 2021; Rosegrant et al., 2009), 2) increasing intersectoral competition (Rosegrant et al., 2009), 3) water, land, and environmental degradation (Rosegrant et al., 2009), 4) increasing water pollution (Rosegrant et al., 2009), 5) unsustainable groundwater consumption (Rosegrant et al., 2009), and 7) climate change (Aliyari et al., 2021; Lobell & Gourdji, 2012; Rosegrant

et al., 2009). Scientists argue that the intensity of these challenges will even be exacerbated over the following decades (Rosegrant et al., 2009).

In the water-rich Mid-Atlantic region (USA), a small percentage of agriculture (four percent) is irrigated (Abler & Shortle, 2000; Boryan et al., 2012; Dong et al., 2019). Groundwater is the primary source of water for irrigated agriculture in this region (Maupin, 2018). Of note is that the percentage of dependence on groundwater for irrigation in this region varies widely. The upper Eastern Shore of Maryland and Delaware are among areas that heavily rely on groundwater resources (Dong et al., 2019). In the case of Maryland, multiple studies have shown that the challenging factors mentioned above have resulted in ever-increasing groundwater withdrawal, extensive groundwater level decline, and saltwater intrusion into the aquifers of this region (Masterson et al., 2016; Paul et al., 2021). Specifically, precipitation uncertainty and nonuniformity, and slightly higher temperatures in the growing season have made farmers of this state extensively increase their irrigation practices (Masterson et al., 2016). This state's recent groundwater pumping data show the ever-increasing withdrawal rate from this source (Paul et al., 2021). It should be mentioned that groundwater also supplies other demands (e.g., drinking water, streams, rivers, and wetlands) in this state (Paul et al., 2021). So, any threat to the groundwater resources available can potentially put human and environmental health in danger in this region.

One of the primary solutions to address such a water crisis is sustainable water resources management. Loucks (1997) defined sustainable water resources systems as "*those systems designed and managed to contribute fully to the objectives of society, now and in the future, while maintaining their ecological, environmental and hydrological integrity.*" Moreover, Sandoval-Solis (2011) underlined that the adaptive capacity of water resource systems has been strongly emphasized recently. This study highlighted the importance of measures that decrease water resource system vulnerability to actual or expected future challenges (Sandoval-Solis et al., 2011).

Water reuse is one of the most critical measures for sustainable water resource management, increasing the adaptive capacity of water resource systems to actual and expected challenges (e.g., climate change) and helping to reach the circular economy (Pronk et al., 2021). Water reuse is defined as the application of treated wastewater for beneficial purposes (e.g., irrigation) (USEPA (US Environmental Protection Agency), 2012). Globally, the application of water reuse in agriculture (i.e., agricultural water reuse) is the most dominant type of water reuse (Eslamian, 2016). Some of the benefits of agricultural water reuse for sustainable water resources management include: it is a highly reliable and drought-proof alternative water source, it also decreases pollution in water bodies, reduces freshwater consumption, manages and recovers nutrients, and avoids new water supply impacts (Shoushtarian & Negahban-Azar, 2020).

In the Chesapeake Bay region, Maryland, decision/ policymakers have started to upgrade wastewater treatment plants (WWTPs) to safely and effectively treat and

manage large amounts of wastewater produced in this region and reduce discharging nutrients from this region to bay (Paul et al., 2021). For example, approximately $1.25 billion has been provided by Maryland's Restoration Fund to upgrade 67 WWTPs in this state, preventing 10 and 1 million pounds of Nitrogen and Phosphorus (respectively) from discharging to the Bay (USEPA, 2016). This fund has provided an excellent opportunity for water resource managers to implement water reuse practices (especially agricultural water reuse) to increase the sustainability of water resources in this area.

Despite the benefits agricultural water reuse practices provide water resources managers to manage water resources sustainably, they add to the complexity of water resources systems, making it more challenging to manage these projects efficiently. This requires water resources managers to look for special tools capable of capturing these complexities and helping them make optimum decisions/ policies. Many researchers have acknowledged the advantages of using computational models of these complex systems to make equitable, efficient, and sustainable decisions in water resources management (Al-Jawad et al., 2019; Isaeva et al., 2019; Johnson, 1986; R. Khan et al., 2020; Sarband et al., 2020). Various methods are available for developing such models, including agent-based modeling, system dynamics, microsimulation, and cellular automata (Berglund, 2015; Crooks et al., 2018).

Agent-based models (ABMs) are computational models for simulating complex systems, using their constituents' perspective (i.e., the "bottom-up" approach) (Bonabeau, 2002; Grimm & Railsback, 2005). "*ABMs are highly effective in explaining how complex patterns emerge from micro-level rules during a period of time*" (Sabzian et al., 2019). Rules (explicit assumptions) are used in agent-based modeling to build the model; then, the model will generate simulated data. The data will be analyzed through quantitative and qualitative methods to conclude (Achorn, 2004). Complexity theory and network science form the basis of agent-based modeling (Sabzian et al., 2019). As a process model, an ABM shows the generation of complex emergence resulting from simple rules (based on complexity theory) (Sabzian et al., 2019). As a pattern model, an ABM is utilized to study the generation of patterns resulting from agents' interactions over time (based on network science) (Sabzian et al., 2019).

ABMs consist of three main components: agents, an environment, and interactions (Berglund, 2015; Macal & North, 2010). Agents in ABMs are autonomous entities defined by their attributes and actions (Berglund, 2015; Sabzian et al., 2019). Based on their attributes, agents can do activities that affect their or other agents' attributes or the environment (Sabzian et al., 2019). "*The environment is composed of all conditions surrounding the agents as they interact within the model*" (Sabzian et al., 2019). It provides agents with resources and information (Berglund, 2015). Interactions define the agents' and the environment's rules of behavior. These include agent-agent/ self, agent-environment, environment-environment/ self, and environment-agent interactions (Sabzian et al., 2019). These interactions are based on

the attributes and rules of behavior of interacting entities (agents or environment); these attributes can be changed due to the interactions.

Various ABMs have been developed to study complex water resources systems (Ghoreishi et al., 2021a). One of the ways to categorize these ABMs is based on the methods/ algorithms used for agents' decision-making processes (Ghoreishi et al., 2021a). Several theories, e.g., rational choice theory/ homo economicus, bounded rationality, theory of planned behavior (TPB), habitual/ reinforcement learning, descriptive norm, and prospect theory, can form the basis of agent's decision making in ABMs (Schlüter et al., 2017). Based on the application, each of these theories has its advantages and disadvantages (An, 2012; Schlüter et al., 2017). For instance, although several studies have used methods based on the rational choice theory in their ABMs, several researchers argue that these methods are not consistent with human decision-making as they are based on idealized assumptions (Levine et al., 2015).

Moreover, several researchers have used ABMs to simulate environmental-friendly technologies adoption (Laciana & Rovere, 2011; Rasoulkhani et al., 2018; Schwarz & Ernst, 2009; Tran, 2012). Tran (2012) studied the role of individual behavior and network influence on energy innovation diffusion using an ABM. This study captured the underlying mechanisms of human decision-making that influenced households' adoption of innovative energy conservation technologies. Ising model was utilized in a study by Laciana and Rovere (2011) to develop an ABM for studying the adoption of technological innovation. Rai and Robinson (2015) developed a theoretically-based and empirically-driven agent-based model of technology adoption, with an application to residential solar photovoltaic. An ABM was also developed in another study to capture the dynamics of water-related innovations adoption among Southern German households (Schwarz & Ernst, 2009).

Building on the TPB, this study applied a framework developed in our previous study (Chapter 4) to simulate agricultural water reuse adoption by farmers in Maryland. TPB was utilized in various studies to simulate human decision-making dynamics and their effects on water resources (Gilg & Barr, 2006; Koutiva & Makropoulos, 2016b; Pouladi et al., 2019; Yazdanpanah et al., 2014). Icek Ajzen introduced the TPB framework in 1991 (Ajzen, 1991). This theory describes how a person's behavioral intention can determine the person's behavior (Ajzen, 1991). This theory claims that control beliefs, subjective norms, and attitudes influence behavioral intention; thus, affecting the person's decisions. A person's attitude toward a behavior is how the person thinks and feels about the behavior and reflects the person's 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: 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 how a person feels capable and confident in their ability to execute the desired behavior and overcome the barriers and challenges of implementing it (Ajzen, 1991).

To the best of our knowledge, farmers' agricultural water reuse adoption and its impacts on local water resources in the Mid-Atlantic region have not been studied so far in the literature. Therefore, in this study, the main objectives were to capture the dynamics of farmers' agricultural water reuse adoption and its impacts on local water resources in Maryland. A comprehensive time-varying uncertainty and sensitivity analysis was also conducted in this study to find the uncertainties in the model output and the most influential factors on model output. Using the ABM developed in this study, we also looked for the optimum policies for managing agricultural water reuse practices to manage local water resources in Maryland under uncertain conditions sustainably, i.e., uncertainties inherent in water resources and climate change scenarios proposed by the Intergovernmental Panel on Climate Change (IPCC). In the remainder of this chapter, Section 2 introduces our study area and methodology, Section 3 presents our results and discussion, and Section 4 summarizes the chapter and areas of further work.

5.2. Methodology

5.2.1. Study area

The study area was located at Easton city, Talbot County, Eastern Shore, MD (Figure 22). This site is located at the Choptank River watershed. According to Dong et al. (2019), this watershed has been experiencing severe groundwater level declines for the past decade due to groundwater withdrawals as it is the primary water source. Paul et al. (2021) identified this site as suitable for implementing agricultural water reuse practices using geospatial multi-criteria decision analysis. The criteria used in this study included the type of crops grown in each area, the distance from farms to WWTPs, the drought index (PDSI) of each area, the amount of groundwater withdrawal, and freshwater consumption in agriculture (2020). The Choptank River watershed has 66 percent agricultural land, 29 percent forested land, and the rest is small municipalities and residential development (Lomax & Stevenson, 1982).

Starting its operation in 1914, the Easton WWTP was the first sanitary wastewater and separate storm system in Maryland (Water & Wastewater Overview – Easton Utilities). This facility is currently one of the major wastewater treatment facilities in Maryland, serving about 7,000 customers in Talbot County with approximately 92 miles of wastewater mains, 20 pumping stations, and an environmentally-friendly treatment facility (Water & Wastewater Overview – Easton Utilities). This facility received the first Bay Restoration Fund ($17.59 million) for its advanced technological upgrades in Maryland in 2007 (MDE Secretary Celebrates Easton Wastewater Facility Grand Opening, 2007). Through this fund, this facility reduced its effluent nutrient concentration to 3 and 0.3 milligrams per liter (mg/l) for Nitrogen and Phosphorus, respectively (Water & Wastewater Overview – Easton Utilities). More than $19 million in low-interest loans was also granted to this facility by this fund to expand the facility's capacity from 12.1 to 15.1 thousand cubic meters per day by 2030 (MDE Secretary Celebrates Easton Wastewater Facility Grand Opening,

2007). This site is one of the potential sites to practice safe and proper agricultural water reuse in Maryland (Paul et al., 2021).

To obtain the study area's land use/ land cover data (2020), the National Agricultural Statistics Service Cropland Data Layers (NASS-CDL) (CropScape - NASS CDL Program) were used. The Maryland Department of Planning (Maryland Department of Planning) and Maryland GIS Data Catalog (Maryland's GIS Data Catalog) were also investigated to find the shapefiles of the watershed, agricultural parcels, calculate farms' acreage, and determine the location of their center points (centroid). The data associated with the Easton WWTP was acquired from The United States Environmental Protection Agency's (EPA) Enforcement and Compliance History Online (EPA Enforcement and Compliance History Online).

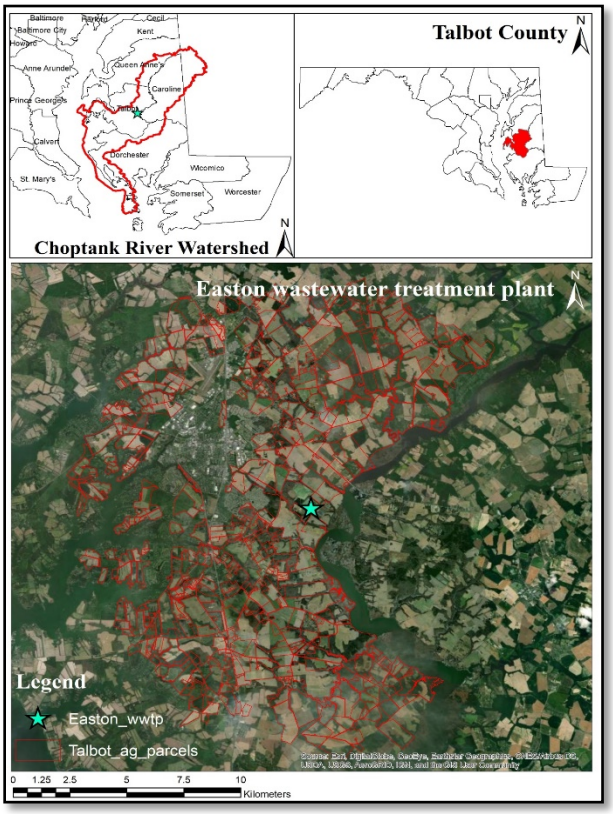


Figure 22. The Easton WWTP and its surrounding agricultural farms (in Talbot County, MD) within a 15 km radius investigated in this study.

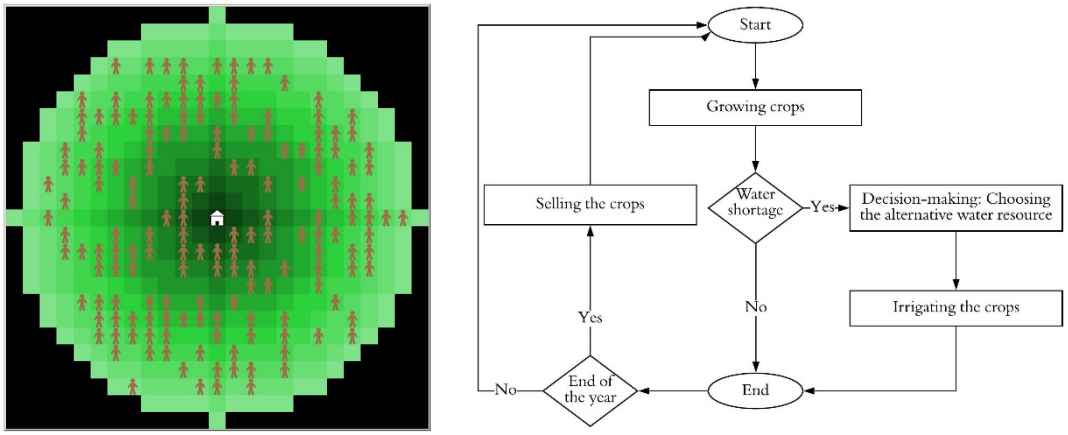
5.2.2. Framework

Our previous work (Chapter 4) extensively explained the agent-based framework used in this study. Here, a brief description is provided; interested readers are encouraged to read our previous paper (Chapter 4). This framework simulates local agricultural water consumption in a virtual agricultural area. TPB inspired the framework to simulate farmers' decision-making regarding adopting agricultural

water reuse and choosing their water source for irrigation. The framework allows users to evaluate various scenarios (e.g., climate change and various planning and management scenarios) to find their impacts on farmers' decisions and ultimately on local water resources sustainability. This model was developed using NetLogo 6.1.1 (Wilensky & Rand, 2015).

5.2.2.1. Environment

The agent-based framework simulated the environment in a stylized manner, inspired by the AgriPoliS (Happe et al., 2006) model (Figure 23 (a)). The environment included 625 (25×25) identical cells. The Easton WWTP was located at the central cell. As corn is the dominant crop cultivated in the area and Maryland (CropScape - NASS CDL Program), Corn farms were explicitly chosen for this study. Similar to Paul et al., (2021), corn farms within a 15 km radius from the Easton WWTP were selected for this study. There were 166 corn farms in the area. Farms' distances (Euclidean distance) were calculated using their center points (centroid) and the WWTP location. Farms' center points (latitude, longitude) were determined using their shapefiles. The distance was further used to categorize farms into 15 (one km long) groups.



(a) (b)

Figure 23. (a) The stylized environment of the ABM developed in this study, (b) Farmers' daily activities algorithm

Cells around the Easton WWTP cell (central cell) were also categorized and color-coded into 15 groups using the Von Neumann neighborhood (Neumann & Burks, 1966). This process started from the closest cells to the central cell (Manhattan distance (Szabo, 2015) = 1) to the farthest cells (Manhattan distance = 15). Therefore, cells in group one were those in Manhattan distance = 1. Then, cells in group two were the cells in Manhattan distance =2, except those in group one. This process continued until all cells were categorized into 15 groups. Next, each farm was stochastically placed in a cell at the start of each run, based on its corresponding group (Figure 23 (a)). For example, at the start of each run, farms whose distance

from Easton WWTP was less than one km were randomly placed in cells group one (Manhattan distance = 1). This procedure helped place farms in the stylized environment quickly and stochastically at the start of each run.

5.2.2.2. Agents (farmers):

After placing all farms into their cells, one agent (farmer) was created for each farm as the farm's primary decision-maker (Figure 23 (a)). Farmers in this model grew corn daily each year (Figure 23 (b)). The data (farm area, distance to WWTP, and crop) corresponding to each farm was also transferred to its farmer for its future decision-making. According to the University of Maryland's Extention (Extension Services) and the United States Department of Agriculture- National Resources Conservation Services (USDA-NRCS & Services, 1975)- corn cultivated in the Eastern Shore of Maryland requires irrigation only in June, July, August, and September. Corn irrigation requirements (per unit area) were based on long-term average rainfall with normal weather conditions and light-textured soils (Extension Services). Based on the University of Maryland's Extention (Extension Services), corn water requirements can be increased to 8.4 millimeters per day in extremely hot/ bad conditions (Extension Services). It can also be decreased to zero in highly wet/ good conditions (Extension Services). As this model runs daily, farmers' daily irrigation demands were calculated according to Equation (7). This method is logically similar to the Blaney–Criddle equation (Blaney, 1952) for estimating monthly evapotranspiration.

Table 41. Corn irrigation requirements in Eastern Shore of Maryland

Month (days)	The monthly net irrigation requirement- millimeter (mm) per hectare
January (31)	0
February (28)	0
March (31)	0
April (30)	0
May (31)	0
June (30)	250.9 (moderate yield), 376.3 (high yield)
July (31)	2,446.1 (moderate yield), 3,669.1 (high yield)
August (31)	2,508.8 (moderate yield), 3,763.2 (high yield)
September (30)	1,003.5 (moderate yield), 1,505.3 (high yield)
October (31)	0
November (30)	0
December (31)	0

$$Farmers' Daily\ Irrigation\ Demand = \left(\frac{Monthly\ Net\ Irrigation\ Demand}{Length\ of\ the\ Month}\right) \times \left(\frac{Irrigation\ Need\ Coefficient}{Irrigation\ System\ Efficiency}\right) \times farm\ area \quad (7)$$

Where *Monthly Net Irrigation Demand* and *Length of the Month* were based on Table 41. Assuming all corn farmers use the sprinkler system for simplification, the irrigation system efficiency was 0.8 (Howell, 2003). The *Irrigation Need Coefficient* was introduced to capture uncertainties in corn irrigation requirements due to alternating weather conditions. For this, it was assumed that extreme hot/ bad conditions, when the corn irrigation requirement would be 8.4 millimeter per day, would occur in August as it has the highest irrigation requirement. Therefore, the monthly irrigation need would be 259.8 millimeters; this is 2.6 times the corn irrigation needs (moderate yield) in August Table 41. So, *Irrigation Need Coefficient* was considered between 0 to 2.6 in this model, assuming that various weather conditions would alter corn irrigation requirement in this model through this factor.

In general, crops irrigation needs vary due to various factors such as weather, soil, irrigation system (Blaney, 1952). However, as determining the exact crop water requirement is out of the scope of this study, we assumed only precipitation and temperature would alter corn water requirements. Therefore, for simplification, the *Irrigation Need Coefficient* was modeled by a quadratic formula (Equation (8)), using daily precipitation and temperature. The unknown parameters in this equation were found using the Lagrange Interpolation method (Berrut & Trefethen, 2006) and three known points (Table 42). The resulting quadratic equation for determining daily *Irrigation Need Coefficient* based on daily temperature and precipitation was according to Equation (9). The minimum, average, and maximum of daily temperatures and precipitations in Maryland (only in those months that farmers need irrigation) were according to the state of Maryland website (Maryland Weather) and IPCC-CORDEX-North America (Gutiérrez et al., 2021).

Daily precipitation and temperature were input to Equation (9) to model the *Irrigation Need Coefficient* stochastically (Tables 43, 44, and 45). For climate change scenarios, IPCC climate change projections (precipitation and temperature) under various scenarios, i.e., RCP 2.6, RCP 4.5, and RCP 8.5, between 2021-2100, were input to the model. For scenario analysis, the user could choose between the "business as usual" (BAU) or climate change conditions; daily temperature and precipitation were stochastically input accordingly to calculate the *Irrigation Need Coefficient* and ultimately the *Farmer's Daily Irrigation Demand*.

$$I\,(T,P) = aT^2 + bT + cTP + dP^2 + eP + error \quad (8)$$

$$I\,(T,P) = 0.0111T^2 - 0.3111T + 0.0608P^2 - 0.9404P + 5.4677 \quad (9)$$

Where I is I$rrigation\ Need\ Coefficient$, T is the temperature (C^{o}), and P is precipitation (mm/day).

Table 42. Weather conditions in Maryland based on IPCC (Gutiérrez et al., 2021) *and corresponding irrigation need coefficients assumed in this study.*

Weather condition	***Irrigation Need Coefficient***	**Temperature (C°)**	**Precipitation (mm/day)**
Normal (long-term average)	1	Average (21)	Average (4.1)
Extremely dry	2.6	Maximum (25.0)	Minimum (2.6)
Extremely wet	0	Minimum (16.0)	Maximum (5.5)

Table 43. Maryland Daily temperature and precipitation projections (2021-2040) based on IPCC-CORDEX-North America (Gutiérrez et al., 2021)

Period	Scenario	Month	Total precipitation percentiles (mm/day)					Mean temperature percentiles (C°)				
			5%	**25%**	**50%**	**75%**	**90%**	**5%**	**25%**	**50%**	**75%**	**90%**
Near-term (0-40)	RCP 2.6	Jun.	3.9	4.2	4.4	4.7	4.9	17.8	18.3	18.6	19.2	19.5
		Jul.	4.0	4.4	4.7	4.8	4.8	20.5	20.9	21.3	21.7	22.2
		Aug.	3.6	4.0	4.2	4.3	4.3	19.8	20.6	21.4	21.9	22.2
		Sep.	3.3	3.5	3.6	3.7	3.7	16.0	17.0	18.0	18.5	18.7
	RCP 4.5	Jun.	3.6	3.8	3.9	4.2	4.4	17.5	18.3	18.9	21.3	21.8
		Jul.	3.3	3.5	3.9	4.2	4.5	20.3	21.0	22.3	24.1	24.5
		Aug.	3.1	3.2	3.7	3.9	4.3	19.8	21.0	21.6	24.1	24.5
		Sep.	2.6	3.2	3.4	3.8	4.3	16.3	17.3	17.7	20.6	21.0
	RCP 8.5	Jun.	3.8	4.1	4.4	4.8	5.5	17.6	18.3	19.6	20.1	21.9
		Jul.	3.6	3.9	4.3	4.8	5.3	20.6	21.2	22.3	23.2	25.0
		Aug.	3.0	3.7	4.2	4.5	4.8	19.6	20.9	21.6	22.3	24.5
		Sep.	2.8	3.4	3.8	4.0	4.5	16.0	17.2	18.0	18.8	21.4

Table 44. Maryland Daily temperature and precipitation projections (2041-2060) based on IPCC-CORDEX-North America (Gutiérrez et al., 2021)

Period	Scenario	Month	Total precipitation percentiles (mm/day)					Mean temperature percentiles (C°)				
			5%	**25%**	**50%**	**75%**	**90%**	**5%**	**25%**	**50%**	**75%**	**90%**
Medium-term (41-60)	RCP 2.6	Jun.	4.0	4.3	4.7	4.8	4.9	18.0	18.6	18.9	19.2	20.0
		Jul.	4.2	4.4	4.7	4.9	4.9	20.7	20.8	21.4	22.3	22.9
		Aug.	3.7	4.1	4.4	4.5	4.5	19.6	20.5	21.4	22.1	22.4
		Sep.	3.4	3.6	3.7	3.7	3.8	16.1	17.1	18.2	18.9	18.9
	RCP 4.5	Jun.	3.7	3.8	3.9	4.1	4.5	18.1	18.9	19.6	22.2	22.5
		Jul.	3.5	3.7	4.0	4.1	4.2	21.0	21.6	22.7	24.7	25.3
		Aug.	3.1	3.3	3.6	3.9	4.1	20.2	21.5	22.1	24.9	25.3
		Sep.	2.6	3.1	3.4	3.9	4.3	16.8	18.1	18.1	21.0	21.4
	RCP 8.5	Jun.	3.7	3.9	4.4	4.8	5.4	18.9	19.5	20.4	21.0	23.4
		Jul.	3.6	3.9	4.2	5.0	5.6	21.6	22.1	23.4	24.1	25.9
		Aug.	3.0	3.7	4.3	4.5	4.8	21.0	21.9	22.7	23.7	25.7
		Sep.	3.0	3.6	3.8	4.2	4.3	16.8	18.2	20.0	22.2	22.3

Table 45. Maryland Daily temperature and precipitation projections (2061-2100) based on IPCC-CORDEX-North America (Gutiérrez et al., 2021)

Period	Scenario	Month	Total precipitation percentiles (mm/day)					Mean temperature percentiles (C°)				
			5%	**25%**	**50%**	**75%**	**90%**	**5%**	**25%**	**50%**	**75%**	**90%**
Long-term (61-80)	RCP 2.6	Jun.	3.9	4.3	4.5	4.7	4.7	18.0	18.2	18.5	19.1	20.0
		Jul.	4.1	4.3	4.6	4.9	5.0	20.4	20.6	21.3	22.1	22.6
		Aug.	3.6	3.8	4.1	4.4	4.6	19.8	20.3	21.3	22.2	22.9
		Sep.	3.4	3.5	3.7	3.8	3.8	15.7	16.9	18.1	18.8	19.3
	RCP 4.5	Jun.	3.7	3.8	3.9	4.3	4.6	18.6	19.1	20.2	22.5	23.0
		Jul.	3.7	3.7	3.8	4.1	4.4	21.1	22.5	23.6	25.4	25.8
		Aug.	3.2	3.2	3.7	4.0	4.1	20.5	22.3	22.9	25.5	26.0
		Sep.	2.7	3.2	3.5	4.1	4.5	17.1	18.7	19.0	21.9	22.2
	RCP 8.5	Jun.	3.7	3.9	4.7	5.1	5.7	20.4	21.0	22.5	23.8	26.0
		Jul.	3.5	4.0	4.4	5.0	5.5	23.4	24.3	25.6	27.0	28.9
		Aug.	2.8	3.9	4.2	4.4	5.1	22.1	24.3	25.3	26.7	29.3
		Sep.	2.3	3.5	4.0	4.3	4.7	18.9	20.3	21.4	23.8	25.6

For farmers with irrigation demand, there were three sources of water available in this study: groundwater (primary source), surface water, and recycled water. The amount of water groundwater could supply farmers for their irrigation was adjustable as 90-100% of *Farmer's Daily Irrigation Need* for scenario analysis. Farmers considered using recycled water only after adopting agricultural water reuse, simulated via a submodel described in the following. Farmers who had not adopted agricultural water reuse first used groundwater for their irrigation based on available amounts. Then they used available surface water to supplement groundwater for their irrigation. The amount of water surface water could supply farmers for their irrigation was adjustable as 90-100% of the remaining *Farmer's Daily Irrigation Need* (after using groundwater) for scenario analysis.

On the other hand, those farmers who had adopted agricultural water reuse had recycled water as an alternative water source for their irrigation. To decide between groundwater and recycled water, farmers chose the cheapest based on groundwater and recycled water unit prices. Those farmers that chose recycled water used recycled water supplied by the WWTP. If the recycled water supplied was insufficient, these farmers used groundwater and surface water to complement the water supplied for their irrigation. According to the 2017 Census of agriculture (Perdue & Hamer, 2019), groundwater and surface water's unit prices were $5.263\text{-}5.461\times10^{-5}$ \$/square meter.day and $4.868\text{-}5.064\times10^{-5}$ \$/square meter.day, respectively in MD. Recycled water unit price was adjustable between 0-0.015 \$/cubic meter.day for the user for scenario analysis.

This part describes the financial aspects of farmers. At the start of the model, it was assumed that farmers' initial money was proportional to their farm size, equal to a year of growing corn (Equation (10)). It should be mentioned that the user could adjust corn yield as either moderate yield (1.4 kg/square meter (Extension Services)) or high yield (1.9 kg/square meter (Extension Services)) for scenario analysis. Corn unit price was also randomly selected from a uniform probability distribution between

minimum and maximum of corn price set by the user for scenario analysis. In this study, the minimum and maximum corn prices were set to 0.094 and 0.236 $/kg, respectively, according to the United States Department of Agriculture-National Agricultural Statistics Services (USDA - National Agricultural Statistics Service - Charts and Maps - Prices Received: Corn Prices Received by Month, US).

For simplicity, it was assumed that all farmers in this model used a center-pivot system for their irrigation. According to Hanna (2006), the approximate lifetime of a center-pivot system is approximately 20 years in Maryland. Therefore, the ages of farmers' irrigation systems (center-pivot) at the start of the model were randomly selected between 0-20 from a uniform probability distribution. Farmers renewed their irrigation system after every 20 years. Hanna (2006) calculated the unit prices (per area) of running a center-pivot irrigation system in Maryland in 2005. Irrigation costs were transferred to the year 2021, accounting for the inflation rate in the U.S. (Equation (11)). The U.S. inflation rate data was collected from the World Bank (Ha et al., 2021). The U.S. inflation rate (from 1990 to 2020) was analyzed through the data Quantile-Quantile plot and the Shapiro-Wilk (1965) test for normality to check whether it was possible to input the inflation rate (r) stochastically using a normal (Gaussian) distribution.

$$Farmers'\ inititial\ money(\$) = farm\ area(ha) \times corn\ yield\left(\frac{kg}{ha}\right) \times corn\ unit\ price(\frac{\$}{kg}) \quad (10)$$

$$P_n = P_1(1+r)^n \quad (11)$$

Where P_n was the price in year n, P_1 was the price in year one, and r was the inflation rate. Accordingly, farmers in this model used these costs to calculate irrigation costs each year (Equations ((12)-((15)).

$$Installation\ cost(\$) = 1360.3(\frac{\$}{ha}) \times farm\ area(\text{ha}) \times (\ (1+r)^n) \quad (12)$$

$$Annual\ depreciation\ cost(\$) = 68.03(\frac{\$}{ac}) \times farm\ area(\text{ha}) \times (\ (1+r)^n) \quad (13)$$

$$Annual\ maintenance\ cost(\$) = 14.7(\frac{\$}{ac}) \times farm\ area(\text{ha}) \times (\ (1+r)^n) \quad (14)$$

$$Annual\ farm\ operations\ cost(\$) = 334(\frac{\$}{ac}) \times farm\ area(\text{ha}) \times (\ (1+r)^n) \quad (15)$$

At the end of each year, farmers sold their crops and calculated their net benefits from growing corn using Equations (16) and (17) (Hanna, 2006).

$$NB = Y \times P - (CO + CM) \quad (16)$$

$$Y \times P(\$) = corn\ price\left(\frac{\$}{kg}\right) \times corn\ yield\left(\frac{kg}{ha}\right) \times farm\ area(ha) \times \left(1 - \frac{farmer's\ water\ shortage\ in\ year\ (CM)}{farmer's\ total\ water\ need\ in\ year\ (CM)}\right) \quad (17)$$

Where *NB* was the net benefit ($), *Y* was the crop yield (kg), *P* was the sales price of the crop ($/kg), *CO* was the annual farm operations cost ($), and *CM* was the annual maintenance cost ($) (Hanna, 2006). Also, after 20 years of application, farmers sold their old irrigation system and bought a new one (Equations (18) and (19)).

$$Farmers'money = farmers'money + old\ system\ worth - new\ system\ cost \quad (18)$$

$$Old\ system\ worth = installation\ cost - 20 \times annual\ depreciation\ cost \quad (19)$$

Adoption submodel: Agricultural water reuse adoption by farmers in this model was simulated using an agent-based submodel described extensively in our previous work (Chapter 4). Here a brief description is provided for brevity. This submodel was proposed based on TPB. The attitude of the farmers was stochastically simulated based on survey data (Suri et al., 2019) (Tables 46, 47, 48, and 49). The subjective norm was simulated by subtracting the number of positive and negative messages received from other farmers. Farmers with a positive attitude toward agricultural water reuse sent positive messages to many other farmers in their network and vice versa. User, for scenario analysis, adjusted the number of messages. The control beliefs were simulated using the financial analysis and the perceptions of farmers' customers. Farmers did a financial analysis based on recycled water price and their previous year's available money and water shortage volume. Customers' perceptions were simulated stochastically 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.

Table 46. Demographics of agents, based on Suri et al., (2019).

Parameter	**Age**	**Knowledge**
Levels (n (%))	18-29 (5.5)	Very (8)
	30-49 (34.3)	Somewhat (22)
	50-69 (53.7)	A little (44)
	70-89 (6.5)	No (28)
Parameter	**Sex**	**Access**
Levels (n (%))	Female (32.8)	Yes (26)
	Male (67.2)	I do not know (19)
		No (55)
Parameter	**Education**	**Race**
Levels (n (%))	Doctorate (0)	American Indian / Alaskan
	Graduate degree (21)	Native (2)
	Some college (16)	Asian (includes India and
	4-year degree (34)	the Middle East) (0)
	2-year degree (4)	Black/ African-American
	High school graduate (18)	(4)
	Less than high school (6)	White (84)
	Prefer not to answer (2)	Prefer not to answer (10)

Table 47. Discrete probabilities distributions used in determining agents' concerns about water reuse, based on Suri et al., (2019).

Concern	Yes	No	Somewhat	Total
Age:18-29	23%	46%	31%	100%
Age:30-49	32.5%	35%	32.5%	100%
Age:50-69	41%	28%	31%	100%
Age:70-69	38%	31%	31%	100%

Table 48. Discrete probabilities distributions used in determining agents' importance of water reuse, based on Suri et al., (2019).

Importance	Very important	Moderately important	Not important	Not answered	Total
Concern: Yes	37.3%	43.4%	15.7%	3.6%	100%
Concern: No	21.7%	33.3%	44.9%	0%	100%
Concern: Somewhat	11.9%	56.7%	31.3%	0%	100%
Knowledge: Very	50%	38.9%	11.1%	0%	100%
Knowledge: Somewhat	44.1%	37.3%	18.6%	0%	100%
Knowledge: A little	17.8%	49.2%	32.2%	0.8%	100%
Knowledge: No	12%	36%	46.7%	5.3%	100%
Access: Yes	47.4%	43.9%	8.7%	0%	100%
Access: No	17.4%	42.1%	38.8%	1.7%	100%
Access: I don't know	13.6%	47.7%	36.4%	2.3%	100%
Education: Less than high school	5.9%	35.3%	58.8%	0%	100%
Education: High school graduate	16.7%	39.5%	43.8%	0%	100%
Education: 2-year degree	40%	30%	30%	0%	100%
Education: 4-year degree	23.3%	47.8%	26.7%	2.2%	100%
Education: Some college	16.7%	45.2%	33.3%	4.8%	100%
Education: Graduate degree	45.5%	38.2%	14.5%	1.8%	100%
Education: Doctorate	0%	0%	0%	0%	100%
Education: Prefer not to answer	0%	16.7%	83.3%	0%	100%

Table 49. Discrete probabilities distributions used in determining agents' attitude toward water reuse, based on Suri et al., (2019).

Attitude	Yes	No	Not answered	Total
Importance: Very important	83.3%	4.5%	12.1%	100%
Importance: Moderately important	52.6%	7%	40.4%	100%
Importance: Not important	23.3%	33.7%	43%	100%
Race: American Indian / Alaskan Native	50%	50%	0%	100%
Race: Asian (includes India and Middle East)	100%	0%	0%	100%
Race: Black/African-American	54.5%	27.3%	18.2%	100%
Race: White	49.5%	14.9%	35.6%	100%
Race: prefer not to answer	55.6%	3.7%	40.7%	100%
Sex: Female	54.9%	11%	34.1%	100%
Sex: Male	49.4%	17.9%	32.7%	100%

5.2.2.3. Agents (WWTP)

Another type of agent in this model was wastewater treatment plants. The only wastewater treatment plant agent in this model was Easton WWTP. The effluent flow rate of this agent was initially set to 12.1 TCM per day, increased linearly to 15.1 TCM per day in 10 years. The capacity of Easton WWTP storage ponds was also assumed to be between 1.03-2.06 MCM. This agent first sent its effluent to its storage ponds/ tanks to fill it. Then discharged the rest to the nearby river (Choptank River). For sending recycled water to the farmers, this agent first sorted farmers, who had already adopted agricultural water reuse, based on their distance (from closest to the farthest). Then, the agent sent its effluent from its storage ponds/ tanks to farmers for their irrigation practices. After sending the requested amount of recycled water to the farmer, the WWTP agent received the recycled water money from each farmer.

5.2.3. Methods

5.2.3.1. Verification, uncertainty analysis, sensitivity analysis, and validation

Verification, uncertainty analysis, sensitivity analysis, and validation of ABMs are four major agent-based modeling challenges due to various factors (e.g., complex adaptive structure, lack of empirical data, number of parameters, and computational intensity) (Aerts, 2020; Brown et al., 2017; Claessens et al., 2012; Crooks et al., 2018; Ghoreishi et al., 2021b; Smajgl et al., 2011; Smajgl & Barreteau, 2017; Venkatramanan et al., 2018). This section discusses the procedures applied to verify, analyze uncertainty and sensitivity, and validate the ABM in this study.

Verification: Verification in this study was conducted to check that the model behaved as expected (i.e., as designed) (Patel et al., 2012b). Three methods of model verification were used in this study, including code testing, expected outcome alignment, and extreme tests . The model code was extensively checked for semantic/ logical errors (code testing). During the expected outcome alignment, general patterns

of simulation dynamics were checked to align with expectations. The model was further verified by running extreme tests to check whether the results show logical patterns and model crashes (Crooks et al., 2018).

Uncertainty-sensitivity analysis: Walker et al. (2003) defined uncertainty as any deviation from the ideal deterministic knowledge of the source system that shows itself at various model parts. Uncertainty analysis (UA) enables us to investigate uncertainty propagation from sources to various model parts, especially model output (Baustert & Benetto, 2017). Morgan et al. (1990) highlighted the importance of UA by arguing that models, especially large and complex models, lose their meaning without uncertainty analysis. Baustert and Benetto (2017) classified uncertainty sources into four classes: parameter uncertainty, uncertainty due to choices, structural uncertainty, and systemic variability. Parameter uncertainty stems from random/ systematic error, spatial/ temporal variability, and inherent randomness. Uncertainty due to choices comes from choices made by modeler/s about model parameters and structure. Structural uncertainty can result from simplifications assumed during model development. The aleatory uncertainty regarding the outcomes of stochastic events can lead to systemic variability, which may alter model results from one simulation to another (Baustert & Benetto, 2017). UA results in a distribution of model results, requiring multiple model runs where factors values are randomly chosen from their distributions (Ligmann-Zielinska et al., 2014).

Sensitivity analysis (SA) often is implemented to determine the factors with the most influence on the outputs of models (Crooks et al., 2018; J. Kang et al., 2021). Razavi and Gupta classified SA methods into three classes, including 1) model-based methods, e.g., one-factor-at-a-time (OAT), factorial design, and response surface approximation via regression; 2) model-free methods, e.g., regional sensitivity analysis, variance-based methods; and 3) globally aggregated measures of local sensitivity. Three requirements are suggested for any SA technique, including "*global, quantitative, and model-free*" (Saltelli, 2002). The technique needs to consider the entire input distribution (global). SA would produce accurate results without assumptions on the model functional relationship to its inputs (model-free) (Borgonovo, 2007).

Saltelli (2002) demonstrated that variance-based methods satisfy the three requirements mentioned above. However, several problems with this method have been recognized so far (Borgonovo, 2007). Bedford (1998) illustrated the shortcomings of using variance-based methods in the presence of correlations among the parameters. Another shortcoming of these methods is that any moment of a random variable can summarize the variable distribution, losing resolution when representing a distribution by a single number (Borgonovo, 2007; Helton & Davis, 2003). To tackle these challenges in SA, (Borgonovo, 2007) introduced a global SA indicator (called δ) as a moment-independent indicator that considers the entire input and output distribution.

In our previous work (Chapter 4), we showed the application of a model-based method (i.e., factorial design) for the SA of an ABM. In this study, we demonstrated the application of a global SA method for an ABM. Time-varying uncertainty and sensitivity analysis (UA-SA) in this study were conducted in tandem. The authors designed this framework using three experiments. The UA-SA was conducted in three stages in this study.

1- First, using simple random sampling over the factors ranges (Table 50), Monte Carlo simulations (2,000 runs) were used to conduct stage one for finding the distributions of the model outputs (UA). The authors chose 2,000 runs for this stage to generate enough samples from the entire factor space to capture the model outputs' uncertainty successfully.

2- As normality is one of the assumptions of the Pearson test for correlation, distributions of the model factors were tested for normality in the next stage, using the Shapiro-Wilk (1965) test, to determine the suitable correlation test. Accordingly, the Spearmen's or Pearson correlation tests were used to check the factors' correlation (linear and non-linear).

3- Time-varying SA was done to find the most influential factors on model outputs using the moment-independent method introduced by Borgonovo (2007) through the SALib (Herman & Usher) Python library. Principles of this method are according to Equations (20) to (24).

$$\Omega_X \subseteq \mathbb{R}^n \tag{20}$$

$$x \in \Omega_X \tag{21}$$

$$y = g(x), \qquad g: \Omega_X \subseteq \mathbb{R}^n \to \Omega_Y \subseteq \mathbb{R}^n \tag{22}$$

$$s_i(x_i) = \int_{\Omega_Y} |f_Y(y) - f_{Y|X_i=x_i}(y)| dy \tag{23}$$

$$\delta_i = \frac{1}{2} E_{X_i}[s_i(X_i)] \tag{24}$$

Where, Ω_X is the set of factors' possible values, $\boldsymbol{x}$ is a single set of factors' possible values (model inputs). $f_X(\boldsymbol{x})$ is the distribution of the existing knowledge state about the factors when uncertainty exists in factors. Therefore, one of the possible X realizations is $\boldsymbol{x}$. $f_{X_i}(x_i)$ is the marginal distribution of one of the X components, where X is a random vector. Equation (22) shows how the model inputs are linked to model output; y is a random variable as X is uncertain. In this moment-independent (distribution-based) SA, the aim is to "*bet on the factor that, if determined, would lead to the greatest expected modification in the distribution of Y"* (Borgonovo et al., 2012). Furthermore, the shift between model output unconditional and conditional distribution is calculated using Equation (23), where$f_Y(y)$ is the model output unconditional distribution, and the conditional output distribution is calculated given that factor X_i is fixed at $x_i f_{Y|X_i=x_i}(y)$. Finally, the expected shift is calculated, Equation (24), to calculate the moment-independent sensitivity index (delta)

(Borgonovo, 2007; Borgonovo et al., 2012). Interested readers are encouraged to refer to Borgonovo (2007) for further details of this method.

Validation: Axtell and Epstein (1994) underlined four levels of ABM performance and analysis. ABMs at level zero are caricatures of reality. Results of ABMs in level 1 are in qualitative agreement with empirical macro-structures. Level two ABMs demonstrate quantitative agreement with empirical macro-structures. ABMs at level three exhibit quantitative agreement with empirical micro-structures . Accordingly, and due to the lack of quantitative empirical macro/micro-level data, the results of this model were validated qualitatively (level 1 ABMs) using empirical macro-level results of Diffusion of Innovations Theory (Rogers et al., 2005).

Table 50. Factors considered in the sensitivity analysis.

Symbol	Factor (Unit)	Description	Probability Distribution
A	Groundwater availability (%)	Percentage of farmers' irrigation needs (daily) that was provided by groundwater	Continuous uniform (93-100)
B	Surface water availability (%)	Percentage of farmers' irrigation needs (daily) provided by surface water after using other water sources.	Continuous uniform (93-100)
C	The unit price of recycled water ($/CM)	The price at which farmers bought recycled water from Easton WWTP	Continuous uniform (0-0.015)
D	Easton WWTP storage pond (MCM)	The volume of Easton WWTP storage pond for storing its treated effluent	Continuous uniform (1.03-2.06)
E	Climate	Climate scenarios which determined precipitation and temperature value, affecting the Irrigation Need Coefficient	Discrete uniform (BAU, RCP 2.6, RCP 4.5, and RCP 8.5)
F	Costumers' perceptions (%)	Positive perception of costumers toward Almonds irrigated with recycled water	Continuous uniform (44-90)
G	Number-of-messages	Number of positive/ negative messages that farmers send to their friends	Continuous uniform (1-20)
H	Corn yield (ton/ha)	Amount of corn produced per unit area by farmers (fixed at the high level for SA)	16.14

5.2.3.2. Water resources sustainability index

Sandoval-Solis et al. (2011) proposed a sustainability index (SI) to measure the sustainability of water resources systems. SI was used in this study to demonstrate the impacts of different management policies of an agricultural water reuse project under various scenarios on the sustainability of local water resources at the study area (Equation (25)).

Five water supply performance criteria were measured as SI for each farmer in this study. Demand ($Demand_t$) was calculated at the end of each growing year as the sum of each farmer's irrigation demand in a year. Supply ($Supply_t$) was also calculated at the end of each growing year as the sum of water supplied to each farmer in a year.

Farmers' deficit (D_t) was also calculated at the end of the growing year using each farmer's supply and demand in a year (Equation (26)). The probability of meeting the demand by the supply during the simulation period was defined as the first criterion, i.e., reliability. Time-based and volume-based reliability were calculated in this study for each farmer at the end of each year (Equations ((27) and ((28)) (Safavi et al., 2015). Each farmer's water supply system capacity for adapting to perturbations was calculated using the resiliency criterion (Equation ((29)). Resiliency was defined as the system's recovery probability from any stress. The severity of failures (vulnerability) was also calculated as the potential value of deficits (Equation ((30)). The worst-case annual deficit defined as the maximum deficit was also calculated in this study using Equation ((31) (Sandoval-Solis et al., 2011).

$$Sustainability\ Index\ (SI) = (Rel_{time}^{i} \times Rel_{vol}^{i} \times Res^{i} \times (1 - Vul^{i}) \times (1 - Max.Def^{i}))^{0.2} \quad (25)$$

$$D_t = Demand_t - Supply_t \quad (26)$$

$$Rel_{time}^{i} = 1 - \frac{Days\ with\ water\ shortage\ in\ year}{Days\ with\ irrigation\ in\ year} \quad (27)$$

$$Rel_{vol}^{i} = 1 - \frac{Farmer\ water\ shortage\ in\ year}{Farmer\ total\ water\ need\ in\ year} \quad (28)$$

$$Res^{i} = \frac{\#\ of\ times\ D_t^i = 0\ followed\ D_t^i > 0}{\#\ of\ times\ D_t^i > 0\ occured} \quad (29)$$

$$Vul^{i} = \frac{\frac{Farmer\ water\ shortage\ in\ year}{\#\ of\ times\ D_t^i > 0\ occured}}{Farmer\ total\ water\ need\ in\ year} \quad (30)$$

$$Max.Def^{i} = \frac{\max D_t^i}{Farmer\ total\ water\ need\ in\ year} \quad (31)$$

5.2.3.3. Simulation experiments

After model verification, UA-SA, and validation, several experiments were defined for exploratory scenario analysis in this study (Table 51). Scenarios were defined to explore potential scenarios regarding various weather and limitations on local water resources. The first scenario (Scenario I) was designed as the BAU scenario to simulate the study area under average weather, with no limitations on local water resources. In the second scenario (Scenario II), the simulations were run under climate change effects, i.e., RCP 2.6 climate projection and low local water sources limitations. Two other scenarios were defined as Scenarios III and IV to simulate the study area under more problematic conditions. The study area under moderate water shortages and limitations on local water resources and RCP 4.5 climate projections was simulated according to Scenario III. Furthermore, to test the area for extreme conditions, Scenario IV was simulated under severe water shortages, limited local water resources, and RCP 8.5 climate projections.

Furthermore, for each scenario, the unit price of recycled water, customers' perceptions, number of messages, and corn yield were set according to the limitations on local water resources and climate change scenarios. The unit price of recycled water, customers' perceptions, and the number of messages were increased as the severity of limitations on local water resources and climate change projections increased. It was assumed that as the severity of limitations on local water resources and climate change projections increases in the study area, decreasing the amount and reliability of farmers' water supply, farmers would be more interested in using an alternative water resource (e.g., recycled water). Thus, the unit price of water increases in the study area as there would be less water available; farmers would spread more word to their friends about using recycled water for their irrigation practices as this is the only available alternative water resource in the area; and people's climate change consciousness would increase, increasing customers' perceptions toward purchasing products irrigated with recycled water. All simulations were repeated 100 times for 80 years of corn production in the study area. 80 years of simulation was chosen because multiple simulation runs showed that this time would be needed for completely capturing the adoption of the water reuse project by farmers in this study.

Table 51. Specifications of the simulation experiments scenarios in this study.

Symbol	Factor	Scenario I	Scenario II	Scenario III	Scenario IV
A	Groundwater availability (%)	100.00	97.00	95.00	93.00
B	Surface water availability (%)	100.00	97.00	95.00	93.00
C	The unit price of recycled water ($/TCM)	0.97	9.70	12.13	14.55
D	Easton WWTP storage pond (MCM)	2.06	2.06	2.06	2.06
E	Climate	BAU	RCP 2.6	RCP 4.5	RCP 8.5
F	Costumers' perceptions (%)	45.00	60.00	75.00	90.00
G	Number-of-messages	3.00	5.00	10.00	15.00
H	Corn yield	High	Moderate	Moderate	Moderate

5.3. Results and discussions

The U.S. inflation rate from 1990 to 2020 showed approximately a normal distribution (Figure 24). Using the data Quantile-Quantile plot (Figure 24 (b)), this probability plot illustrated the theoretical versus actual quantiles of the U.S. inflation rate. As the points were approximately sitting on the straight red line (Figure 24 (b)), we could conclude that the U.S. inflation rate had an approximately normal distribution. Furthermore, the result of a powerful normality test, i.e., the Shapiro-Wilk (1965) test, also demonstrated that the data distribution could be assumed to be normal/ gaussian ($P = 0.406 > 0.05$). Therefore, the inflation rate (r) was stochastically modeled in this study (mean = 2.31, standard deviation 1.01; Figure 24 (c)). For brevity, the model verification results were not included in this paper (Chapter). Interested readers are encouraged to read our previous work (Chapter 4), where the verification results were extensively studied.

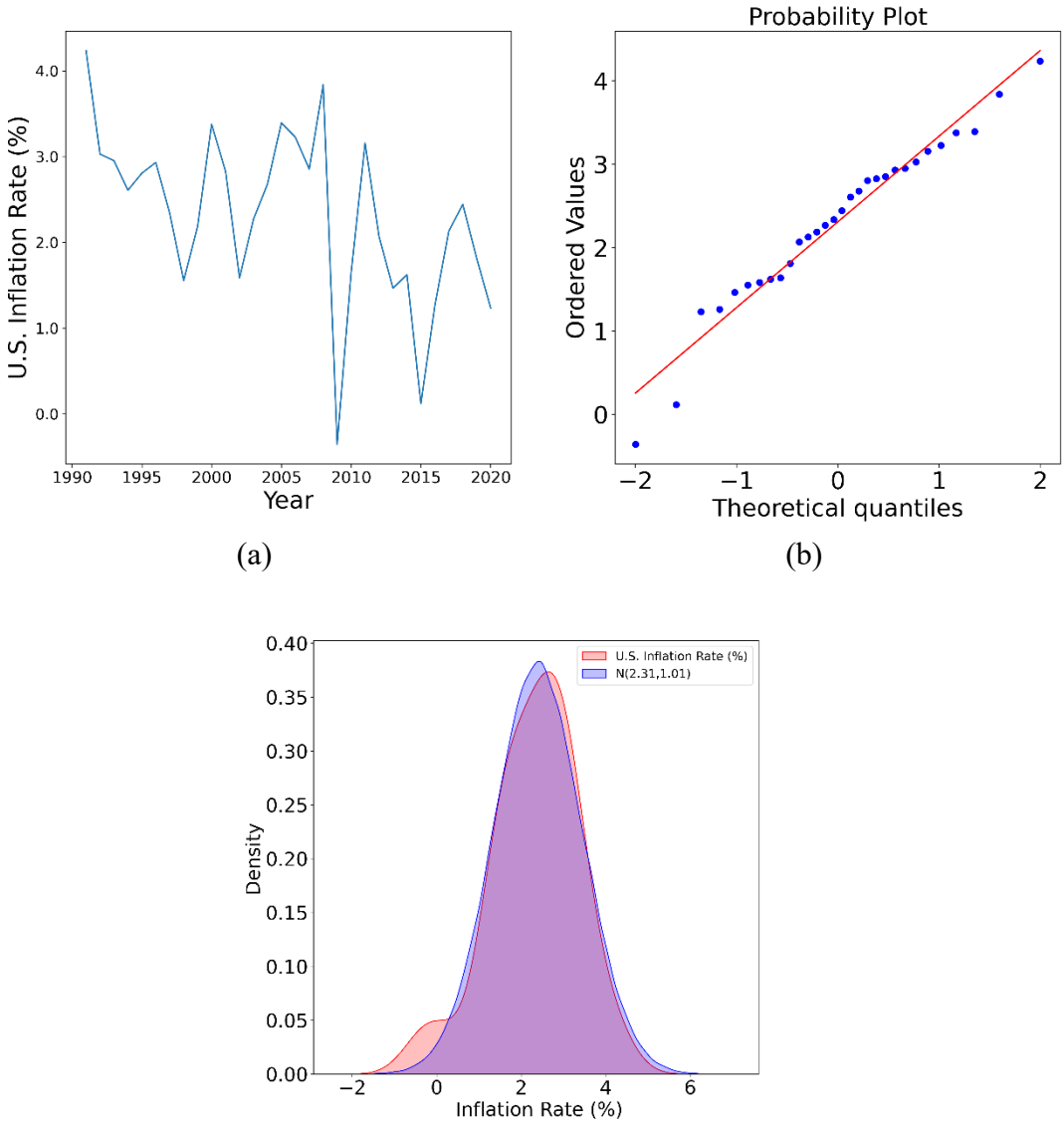


Figure 24. Line (a), quantile-quantile (b), and kernel density estimation plots of the U.S. inflation rate from 1990 to 2020.

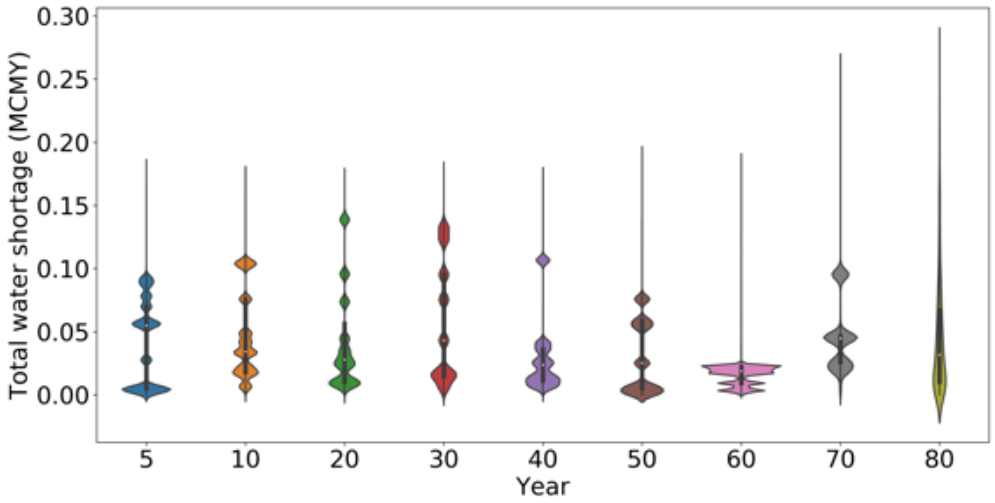
5.3.1. Results of UA-SA

Results of UA illustrated the distribution of six model outputs in years 5, 10, 20, 30, 40, 50, 60, 70, and 80 (Figure 25). Farmers' total yearly water shortage, total yearly groundwater consumption, total yearly surface water consumption, total yearly recycled water consumption, agricultural water reuse adoption, and mean of SI violin plots showed no specific distribution trends except for a gradual rise in the ranges of total yearly water shortage, total yearly groundwater consumption, and total yearly surface water consumption from year five to 60 and then an abrupt increase in years

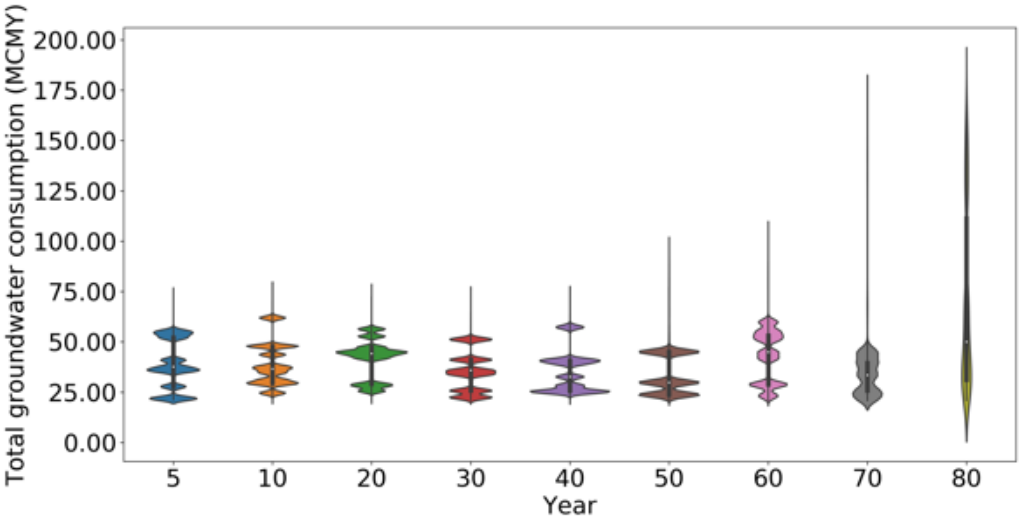
70 and 80. These could be due to the effects of IPCC projections (T and P) in RCP 4.5 and RCP 8.5 scenarios.

The total yearly water shortage range increased from 0-19 million cubic meters per year (MCMY) in year five to 0-28 MCMY in year 70. This result also showed that distributions in different years were multi-modal except in year 80 (Figure 25 (a)). Total groundwater consumption uncertainty increased from 25-75 MCMY in year five to 25-190 MCMY in year 80 (Figure 25 (b)). Total yearly groundwater consumption also had multi-modal distributions except in year 80. An increase in the total yearly surface water consumption range (from 0-3 MCMY to 0-4 MCMY) was observed (Figure 25 (c)). The violin plot showed multi-modal distributions in all years except year 80, similar to the previous results.

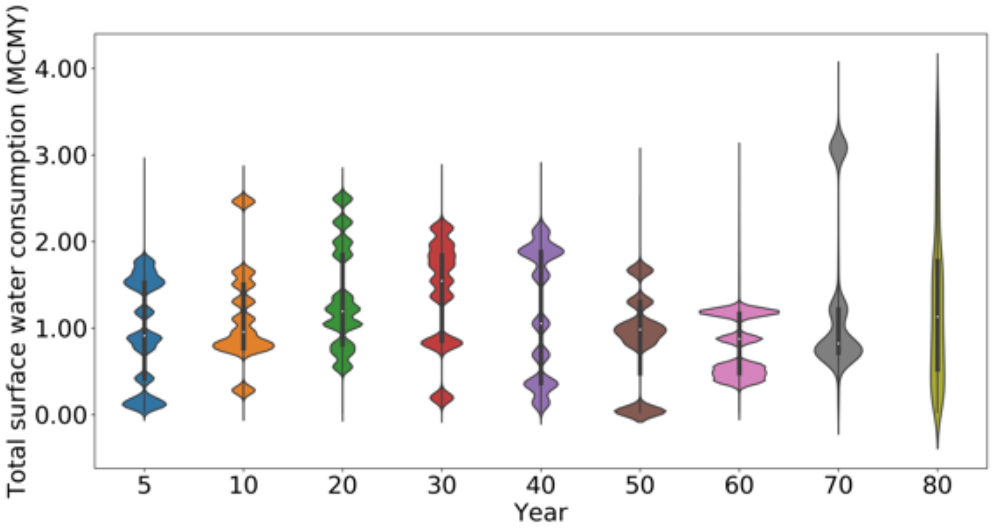
The number of modes in the total yearly recycled water consumption density plots decreased as time went on from year 5 to year 80, with a gradual rising trend (Figure 25 (d)). Furthermore, the results of UA demonstrated an increasing trend in the density of the number of farmers who adopted agricultural water reuse during the 80 years of simulation. The increasing trend reached a plateau approximately near year 60 (Figure 25 (e)). A slow rising trend was observed in the ranges of the mean of farmers' SI from 0-0.4 to 0-0.55 (Figure 25 (f)). The number of the modes in this figure was also decreased as time went on; the violin plots of the mean of farmers' SI were bimodal after year 60.



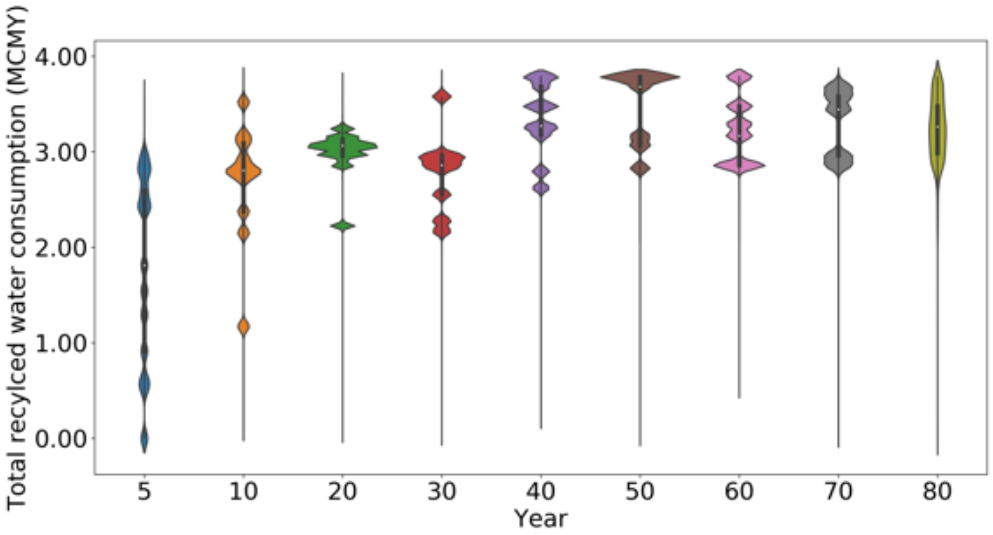
(a)


Total groundwater consumption (MCMY)
200.00
175.00
150.00
125.00
100.00
75.00
50.00
25.00
0.00
5
10
20
30
40
50
60
70
80
Year

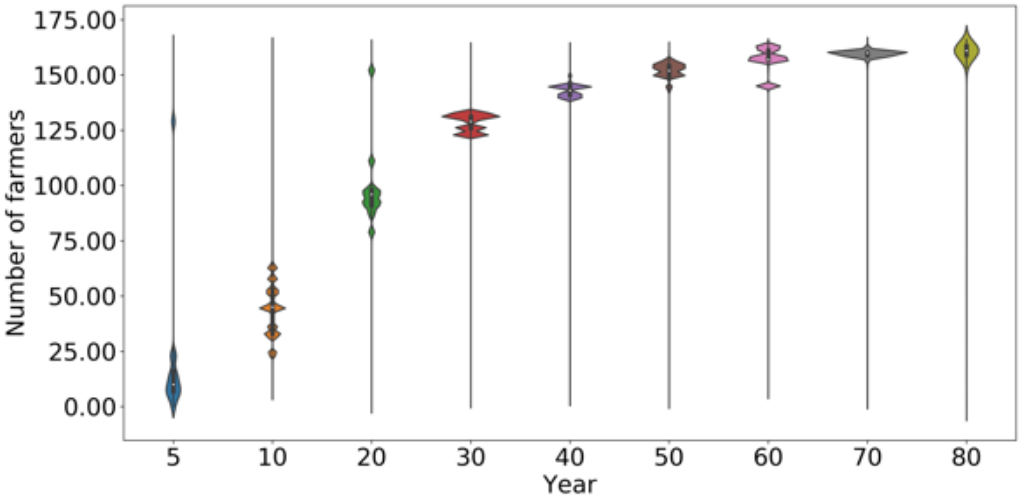
(b)


Total surface water consumption (MCMY)
4.00
3.00
2.00
1.00
0.00
5
10
20
30
40
50
60
70
80
Year

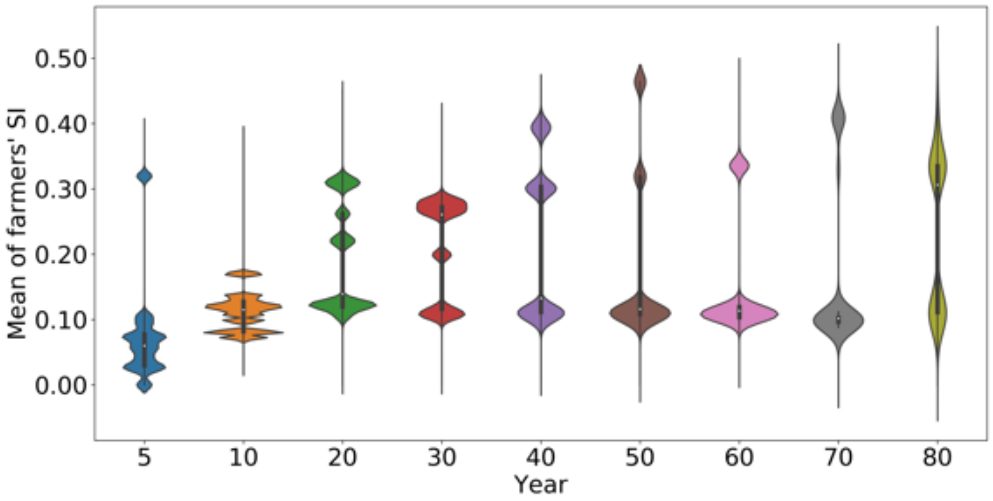
(c)


Total recylced water consumption (MCMY)
4.00
3.00
2.00
1.00
0.00
5
10
20
30
40
50
60
70
80
Year

(d)


Number of farmers
175.00
150.00
125.00
100.00
75.00
50.00
25.00
0.00
5
10
20
30
40
50
60
70
80
Year

(e)



(f)

Figure 25. Uncertainties observed in the model outputs (a) total yearly water shortage, (b) total yearly groundwater consumption, (c) total yearly surface water consumption, (d) total yearly recycled water consumption, (e) the cumulative number of farmers who adopted agricultural water reuse, and (f) mean of farmers' SI.

The results of the Shapiro-Wilk test on model inputs showed that none of the factors were normally (Gaussian) distributed. Therefore, Spearman's correlation method was successfully selected and conducted to investigate any linear or non-linear relationship between model factors. This test demonstrated only one strong correlation among the model factors (Spearman's coefficient > 0.7 or < -0.7). A positive approximate correlation was observed between precipitation, E (P), and temperature, E (T), (Table 52). The correlations between the other parameters were very weak (-0.19 < Spearman's coefficient > 0.19). Therefore, it was necessary to use a moment-independent SA method in this study according to (Bedford, 1998).

Table 52. Results of correlation analysis between model factors using Spearman's method

	A	**B**	**C**	**D**	**E (P)**	**E (T)**	**F**	**G**
A	1.00	…	…	…	…	…	…	…
B	0.03	1.00	…	…	…	…	…	…
C	0.01	-0.01	1.00	…	…	…	…	…
D	-0.05	0.00	0.01	1.00	…	…	…	…
E (P)	-0.01	0.0	-0.01	-0.01	1.00	…	…	…
E (T)	0.00	0.01	0.01	-0.01	0.75	1.00	…	…
F	0.00	0.00	0.03	-0.02	0.01	0.01	1.00	…
G	0.00	-0.03	0.00	-0.01	0.01	0.01	-0.01	1.00

The results of SA on the total yearly water shortage showed the dynamics of input parameters influence through 80 years of simulation (Figure 6 (a)). Climate change (temperature, E (T), and precipitation, E (P)) and the WWTP's storage capacity (D) were among the top three influential factors on the total yearly water shortage through

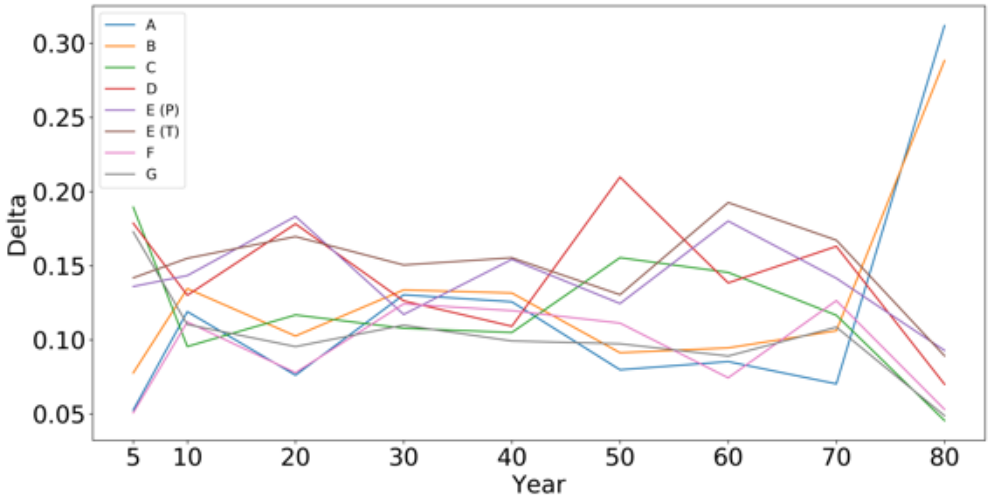
the years (Figure 26 (a)). The unit price of recycled water (C) and temperature, E (T), were on average the most influential factors on the total yearly groundwater consumption (Figure 26 (b)). The WWTP's storage capacity (D) and precipitation, E (P), were consistently among the top three parameters with significant influence on the total yearly surface water consumption (Figure 26 (c)). Fluctuations observed in the SA of total yearly recycled water consumption were higher in years 40, 50, and 80 in comparison to the other years (Figure 26 (d)). However, in total, the SA result of total yearly recycled water consumption compared with other model outputs demonstrated fewer fluctuations in the dynamics of input parameters influences (Figure 26). Input parameters with the most influence on the total yearly recycled water consumption included precipitation, E (P), the WWTP's storage capacity (D), and temperature, E (T).

Moreover, the results of SA on the number of farmers who adopted agricultural water reuse showed the top three influential parameters were climate change (precipitation, E (P), and temperature, E (T)) and the WWTP's storage capacity (D) (Figure 26 (e)). Of note was that the influence of the unit price of recycled water (C) was increased after year 30, putting it as the top four influential factors on the farmer's adoption rate. This result also showed that the number of messages farmers sent to other farmers in their networks was consistently one of the bottom three influential factors on their adoption rate. Among the parameters with the most effects on the mean of farmers' SI, climate change (E(P) and E(T)), the unit price of recycled water (C), and the WWTP's storage capacity (D) were in total among the top four (Figure 26 (f)).

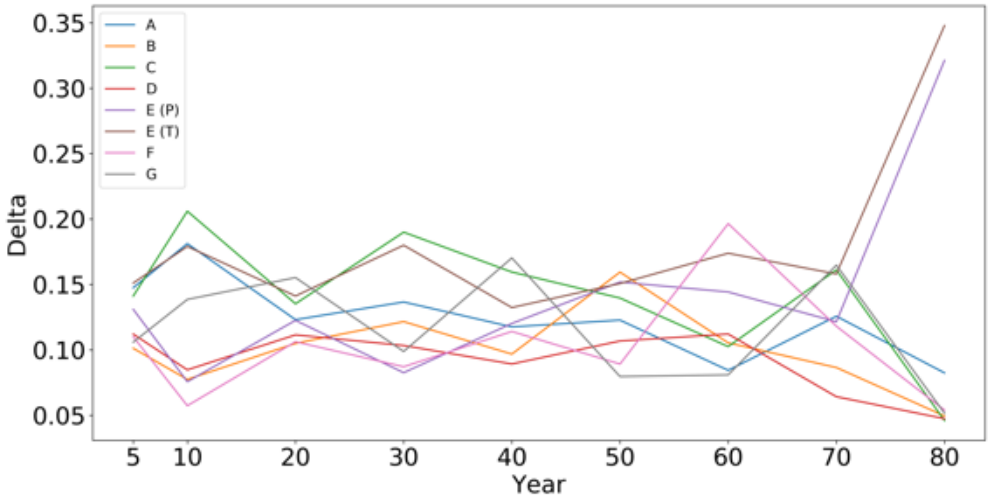
Considering all the SA results, one can find the factors with the most influence on the model outputs were climate change (E(P) and E(T)), the WWTP's storage capacity (D), and the unit price of recycled water (C). However, it should be noted that other factors' influence on the model outputs should not be neglected as many fluctuations in the effects were observed. The results of time-varying SA on the model outputs using the moment-independent method (delta) illustrated the complexities inherent in this ABM (Figure 26). These results showed the importance of uncertainties in input parameters with respect to the entire output parameters distributions. It should be noted that the calculation of delta was done in a way that the whole distribution of all the model inputs were simultaneously considered with respect to the distribution of each of the model outputs, given the current state of knowledge and without considering an artificially hypothesized change in the model inputs (Borgonovo, 2007).

Therefore, according to these results, it was evident that the order of most important parameters with significant influence on the entire distribution of model outputs continuously changed over time. This result indicated that the application of time-independent SA methods would be insufficient for the SA of these types of models (i.e., complex models). For example, in our previous work (Chapter 4), we conducted a SA using the design of experiments (factorial design) for only three specific years during 84 years of crop production in California and found the most important factors on the model outputs. However, the results of this study demonstrated the necessity of

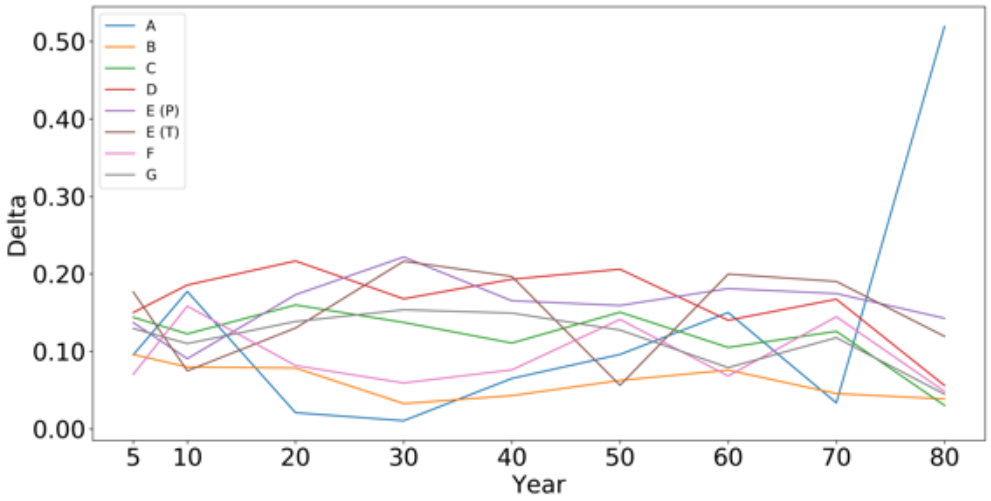
time-varying SA for such complex simulation models. The results of this study were also in accordance with other studies (Ghoreishi et al., 2021; J. D. Herman et al., 2013; Ligmann-Zielinska et al., 2014).



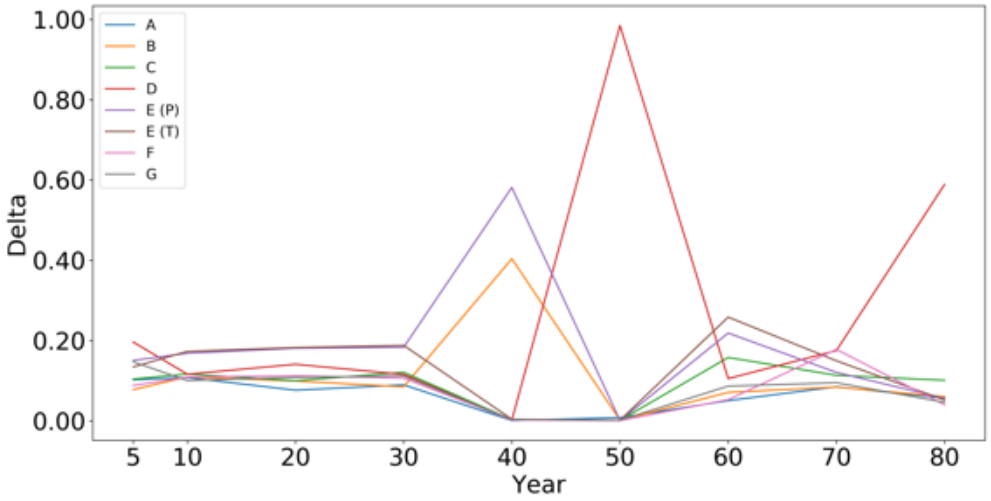
(a)



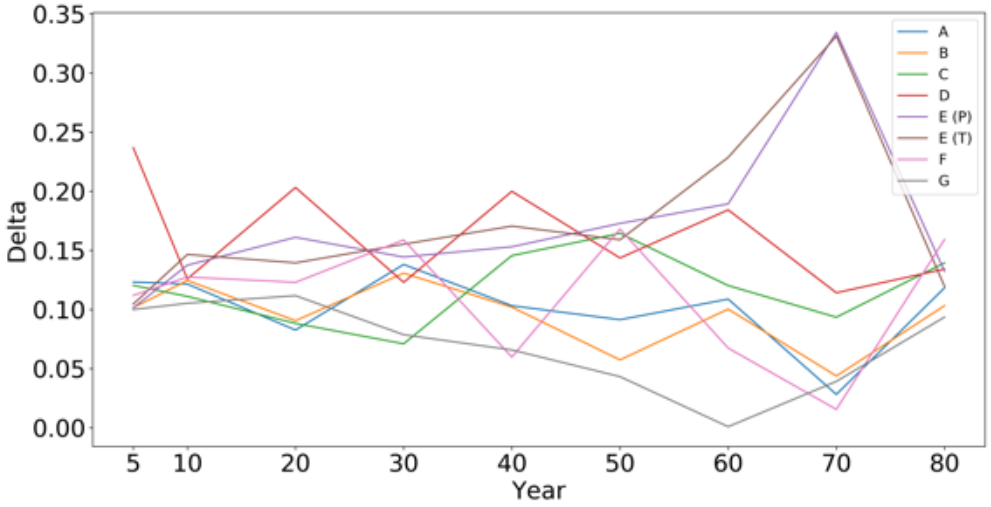
(b)


A
B
C
D
E (P)
E (T)
F
G
Delta
0.00
0.10
0.20
0.30
0.40
0.50
5
10
20
30
40
50
60
70
80
Year

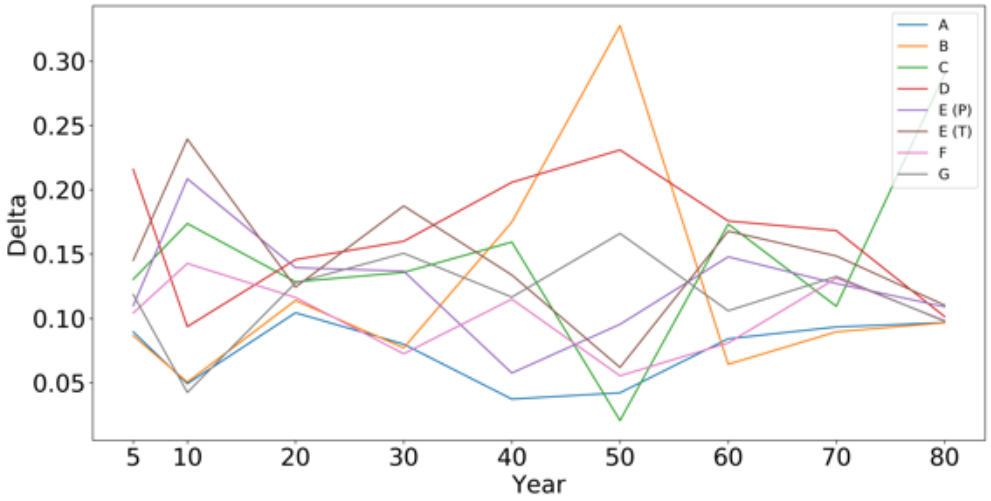
(c)


A
B
C
D
E (P)
E (T)
F
G
Delta
0.00
0.20
0.40
0.60
0.80
1.00
5
10
20
30
40
50
60
70
80
Year

(d)



(e)



(f)

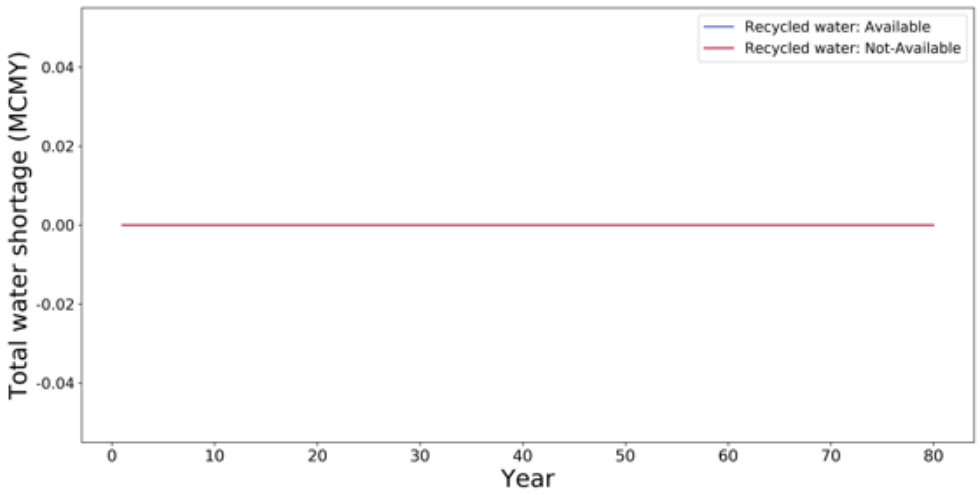
Figure 26. Time-varying SA results using the moment-independent method (delta) for various model outputs (a) total water shortage, (b) total groundwater consumption, (c) total surface water consumption, (d) total recycled water consumption, (e) the cumulative number of farmers who adopted agricultural water reuse, and (f) mean of farmers' SI.

5.3.2. Results of simulation experiments and model validation

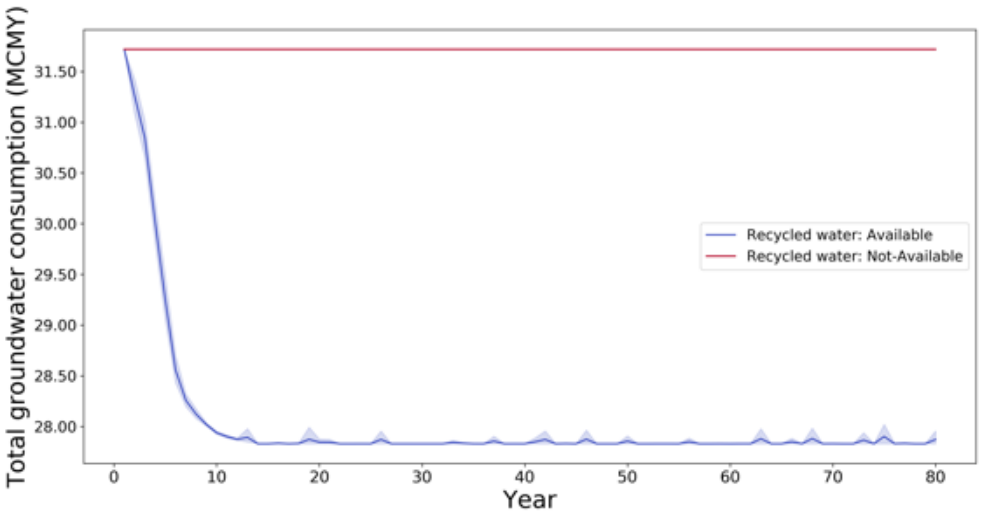
As groundwater and surface water were completely (100%) available for farmers to use in their irrigation practices in scenario I, farmers' total yearly water shortage and total yearly surface water consumption were zero under this scenario (Figure 27 (a) and (c)). Therefore, implementing agricultural water reuse did not significantly

change farmers' total yearly water shortage and total yearly surface water consumption, under the scenario I, as these lines were overlapping. On the contrary, total yearly groundwater consumption was significantly decreased from 31.72 to 27.83 MCMY, on average 3.879 MCMY(12.23 %) decrease, in almost 15 years when recycled water was available for farmers to use for their irrigation practices (Figure 27 (b)). Accordingly, the amount of recycled water used by farmers in this scenario was increased from zero to 3.89 MCMY in almost 15 years under the scenario I (Figure 27 (d)).

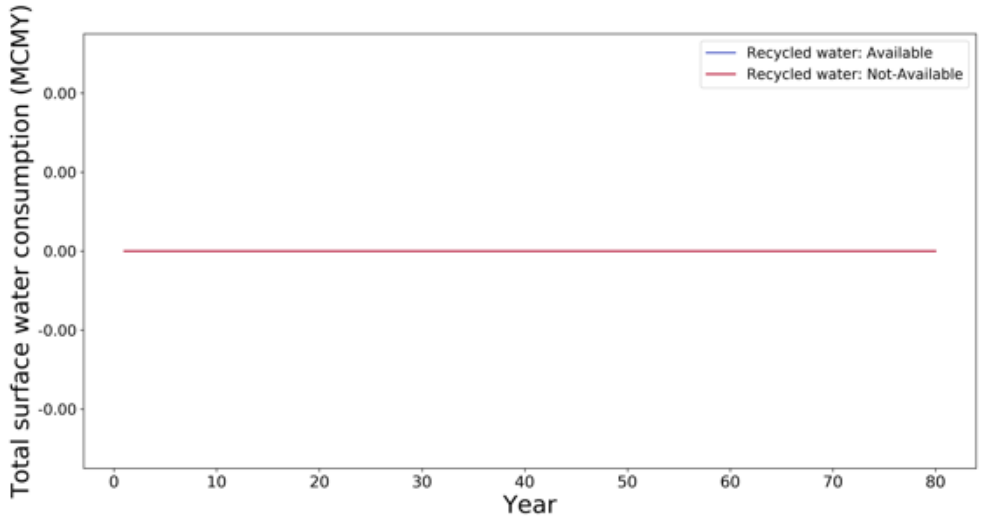
The trend of agricultural water reuse adoption by farmers under the scenario I was in accordance with the Theory of Diffusion of Innovations (Rogers et al., 2005). The trend rose until it reached a plateau at approximately year 50 (Figure 27 (e)). The mean of farmers' SI was constant at one, indicating that recycled water maintained farmers' SI and decreased groundwater consumption successfully (Figure 27 (f), Table 53 and Table 54). These results also indicated that the unit price of recycled water and the WWTP's storage capacity, as two of the most influential factors on model outputs according to SA results, were reasonably chosen according to the other conditions under this scenario. This ensured farmers would use recycled water for their irrigation practices, and the total yearly groundwater consumption would be significantly decreased accordingly.



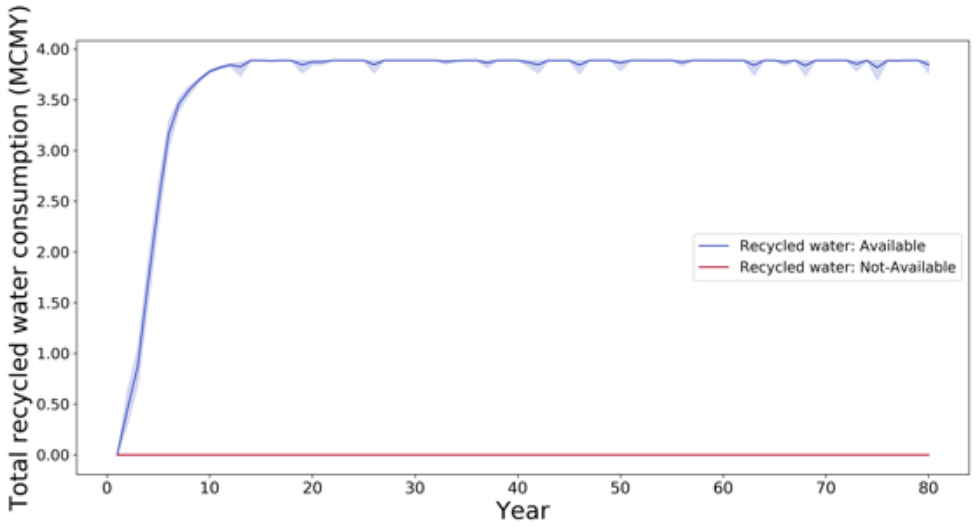
(a)


Total groundwater consumption (MCMY)
31.50
31.00
30.50
30.00
29.50
29.00
28.50
28.00
0
10
20
30
40
50
60
70
80
Year
Recycled water: Available
Recycled water: Not-Available

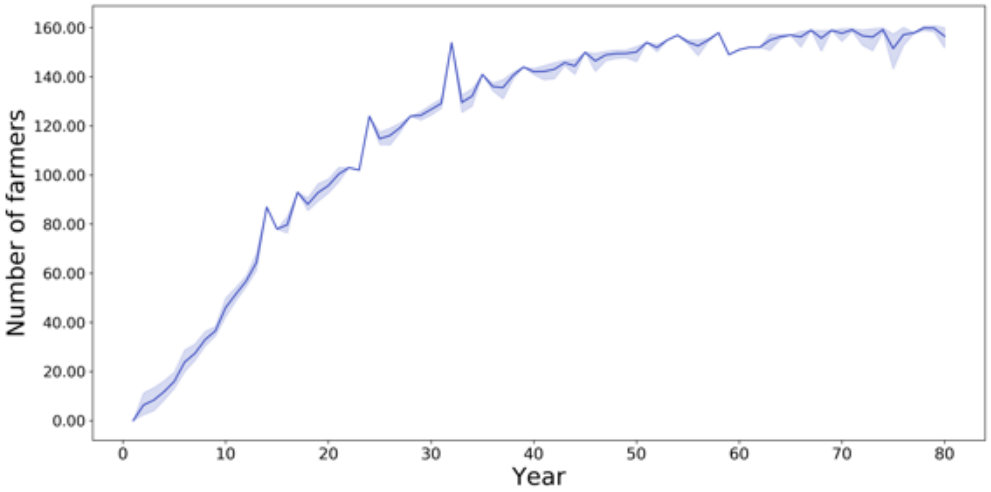
(b)


Total surface water consumption (MCMY)
0.00
0.00
0.00
-0.00
-0.00
0
10
20
30
40
50
60
70
80
Year
Recycled water: Available
Recycled water: Not-Available

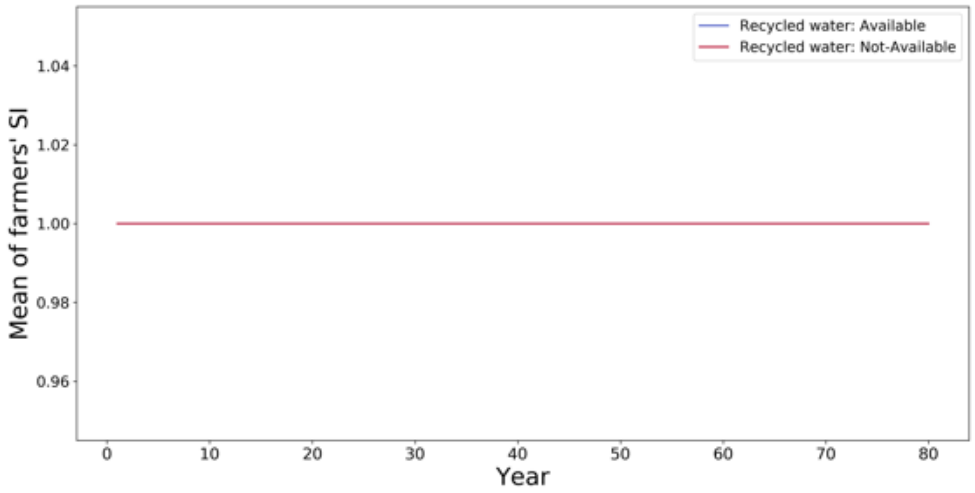
(c)


Total recycled water consumption (MCMY)
4.00
3.50
3.00
2.50
2.00
1.50
1.00
0.50
0.00
0
10
20
30
40
50
60
70
80
Year
Recycled water: Available
Recycled water: Not-Available

(d)


Number of farmers
160.00
140.00
120.00
100.00
80.00
60.00
40.00
20.00
0.00
0
10
20
30
40
50
60
70
80
Year

(e)



(f)

Figure 27. Simulation experiments results under the scenario I (a) total yearly water shortage, (b) total yearly groundwater consumption, (c) total yearly surface water consumption, (d) total yearly recycled water consumption, (e) cumulative adoption curve of agricultural water reuse adoption by farmers, and (f) yearly mean of farmers' SI (MCMY = Millions Cubic Meters per Year; the 95% confidence intervals were calculated using bootstrap resampling method).

Table 53. Distributions of the farmers' SI components without agricultural water reuse under scenario I

	Mean of farmers' water supply reliability (volume-based)	Mean of farmers' water supply reliability (time-based)	Mean of farmers' water supply resiliency	Mean of farmers' water supply vulnerability	Mean of farmers' water supply maximum deficiency
Mean	1	1	1	0	0
Standard deviation	0	0	0	0	0
Min	1	1	1	0	0
25%	1	1	1	0	0
50%	1	1	1	0	0
75%	1	1	1	0	0
Max	1	1	1	0	0

Table 54. Distributions of the farmers' SI components with agricultural water reuse under scenario I

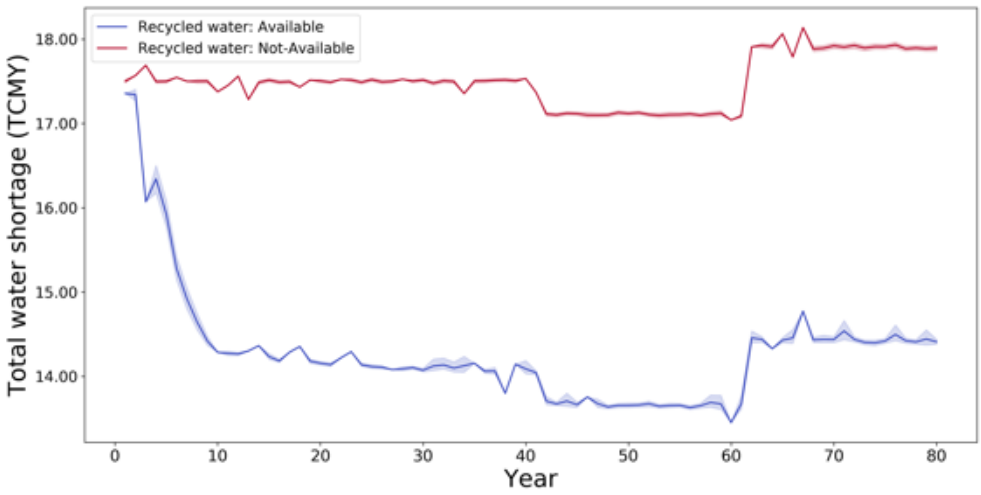
	Mean of farmers' water supply reliability (volume-based)	Mean of farmers' water supply reliability (time-based)	Mean of farmers' water supply resiliency	Mean of farmers' water supply vulnerability	Mean of farmers' water supply maximum deficiency
Mean	1	1	1	0	0
Standard deviation	0	0	0	0	0
Min	1	1	1	0	0
25%	1	1	1	0	0
50%	1	1	1	0	0
75%	1	1	1	0	0
Max	1	1	1	0	0

Under scenario II, the results of simulations showed that implementing agricultural water reuse could significantly decrease the effects of climate change (under RCP 2.6) on local water resources in the study area (Figure 28). This project significantly reduced the total yearly water shortage (Figure 28 (a)). The decrease had a rising trend; on average, the agricultural water reuse project could decrease the total yearly water shortage by 3.209 TCMY (variance = 0.414 $TCMY^2$). The highest and lowest amount of decrease in the total yearly water shortage were 3.718 and 0.145 TCMY, respectively, under scenario II. Similarly, the total yearly groundwater and surface water consumption were significantly reduced due to the agricultural water reuse project (Figure 28 (b) and (c)). Under scenario II, the minimum, average, maximum, and variance of total yearly groundwater consumption reduction were 0.156, 3.459, 4.008 (MCMY), and 0.480 ($MCMY^2$), respectively. Recycled water could successfully substitute surface water for farmers under scenario II, significantly decreasing total yearly surface water consumption (minimum = 4.690 TCMY, average= 103.766 TCMY, maximum = 120.227 TCMY, and variance = 432.331 $TCMY^2$).

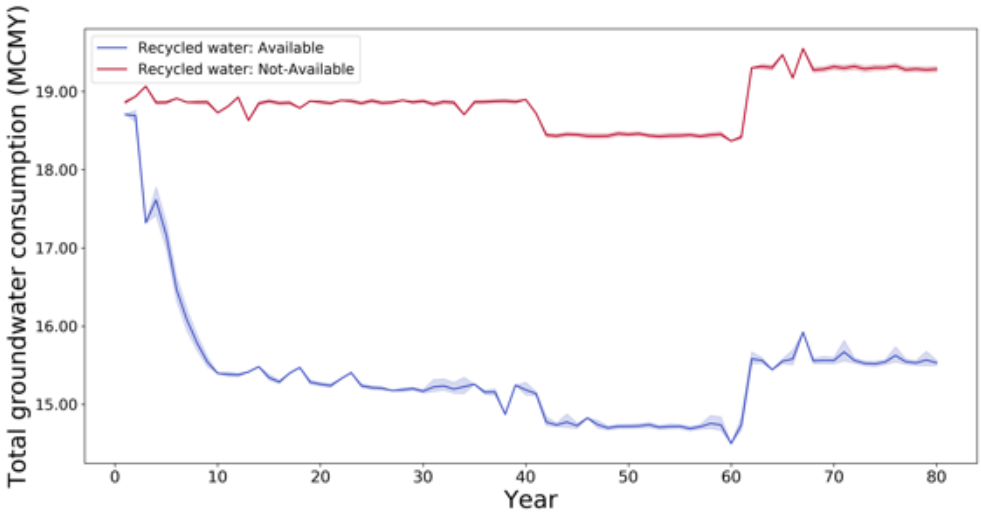
The total yearly recycled water consumption had a fast-rising trend until around year 15, then it continued with an approximately steady rate, supplying farmers with approximately 3.888 MCMY recycled water (Figure 28 (d)). Similar to scenario I, agricultural water reuse adoption by farmers had a gradual rising trend until approximately year 50, when it reached a plateau (Figure 28 (e)). The adoption trend was also in accordance with the Theory of Diffusion of Innovations (Rogers et al., 2005). The agricultural water reuse project also led to increasing the mean of farmers'

SI significantly under scenario II (Figure 28 (f)). The mean of farmers' SI also reached a plateau at approximately year 15, with the mean of farmers' SI = 0.15.

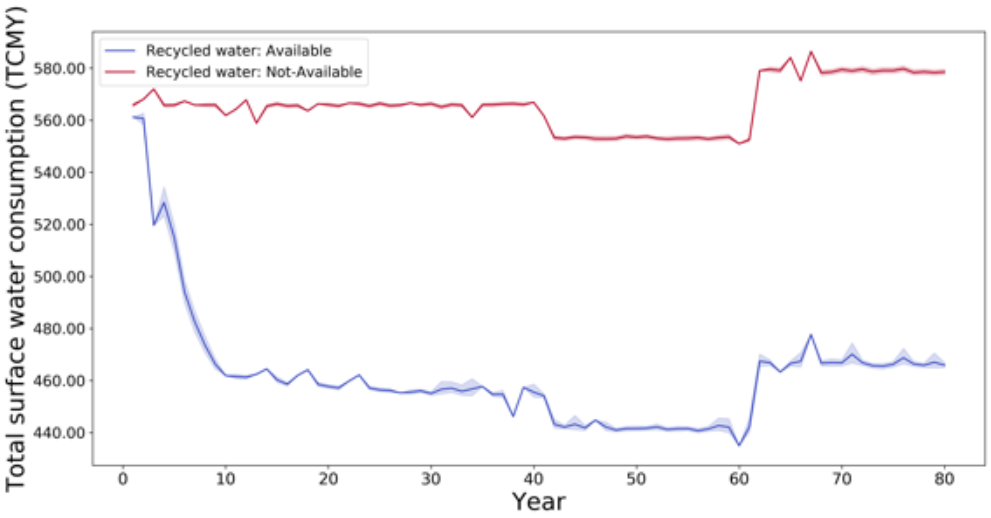
Most of the components of farmers' SI (time-based reliability, resiliency, and maximum deficiency) were also significantly enhanced due to the implementation of the agricultural water reuse (Table 55 and Table 56). Results of this scenario also indicated that the unit price of recycled water and the WWTP's storage capacity, as two of the most influential factors, were suitable for significantly decreasing farmers' water shortage, groundwater consumption, and surface water consumption, and increasing their SI.



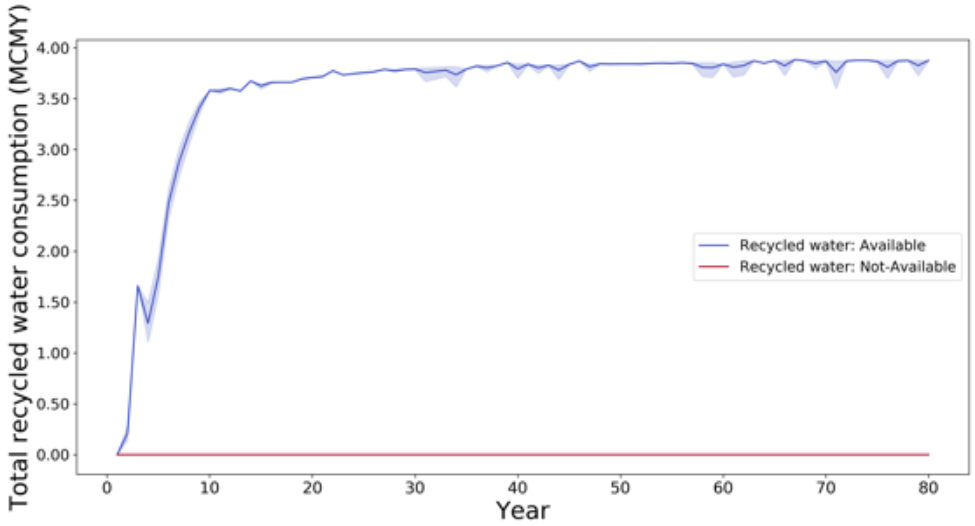
(a)



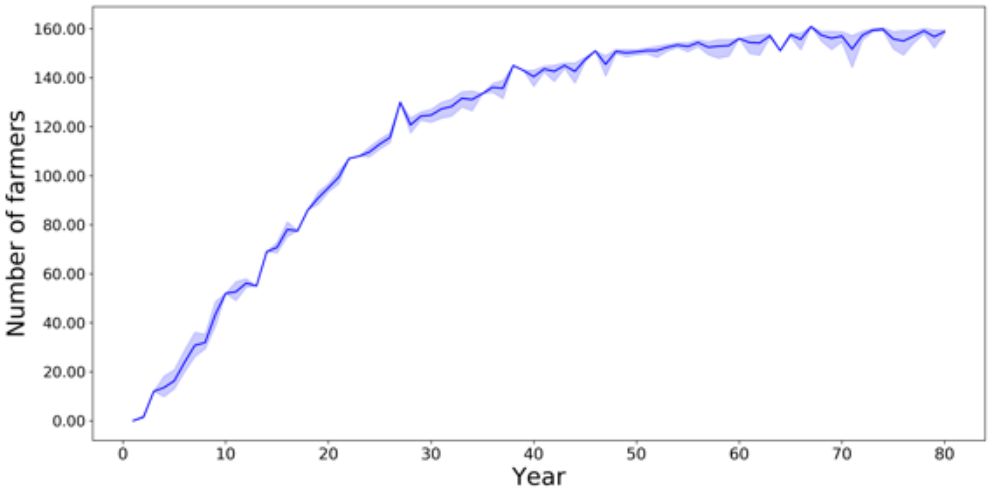
(b)


Recycled water: Available
Recycled water: Not-Available
Total surface water consumption (TCMY)
580.00
560.00
540.00
520.00
500.00
480.00
460.00
440.00
0
10
20
30
40
50
60
70
80
Year

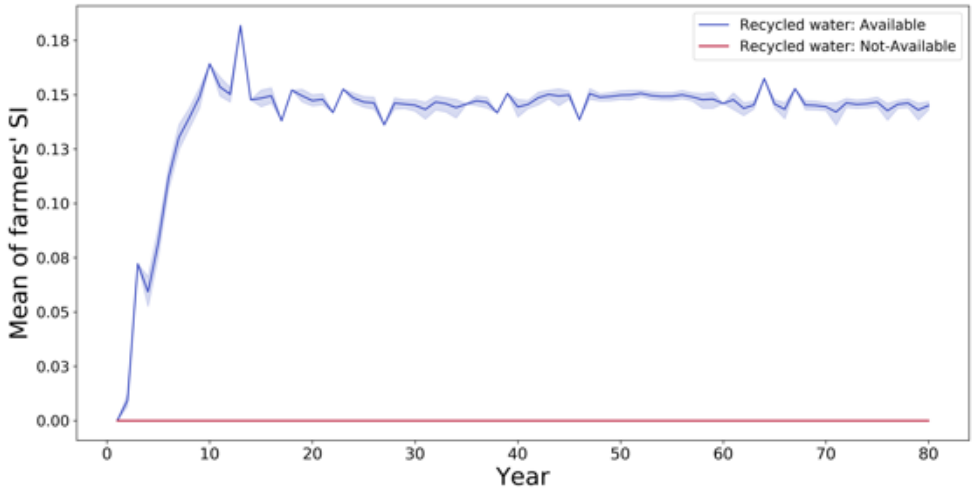
(c)


Total recycled water consumption (MCMY)
4.00
3.50
3.00
2.50
2.00
1.50
1.00
0.50
0.00
0
10
20
30
40
50
60
70
80
Year
Recycled water: Available
Recycled water: Not-Available

(d)



(e)



(f)

Figure 28. Simulation experiments results under scenario II (a) total yearly water shortage, (b) total yearly groundwater consumption, (c) total yearly surface water consumption, and (d) total yearly recycled water consumption, (e) cumulative adoption curve of agricultural water reuse adoption by farmers, and (f) yearly mean of farmers' SI (MCMY = Millions Cubic Meters per Year; the 95% confidence intervals were calculated using bootstrap resampling method).

Table 55. Distributions of the farmers' SI components without agricultural water reuse under scenario II

	Mean of farmers' water supply reliability (volume-based)	Mean of farmers' water supply reliability (time-based)	Mean of farmers' water supply resiliency	Mean of farmers' water supply vulnerability	Mean of farmers' water supply maximum deficiency
Mean	0.969	0.000	0.000	2.533×10^{-4}	1.430×10^{-5}
Standard deviation	8.240×10^{-12}	0.000	0.000	2.270×10^{-15}	2.370×10^{-7}
Min	0.969	0.000	0.000	2.533×10^{-4}	1.350×10^{-5}
25%	0.969	0.000	0.000	2.533×10^{-4}	1.410×10^{-5}
50%	0.969	0.000	0.000	2.533×10^{-4}	1.420×10^{-5}
75%	0.969	0.000	0.000	2.533×10^{-4}	1.440×10^{-5}
Max	0.969	0.000	0.000	2.533×10^{-4}	1.520×10^{-5}

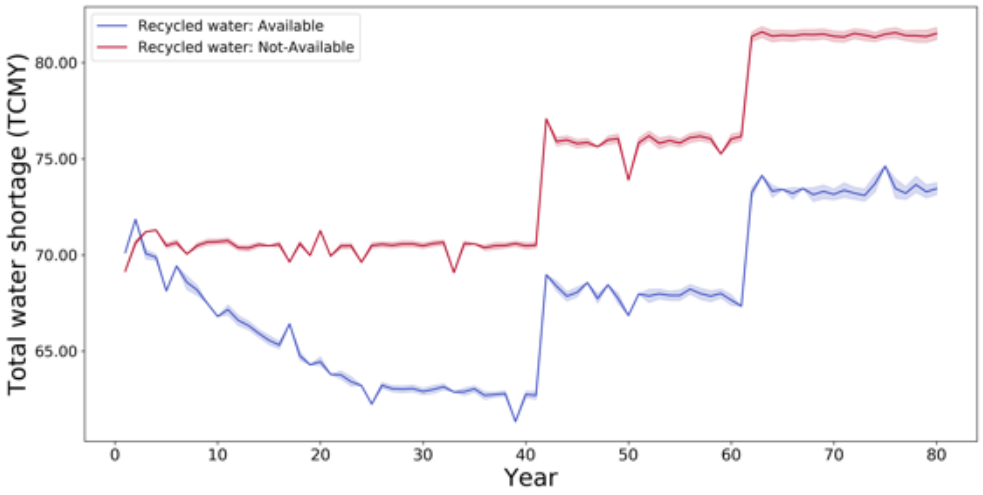
Table 56. Distributions of the farmers' SI components with agricultural water reuse under scenario II

	Mean of farmers' water supply reliability (volume-based)	Mean of farmers' water supply reliability (time-based)	Mean of farmers' water supply resiliency	Mean of farmers' water supply vulnerability	Mean of farmers' water supply maximum deficiency
Mean	0.974	0.255	0.071	2.905×10^{-4}	1.370×10^{-5}
Standard deviation	0.002	0.108	0.023	2.490×10^{-5}	2.970×10^{-7}
Min	0.969	0.000	0.000	1.953×10^{-4}	1.070×10^{-5}
25%	0.975	0.290	0.068	2.785×10^{-4}	1.350×10^{-5}
50%	0.975	0.278	0.073	2.974×10^{-4}	1.380×10^{-5}
75%	0.975	0.346	0.080	3.124×10^{-4}	1.380×10^{-5}
Max	0.977	0.401	0.230	3.369×10^{-4}	1.500×10^{-5}

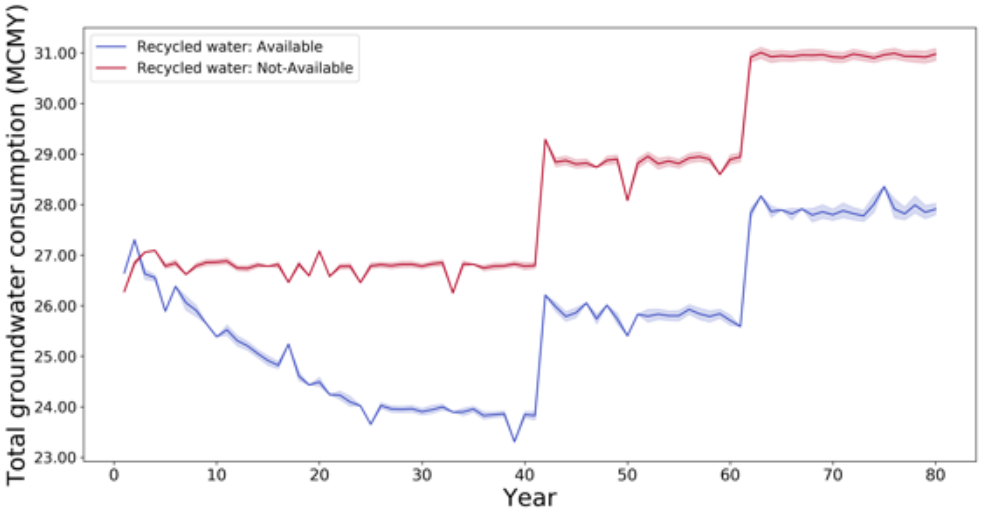
Total yearly water shortage under scenario III (RCP 4.5) was also reduced significantly by implementing agricultural water reuse (Figure 29 (a)). The decrease showed a rising trend with a minimum -1.212 TCMY, which happened in the first two years; however, it increased rapidly, reaching the maximum of 9.253 TCMY at year 30 and continued approximately with this amount. The mean and variance of

total yearly water shortage reduction were 6.614 TCMY and 5.480 $TCMY^2$, respectively. Similarly, the agricultural water reuse project could significantly decrease the total yearly groundwater consumption under the RCP 4.5 climate change projections (Figure 29 (b)). The rising trend of decreasing the total yearly groundwater consumption approximately reached a constant value of about 3.510 MCMY after year 30. This decrease's minimum, maximum, mean, and variance were -0.460, 3.516, 2.513 MCMY, and 0.791 $MCMY^2$, respectively. The simulations results demonstrated a similar rising pattern in the total yearly surface water consumption decrease, reaching a plateau around year 30 at about 0.150 MCMY (minimum = -0.230, maximum = 0.176, mean = 0.123 MCMY, and variance = 0.002 $MCMY^2$) (Figure 29 (c)).

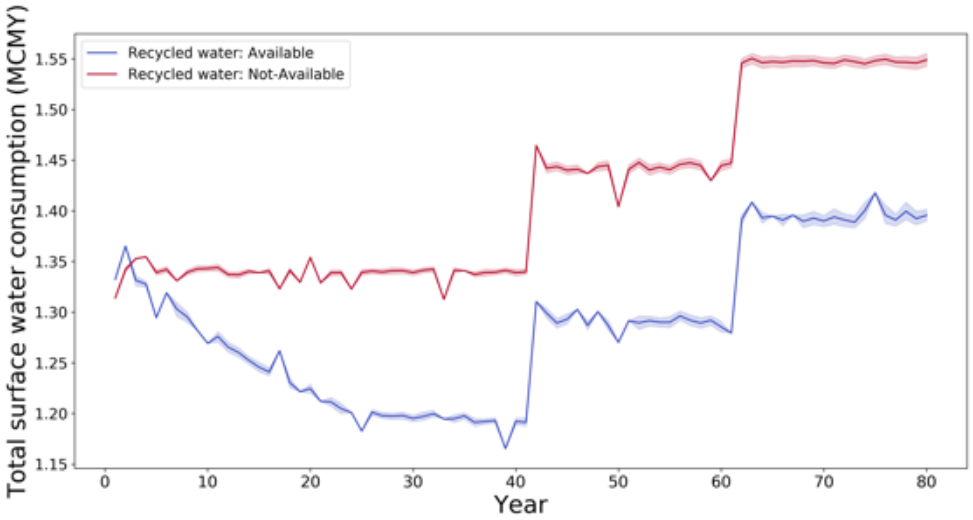
The results of the total yearly recycled water consumption illustrated that it was increased to 3.332 MCMY in about 30 years and then continued until the end of the simulations (Figure 29 (d)). Farmers, on average, used 2.688 MCMY of recycled water (variance = 0.875 $MCMY^2$) throughout the simulations under scenario III. The rising trend was also observed in the number of farmers who adopted agricultural water reuse each year under scenario III (RCP 4.5), conforming with the Diffusion of Innovations Theory (Rogers et al., 2005) (Figure 29 (e)). Likewise, the mean of farmers' SI showed a rising trend when recycled water was available for farmers to use (Figure 29 (f)). Simulation results also depicted that implementing the agricultural water reuse significantly enhanced some of the components of the farmers' SI, i.e., time-based reliability and resiliency (Tables 57 and 58).



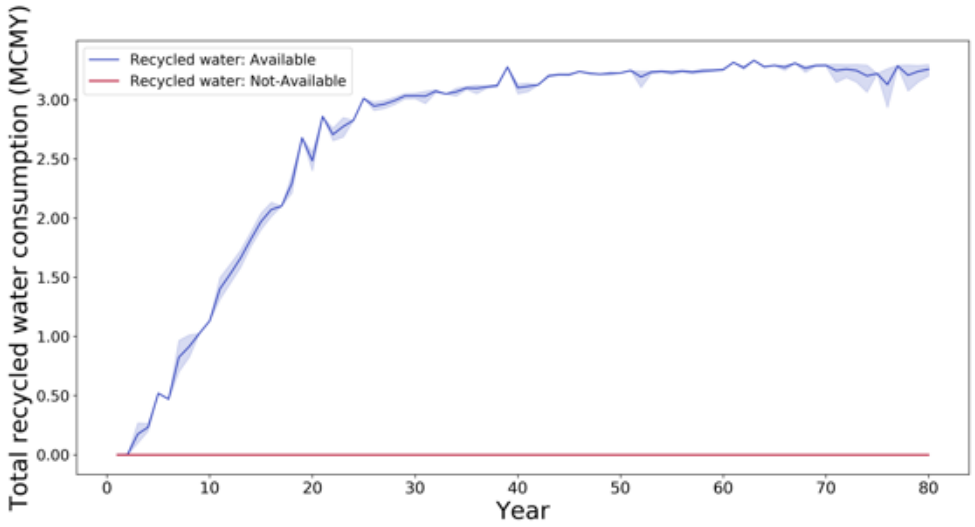
(a)


Recycled water: Available
Recycled water: Not-Available
Total groundwater consumption (MCMY)
31.00
30.00
29.00
28.00
27.00
26.00
25.00
24.00
23.00
0
10
20
30
40
50
60
70
80
Year

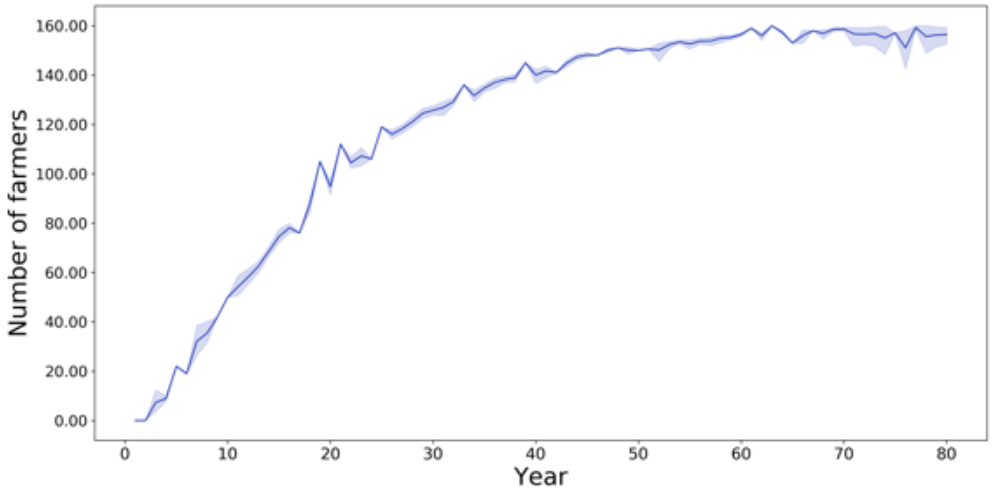
(b)


Recycled water: Available
Recycled water: Not-Available
Total surface water consumption (MCMY)
1.55
1.50
1.45
1.40
1.35
1.30
1.25
1.20
1.15
0
10
20
30
40
50
60
70
80
Year

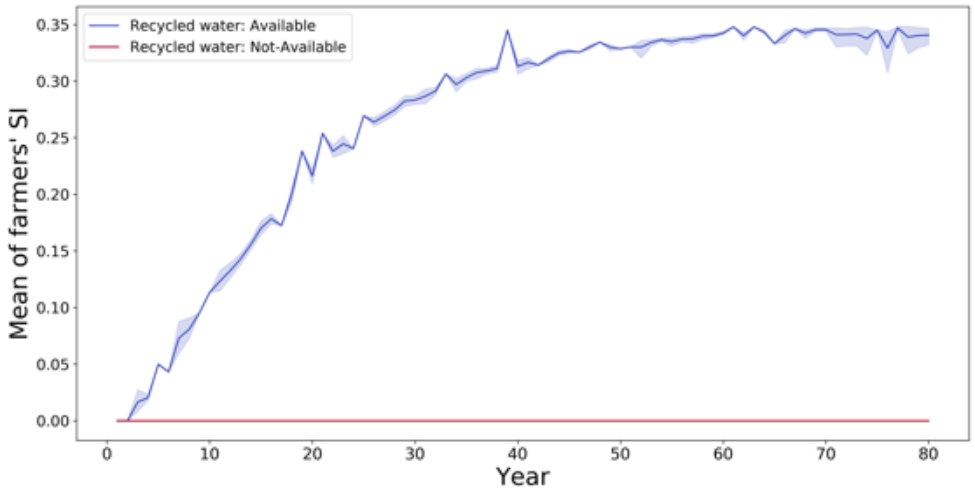
(c)


Recycled water: Available
Recycled water: Not-Available
Total recycled water consumption (MCMY)
3.00
2.50
2.00
1.50
1.00
0.50
0.00
0
10
20
30
40
50
60
70
80
Year

(d)


Number of farmers
160.00
140.00
120.00
100.00
80.00
60.00
40.00
20.00
0.00
0
10
20
30
40
50
60
70
80
Year

(e)



(f)

Figure 29. Simulation experiments results under scenario III (a) total yearly water shortage, (b) total yearly groundwater consumption, (c) total yearly surface water consumption, and (d) total yearly recycled water consumption, (e) cumulative adoption curve of agricultural water reuse adoption by farmers, and (f) yearly mean of farmers' S (MCMY = Millions Cubic Meters per Year; the 95% confidence intervals were calculated using bootstrap resampling method).

Table 57. Distributions of the farmers' SI components without agricultural water reuse under scenario III

	Mean of farmers' water supply reliability (volume-based)	Mean of farmers' water supply reliability (time-based)	Mean of farmers' water supply resiliency	Mean of farmers' water supply vulnerability	Mean of farmers' water supply maximum deficiency
Mean	0.948	0.000	0.000	4.303×10^{-4}	4.230×10^{-5}
Standard deviation	4.440×10^{-12}	0.000	0.000	2.120×10^{-15}	8.790×10^{-7}
Min	0.948	0.000	0.000	4.30328×10^{-4}	3.860×10^{-5}
25%	0.948	0.000	0.000	4.30328×10^{-4}	4.140×10^{-5}
50%	0.948	0.000	0.000	4.30328×10^{-4}	4.240×10^{-5}
75%	0.948	0.000	0.000	4.30328×10^{-4}	4.290×10^{-5}
Max	0.948	0.000	0.000	4.30328×10^{-4}	4.660×10^{-5}

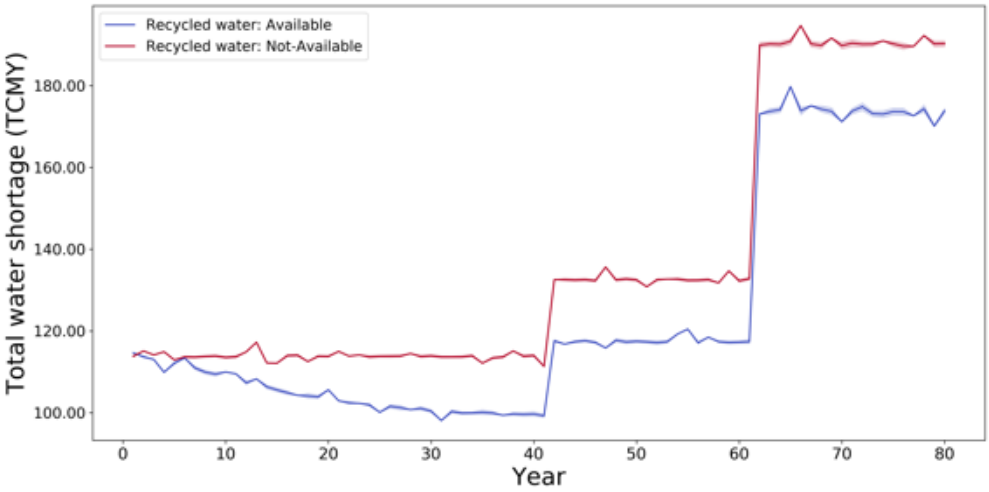
Table 58. Distributions of the farmers' SI components with agricultural water reuse under scenario III

	Mean of farmers' water supply reliability (volume-based)	Mean of farmers' water supply reliability (time-based)	Mean of farmers' water supply resiliency	Mean of farmers' water supply vulnerability	Mean of farmers' water supply maximum deficiency
Mean	0.950	0.192	7.064×10^{-3}	5.393×10^{-4}	4.240×10^{-5}
Standard deviation	2.385×10^{-4}	0.160	6.352×10^{-3}	9.000×10^{-5}	6.730×10^{-7}
Min	0.948	0.000	0.000	4.303×10^{-4}	3.920×10^{-5}
25%	0.948	0.000	0.000	4.303×10^{-4}	4.200×10^{-5}
50%	0.950	0.148	4.858×10^{-4}	5.185×10^{-4}	4.220×10^{-5}
75%	0.953	0.374	0.014	6.403×10^{-4}	4.280×10^{-5}
Max	0.954	0.420	0.031	6.665×10^{-4}	4.660×10^{-5}

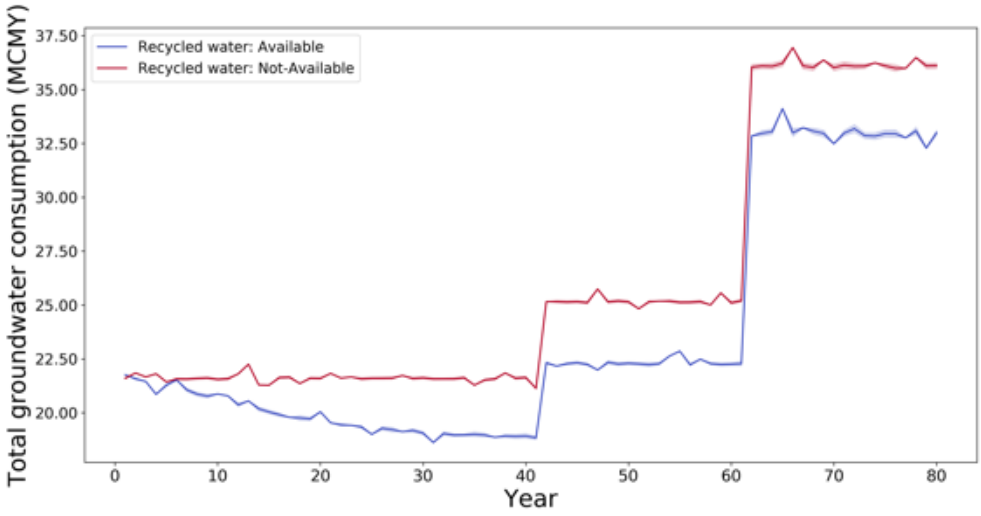
Moreover, the agricultural water reuse project could significantly impact the local water resources consumption and sustainability under scenario IV, RCP 8.5 (Figure 30). Similar to other scenarios, the total yearly water shortage significantly reduced during the 80 years of simulation (Figure 30 (a)). The decrease had a rising trend starting from -0.824 TCMY and reaching 28.829 TCMY over the first 40 years of simulation, then continued with an approximately constant value (mean = 12.503 TCMY and variance 25.134 $TCMY^2$). The results of simulations under scenario IV showed farmers' total yearly groundwater consumption was decreased, on average, 2.373 MCMY (variance = 0.905 $MCMY^2$). The maximum and minimum decrease in the total yearly groundwater consumption were -0.154 and 3.953 MCMY, respectively (Figure 30 (b)). Farmers' total yearly surface water consumption was also reduced due to the implementation of the agricultural water reuse project (Figure 30 (c)). Overall, the reduction was increased as time went on, reaching the maximum value of 0.277 MCMY over the 80 years of simulation under scenario IV (Mean = 0.166 MCMY and variance = 0.004 $MCMY^2$).

Under scenario IV (RCP 8.5), farmers increasingly adopted and used recycled water for their irrigation purposes (Figure 30 (d) and (e)). Farmers' total yearly recycled water consumption increased from zero to 3.426 MCMY during the 80 years. The total yearly recycled water curve first reached a plateau in around year 40; then it was continued until year 60 when the curve rapidly jumped to its maximum and continued until year 80. The farmers' adoption curve under this scenario was also in accordance with the Diffusion of Innovations Theory (Rogers et al., 2005), showing a rising trend similar to the previous scenarios (Figure 30 (e)). The mean of farmer's SI

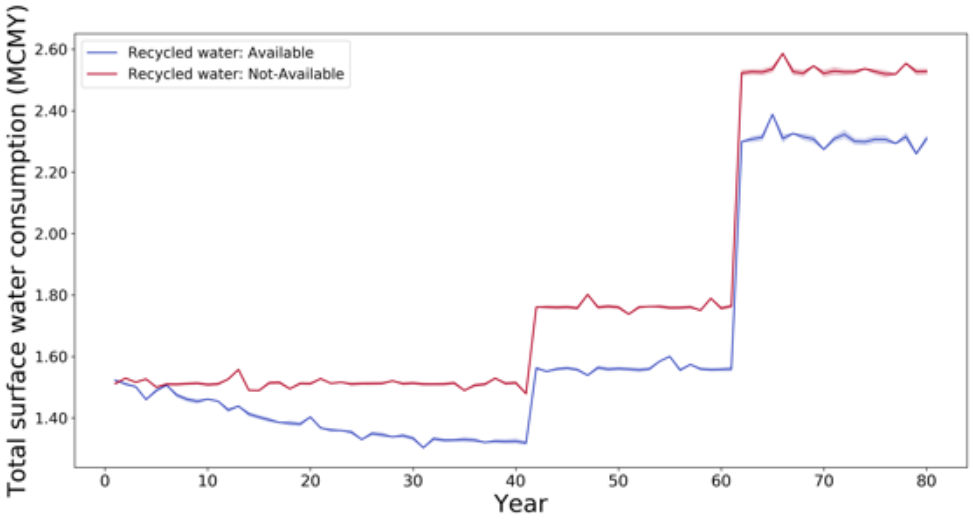
demonstrated a similar rising trend to the farmers' adoption curve, reaching a plateau around year 40. Among the farmers' SI components, only the farmers' water supply reliability (time-based) and resiliency were significantly increased due to the agricultural water reuse project (Table 59 and Table 60).



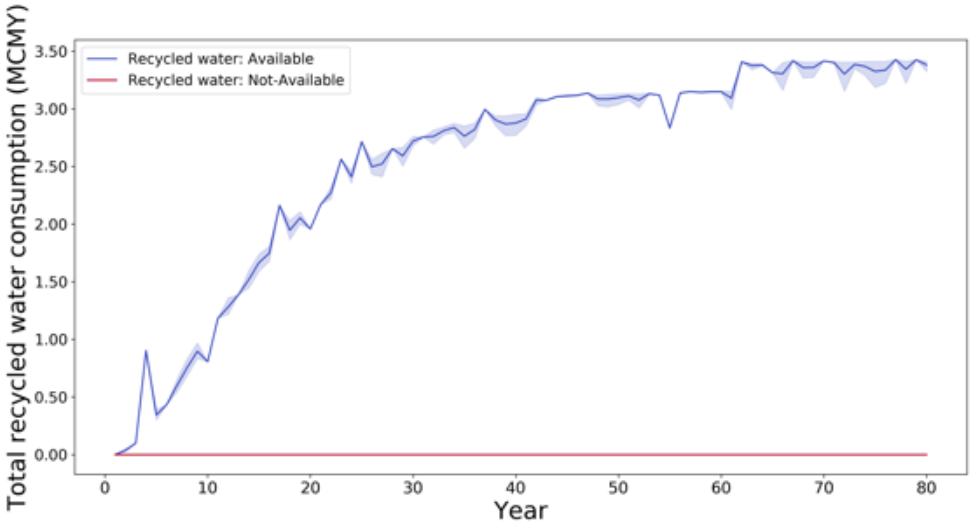
(a)



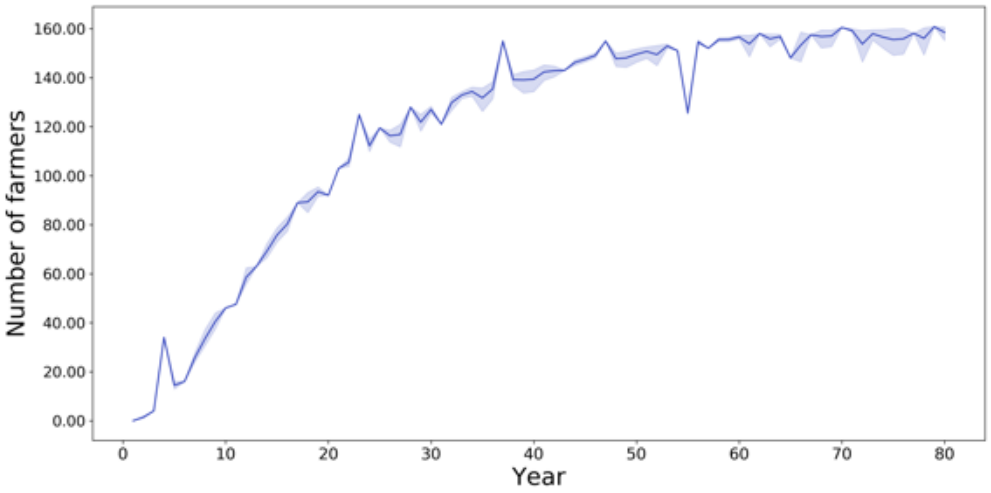
(b)


Recycled water: Available
Recycled water: Not-Available
Total surface water consumption (MCMY)
2.60
2.40
2.20
2.00
1.80
1.60
1.40
0
10
20
30
40
50
60
70
80
Year

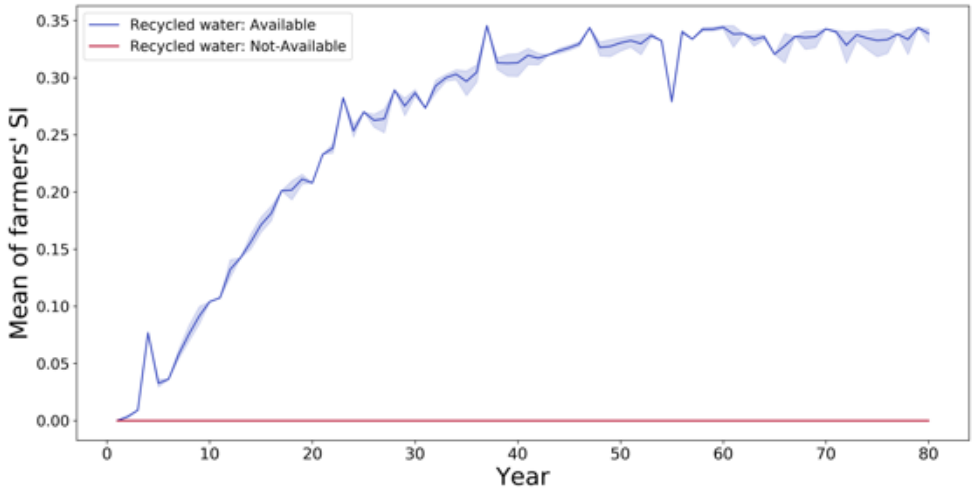
(c)


Recycled water: Available
Recycled water: Not-Available
Total recycled water consumption (MCMY)
3.50
3.00
2.50
2.00
1.50
1.00
0.50
0.00
0
10
20
30
40
50
60
70
80
Year

(d)



(e)



(f)

Figure 30. Simulation experiments results under scenario IV (a) total yearly water shortage, (b) total yearly groundwater consumption, (c) total yearly surface water consumption, and (d) total yearly recycled water consumption, (e) cumulative adoption curve of agricultural water reuse adoption by farmers, and (f) yearly mean of farmers' SI (MCMY = Millions Cubic Meters per Year; the 95% confidence intervals were calculated using bootstrap resampling method).

Table 59. Distributions of the farmers' SI components without agricultural water reuse under scenario IV

	Mean of farmers' water supply reliability (volume-based)	Mean of farmers' water supply reliability (time-based)	Mean of farmers' water supply resiliency	Mean of farmers' water supply vulnerability	Mean of farmers' water supply maximum deficiency
Mean	0.925	0.000	0.000	6.139×10^{-4}	8.500×10^{-5}
Standard deviation	5.930×10^{-12}	0.000	0.000	1.380×10^{-16}	2.940×10^{-6}
Min	0.925	0.000	0.000	6.139×10^{-4}	7.760×10^{-5}
25%	0.925	0.000	0.000	6.139×10^{-4}	8.310×10^{-5}
50%	0.925	0.000	0.000	6.13934×10^{-4}	8.470×10^{-5}
75%	0.925	0.000	0.000	6.139×10^{-4}	8.630×10^{-5}
Max	0.925	0.000	0.000	6.139×10^{-4}	1.047×10^{-5}

Table 60. Distributions of the farmers' SI components with agricultural water reuse under scenario IV

	Mean of farmers' water supply reliability (volume-based)	Mean of farmers' water supply reliability (time-based)	Mean of farmers' water supply resiliency	Mean of farmers' water supply vulnerability	Mean of farmers' water supply maximum deficiency
Mean	0.930	0.209	7.290×10^{-4}	7.855×10^{-4}	8.420×10^{-5}
Standard deviation	0.003	0.152	5.580×10^{-4}	1.231×10^{-4}	3.100×10^{-5}
Min	0.925	0.000	0.000	6.139×10^{-4}	7.777×10^{-5}
25%	0.926	0.047	1.555×10^{-3}	6.544×10^{-4}	8.220×10^{-5}
50%	0.929	0.187	6.121×10^{-3}	7.705×10^{-4}	8.330×10^{-5}
75%	0.933	0.358	1.176×10^{-2}	9.103×10^{-4}	8.580×10^{-5}
Max	0.935	0.458	1.997×10^{-2}	9.987×10^{-4}	1.041×10^{-4}

In general, the results of simulating the four scenarios showed that implementing this agricultural water reuse project in the study area could successfully decrease farmers' water shortages and groundwater/ surface water consumption. Of note was that as the severity of climate change scenarios increased in the scenario analysis, the time

needed for the recycled water to be fully used by farmers increased significantly. Under scenarios I and II, this time were approximately 15 years. However, it was increased to 30 and 40 years in scenarios III and IV, respectively.

Moreover, the percentage of decrease in the farmers' water shortage and groundwater/surface water consumption were decreased by increasing the severity of climate change scenarios. The percentage decreased from approximately 19.5% in scenario I to 10.3% in scenario II and 10.2% in scenario IV. This result illustrated that the agricultural water reuse project capacity to alleviate the consequences of climate change would decrease by increasing the severity of climate change. Moreover, among the farmers' SI components, time-based reliability and resiliency were significantly increased in all scenarios by implementing the agricultural water reuse project. Recycled water was able to increase the probability of meeting the farmers' demand and increased farmers' water supply capacity to adapt to perturbations.

Limitations and strengths of the study: George P. Box once argued, "*all models are wrong, but some are useful*" (Box, 1976). Accordingly, while the model developed in this research has various limitations, it has its strengths and can be helpful for water resources decision-makers and researchers. Authors made various assumptions throughout developing the model due to lack of data or simplifying the problem under study. Some of the limitations of this study are as follows:
One of the limitations of this study was modeling the environment in a stylized way. As ABMs are stochastic models with high computational costs, the authors decided to reduce the complexity of the model environment by stylizing it. Such simplification was done previously in the AgriPoliS (Happe et al., 2006) model. The authors also categorized farmers based on their Euclidean distance to the WWTP. This could lead to neglecting real-world properties of the path between farms and the WWTP (e.g., height difference and the real-world path and obstacles between the two). This distance was also calculated using the centroid of farm parcels, neglecting the actual geometric characteristics of farm parcels. This assumption could affect the calculated distances of farmers to the WWTP, changing farmers' turns in receiving recycled water from the WWTP.

To simplify the problem, the authors also selected only one type of crop grown in the study area (corn) and no crop rotation in this study. However, this limits the ability of this model to capture the water consumption dynamics of the study area comprehensively. Another limitation of this study was the farmers' water consumptions rates. The assumption and data used in this study were monthly-aggregated irrigation needs in Maryland which could decrease the accuracy of simulating farmers' daily irrigation needs. Furthermore, assuming only temperature and precipitation could affect the farmers' irrigation needs under the climate change scenarios was another assumption in this study that could affect the farmers' water consumption and the study result. Some assumptions regarding farmers' financial matters (e.g., assuming all of them used sprinkler irrigation systems) could affect the model results. It should be noted that this study should be used to gain valuable insights regarding implementing such agricultural water reuse project in the study

area, how farmers would adopt this practice and its impacts on the local water resources rather than predicting or reproducing the correct absolute estimates of water consumption and farmers' adoption behavior.

While simulation models of real-world problems (e.g., the model in this study) include various limitations, they have some strengths and could help increase our understanding of the world and get valuable insights. Some of these research strengths include: To the best of our knowledge, this study is the first to investigate the micro-level dynamics of agricultural water reuse adoption by farmers and its impacts on local water resources in the Eastern Shore of Maryland. The authors used agent-based modeling, a well-known method for capturing these farm-level dynamics. A well-established and famous psychological theory (TPB) formed the basis of processes involved in this model to simulate farmers' adoption process. A complete UA-SA was conducted for this complex simulation model to get an insight into the most important factors with significant influence on the model outputs. Moreover, a sustainability index, extensively used and recognized by the scientific community, was used in this study to evaluate the impacts of implementing such projects on the sustainability of local water resources.

Recommendation for future research: In general, any future research can investigate methods for addressing the limitations of this study and compare the results. However, the authors recommend several ideas for continuing this research and addressing its limitations. In terms of modeling farmers' behavior, future research can use other human decision-making methods to determine the differences between such methods of developing agents in agent-based models in modeling farmers' behavior. Another recommendation in this regard is to use various methods for modeling farmers' decision-making process to increase the heterogeneity of farmers. Researchers are also urged to collect farm-level hydrologic data (e.g., groundwater consumption, evapotranspiration) to expand the model developed in this study. Researchers can also include other crops and crop rotations in future studies. Another suggestion is to couple this model with a hydrologic model (e.g., ARCSWAT) to find the impacts of the agricultural water reuse project on the surface water quality of the study area, especially with regards to nutrients (e.g., Nitrogen and Phosphorus) concentrations in the surface water bodies.

5.4. Conclusions

Agricultural water reuse is considered one of the most reliable measures that water resource decision-makers can use for alleviating the consequences of climate change on the sustainability of water resources. Introducing water reuse schemes into the portfolio of water supplies of an area increases the complexities inherent in water resources systems. Decision-makers need tools (e.g., simulation models) to help them capture these complexities and make better-informed decisions.

This study investigated the implementation of an agricultural water reuse project in the Eastern Shore of Maryland using agent-based modeling. We could successfully

capture the complex dynamics of agricultural water reuse adoption by local farmers and its impacts on the sustainability of local water resources. This study used a global SA method to find the factors with the most significant effects on the model outputs, including climate change effects (precipitation and temperature), WWTP's storage capacity, and the unit price of recycled water. Decision-makers need to pay special attention to determining the unit price of recycled water and WWTPs' storage capacities to ensure the success of agricultural water reuse projects. Based on the SA results, we also urge other researchers to conduct time-varying SA, especially when dealing with models of complex systems as their sensitivity includes complex dynamics.

This study also simulated the project under various scenarios (e.g., climate change). The results demonstrated that the agricultural water reuse project could significantly decrease farmers' water shortage and groundwater/surface water consumption and increase their water supply sustainability if appropriately managed. However, the impacts of the agricultural water reuse project were decreased under severe climate change scenarios. Furthermore, the results showed that farmers' water supply reliability, resiliency, and sustainability increased significantly by introducing recycled water into the area.

Chapter 6: Optimization of agent-based models: Application in planning and management of an agricultural water reuse project

Abstract

Optimization of agent-based models has several challenges due to complexities inherent in these simulation models and their high dimensionality. The literature also suffers from a lack of studies investigating agent-based models' optimization. In this study, we showed the application of reinforcement learning as a machine learning method for multi-objective simulation-based optimization of an agent-based model. We employed an agent-based model developed in our previous study (Chapter 5) to investigate the adoption of agricultural water reuse by farmers and its impacts on local water resources. We used two parameters of this model identified as two of the most influential factors on the model by sensitivity analysis in our previous work. Using reinforcement learning, a manager agent who had access to those parameters was created in this study to optimize the agricultural water reuse project. The idea was to get valuable insights from the decision-making of an artificially intelligent decision-maker.

Sensitivity analysis results showed that the manager agent's parameters could significantly affect its decisions for optimizing the model. Using proper values for these parameters could let the manager reach better results, although delayed. The model was tested under various climate change and water resource limitations scenarios. The results showed that the agent could successfully optimize the model by optimizing its various objectives. Comparing the results of this study with our previous study showed that the agent had to sacrifice minimizing farmers' groundwater consumption in favor of maximizing their water supply sustainability, recycled water users, the unit price of recycled water, and minimizing the storage capacity of the wastewater treatment plant that provided the recycled water in the project. Researchers and decision-makers can use the results of this study to gain valuable insight regarding using reinforcement learning for optimization of agent-based models and sustainably managing agricultural water reuse projects under various scenarios.

6.1. Introduction

Agent-based modeling is one of the promising computational methods for simulating complex systems such as water resources systems (Berglund, 2015; Ghoreishi et al., 2021b). Various studies have successfully shown the application of agent-based modeling for studying water resources management (Ali et al., 2017; Bahrami et al., 2022; Hung & Yang, 2021; Zolfagharipoor & Ahmadi, 2021). As a "bottom-up" model, an agent-based model (ABM) can successfully simulate agents' interactions and the environment in the complex system under study (Crooks et al., 2018; Grimm, 2019). ABMs can be used as in silico laboratories for investigating the questions

posed on systems (Oremland & Laubenbacher, 2014). Questions concerning conditions that can lead to specific goals in ABMs are considered optimization problems (Oremland & Laubenbacher, 2014).

Literature has pointed out several challenges of ABMs optimization due to the complexities in their objectives functions surfaces and their high dimensionality. As ABMs simulate complex systems, including heterogeneous agents and their interactions with other agents and the environment, their objective function surfaces show various complexities. The objective function surfaces can often include various jumps/ discontinuities due to changes in variables. These points are tipping points where a significant change happens to the objective function surface. On the other hand, there are often large continuous areas with minor changes in the objective function surface of ABMs. Moreover, due to the complex nature of ABMs, multiple local extrema can be assumed in the objective function surface. Therefore, in summary, the objective function surfaces of ABMs are complex, unknown, and probably ragged, but convex surfaces (Deckert & Klein, 2014).

Furthermore, it should be noted that ABMs objective function surfaces are not static and have to be approximated by multiple replications due to the stochasticity of these models (Deckert & Klein, 2014). (Oremland & Laubenbacher, 2014) underlined that ABMs optimization must be carefully accomplished due to their inherent stochasticity. This feature of ABMs also was mentioned as the primary factor differentiating classical optimization approaches from simulation-based optimization algorithms in the literature (Deckert & Klein, 2014). Multiple replications are necessary to find the solution to the optimization problem (Deckert & Klein, 2014). Another challenge of ABMs' optimization is their high dimensionality, i.e., including various continuous or discrete parameters (Lin & Lee, 2006). Computational costs, time, and difficulty of optimization increase as the number of effective parameters, especially continuous parameters, increases in ABMs. Overall, in optimizing ABMs, identifying the best solution (global solution) is not possible (Deckert & Klein, 2014; Lin & Lee, 2006; Oremland & Laubenbacher, 2014). Thus, the ultimate goal of optimization algorithms has to be finding and validating a "best possible" solution with the "best possible" precision (Deckert & Klein, 2014; Lin & Lee, 2006).

Although agent-based modeling has been extensively used for various applications, optimization of ABMs is relatively scarce in the literature (Deckert & Klein, 2014). Deckert and Klein (2014) claimed that most optimization methods used for ABMs were basic (manual) calibration of simulation parameters to fit the observed empirical data or system characteristics; however, a minimal number of studies used advanced optimization methods. Existing algorithms can be categorized in escalating order of ambiguity based on their underlying simulation assumptions into four groups (Deckert & Klein, 2014).

The first group of algorithms with close structural relationships among variables and output include metamodel optimization approaches (Deckert & Klein, 2014) such as Response Surface Methodology (RSM) (Gosavi, 2015) and Neural Networks

(Gosavi, 2015). The second group of algorithms is gradient approaches that the objective values space show monotonous slope (at least in local areas) (Deckert & Klein, 2014) such as Finite Differences Stochastic Approximation (Spall, 2004). The third group of algorithms is point-to-point metaheuristics (Ólafsson, 2006) (such as Simulated Annealing (Henderson et al., 2003) and Tabu search (Gendreau, 2003)), population-based metaheuristics methods (e.g., Evolutionary Algorithms (EA) (Eiben & Smith, 2007)) (Deckert & Klein, 2014). The fourth algorithms are that the simulation is entirely a "black box," such as Global Random Search (Andradóttir, 2006; Deckert & Klein, 2014).

In the literature, an ABM was developed to simulate and optimize resource allocation to control epidemics using a statistical simulation-optimization technique (i.e., RSM) (Kasaie et al., 2010). Lollini et al. used a genetic algorithm for finding optimal cancer vaccination protocols through agent-based modeling (Lollini et al., 2006). Using genetic algorithms with a fixed number of replications, Calvez and Hutzler (Calvez & Hutzler, 2005) optimized an ABM of ant foraging. Specifically, they formulated the validation part of developing the ABM as an optimization problem, minimizing the error function. Similarly, an ABM was developed and optimized for emergency response planning using a multi-objective optimization problem (multi-objective evolutionary algorithms) (Narzisi et al., 2006). Heppenstall et al. (2007) presented a novel agent-based framework for developing, parametrizing, verifying, and optimizing a retail petrol market through a genetic algorithm.

This study used machine learning (ML) to test an optimization algorithm on an ABM developed in our previous study (Chapter 5). This ABM was developed to simulate the dynamics of agricultural water reuse adoption by farmers and its impacts on local water resources. Water reuse is one of the most reliable techniques for sustainable water resources management (Asano et al., 2007a; Eslamian, 2016; Pronk, Stofberg, Van Dooren, et al., 2021). It is one of the techniques that can potentially help water resources managers alleviate the consequences of climate change and population growth on water resources and human/environmental health (Paul et al., 2020, 2021; Shoushtarian & Negahban-Azar, 2020). It has been locally utilized for various applications (e.g., drinking water, urban and agricultural irrigation, industry, horticulture, environment, and groundwater recharge) worldwide (Eslamian, 2016; Lautze et al., 2014; Lazarova & Bahri, 2004; Pintilie et al., 2016; Shoushtarian & Negahban-Azar, 2020; Wu et al., 2009; Zuurbier et al., 2018). As the agriculture sector uses the highest portion (70%) of water withdrawn globally (Gleick et al., 2012), agricultural water reuse can potentially be one of the most influential water reuse applications on the sustainability of global water resources.

One of the challenges associated with agricultural water reuse projects is their management (Shoushtarian & Negahban-Azar, 2020). These projects' health, social, economic, technical, and legal aspects make their management challenging for water resources managers. Researchers have suggested simulation models (e.g., ABMs) to study complex water resources systems. Therefore, in this study, the developed ABM was optimized to reach multiple goals, such as maximizing the sustainability and

adoption of agricultural water reuse projects. The ultimate goal was to find the optimum strategies to plan and manage agricultural water reuse projects to manage water resources sustainably.

The literature has never studied optimized planning and management of agricultural water reuse projects to the best of our knowledge. Therefore, the main goal of this study was to investigate the optimization of an ABM developed for simulating an agricultural water reuse project using a novel ML method, i.e., Reinforcement Learning (RL). The results of this study can shed light on ways for sustainably planning and managing agricultural water reuse projects. Scientists and water resource managers can use this study's results to find optimal solutions- derived from artificial intelligence- for implementing sustainable agricultural water reuse projects. The results also demonstrate the capabilities of a novel algorithm in optimizing an ABM. The remainder of this paper describes the methods used in this study (Section 6.2.), illustrates the results of the study and discusses the findings (Section 6.3.), and concludes the paper, proposing new areas for further work (Section 6.4.).

6.2. Methodology

6.2.1. ABM

6.2.1.1. The model

In this study, an ABM developed in our previous work (Chapter 5) was utilized. An extensive description of the ABM framework, development process and details, uncertainty-sensitivity analysis, validation, and scenario analysis were presented in our previous work (Chapter 5). Interested readers are encouraged to read our previous work to understand the model's details further. Here, a very brief description of the ABM is presented.

First, based on the Theory of Planned Behavior (TPB) (Ajzen, 1991), a framework was proposed in our previous work (Chapter 4) for developing ABMs capable of capturing the dynamics of agricultural water reuse adoption by farmers and its impacts on local water resources. Like other ABMs, this model included an environment, multiple agents, and interactions among them. The authors simulated the environment in a stylized manner, inspired by the AgriPoliS (Happe et al., 2006) model. Local empirical data related to farms (e.g., farm area/parcels/locations and crop types) was used to place farms in the stylized environment.

The model included two types of agents, including farmer agents and wastewater treatment plant (WWTP) agents. A farmer agent represented each farm. In total, 166 farmer agents were simulated in this model. Farmer agents were responsible for providing water required by each farm to grow its crop in each farming season. Farmers were specifically responsible for making decisions regarding the source of irrigation water. Farmers could choose between the available water sources in the study area (e.g., groundwater, surface water, and recycled water). It was also assumed that farmers selected the cheapest available option for irrigating their crops in this

model. It should be mentioned that farmers considered recycled water in their decision-making only after adopting it. Agricultural water reuse adoption by farmers was simulated using a sub-model. This sub-model utilized farmers' attitudes toward agricultural water reuse, network, economic status, previous year water shortage, and their customers' perceptions toward buying crops irrigated by recycled water to capture the dynamics of farmers' agricultural water reuse adoption.

Table 61. Farmers' attributes used in this ABM for this study

Attribute	Description
R	The distance (Km) between farm centroid and the WWTP
Irrigation method	Irrigation system that farmer used for irrigation. For simplification, it was assumed that all farmers used sprinkler system in this study.
Farm	Farm area (acre)
Crop	The crop grown by farmer (this paper studied corn farms)
Money	Farmer's money ($)
G-water	The amount of groundwater used by farmer (CM)
R-water	The amount of recycled water used by farmer (CM)
S-water	The amount of surface water used by farmer (CM)
Water need	Farmer's daily water need (CM per day)
Farmer water shortage	Farmer's daily water shortage (CM per day)
Irrigation equipment year	Farmer's irrigation equipment age
Installation cost	Costs that farmer has to pay for buying and installing famer's new irrigation system ($)
Annual depreciation	Farmer's irrigation system annual depreciation costs ($/year)
Annual maintenance	Farmer's irrigation system annual maintenance ($/year)
Operation costs	Yearly farming operation costs of each farmer ($/year)
Adoption	Farmer's adoption status
Alternative source	Farmer's alternative water source
Groundwater cost	Farmer's groundwater cost ($)
Surface water cost	Farmer's surface water cost ($)
Recycled water cost	Farmer's recycled water cost ($)
Farmer-vol-rel	Farmer's water supply volumetric reliability in each year
Farmer-time-rel	Farmer's water supply time-based reliability in each year
Farmer-res	Farmer's water supply resiliency in each year
Farmer-vul	Farmer's water supply vulnerability in each year
Farmer-max-def	Farmer's water supply maximum deficiency in each year
Farmer-si	Farmer's water supply SI in each year
Age	Farmer's age
Concern	Farmer's concern about water reuse
Knowledge	Farmer's knowledge about water reuse
Access	Farmer's access to water reuse sources
Education	Farmer's education level
Race	Farmer's race
Importance	Importance of water reuse for farmer
Gender	Farmer's gender
Attitude	Farmer's attitude toward agricultural water reuse
Friends	Other farmers in the farmer's network

On the other hand, the WWTP agent sent recycled water from its storage ponds/tanks to those farmers that had already adopted agricultural water reuse based on available recycled water and their distance to the plant (the closer, the higher the priority). A

summary of agents' attributes, model inputs, and main equations is provided in Table 61Table 62Table 63. At the end of each year, farmers sold their corn and earned a profit. The model ran daily for 80 years to fully capture the dynamics of agricultural water reuse adoption.

Table 62. WWTP's attributes used in this ABM for this study

Attribute	Description
Average daily flow	The WWTP's average daily effluent flowrate (MCMY)
Storage	The capacity of the WWTP's storage ponds/tanks to store recycled water (MCM)
WWTP money	The WWTP's money received daily from farmers for selling recycled water ($)

Table 63. Inputs of the ABM used in this study

Symbol	Factor (Unit)	Description	Range/values
A	Groundwater availability (%)	Percentage of farmers' irrigation needs (daily) that was provided by groundwater	(70-100)
B	Surface water availability (%)	Percentage of farmers' irrigation needs (daily) provided by surface water after using other water sources.	(0-100)
C	The unit price of recycled water ($/MCM)	The price at which farmers bought recycled water from Easton WWTP	(0-2.43)
D	Easton WWTP storage pond (CM)	Volume of Easton WWTP storage pond for storing its treated effluent	(1,028-10,280)
E	Climate	Climate scenarios which determined precipitation and temperature value, affecting the Irrigation Need Coefficient	BAU[1], RCP 2.6, RCP 4.5, and RCP 8.5
F	Costumers' perceptions (%)	Positive perception of costumers toward Almonds irrigated with recycled water	(44-90)
G	Number-of-messages	Number of positive/ negative messages that farmers send to their friends	(1-20)
H	Corn yield (ton/ha)	Amount of corn produced per unit area by farmers (fixed at the high level for SA)	(12.11-16.14)

[1] Business as usual

6.2.1.2. Study area

The study area was located at Easton, Talbot County, Maryland. This area was identified as a suitable area for implementing agricultural water reuse by Paul et al. (Paul et al., 2021) as the area has been suffering from severe groundwater level declines (Dong et al., 2019), and it is primarily agricultural land (66%) (Lomax & Stevenson, 1982). Corn is one of the major crops grown yearly in the area. Accordingly, corn farms in a 15 Km radius from the Easton WWTP were selected for this study (166 farms). According to the WWTP development plans, the Easton WWTP capacity was linearly increased from 12.1 to 15.1 thousand cubic meters per

day in the first ten years of simulations (MDE Secretary Celebrates Easton Wastewater Facility Grand Opening).

6.2.2. ABM optimization using RL

The majority of methods for optimizing sequential problems require a transition probability matrix. However, as this study used an ABM, no Markov process and transition probability matrix were involved. Thus, it was necessary to use a model-free technique to optimize this ABM that could blindly explore the solution space (Jalalimanesh et al., 2017). ML provides powerful tools/ methods for this, according to the literature (Jalalimanesh et al., 2017).

ML methods can generally be categorized into three basic categories: supervised, unsupervised, and RL (Sutton & Barto, 2018). RL is concerned with an agent's decision-making in an environment to maximize a reward (Sutton & Barto, 2018). There are three primary sets involved in RL, including state (S), action (A), and reward (R) (Figure 31). The agent generally follows policy π and takes an A based on its internal rules and its current S at time t. Accordingly, the environment sends an R(S, A) to the agent based on a predefined metric (i.e., how well the agent behaved according to the metric). Then, the agent updates its policy (Sutton & Barto, 2018). Next time, the agent chooses a better A according to its S and corresponding R.

Three major approaches have been introduced for RL, including value-based, policy-based, and model-based. In value-based approaches, agents try to maximize a value function iteratively to find the optimum value function ultimately. In this approach, the policy is updated implicitly by the value function (Sutton & Barto, 2018). The algorithm generally tries to allocate an R to each pair of (S, A) using a function at each time step. RL literature has named this function Q-function. Therefore, the agent will choose the best A in each S based on its corresponding R using the Q-function. Q is utilized to update the policy.

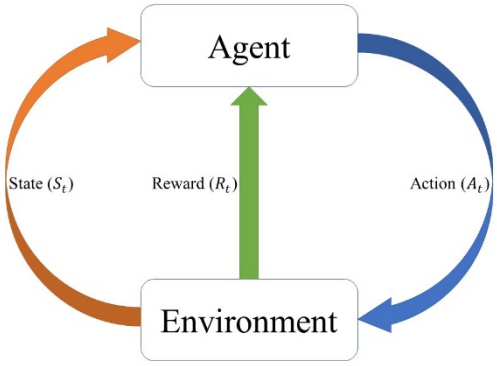


Figure 31. RL schematic process (Sutton & Barto, 2018)

Various algorithms have been introduced to update the Q-function based on timing and method of updating the Q function, such as Temporal Difference learning

algorithms (Harati et al., 2021). In this type of algorithm, Q is updated each time step. One of the well-known methods of these types of algorithms is called Q-Learning. In this method, the algorithm's policy π selects A when the system is at S. This A results in its corresponding R and next state (S′). Next, the algorithm chooses the pair (S′, A′), registered in Q, with the maximum value R to correct Q (Equation (32)) (Harati et al., 2021; Sutton & Barto, 2018).

$$Q_{new}(S,A) \leftarrow Q_{old}(S,A) + \alpha[R + \gamma \times max_a Q(\mathrm{S}', \mathrm{A}') - \mathrm{Q}(\mathrm{S}, \mathrm{A})] \tag{32}$$

Where $\gamma,\ \gamma \in (0,1)$, is the discounting rate/ factor, and α is the learning rate or the step size (Sutton & Barto, 2018). γ reflects the timely importance of rewards for the agent. The closer this parameter to one, the higher the importance of future rewards (delayed rewards) for the agent, and vice versa (Sutton & Barto, 2018). The learning rate ($\alpha \in [0,1]$) indicates how eager the agent is to learn new information, i.e., representing the concepts of exploration and exploitation. As the learning rate gets closer to zero, the agent's interest in learning decreases; the agent wants to exploit its current information. On the other hand, as the learning rate gets closer to one, the agent is only interested in learning new information, i.e., the agent prefers to consider only the most recent information, ignoring prior knowledge to explore possibilities (Sutton & Barto, 2018).

To avoid suboptimal solutions, Q-learning can use a simple algorithm, called the Epsilon-Greedy algorithm, among the available ones to balance between the exploitation and exploration, ensuring that the agent explores enough. The algorithm conducts this by exploiting most of the time and rarely exploring with a probability of epsilon (Equation (33)). Accordingly, the agent performs the optimum A with a probability of $1 - \varepsilon$ and performs a random action with the probability of ε. For further details of Q-Learning, the interested reader is referred to (Sutton & Barto, 2018).

$$a_t = \begin{cases} max\, Q(\mathrm{a});\ P = 1 - \varepsilon \\ random\ (a); P = \ \varepsilon \end{cases} \tag{33}$$

Q-Learning algorithm has been used in many agent-based modeling studies, illustrating exciting results about its capabilities. For example, Brearcliffe and Crooks (2019) utilized various ML methods (e.g., Q-Learning) to extend the famous Sugarscape ABM. This paper demonstrated that ML methods could be used to create intelligent agents in ABMs; however, this does not always result in better results. This study also highlighted the impacts of various ML methods (i.e., evolutionary computing, Q-Learning, and SARSA) on the ABMs results. Q-Learning was also used in an ABM for optimizing allocations in an urban water resource context (Ni et al., 2014). This study demonstrated that the algorithm could allocate water resources optimally, and the objectives of all the stakeholder agents could be successfully achieved. Hung and Yang (2021) also used the Q-Learning method to create intelligent agents (farmers) who could learn and adjust their demands based on their interactions with the water systems. Another study improved the ability of an ABM to

achieve optimal forest harvesting strategies using Q-Learning (Bone & Dragićević, 2010).

In this study, Q-Learning was also used to optimize the planning and management of an agricultural water reuse project. The authors were initially inspired by the Alpha Go project (Silver et al., 2016) in creating an intelligent agent (manager) for this study. Alpha Go (Silver et al., 2016) was an incredible cutting-edge project, showcasing the capabilities of RL in beating the best human professional Go player in the world (Lee Sedol). Using deep neural networks, Alpha Go illustrated such a creative playing style that no human could think of (AlphaGo | DeepMind). Worldwide professional go players got new insights from Alpha Go playing strategies. Although this study was not as complex as the Alpha Go project, it tried to investigate the idea of using RL for getting creative and new insights from the application of RL for sustainably planning and managing agricultural water reuse projects.

For this, a manager agent was explicitly created using the Q-Learning algorithm. The agent was created using the Q-Learning NetLogo extension (Kons, 2019). The manager in this study was another type of agent created at the start of the model who had access to some of the model input variables. The idea was to let the manager determine the unit price of recycled water and the WWTP's storage capacity to achieve the goals determined for an agricultural water reuse project. The main reason for selecting these two variables was that they were the two of the most influential factors on the model outputs in our previous work. The manager could change these two variables in their acceptable ranges to achieve its goal successfully.

As the Q-Learning algorithm is generally considered when S and A are both discrete (Gaskett et al., 1999), these variables were discretized using 7 and 5 levels of recycled water unit price and the WWTP's storage capacity. The levels defined for the recycled water unit price were 0, 2.4, 4.9, 7.3, 9.7, 12.1, and 14.6 $/TCM. 1.03, 1.29, 1.54, 1.80, and 2.06 MCM were also the levels considered by the manager agent for the WWTP's storage capacity. In total, the manager was able to choose between 35 actions each day. This simplifying assumption helped decrease the action space, decreasing the time and calculations needed to converge the results.

Moreover, 16 states were defined for the manager by considering four conditions for each month (June, July, August, and September) when farmers needed irrigation. The four conditions included wet, normal, shortage, and severe shortage. The manager calculated farmers' maximum daily irrigation need according to the month to determine the S. Then, the manager could accordingly determine its A each day (Table 64). In this model, each day represented an episode in the RL algorithm. To decrease the ε gradually it was multiplied by a factor (θ) at the end of each episode. Sensitivity analysis was performed to determine the best values of θ, ε, γ, and α for simulations in this study.

Moreover, the reward function (R) was determined to reward the manager agent for each month (June, July, August, and September). The R was scalarized using the Weighted Sum Scalarization Method (Messac, 2015) to convert the multi-objective optimization problem to a one-objective optimization problem. The manager's objectives were to minimize farmers' groundwater consumption and WWTP's storage capacity; and maximize the number of farmers who used recycled water, recycled water unit price, and farmers' SI (Equation (34)). The decision-maker (user) could determine the objectives' weights based on the decision maker's priorities. All weights and objective functions were normalized to decrease the degrees of freedom to 4 (n-1). Normalizing weights also enabled the model to modify any weights, given by the user, to a number between 0-1while preserving the relative importance of objectives. Normalizing the objective functions not only converted them to a number between 0-1 but also eliminated their units, making the R a unitless function.

Table 64. The manager's S in this study

Water shortage level	**The manager condition**	**The manager's S**
Total farmers' daily water shortage (DS) < 0.25 ×farmers' maximum daily irrigation needs (DI)	Wet	June-wet, July-wet, August-wet, September-wet
0.25DI ≤ DS < 0.5DI	Normal	June-normal, July-normal, August- normal, September-normal
0.25DI ≤ DS < 0.75DI	Shortage	June-shortage, July-shortage, August-shortage, September-shortage
0.75DI ≤ DS	Severe shortage	June-severe-shortage, July-severe-shortage, August-severe-shortage, September-severe-shortage

$$R_t = \frac{W_{SI}}{W_{total}} \times SI_t - \frac{W_{GW}}{W_{total}} \times GW_t + \frac{W_{RU}}{W_{total}} \times RU_t + \frac{W_{RP}}{W_{total}} \times RP_t - \frac{W_{ST}}{W_{total}} \times ST_t \quad (34)$$

$$GW = \frac{\sum farmers'\ groundwater\ consumption}{maximum\ daily\ irrigation\ need} \quad (35)$$

Where R_t was the reward function of the manager agent at the time (day) t, $W_{total}$was the sum of all of the weights, $W_{SI}$was the weight of farmer's SI, $W_{GW}$was the weight of farmer's groundwater consumption, $W_{RU}$was the weight of recycled water users, $W_{RP}$was the weight of recycled water unit price, W_{ST} was the weight of the WWTP's storage capacity, $SI_t$was the mean of farmer's SI at the time (day) t, $RU_t$was the number of farmers who used recycled water divided by the total number of farmers at

the time (day) t, and RP_t was the unit price of recycled water divided by the maximum unit price of recycled water, 14.6 $/TCM, at the time (day) t, ST_t was the WWTP's storage capacity divided by its maximum value (2.06 MCM). The maximum daily irrigation need was calculated for each month when irrigation happened, multiplying the total area of farms by each month's maximum daily irrigation need (June: 0.51 mm; July: 4.83 mm; August: 4.95 mm; September: 2.03 mm).

6.2.2.1. Verification and sensitivity analysis (SA)

Our previous work (Chapter 5) illustrated the verification and SA of the ABM used in this study. In this study, the verification step included testing whether the manager agent behaved as designed. Specifically, the expected outcome alignment (Crooks et al., 2018) method was utilized to verify the model. First, the model was tested to check whether the manager agent could successfully change the model input parameters according to its specifications. Various parameters of the manager agent (i.e., W_{SI}, W_{GW}, W_{RU}, W_{RP}, W_{ST}, θ, ε, γ, and α) were changed to investigate whether the manager agent behaved accordingly. For example, W_{RP} was set to various levels (e.g., minimum, average, and maximum) while keeping all the other factors constant to see how the manager agent changed the unit price of recycled water. Second, other model input factors (i.e., groundwater and surface water availability, climate projections, costumers' perceptions, number of messages, and corn yield) were altered to create specific circumstances (e.g., water shortage) to check whether the manager agent behaved accordingly.

Table 65. Specifications of the SA experiments in this study.

Symbol	Factor	Value/s	Symbol	Factor	Value/s
A	Groundwater availability (%)	95	J	W_{GW}	1, 50, 100
B	Surface water availability (%)	95	K	W_{RU}	1, 50, 100
C[1]	The unit price of recycled water ($/TCM)	0-14.6	L	W_{RP}	1, 50, 100
D[1]	Easton WWTP storage pond (MCM)	1.03-2.06	M	W_{ST}	1, 50, 100
E[2]	Climate	BAU	N	θ	0.995, 0.997, 0.999
F	Costumers' perceptions (%)	65	O	ε	0.1, 0.5, 0.9
G	Number-of-messages	10	P	γ	0.1, 0.5, 0.9
H	Corn yield	Moderate	Q	α	0.1, 0.5, 0.9
I	W_{SI}	1, 50, 100			

[1] Parameter to be optimized by the manager agent
[2] Bussiness as usual (long term average)

SA was also performed to find the most influential factors on the manager agent decisions. θ, ε, γ, α, and all the weights included in the manager's reward function were used in this step (Table 65). While keeping all of the other parameters constant, each of these parameters was altered one at a time to test the expected outcome and analyze the sensitivity of the manager agent's decision-making. In the literature, this

method is called one factor at a time (OFAT or OAT). Although this method has certain shortcomings in SA of ABMs (Razavi & Gupta, 2015), its simplicity and the fact that the SA was not the main point of this study were the main reasons behind its selection for this study by the authors (Razavi & Gupta, 2015). All simulations were repeated 100 times due to the stochastic nature of ABMs.

6.2.2.2. Scenario analysis

The model was used to analyze four scenarios (Table 66). Scenarios were similar to our previous study (Chapter 5) to compare the results of the two studies, illustrating the capabilities of the manager agent in optimizing the model. The four scenarios were defined based on various water resources and climate change conditions, projected by the Intergovernmental Panel on Climate Change (IPCC). The first scenario (Scenario I) was designed as the BAU scenario to simulate the study area under average weather, with no limitations on local water resources. The second scenario (Scenario II) was defined as the first scenario under climate change effects, i.e., RCP 2.6 climate projection, and low local water sources limitations. Two other scenarios were defined as Scenarios III and IV to simulate the study area under more problematic conditions. The study area under moderate water shortages and limitations on local water resources and RCP 4.5 climate projections was simulated according to Scenario III. Furthermore, to test the area for extreme conditions, Scenario IV simulated severe water shortages, limited local water resources, and RCP 8.5 climate projections. All scenarios were repeated 100 times to capture the uncertainties in the ABM.

In all scenarios, the manager agent's objective was to optimize recycled water unit price and the WWTP's storage capacity to achieve its goals. All other factors were set according to the limitations on local water resources and climate change scenarios. The customers' perceptions and the number of messages were increased as the severity of limitations on local water resources and climate change projections increased. It was assumed that as the severity of limitations on local water resources and climate change projections increases in the study area, decreasing the amount and reliability of farmers' water supply, farmers would be more interested in using an alternative water resource (e.g., recycled water). Thus, farmers would spread more word to their friends about using recycled water for their irrigation practices as this is the only available alternative water resource in the area. Also, people's climate change consciousness would increase under these conditions, increasing customers' positive perceptions toward purchasing products irrigated with recycled water.

Corn yield was set to "high" only in scenario I; and to "moderate" in scenarios II, III, and IV to modify farmers' irrigation needs based on various water resources and climate change conditions. For the manager's reward function, sustainability of farmer's water supply had the most priority in all scenarios. As the water resources conditions and climate change projections worsened, the relative importance of farmers' groundwater consumption, the number of farmers who used recycled water, the unit price of recycled water, and WWTP's storage capacity increased.

Table 66. Specifications of the simulation experiments scenarios in this study.

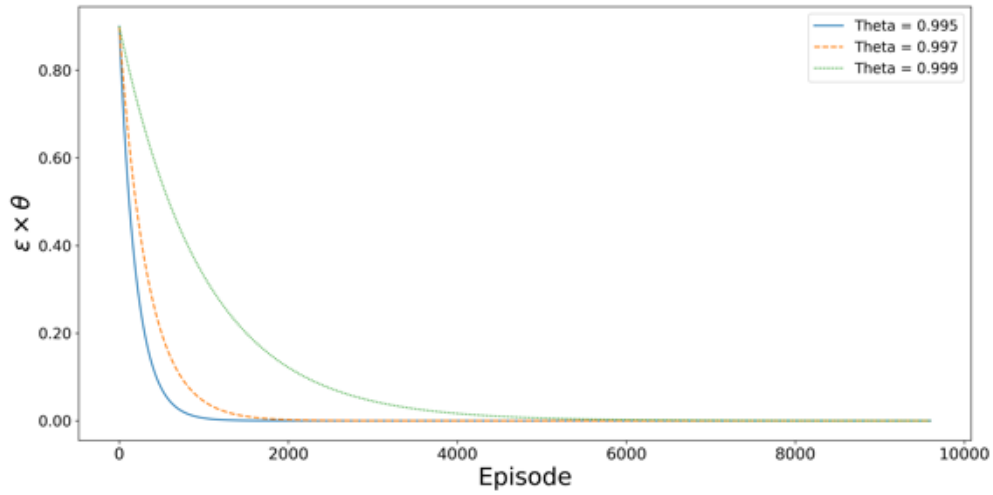
Symbol	Factor	Scenario I	Scenario II	Scenario III	Scenario IV
A	Groundwater availability (%)	100.00	97.00	95.00	93.00
B	Surface water availability (%)	100.00	97.00	95.00	93.00
C	The unit price of recycled water ($/TCM)	0-14.6	0-14.6	0-14.6	0-14.6
D	Easton WWTP storage pond (MCM)	1.03-2.06	1.03-2.06	1.03-2.06	1.03-2.06
E	Climate	BAU	RCP 2.6	RCP 4.5	RCP 8.5
F	Costumers' perceptions (%)	45.00	60.00	75.00	90.00
G	Number-of-messages	3.00	5.00	10.00	15.00
H	Corn yield	High	Moderate	Moderate	Moderate
I	W_{SI}	100.00	100.00	100.00	100.00
J	W_{GW}	80.00	85.00	90.00	95.00
K	W_{RU}	35.00	50.00	75.00	100.00
L	W_{RP}	55.00	60.00	75.00	80.00
M	W_{ST}	20.00	40.00	60.00	80.00
M	θ	0.997	0.997	0.997	0.997
N	ε	0.5	0.5	0.5	0.5
O	γ	0.5	0.5	0.5	0.5
P	α	0.5	0.5	0.5	0.5

6.3. Results and discussions

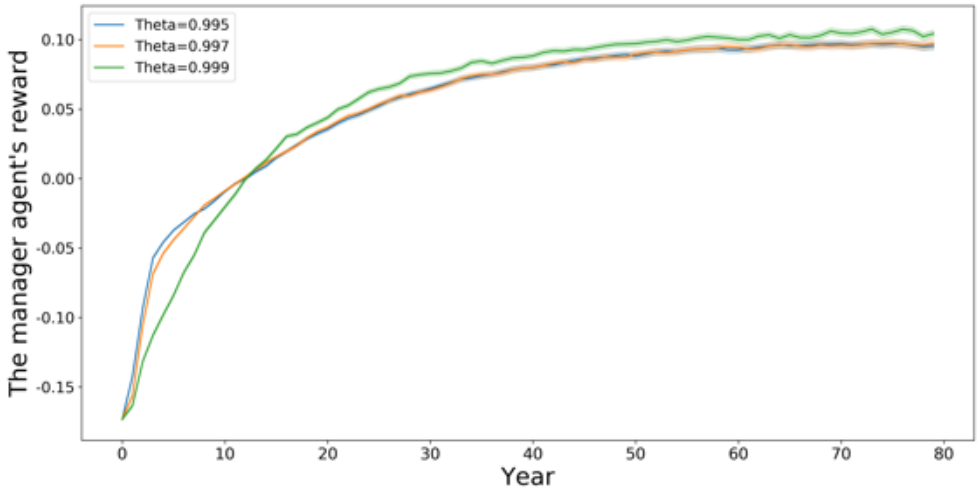
6.3.1. Results of SA

The results of the verification step were not included in this section for brevity. Interested readers are encouraged to read our previous work (Chapter 4), where we extensively studied the verification of an ABM similar to the one used in this study. As mentioned before, the epsilon-greedy method decreases the probability of taking random actions incrementally, ensuring that the algorithm does not get stuck in local optima. The algorithm conducted this by multiplying a constant (i.e., θ) to ε in each episode. For the SA section of this study, first, the sensitivity of the manager agent's decision-making to various θ values were investigated (Figure 32).

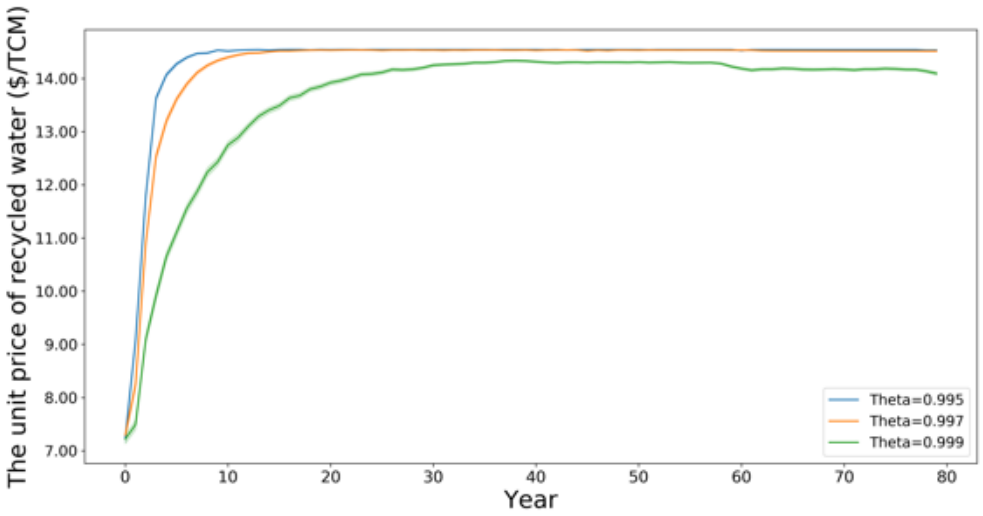
These results showed that increasing θ from 0.995 to 0.997 and 0.999 significantly impacted the manager agent's probability of taking random actions. As the θ increased, the intensity of decrease in the probability of selecting random actions decreased, increasing the time (number of episodes) taken to reach a plateau (Figure 32 (a)). The results also demonstrated that the manager agent's rewards only significantly changed when θ increased from 0.997 to 0.999. At θ = 0.999, the manager agent maximized its reward with a slower slope; however, the agent was able to reach a higher reward compared to the other two experiments (Figure 32 (b)).


Theta = 0.995
Theta = 0.997
Theta = 0.999
ε × θ
0.80
0.60
0.40
0.20
0.00
0
2000
4000
6000
8000
10000
Episode

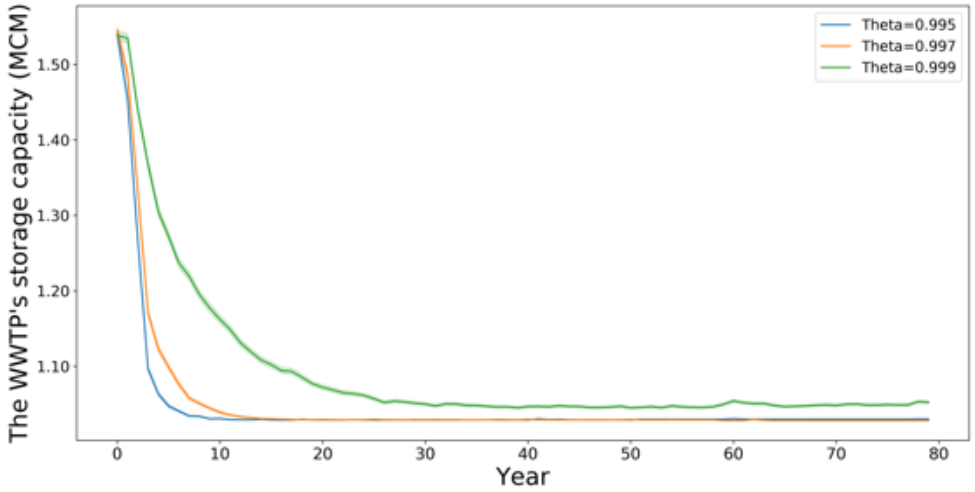
(a)


Theta=0.995
Theta=0.997
Theta=0.999
The manager agent's reward
0.10
0.05
0.00
-0.05
-0.10
-0.15
0
10
20
30
40
50
60
70
80
Year

(b)



(c)



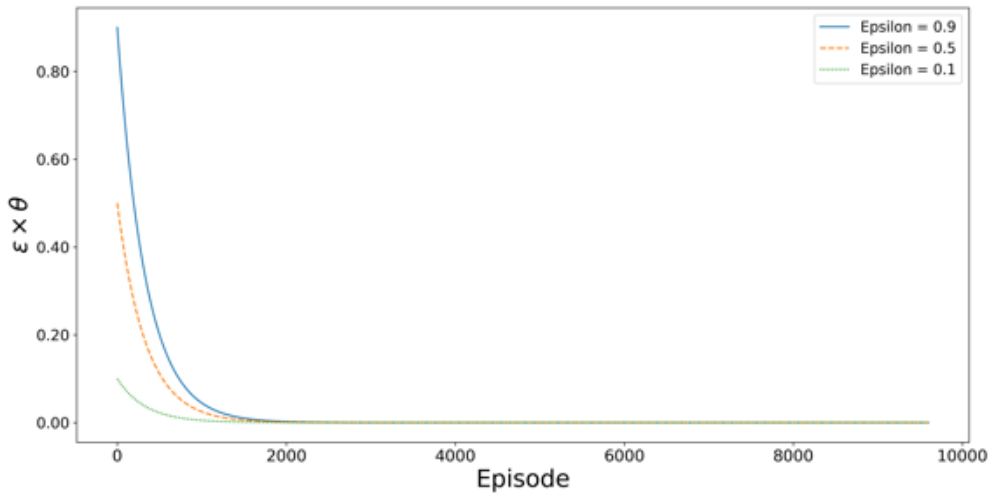
(d)

Figure 32. Results of SA for parameter θ; (a) $\varepsilon \times \theta$, (b) the manager agent's reward, (c) the unit price of recycled water ($/TCM), and (d) WWTP's storage capacity (MCM); $W_{SI} = 50$, $W_{SH} = 50$, $W_{GW} = 50$, $W_{RU} = 50$, $W_{RP} = 50$, $W_{ST} = 50$, $\theta = 0.995, 0.997, 0.999$, $\varepsilon = 0.9$, $\gamma = 0.5$, and $\alpha = 0.5$ (the 95% confidence intervals were calculated using bootstrap resampling method).

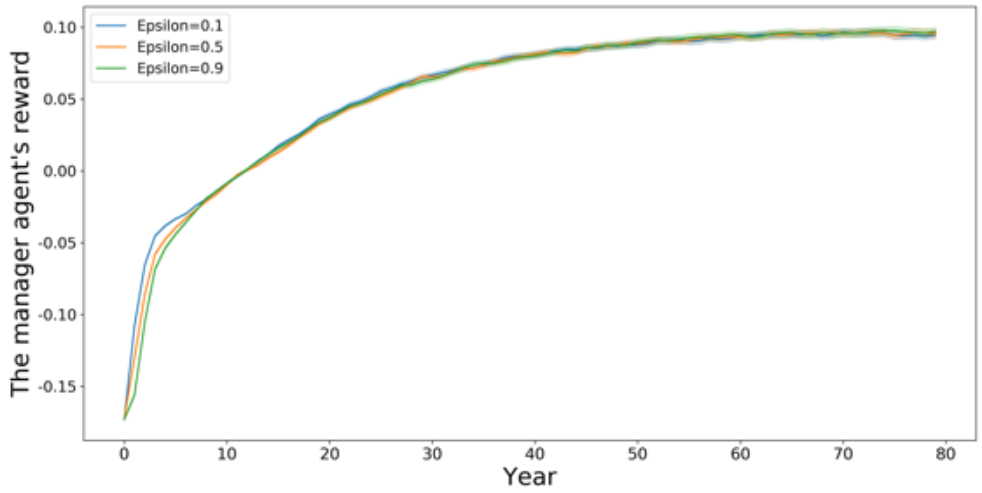
The results of SA furthermore illustrated that increasing θ could significantly change the manager agent's decision-making regarding finding the optimum values for the unit price of recycled water and the WWTP's storage capacity. Increasing θ from 0.995 to 0.997 only delayed the agent in finding the optimum values; however, increasing θ from 0.997 to 0.999 not only increased the time but also resulted in finding different optimum values (Figure 32 (c) and (d)).

These results pointed out the importance of setting θ value for finding the optimum values for the unit price of recycled water and the WWTP's storage capacity. This could be because the agent could get stuck in local optima when θ were less than 0.999, having less time to test more random points. This clearly showed the dilemma that researchers often have to deal with when working with optimization problems. Optimization algorithms sometimes can find better results if given the proper time. Researchers have to decide between finding better results with higher times or finding less optimum results with less time. The decision often depends on the resources available (e.g., time and money) and the importance of finding better results with resources spent. Researchers also should notice that specifying more time for the optimization algorithms does not guarantee better results all the time.

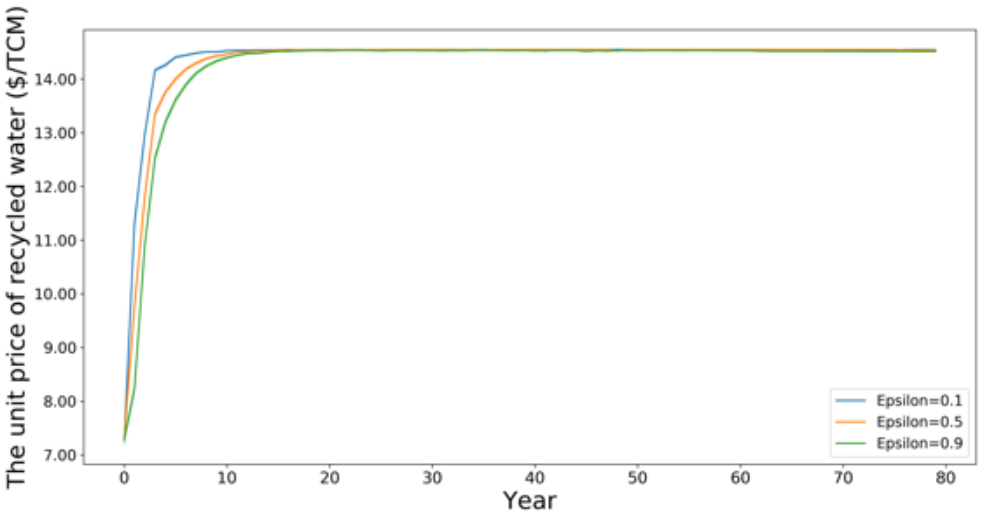
Moreover, the SA results depicted that altering ε did not significantly change the manager agent's decisions (Figure 33). The probability curves of trying random actions by the manager agent decreased with various slopes (the higher the ε, the higher the slope); however, they reached a plateau at the approximately same time and probability (Figure 33 (a)). Increasing ε from 0.1 to 0.9 did not significantly change the manager's reward, the unit price of recycled water, and the WWTP's storage capacity (Figure 33 (b), (c), and (d)). The only significant change was that the time that took the manager agent to find the optimum values for the unit price of recycled water and WWTP's storage capacity parameters were decreased from 15 to 7 years by changing ε from 0.9 to 0.1, respectively (Figure 33 (c) and (d)).



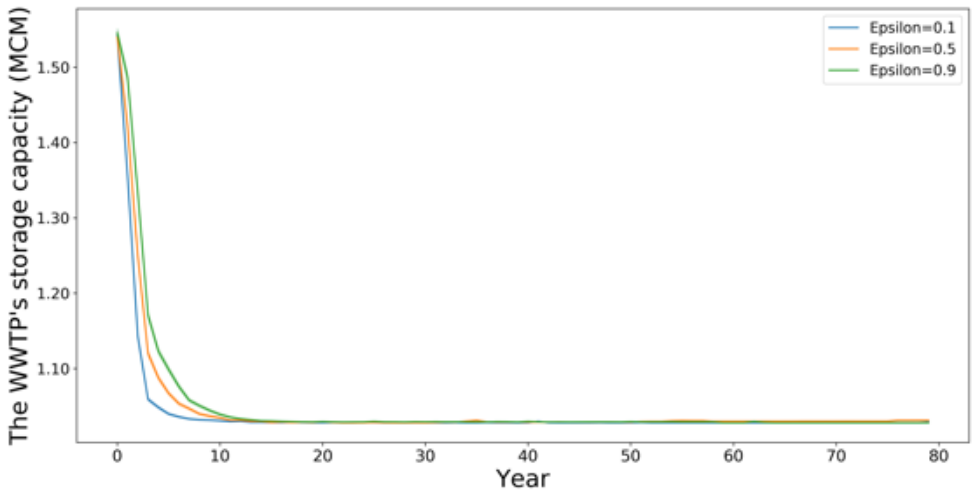
(a)


Epsilon=0.1
Epsilon=0.5
Epsilon=0.9
The manager agent's reward
0.10
0.05
0.00
-0.05
-0.10
-0.15
0
10
20
30
40
50
60
70
80
Year

(b)


The unit price of recycled water ($/TCM)
14.00
13.00
12.00
11.00
10.00
9.00
8.00
7.00
0
10
20
30
40
50
60
70
80
Year
Epsilon=0.1
Epsilon=0.5
Epsilon=0.9

(c)



(d)

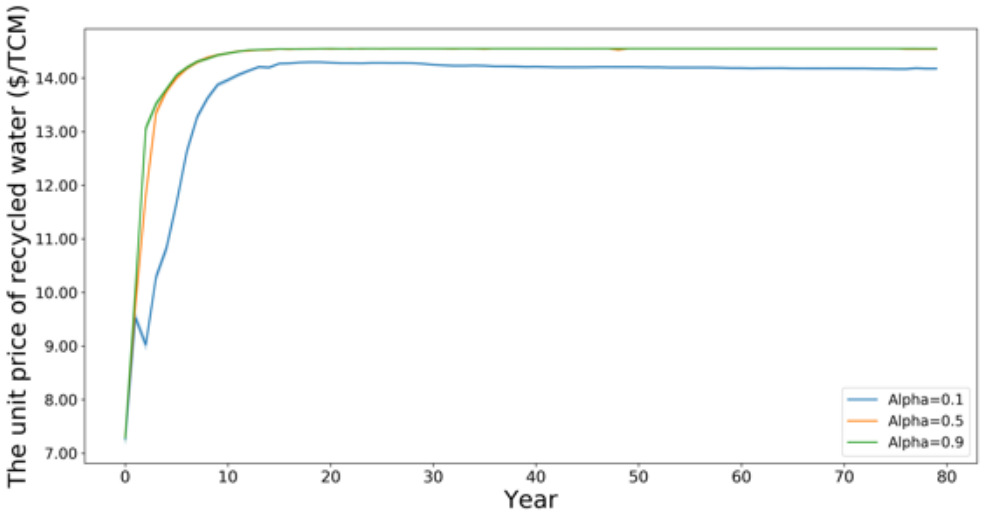
Figure 33. Results of SA for parameter ε; (a) $\varepsilon \times \theta$, (b) the manager agent's reward, (c) the unit price of recycled water ($/TCM), and (d) WWTP's storage capacity (MCM); $W_{SI} = 50$, $W_{SH} = 50$, $W_{GW} = 50$, $W_{RU} = 50$, $W_{RP} = 50$, $W_{ST} = 50$, $\theta = 0.997$, $\varepsilon = 0.1, 0.5, 0.9$, $\gamma = 0.5$, and $\alpha = 0.5$ (the 95% confidence intervals were calculated using bootstrap resampling method).

Decreasing α (i.e., learning rate or the step size) affected the manager agent's decisions significantly only when it was decreased from 0.5 to 0.1 (Figure 34 (a), (b), and (c)). As the learning rate/ the step size decreased, the manager agent tended to remember more about its past decisions and results. Thus, as the α decreased to 0.1, it took more time for the agent to reach optimal values for the unit price of recycled water and the WWTP's storage capacity. The optimal values of these parameters were also different compared with when α were 0.5 or 0.9 (Figure 34 (a) and (b)). Decreasing the α to 0.1 also increased the time needed for the agent to maximize its reward, reaching a higher reward than the other experiments (Figure 34 (c)).

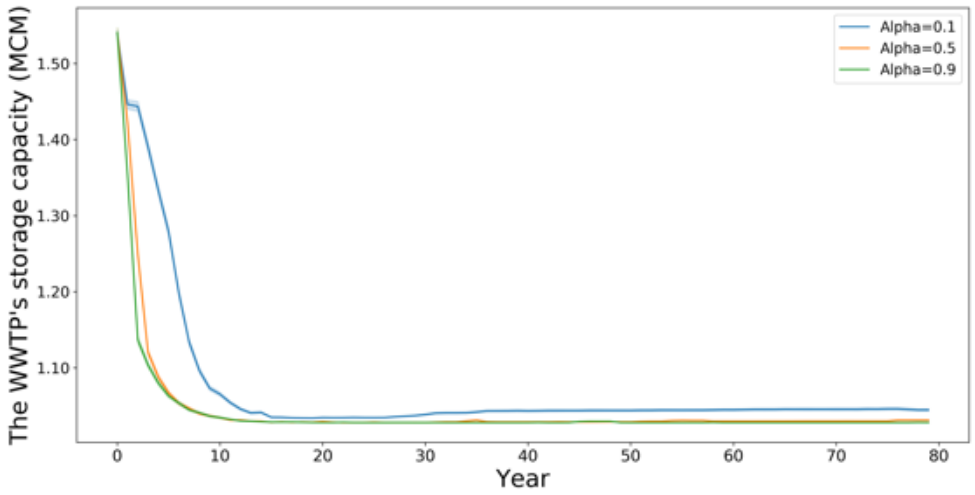
SA for γ showed inverse results compared with the SA results for α (Figure 34). By increasing γ (discount factor), the manager agent was more interested in long-term high rewards. This increased the time it took for the agent to find the optimum values for optimizing parameters and maximizing its reward. This also resulted in finding different optimum values for the unit price of recycled water and the WWTP's storage capacity and higher rewards (Figure 34 (d), (e), and (f)). Overall, the results of SA of α, γ, ε, and θ were in accordance with the principles of RL (Q-learning method) (Sutton & Barto, 2018).

Moreover, the results of SA depicted that altering the weight of groundwater consumption (W_{GW}) could significantly impact the manager agent's decisions (Figure 35 (a), (b), and (c)). According to these results, the manager agent decreased the unit price of recycled water as W_{GW} increased (Figure 35 (a)). This could be due to increasing recycled water consumption and decreasing groundwater consumption as

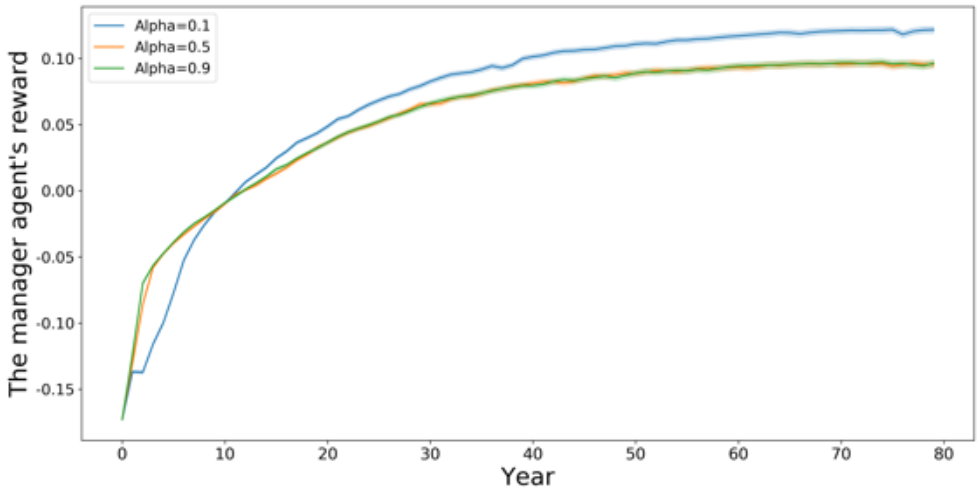
much as possible. The manager agent also increased the WWTP's storage capacity as W_{GW} increased, increasing the amount of available recycled water for farmers to use in their irrigation practices (Figure 35 (b)). The manager agent was able to maximize its rewards in all the three experiments; however, increasing W_{GW} significantly decreased its rewards. This result was acceptable according to the agent's reward function (Equation (34)). The groundwater consumption weight was input to this function with a negative multiplier to minimize the groundwater consumption. Therefore, it was logical that increasing this weight decreased the reward function. Increasing W_{GW} also increased the time needed for the manager to optimize its rewards (Figure 35 (c)).



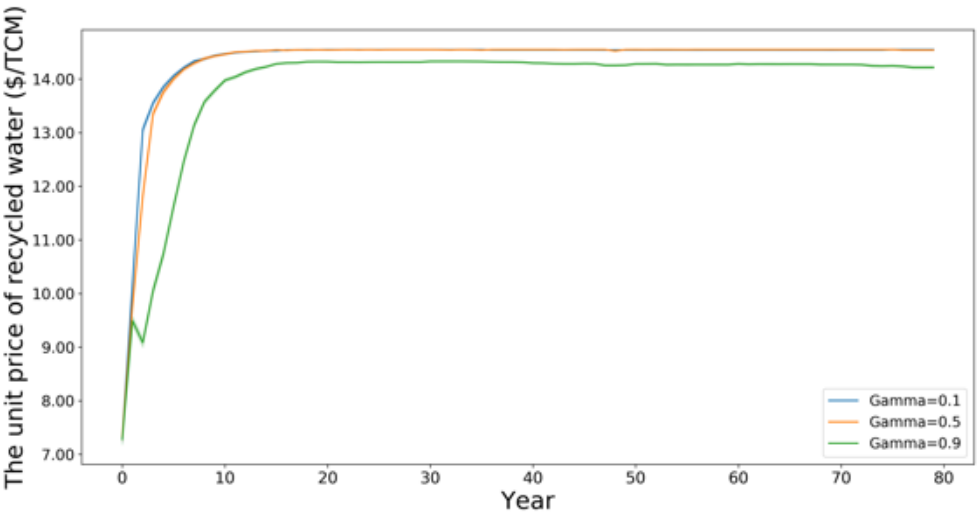
(a)



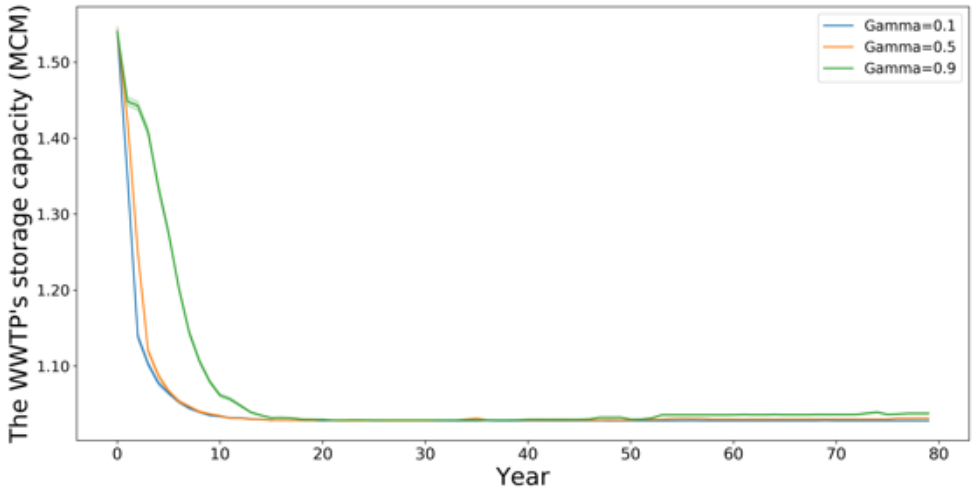
(b)


Alpha=0.1
Alpha=0.5
Alpha=0.9
The manager agent's reward
0.10
0.05
0.00
-0.05
-0.10
-0.15
0
10
20
30
40
50
60
70
80
Year

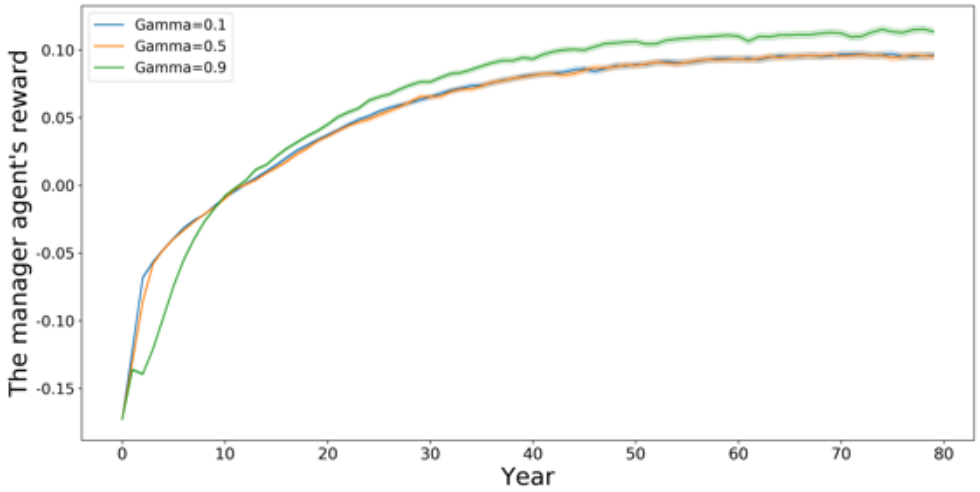
(c)


The unit price of recycled water ($/TCM)
14.00
13.00
12.00
11.00
10.00
9.00
8.00
7.00
0
10
20
30
40
50
60
70
80
Year
Gamma=0.1
Gamma=0.5
Gamma=0.9

(d)



(e)



(f)

Figure 34. Results of SA for parameters α and γ, (a) and (d) the unit price of recycled water ($/TCM); (b) and (e) WWTP's storage capacity (MCM); (c) and (f) the manager agent's reward; $W_{SI} = 50$, $W_{SH} = 50$, $W_{GW} = 50$, $W_{RU} = 50$, $W_{RP} = 50$, $W_{ST} = 50$, $\theta = 0.997$, $\varepsilon = 0.5$, $\gamma = 0.1, 0.5, 0.9$, *and* $\alpha = 0.1, 0.5, 0.9$ *(the 95% confidence intervals were calculated using bootstrap resampling method).*

Increasing the weight of recycled water users W_{RU} led to significantly decreasing the unit price of recycled water by the manager agent (Figure 35 (d)). The manager agent could decrease the unit price of recycled water to ensure more farmers use it for their irrigation. The manager agent also increased the WWTP's storage capacity significantly as W_{RU} increased, making sure enough recycled water would be available for an increasing number of recycled water users (Figure 35 (e)). Increasing

W_{RU} from one to 50 resulted in a much higher increase in the manager agent's reward than when it was increased from 50 to 100 (Figure 35 (f)). In all the experiments, the manager could maximize its reward. The time it took the manager agent to increase its reward to reach a plateau also increased as the W_{RU} increased (Figure 35 (f)).

Results of SA on the weight of recycled water unit price illustrated that increasing the weight of recycled water unit price (W_{RP}) from 50 to 100 increased the unit price of recycled water the manager agent selected (Figure 35 (g)). However, decreasing W_{RP} from 50 to 1 led to increasing the unit price of recycled water by the manager agent. This could be due to the effects of the unit price of recycled water on the other parameters and the fact that setting W_{RP}= 1 equalized the importance of all objectives for the manager agent. SA results in our previous study showed that the unit price of recycled water had a significant impact on farmers' SI and groundwater consumption; SA results in this study also depicted that decreasing the unit price of recycled water could increase the number of recycled water users (Figure 35 (d)). Therefore, as the manager agent increased the unit price of recycled water, those objectives that the agent tried to maximize (i.e., SI and RU) decreased.

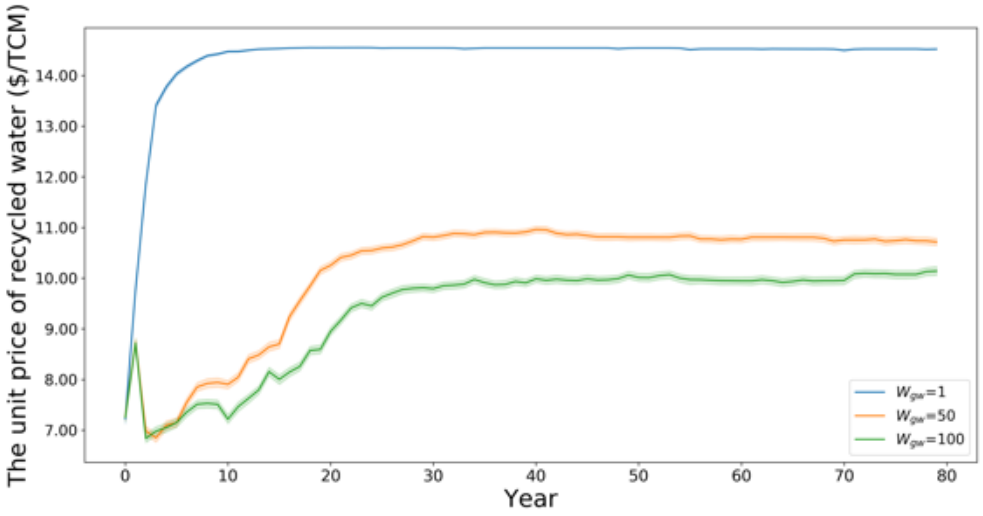
On the other hand, increasing the unit price of recycled water increased those objectives (i.e., GW) that the agent tried to minimize. Thus, when all the weights were equal, the manager agent had to substantially increase the unit price of recycled water to maximize its reward, negating the other objectives opposing effects on its reward. However, in the case where W_{RP} was set to 50 or 100, the effect of W_{RP} could outweigh the other objectives opposing effects. These results furthermore showed that when W_{RP} was increased from 50 to 100, the manager agent decreased the WWTP's storage capacity as there would be fewer recycled water users, trying to maximize its reward (Figure 35 (h)). On the other hand, the manager agent had to substantially decrease the WWTP's storage capacity when W_{RP} was set to one, decreasing the minimizing effects of WWTP's storage capacity on its reward. The SA results on the manager agent also demonstrated that the agent could maximize its rewards in all experiments. However, it took more time for the manager to maximize its rewards when all its weights were equal, reaching a significantly lower reward than when W_{RP} was set to 50 or 100 (Figure 35 (i)).

Increasing the weight of farmers' SI decreased the unit price of recycled water and increased the WWTP's storage capacity significantly (Figure 36 (a) and (b)). As mentioned above, the unit price of recycled water significantly affected the farmer's SI; thus, the manager agent increased the unit price of recycled water as the SI weight increased. The agent also increased the WWTP's storage capacity as the SI weight increased to ensure enough recycled water was available for the increasing number of recycled water users. Increasing W_{SI} from one to 50 significantly increased the manager agent's rewards (Figure 36 (c)). On the contrary, increasing W_{SI} from 50 to 100 had no significant change on the manager's rewards.

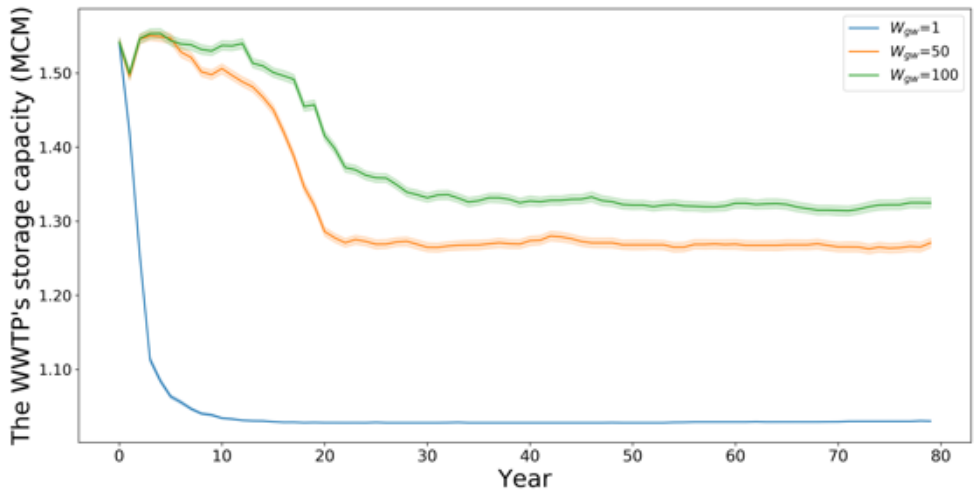
Results of SA on the weight of WWTP's storage capacity (W_{ST}) illustrated that it had a significant effect on the unit price of recycled water selected by the manager agent

in some years (Figure 36 (d)). From years 0-15, the manager agent sharply increased the unit price of recycled water until it reached a plateau around year 15 when $W_{ST} = 1$. However, it fluctuated from the start till year five, then abruptly increased till it reached its plateau approximately around year 15 when W_{ST} was equal to 50 and 100. There were no significant differences between years 15 to 25, after which the results showed that the manager agent tended to select lower unit prices of recycled water as W_{ST} increased. The manager agent could make this decision to optimize the other objectives, maximizing its reward.

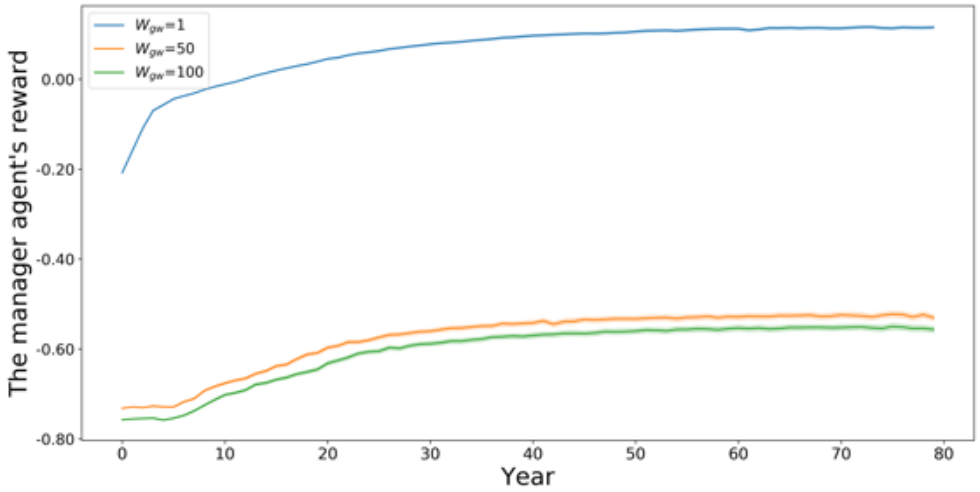
Altering W_{ST} from 1 to 50 and 100 only affected the WWTP's storage capacity significantly before year 15 (Figure 36 (e)). During this time, the manager agent decreased the WWTP's storage capacity with a lower slope when the weight was equal to 50 and 100 compared to when it was equal to one. Of note was that no significant change was observed when W_{ST} was equal to 50 or 100. After year 15 to the end, the manager agent was able to find the minimum value for the WWTP's storage capacity with no significant difference between the three experiments. The agent also maximized its rewards in all experiments with significant differences between them (Figure 36 (f)). As W_{ST} increased, the manager's rewards decreased. The decrease was significantly higher when W_{ST} increased from 1 to 50 compared to when it was increased from 50 to 100.



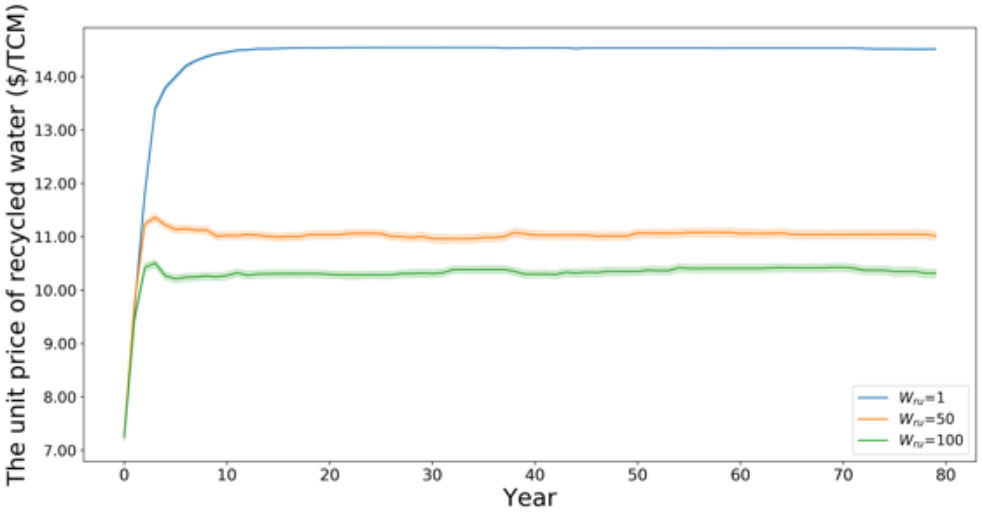
(a)


The WWTP's storage capacity (MCM)
1.50
1.40
1.30
1.20
1.10
0
10
20
30
40
50
60
70
80
Year
W_{gw}=1
W_{gw}=50
W_{gw}=100

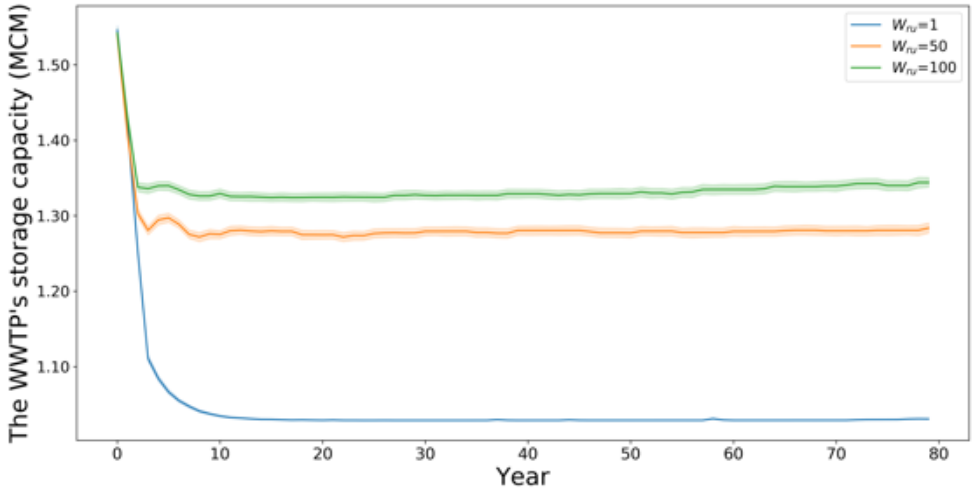
(b)


The manager agent's reward
0.00
-0.20
-0.40
-0.60
-0.80
0
10
20
30
40
50
60
70
80
Year
W_{gw}=1
W_{gw}=50
W_{gw}=100

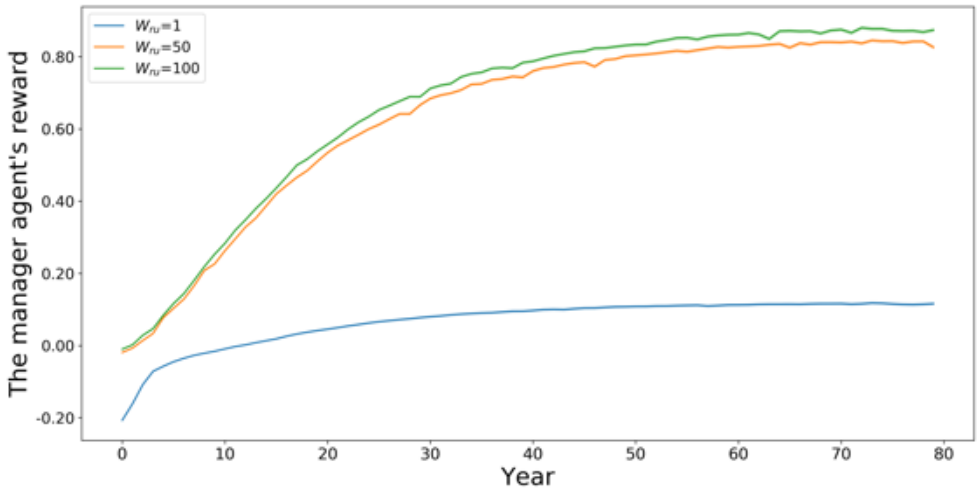
(c)


The unit price of recycled water ($/TCM)
14.00
13.00
12.00
11.00
10.00
9.00
8.00
7.00
0
10
20
30
40
50
60
70
80
Year
W_{ru}=1
W_{ru}=50
W_{ru}=100

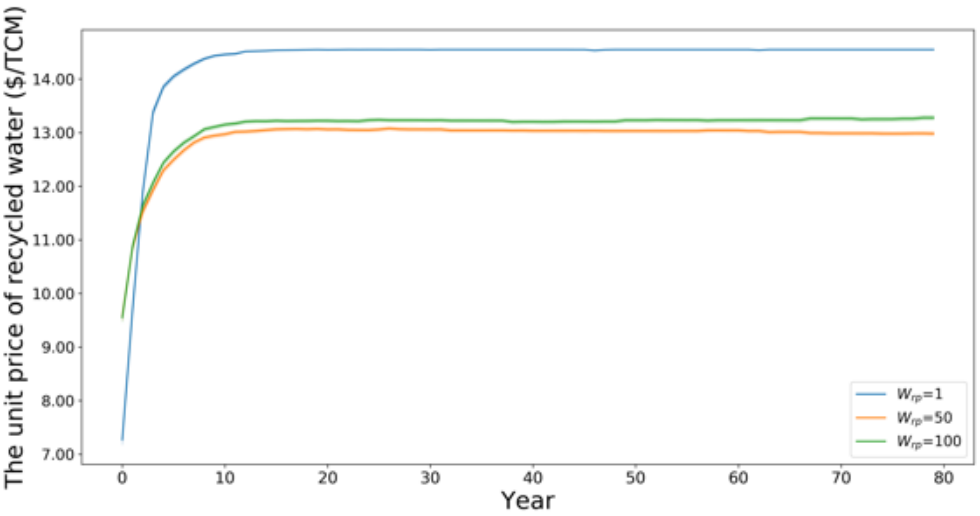
(d)


The WWTP's storage capacity (MCM)
1.50
1.40
1.30
1.20
1.10
0
10
20
30
40
50
60
70
80
Year
W_{ru}=1
W_{ru}=50
W_{ru}=100

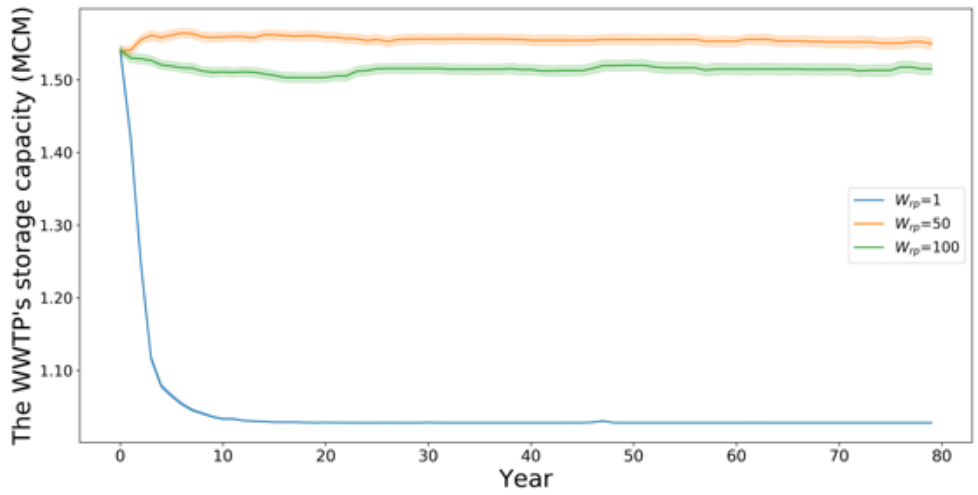
(e)


W_{ru}=1
W_{ru}=50
W_{ru}=100
The manager agent's reward
0.80
0.60
0.40
0.20
0.00
-0.20
0
10
20
30
40
50
60
70
80
Year

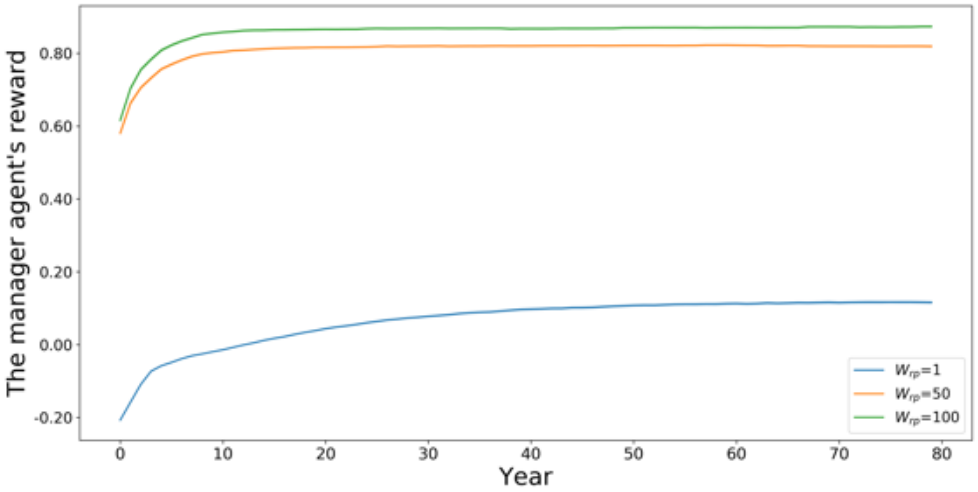
(f)


The unit price of recycled water ($/TCM)
14.00
13.00
12.00
11.00
10.00
9.00
8.00
7.00
0
10
20
30
40
50
60
70
80
Year
W_{rp}=1
W_{rp}=50
W_{rp}=100

(g)

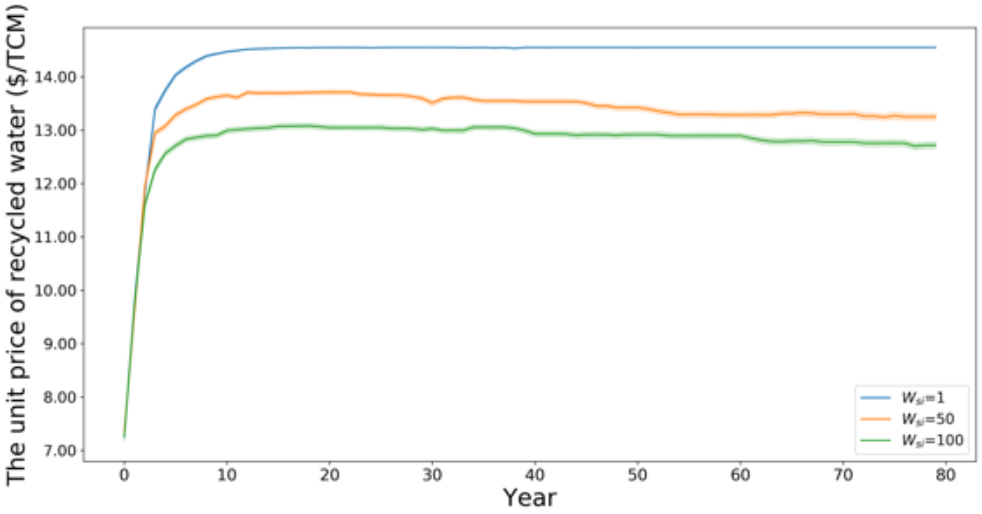


(h)

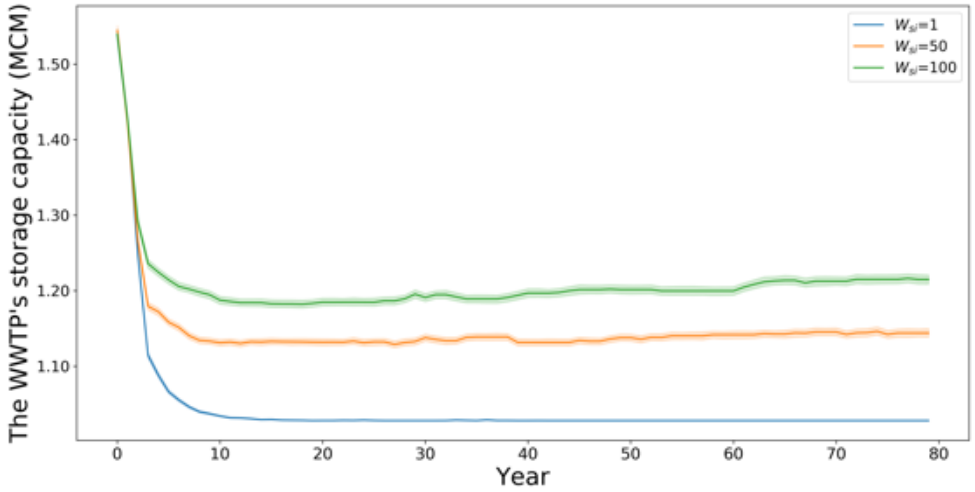


(i)

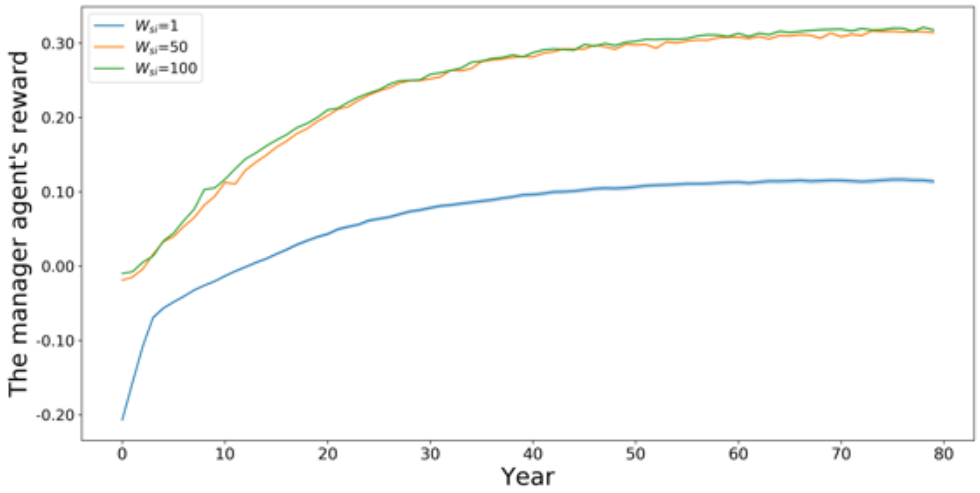
Figure 35. Results of SA for parameters W_{GW}, W_{RU} and W_{RP}, (a), (d), and (g) the unit price of recycled water ($/TCM); (b), (e), and (h) WWTP's storage capacity (MCM); (c), (f), and (i) the manager agent's reward; $W_{SI} = 1$, $W_{GW} = 1, 50, 100$, $W_{RU} = 1, 50, 100$, $W_{RP} = 1, 50, 100$, $W_{ST} = 1$, $\theta = 0.997$, $\varepsilon = 0.5$, $\gamma = 0.5$ and $\alpha = 0.5$ (the 95% confidence intervals were calculated using bootstrap resampling method).


The unit price of recycled water ($/TCM)
14.00
13.00
12.00
11.00
10.00
9.00
8.00
7.00
0
10
20
30
40
50
60
70
80
Year
W_{SI}=1
W_{SI}=50
W_{SI}=100

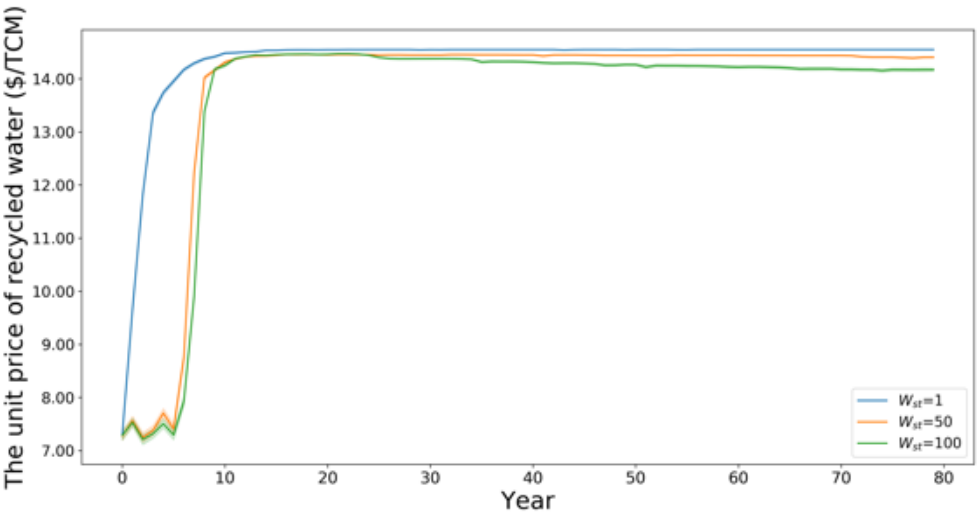
(a)


The WWTP's storage capacity (MCM)
1.50
1.40
1.30
1.20
1.10
0
10
20
30
40
50
60
70
80
Year
W_{SI}=1
W_{SI}=50
W_{SI}=100

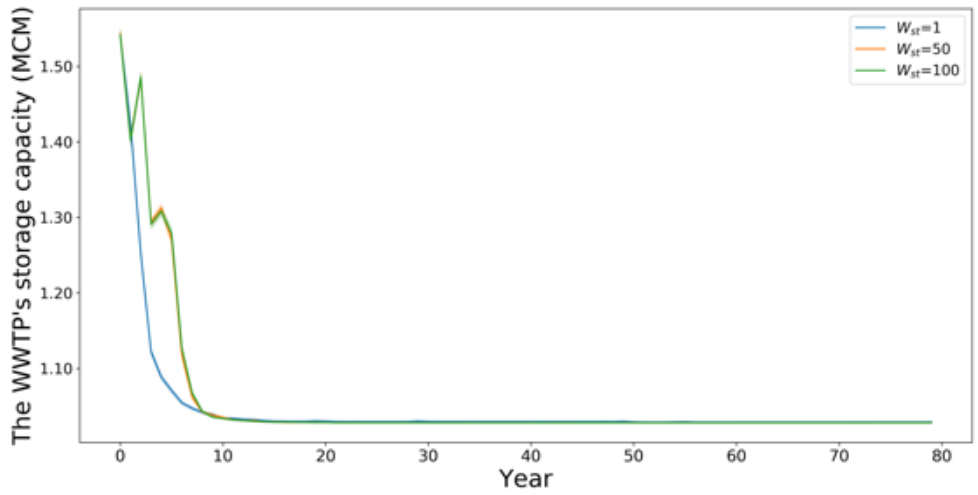
(b)


W_{st}=1
W_{st}=50
W_{st}=100
The manager agent's reward
0.30
0.20
0.10
0.00
-0.10
-0.20
0
10
20
30
40
50
60
70
80
Year

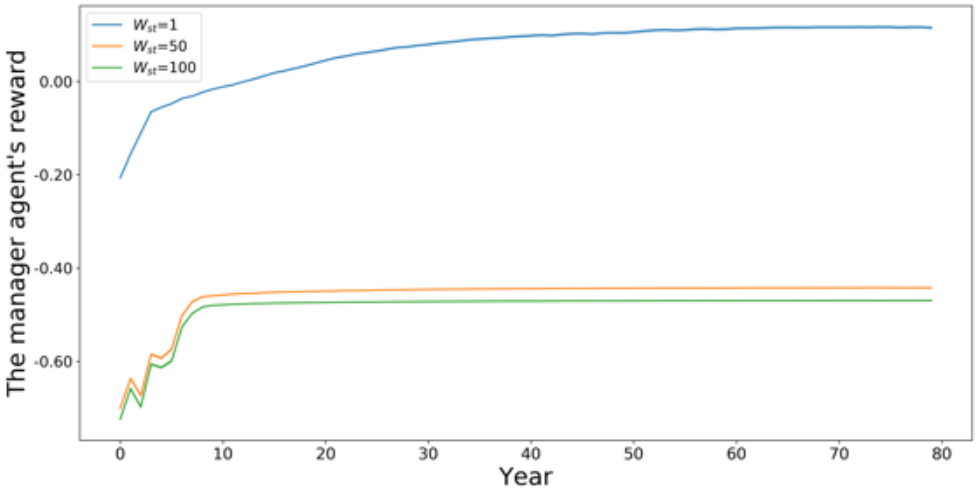
(c)


The unit price of recycled water ($/TCM)
14.00
13.00
12.00
11.00
10.00
9.00
8.00
7.00
0
10
20
30
40
50
60
70
80
Year
W_{st}=1
W_{st}=50
W_{st}=100

(d)



(e)



(f)

Figure 36. Results of SA for parameters W_{SI} and W_{ST}, (a), (d) the unit price of recycled water ($/CM), (b) and (e) WWTP's storage capacity (MCM), (c) and (f) the manager agent's reward; $W_{SI} = 0, 50, 100$, $W_{SH} = 50$, $W_{GW} = 50$, $W_{RU} = 50$, $W_{RP} = 50$, $W_{ST} = 0, 50, 100$, $\theta = 0.997$, $\varepsilon = 0.2$, $\gamma = 0.5$, and $\alpha = 0.5$ (the 95% confidence intervals were calculated using bootstrap resampling method).

6.3.2. Results of scenario analysis

Under scenario I, there were no limitations on the availability of water resources (groundwater and surface water) for farmers to use in their irrigation practices. Therefore, the ultimate goal of the manager agent was to set suitable values for C and

D to facilitate the introduction of recycled water into the portfolio of water supplies in the study area so that it could successfully substitute a part of groundwater consumption, optimizing its objectives.

In general, the agent could successfully decrease farmers' groundwater consumption and maintain their SI (Figure 37). The manager agent steeply increased C in the early years, maximizing the unit price of recycled water (Figure 37 (a)). In June, parameter C was dramatically raised from 7.3 $/TCM to approximately 12 $/TCM in the first 15 years, maintaining it approximately the same until year 45. Starting from year 45, the manager agent steadily raised C to 12.3 $/TCM until year 80 (Figure 37 (a)). The agent did almost the same in the first 15 years during July and August, sharply increasing C, however, to a higher unit price (approximately 13 $/TCM). The agent maintained C stable until approximately year 35, then moderately jumped it to 13.5 $/TCM over the next 45 years in July. C stayed approximately constant at 13 $/TCM in August until the end of simulations. On the other hand, September was the only month during which the agent could not maintain an approximate maximum for C. After rapidly rocketing to approximately 14 $/TCH during the first seven years, C considerably fluttered between 11 and 14 $/TCH. First, it was dropped from 14 to 11 $/TCH until approximately year 35; then, it substantially went up to almost 14 $/TCH until the end of the simulations (Figure 37 (a)).

In simulations, the manager agent could also minimize the WWTP's storage capacity (Figure 37 (b)). In June, D was dramatically dropped from approximately 1.55 MCM to 1.35 MCM over the first 15 years, continuing with the same value for 30 years then gradually decreasing to approximately 1.32 MCM till the end of simulations. The agent also decreased D in July and August during the first 15 years, however, with a lower slope than in June. In July, D fell from 1.55 MCM to 1.46 MCM in approximately the first 15 years, staying stable until year 35, when it was slowly increased to almost 1.5 MCM until year 80. D declined with a lower speed in August than July, where it reached 1.44 MCM over the first 15 years, remaining approximately constant until the end of simulations. However, D significantly zig-zagged during September. The WWTP's storage capacity first plummeted from 1.55 MCM to almost 1.32 MCM during the first 15 years in September, then increased to 1.47 MCM until year 40 and plunged to approximately 1.13 MCM until the end of simulations (Figure 37 (b)).

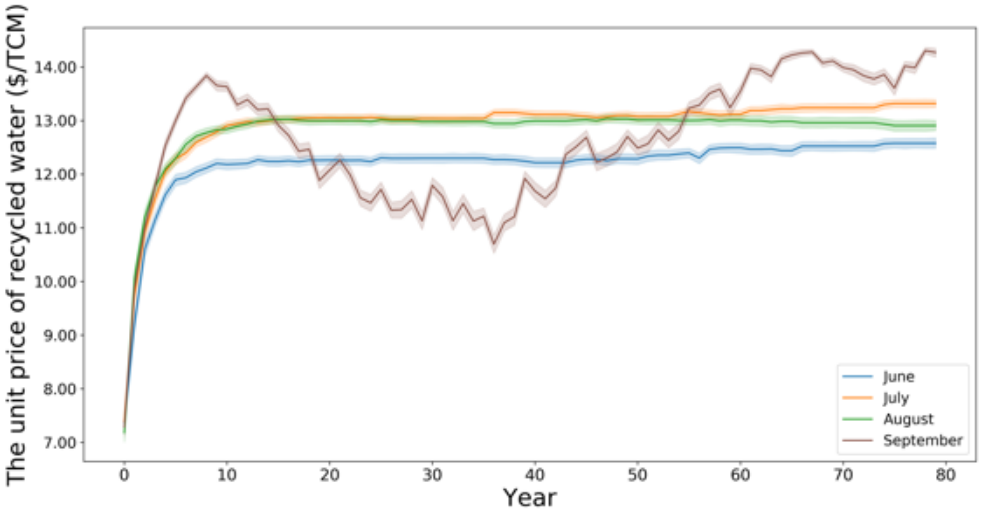
The agent could successfully maximize its rewards in all the months (Figure 37 (c)). In June, this curve started its rising with a high slope, decreasing it over time as the simulations went on. The manager agent's rewards quickly stabilized in July and August, with lower rewards than June. On the other hand, the agent's rewards in September first dropped until year 15, continuing with the same amount until it went up from year 35 to reach its maximum around year 65. In June, the farmers' total yearly groundwater consumption was decreased from 1.24 to 0.04 MCM (94.4%) over the 80 years (Figure 37 (d)). Gradual declines were observed in July and August when the farmers' total yearly groundwater consumption slowly dropped from 12.5 to 12.4 (0.8%) and from 12.8 to 12.7 MCM (0.8%), respectively. The manager agent

significantly decreased the farmers' total yearly groundwater consumption from 5.1 to 3.6 MCM (29.4%) over the 80 years of simulations in September.

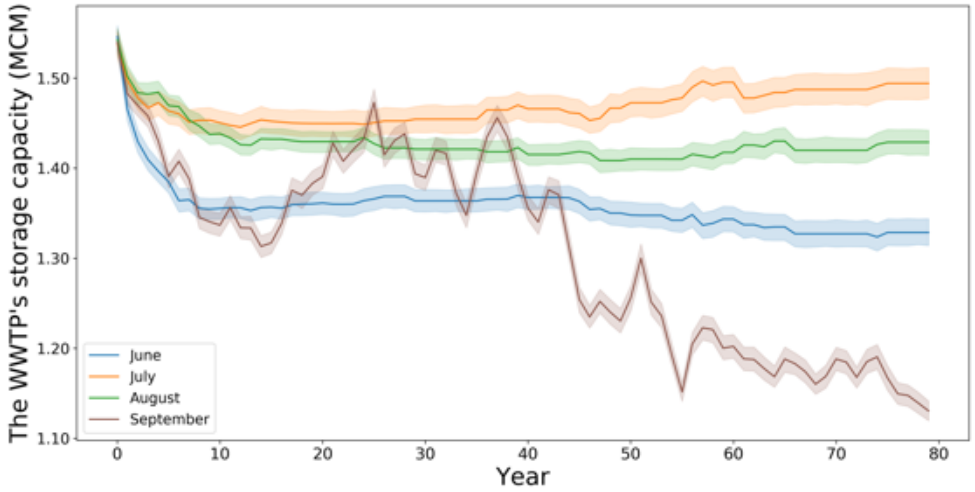
Moreover, the manager agent was able to manage the project successfully so that farmers' SI remained constant (one) even after introducing recycled water into their water supplies portfolio (Figure 37 (e)). The scenario analysis results further depicted that the number of farmers who used recycled water for their irrigation practices had an increasing trend during June and September (Figure 37 (f)). However, the number of recycled water users (mean) fluctuated between zero and four during July and August.

Our previous work (Chapter 5) showed that recycled water consumption jumped from the beginning and reached a plateau at approximately year 15, while farmers increasingly adopted agricultural water reuse until the end of simulations. The results of this study depicted trends in accordance with our previous study (Chapter 5). The manager agent could successfully increase and decrease the unit price of recycled water and the WWTP's storage capacity, respectively, during the time it was used increasingly by farmers (Figure 37 (a) and (b)). However, as the recycled water consumption reached its maximum (around year 15), the agent had to stop the increase and decrease in C and D, respectively. Of note was that as the farmers' irrigation need was lower in June compared to July and August, the maximum and minimum of C and D were lower, respectively. Also, as the number of recycled water users went up, the agent could increase and decrease C and D in June after year 45.

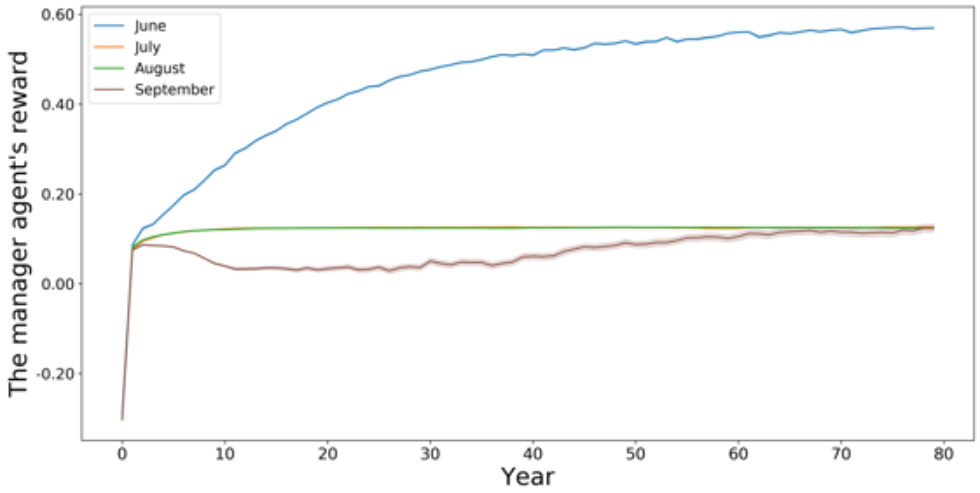
The agent had to increase D in July and August as the farmers' irrigation needs were significantly higher than June to provide enough recycled water to farmers, maximizing its rewards. Under this scenario in September, the agent's rewards decreased first, then it could stabilize and maximize it after years 10 and 35, respectively. The reason behind this behavior could be the random actions chosen by the agent manager. As time went on and the probability of taking random actions decreased, the agent could bounce back its rewards by first stabilizing it and then raising it to values previously taken in July and August.


The unit price of recycled water ($/TCM)
14.00
13.00
12.00
11.00
10.00
9.00
8.00
7.00
0
10
20
30
40
50
60
70
80
Year
June
July
August
September

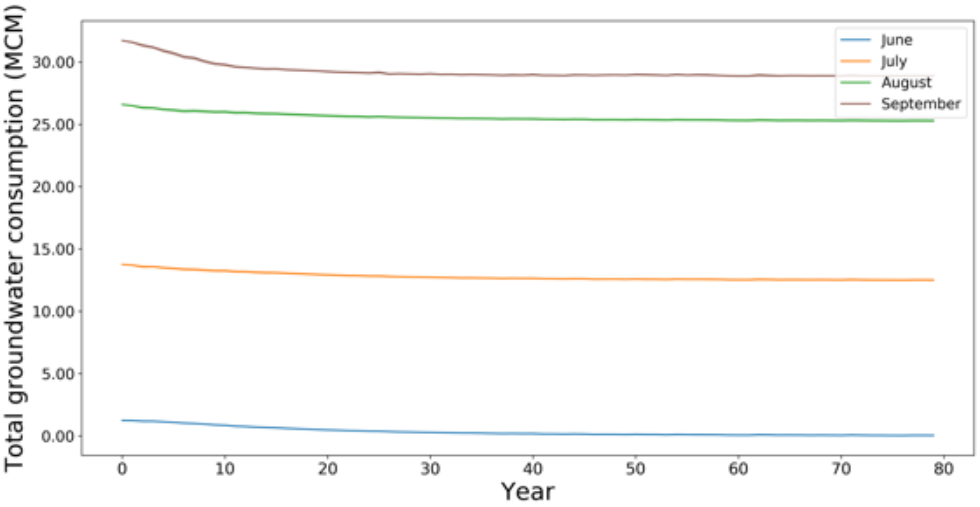
(a)


The WWTP's storage capacity (MCM)
1.50
1.40
1.30
1.20
1.10
0
10
20
30
40
50
60
70
80
Year
June
July
August
September

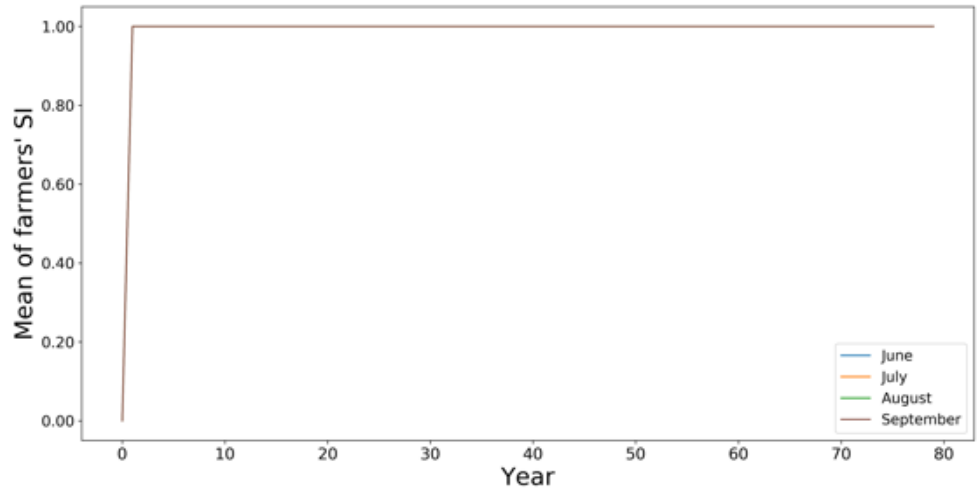
(b)


June
July
August
September
The manager agent's reward
0.60
0.40
0.20
0.00
-0.20
0
10
20
30
40
50
60
70
80
Year

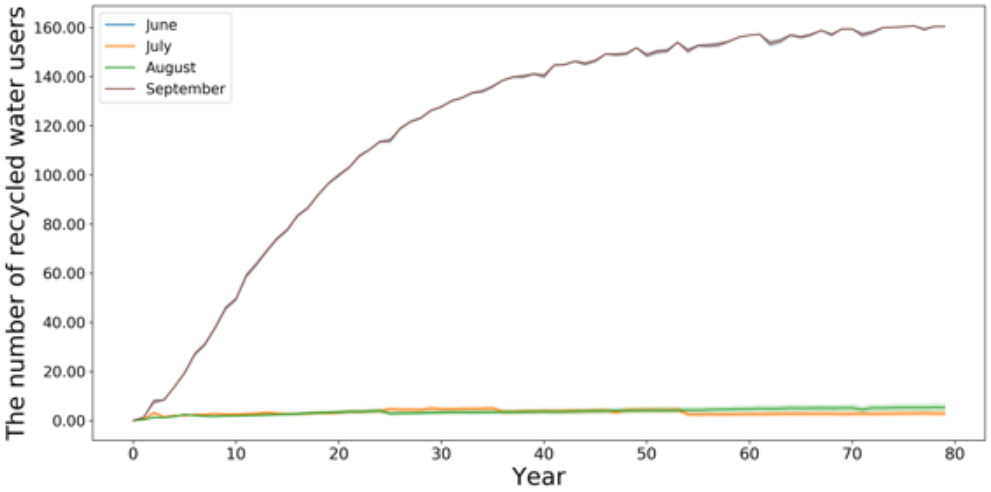
(c)


June
July
August
September
Total groundwater consumption (MCM)
30.00
25.00
20.00
15.00
10.00
5.00
0.00
0
10
20
30
40
50
60
70
80
Year

(d)



(e)



(f)

Figure 37. Results of scenario analysis (I), (a) the unit price of recycled water ($/CM), (b) WWTP's storage capacity (MCM), (c) the manager agent's reward, (d) total yearly groundwater consumption (cumulative), (e) mean of farmers' SI, and (f) the number of recycled water users (the 95% confidence intervals were calculated using bootstrap resampling method).

Furthermore, the low number of recycled water users in July and August illustrated that the available recycled water was not enough to supply more than five farmers in these months. This could be due to the high volume of farmers' irrigation needs in those two months. Putting specific caps on each farmer's recycled water use may increase the number of recycled water users in these months, increasing the equity in the study area. However, further study should be done regarding this as water rights is

one of the challenging aspects of agricultural water reuse projects (Shoushtarian & Negahban-Azar, 2020). In this case, as the assumption was that the WWTP prioritized farmers based on their distance, those four farmers closest to the WWTP used all the produced recycled water by the WWTP in July and August.

Under scenario II, the manager agent could successfully manage the agricultural water reuse project by maximizing C and its rewards and minimizing D (Figure 38). In June, July, and August, the unit price of recycled water and the WWTP's storage capacity sharply climbed and fell to approximately 14.6 $/TCM and 1.03 MCM over the first 15 years and remained almost stable afterward, respectively (Figure 38 (a) and (b)). On the other hand, in September, the manager agent steeply raised C to approximately 14 $/TCH in the first 15 years; the agent had to fluctuate C between 13.5 and 14 $/TCH until year 40. C approximately maintained stable over the next 20 years when it fluctuated again with an overall gradual decreasing trend until the end of simulations. D showed the opposite results compared to C by rapidly decreasing to almost 1.1 MCM over the first 15 years, fluctuating between 1.1 and 1.2 MCM until year 40, remaining almost stable over the next 20 years, and then fluctuating again with an overall gradual increasing trend until year 80 (Figure 38 (b)).

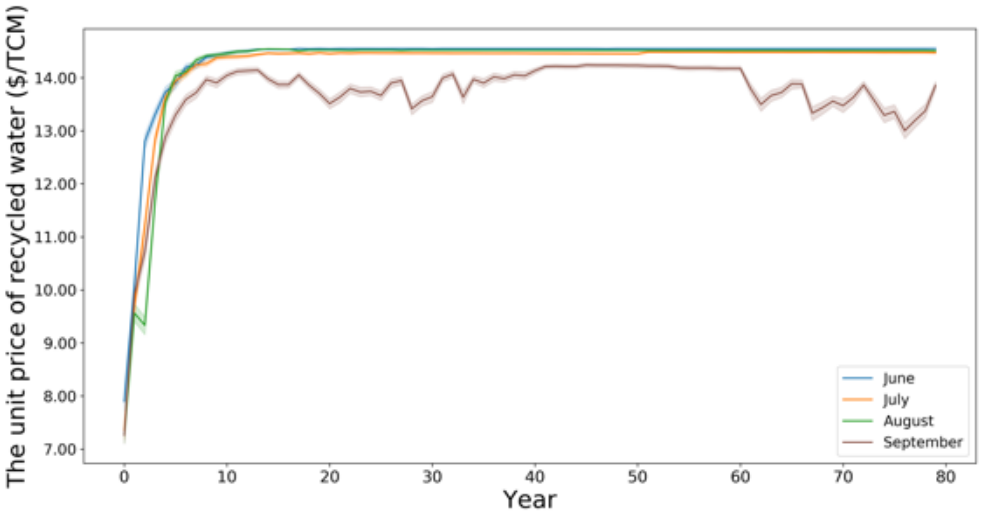
The agent was also able to maximize its rewards in all months (Figure 38 (c)). The manager reached its highest and lowest rewards in June and August, respectively. This could be due to the farmers' irrigation needs in these months, as August and June had the most and the least irrigation needs in this study. Farmers' total yearly groundwater consumption was decreased from 0.45 to 0.02 MCM (95.6%) in June, from 6.95 to 5.82 MCM (16.3%) in July, and from 2.86 to 1.90 MCM (33.6%) in September. Of note was that the groundwater consumption was increased in August from 8.60 to 8.79 MCM (2.2%; Figure 38 (d)). The mean of farmers' SI considerably went up from zero to over 0.4 and reached a plateau near year 40 in all months (Figure 38 (e)). Moreover, in June and September, the number of farmers who used the recycled water significantly increased during the whole time of simulations (Figure 38 (f)). This number in July increased with a slower slope than in the other two months and had a sharp decrease point in year 40, rising with a much slower rate afterward. In August, the number of recycled water users fluctuated between zero and four, reaching 20 between years 40 to 60.

Conforming with the results of our previous study (Chapter 5), the results of this study depicted that the manager agent could maximize and minimize C and D, respectively, until about year 15 when the recycled water consumption reached its maximum (Figure 38 (a)). Fluctuations observed in C and D in September after year 15 could be since most of the available recycled water was consumed by farmers in the previous months, especially in July and August. Therefore, less available recycled water forced the manager agent to look for optimum values for C and D by altering them continuously, maximizing its rewards.

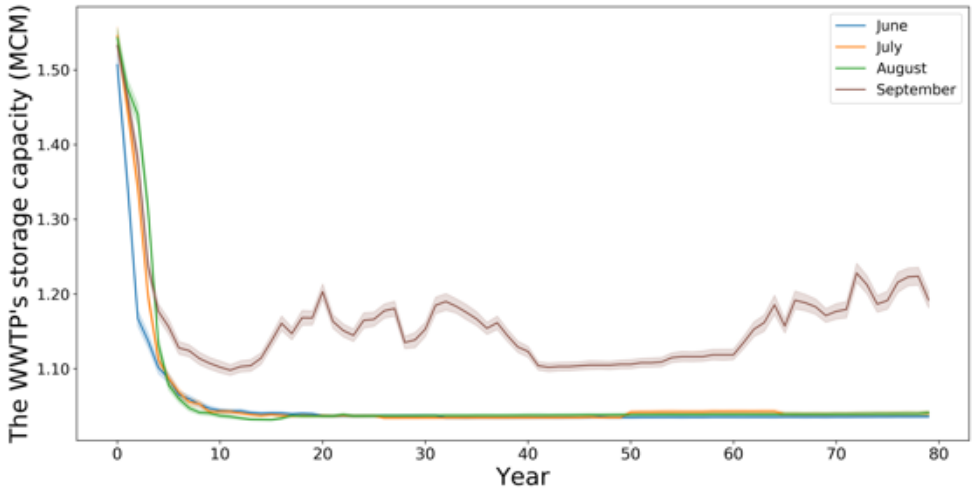
Of note was the period (between years 40 and 60) that the agent kept C and D approximately steady in September (Figure 38 (a) and (b)). As our previous study

(Chapter 5) showed, under RCP 2.6, this period was when the farmers' irrigation needs decreased significantly due to climate change effects. As the results of groundwater consumption depicted (Figure 38 (d)), climate change effects did not significantly impact farmers' groundwater consumption in June. On the other hand, during years 40 and 60 in July, farmers' groundwater consumption increased; however, it was decreased in August and September. Accordingly, the manager agent could quickly maximize its rewards by stabilizing C and D at their maximum and minimum values, respectively.

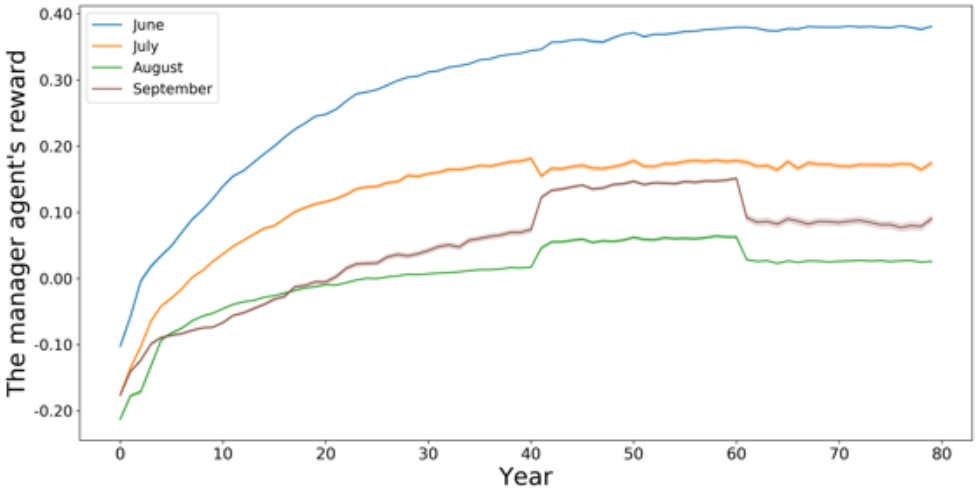
Other curves clearly demonstrated how this period decreased farmers' groundwater consumption. Thus, the agent's rewards and mean of farmers' SI had a sudden jump over this period. Of note was that, after year 40, farmers' groundwater consumption increased, number of recycled water users sharply decreased, resulting in a sudden fall in the managers' rewards. It should also be noted that the number of recycled water consumers in August increased over this period as their irrigation needs were less, thus more farmers could successfully use the recycled water for their irrigation practices (Figure 38 (f)).



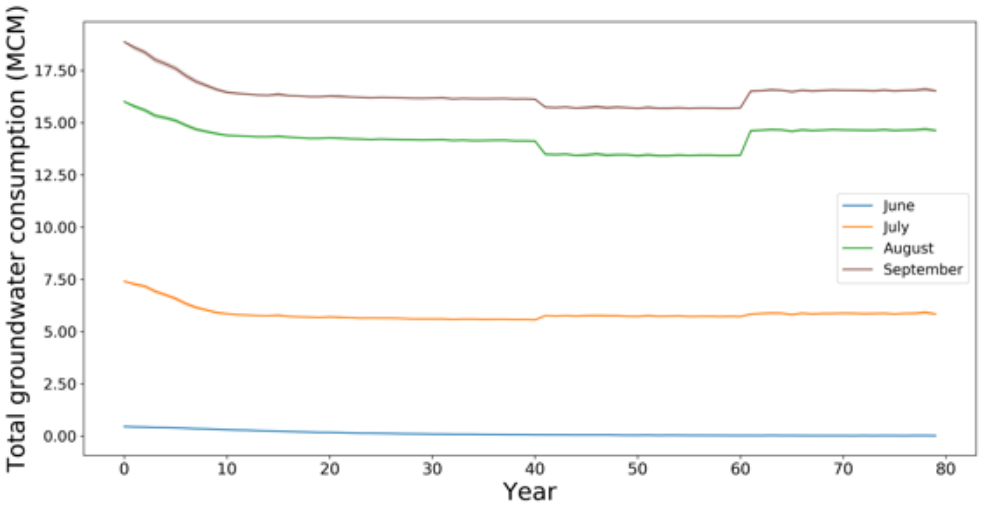
(a)


June
July
August
September
The WWTP's storage capacity (MCM)
1.50
1.40
1.30
1.20
1.10
0
10
20
30
40
50
60
70
80
Year

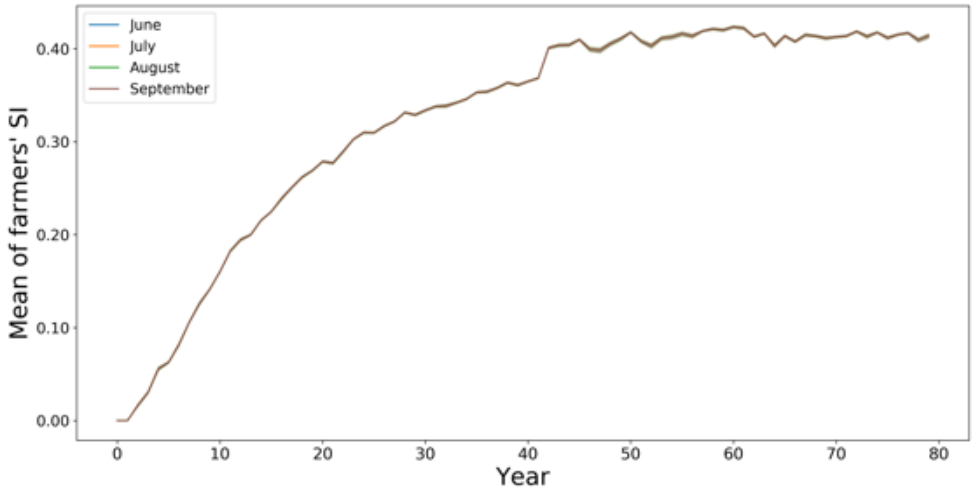
(b)


June
July
August
September
The manager agent's reward
0.40
0.30
0.20
0.10
0.00
-0.10
-0.20
0
10
20
30
40
50
60
70
80
Year

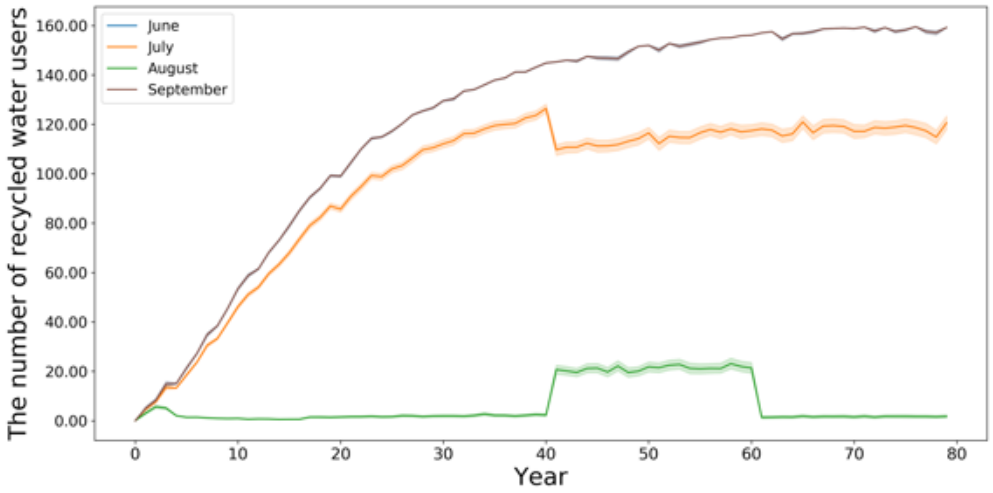
(c)


Total groundwater consumption (MCM)
17.50
15.00
12.50
10.00
7.50
5.00
2.50
0.00
0
10
20
30
40
50
60
70
80
Year
June
July
August
September

(d)


Mean of farmers' SI
0.40
0.30
0.20
0.10
0.00
0
10
20
30
40
50
60
70
80
Year
June
July
August
September

(e)



(f)

Figure 38. Results of scenario analysis (II), (a) the unit price of recycled water ($/CM), (b) WWTP's storage capacity (MCM), (c) the manager agent's reward, (d) total yearly groundwater consumption, (e) mean of farmers' SI, and (f) the number of recycled water users (the 95% confidence intervals were calculated using bootstrap resampling method).

Figure 39 and Figure 40 depicted the results of simulations under scenarios III and IV. Benefiting from RL, the manager agent optimized the unit price of recycled water and the WWTP's storage capacity to sustainably manage the agricultural water reuse project under these two climate change scenarios. Due to climate change projections, our previous work (Chapter 5) showed that farmers' groundwater consumption fluctuations were more severe in scenarios III and IV than in scenario II. However, the agent successfully adapted its decisions accordingly, maximizing its rewards (Figure 39 and Figure 40).

In June, as the farmers' irrigation needs were relatively lower than the other months, under scenarios III and IV, the manager agent could successfully maximize and minimize C and D, respectively (Figure 39 and Figure 40 (a) and (b)). Over the first 15 years, while the recycled water consumption increased, the agent significantly jumped and decreased C and D to almost 14.6 $/TCH and 1.03 MCM and maintained them approximately constant under both scenarios, respectively. During this month (under both scenarios), the manager agent's rewards, mean of farmers' SI, and the number of farmers who used recycled water depicted increasing trends with decreasing slopes over time (Figure 39 and Figure 40 (c), (e), and (f)). Under scenario IV, the mean of farmers' SI showed a quick jump near year 60 due to the manager agent's sudden decrease and increase in C and D. Farmers' total yearly groundwater consumption in June dropped from 0.69 to 0.04 MCM (94.2%) and from 0.50 to 0.04 MCM (92%) under scenarios III and IV, respectively (Figure 39 and Figure 40 (d)).

While farmers' irrigation demands were significantly higher in July and August than in June, the manager optimized C and D approximately with the same values after the first 15 years (Figure 39 and Figure 40 (a) and (b)). However, as the farmers' irrigation demands increased due to climate change during these months, especially in years 40 and 60, the agent had to adapt its decisions and change C and D accordingly. Under scenario III, the agent fluctuated C and D after year 40 (in July) to increase the number of recycled water users and recycled water consumed. The agent was able to increase its rewards each time (year 40 and 60) it was dropped due to climate change effects (Figure 39 (c)). Under scenario IV, during July, the agent dropped and jumped C and D significantly from year 60 and then increased and decreased them to deal with the severe impact of climate change (RCP 8.5) on farmers' irrigation needs.

The manager agent did the same in years 40 and 60 in August as the climate change impacts were more severe in this month than in July under scenario IV. In August, under scenario III, the agent gently declined and increased C and D to maximize its rewards. The agent increased the number of recycled water users and the recycled water consumed during July and August to increase its rewards after dropping significantly due to the climate change effects. In July, farmers' groundwater consumption increased from 10.93 to 12.74 MCM (16.6%) and from 8.97 to 14.41 MCM (60.6%) under scenarios III and IV, respectively. The increase in groundwater consumption during August, under scenarios III and IV, were from 11.84 to 13.76 MCM (16.2%) and from 9.31 to 15.39 MCM (65.3%), respectively (Figure 39 and Figure 40 (d)).

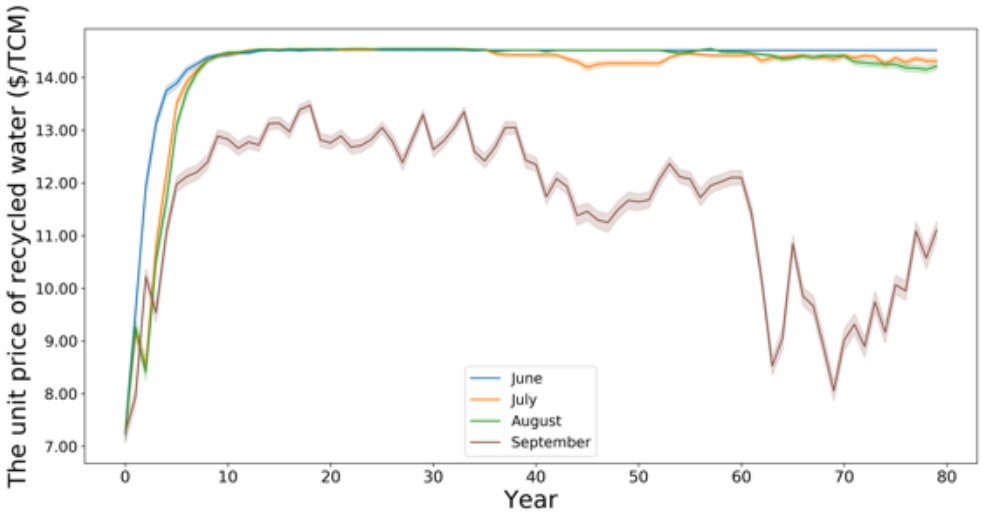
Similar to scenarios I and II, optimizing C and D for the manager agent to sustainably manage the agricultural water reuse project was more challenging in September than the three previous months of irrigation under scenarios III and IV. Although farmers' irrigation needs were significantly lower in September than July and August, the manager agent had to considerably decrease and increase C and D compared to their values in scenarios III and IV to maximize its rewards successfully. This could be due to high volumes of recycled water consumption during July and August, resulting in less available recycled water for farmers to use in September. Fluctuations in C and D values were observed after year 15 when the recycled water consumption reached its maximum capacity. Thus, the manager agent could not maximize and minimize C and D to the optimized values in previous months. Under scenario III, C was sharply increased to 13 $/TCM in the first 15 years, zig-zagging with a decreasing trend in the following years (Figure 39 (a)).

Of note were the sharp decreases near years 40 and 60 when the farmer's irrigation needs suddenly increased due to climate change. Under this scenario, the manager agent decreased D to approximately 1.17 MCM in the first 15 years, fluctuating with an increasing trend until the years afterward (Figure 39 (b)). Significant changes in C and D by the manager agent were observed near years 40 and 60 when the climate change impacts considerably jumped farmers' irrigation needs; however, the agent was able to adapt its decisions to the new conditions successfully. Each time the

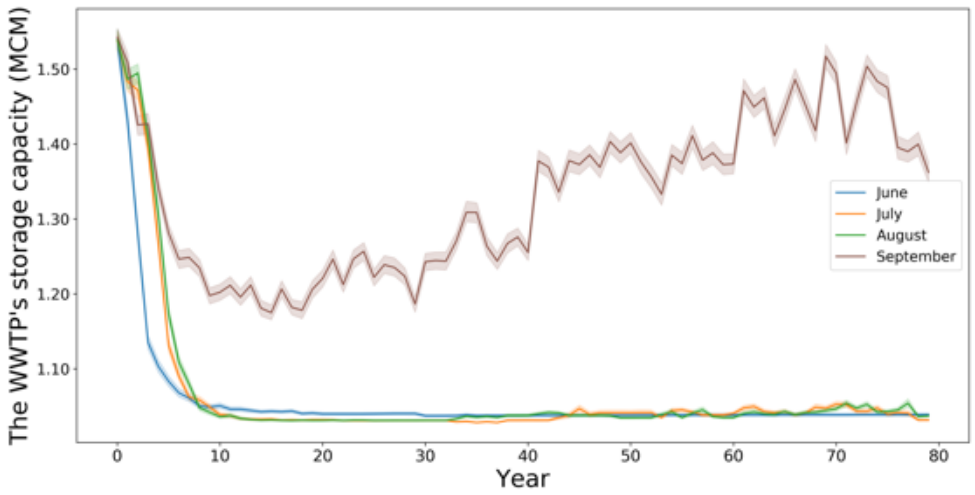
farmers' irrigation demand jumped, the agent tried to find optimum values for C and D by continuously trying various levels of C and D.

The manager agent continuously tried to maximize its rewards during September. However, from approximately year 5 to 15, its rewards showed decreasing trends under scenario III. The slope of increase in the mean of farmer's SI showed lower results than the previous years. The agent learned that C and D had to be decreased and increased due to low recycled water availability, respectively. Doing this, the manager agent's rewards bounced back with an increasing trend. The rewards depicted two other sudden declines in years 40 and 60 due to climate change effects on farmers' irrigation needs. However, the manager agent could bounce its rewards back to maximize it.

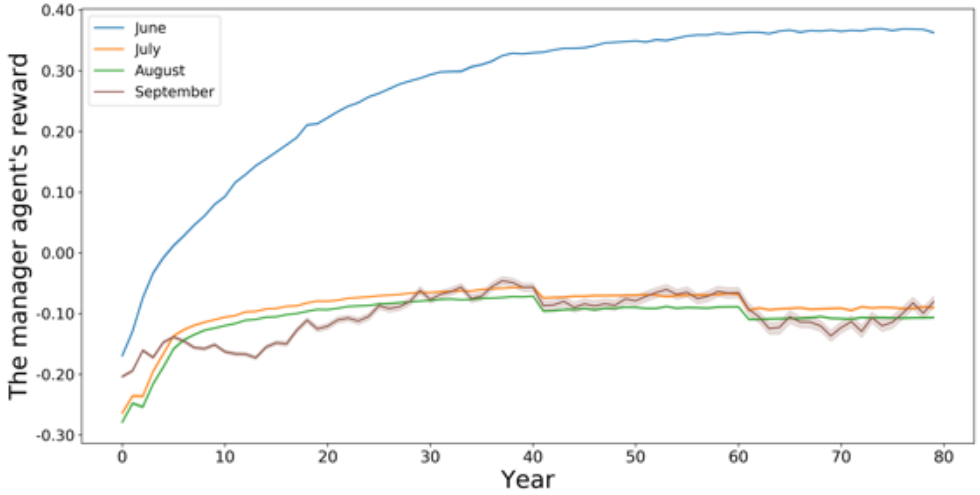
Under scenario IV, the overall trend of the agent's rewards increased; however, it was sharply decreased in year 40 due to climate change effects. The agent could manage this decrease by abruptly decreasing C and increasing D. Farmers' groundwater consumption was decreased and increased from 3.37 to 2.28 MCM (32.3%) and from 2.77 to 2.66 MCM (4.0%) in September under scenarios III and IV, respectively. Of note was the quick response of the agent to cope with the sudden changes of farmers' irrigation demands caused by climate change effects, increasing the number of recycled water users and its rewards, and decreasing the farmers' groundwater consumption growing trend.



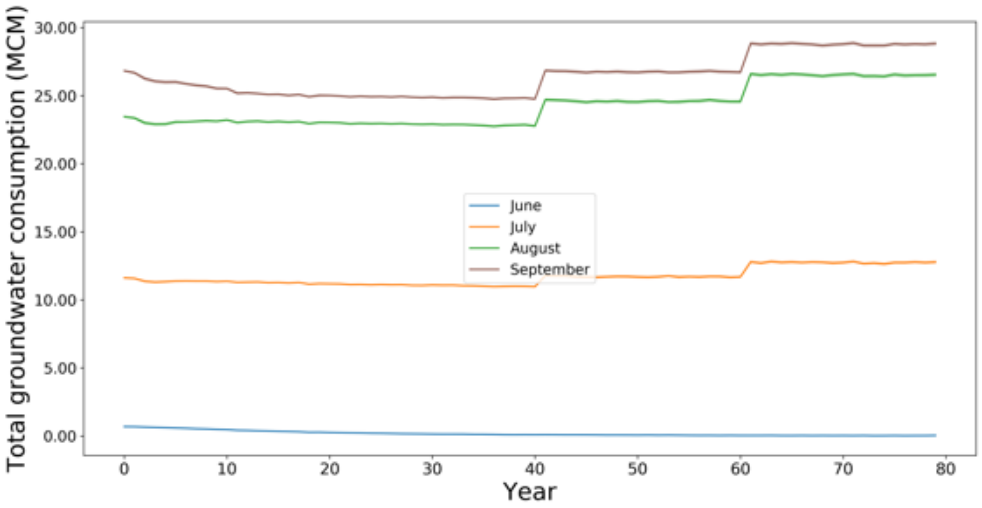
(a)


The WWTP's storage capacity (MCM)
1.50
1.40
1.30
1.20
1.10
0
10
20
30
40
50
60
70
80
Year
June
July
August
September

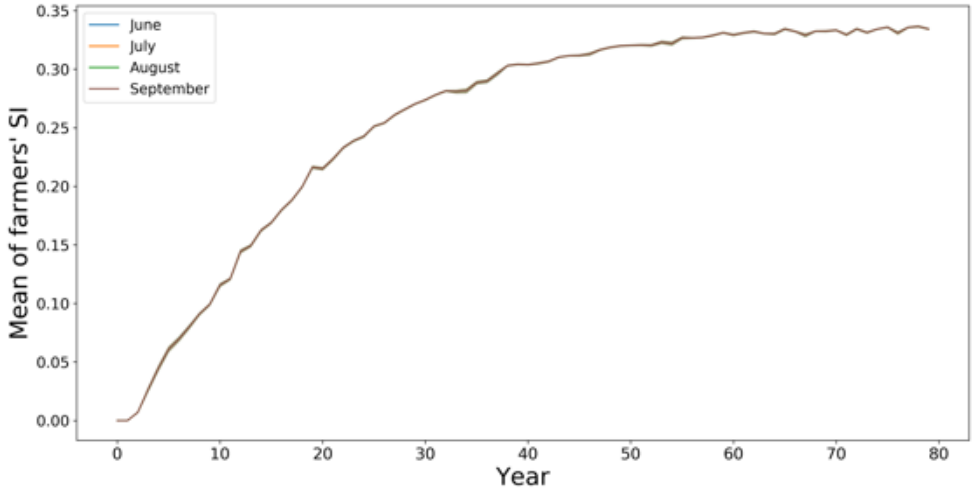
(b)


The manager agent's reward
0.40
0.30
0.20
0.10
0.00
-0.10
-0.20
-0.30
0
10
20
30
40
50
60
70
80
Year
June
July
August
September

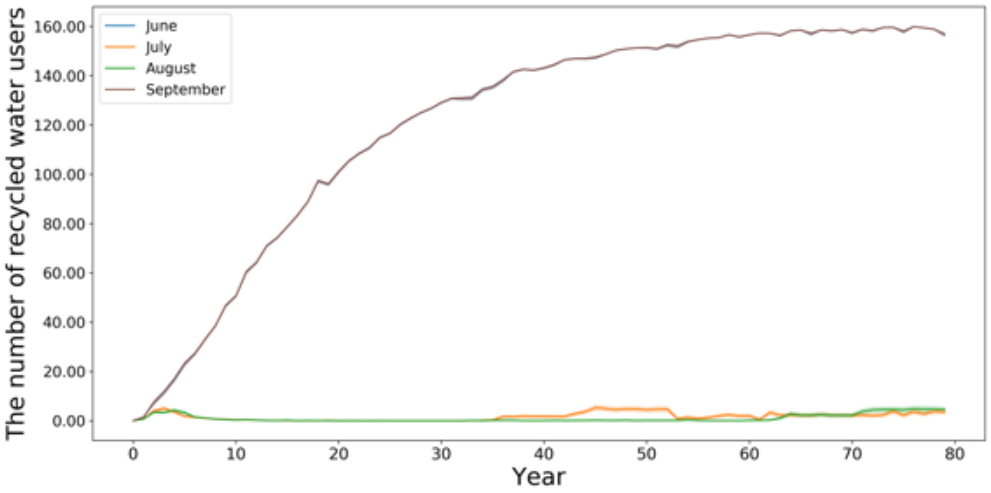
(c)


Total groundwater consumption (MCM)
30.00
25.00
20.00
15.00
10.00
5.00
0.00
0
10
20
30
40
50
60
70
80
Year
June
July
August
September

(d)

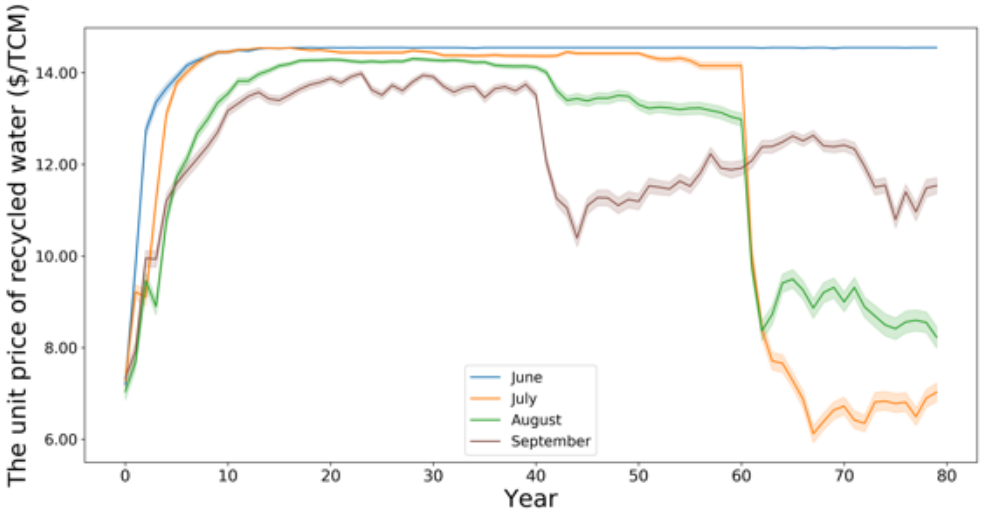

Mean of farmers' SI
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0
10
20
30
40
50
60
70
80
Year
June
July
August
September

(e)

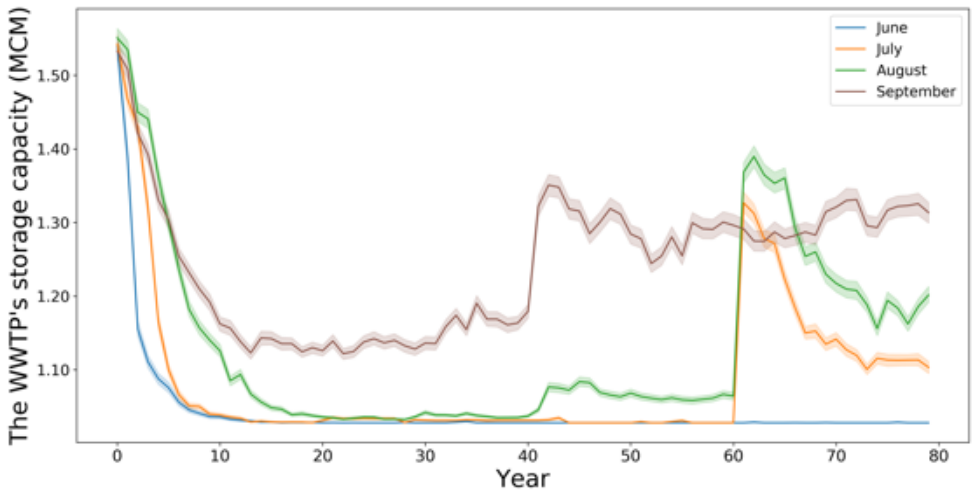


(f)

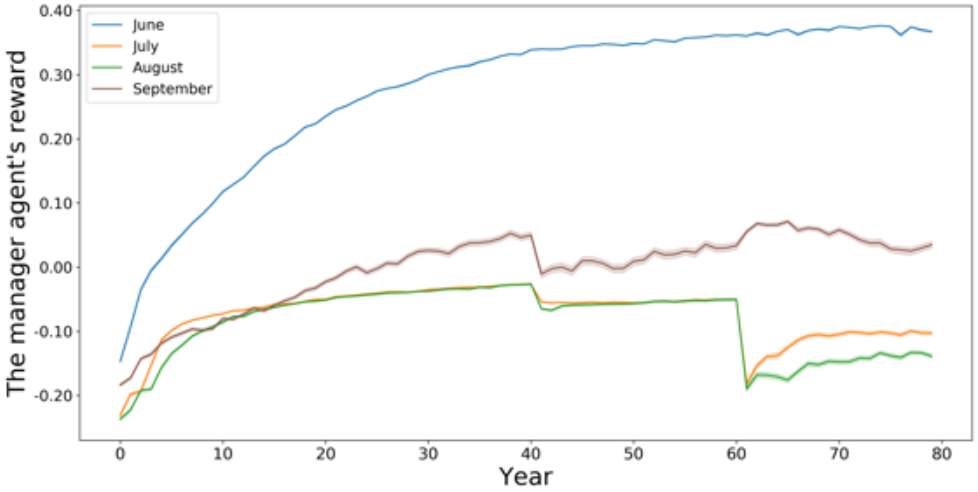
Figure 39. Results of scenario analysis (III), (a) the unit price of recycled water ($/CM), (b) WWTP's storage capacity (MCM), (c) the manager agent's reward, (d) total yearly groundwater consumption, (e) mean of farmers' SI, and (f) the number of recycled water users (the 95% confidence intervals were calculated using bootstrap resampling method).



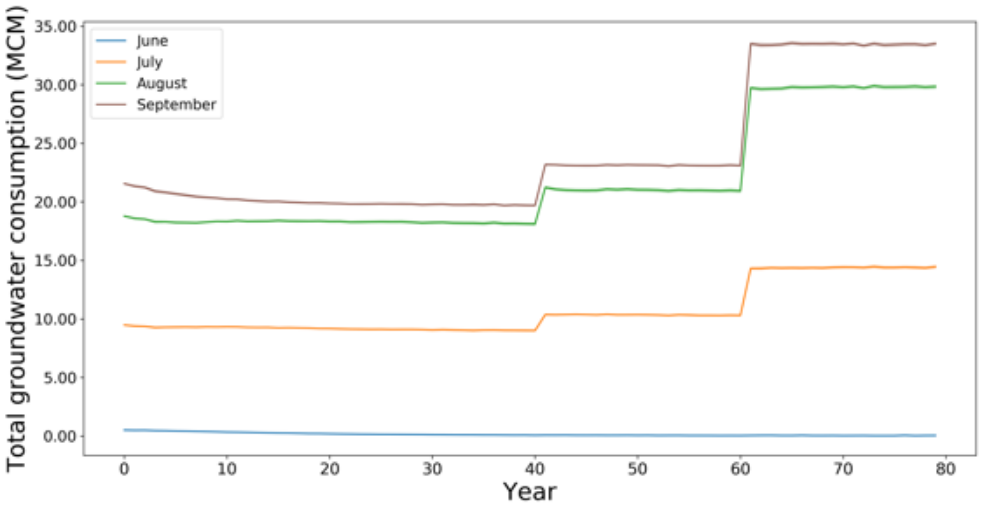
(a)


June
July
August
September
The WWTP's storage capacity (MCM)
1.50
1.40
1.30
1.20
1.10
0
10
20
30
40
50
60
70
80
Year

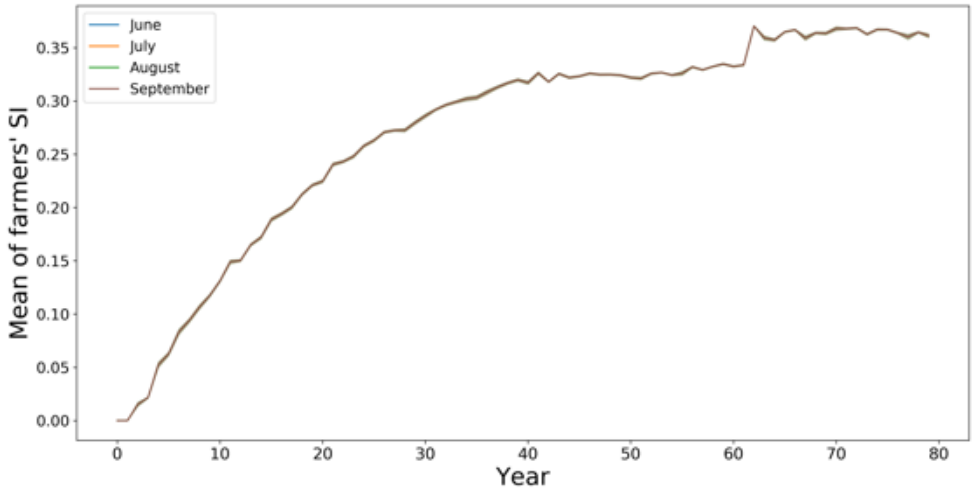
(b)


June
July
August
September
The manager agent's reward
0.40
0.30
0.20
0.10
0.00
-0.10
-0.20
0
10
20
30
40
50
60
70
80
Year

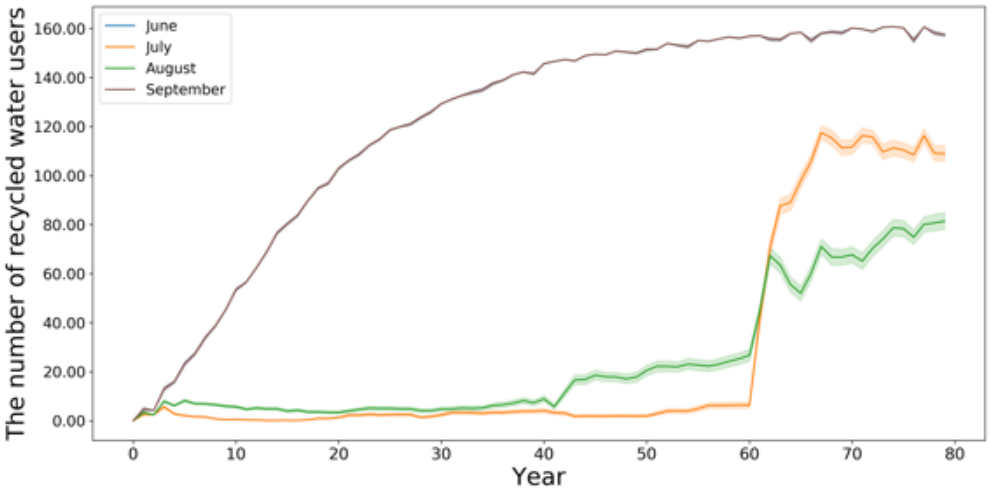
(c)


Total groundwater consumption (MCM)
35.00
30.00
25.00
20.00
15.00
10.00
5.00
0.00
June
July
August
September
0
10
20
30
40
50
60
70
80
Year

(d)


Mean of farmers' SI
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
June
July
August
September
0
10
20
30
40
50
60
70
80
Year

(e)



(f)

Figure 40. Results of scenario analysis (IV), (a) the unit price of recycled water ($/CM), (b) WWTP's storage capacity (MCM), (c) the manager agent's reward, (d) total yearly groundwater consumption, (e) mean of farmers' SI, and (f) the number of recycled water users (the 95% confidence intervals were calculated using bootstrap resampling method).

Comparing the scenario analysis results of this study with our previous work (Chapter 5), the manager agent was successful in multi-objective optimization. Although the groundwater consumption reduction in our previous study was more than this study, the manager agent reached better results in maximizing farmers' SI and unit price of recycled water and minimizing the WWTP's storage capacity.

Under scenario I, the manager agent could increase C from 0.97 $/TCM, used in our previous study (Chapter 5), to 7.3-14 $/TCM. The WWTP's storage capacity was also decreased from 2.06 MCM, used in our previous study (Chapter 5), to 1.13-1.6 MCM by the manager agent. It should be mentioned that farmers' SI remained constant at one in both studies under this scenario. However, the manager agent could not increase farmers' groundwater consumption reduction in this study. In our previous study (Chapter 5), the reduction was about 3.9 MCM compared to the 3 MCM reduction obtained by the manager agent in this study.

Reduction in farmers' groundwater consumption was also lower in this study (2.3 MCM) than in our previous study (3.11 MCM) under scenario II. However, the unit price of recycled water and farmers' SI was increased in this study compared to the previous one. C was increased from 9.7 $/TCM to 12.1-14.6 $/TCM. Farmer's SI in our previous study reached its plateau at 0.15 in the first 15 years; however, in this study, it climbed to 0.4 over the first 65 years of simulations. D was also reduced from 2.06 MCM, in our previous study, to 1.03-1.2 MCM in this study.

Under scenario III, farmers' SI showed almost the same results as our previous study, reaching 0.35 over 80 years. Farmers' groundwater consumption was also increased more over the 80 years of simulations in this study (2 MCM) compared to the previous one (1.2 MCM). However, the agent successfully maximized the unit price of recycled water by increasing it from 1.25 $/TCM, set in our previous study, to 1.03-1.5 $/TCM in this study. Under scenario IV, the increase in farmers' groundwater consumption was lower in this study (10.95 MCM) compared to our previous study (11.45 MCM) over the 80 years of simulations. The manager agent also increased SI in this study compared to the previous one from 0.35 (over 80 years) to 0.37 (over 60 years). The WWTP's storage capacity was also decreased from 2.06 MCM, in the previous study, to 1.03-1.4 MCM in this study. The manager agent decreased the unit price of recycled water in this study (6.5-14.6 $/TCM) compared to the previous one (14.6 $/TCM).

Because the manager agent had to optimize various objectives in this study, the agent had to increase the groundwater consumption in some scenarios in favor of other objectives (i.e., farmers' SI, recycled water unit price, and the WWTP's storage capacity). Of note was that the agent could continuously adapt its decision to various situations and optimize C and D under various scenarios and even years.

6.4. Conclusions

Agricultural water reuse is considered one of the most reliable and sustainable solutions available for addressing the worldwide water crisis. Decision-makers must consider multiple criteria and objectives (e.g., socio-economic, hydrologic, climatic, and financial) to manage agricultural water reuse projects efficiently. Complexities inherent in human-water systems and climate change effects on these systems make such decision-making challenging for water resources managers and decision-makers.

This paper presented the application of a coupled ABM-RL model for making better-informed decisions for sustainably managing agricultural water reuse projects. For this, a simulation-based multi-objective optimization problem was studied in this paper to investigate the optimum strategies that a decision-maker can take to address the local water crisis and increase the sustainability of farmers' water supplies. This paper implemented RL in an ABM developed in our previous study to find the optimum strategies for managing the project and compared the results.

RL was utilized to create an artificially intelligent manager agent who tried to find optimized solutions with multiple objectives. The manager agent's objectives were to maximize farmers' water supply sustainability, the number of farmers who used recycled water, the unit price of recycled water, and minimize farmers' groundwater consumption and the WWTP's storage capacity. The idea was to showcase the idea of using such methodology for getting valuable insights from the decisions made, which were supported by artificial intelligence.

SA results showed the importance of θ, ε, γ, and α parameters on the manager agent's decisions. θ and ε ensured that the manager agent did not always exploit its knowledge and, with a decreasing probability over time, explored for other information stochastically outside its previous knowledge. This method ensured the manager agent did not get stuck in local optima while the optimization process was going on. The results clearly illustrated that the sooner the probability of exploring decreased, the sooner the agent reached a decision; however, not always the optimum decision. Results furthermore depicted that increasing and decreasing the discount factor (γ) and learning rate (α) led to increasing the time the manager agent searched for the optimum results; however, it reached better results. These results clearly showed the trade-off between resources (time and calculations) and better results that researchers need to consider when dealing with optimization problems. Although, it should be mentioned that more resources spent do not guarantee better results always.

The model was run under various scenarios (e.g., limited water resources and climate change) to investigate how the manager agent made decisions under these scenarios and compare them to our previous study. As the main aim of our previous study was to demonstrate the capabilities of agricultural water reuse projects, its main aim was to decrease the farmers' groundwater consumption and increase their SI. However, optimizing a multi-objective problem resulted in sacrificing groundwater consumption by the manager agent in some cases. As the weight of the farmers' SI was higher than the other weights in all scenarios, the manager agent could successfully increase farmers' SI in all scenarios. The agent also successfully increased the unit price of recycled water and decreased the WWTP's storage capacity in all scenarios. Of note was the ability of the artificially intelligent manager agent to adapt its decisions to various situations and optimize the unit price of recycled water and the WWTP's storage capacity, as two of the most influential factors on the project, under various scenarios and even years.

Besides the limitations that existed in the ABM, extensively discussed in our previous study (Chapter 5), there was some limitation in this study which addressing them can enhance the results of this paper and show the capabilities of RL for optimizing ABMs. One of the major limitations in this study was discretizing two optimizing parameters (C and D). One of the ways to overcome this shortcoming is to utilize the deep Q-learning method (i.e., deep reinforcement learning) by using deep neural networks. This can allow researchers to use continuous parameter spaces for ABM optimization. Researchers can also include more parameters and objectives to compare the results to this study. Future research can also apply different optimization methods (i.e., particle swarm optimization and genetic algorithms) and compare their results with this study.

Chapter 7: Summary and conclusions

The worldwide water crisis (e.g., freshwater shortage, water pollution, population growth, urbanization, and ever-increasing and unsustainable development) has made countries around the world to look for sustainable and reliable solutions for addressing the crisis. Water reuse as one of the prominent options available for tackling the water crisis has attracted many countries to heavily invest and practice water reuse for various applications. In general, agricultural water reuse is the dominant water reuse application in the world. It has been practiced since a long time ago; however, not always in a safe and sustainable manner.

Despite numerous benefits associated with agricultural water reuse practices (e.g., increasing water supply system reliability, resiliency toward various stresses, and sustainability), it comes with numerous challenges. Sustainable planning and managing agricultural water reuse practices require decision-makers consider these challenges simultaneously. Such decision-making makes decision-makers look for suitable tools capable of capturing the complex adaptive dynamics of agricultural water reuse practices. DSSs are suitable tools that can provide decision-makers with such capabilities. However, existing DSSs in the literature have some gaps that need to be addressed by the scientific and professional community to help decision-makers make sustainable and better-informed decisions.

This dissertation was conducted to identify such gaps and try to tackle some of them as an effort to help the scientific, professional, and decision-making community regarding sustainable planning and management of agricultural water reuse practices worldwide. Chapters 1 and 2 of this dissertation presented an introduction and literature review on the DSS developed in this dissertation. The remaining chapters of this dissertation can generally be categorized into two sections. The first section (i.e., Chapter 3) investigated safety (i.e., water quality) aspects of agricultural water reuse practices. The second section (i.e., Chapters 4, 5, and 6) studied water system planning and management (i.e., water quantity) aspects of agricultural water reuse practices.

Worldwide agricultural water reuse regulations and guidelines were critically reviewed in the first section of this dissertation. In total, 70 regulations and guidelines from various international organizations, countries, and states (EPA, ISO, FAO, WHO, U.S. (statewide), European Commission, Canada (by provinces), Australia, Mexico, Iran, Egypt, Tunisia, Jordan, Israel, Oman, China, Kuwait, Saudi Arabia, France, Cyprus, Spain Greece, Portugal, and Italy) were studied in this dissertation. The main goal here was to evaluate existing regulations and guidelines regarding recycled water quality and treatment processes required for implementing agricultural water reuse practices. Peer-reviewed articles were also used to compare and find the gaps in those regulations and guidelines.

Results (Chapter 3) showed that the regulations and guidelines were mainly human health centered, insufficient regarding some potentially dangerous pollutants such as emerging constituents, and with large discrepancies when compared with each other. In addition, some important water quality parameters, such as pathogens, heavy metals, and salinity, were only included in a few of the regulations and guidelines investigated in this study. Finally, specific treatment processes were only mentioned in some of the regulations and guidelines, with high levels of discrepancy.

While agricultural water reuse can potentially give us the means to address the water crisis, the discrepancies in regulations and guidelines are one of the main barriers to successfully implementing water reuse practices. However, this does not mean that the practice of water reuse in agriculture should be construed as unsafe compared to other available water sources such as rivers, streams, and pond water. As to all types of water sources, special care is required to ensure recycled water quality matches crop needs, public health is protected, salinity is controlled, and both soil and groundwater conditions are kept sustainable. The scientific, professional, and decision-making community can use the results of this section to address the gaps and discrepancies identified in those regulations and guidelines to ensure safe implementation of agricultural water reuse practices worldwide.

In the second section of this dissertation a socio-hydrological framework was proposed to capture the complex adaptive dynamics of agricultural water reuse adoption by famers and its impacts on local water resources sustainability. This framework used a "bottom-up" approach (i.e., ABM) to successfully capture the dynamics mentioned using empirical data from two case studies in CA and MD. The agent-based models developed in this dissertation evaluated the water consumption dynamics and how the adoption of recycled water use by farmers impacted the local water resources. The framework also benefited from TPB for capturing the dynamics of farmers' decision-making regarding water reuse adoption.

Moreover, DOE was utilized for SA of agent-based model developed to study the case in CA (Chapter 4). This model demonstrated that agricultural water reuse could successfully decrease total water shortage, groundwater over-drafting, and transferred water consumption of farmers in CA if planned and managed correctly. The model, similar to the literature, suggested 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 by SA. 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.

Using the framework proposed in Chapter 4, another agent-based model was developed to study an agricultural water reuse practice in the Eastern Shore of MD. The complex dynamics of agricultural water reuse adoption by local farmers and its

impacts on the sustainability of local water resources were successfully captured in this chapter. This study used a global SA method to find the factors with the most significant effects on the model outputs, including climate change effects (precipitation and temperature), WWTP's storage capacity, and the unit price of recycled water. This was conducted to address the shortcoming of DOE in SA of complex adaptive systems (i.e., agricultural water reuse). Decision-makers need to pay special attention to determining the unit price of recycled water and WWTPs' storage capacities to ensure the success of agricultural water reuse practices. Based on the SA results, the author also urge other researchers to conduct time-varying SA, especially when dealing with models of complex systems as their sensitivity includes complex dynamics.

This dissertation (Chapter 5) also simulated the project under various scenarios (e.g., climate change). The results demonstrated that the agricultural water reuse project could significantly decrease farmers' water shortage and groundwater/ surface water consumption and increase their water supply sustainability if appropriately planned and managed. However, the impacts of the agricultural water reuse project were decreased under severe climate change scenarios. Furthermore, the results showed that farmers' water supply reliability, resiliency, and sustainability increased significantly by introducing recycled water into the area.

The next chapter (Chapter 6) was the next step of the previous chapter. In this chapter two of the most influential factors on the model developed in the previous chapter were used to optimize the sustainability of the agricultural water reuse. For this aim, a RL technique (i.e., Q-Learning) was utilized to conduct multi-objective simulation-based optimization using the model developed in the previous chapter. The ultimate goal in this chapter was investigating the optimum strategies that a decision-maker can take to address the local water crisis and increase the sustainability of farmers' water supplies. The objectives included maximizing farmers' water supply sustainability, the number of farmers who used recycled water, the unit price of recycled water, and minimizing farmers' groundwater consumption and the WWTP's storage capacity. The idea was to showcase the idea of using such methodology for getting valuable insights from the decisions made, which were supported by artificial intelligence. The model was run under various scenarios (e.g., limited water resources and climate change) to investigate how the manager agent made decisions under these scenarios and compare them to our previous study (Chapter 5).

The results demonstrated that manager agent could successfully increase farmers' SI in all scenarios. The agent also successfully increased the unit price of recycled water and decreased the WWTP's storage capacity in all scenarios. Of note was the ability of the artificially intelligent manager agent to adapt its decisions to various situations and optimize the unit price of recycled water and the WWTP's storage capacity, as two of the most influential factors on the project, under various scenarios and even years. However, optimizing a multi-objective problem resulted in sacrificing groundwater consumption by the manager agent in some cases.

It should be mentioned that the socio-hydrological framework proposed in this dissertation form the basis of the two models developed for CA and MD studies. So, in basis, they are the same; however, due to the differences between the environment and agents in those models they vary in their details completely.

Comparing the environment in the two models, they were completely different although they were both developed in a stylized manner. The environment in the CA case study was divided into three regions (i.e., northern, central, and southern regions) according to empirical data from the DPWD. According to the empirical location of each farm in those three regions, the farms were stochastically located in the three areas of environment at the start of each simulation run. On the other hand, farms in MD case study were clustered based on their distance to the WWTP in 15 one-kilometer-long clusters. The farms were then stochastically located in their corresponding group at the start of each simulation run.

Comparing the agents in the two models, they were very different in their details too. First, comparing their irrigation requirement, Almond farmers in the CA case study needed an irrigation source throughout the year, while corn farmers in the MD case study required the source just in 4 months of June, July, August, and September. The primary water sources in the CA case study were precipitation and the CVP allocation, while in the MD case study included groundwater and surface water as the primary water sources. Regarding the available alternative water sources, the MD case study included recycled water, groundwater, and transferred water; however, the only alternative water source in the MD case study was recycled water. Regarding the financial aspects of the agents, the model in the MD case study was the next level of the model in the CA case study as it included more details of farmers financial aspects. The only processes that would affect farmers financial attributes in the CA case study were the money they had to spend for using their water sources (except precipitation) and the money they would earn by selling their crops at the end of each year. On the other hand, various factors were considered in the MD case study, including annual farm operations costs the annual maintenance costs. For further differences, the interested reader is referred to Chapters 4 and 5 of this dissertation.

Comparing the results of the two case studies (i.e., CA and MD), it was first apparent that the socio-hydrological framework proposed in this dissertation was versatile enough to be used for two case studies with completely different conditions. The results of both studies further illustrated that the agricultural water reuse adoption by farmers is a time-consuming process which can be affected by various parameters such as socio-economic parameters. Although the study conducted by Suri et al. (2019) showed that the farmers in the CA were more willing to use recycled water for their irrigation purposes rather than MD farmers, the rate of the application of recycled water by farmers in each years showed that the rate was higher in the MD area comparing the CA area (considering farmers that needed an alternative water source for their irrigation practices). These results can be due to the fact that farmers the MD case study had access to only one source of alternative water (i.e., recycled

water), comparing with the situation for CA farmers where they had access to three alternative sources (i.e., recycled water, groundwater, and transferred water).

Both of the case studies results demonstrated that the agricultural water reuse projects could successfully address the water crisis in the case studies. These results showed that the projects were able to significantly decrease farmers water shortage (CA: by 57.7%, MD: by 19.5%), and groundwater consumption (CA: by 74.1%, MD: by 19.5%). As the capacity of WWTPs in the CA case study were higher than MD case study, more recycled water was available to farmers in CA. Both of the models showed that the climate change effects, and the unit price of recycled water were the factors with significant effect on both models developed for the CA and MD case studies.

The scientific, professional, and decision-making community can benefit from the result of the second section of this dissertation to gain valuable insights in planning and managing agricultural water reuse practices worldwide. The author, specifically, urges the scientific community to use the framework and models developed in this dissertation to address its limitations for helping decision-makers make better-informed decisions in planning and managing agricultural water reuse practices, addressing the worldwide water crisis.

Moreover, scientific researchers are urged to use the results of this dissertation, build upon the models developed by the author, and include more data and details to the models to extend the scope and details of this study. For example, more geospatial data (e.g., soil type, topography, location of natural and engineered infrastructure) regarding the study case, farms and farmers' characteristics, and the environment can potentially improve the results of this dissertation. This allows future research to improve this dissertation by focusing and elaborating on its simplifying assumptions using empirical data from various components of these models (e.g., farmers, farms, various crops grown in the study site, complexities inherent in the hydrology of agricultural areas, and climatic conditions).

Bibliography

314 CMR 20: Reclaimed Water Permit Program and Standards. (n.d.). Retrieved November 14, 2019, from https://www.mass.gov/regulations/314-CMR-20-reclaimed-water-permit-program-and-standards

7101 Regulations Governing the Design, Installation and Operation of On-Site Wastewater Treatment and Disposal Systems. (n.d.). Retrieved November 12, 2019, from http://regulations.delaware.gov/AdminCode/title7/7000/7100/7101.shtml

Abdelmoula, S., Sorour, M. T., & Aly, S. A. A. (2021). Cost Analysis and Health Risk Assessment of Wastewater Reuse from Secondary and Tertiary Wastewater Treatment Plants. *Sustainability 2021, Vol. 13, Page 13125*, *13*(23), 13125. https://doi.org/10.3390/SU132313125

Abdel-Shafy, H. I., & Mansour, M. S. M. (2013). Overview on water reuse in Egypt: present and future. *Sustainable Sanitation Practice*, *14*(1), 17–25.

Abler, D. G., & Shortle, J. S. (2000). Climate change and agriculture in the Mid-Atlantic Region. *Climate Research*, *14*(3), 185–194.

Abu-Madi, M. O. R. (2004). *Incentive Systems for Wastewater Treatment and Reuse in Irrigated Agriculture in the MENA Region, Evidence from Jordan and Tunisia*. CRC Press.

Abusam, A., & Shahalam, A. B. (2013). Wastewater reuse in Kuwait: opportunities and constraints. *WIT Transactions on Ecology and the Environment*, *179*, 745–754.

Achorn, E. (2004). Integrating agent-based models with quantitative and qualitative research methods. *Australian Association for Research in Education 2004 Conference Papers ACH04769*.

Adegoke, A. A., Amoah, I. D., Stenström, T. A., Verbyla, M. E., & Mihelcic, J. R. (2018). Epidemiological evidence and health risks associated with agricultural reuse of partially treated and untreated wastewater: A review. In *Frontiers in Public Health* (Vol. 6, Issue DEC). Frontiers Media S.A. https://doi.org/10.3389/fpubh.2018.00337

Aerts, J. C. J. H. (2020). Integrating agent-based approaches with flood risk models: A review and perspective. *Water Security*, *11*, 1–9.

Afshar, A., & Mariño, M. A. (1989). Optimization Models for Wastewater Reuse in Irrigation. *Journal of Irrigation and Drainage Engineering*, *115*(2), 185–202. https://doi.org/10.1061/(ASCE)0733-9437(1989)115:2(185)

Aharoni, A., & Cikurel, H. (2006). Mekorot's research activity in technological improvements for the production of unrestricted irrigation quality effluents. *Desalination*, *187*(1–3), 347–360.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211.

Akhbari, M., & Grigg, N. S. (2013). A framework for an agent-based model to manage water resources conflicts. *Water Resources Management*, *27*(11), 4039–4052.

Al Khateeb, N. (2001). Sociocultural acceptability of wastewater reuse in Palestine. In *Water management in Islam* (pp. 79–84). United Nations Univ. Press/Int. Development Research Centre, New York.

Alabama Environmental Regulations and Laws. (n.d.). Retrieved November 12, 2019, from http://www.adem.state.al.us/alEnviroRegLaws/default.cnt

Alam, S., Gebremichael, M., Li, R., Dozier, J., & Lettenmaier, D. P. (2019). Climate change impacts on groundwater storage in the Central Valley, California. *Climatic Change*, *157*(3–4), 387–406.

Al-Amin, S., Berglund, E. Z., Mahinthakumar, G., & Larson, K. L. (2018). Assessing the effects of water restrictions on socio-hydrologic resilience for shared groundwater systems. *Journal of Hydrology*, *566*, 872–885.

Alarcón, J., & Pedrero, F. (2009). Effects of treated wastewater irrigation on lemon trees. *Desalination*, *246*, 631–639.

Alcalde Sanza, L., & Gawlik, B. M. (2014). Water Reuse in Europe: Relevant guidelines, needs for and barriers to innovation. In *JRC Science and Policy Reports*. https://doi.org/10.2788/29234

Alcántara, E., Romera, F. J., & De la Guardia, M. D. (1988). Genotypic differences in bicarbonate-induced iron chlorosis in sunflower. *Journal of Plant Nutrition*, *11*(1), 65–75.

Alderson, M. P., dos Santos, A. B., & Mota Filho, C. R. (2015). Reliability analysis of low-cost, full-scale domestic wastewater treatment plants for reuse in aquaculture and agriculture. *Ecological Engineering*, *82*, 6–14. https://doi.org/10.1016/j.ecoleng.2015.04.081

Alfarra, A. (2010). *Treated Wastewater for Irrigated Agriculture in the Jordan Valley*. 134.

Alhendawi, R. A., Römheld, V., Kirkby, E. A., & Marschner, H. (1997). Influence of increasing bicarbonate concentrations on plant growth, organic acid accumulation in roots and iron uptake by barley, sorghum, and maize. *Journal of Plant Nutrition*, *20*(12), 1731–1753.

Ali, A. M., Shafiee, M. E., & Berglund, E. Z. (2017). Agent-based modeling to simulate the dynamics of urban water supply: Climate, population growth, and water shortages. *Sustainable Cities and Society*, *28*, 420–434.

Aliyari, F., Bailey, R. T., & Arabi, M. (2021). Appraising climate change impacts on future water resources and agricultural productivity in agro-urban river basins. *Science of The Total Environment*, *788*, 147717.

Al-Jasser, A. O. (2011). Saudi wastewater reuse standards for agricultural irrigation: Riyadh treatment plants effluent compliance. *Journal of King Saud University-Engineering Sciences*, *23*(1), 1–8.

Al-Jawad, J. Y., Alsaffar, H. M., Bertram, D., & Kalin, R. M. (2019). A comprehensive optimum integrated water resources management approach for multidisciplinary water resources management problems. *Journal of Environmental Management*, *239*, 211–224. https://doi.org/10.1016/j.jenvman.2019.03.045

Alkhamisi, S. A., Abdelrahman, H. A., Ahmed, M., & Goosen, M. F. A. (2011). Assessment of reclaimed water irrigation on growth, yield, and water-use efficiency of forage crops. *Applied Water Science*, *1*(1–2), 57–65. https://doi.org/10.1007/s13201-011-0009-y

Almasri, M. N., & McNeill, L. S. (2009). Optimal planning of wastewater reuse using the suitability approach: A conceptual framework for the West Bank, Palestine. *Desalination*, *248*(1–3), 428–435. https://doi.org/10.1016/j.desal.2008.05.084

AlphaGo | DeepMind. (n.d.). Retrieved December 12, 2021, from https://deepmind.com/research/case-studies/alphago-the-story-so-far

An, L. (2012). Modeling human decisions in coupled human and natural systems: Review of agent-based models. *Ecological Modelling*, *229*, 25–36.

Anderson, P., Denslow, N., Drewes, J. E., Olivieri, A., Schlenk, D., & Snyder, S. (2010). *Monitoring Strategies for Chemicals of Emerging Concern (CECs) in Recycled Water*. *April*.

Andradóttir, S. (2006). An overview of simulation optimization via random search. *Handbooks in Operations Research and Management Science*, *13*, 617–631.

Angelakis, A. N., Asano, T., Bahri, A., Jimenez, B. E., & Tchobanoglous, G. (2018). Water reuse: From ancient to modern times and the future. *Frontiers in Environmental Science*, *6*(MAY). https://doi.org/10.3389/fenvs.2018.00026

Angelakis, A. N., & Gikas, P. (2014). Water reuse: Overview of current practices and trends in the world with emphasis on EU states. *Water Utility Journal*, *8*, 67–78.

Angelakis, A. N., Marecos Do Monte, M. H. F., Bontoux, L., & Asano, T. (1999). The status of wastewater reuse practice in the Mediterranean basin: Need for guidelines. *Water Research*, *33*(10), 2201–2217. https://doi.org/10.1016/S0043-1354(98)00465-5

Angelakis, A. N., Tsagarakis, K. P., Kotselidou, O. N., & Vardakou, E. (2000). The Necessity for Establishment of Greek Regulations on Wastewater Reclamation and Reuse. *Report for the Ministry of Public Works and Environment and Hellenic Union of Municipal Enterprises for Water Supply and Sewage. Larissa-Greece*, 110.

Anugoolprasert, O., Kinoshita, S., Naito, H., Shimizu, M., & Ehara, H. (2012). Effect of low pH on the growth, physiological characteristics and nutrient absorption of sago palm in a hydroponic system. *Plant Production Science*, *15*(2), 125–131.

Anwar, H. N., Nosheen, F., Hussain, S., & Nawaz, W. (2010). Socio-economics consequences of reusing wastewater in agriculture in Faisalabad. *Pakistan Journal of Life and Social Sciences*, *8*(2), 102–105.

Arizona Administrative Code | Table of Contents by Title. (n.d.). Retrieved November 12, 2019, from https://apps.azsos.gov/public_services/CodeTOC.htm#ID18

Asano, T., Burton, F. L., Leverenz, H. L., Tsuchihashi, R., & Tchobanoglous, G. (2007a). *Water Reuse*.

Asano, T., Burton, F. L., Leverenz, H. L., Tsuchihashi, R., & Tchobanoglous, G. (2007b). *Water reuse: issues, technologies, and applications*. New York, US: McGraw-Hill.

Atlantic Canada Wastewater Guidelines Manual | Government of Prince Edward Island. (n.d.). Retrieved November 13, 2019, from https://www.princeedwardisland.ca/en/publication/atlantic-canada-wastewater-guidelines-manual

Australian Guidelines for Water Recycling. (n.d.). Retrieved November 14, 2019, from https://www.nhmrc.gov.au/about-us/publications/australian-guidelines-water-recycling

Axelrod, R. (1997). *The complexity of cooperation: Agent-based models of competition and collaboration* (Vol. 3). Princeton University Press.

Axtell, R., & Epstein, J. (1994). Agent-based modeling: Understanding our creations. *The Bulletin of the Santa Fe Institute 9.4 (1994): 28-32.*, *9*(4), 28–32. https://nyuscholars.nyu.edu/en/publications/agent-based-modeling-understanding-our-creations

Ayers, R. S., & Westcot, D. W. (1985). *Water quality for agriculture*. Food and Agriculture Organization of the United Nations.

Bahrami, N., Afshar, A., & Afshar, M. H. (2022). An agent-based framework for simulating interactions between reservoir operators and farmers for reservoir management with dynamic demands. *Agricultural Water Management*, *259*, 107237.

Bahri, A. (2001). Water reuse in Tunisia: stakes and prospects. *Atelier Du PCSI (Programme Commun Systèmes Irrigués) Sur Une Maîtrise Des Impacts Environnementaux de l'Irrigation*, 11-p.

Barabási, A.-L., & Albert, R. (1999). Emergence of scaling in random networks. *Science*, *286*(5439), 509–512.

Barbagallo, S., Cirelli, G. L., & Indelicato, S. (2001). Wastewater reuse in Italy. *Water Science and Technology*, *43*(10), 43–50.

Barreteau, O., & Bousquet, F. (2000). SHADOC: a multi-agent model to tackle viability of irrigated systems. *Annals of Operations Research*, *94*(1–4), 139–162.

Baustert, P., & Benetto, E. (2017). Uncertainty analysis in agent-based modelling and consequential life cycle assessment coupled models: A critical review. *Journal of Cleaner Production*, *156*, 378–394. https://doi.org/10.1016/J.JCLEPRO.2017.03.193

B.C. Irrigation Management Guide - Province of British Columbia. (n.d.). Retrieved November 13, 2019, from https://www2.gov.bc.ca/gov/content/industry/agriculture-seafood/agricultural-land-and-environment/water/irrigation/irrigation-management-guide

Becker, N. (2011). Is desalination the most sustainable alternative for water-shortage mitigation in Israel? *Int. J. Sustainable Economy*, *3*(4).

Bedford, T. (1998). Sensitivity indices for (tree-) dependent variables. *Proceedings of the Second International Symposium on Sensitivity Analysis of Model Output (SAMO98)*, 17–20.

Berglund, E. Z. (2015). Using Agent-Based Modeling for Water Resources Planning and Management. *Journal of Water Resources Planning and Management*, *141*(11), 04015025. https://doi.org/10.1061/(asce)wr.1943-5452.0000544

Berrut, J. P., & Trefethen, L. N. (2006). Barycentric Lagrange Interpolation. *Http://Dx.Doi.Org/10.1137/S0036144502417715*, *46*(3), 501–517. https://doi.org/10.1137/S0036144502417715

Bert, F., North, M., Rovere, S., Tatara, E., Macal, C., & Podestá, G. (2015). Simulating agricultural land rental markets by combining agent-based models with traditional economics concepts: The case of the Argentine Pampas. *Environmental Modelling & Software*, *71*, 97–110.

Bithell, M., & Brasington, J. (2009). Coupling agent-based models of subsistence farming with individual-based forest models and dynamic models of water distribution. *Environmental Modelling & Software*, *24*(2), 173–190.

Bixio, D., Thoeye, C., Wintgens, T., Ravazzini, A., Miska, V., Muston, M., Chikurel, H., Aharoni, A., Joksimovic, D., & Melin, T. (2008). Water reclamation and reuse: implementation and management issues. *Desalination*, *218*(1–3), 13–23.

Blaney, H. F. (1952). *Determining water requirements in irrigated areas from climatological and irrigation data*.

Blumenthal, U. J., Mara, D. D., Peasey, A., Ruiz-Palacios, G., & Stott, R. (2000). Guidelines for the microbiological quality of treated wastewater used in agriculture: Recommendations for revising WHO guidelines. *Bulletin of the World Health Organization*, *78*(9), 1104–1116. https://doi.org/10.1590/S0042-96862000000900006

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences of the United States of America*, *99*(SUPPL. 3), 7280–7287. https://doi.org/10.1073/pnas.082080899

Bone, C., & Dragićević, S. (2010). Simulation and validation of a reinforcement learning agent-based model for multi-stakeholder forest management. *Computers, Environment and Urban Systems*, *34*(2), 162–174. https://doi.org/10.1016/J.COMPENVURBSYS.2009.10.001

Borboudaki, K. E., Paranychianakis, N. v., & Tsagarakis, K. P. (2005). Integrated wastewater management reporting at tourist areas for recycling purposes, including the case study of Hersonissos, Greece. *Environmental Management*, *36*(4), 610–623. https://doi.org/10.1007/s00267-004-0115-9

Borgonovo, E. (2007). A new uncertainty importance measure. *Reliability Engineering & System Safety*, *92*(6), 771–784.

Borgonovo, E., Castaings, W., & Tarantola, S. (2012). Model emulation and moment-independent sensitivity analysis: An application to environmental modelling. *Environmental Modelling & Software*, *34*, 105–115.

Borgonovo, E., Pangallo, M., Rivkin, J., Rizzo, L., & Siggelkow, N. (2022). Sensitivity analysis of agent-based models: a new protocol. *Computational and Mathematical Organization Theory*, 1–43. https://doi.org/10.1007/S10588-021-09358-5/FIGURES/7

Boryan, C., Yang, Z., & Di, L. (2012). Deriving 2011 cultivated land cover data sets using usda national agricultural statistics service historic cropland data layers. *2012 IEEE International Geoscience and Remote Sensing Symposium*, 6297–6300.

Box, G. E. P. (1976). Science and statistics. *Journal of the American Statistical Association*, *71*(356), 791–799. https://doi.org/10.1080/01621459.1976.10480949

Brearcliffe, D. K., & Crooks, A. (2019). *Creating Intelligent Agents : Combining Agent-Based Modeling with Machine Learning*. *ML*, 1–20.

Brissaud, F. (2008). Criteria for water recycling and reuse in the Mediterranean countries. *Desalination*, *218*(1–3), 24–33. https://doi.org/10.1016/j.desal.2006.07.016

Bromley, J. (2005). Guidelines for the use of Bayesian networks as a participatory tool for Water Resource Management. *Management of the Environment and Resources Using Integrated Techniques*, *July*, 137.

Brown, C., Alexander, P., Holzhauer, S., & Rounsevell, M. D. A. (2017). Behavioral models of climate change adaptation and mitigation in land-based sectors. *Wiley Interdisciplinary Reviews: Climate Change*, *8*(2), e448.

Brown, T. C., Mahat, V., & Ramirez, J. A. (2019). Adaptation to Future Water Shortages in the United States Caused by Population Growth and Climate Change. *Earth's Future*, *7*(3), 219–234. https://doi.org/10.1029/2018EF001091

Butler, D., Ward, S., Sweetapple, C., Astaraie-Imani, M., Diao, K., Farmani, R., & Fu, G. (2017). Reliable, resilient and sustainable water management: the Safe & SuRe approach. *Global Challenges*, *1*(1), 63–77.

California Code of Regulations. (n.d.). Retrieved November 17, 2019, from https://govt.westlaw.com/calregs/Browse/Home/California/CaliforniaCodeofRegulations?guid=IE8ADB4F0D4B911DE8879F88E8B0DAAAE&originationContext=documenttoc&transitionType=Default&contextData=(sc.Default)

California legislative Information (Water Code). (n.d.). Retrieved November 12, 2019, from https://leginfo.legislature.ca.gov/faces/codes_displayText.xhtml?lawCode=WAT&division=7.&title=&part=&chapter=7.&article=7

Calvez, B., & Hutzler, G. (2005). Automatic tuning of agent-based models using genetic algorithms. *International Workshop on Multi-Agent Systems and Agent-Based Simulation*, 41–57.

Capodaglio, A. (2017). Integrated, Decentralized Wastewater Management for Resource Recovery in Rural and Peri-Urban Areas. *Resources*, *6*(2), 22. https://doi.org/10.3390/resources6020022

Carballa, M., Omil, F., & Lema, J. M. (2005). Removal of cosmetic ingredients and pharmaceuticals in sewage primary treatment. *Water Research*, *39*(19), 4790–4796. https://doi.org/10.1016/j.watres.2005.09.018

Carr, G., Potter, R. B., & Nortcliff, S. (2011). Water reuse for irrigation in Jordan: Perceptions of water quality among farmers. *Agricultural Water Management*, *98*(5), 847–854.

Chapter 445a - Water Controls. (n.d.). Retrieved November 15, 2019, from https://www.leg.state.nv.us/NAC/NAC-445A.html

Chen, Z., Ngo, H. H., & Guo, W. (2012). A critical review on sustainability assessment of recycled water schemes. *Science of the Total Environment*, *426*, 13–31.

Chu, J., Chen, J., Wang, C., & Fu, P. (2004). Wastewater reuse potential analysis: Implications for China's water resources management. *Water Research*, *38*(11), 2746–2756. https://doi.org/10.1016/j.watres.2004.04.002

Claessens, L., Antle, J. M., Stoorvogel, J. J., Valdivia, R. O., Thornton, P. K., & Herrero, M. (2012). A method for evaluating climate change adaptation strategies for small-scale farmers using survey, experimental and modeled data. *Agricultural Systems*, *111*, 85–95.

Clumpner, G. (2016). *Recycled Water Pricing Alternatives - NBS*. https://www.nbsgov.com/blog/2016/09/29/recycled-water-pricing-alternatives/#_ftn1

Crooks, A., Malleson, N., Manley, E., & Heppenstall, A. (2018). *Agent-based modelling and geographical information systems: a practical primer*. SAGE Publications Limited.

CropScape - NASS CDL Program. (n.d.). Retrieved November 15, 2021, from https://nassgeodata.gmu.edu/CropScape/

Dawoud, M. A. (2005). The role of desalination in augmentation of water supply in GCC countries. *Desalination*, *186*(1–3), 187–198.

Deckert, A., & Klein, R. (2014). Simulation-based optimization of an agent-based simulation. *NETNOMICS: Economic Research and Electronic Networking*, *15*(1), 33–56.

Didier, B. (2018). *EU Legislation in Progress Water reuse Setting minimum requirements*. *0169*(September).

Dong, Y., Jiang, C., Suri, M. R., Pee, D., Meng, L., & Rosenberg Goldstein, R. E. (2019). Groundwater level changes with a focus on agricultural areas in the Mid-Atlantic region of the United States, 2002–2016. *Environmental Research*, *171*(December 2018), 193–203. https://doi.org/10.1016/j.envres.2019.01.004

Drechsel, P., Cofie, O. O., van Veenhuizen, R., & Larbi, T. O. (2008). Linking research, capacity building, and policy dialogue in support of informal irrigation in urban West Africa. *Irrigation and Drainage*, *57*(3), 268–278. https://doi.org/10.1002/ird.430

Drewes, J. E., Hübner, U., Zhiteneva, V., & Karakurt, S. (2017). *Characterization of unplanned water reuse in the EU Final Report Prepared by*. 1–61.

Easa, M. E. S., Shereif, M. M., Shaaban, A. I., & Mancy, K. H. (1995). Public health implications of waste water reuse for fish production. *Water Science and Technology*, *32*(11), 145–152. https://doi.org/10.1016/0273-1223(96)00128-X

Edelstein, M., Ben-Hur, M., Cohen, R., Burger, Y., & Ravina, I. (2005). Boron and salinity effects on grafted and non-grafted melon plants. *Plant and Soil*, *269*(1–2), 273–284.

Eiben, A., & Smith, J. (2007). Introduction to evolutionary computing (corrected 2nd printing). *Natural Computing Series. Berlin: Springer*.

Elsawah, S., Guillaume, J. H. A., Filatova, T., Rook, J., & Jakeman, A. J. (2015). A methodology for eliciting, representing, and analysing stakeholder knowledge for decision making on complex socio-ecological systems: from cognitive maps to agent-based models. *Journal of Environmental Management*, *151*, 500–516.

EPA Enforcement and Compliance History Online . (n.d.). Retrieved November 15, 2021, from https://echo.epa.gov/facilities/facility-search/results

Eslamian, S. (Ed.). (2016). *Urban Water Reuse Handbook*.

EU level instrument on water reuse-Final report EU-level instruments on water reuse Final report to support the Commission's Impact Assessment. (2016). https://doi.org/10.2779/974903

Extension Services, U. of M. (n.d.). *Estimating Irrigation Water Requirements to Optimize Crop Growth Why Estimate Water Needs?* Retrieved November 14, 2021, from www.extension.umd.edu

Falkenberg, T., Saxena, D., & Kistemann, T. (2018). Impact of wastewater-irrigation on in-household water contamination. A cohort study among urban farmers in Ahmedabad, India. *Science of the Total Environment*, *639*, 988–996. https://doi.org/10.1016/j.scitotenv.2018.05.117

Famiglietti, J. S., Lo, M., Ho, S. L., Bethune, J., Anderson, K. J., Syed, T. H., Swenson, S. C., de Linage, C. R., & Rodell, M. (2011). Satellites measure recent rates of groundwater depletion in California's Central Valley. *Geophysical Research Letters*, *38*(3).

FAO. (2015). *Chapter 5: Irrigation water requirements*. Natural Resources Management and Environment Departmen. http://www.fao.org/3/w4347e/w4347e0c.htm

Farhadi, S., Nikoo, M. R., Rakhshandehroo, G. R., Akhbari, M., & Alizadeh, M. R. (2016). An agent-based-nash modeling framework for sustainable groundwater management: A case study. *Agricultural Water Management*, *177*, 348–358.

Fatta-Kassinos, D., Kalavrouziotis, I. K., Koukoulakis, P. H., & Vasquez, M. I. (2011). The risks associated with wastewater reuse and xenobiotics in the agroecological environment. In *Science of the Total Environment* (Vol. 409, Issue 19, pp. 3555–3563). Elsevier. https://doi.org/10.1016/j.scitotenv.2010.03.036

Fent, K., Weston, A. A., & Caminada, D. (2006). Ecotoxicology of human pharmaceuticals. In *Aquatic Toxicology* (Vol. 76, Issue 2, pp. 122–159). Elsevier. https://doi.org/10.1016/j.aquatox.2005.09.009

Fielding, K. S., Dolnicar, S., & Schultz, T. (2019a). Public acceptance of recycled water. *International Journal of Water Resources Development*, *35*(4), 551–586. https://doi.org/10.1080/07900627.2017.1419125

Fielding, K. S., Dolnicar, S., & Schultz, T. (2019b). Public acceptance of recycled water. *International Journal of Water Resources Development*, *35*(4), 551–586. https://doi.org/10.1080/07900627.2017.1419125

Figueras, M., & Borrego, J. J. (2010). New perspectives in monitoring drinking water microbial quality. *International Journal of Environmental Research and Public Health*, *7*(12), 4179–4202.

Filatova, T., Verburg, P. H., Parker, D. C., & Stannard, C. A. (2013). Spatial agent-based models for socio-ecological systems: Challenges and prospects. *Environmental Modelling & Software*, *45*, 1–7.

Flaherty, C. M., & Dodson, S. I. (2005). Effects of pharmaceuticals on Daphnia survival, growth, and reproduction. *Chemosphere*, *61*(2), 200–207. https://doi.org/10.1016/j.chemosphere.2005.02.016

Florida Administrative Rules- Rule Chapter 62-610. (n.d.). Retrieved November 12, 2019, from https://www.flrules.org/gateway/ChapterHome.asp?Chapter=62-610

Gallegos, E., Warren, A., Robles, E., Campoy, E., Calderon, A., Sainz, M. G., Bonilla, P., & Escolero, O. (1999). The effects of wastewater irrigation on groundwater quality in Mexico. *Water Science and Technology*, *40*(2), 45–52. https://doi.org/10.1016/S0273-1223(99)00429-1

Gaskett, C., Wettergreen, D., & Zelinsky, A. (n.d.). *Q-Learning in Continuous State and Action Spaces*.

Geilfus, C.-M. (2018). Review on the significance of chlorine for crop yield and quality. *Plant Science*, *270*, 114–122.
Geldof, G. D. (1995). Policy analysis and complexity-A non-equilibrium approach for integrated water management. *Water Science and Technology*, *31*(8), 301.
Gendreau, M. (2003). An introduction to tabu search. In *Handbook of metaheuristics* (pp. 37–54). Springer.
Ghoreishi, M., Razavi, S., & Elshorbagy, A. (2021a). Understanding human adaptation to drought: agent-based agricultural water demand modeling in the Bow River Basin, Canada. *Hydrological Sciences Journal*, *66*(3), 389–407. https://doi.org/10.1080/02626667.2021.1873344
Ghoreishi, M., Razavi, S., & Elshorbagy, A. (2021b). Understanding Human Adaptation to Drought: Agent-Based Agricultural Water Demand Modeling in the Bow River Basin, Canada. *Hydrological Sciences Journal*, 02626667.2021.1873344. https://doi.org/10.1080/02626667.2021.1873344
Ghoreishi, M., Sheikholeslami, R., Elshorbagy, A., Razavi, S., & Belcher, K. (2021). Peering into agricultural rebound phenomenon using a global sensitivity analysis approach. *Journal of Hydrology*, *602*, 126739. https://doi.org/10.1016/J.JHYDROL.2021.126739
Gilg, A., & Barr, S. (2006). Behavioural attitudes towards water saving? Evidence from a study of environmental actions. *Ecological Economics*, *57*(3), 400–414.
Gleick, P. H., Allen, L., Christian-Smith, J., Cohen, M. J., Cooley, H., Heberger, M., Morrison, J., Palaniappan, M., & Schulte, P. (2012). *The World's Water Volume 7: The Biennial Report on Freshwater Resources*. Island press.
Gonzalez-Serrano, E., Rodriguez-Mirasol, J., Cordero, T., Koussis, A. D., Rodriguez, J. J., & Gonzalez-Serrano, E. (2005). Cost of reclaimed municipal wastewater for applications in seasonally stressed semi-arid regions. *International Water Association* , *54*(6), 355–269.
Gosavi, A. (2015). *Simulation-based optimization*. Springer.
Grignard, A., Taillandier, P., Gaudou, B., Vo, D. A., Huynh, N. Q., & Drogoul, A. (2013). GAMA 1.6: Advancing the art of complex agent-based modeling and simulation. *International Conference on Principles and Practice of Multi-Agent Systems*, 117–131.
Grimm, V. (2019). Ecological Models: Individual-Based Models. In *Encyclopedia of Ecology* (pp. 65–73). https://doi.org/10.1016/b978-0-12-409548-9.11144-3
Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, S. K., Huse, G., Huth, A., Jepsen, J. U., Jørgensen, C., Mooij, W. M., Müller, B., Pe'er, G., Piou, C., Railsback, S. F., Robbins, A. M., … DeAngelis, D. L. (2006). A standard protocol for describing individual-based and agent-based models. *Ecological Modelling*, *198*(1–2), 115–126. https://doi.org/10.1016/j.ecolmodel.2006.04.023
Grimm, V., & Railsback, S. F. (2005). *Individual-based modeling and ecology* (Vol. 8). Princeton university press.
Groeneveld, J., Müller, B., Buchmann, C. M., Dressler, G., Guo, C., Hase, N., Hoffmann, F., John, F., Klassert, C., & Lauf, T. (2017). Theoretical foundations of human decision-making in agent-based land use models–A review. *Environmental Modelling & Software*, *87*, 39–48.

Guidelines for municipal wastewater irrigation. (n.d.). Retrieved November 13, 2019, from https://open.alberta.ca/publications/0778511502

Gutiérrez, J.M., Jones, R.G., Narisma, G.T., Alves, L.M., Amjad, M., Gorodetskaya, I.V., Grose, M., Klutse, N.A.B., Krakovska, S., Li, J., Martínez-Castro, D., Mearns, L.O., Mernild, S.H., Ngo-Duc, T., van den Hurk, B. Yoon, J.-H. (2021). *IPCC WGI Interactive Atlas*. Atlas. In Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the 6th AR of the IPCC. Cambridge University Press. In Press. Interactive Atlas Available from Available from Http://Interactive-Atlas.Ipcc.Ch/. https://interactive-atlas.ipcc.ch/regional-information#eyJ0eXBlIjoiQVRMQVMiLCJjb21tb25zIjp7ImxhdCI6LTY1MDc0MDcsImxuZyI6MzM3MTc4OSwiem9vbSI6NiwicHJvaiI6IkVQU0c6NTQwMzAiLCJtb2RlIjoiY29tcGxldGVfYXRsYXMifSwicHJpbWFyeSI6eyJzY2VuYXJpbyI6InJjcDg1IiwicGVyaW9kIjoi

Ha, J., Kose, M. A., & Ohnsorge, F. (2021). *One-stop source: A global database of inflation*.

Hanjra, M. A., Blackwell, J., Carr, G., Zhang, F., & Jackson, T. M. (2012). Wastewater irrigation and environmental health: Implications for water governance and public policy. *International Journal of Hygiene and Environmental Health*, *215*(3), 255–269. https://doi.org/10.1016/j.ijheh.2011.10.003

Hanjra, M. A., Drechsel, P., Wichelns, D., & Qadir, M. (2015). Transforming urban wastewater into an economic asset: Opportunities and challenges. In *Wastewater* (pp. 271–278). Springer.

Hanna, K. N. (2006). *INTEGRATED ECONOMIC DECISION SUPPORT SYSTEM MODEL FOR DETERMINING IRRIGATION APPLICATION AND PROJECTED AGRICULTURAL WATER DEMAND ON A WATERSHED SCALE*.

Happe, K., Kellermann, K., & Balmann, A. (2006). Agent-based Analysis of Agricultural Policies: an Illustration of the Agricultural Policy Simulator AgriPoliS, its Adaptation and Behavior. *Ecology and Society*, *11*(1).

Harati, S., Perez, L., & Molowny-Horas, R. (2021). Promoting the Emergence of Behavior Norms in a Principal–Agent Problem—An Agent-Based Modeling Approach Using Reinforcement Learning. *Applied Sciences 2021, Vol. 11, Page 8368*, *11*(18), 8368. https://doi.org/10.3390/APP11188368

Hashimoto, T., Stedinger, J. R., & Loucks, D. P. (1982). Reliability, resiliency, and vulnerability criteria for water resource system performance evaluation. *Water Resources Research*, *18*(1), 14–20. https://doi.org/10.1029/WR018I001P00014@10.1002/(ISSN)1944-7973.RISK1

Helmecke, M., Fries, E., & Schulte, C. (2020). Regulating water reuse for agricultural irrigation: risks related to organic micro-contaminants. *Environmental Sciences Europe*, *32*(1), 1–10. https://doi.org/10.1186/s12302-019-0283-0

Helton, J. C., & Davis, F. J. (2003). Latin hypercube sampling and the propagation of uncertainty in analyses of complex systems. *Reliability Engineering & System Safety*, *81*(1), 23–69.

Henderson, D., Jacobson, S. H., & Johnson, A. W. (2003). The theory and practice of simulated annealing. In *Handbook of metaheuristics* (pp. 287–319). Springer.
Heppenstall, A. J., Evans, A. J., & Birkin, M. H. (2007). Genetic algorithm optimisation of an agent-based model for simulating a retail market. *Environment and Planning B: Planning and Design*, *34*(6), 1051–1070.
Heppenstall, A. J. J., Crooks, A. T., See, L. M., & Batty, M. (2012). Agent-based models of geographical systems. In *Agent-Based Models of Geographical Systems*. https://doi.org/10.1007/978-90-481-8927-4
Herman, J. D., Reed, P. M., & Wagener, T. (2013). Time-varying sensitivity analysis clarifies the effects of watershed model formulation on model behavior. *Water Resources Research*, *49*(3), 1400–1414. https://doi.org/10.1002/WRCR.20124
Herman, J., & Usher, W. (n.d.). *SALib: an open-source Python library for sensitivity analysis. J. Open Source Softw. 2 (9)(2017)*.
Hogan, A., & Young, M. (2013). Visioning a future for rural and regional Australia. *Cambridge Journal of Regions, Economy and Society*, *6*(2), 319–330. https://doi.org/10.1093/cjres/rst005
Holland, J. H., & Miller, J. H. (1991). Artificial adaptive agents in economic theory. *The American Economic Review*, *81*(2), 365–370.
Horton, R., Yohe, G., Easterling, W., Kates, R., Ruth, M., Sussman, E., Whelchel, A., Wolfe, D., & Lipschultz, F. (2014). Ch. 16: Northeast, climate change impacts in the United States. *The Third National Climate Assessment*, 371–395.
Howell, T. A. (2003). Irrigation efficiency. *Encyclopedia of Water Science*. https://doi.org/10.1081/E-EWS 120010252
Huang, R., Southall, N., Wang, Y., Yasgar, A., Shinn, P., Jadhav, A., Nguyen, D. T., & Austin, C. P. (2011). The NCGC pharmaceutical collection: A comprehensive resource of clinically approved drugs enabling repurposing and chemical genomics. In *Science Translational Medicine* (Vol. 3, Issue 80). https://doi.org/10.1126/scitranslmed.3001862
Huber, R., Bakker, M., Balmann, A., Berger, T., Bithell, M., Brown, C., Grêt-Regamey, A., Xiong, H., Le, Q. B., & Mack, G. (2018). Representation of decision-making in European agricultural agent-based models. *Agricultural Systems*, *167*, 143–160.
Hung, F., & Yang, Y. C. E. (2021). Assessing Adaptive Irrigation Impacts on Water Scarcity in Nonstationary Environments—A Multi-Agent Reinforcement Learning Approach. *Water Resources Research*, *57*(9), e2020WR029262.
Hurlimann, A., & McKay, J. (2007). Urban Australians using recycled water for domestic non-potable use—An evaluation of the attributes price, saltiness, colour and odour using conjoint analysis. *Journal of Environmental Management*, *83*(1), 93–104. https://doi.org/10.1016/J.JENVMAN.2006.02.008
Hussain, A., Alamzeb, S., & Begum, S. (2013). Accumulation of heavy metals in edible parts of vegetables irrigated with waste water and their daily intake to adults and children, District Mardan, Pakistan. *Food Chemistry*, *136*(3–4), 1515–1523.
Idaho Department of Environmental Quality. (n.d.). Retrieved November 14, 2019, from https://www.deq.idaho.gov/media/516329-guidance_reuse_0907.pdf

IISS (The International Institute for Strategic Studies). (1999). Global water shortages. *Strategic Comments*, *5*(6), 1–2. https://doi.org/10.1080/793510471

Ilias, A., Panoras, A., & Angelakis, A. (2014). Wastewater recycling in greece: The case of thessaloniki. *Sustainability*, *6*(5), 2876–2892.

Inbar, Y. (2007). New standards for treated wastewater reuse in Israel. In *Wastewater reuse–Risk assessment, decision-making and environmental security* (pp. 291–296). Springer.

Indiana Administrative Code. (n.d.). Retrieved November 13, 2019, from https://casetext.com/regulation/indiana-administrative-code/title-327-water-pollution-control-division/article-61-land-application-of-biosolid-industrial-waste-product-and-pollutant-bearing-water

Iran Ministry of Energy- Guidelines for wastewater reuse. (n.d.). Retrieved November 14, 2019, from http://waterstandard.wrm.ir/SC.php?type=component_sections&id=278&sid=299

Isaeva, I. I., Voronin, A. A., Khoperskov, A. V., Dubinko, K. E., & Klikunova, A. Y. (2019). Decision support system for the socio-economic development of the northern part of the volga-akhtuba floodplain (Russia). *Communications in Computer and Information Science*, *1083*, 63–77. https://doi.org/10.1007/978-3-030-29743-5_5

ISO 16075-2:2015 - Guidelines for treated wastewater use for irrigation projects. (n.d.). Retrieved November 11, 2019, from https://www.iso.org/standard/62758.html

Jalalimanesh, A., Shahabi Haghighi, H., Ahmadi, A., & Soltani, M. (2017). Simulation-based optimization of radiotherapy: Agent-based modeling and reinforcement learning. *Mathematics and Computers in Simulation*, *133*, 235–248. https://doi.org/10.1016/j.matcom.2016.05.008

Janssen, M. A., & Ostrom, E. (2006). Empirically based, agent-based models. *Ecology and Society*, *11*(2).

Jaramillo, M. F., & Restrepo, I. (2017). Wastewater Reuse in Agriculture: A Review about Its Limitations and Benefits. *Sustainability*, *9*(10), 1734.

Jeong, H., & Adamowski, J. (2016). A system dynamics based socio-hydrological model for agricultural wastewater reuse at the watershed scale. *Agricultural Water Management*, *171*, 89–107.

Jeong, H., Kim, H., & Jang, T. (2016). Irrigation water quality standards for indirect wastewater reuse in agriculture: A contribution toward sustainablewastewater reuse in South korea. *Water (Switzerland)*, *8*(4). https://doi.org/10.3390/w8040169

Jiang, W., Hou, Q., Yang, Z., Yu, T., Zhong, C., Yang, Y., & Fu, Y. (2014). Annual input fluxes of heavy metals in agricultural soil of Hainan Island, China. *Environmental Science and Pollution Research*, *21*(13), 7876–7885.

Jiménez, B., & Asano, T. (2008). Water Reuse: An International Survey of Current Practice. *Issues and Needs, IWA (International WATER ASSN)*.

Johnson, L. E. (1986). Water resource management decision support systems. *Journal of Water Resources Planning and Management*, *112*(3), 308–325. https://doi.org/10.1061/(ASCE)0733-9496(1986)112:3(308)

JRC. (2017). *Minimum quality requirements for water reuse in agricultural irrigation and aquifer recharge*. https://doi.org/10.2760/887727

Kahinda, J. M., Rockström, J., Taigbenu, A. E., & Dimes, J. (2007). Rainwater harvesting to enhance water productivity of rainfed agriculture in the semi-arid Zimbabwe. *Physics and Chemistry of the Earth, Parts A/B/C*, *32*(15–18), 1068–1073.

Kandiah, V. K., Berglund, E. Z., & Binder, A. R. (2019a). An agent-based modeling approach to project adoption of water reuse and evaluate expansion plans within a sociotechnical water infrastructure system. *Sustainable Cities and Society*, *46*, 101412.

Kandiah, V. K., Berglund, E. Z., & Binder, A. R. (2019b). An Agent-based Modeling Approach to Project Adoption of Water Reuse and Evaluate Expansion Plans within a Sociotechnical Water Infrastructure System. *Sustainable Cities and Society*. https://doi.org/10.1016/J.SCS.2018.12.040

Kang, J., Michels, A., Crooks, A., Aldstadt, J., & Wang, S. (2021). An integrated framework of global sensitivity analysis and calibration for spatially explicit agent-based models. *Transactions in GIS*.

Kang, Y.-I., Park, J.-M., Kim, S.-H., Kang, N.-J., Park, K.-S., Lee, S.-Y., & Jeong, B. R. (2011). Effects of root zone pH and nutrient concentration on the growth and nutrient uptake of tomato seedlings. *Journal of Plant Nutrition*, *34*(5), 640–652.

Kansas EPA 503 Land Application of Septage. (n.d.). Retrieved November 14, 2019, from http://www.kdheks.gov/nps/lepp/KDHE_BOWLandAppof503DomesticSeptageDocwithCover.pdf

Karaivazoglou, N. A., Papakosta, D. K., & Divanidis, S. (2005). Effect of chloride in irrigation water and form of nitrogen fertilizer on Virginia (flue-cured) tobacco. *Field Crops Research*, *92*(1), 61–74.

Kasaie, P., Kelton, W. D., Vaghefi, A., & Naini, S. G. R. J. (2010). Toward optimal resource-allocation for control of epidemics: an agent-based-simulation approach. *Proceedings of the 2010 Winter Simulation Conference*, 2237–2248.

Kelly, R. A., Jakeman, A. J., Barreteau, O., Borsuk, M. E., ElSawah, S., Hamilton, S. H., Henriksen, H. J., Kuikka, S., Maier, H. R., & Rizzoli, A. E. (2013). Selecting among five common modelling approaches for integrated environmental assessment and management. *Environmental Modelling & Software*, *47*, 159–181.

Khan, N. (2018). Natural Ecological Remediation and Reuse of Sewage Water in Agriculture and Its Effects on Plant Health. *Sewage*, 1.

Khan, R., Zakarya, M., Balasubramaniam, V., Jan, M. A., & Menon, V. G. (2020). Smart Sensing-enabled Decision Support System for Water Scheduling in Orange Orchard. *IEEE Sensors Journal*, 1–1. https://doi.org/10.1109/jsen.2020.3012511

Kidd, K. A., Blanchfield, P. J., Mills, K. H., Palace, V. P., Evans, R. E., Lazorchak, J. M., & Flick, R. W. (2007). Collapse of a fish population after exposure to a synthetic estrogen. *Proceedings of the National Academy of Sciences of the United States of America*, *104*(21), 8897–8901. https://doi.org/10.1073/pnas.0609568104

Kleijnen, J. P. C. (2005). An overview of the design and analysis of simulation experiments for sensitivity analysis. *European Journal of Operational Research*, *164*(2), 287–300. https://doi.org/10.1016/j.ejor.2004.02.005

Knox, J., Jeffrey, P., Van Long, L., McNeil, D., Smith, H., Haines, R., Mudgal, S., & Saïdi, N. (2015). *Optimising water reuse in the EU Final report – Part I*. https://doi.org/10.2779/603205

Kock, B. E. (2008). *Agent-based models of socio-hydrological systems for exploring the institutional dynamics of water resources conflict*. Massachusetts Institute of Technology.

Kons, K. (2019). *Q-Learning NetLogo extension*. https://github.com/KevinKons/qlearning-netlogo-extension

Kosegarten, H. U., Hoffmann, B., & Mengel, K. (1999). Apoplastic pH and Fe3+ reduction in intact sunflower leaves. *Plant Physiology*, *121*(4), 1069–1079.

Koutiva, I., & Makropoulos, C. (2016a). Modelling domestic water demand: An agent based approach. *Environmental Modelling & Software*, *79*, 35–54.

Koutiva, I., & Makropoulos, C. (2016b). Modelling domestic water demand: An agent based approach. *Environmental Modelling and Software*, *79*, 35–54. https://doi.org/10.1016/j.envsoft.2016.01.005

Kuil, L., Carr, G., Viglione, A., Prskawetz, A., & Blöschl, G. (2016). Conceptualizing socio-hydrological drought processes: The case of the Maya collapse. *Water Resources Research*, *52*(8), 6222–6242.

Kulkarni, P., Olson, N. D., Paulson, J. N., Pop, M., Maddox, C., Claye, E., Goldstein, R. E. R., Sharma, M., Gibbs, S. G., & Mongodin, E. F. (2018). Conventional wastewater treatment and reuse site practices modify bacterial community structure but do not eliminate some opportunistic pathogens in reclaimed water. *Science of the Total Environment*, *639*, 1126–1137.

Laciana, C. E., & Rovere, S. L. (2011). Ising-like agent-based technology diffusion model: Adoption patterns vs. seeding strategies. *Physica A: Statistical Mechanics and Its Applications*, *390*(6), 1139–1149.

Lautze, J., Stander, E., Drechsel, P., da Silva, A. K., & Keraita, B. (2014). Global experiences in water reuse. *CGIAR Research Program on Water, Land and Ecosystems (WLE). International Water Management Institute (IWMI), Colombo, Sri Lanka*, *31*.

Law, A. M., Kelton, W. D., & Kelton, W. D. (2000). *Simulation modeling and analysis* (Vol. 3). McGraw-Hill New York.

Lazarova, V., & Bahri, A. (2004). *Water reuse for irrigation: agriculture, landscapes, and turf grass*. CRC Press.

Lazarova, V., & Bahri, A. (2005). Water Reuse for Irrigation Agriculture, Landscapes, and Turf Grass. In *New York*.

Levine, J., Chan, K. M. A., & Satterfield, T. (2015). From rational actor to efficient complexity manager: Exorcising the ghost of Homo economicus with a unified synthesis of cognition research. *Ecological Economics*, *114*, 22–32.

Ligmann-Zielinska, A., Kramer, D. B., Cheruvelil, K. S., & Soranno, P. A. (2014). Using Uncertainty and Sensitivity Analyses in Socioecological Agent-Based Models to Improve Their Analytical Performance and Policy Relevance. *PLOS ONE*, *9*(10), e109779. https://doi.org/10.1371/JOURNAL.PONE.0109779

Lin, X., & Lee, L. H. (2006). A new approach to discrete stochastic optimization problems. *European Journal of Operational Research*, *172*(3), 761–782.
Liquid Waste Disposal and Treatment. (n.d.). Retrieved November 14, 2019, from http://164.64.110.134/parts/title20/
Lobell, D. B., & Gourdji, S. M. (2012). The influence of climate change on global crop productivity. *Plant Physiology*, *160*(4), 1686–1697.
Lollini, P.-L., Motta, S., & Pappalardo, F. (2006). Discovery of cancer vaccination protocols with a genetic algorithm driving an agent based simulator. *BMC Bioinformatics*, *7*(1), 1–9.
Lomax, K. M., & Stevenson, J. (1982). *Diffuse source loadings from flat coastal plain watersheds: water movement and nutrient budgets*.
Loucks, D. P. (1997). Quantifying trends in system sustainability. *Hydrological Sciences Journal*, *42*(4), 513–530.
Lu, Z., Wei, Y., Feng, Q., Western, A. W., & Zhou, S. (2018). A framework for incorporating social processes in hydrological models. *Current Opinion in Environmental Sustainability*, *33*, 42–50.
Lyu, S., Chen, W., Zhang, W., Fan, Y., & Jiao, W. (2016). Wastewater reclamation and reuse in China: opportunities and challenges. *Journal of Environmental Sciences*, *39*, 86–96.
Macal, C. M., & North, M. J. (2010). *Tutorial on agent-based modelling and simulation. J Simul 2010; 4: 151–62*.
Mahesh, J., Amerasinghe, P., & Pavelic, P. (2015). An integrated approach to assess the dynamics of a peri-urban watershed influenced by wastewater irrigation. *Journal of Hydrology*, *523*, 427–440. https://doi.org/10.1016/j.jhydrol.2015.02.001
Maja, M. M., & Ayano, S. F. (2021). The Impact of Population Growth on Natural Resources and Farmers' Capacity to Adapt to Climate Change in Low-Income Countries. *Earth Systems and Environment*, 1–13.
Maloupa, E., Traka-Mavrona, K., Papadopoulos, A., Papadopoulos, F., & Pateras, D. (1999). Wastewater re-use in horticultural crops growing in soil and soilless media. *Acta Horticulturae*, *481*, 603–607. https://doi.org/10.17660/actahortic.1999.481.71
Mara, D., Hamilton, A., Sleigh, A., & Karavarsamis, N. (2010). Discussion paper: options for updating the 2006 WHO guidelines. *WHO, FAO, IDRC, IWMI*.
Marcus, I. M., Wilder, H. A., Quazi, S. J., & Walker, S. L. (2013). Linking microbial community structure to function in representative simulated systems. *Appl. Environ. Microbiol.*, *79*(8), 2552–2559.
Marecos do Monte, H., Silva e Sousa, M., & Silva Neves, A. (1989). Effects on Soil and Crops of Irrigation with Primary and Secondary Effluents. *Water Science and Technology*, *21*(6–7), 427–434. https://doi.org/10.2166/wst.1989.0245
Marecos do Monte, M. H. F. . (2007). Guidelines for good practice of water reuse for irrigation: Portuguese standard NP 4434. In *Wastewater Reuse–Risk Assessment, Decision-Making and Environmental Security* (pp. 253–265). Springer.
Martendal, E., Budziak, D., & Carasek, E. (2007). Application of fractional factorial experimental and Box-Behnken designs for optimization of single-drop

microextraction of 2, 4, 6-trichloroanisole and 2, 4, 6-tribromoanisole from wine samples. *Journal of Chromatography A*, *1148*(2), 131–136.
Maryland Department of Planning. (n.d.). Retrieved November 15, 2021, from https://planning.maryland.gov/Pages/OurProducts/DownloadFiles.aspx
Maryland Department of Environment. (2017). *MDE's Water Reuse Initiative*. https://mde.maryland.gov/programs/Water/waterconservation/Pages/reuse_initiative.aspx
Maryland Department of Environment- Wastewater permits- Guidelines for Use of Reclaimed Water. (n.d.). Retrieved November 14, 2019, from https://mde.maryland.gov/programs/Water/wwp/Pages/WaterReuseGuidelines.aspx
Maryland Weather. (n.d.). Retrieved November 16, 2021, from https://msa.maryland.gov/msa/mdmanual/01glance/html/weather.html
Maryland's GIS Data Catalog. (n.d.). Retrieved November 15, 2021, from https://data.imap.maryland.gov/
Marzougui, N., Sabbahi, S., Guasmi, F., Hammami, A., Haddad, M., & Rejeb, S. (n.d.). Effects of wastewater quality on Henna (Lawsonia inermis L.) germination and seedling growth: a case study, Tunisia. *International Journal of Environment, Agriculture and Biotechnology*, *3*(1).
Massey, D. T. (1983). Features of Federal Law That Encourage Adoption of Land Application of Wastewater. *Journal of Water Resources Planning and Management*, *109*(2), 121–133. https://doi.org/10.1061/(ASCE)0733-9496(1983)109:2(121)
Masterson, J. P., Pope, J. P., Fienen, M. N., Monti Jr, J., Nardi, M. R., & Finkelstein, J. S. (2016). *Assessment of groundwater availability in the Northern Atlantic Coastal Plain aquifer system from Long Island, New York, to North Carolina*. US Geological Survey.
Matos, C., Pereira, S., Amorim, E. v., Bentes, I., & Briga-Sá, A. (2014). Wastewater and greywater reuse on irrigation in centralized and decentralized systems - An integrated approach on water quality, energy consumption and CO 2 emissions. *Science of the Total Environment*, *493*, 463–471. https://doi.org/10.1016/j.scitotenv.2014.05.129
Maupin, M. A. (2018). *Summary of estimated water use in the united states in 2015*. US Geological Survey.
McNeal, B. L. (1968). Prediction of the effect of mixed-salt solutions on soil hydraulic conductivity. *Soil Science Society of America Journal*, *32*(2), 190–193.
McNeal, B. L., & Coleman, N. T. (1966). Effect of solution composition on soil hydraulic conductivity. *Soil Science Society of America Journal*, *30*(3), 308–312.
McNeal, B. L., Layfield, D. A., Norvell, W. A., & Rhoades, J. D. (1968). Factors influencing hydraulic conductivity of soils in the presence of mixed-salt solutions. *Soil Science Society of America Journal*, *32*(2), 187–190.
MDE Secretary Celebrates Easton Wastewater Facility Grand Opening. (n.d.). Retrieved November 15, 2021, from https://mde.state.md.us/programs/ResearchCenter/eMDE/Pages/vol3no3/eastonwwtp.aspx

Mendelsohn, R., & Dinar, A. (2003). Climate, water, and agriculture. *Land Economics*, *79*(3), 328–341.
Menegaki, A. N., Hanley, N., & Tsagarakis, K. P. (2007). The social acceptability and valuation of recycled water in Crete: A study of consumers' and farmers' attitudes. *Ecological Economics*, *62*(1), 7–18.
Menegaki, A. N., Mellon, R. C., Vrentzou, A., Koumakis, G., & Tsagarakis, K. P. (2009). What's in a name: Framing treated wastewater as recycled water increases willingness to use and willingness to pay. *Journal of Economic Psychology*, *30*(3), 285–292.
Merced County GIS. (2019). *Updated Merced County Assessor Parcel*. http://geostack-mercedcounty.opendata.arcgis.com/datasets/updated-merced-county-assessor-parcel?geometry=-120.688%2C37.181%2C-120.606%2C37.193
Messac, A. (2015). *Optimization in practice with MATLAB®: for engineering students and professionals*. Cambridge University Press.
Metcalf and Eddy, I., Asano, T., Burton, F. L., Leverenz, H., Tsuchihashi, R., & Tchobanoglous, G. (2007). *Water reuse*. McGraw-Hill Professional Publishing.
Miller-Robbie, L., Ramaswami, A., & Amerasinghe, P. (2017). Wastewater treatment and reuse in urban agriculture: Exploring the food, energy, water, and health nexus in Hyderabad, India. *Environmental Research Letters*, *12*(7), 75005.
Mimi, Z., & Abu Madi, M. (2009). *Building a participatory national consensus on wastewater reclamation and reuse in Palestine*.
Minimum quality requirements for water reuse in agricultural irrigation and aquifer recharge - Towards a water reuse regulatory instrument at EU level Réédition. (n.d.). Retrieved November 15, 2019, from https://ec.europa.eu/jrc/en/publication/eur-scientific-and-technical-research-reports/minimum-quality-requirements-water-reuse-agricultural-irrigation-and-aquifer-recharge
Ministerial Decision No. 145 of 1993 issuing the Regulations on waste water reuse and discharge. (n.d.). Retrieved November 13, 2019, from https://www.ecolex.org/details/legislation/ministerial-decision-no-145-of-1993-issuing-the-regulations-on-waste-water-reuse-and-discharge-lex-faoc044940/
Minnesota Pollution Control Agency. (n.d.). Retrieved November 14, 2019, from https://www.pca.state.mn.us/sites/default/files/wq-wwr1-01.pdf
Mitchell, M. (2006). Complex systems: Network thinking. *Artificial Intelligence*, *170*(18), 1194–1212.
Montana Department of Environmental Quality. (n.d.). Retrieved November 13, 2019, from http://deq.mt.gov/Water/Resources/circulars
Morgan, M. G., Henrion, M., & Small, M. (1990). *Uncertainty: a guide to dealing with uncertainty in quantitative risk and policy analysis*. Cambridge university press.
Munns, R. (2002). Comparative physiology of salt and water stress. *Plant, Cell & Environment*, *25*(2), 239–250.
Narzisi, G., Mysore, V., & Mishra, B. (2006). Multi-objective evolutionary optimization of agent-based models: An application to emergency response planning. *Computational Intelligence*, *2006*, 224–230.

Nash, J. P., Kime, D. E., Van der Ven, L. T. M., Wester, P. W., Brion, F., Maack, G., Stahlschmidt-Allner, P., & Tyler, C. R. (2004). Long-term exposure to environmental concentrations of the pharmaceutical ethynylestradiol causes reproductive failure in fish. *Environmental Health Perspectives*, *112*(17), 1725–1733. https://doi.org/10.1289/ehp.7209

Nazari, R., Eslamian, S., & Khanbilvardi, R. (2012). Water reuse and sustainability. *Ecological Water Quality–Water Treatment and Reuse, Edited by: Voudouris, D*, 241–254.

Nebraska Administrative Code- Nebraska Department of Environmental Quality. (n.d.). Retrieved November 15, 2019, from http://deq.ne.gov/RuleAndR.nsf/RuleAndReg.xsp?documentId=D538E1B3F1ECD8BF862567600058E475&action=openDocument

Neumann, J., & Burks, A. W. (1966). *Theory of self-reproducing automata* (Vol. 1102024). University of Illinois press Urbana.

Ni, J., Liu, M., Ren, L., & Yang, S. X. (2014). A multiagent Q-learning-based optimal allocation approach for urban water resource management system. *IEEE Transactions on Automation Science and Engineering*, *11*(1), 204–214. https://doi.org/10.1109/TASE.2012.2229978

Nikolic, V. V, & Simonovic, S. P. (2015). Multi-method Modeling Framework for Support of Integrated Water Resources Management. *Environ. Process*, *2*, 461–483. https://doi.org/10.1007/s40710-015-0082-6

North Carolina Office of Administrative Hearings. (n.d.). Retrieved November 14, 2019, from http://ncrules.state.nc.us/searchRules.asp?searchCriteria=treatment&title=&chapter=&returnType=Rule&resultsPage=20

North Dakota Administrative Code- Title 33. (n.d.). Retrieved November 12, 2019, from https://www.legis.nd.gov/information/acdata/html/33-16.html

North, M. J., & Macal, C. M. (2007). Chapter 11: ABMS Verification and Validation. In *Managing Business Complexity : Discovering Strategic Solutions with Agent-Based Modeling and Simulation* (Issue February 2014, pp. 221–234). https://doi.org/10.1093/acprof

North Valley Regional Recycled Water Program. (2013). *II*.

Novo, A., André, S., Viana, P., Nunes, O. C., & Manaia, C. M. (2013). Antibiotic resistance, Antimicrobial residues and bacterial community composition in urban wastewater. *Water Research*, *47*(5), 1875–1887. https://doi.org/10.1016/j.watres.2013.01.010

NPDES Rules. (n.d.). Retrieved November 12, 2019, from https://www.iowadnr.gov/environmental-protection/water-quality/npdes-wastewater-permitting/npdes-rules

NRMMC. (2006). Australian Guidelines for Water Recycling: Managing Health and Environmental Risks (Phase 1). *Protection and Heritage Council, Australian Health*, 389. http://www.ephc.gov.au/sites/default/files/WQ_AGWR_GL__Managing_Health_Environmental_Risks_Phase1_Final_200611.pdf

Ohio Laws and Rules. (n.d.). Retrieved November 14, 2019, from http://codes.ohio.gov/oac/3745-42-13

Okun, D. A. (1997). Distributing reclaimed water through dual systems. *Journal / American Water Works Association*, *89*(11), 52–64. https://doi.org/10.1002/j.1551-8833.1997.tb08321.x

Ólafsson, S. (2006). Metaheuristics. *Handbooks in Operations Research and Management Science*, *13*, 633–654.

Oregon Secretary of State- Department of Environmental Quality. (n.d.). Retrieved November 12, 2019, from https://secure.sos.state.or.us/oard/displayDivisionRules.action?selectedDivision=1470

Oremland, M., & Laubenbacher, R. (2014). Optimization of agent-based models: Scaling methods and heuristic algorithms. *Journal of Artificial Societies and Social Simulation*, *17*(2), 6.

Pachepsky, Y., Kierzewski, R., Stocker, M., Sellner, K., Mulbry, W., Lee, H., & Kim, M. (2018). Temporal stability of Escherichia coli concentrations in waters of two irrigation ponds in Maryland. *Appl. Environ. Microbiol.*, *84*(3), e01876-17.

Pande, S., & Savenije, H. H. G. (2016). A sociohydrological model for smallholder farmers in M aharashtra, I ndia. *Water Resources Research*, *52*(3), 1923–1947.

Paranychianakis, N. v, Salgot, M., Snyder, S. A., & Angelakis, A. N. (2015). Water reuse in EU states: necessity for uniform criteria to mitigate human and environmental risks. *Critical Reviews in Environmental Science and Technology*, *45*(13), 1409–1468.

Part 372, Illinois design standards for slow rate land application of treated wastewater. (n.d.). Retrieved November 13, 2019, from http://www.ilga.gov/commission/jcar/admincode/035/03500372sections.html

Patel, A., Crooks, A., & Koizumi, N. (2012a). Slumulation: An agent-based modeling approach to slum formations. *JASSS*, *15*(4). https://doi.org/10.18564/jasss.2045

Patel, A., Crooks, A., & Koizumi, N. (2012b). Slumulation: An agent-based modeling approach to slum formations. *Journal of Artificial Societies and Social Simulation*, *15*(4), 2.

Paul, M., Negahban-Azar, M., Shirmohammadi, A., & Montas, H. (2020). Assessment of agricultural land suitability for irrigation with reclaimed water using geospatial multi-criteria decision analysis. *Agricultural Water Management*. https://doi.org/10.1016/j.agwat.2019.105987

Paul, M., Negahban-Azar, M., Shirmohammadi, A., & Montas, H. (2021). Developing a multicriteria decision analysis framework to evaluate reclaimed wastewater use for agricultural irrigation: The case study of maryland. *Hydrology*, *8*(1), 1–18. https://doi.org/10.3390/hydrology8010004

Peasey, A., Blumenthal, U., Mara, D., & Ruiz-Palacios, G. (2000). A review of policy and standards for wastewater reuse in agriculture: a Latin American perspective. *WELL Study, Task*, *68*.

Pennington, M. J., Rothman, J. A., Jones, M. B., McFrederick, Q. S., Gan, J., & Trumble, J. T. (2018). Effects of contaminants of emerging concern on Myzus persicae (Sulzer, Hemiptera: Aphididae) biology and on their host plant, Capsicum annuum. *Environmental Monitoring and Assessment*, *190*(3). https://doi.org/10.1007/s10661-018-6503-z

Perdue, S., & Hamer, H. (2019). *2018 Irrigation and Water Management Survey Volume 3 • Special Studies • Part 1 United States Department of Agriculture 2017 Census of Agriculture Contents III*.

Perry, C., Steduto, P., Allen, R. G., & Burt, C. M. (2009). Increasing productivity in irrigated agriculture: Agronomic constraints and hydrological realities. *Agricultural Water Management*, *96*(11), 1517–1524.

Pintilie, L., Torres, C. M., Teodosiu, C., & Castells, F. (2016). Urban wastewater reclamation for industrial reuse: An LCA case study. *Journal of Cleaner Production*, *139*, 1–14.

Pistocchi, A., Aloe, A., Dorati, C., Alcalde Sanz, L., Bouraoui, F., Gawlik, B., Grizzetti, B., Pastori, M., & Vigiak, O. (2018). *The potential of water reuse for agricultural irrigation in the EU a hydro-economic analysis.* (Issue September). https://doi.org/10.2760/263713

Plans and Specifications - South Dakota Department of Environment and Natural Resources. (n.d.). Retrieved November 13, 2019, from https://denr.sd.gov/plansprg.aspx

Po, M., Nancarrow, B. E., & Kaercher, J. D. (2003). *Literature review of factors influencing public perceptions of water reuse* (Vol. 54, Issue 3). Citeseer.

Point and Nonpoint Source Management. (n.d.). Retrieved November 14, 2019, from http://www.depgreenport.state.pa.us/elibrary/GetFolder?FolderID=4618

Pope, A. J., & Gimblett, R. (2015). Linking Bayesian and agent-based models to simulate complex social-ecological systems in semi-arid regions. *Frontiers in Environmental Science*, *3*, 55.

Pouladi, P., Afshar, A., Afshar, M. H., Molajou, A., & Farahmand, H. (2019). Agent-based socio-hydrological modeling for restoration of Urmia Lake: Application of theory of planned behavior. *Journal of Hydrology*, *576*, 736–748. https://doi.org/10.1016/j.jhydrol.2019.06.080

Power, K. (2010). *Recycled water use in Australia: regulations, guidelines and validation requirements for a national approach*. National Water Commission Canberra, Australia.

Pronk, G. J., Stofberg, S. F., Van Dooren, T. C. G. W., Dingemans, M. M. L., Frijns, J., Koeman-Stein, N. E., Smeets, P. W. M. H., & Bartholomeus, R. P. (2021). Increasing Water System Robustness in the Netherlands: Potential of Cross-Sectoral Water Reuse. *Water Resources Management*, *35*(11), 3721–3735. https://doi.org/10.1007/s11269-021-02912-5

Pronk, G. J., Stofberg, S. F., van Dooren, T., Dingemans, M. M. L., Frijns, J., Koeman-Stein, N. E., Smeets, P., & Bartholomeus, R. P. (2021). Increasing Water System Robustness in the Netherlands: Potential of Cross-Sectoral Water Reuse. *Water Resources Management*, *35*(11), 3721–3735.

Proposal for a Regulation of the European Parliament and of the Council on minium requirements for water reuse. (n.d.). Retrieved February 27, 2020, from https://ec.europa.eu/info/law/better-regulation/have-your-say/initiatives/1774-Proposal-for-a-Regulation-of-the-European-Parliament-and-of-the-Council-on-minium-requirements-for-water-reuse

Qadir, M., Sharma, B. R., Bruggeman, A., Choukr-Allah, R., & Karajeh, F. (2007). Non-conventional water resources and opportunities for water augmentation to

achieve food security in water scarce countries. In *Agricultural Water Management* (Vol. 87, Issue 1, pp. 2–22). Elsevier. https://doi.org/10.1016/j.agwat.2006.03.018

Quist-Jensen, C. A., Macedonio, F., & Drioli, E. (2015). Membrane technology for water production in agriculture: Desalination and wastewater reuse. In *Desalination* (Vol. 364, pp. 17–32). Elsevier. https://doi.org/10.1016/j.desal.2015.03.001

Ragusa, S. R., De Zoysa, D. S., & Rengasamy, P. (1994). The effect of microorganisms, salinity and turbidity on hydraulic conductivity of irrigation channel soil. *Irrigation Science*, *15*(4), 159–166.

Rahman, M. M., Hagare, D., & Maheshwari, B. (2016). Use of recycled water for irrigation of open spaces: benefits and risks. In *Balanced urban development: options and strategies for liveable cities* (pp. 261–288). Springer.

Rai, V., & Robinson, S. A. (2015). Agent-based modeling of energy technology adoption: Empirical integration of social, behavioral, economic, and environmental factors. *Environmental Modelling & Software*, *70*, 163–177.

Rao, K., Hanjra, M. A., Drechsel, P., & Danso, G. (2015). Business models and economic approaches supporting water reuse. In *Wastewater: Economic Asset in an Urbanizing World* (pp. 195–216). Springer Netherlands. https://doi.org/10.1007/978-94-017-9545-6_11

Raso, J. (2013). *Updated Report On Wastewater Reuse in The European Union*.

Rasoulkhani, K., Logasa, B., Presa Reyes, M., & Mostafavi, A. (2018). Understanding fundamental phenomena affecting the water conservation technology adoption of residential consumers using agent-based modeling. *Water*, *10*(8), 993.

Rasoulkhani, K., Logasa, B., Reyes, M. P., & Mostafavi, A. (2018). Understanding fundamental phenomena affecting the water conservation technology adoption of residential consumers using agent-based modeling. *Water (Switzerland)*, *10*(8). https://doi.org/10.3390/w10080993

Razavi, S., & Gupta, H. v. (2015). What do we mean by sensitivity analysis? The need for comprehensive characterization of "global" sensitivity in Earth and Environmental systems models. *Water Resources Research*, *51*(5), 3070–3092. https://doi.org/10.1002/2014WR016527

Removal of pharmaceuticals and personal care products - results of the Poseidon project. (n.d.). Retrieved November 12, 2019, from https://www.dora.lib4ri.ch/eawag/islandora/object/eawag%3A12147

Renan de Souza Santos, K., Jacinavicius, F. R., & Leite, C. (2011). Effects of the pH on growth and morphology of Anabaenopsis elenkinii Miller (Cyanobacteria) isolated from the alkaline shallow lake of the Brazilian Pantanal. *Fottea*, *11*(1), 119–126.

Rizzo, L., Manaia, C., Merlin, C., Schwartz, T., Dagot, C., Ploy, M. C., Michael, I., & Fatta-Kassinos, D. (2013). Urban wastewater treatment plants as hotspots for antibiotic resistant bacteria and genes spread into the environment: A review. In *Science of the Total Environment* (Vol. 447, pp. 345–360). https://doi.org/10.1016/j.scitotenv.2013.01.032

RMC Water and Environment. (2013). *North Valley Regional Recycled Water Program Feasibility Study* (Vol. 1, Issue 1).

Rogers, E. M., Medina, U. E., Rivera, M. A., & Wiley, C. J. (2005). Complex Adaptive Systems and The Diffusion of Innovations. *The Innovation Journal: The Public Sector Innovation Journal*, *10*(3), 1–26.

Rosegrant, M. W., Ringler, C., & Zhu, T. (2009). Water for agriculture: maintaining food security under growing scarcity. *Annual Review of Environment and Resources*, *34*, 205–222.

Rout, G. R., & Das, P. (2009). Effect of metal toxicity on plant growth and metabolism: I. Zinc. In *Sustainable agriculture* (pp. 873–884). Springer.

Ruan, J., Gerendás, J., Härdter, R., & Sattelmacher, B. (2007). Effect of nitrogen form and root-zone pH on growth and nitrogen uptake of tea (Camellia sinensis) plants. *Annals of Botany*, *99*(2), 301–310.

Rules and Regulations - Oklahoma Department of Environmental Quality. (n.d.). Retrieved November 14, 2019, from https://www.deq.ok.gov/asd/rules-and-regulations/

Sabzian, H., Shafia, M. A., Maleki, A., Hashemi, S. M. S., Baghaei, A., & Gharib, H. (2019). *Theories and Practice of Agent based Modeling: Some practical Implications for Economic Planners*.

Safavi, H. R., Golmohammadi, M. H., & Sandoval-Solis, S. (2015). Expert knowledge based modeling for integrated water resources planning and management in the Zayandehrud River Basin. *Journal of Hydrology*, *528*, 773–789. https://doi.org/10.1016/j.jhydrol.2015.07.014

Sainju, U. M., Ghimire, R., & Pradhan, G. P. (2019). Nitrogen Fertilization I: Impact on Crop, Soil, and Environment. In *Nitrogen in Agricultural Systems*. IntechOpen.

Sakellariou-Makrantonaki, M., Tentas, I., Koliou, A., Kalfountzos, D., & Vyrlas, P. (2003). Irrigation of ornamental shrubs with treated municipal wastewater. *Proceedings of the 8 Th International Conference on Environmental Science and Technology*, *B*(September), 707–714. http://gnest.org/cest8/8cest_papers/abstracts_pdf_names/posters_abs/p164_Sakellariou.pdf

Saltelli, A. (2002). Sensitivity analysis for importance assessment. *Risk Analysis*, *22*(3), 579–590.

Saltelli, A., Aleksankina, K., Becker, W., Fennell, P., Ferretti, F., Holst, N., Li, S., & Wu, Q. (2019). Why so many published sensitivity analyses are false: A systematic review of sensitivity analysis practices. *Environmental Modelling & Software*, *114*, 29–39. https://doi.org/10.1016/J.ENVSOFT.2019.01.012

Saltelli, A., Bammer, G., Bruno, I., Charters, E., di Fiore, M., Didier, E., Nelson Espeland, W., Kay, J., lo Piano, S., Mayo, D., Pielke, R., Portaluri, T., Porter, T. M., Puy, A., Rafols, I., Ravetz, J. R., Reinert, E., Sarewitz, D., Stark, P. B., … Vineis, P. (2020). Five ways to ensure that models serve society: a manifesto. *Nature 2021 582:7813*, *582*(7813), 482–484. https://doi.org/10.1038/d41586-020-01812-9

San Joaquin County Geographic Information Systems. (2020). *San Joaquin County GIS Map Server*. https://www.sjmap.org/GISDataDownload.htm

Sandoval-Solis, S., McKinney, D. C., & Loucks, D. P. (2011). Sustainability index for water resources planning and management. *Journal of Water Resources Planning and Management*, *137*(5), 381–390. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000134

Sarband, E. M., Araghinejad, S., & Attari, J. (2020). Developing an Interactive Spatial Multi-Attribute Decision Support System for Assessing Water Resources Allocation Scenarios. *Water Resources Management*, *34*(2), 447–462. https://doi.org/10.1007/s11269-019-02291-y

Savchenko, O. M., Kecinski, M., Li, T., & Messer, K. D. (2019). Reclaimed water and food production: Cautionary tales from consumer research. *Environmental Research*. https://doi.org/10.1016/j.envres.2018.12.051

Savchenko, O. M., Kecinski, M., Li, T., Messer, K. D., & Xu, H. (2018). Fresh foods irrigated with recycled water: A framed field experiment on consumer responses. *Food Policy*, *80*, 103–112. https://doi.org/10.1016/j.foodpol.2018.09.005

Schaefer, K., Exall, K., & Marsalek, J. (2004). Water Reuse and Recycling in Canada: A Status and Needs Assessment. *Canadian Water Resources Journal*, *29*(3), 195–208. https://doi.org/10.4296/cwrj195

Schelling, T. C. (1971). Dynamic models of segregation. *Journal of Mathematical Sociology*, *1*(2), 143–186.

Schlüter, M., Baeza, A., Dressler, G., Frank, K., Groeneveld, J., Jager, W., Janssen, M. A., McAllister, R. R. J., Müller, B., Orach, K., Schwarz, N., & Wijermans, N. (2017). A framework for mapping and comparing behavioural theories in models of social-ecological systems. *Ecological Economics*, *131*, 21–35. https://doi.org/10.1016/j.ecolecon.2016.08.008

Schreuder, M. D. J., & Brewer, C. A. (2001). Effects of short-term, high exposure to chlorine gas on morphology and physiology of Pinus ponderosa and Pseudotsuga menziesii. *Annals of Botany*, *88*(2), 187–195.

Schwarz, N., & Ernst, A. (2009). Agent-based modeling of the diffusion of environmental innovations—An empirical approach. *Technological Forecasting and Social Change*, *76*(4), 497–511.

Scott, C., Bailey, C., Marra, R., Woods, G., Ormerod, K. J., & Lansey, K. (2012). Scenario Planning to Address Critical Uncertainties for Robust and Resilient Water–Wastewater Infrastructures under Conditions of Water Scarcity and Rapid Development. *Water*, *4*(4), 848–868. https://doi.org/10.3390/w4040848

Seguí-Amórtegui, L., Alfranca-Burriel, O., Guerrero-Garcia-Rojas, H., & Moeller-Chávez, G. (2005). Price for water reclamation, how can it be established? A Mexican case study. *Water Supply*, *5*(2), 87–96. https://doi.org/10.2166/WS.2005.0025

Shahabi, A., Malakouti, M. J., & Fallahi, E. (2005). Effects of bicarbonate content of irrigation water on nutritional disorders of some apple varieties. *Journal of Plant Nutrition*, *28*(9), 1663–1678.

Shapiro, S. S., & Wilk, M. B. (1965). An analysis of variance test for normality (complete samples). *Biometrika*, *52*(3/4), 591–611.

Sharpley, A., & Beegle, D. (2001). Managing Phosphorus for Agriculture and the Environment. *Pennsylvania State University*, 1–16.

Shatanawi, M., & Fayyad, M. (1996). Effect of Khirbet As-Samra treated effluent on the quality of irrigation water in the Central Jordan Valley. *Water Research*, *30*(12), 2915–2920.

Sheidaei, F., Karami, E., & Keshavarz, M. (2016). Farmers' attitude towards wastewater use in Fars Province, Iran. *Water Policy*, *18*(2), 355–367.

Sheikh, B., Nelson, K., Thebo, A., Haddad, B., Gardner, T., Kelly, J., Adin, A., Tsuchihashi, R., Spurlock, S., & Funamizu, N. (2018). *Agricultural Use of Recycled Water: Impediments and Incentives*.

Shoushtarian, F., & Negahban-Azar, M. (2020). Worldwide Regulations and Guidelines for Agricultural Water Reuse: A Critical Review. *Water*, *12*(4), 971. https://doi.org/10.3390/w12040971

Shrestha, E., Ahmad, S., Johnson, W., Shrestha, P., & Batista, J. R. (2011). Carbon footprint of water conveyance versus desalination as alternatives to expand water supply. *Desalination*, *280*(1–3), 33–43.

Shuval, H., Lampert, Y., & Fattal, B. (1997). Development of a risk assessment approach for evaluating wastewater reuse standards for agriculture. *Water Science and Technology*, *35*(11–12), 15–20.

Silver, D., Huang, A., Maddison, C. J., Guez, A., Sifre, L., van den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M., Dieleman, S., Grewe, D., Nham, J., Kalchbrenner, N., Sutskever, I., Lillicrap, T., Leach, M., Kavukcuoglu, K., Graepel, T., & Hassabis, D. (2016). Mastering the game of Go with deep neural networks and tree search. *Nature 2016 529:7587*, *529*(7587), 484–489. https://doi.org/10.1038/nature16961

Smajgl, A., & Barreteau, O. (2017). Framing options for characterising and parameterising human agents in empirical ABM. *Environmental Modelling & Software*, *93*, 29–41.

Smajgl, A., Brown, D. G., Valbuena, D., & Huigen, M. G. A. (2011). Empirical characterisation of agent behaviours in socio-ecological systems. *Environmental Modelling & Software*, *26*(7), 837–844.

Spall, J. C. (2004). Stochastic optimization, Handbook of computational statistics. *Vol. II*, *6*, 170.

Spanish Regulations for Water Reuse- Royal Decree 1620/2007 of 7 December. (n.d.). Retrieved November 14, 2019, from http://www.boe.es/boe/dias/2007/12/08/pdfs/A50639-50661.pdf

Stanislaus County GIS Division. (2014). *Assessor's Parcels, Stanislaus County, California, 2019*. https://purl.stanford.edu/sq899tr7228

State of Hawaii, Department of Health-Wastewater Branch. (n.d.). Retrieved November 13, 2019, from https://health.hawaii.gov/wastewater/home/reuse/

Suarez, D. L., Wood, J. D., & Lesch, S. M. (2006). Effect of SAR on water infiltration under a sequential rain–irrigation management system. *Agricultural Water Management*, *86*(1–2), 150–164.

Suri, M. R., Dery, J. L., Pérodin, J., Brassill, N., He, X., Ammons, S., Gerdes, M. E., Rock, C., & Goldstein, R. E. R. (2019). U.S. farmers' opinions on the use of nontraditional water sources for agricultural activities. *Environmental Research*, *172*(June 2018), 345–357. https://doi.org/10.1016/j.envres.2019.02.035

Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction*. MIT press.
Szabo, F. (2015). *The linear algebra survival guide: illustrated with Mathematica*. Academic Press.
Taillandier, P., Gaudou, B., Grignard, A., Huynh, Q.-N., Marilleau, N., Caillou, P., Philippon, D., & Drogoul, A. (2019). Building, composing and experimenting complex spatial models with the GAMA platform. *GeoInformatica*, *23*(2), 299–322.
Technical Manuals and Guidance Documents. (n.d.). Retrieved November 14, 2019, from https://www.state.nj.us/dep/dwq/techman.htm
Texas Administrative Code. (n.d.). Retrieved November 13, 2019, from https://texreg.sos.state.tx.us/public/readtac$ext.ViewTAC?tac_view=4&ti=30&pt=1&ch=210
Thomidis, T., Zioziou, E., Koundouras, S., Karagiannidis, C., Navrozidis, I., & Nikolaou, N. (2016). Effects of nitrogen and irrigation on the quality of grapes and the susceptibility to Botrytis bunch rot. *Scientia Horticulturae*, *212*, 60–68.
Tillman, D., Larsen, T. A., Pahl-Wostl, C., & Gujer, W. (1999). Modeling the actors in water supply systems. *Water Science and Technology*, *39*(4), 203–211.
Tillman, T., Larsen, T. A., Pahl-Wostl, C., & Gujer, W. (2001). Interaction analysis of stakeholders in water supply systems. *Water Science and Technology*, *43*(5), 319–326.
Tortorello, M. L. (2003). Indicator organisms for safety and quality—uses and methods for detection: minireview. *Journal of AOAC International*, *86*(6), 1208–1217.
Tran, M. (2012). Agent-behaviour and network influence on energy innovation diffusion. *Communications in Nonlinear Science and Numerical Simulation*, *17*(9), 3682–3695.
Troy, T. J., Pavao-Zuckerman, M., & Evans, T. P. (2015). Debates—Perspectives on socio-hydrology: Socio-hydrologic modeling: Tradeoffs, hypothesis testing, and validation. *Water Resources Research*, *51*(6), 4806–4814.
Tzanakakis, V. E., Paranychianaki, N. v., & Angelakis, A. N. (2007). Soil as a wastewater treatment system: Historical development. *Water Science and Technology: Water Supply*, *7*(1), 67–75. https://doi.org/10.2166/ws.2007.008
Tzanakakis, V., Koo-Oshima, S., Haddad, M., Apostolidis, N., & Angelakis, A. (2014). The history of land application and hydroponic systems for wastewater treatment and reuse. *Evolution of Sanitation and Wastewater Technologies through the Centuries; IWA Publishing: London, UK*, 457.
United Nations. (2007). Coping with water scarcity: challenge of the twenty-first century. Report for World Water Day 2007. *World Water Day, United Nations, Rome, Italy*, 1–29.
UN-WWAP. (2012). *The United Nations World Water Development Report 4: Managing Water Under Uncertainty and Risk*. United Nations World Water Assessment Programme, UNESCO Paris.
Urkiaga, A., de las Fuentes, L., Bis, B., Chiru, E., Balasz, B., & Hernández, F. (2008). Development of analysis tools for social, economic and ecological effects of water reuse. *Desalination*, *218*(1–3), 81–91.

U.S. Department of Agriculture. (2018). *CropScape - NASS CDL Program*. National Agricultural Statistics Service. https://nassgeodata.gmu.edu/CropScape/

USDA - National Agricultural Statistics Service - Charts and Maps - Prices Received: Corn Prices Received by Month, US. (n.d.). Retrieved January 17, 2022, from https://www.nass.usda.gov/Charts_and_Maps/Agricultural_Prices/pricecn.php

USDA-NASS. (2019). *2018 Irrigation and Water Management Survey*. *3*(November), 1–269.

USDA-NRCS, & Services, U. of M. E. S. (1975). *Sprinkler Irrigation Guide-Maryland*.

USEPA. (2016). *Chesapeake Bay Progress: Wastewater Pollution Reduction Leads the Way*. https://www.epa.gov/sites/default/files/2016-06/documents/wastewater_progress_report_06142016.pdf

USEPA (US Environmental Protection Agency). (2012). *Guidelines for Water Reuse* (Issue EPA/600/R).

Utah Administrative Code- R317. Environmental Quality, Water Quality. (n.d.). Retrieved November 14, 2019, from https://rules.utah.gov/publicat/code/r317/r317.htm

Utomo, D. S., Onggo, B. S., & Eldridge, S. (2018). Applications of agent-based modelling and simulation in the agri-food supply chains. *European Journal of Operational Research*, *269*(3), 794–805. https://doi.org/10.1016/J.EJOR.2017.10.041

Van Emmerik, T. H. M., Li, Z., Sivapalan, M., Pande, S., Kandasamy, J., Savenije, H. H. G., Chanan, A., & Vigneswaran, S. (2014). Socio-hydrologic modeling to understand and mediate the competition for water between agriculture development and environmental health: Murrumbidgee River basin, Australia. *Hydrology and Earth System Sciences*.

Venkatramanan, S., Lewis, B., Chen, J., Higdon, D., Vullikanti, A., & Marathe, M. (2018). Using data-driven agent-based models for forecasting emerging infectious diseases. *Epidemics*, *22*, 43–49.

Verbyla, M. E., Symonds, E. M., Kafle, R. C., Cairns, M. R., Iriarte, M., Mercado Guzmán, A., Coronado, O., Breitbart, M., Ledo, C., & Mihelcic, J. R. (2016). Managing Microbial Risks from Indirect Wastewater Reuse for Irrigation in Urbanizing Watersheds. *Environmental Science and Technology*, *50*(13), 6803–6813. https://doi.org/10.1021/acs.est.5b05398

Vergine, P., Salerno, C., Libutti, A., Beneduce, L., Gatta, G., Berardi, G., & Pollice, A. (2017). Closing the water cycle in the agro-industrial sector by reusing treated wastewater for irrigation. *Journal of Cleaner Production*, *164*, 587–596. https://doi.org/10.1016/j.jclepro.2017.06.239

Vinten, A. J. A., Mingelgrin, U., & Yaron, B. (1983). The Effect of Suspended Solids in Wastewater on Soil Hydraulic Conductivity: II. Vertical Distribution of Suspended Solids 1. *Soil Science Society of America Journal*, *47*(3), 408–412.

Virginia Administrative Code. (n.d.). Retrieved November 14, 2019, from https://law.lis.virginia.gov/admincode/title9/agency25/chapter740/

von Neumann, J. (1966). Theory of self-reproducing automata. University of Illinois. *Urbana*, *196*(6).

Walker, W. E., Harremoës, P., Rotmans, J., Van Der Sluijs, J. P., Van Asselt, M. B. A., Janssen, P., & Krayer von Krauss, M. P. (2003). Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support. *Integrated Assessment*, *4*(1), 5–17.

Wang, Y., Liang, J., Yang, J., Ma, X., Li, X., Wu, J., Yang, G., Ren, G., & Feng, Y. (2019). Analysis of the environmental behavior of farmers for non-point source pollution control and management: An integration of the theory of planned behavior and the protection motivation theory. *Journal of Environmental Management*, *237*, 15–23.

Washington State Legislature- Chapter 90.46. (n.d.). Retrieved November 13, 2019, from https://app.leg.wa.gov/rcw/default.aspx?cite=90.46&full=true

Wass, J. A. (2010). First Steps in Experimental Design— The Screening Experiment. *Journal of Validation Technology*, *16*(2), 46–53.

Wastewater quality guidelines for agricultural use. (n.d.). Retrieved November 10, 2019, from http://www.fao.org/3/t0551e/t0551e04.htm

Wastewater reuse for Agricultural Irrigation and Its Impact on Health. (n.d.). Retrieved November 12, 2019, from http://cepis.org.pe/wastewater-reuse-agricultural-irrigation/

Wastewater Technical & Environmental Review Guidance and Forms. (n.d.). Retrieved November 14, 2019, from https://epd.georgia.gov/forms-permits/watershed-protection-branch-forms-permits/wastewater-permitting/wastewater-technical

Water & Wastewater Overview – Easton Utilities. (n.d.). Retrieved November 15, 2021, from https://eastonutilities.com/water-overview/

Water Quality Control Commission regulations- Colorado Department of Public Health and Environment. (n.d.). Retrieved November 13, 2019, from https://www.colorado.gov/pacific/cdphe/water-quality-control-commission-regulations

Water Regulations & Standards: Water Pollution Control Permits. (n.d.). Retrieved November 12, 2019, from https://www.scdhec.gov/environment/water-quality/water-regulations-standards/water-regulations-standards-water-pollution

Water Security Agency. (2014). *Treated Municipal Wastewater Irrigation Guidelines- EPB 235*. http://www.saskh20.ca/dwbinder/epb235.pdf

Weng, S. Q., Huang, G. H., & Li, Y. P. (2010). An integrated scenario-based multi-criteria decision support system for water resources management and planning - A case study in the Haihe River Basin. *Expert Systems with Applications*, *37*(12), 8242–8254. https://doi.org/10.1016/j.eswa.2010.05.061

Wilensky, U. (1999). *NetLogo*. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL. http://ccl.northwestern.edu/netlogo/

Wilensky, U., & Rand, W. (2015). *An introduction to agent-based modeling: modeling natural, social, and engineered complex systems with NetLogo*. Mit Press.

Wisconsin Legislature: Chapter NR 206-LAND DISPOSAL OF MUNICIPAL AND DOMESTIC WASTEWATERS. (n.d.). Retrieved November 12, 2019, from http://docs.legis.wisconsin.gov/code/admin_code/nr/200/206

Wise, S., & Crooks, A. T. (2012). Agent-based modeling for community resource management: Acequia-based agriculture. *Computers, Environment and Urban Systems*, *36*(6), 562–572.
Wolfram, S. (2002). *A new kind of science* (Vol. 5). Wolfram media Champaign, IL.
World Health Organization. (2006a). *A compendium of standards for wastewater reuse in the eastern Mediterranean region*.
World Health Organization. (2006b). *Safe Use of Wastewater , Excreta and Greywater Guidelines for the Safe Use of*. *II*, 204. https://doi.org/10.1007/s13398-014-0173-7.2
World Health Organization. (2006c). *Safe Use of Wastewater , Excreta and Greywater Guidelines for the Safe Use of*. *II*, 204. https://doi.org/10.1007/s13398-014-0173-7.2
Wu, L., Chen, W., French, C., & Chang, A. C. (2009). *Safe application of reclaimed water reuse in the southwestern United States* (Vol. 8357). UCANR Publications.
WWAP (United Nations World Water Assessment Programme). (2017). The United Nations World Water Development Report 2017. Wastewater: The Untapped Resource. In *The United Nations World Water Development Report*. https://doi.org/10.1017/CBO9781107415324.004
WWTF - Operations & Maintenance- Rhode Island -Department of Environmental Management. (n.d.). Retrieved November 14, 2019, from http://www.dem.ri.gov/programs/water/wwtf/wwtf-operations-maintenance.php
Wyoming Adminstration Rules. (n.d.). Retrieved November 14, 2019, from https://rules.wyo.gov/DownloadFile.aspx?source_id=8701&source_type_id=81&doc_type_id=110&include_meta_data=Y&file_type=pdf&filename=8701.pdf&token=011159243183231055190169193045157099155057074237
Xiao, M., Koppa, A., Mekonnen, Z., Pagán, B. R., Zhan, S., Cao, Q., Aierken, A., Lee, H., & Lettenmaier, D. P. (2017). How much groundwater did California's Central Valley lose during the 2012–2016 drought? *Geophysical Research Letters*, *44*(10), 4872–4879.
Yazdanpanah, M., Hayati, D., Hochrainer-Stigler, S., & Zamani, G. H. (2014). Understanding farmers' intention and behavior regarding water conservation in the Middle-East and North Africa: A case study in Iran. *Journal of Environmental Management*, *135*, 63–72.
Zarghami, M., & Akbariyeh, S. (2012). System dynamics modeling for complex urban water systems: Application to the city of Tabriz, Iran. *Resources, Conservation and Recycling*, *60*, 99–106. https://doi.org/10.1016/j.resconrec.2011.11.008
Zhang, D., Sial, M. S., Ahmad, N., Filipe, J. A., Thu, P. A., Zia-Ud-din, M., & Caleiro, A. B. (2020). Water Scarcity and Sustainability in an Emerging Economy: A Management Perspective for Future. *Sustainability 2021, Vol. 13, Page 144*, *13*(1), 144. https://doi.org/10.3390/SU13010144
Zhu, Z. J. Y., & McBean, E. A. (2007). Selection of water treatment processes using Bayesian decision network analyses. *Journal of Environmental Engineering and Science*, *6*(1), 95–102. https://doi.org/10.1139/S06-030

Zolfagharipoor, M. A., & Ahmadi, A. (2021). Agent-based modeling of participants' behaviors in an inter-sectoral groundwater market. *Journal of Environmental Management*, *299*, 113560.

Zozaya, S., Rock, C. M., Onumajuru, C., Brassill, N., Goldstein, R. R., Suri, M. R., & Dery, J. L. (2018). Understanding grower perceptions and attitudes on the use of nontraditional water sources, including reclaimed or recycled water, in the semi-arid Southwest United States. *Environmental Research*, *170*(July 2018), 500–509. https://doi.org/10.1016/j.envres.2018.12.039

Zuurbier, K., Smeets, P., Roest, K., & van Vierssen, W. (2018). Use of Wastewater in Managed Aquifer Recharge for Agricultural and Drinking Purposes: The Dutch Experience. In *Safe Use of Wastewater in Agriculture* (pp. 159–175). Springer.