Quantifying the Synergies in the Water-Energy Nexus Generated by Renewable Energy in a Water-Limited Metropolitan Region through Integrated Modeling

by

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ABSTRACT

The Water-Energy Nexus (WEN) is a concept that recognizes the interdependence of water and energy systems. The Phoenix metropolitan region (PMA) in Arizona has significant and potentially vulnerable WEN interactions. Future projections indicate that the population will increase and, with it, energy needs, while changes in future water demand are more uncertain. Climate change will also likely cause a reduction in surface water supply sources. Under these constraints, the expansion of renewable energy technology has the potential to benefit both water and energy systems and increase environmental sustainability by meeting future energy demands while lowering water use and CO_2 emissions. However, the WEN synergies generated by renewables have not yet been thoroughly quantified, nor have the related costs been studied and compared to alternative options.

Quantifying WEN intercations using numerical models is key to assessing renewable energy synergy. Despite recent advances, WEN models are still in their infancy, and research is needed to improve their accuracy and identify their limitations. Here, I highlight three research needs. First, most modeling efforts have been conducted for large-scale domains (e.g., states), while smaller scales, like metropolitan regions, have received less attention. Second, impacts of adopting different temporal (e.g., monthly, annual) and spatial (network granularity) resolutions on simulation accuracy have not been quantified. Third, the importance of simulating feedbacks between water and energy components has not been analyzed.

This dissertation fills these major research gaps by focusing on long-term water allocations and energy dispatch in the metropolitan region of Phoenix. An energy model is developed using the Low Emissions Analysis Platform (LEAP) platform and is subsequently coupled with a water management model based on the Water Evaluation and Planning (WEAP) platform. Analyses are conducted to quantify (1) the value of adopting coupled models instead of single models that are externally coupled, and (2) the accuracy of simulations based on different temporal resolutions of supply and demand and spatial granularity of the water and energy networks. The WEAP-LEAP integrated model is then employed under future climate scenarios to quantify the potential of renewable energy technologies to develop synergies between the PMA's water and energy systems.

DEDICATION

This work is dedicated to my loving parents Mustapha and Malika.

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TABLE OF CONTENTS

Page

LIST OF TABLES x

LIST OF FIGURES xi

CHAPTER

1 INTRODUCTION 1

1.1. Background 1

1.2. Modeling the Macro-Level Water-Energy Nexus 4

1.3. The Phoenix Metropolitan Area 7

1.4. Research Objectives and Dissertation Structure 8

2 A METROPOLITAN SCALE ANALYSIS OF THE IMPACTS OF FUTURE ELECTRICITY MIX ALTERNATIVES ON THE WATER-ENERGY NEXUS 10

2.1. Introduction 10

2.2. Study Region and its WEN Interactions 15

2.3. Datasets 19

2.4. Methodology 20

2.4.1. Overview of the LEAP Model 20

2.4.2. Model Setup in the Phoenix AMA 21

2.4.2.1. Energy Supply 21

2.4.2.2. Energy Demand 22

2.4.3. Model Validation 26

2.4.4. Future Scenarios 26

CHAPTER Page

2.4.4.1. Scenario Description 26

2.4.4.2 Scenario Comparison 31

2.5. Results 32

2.5.1. Historical Simulations 32

2.5.1.1. Model Validation..32

2.5.1.2. Quantification of the WEN Interactions in Historical Conditions 35

2.5.2. Future Projections...37

2.5.2.1. Future Changes of the WEN Interactions......................37

2.5.2.2. CO_2 Emissions..39

2.5.2.3. Economic Assessment of Future Energy Mixes 40

2.6. Discussion 42

2.6.1. Implications for Future Planning...42

2.6.2. WEN Interactions and Potential for Synergies.........................44

2.6.3. Limitations and Future Work 45

2.7. Conclusions 46

3 VALUE OF SPATIOTEMPORAL RESOLUTIONS AND FEEDBACK LOOPS IN WATER-ENERGY NEXUS MODELING 48

3.1. Introduction 48

3.2. Materials and Methods...54

3.2.1. Study Area 55

3.2.2. Overview of WEAP, LEAP, and Coupled WEAP-LEAP Modeling Platforms 57

3.2.3. Set up of WEAP, LEAP, and Coupled WEAP-LEAP in the Phoenix AMA...59

3.2.4. Modeling Configurations 66

3.3. Results 68

3.3.1. Effects of Time Resolution...68

3.3.2. Effects of Spatial Granularity...74

3.3.3. Importance of Coupling..77

3.4. Discussion and Summary...82

3.4.1. Data Availability and Spatiotemporal Disaggregation Are Key83

3.4.2. Value of Higher Temporal Resolution 85

3.4.3. Value of Higher Spatial Granularity 88

3.4.4. Utility of Coupled Simulations...89

3.5. Conclusions 91

4 CONTRIBUTION OF RENEWABLE ENERGY TO GROUNDWATER SUSTAINABILITY IN THE PHOENIX METROPOLITAN REGION 94

4.1. Introduction 94

4.2. Materials and Methods...97

4.2.1. Study Region and its Future Electricity Generation Mix 97

4.2.2. Development of a Water-Energy-Climate Nexus Model in the Phoenix AMA....99

4.2.3. Modeling Configurations 105

4.3. Results 106

4.3.1. Groundwater Use for Power Generation 107

4.3.2. Reclaimed Water (RW) Use....109

4.3.3. Trade-Offs Between Groundwater Sustainability and the Dependence on Purchased Electricity 111

4.3.4. Effects of Climate....114

4.4. Discussion and Summary....117

4.4.1. Utility of the Groundwater Abstraction Cap Strategy....117

4.4.2. Impacts of Renewable Energies on Trade-Off Between Groundwater Sustainability and Purchased Electricity....118

4.5. Conclusions 119

5 CONCLUSIONS AND PERSPECTIVES 121

5.1. Conclusions and Implications....121

5.2. Future Work 124

REFERENCES 128

APPENDIX Page

A COMPUTATION OF THE ENERGY DEMAND FOR EACH SECTOR AND SUBSECTORS OF THE LEAP MODEL..146

B INPUT DATA FOR THE PHOENIX AMA POWER SYSTEM 154

C DATA SOURCES 160

D COST ESTIMATION OF FUTURE ENERGY MIXES..............................163

E CONFIGURATION OF THE WEAP NETWORK 165

LIST OF TABLES

Table Page

1. Energy Ddemand Structure of the Phoenix AMA Implemented in LEAP..... 24

2. Future Scenarios of Energy Supply and Associated Goals. RPS is the Renewable Portfolio Standard. 29

3. Datasets used to set up, apply, and test WEAP and LEAP in the Phoenix AMA. 61

4. Power Plants Located Within the Phoenix AMA and their Fuel Type, Total Capacity, SRP and APS Capacity Entitlement, Mean Annual Electricity Generation, and Water Sources.. 64

5. Characteristics of Modeling Configurations. 67

6. Future Scenarios of Energy Supply and Associated Goals............................. 99

7. Datasets Used to Study the Influence of Climate Variables on Water and Energy Demand and Supply. 104

8. Modeling Configurations to Study the GW Sustainability vs. Electricity Purchases Tradeoff.. 106

9. Values of the Regression Coefficients and the Power Transformation Used in the Determination of Residential and Commercial Energy Intensities......... 148

10. Characteristics of Power Plants Generating Electricity for SRP, APS, and CAP Implemented in the LEAP Model Setup. 156

11. Overview of Datasets Used to Setup the LEAP Model in the Phoenix AMA 161

LIST OF FIGURES

Figure Page

1. Illustration of Some of the Interdependencies Between Water and Energy. 2

2. Power Plant Curtailment Reports for Water-Related Reasons in the Years 2000-2015 (NREL 2016). 3

3. The Phoenix Active Management Area (AMA) in Central Arizona, Along with (i) Service Areas of APS and SRP Energy Utilities; (ii) Power Plants Located in Arizona with Indication of Fuel Type and Capacity Entitlement of Arizona Public Service Company (APS) and Salt River Project (SRP) as of 2017; (iii) Cropland Areas in 2017; (iv) Main Water (WTP) and Wastewater Treatment Plants (WWTP); (v) Salt, Verde and Gila Rivers; and (v) Central Arizona Project (CAP) Aqueduct. 16

4. Energy and Water Portfolios of the Phoenix AMA. (a) Combined Fuel Mix for Energy Generation of SRP, APS, and CAP in 2009, Excluding Distributed Renewable Energy (see Table 10 and EIA, 2018a). (b) Water Supply Sources in the Phoenix AMA in 2009 (Janice and Guenther, 2010). GW is Groundwater; CAP is Central Arizona Project; SRP is Salt River Project..... 17

Figure Page

5. Stages of the Urban Water Life Cycle in the Phoenix Active Management Area and Related Energy Intensive Activities. In Each Box, Bold Font is Used for the Water Source, User, or Infrastructure and Italic Font for the Energy Intensive Activities. GW is Groundwater; CAP is Central Arizona Project; SRP is Salt River Project; WTP is Water Treatment Plant; WRF is Water Reclamation Facility; and WWTP is Wastewater Treatment Plant................ 19

6. (a) Annual Water Demand for the Municipal, Agricultural, Industrial and Indian Sectors as Defined by ADWR (Janice & Guenther, 2010). (b) Mean of Annual Water Volume Supplied by SRP, CAP, Groundwater, and Reclaimed Water Simulated by WEAP Under the Same Climate Variability Observed in the Past. (c) Same as (b) but Under Megadrought Conditions. Figure Adapted from (Guan et al., 2020).. 31

7. Comparison Between (i) Observed (obs) Electricity Sales to Residential, Commercial, and Industrial Customers in Arizona, and (ii) Estimates (sim) of Energy Demand for Each Sector Obtained Through the Approaches Described in Section 4.2.1 and Appendix A. For this Verification, we Used the Population Estimates from the Office of Economic Opportunity (Office of Economic Opportunity 2018). 33

Figure Page

8. Comparison Between Simulated (sim) and Observed (obs) Electricity Generation of Power Plants Aggregated by Fuel Type During the Historical Period 2001-2018. The Simulations are Produced by Running LEAP in the Phoenix AMA, while the Observations Are Obtained from EIA Considering the Capacities of APS, SRP, and CAP Power Plants. Panel (a) Shows Results for Renewable, Natural Gas, Nuclear, and Coal-Fired Power Plants, While Panel (b) Reports Results for Each Source of the Renewable Energy, Including Hydroelectric, Solar and Wind. 35

9. (a) Sankey Diagram for the Energy Fluxes in TWh in the Phoenix Active Management Area in 2009. Ren is Renewable Energy, Res is the Residential Sector, Com is the Commercial Sector, Ind is the Industrial Sector, Water is the Energy Embedded in Water, Other is the Energy Consumed in Activities Unrelated to Water. (b) Zoom on Single Activities Where Energy is Embedded in Water, with Units in GWh. Differences in Total Values are Due to Rounding. Acronyms are Defined in the Main Text. 36

10. (a) Energy Embedded in Water Infrastructure, Energy for Water Heating, and Energy for Activities Unrelated to Water in all Scenarios. (b) Energy Embedded in Water Infrastructure in BAU. (c) Same as (b) but for BAU-Shortage. Acronyms Are Defined in the Main Text. 38

Figure Page

11. (a) Water Withdrawals by all Power Plants in BAU and Renewable Scenarios. (b) CO2 Emissions in BAU and Renewable Scenarios. Note that: (i) Results for the BAU and BAU-Shortage Scenarios Are Comparable Because of the Similar Total Energy Demand, and (ii) Results for Renewable and Solar Scenarios are the Same Because their Energy Mix of Carbon Emitting Sources is the Same. 40

12. Added and Retired Capacities (left vertical axis) Grouped by Fuel Type Along with the Associated Overnight Costs and the Fixed Operations and Maintenance (O&M) Costs (right vertical axis). Values Are Cumulated from 2019 to 2060. 41

13. Fuel Energy and Generated Electricity Grouped by Fuel Type (Left Vertical Axis), Along with Fuel and Variable O&M Costs (right vertical axis). Values Are Cumulated From 2019 to 2060. 42

14. The Phoenix Active Management Area (AMA) in Central Arizona, Along with the Location of Power Plants with the Indication of Fuel Type and Capacity; Main Water Treatment Plants (WTP), Wastewater Treatment Plants (WWTP), and Water Reclamation Facility (WRF); the Salt, Verde and Gila Rivers; the Central Arizona Project (CAP) Aqueduct; Canals of the Salt River Project (SRP); and Cropland and Urban Areas of the Phoenix Metropolitan Region. 55

Figure Page

15. Schematic of (a) Water and (b) Energy Systems in the Phoenix AMA. Acronyms Are Defined in the Main Text. 61

16. Modeling Approaches of Water and Energy Systems in (a) Standalone and (b) Coupled Modes. See Text for Details. 66

17. Monthly Electricity Generation in 2008-2017 (Left Panels) and Monthly Means Across all Years (Right Panels) Reported by EIA (2019) and Simulated by Coupled WEAP-LEAP Under the 1A and 1M Configurations at (a)-(b) Santan, (c)-(d) Redhawk, and (e)-(f) Palo Verde Power Plants. 69

18. (a) Mean Monthly Water Allocations From RW and GW to the Power Node Simulated in the 1M Configuration, and (b) Single Mean Monthly Value Derived From the 1A Setup. 71

19. Water Allocations From CAP. (a) Time Series of CAP Annual Volumes to All Demand Nodes Estimated by ADWR (2018) (Obs) and Simulated Under 1A and 1M Configurations. (b)-(c) Monthly Simulations of CAP Supplies to the Municipal Node in 2010 and 2012, Respectively (See Main Text for Details on Legend). 73

20. Monthly Mean Energy Embedded in Transporting and Treating RW, SRP, GW, and CAP Water Simulated Under 1A and 1M Along with the Percent Difference. 74

Figure Page

21. Sankey Diagrams Showing Mean Monthly Water Allocations From Sources to Power Users Simulated Under (a)-(c)-(e) 1M and (b)-(d)-(f) 9M, Along with Embedded Energy. Means Are Computed Across (a)-(b) all Months of all Simulated Years; (c)-(d) all Februarys; and (e)-(f) all Augusts................. 76

22. (a)-(c) Simulation of Water Allocations for Power Generation at (a) Santan, (b) Redhawk, and (c) Palo Verde Power Plants Using Standalone and Coupled Configurations. (d)-(f) Same as (a)-(c) but for Electricity Generation, Along with Estimates from EIA (2019).. 79

23. Sankey Diagrams Showing the Mean Monthly Water Supply from RW, GW, and CAP to the Power Users Along with the Energy Embedded in Treating and Pumping these Fluxes as Simulated by the (a) Standalone and (b) Coupled Models.. 80

24. Simulations of (a)-(b) CAP, (c)-(d) GW, and (e)-(f) RW Water Allocations for Power Generation Using the Standalone and Coupled Models. For Each Water Source, the Monthly Time Series and Scatterplots Between the Two Estimates Are Shown. In the Scatterplots, the Thinner (Thicker) line is the 1:1 Line (Linear Regression).. 81

25. Simulation of RW Water Allocations to (a) West Phoenix, (b) Redhawk, and (c) Palo Verde Power Plants Using Standalone and Coupled Configurations.82

Figure Page

26. The Salt and Verde River Basins with Location of the Reservoirs Managed by SRP. The Most Upstream Reservoirs Are the Roosevelt and Horseshoe Reservoirs on the Salt and Verde Rivers, Respectively. The Map also Shows the Location of Two USGS Streamflow Stations: “Verde River above Horseshoe Dam, AZ” and “Salt River Near Roosevelt, AZ”, which Represent Outlets to the Horseshoe and Roosevelt Catchments and the Location of 12 Snow Stations.. 102

27. Integrated Modeling of Water, Energy, and Climate.................................... 105

28. Total GW Use for Power Generation in Million m^3 Using the Model Configurations (a) B4.5-0 and R4.5-0; (b) B4.5-0, B4.5-25, B4.5-50, B4.5-75, and B4.5-100; (c) R4.5-0, R4.5-25, R4.5-50, R4.5-75, and R4.5-100. The Dotted Lines in the Top Panel Represent the Linear Regressions and the Colors in the Other Two Panels Represent the Various GW Abstraction Caps, Shown as Percentages in the Legend in Panel (b). 108

29. Simulations of RW Use in Million m^3 for (a) Power Generation and (b) other Purposes. 111

30. Simulations of Total Purchased Electricity vs Total GW Savings Under SSP2 112

31. Mean Monthly Purchased Electricity Simulated Under B4.5-25 and R4.5-25, Along with Load Shape (EIA 2020b). 114

Figure Page

32. Population and Energy Demand According to SSP2-4.5 and SSP5-8.5. (a) Population Projections in the Phoenix AMA; (b) Total Energy Demand; (c) Total Energy Demand Per Capita. 115

33. Total GW Use for Power Generation vs Total RW Use for Power Generation. 116

34. Simulations of Total Purchased Electricity vs Total GW Savings Under SSP5. 117

35. Observed (Obs) and Simulated (Sim) Electricity Intensity in (a) the Five WTPs and (b) the Two WWTPs and the WRF Owned by the City of Phoenix. 153

36. Annual Load Shape at Hourly Resolution of the Phoenix AMA Power System (EIA 2018d). 155

37. Configuration of the WEAP Network Simulating Water Allocation From Supply Sources to Demand Nodes in the Phoenix Active Management Area (AMA). This Configuration Includes One Node Representing Water Demand From all Power Plants Combined. Note that, although GW_SRP is Represented with a Demand Node, it Practically Acts as a Source Node that Accounts for the Groundwater Pumped by SRP... 166

Figure Page

38. Configuration of the Network in WEAP Simulating the Water Allocation From the Supply Sources to the Main Demand Nodes in the Phoenix AMA. This Configuration Includes Nine Nodes Representing the Water Demands for Power Generation by Each Power Plant Located Within the Phoenix AMA Boundaries. Note that, although GW_SRP is Represented with a Demand Node, it Practically Acts as a Source Node that Accounts for the Groundwater Pumped by SRP. 167

CHAPTER 1

INTRODUCTION

1.1. Background

Water and energy are critical for human survival and socioeconomic development (Rao et al. 2017; Rio Carrillo and Frei 2009). Ensuring the security and sustainability of these two resources is then a top priority of every government (U.S. DOE 2014). However, these limited resources are increasingly stressed by higher demands resulting from population growth, urbanization, global warming, and droughts. To overcome these challenges, research has been increasingly conducted in recent years on the interdependencies between these two resources (Hamiche, Stambouli, and Flazi 2016). At a basic level, water is required for generating hydroelectricity, processing and refining fuel, and cooling thermoelectric power plants. Similarly, energy is needed for water treatment, conveyance, and desalination (Figure 1). Depending on the geographical location, each resource may require a large amount of the other to be accessed and delivered (Khan, Linares, and García-González 2017). For example, power plants currently account for 13% of total water consumption in the United States, while the energy necessary to convey, transport, treat, and heat water represents approximately 13% of total primary energy consumption (Dieter et al. 2018; Sanders and Webber 2012). Such interdependencies and dependencies are known as the water-energy nexus (WEN) (Rio Carrillo and Frei 2009; Siddiqi and Anadon 2011; U.S. DOE 2014). Due to the existence of close interactions within the WEN, the security of one resource could be jeopardized by the negative impacts that weather events (e.g., heat and cold waves) and human activities (e.g., terrorist attacks) have on the other. In the U.S., there have been several instances where the generation of electricity (which is the energy form of interest in this research and will be used interchangeably with "energy" in the rest of this dissertation) has been curtailed or power plants have been completely shut down because of (i) droughts and low water availability, and (ii) heat waves causing temperatures of river waters to increase beyond the point of usability for cooling, or water discharge temperatures to exceed legal thresholds (NREL 2016) (Figure 2). Transitioning the operation and management of water and energy sectors away from the traditional "silo" to an integrated approach has then become an urgent need, especially considering the additional stress that climate change, population growth, and urbanization will exert on these two resources in the near future (Dai et al. 2018; Rio Carrillo and Frei 2009; Scott 2011; Siddiqi and Anadon 2011; van Vliet, Sheffield, et al. 2016) (Figure 1).

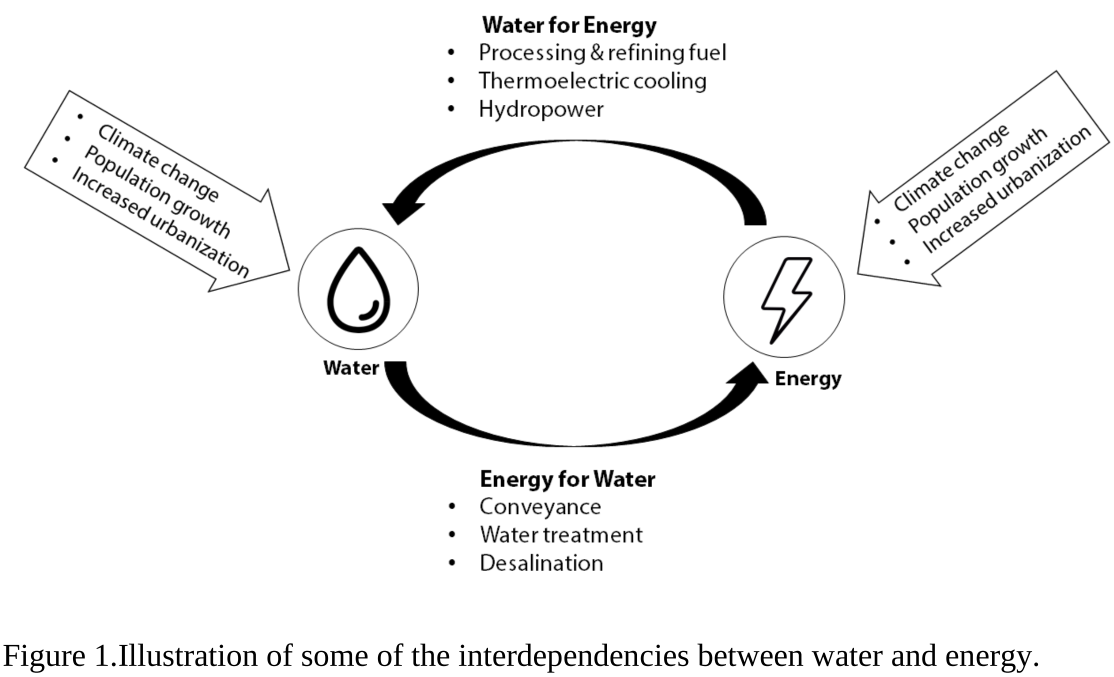

Figure 1.Illustration of some of the interdependencies between water and energy.

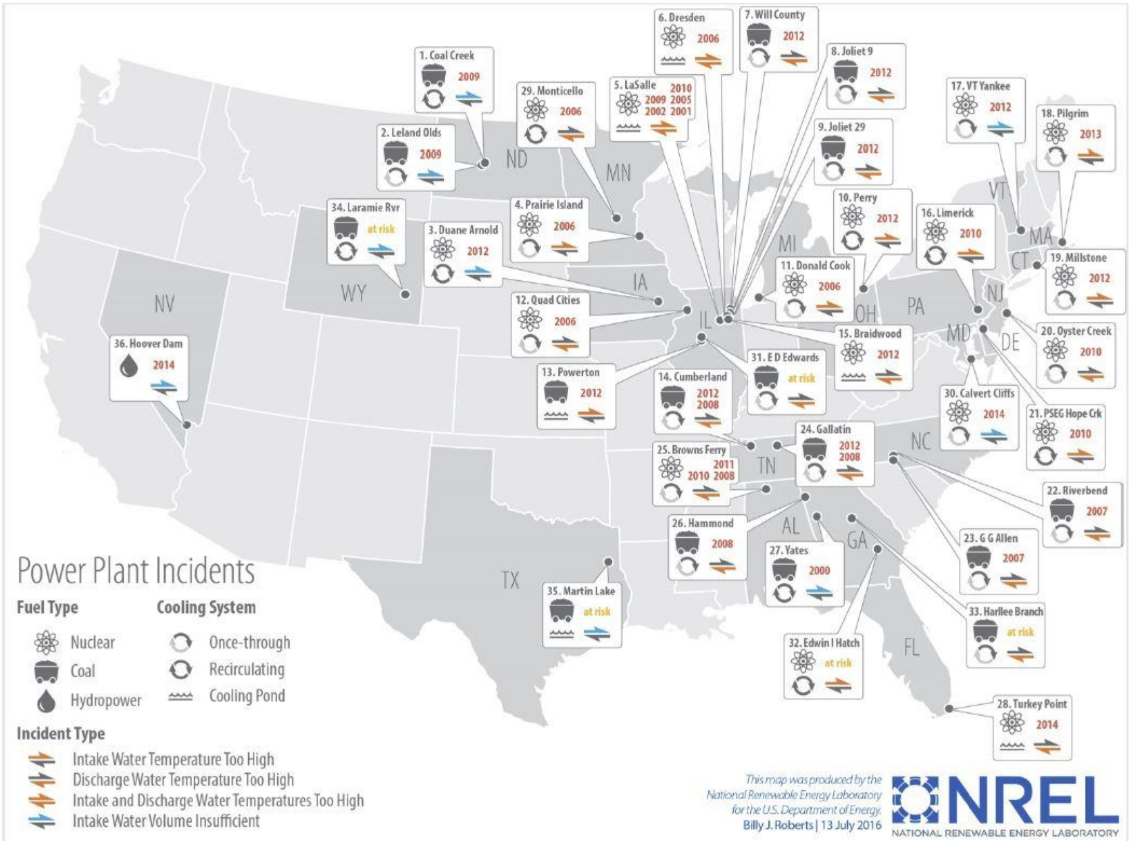

Figure 2. Power plant curtailment reports for water-related reasons in the years 2000-2015 (NREL 2016).

The integrated management of water and energy is key to promoting a decision-making process that accounts for the implications on both systems and ensures that solutions address goals in both sectors (U.S. DOE 2014). Over the last decade, researchers have applied models of the WEN interactions to identify synergies and trade-offs in various regions of the world (Bartos and Chester 2014; Cheng-Li 2002; Grubert and Sanders 2018; Macknick et al. 2012; Yillia 2016) that could support the development of integrated policies that optimize resource use (Gjorgiev and Sansavini 2018; Scott and Pasqualetti 2010) and, potentially, the achievement of sustainable development goals

(Wang et al. 2019) including CO_2 emissions reduction (Rao et al. 2017). The deployment of renewable energy technologies has been identified as one of the most effective solutions that could lead to significant benefits for both sectors (Scott & Pasqualetti, 2010). This is because renewable technologies allowo generating electricity with low to no carbon emissions while requiring negligible water use (Zhang et al. 2020). For example, in Saskatchewan, Canada, the expansion of wind turbines reduces greenhouse gas emissions, industrial water demand, and groundwater use by 2.0, 5.7, and 3.8%, respectively (Wu et al. 2021). Furthermore, in California, it was estimated that the addition of solar and wind generating stations could generate substantial water savings that contribute to groundwater sustainability (He et al. 2019). These two examples are among the first studies to demonstrate that an increase in renewable energy promotes groundwater sustainability. Preserving groundwater in regions where aquifers play a major role in supplying water can limit local electricity generation, necessitating power companies to purchase additional electricity from the market. A rapid adoption of renewables could reduce such a requirement. However, the feedback produced by renewable energy in the WEN is not yet well understood (He et al. 2019) and further studies are needed placing special attention on the links between renewable energy and groundwater sustainability.

1.2. Modeling the Macro-Level Water-Energy Nexus

Macro-level WEN applications are defined by Dai et al. (2018) as those with scales larger than the city as opposed to WEN studies dealing with micro-level scales (e.g., quantifying the energy consumption of various water uses in residential buildings).

Given the complex one- and two-way interactions that could exist in macro-level WEN systems and the lack of observational data, a necessary task to study synergies in the WEN and assess the benefits of renewables is to apply numerical models. Different modeling approaches have been used for this purpose (Dai et al. 2018; Hamiche et al. 2016) and addressed geographical scales that range from national (Welsch et al. 2014), to regional (Yates et al., 2013a, 2013b), to metropolitan (Guan et al. 2020). For instance, Schuck and Green (2002) relied on econometrics principles to quantify the potential of electricity price variation to conserve water and energy resources. Grubert and Webber (2015) used a life-cycle assessment method to estimate future changes in water and energy interdependencies according to various policy choices. Stercke et al. (2020) created a system dynamics model to explore global and local sustainable development goals that are related to the WEN. Khan et al. (2018) and Gjorgiev and Sansavini (2018) developed resource optimization models to simulate the impacts of changes in water temperature on power generation. The same goal was pursued by van Vliet et al. (2016b) combining a large-scale hydrologic model with a stream temperature and hydropower and thermoelectric models. Obringer et al. (2019) investigated the implications of climate change for the WEN using statistical modeling.

Most previous studies of integrated water and energy systems rely on a single model to simulate one system and process its outputs to infer information from the other system (Khan et al. 2017). In particular, in most studies (e.g., Bouckaert et al., 2012; Faeth et al., 2014), modeling tools are utilized to explicitly simulate the energy sector and estimate its water requirements without including an appropriate representation of the water infrastructure, its internal dynamics, and the interactions with the energy components. Other work has applied water management models to simulate the water system and post-processed its outputs to estimate energy demand for water-related uses (e.g., Baki and Makropoulos, 2014; Guan et al., 2020).

A more accurate representation of WEN interdependencies would instead require the use of models that explicitly simulate each system and are integrated by linking the computer codes (i.e., hard links) or exchanging data in real-time (i.e., soft links). Currently, integrated or coupled WEN models that capture the feedback loops between the two systems have been adopted in a limited number of cases. These include both (i) the coupling with soft links of existing water and energy models (van Vliet, Wiberg, et al. 2016; Voisin et al. 2020), as done with the Water Evaluation and Planning (WEAP) and the Long-range Energy Alternatives Planning (LEAP) platforms (Dale et al. 2015; Lin et al. 2019; Liu et al. 2021); and (ii) the development of hard-linked water-energy optimization (Khan et al. 2018; Parkinson and Djilali 2015) and integrated assessment (Liu et al., 2019; Miara et al., 2017) models. Despite these promising studies, their number is still limited and the added values of coupled simulations compared to simpler approaches based on single models and data postprocessing has not been yet properly quantified.

As summarized in a review study by Dai et al. (2018), WEN applications have been conducted at different temporal resolutions or time steps. These include (i) sub-hourly real-time simulations of water distribution systems and power transmission networks (Khatavkar and Mays 2018; Santhosh, Farid, and Youcef-Toumi 2014); and (ii) analyses at monthly and annual scales of infrastructure expansion, effects of policies, and environmental impacts (Jääskeläinen et al. 2018; Zhou et al. 2019). Moreover, WEN models have incorporated the physical components of water and energy systems with various levels of detail. For instance, simulations of electricity generation and water demands have been performed both at (i) fine spatial resolution (or granularity), accounting for each power plant (e.g., Mu et al., 2020), and at (ii) a coarser resolution, aggregating the generating stations based on fuel type and cooling technologies (e.g., Zhou et al., 2019). In general, WEN models that are applied to large-scale studies are based on higher levels of aggregation. While informative to developing regional policies and assessments, these applications have limited ability to suggest quantitative recommendations at local scales, such as metropolitan regions.

1.3. The Phoenix Metropolitan Area

One of the U.S. metropolitan areas with strong and potentially vulnerable water-energy interactions is the Phoenix Metropolitan Area (PMA), in Arizona. In this desert region, the population has tripled over the last 40 years, causing a change in the sectoral water end energy demands, along with associated supply portfolios and infrastructure (EIA 2018c; Higdon and Thompson 1980; Janice and Guenther 2010). Future projections suggest that the population will continue to grow, as will energy demand, while more uncertainty exists regarding future water demand (Eden et al., 2015; Guan et al., 2020; Sampson et al., 2016). The regional water supply sources are energy-intensive and vulnerable to the impacts of climate change, and there is a significant risk of shortage under drought conditions (e.g., Arizona Department of Water Resources and Central

Arizona Project, 2018; Reidmiller et al., 2018). As a result, water supply portfolios may be adapted in the future to meet demands, impacting the associated energy needs (Boehm 2018). Furthermore, local power utilities generate electricity mainly from fossil-fuel and nuclear power plants that require groundwater and reclaimed water for their operation (APS 2017; Janice and Guenther 2010). Due to the full allocation of water rights, along with current water management rules that govern groundwater use (Higdon and Thompson 1980), the supply available for additional water-intensive power plants is limited (Scott and Pasqualetti 2010). The development of renewable energy infrastructure has then been promoted as a solution to meet future energy demands in part due to lower water requirements (Bartos and Chester 2014; Scott and Pasqualetti 2010); however, the cost of these investments should be properly evaluated and compared with alternative solutions.

1.4. Research Objectives and Dissertation Structure

This dissertation will gain insights into the critical research gaps described above. It will first quantify the value of spatiotemporal resolutions and feedback loops in integrated WEN modeling. Then, it will use the integrated model to explore the potential of renewable energy technologies to generate synergies between the water and energy systems of the PMA under climate change. A significant emphasis will be placed on the ability of renewables to achieve groundwater sustainability. The following research questions will be addressed in the subsequent chapters:

1. What are the impacts of possible future electricity mix scenarios on the WEN at the metropolitan scale? [Chapter 2]

2. How does the adoption of single and coupled models under different spatial and temporal resolutions affect the accuracy of water-energy nexus simulations? [Chapter 3]
3. Will renewable energies be able to mitigate the trade-off between groundwater sustainability and the dependence on purchased electricity in the PMA under future climate scenarios? [Chapter 4]

CHAPTER 2

A METROPOLITAN SCALE ANALYSIS OF THE IMPACTS OF FUTURE ELECTRICITY MIX ALTERNATIVES ON THE WATER-ENERGY NEXUS

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2.1. Introduction

Water and energy are fundamental resources necessary for human life, economic growth, and social progress (Rao et al., 2017; Rio Carrillo and Frei, 2009). For example, water is used to generate electricity in hydroelectric stations, to extract and process fuel, and to cool thermoelectric power plants; on the other hand, energy is utilized to source, convey, and treat water (Siddiqi and Anadon, 2011). These interdependencies are collectively referred to as the water-energy nexus (WEN) (Rio Carrillo and Frei, 2009; Siddiqi and Anadon, 2011). Numerous studies have quantified tradeoffs and synergies between water and energy systems (Grubert & Sanders, 2018; Bartos & Chester, 2014; Cheng-Li, 2002; Khatavkar & Mays, 2018; Macknick et al., 2012) to support the development of integrated polices that optimize resource use (Gjorgiev and Sansavini, 2018; Scott, 2011; Scott and Pasqualetti, 2010; U.S. DOE, 2014; White et al., 2017) and, potentially, the achievement of sustainable development goals (Wang et al., 2019), including the reduction of CO_2 emissions (Rao et al., 2017). These studies have been conducted at transnational (Rao et al., 2017; Siddiqi and Anadon, 2011), national (Jääskeläinen et al., 2018; Welsch et al., 2014), regional (Yates et al., 2013; Zhou et al., 2019) and local scales (Dale et al., 2015; Perrone et al., 2011) through qualitative (Scott et al., 2011) and quantitative (Bartos and Chester, 2014; Dale et al., 2015; Yates et al., 2013) approaches. Despite these promising efforts, currently, the water and energy sectors are largely managed independently; that is, planning, management, and policy decisions are made within each sector with limited consideration of the effects of one sector on the other (Scott and Pasqualetti, 2010; White et al., 2017).

A recent report from the U.S. Department of Energy (U.S. DOE, 2014) highlighted an urgent need to adopt an integrated approach for water and energy management as population and climate trends are increasing the vulnerability of these two systems. This is especially true in southwestern U.S., where population has increased dramatically over the last three decades, causing a rise in energy and water needs (U.S. Census Bureau, 2019). In this arid and drought-prone region (Cayan et al., 2010) with limited freshwater resources, the water supply systems are energy intensive since they rely on groundwater, inter-basin surface water transfers, and water reclamation (Janice and Guenther, 2010). The WEN of southwestern U.S. has been studied by Yates et al. (Yates et al., 2013) using a water resource system model. Specifically, these authors found that transitioning to low-carbon technologies and investing in energy efficiency could lead to significant water savings in southwestern states. For example, they estimated that, in the period 2010-2050, water savings in Lake Mead and Lake Powell could total ~2.2 billion m^3 (~1.8 million acre feet) and the groundwater storage could increase up to ~7 billion m^3 (~5.7 million acre feet). Results of this and similar modeling efforts are highly informative at regional scales; however, the simplifications and high level of aggregation adopted to model large regions limit the ability to draw quantitative recommendations at local scales, such as metropolitan regions (Yates et al., 2013).

One of the metropolitan areas of southwestern U.S. with strong and potentially vulnerable water-energy interactions is the metropolitan region of Phoenix, Arizona. In this desert region, population has tripled over the last 40 years, causing a change of the sectoral water end energy demands, along with associated supply portfolios and infrastructure (EIA, 2018a; Higdon and Thompson, 1980; Janice and Guenther, 2010). Future projections suggest that population will continue to grow, as will energy demand, while more uncertainty exists regarding future water demand (ADWR, 2014; Guan et al., 2020; Sampson et al., 2016). The regional water supply sources are energy-intensive and vulnerable to the impacts of climate change, and there is significant risk of shortage under drought conditions (e.g., ADWR and CAP, 2018; Reidmiller et al., 2018). As a result, water supply portfolios may be adapted in the future to meet demands, impacting the associated energy needs (Boehm, 2018). Furthermore, Phoenix metropolitan area utilities generate electricity mainly from fossil-fuel and nuclear power plants that require groundwater and reclaimed water for their operation (APS, 2017; Janice and Guenther, 2010). Due to the full allocation of water rights, along with current water management rules that govern groundwater use (Higdon and Thompson 1980), the supply available for additional water-intensive power plants is limited (Scott and Pasqualetti, 2010). The development of renewable energy infrastructure has been promoted as a solution to meet future energy demands in part due to lower water requirements (Bartos and Chester, 2014; Scott and Pasqualetti, 2010); however, the cost of these investments should be properly evaluated and compared with alternative solutions.

This overview illustrates how several climatic and economic factors can significantly affect the vulnerability of the water and energy systems in the Phoenix metropolitan area, supporting the need for research that assists the development of evidence-based policies for sustainable resource management. In this study, we contribute to this need by quantifying several critical water-energy nexus interactions under a set of plausible future energy mix generation technologies. For this aim, we use the Long-range Energy Alternatives Planning (LEAP) platform, a tool able to simulate energy demand and supply while accounting for the characteristics of individual power plants and the energy demand of all sectors (Heaps, 2020). We set up LEAP by (i) focusing on the power plants managed by the two largest energy utilities of the region, and (ii) creating an energy demand structure for the residential, commercial and industrial sectors that explicitly captures the water-related energy uses. We first build confidence on our model setup by comparing simulated electricity generation and consumption against observed values reported by the U.S. Energy Information Administration (EIA) in the period 2001-2018. We then generate projections of future energy demand for the period 2019-2060 and simulate electricity generation under three fuel mix scenarios that transition more or less ambitiously to renewable energy sources. In doing so, we utilize projections of water allocations from the different supply sources simulated by Guan et al. (2020) through the Water Evaluation and Planning (WEAP) platform (Yates et al., 2005) under the assumption that climate will not impact surface water resources. In addition, we simulate the most probable (or "business as usual") energy scenario under a multidecadal megadrought using water allocations also simulated by Guan et al. (Guan et al., 2020) for this extreme condition. We compare the four future scenarios by calculating key variables of the WEN, CO_2 emissions, and the associated costs.

Our work provides several novel contributions. First, we conduct analyses of the WEN at a metropolitan scale with an unprecedented level of detail in the southwestern U.S., completing and expanding recent regional studies (Bartos and Chester, 2014; Yates et al., 2013). Second, we integrate several data sources to rigorously parameterize and test the energy model; this effort, focused on a metropolitan region with challenges common to other areas of the world, provides useful benchmarks for future analyses at the metropolitan scale, which so far have been limited by the lack of data at this spatial granularity. To our knowledge, this is the first time that a well-calibrated energy model is used to simulate energy generation at the metropolitan scale for multidecadal time periods, with water allocations prescribed by a well-calibrated water management model to reliably quantify water-energy interactions. This effort represents a necessary preliminary step towards (i) the future coupling of the two models to simulate the two-way feedbacks between energy and water systems, and (ii) the development of model that serves as a type of boundary object (White et al., 2010), following efforts by White et al. (White et al., 2017) to understand and support policy discourse for integrated nexus governance. While focused on Phoenix, the modeling approach can be transferred to other metropolitan regions.

2.2. Study Region and its WEN Interactions

To properly capture the WEN interactions in the Phoenix metropolitan area, we selected the Phoenix Active Management Area (AMA) as our study region. The AMA is a hybrid hydrogeological-political unit of 14623 km^2 that includes the Phoenix metropolitan region and is defined by the regional groundwater basin (Figure 3). The AMA has specific water management rules, defined by the Arizona Groundwater Management Act (GMA) of 1980 and overseen by the Arizona Department of Water Resources (ADWR). The primary goal for the Phoenix AMA is to achieve "safe-yield" by 2025 (ADWR, 2010), which is defined as a balance between annual withdrawals from and recharges into the aquifer. The region included in the AMA has experienced rapid population growth in recent decades, increasing from about 1.4 million people in 1980 to 4.5 million in 2018. Because of existing water rights and management rules, this growth has been possible by developing new houses in cropland areas, which have sharply declined from ~1400 km^2 in 1980 to ~650 km^2 in 2009 (ADWR, 2010). Because of these modifications, the water and energy infrastructures have been significantly expanded and modified. The water and energy portfolios in the Phoenix AMA as of 2009 are shown in Figure 4.

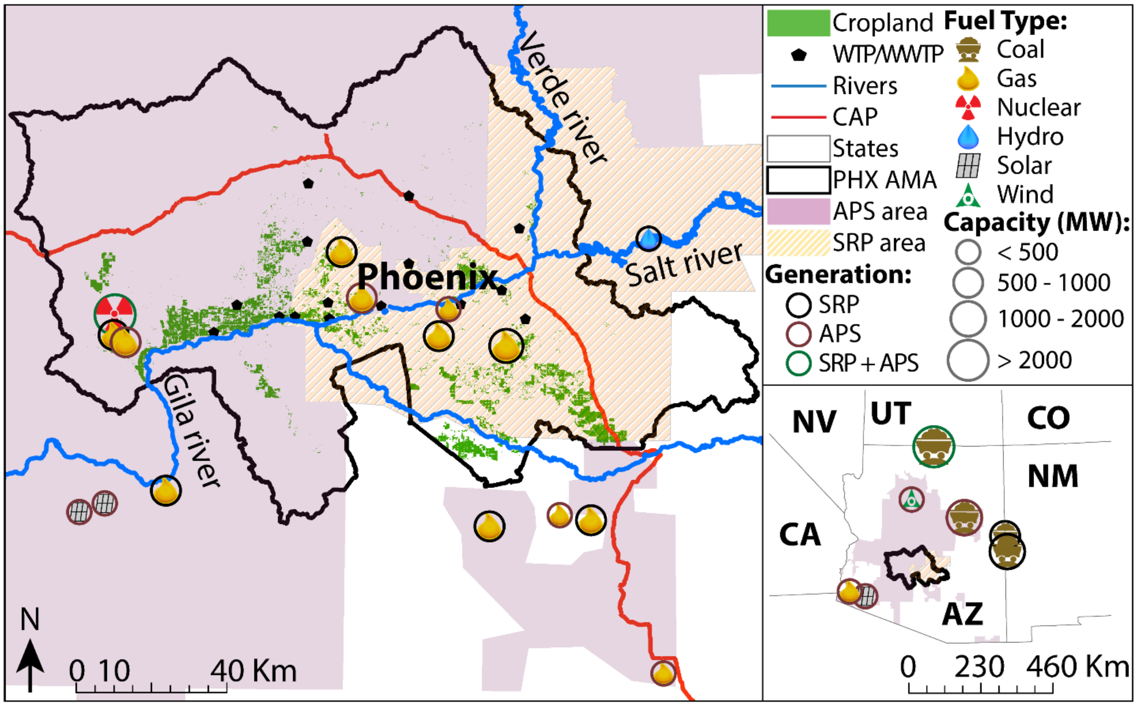

Figure 3. The Phoenix Active Management Area (AMA) in central Arizona, along with (i) service areas of APS and SRP energy utilities; (ii) power plants located in Arizona with indication of fuel type and capacity entitlement of Arizona Public Service Company (APS) and Salt River Project (SRP) as of 2017; (iii) cropland areas in 2017; (iv) main water (WTP) and wastewater treatment plants (WWTP); (v) Salt, Verde and Gila Rivers; and (v) Central Arizona Project (CAP) aqueduct.

Energy in the Phoenix AMA is supplied by two utilities: Salt River Project (SRP) and Arizona Public Service Company (APS). Figure 3 shows the corresponding service areas, along with the location of their power plants with >100 MW of capacity (>40 MW in the case of wind and solar). Table 10 provides details on each power plant. As presented in Figure 4a, the energy generated in centralized power plants and delivered by APS and SRP is dominated by coal with 50% of the total energy generation. This portion includes the energy produced by the Navajo generating station, located close to the border between Arizona and Utah. This plant was built to supply electricity to the Central

Arizona Project (CAP), which transports Colorado River water from Lake Havasu to central and southern Arizona through an aqueduct of 541 km. CAP owns the largest share of the Navajo generating station and is both the largest supplier of water in Arizona and its largest single consumer of electricity (Eden et al., 2011). The other portion of the energy mix is almost evenly split between nuclear and natural gas. Only a very small portion (<1%) is generated from renewable sources. Recently, SRP and APS have increased their capacity entitlement in solar and wind power sources (APS, 2017; SRP, 2018) and purchased additional distributed renewable energy (PWCC, 2018a).

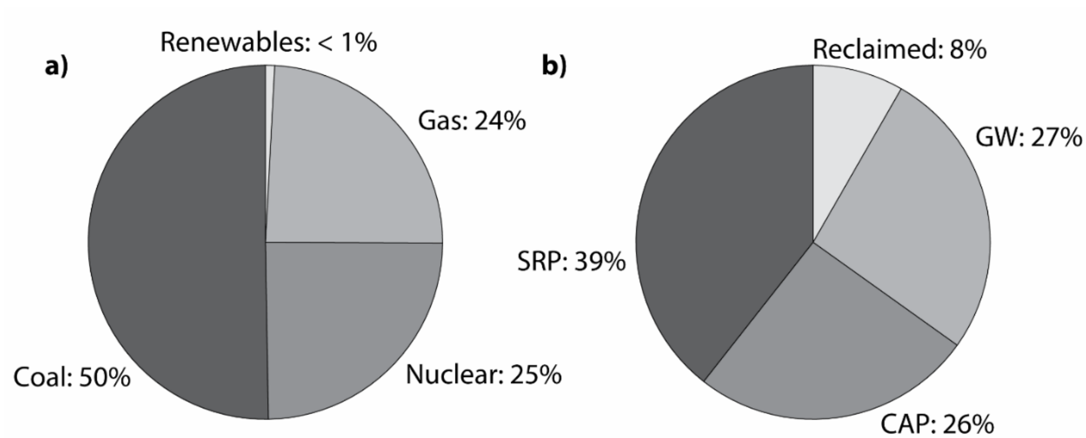

Figure 4**.** Energy and water portfolios of the Phoenix AMA. (a) Combined fuel mix for energy generation of SRP, APS, and CAP in 2009, excluding distributed renewable energy (see Table 10 and EIA, 2018a). (b) Water supply sources in the Phoenix AMA in 2009 (Janice and Guenther, 2010). GW is groundwater; CAP is Central Arizona Project; SRP is Salt River Project.

Water is currently supplied to the Phoenix AMA by four main sources, including (i) surface water from the Salt and Verde Rivers, which is managed by SRP; (ii) surface water from the Colorado River, which is provided by CAP; (iii) groundwater; and (iv) reclaimed water. Figure 3 shows the location of surface water sources and of the plants treating potable water and wastewater. Since the creation of the AMA, the use of groundwater has declined from 47% in 1985 to 27% in 2009, while renewable surface water sources have increased from 52% to 65% (Figure 4b; ADWR, 2010). This change has been possible by the availability of CAP water starting at the end of the 1980s. Unfortunately, access to CAP water is threatened by declining Colorado River flows (Cayan et al., 2010; Gautam and Mascaro, 2018; Udall and Overpeck, 2017). In the event of shortage declaration, CAP water supplies will be curtailed because of CAP's junior priority rights to Colorado River entitlements compared to California and Nevada (USBR, 2007).

To better illustrate the WEN interactions in our study region and support the description of the modeling framework, Figure 5 presents a flowchart of the energy use of each component of the water life cycle. Boxes show each water source, user, or infrastructure (in bold font) and the associated energy use (in italic font). Arrows indicate water fluxes. Water from the surface and subsurface supply sources (CAP, SRP, and groundwater) is sent to the water treatment plants (WTPs) or directly to the agricultural water end-user. Energy is used for pumping CAP water and groundwater, treating water in the WTPs, and pumping water in the distribution system. Water is conveyed from the WTPs to the residential, commercial and industrial water end-users and, from these, it is sent to wastewater treatment plants (WWTPs) and water reclamation facilities (WRFs). Energy is required by the residential and commercial water end-users to heat water, by the agricultural end-user for booster pumps, and by the industrial end-users for processing (not modeled here). WWTPs and WRFs use energy in their associated treating and pumping processes. WWTPs send a portion of the treated water to the WRFs and discharge the rest in the Salt River or into aquifer recharge sites. Reclaimed water is instead sent from the WRFs to commercial, industrial and irrigation water end-users.

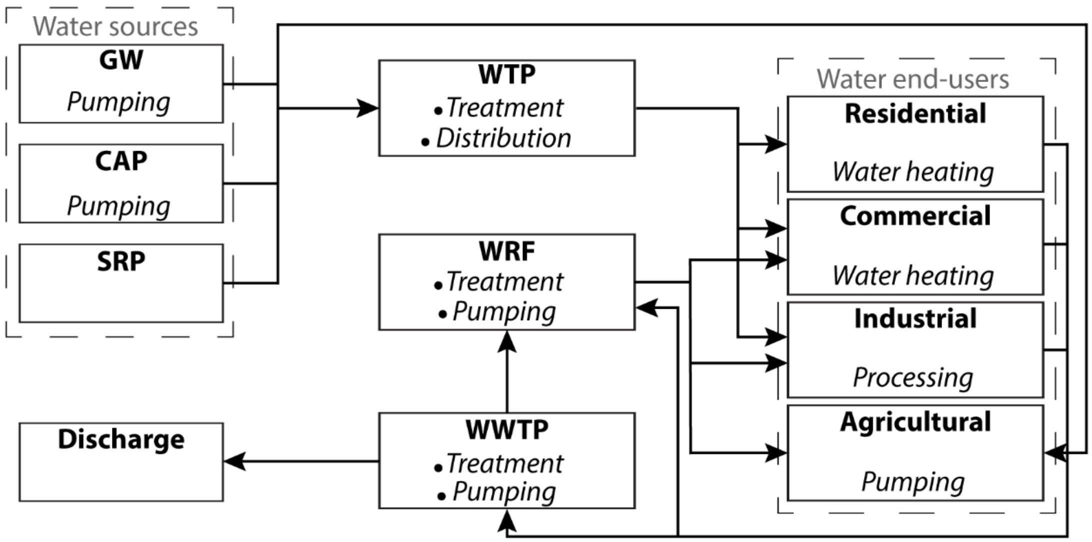

Figure 5. Stages of the urban water life cycle in the Phoenix active management area and related energy intensive activities. In each box, bold font is used for the water source, user, or infrastructure and italic font for the energy intensive activities. GW is groundwater; CAP is Central Arizona Project; SRP is Salt River Project; WTP is water treatment plant; WRF is water reclamation facility; and WWTP is wastewater treatment plant.

2.3. Datasets

To set up our model of energy supply and demand, test it against historical observations, and apply it to generate future projections, we integrated datasets from 22 different regional, state, and federal agencies and utilities. The datasets and associated references are listed in Table C1, where they are grouped based on their use in the model.

The data include different items, such as generation and water requirements of power plants, transmission losses, electricity sales per residential and commercial customers, energy intensity of water and wastewater treatment plants, energy expenses for pumping water, and sectorial water supply from different sources. Depending on the agency, data have different time frequency and spatial granularity. For example, some reports and databases are updated each year, while others (mainly those at national scale) have lower frequency. National agencies often provide state-averaged values, while regional entities provide data at county or city scale.

2.4. Methodology

2.4.1. Overview of the LEAP model

The Long-range Energy Alternatives Planning (LEAP) system is an integrated energy-economy-environment modeling tool developed by the Stockholm Environment Institute (Heaps, 2020). LEAP uses a hybrid bottom-up and top-down macroeconomic techniques to model energy demand and a mass balance approach and simple dispatch rules to simulate the energy fluxes from supply sources to demand end-users. Moreover, it allows for the analysis of multiple user-defined scenarios in terms of policy, economy, and environment. LEAP produces several outputs including time series of energy demand, energy supply, and CO_2 emissions, among others. In previous applications, the model has been mainly run with an annual time-step, but it can also be applied at smaller time scales to capture the seasonality in electricity supply and demand. Examples of previous LEAP applications include studies aimed at assessing CO_2 mitigation strategies (Handayani et al., 2017; Ouedraogo, 2017), providing long-term forecast of nationwide electricity demand (Ishaque, 2017), evaluating governmental plans for future expansion of power generation capacity (Aliyu et al., 2013), and quantifying energy demand and CO_2 emissions of the transportation sector (Fan et al., 2017; Hong et al., 2016).

2.4.2. Model setup in the Phoenix AMA

We initially point out that, in this paper, we use the words energy and electricity interchangeably since electricity is the dominant form of energy in studies related to the WEN (e.g., (Dale et al., 2015; Smith and Liu, 2017)). We set up the LEAP model with an annual time resolution to simulate the energy production and allocation of SRP and APS, the two utilities serving the Phoenix AMA. Note that, while the area served by these companies is larger than the Phoenix AMA (Figure 3), the population served is only slightly larger than the population residing within the Phoenix AMA (e.g., ~4.7 vs. ~4.6 million in 2017). For the Navajo generating station, we also considered the share of electricity generation owned by CAP. To model energy flows, LEAP requires defining the energy supply sources and the demand structure. These are described in the next sections.

2.4.2.1. Energy supply

The energy supply is represented in LEAP through modules that capture the different stages from extraction of primary resources to energy transportation to the demand sectors. Each module includes one or more processes, with characteristics specified by the user. We used two modules in our setup, including electricity generation, and electricity transmission and distribution. In the electricity generation module, we inputted the characteristics of each power plant producing electricity for APS, SRP, and

CAP (see Table 10). These plants are assumed able to satisfy the energy demand in our study region (i.e., no electricity must be imported). Because of their relatively small capacities, the existing solar and wind generating stations were modeled as two distinct combined power plants, respectively. For this power system, we assumed 15% of planned reserve margin (PWCC, 2018a) and we derived the load shape from EIA (EIA, 2018b; Figure 36). For the electricity transmission and distribution module, we assumed ~5% of energy losses (EIA, 2018c).

2.4.2.2. Energy demand

We created an energy demand structure with the main goal of tracking the energy embedded in all water uses and infrastructures. The demand structure includes sectors and subsectors, along with the associated end-users, activity levels and energy intensities (Table 1). For each sector or subsector, the energy demand is calculated as the product between activity level and energy intensity. A detailed description of the demand structure of Table 1 and its use for the computation of the sectorial energy demand is given in Appendix A; here, we provide a brief overview. Following EIA, we defined the residential, commercial, and industrial sectors as the three main energy consuming sectors. The energy end-users are their respective customers. For the residential and commercial sectors, we used population as activity level and derived the energy intensities from published values (see Appendix A). For these sectors, the only water-related energy use is water heating. To track the energy embedded in water, we subdivided the industrial sector into water-unrelated and water infrastructure subsectors. The latter was further subdivided into five subsectors of energy demand. The first four are water users defined by ADWR including municipal, agricultural, Indian communities, and industrial demands (Janice and Guenther, 2010). For these: (i) the associated energy end-users are CAP, SRP, and groundwater; (ii) the activity level is the annual water volume that is either transported, treated or pumped; and (iii) the energy intensities were derived as described in Appendix A. The fifth subsector of energy demand accounts for water treatment facilities (WWTPs and WRFs). To compute the energy demands of the industrial subsectors, we first estimated the overall energy demand of the industrial sector as a function of population and electricity price (see equation (7)). Next, we calculated the energy demand in each of the water infrastructure subsectors and, finally, we computed the energy demand in the water-unrelated subsector as the difference between the total demand and the demands of the water infrastructure subsectors.

Table 1**.** Energy demand structure of the Phoenix AMA implemented in LEAP.

Sector	**Subsector level 1**	**Subsector level 2**	**End-user**	**Activity level**	**Energy intensity**
Residential	---	---	Residential customers	Population	Per capita demand [kWh/capita]: Uses unrelated to water [%] Water heating [%]
Commercial	---	---	Commercial customers	Population	Per capita demand [kWh/capita]: Uses unrelated to water [%] Water heating [%]
Industrial	Industrial water-unrelated	---	Industrial customers	No data	Equation (7) minus total energy demand in the water infrastructure subsector [kWh]
	Water infrastructure	Municipal	CAP	Water volume [m^3]	Conveyance [kWh/m^3] Treatment and distribution [kWh/m^3]
			SRP	Water volume [m^3]	Treatment and distribution [kWh/m^3]
			Groundwater	Water volume [m^3]	Pumping [kWh/m^3] Treatment and distribution [kWh/m^3]
		Agricultural	CAP	Water volume [m^3]	Conveyance [kWh/m^3] Booster pumping [kWh/m^3]
			SRP	Water volume [m^3]	Booster pumping [kWh/m^3]
			Groundwater	Water volume [m^3]	Pumping [kWh/m^3]

Sector	Subsector level 1	Subsector level 2	End-user	Activity level	Energy intensity
		Indian	CAP	Water volume [m^3]	Conveyance [kWh/m^3] Treatment and distribution [kWh/m^3]
Industrial	Water infrastructure	Indian	SRP	Water volume [m^3]	Treatment and distribution [kWh/m^3]
			Groundwater	Water volume [m^3]	Pumping [kWh/m^3] Treatment and distribution [kWh/m^3]
		Industrial	CAP	Water volume [m^3]	Conveyance [kWh/m^3] Treatment and distribution [kWh/m^3]
			SRP	Water volume [m^3]	Treatment and distribution [kWh/m^3]
			Groundwater	Water volume [m^3]	Pumping [kWh/m^3] Treatment and distribution [kWh/m^3]
		WWTP	WWTP	Water volume [m^3]	Treatment in WWTPs [kWh/m^3]
			WRF	Water volume [m^3]	Treatment in WRFs and pumping [kWh/m^3]

2.4.3. Model validation

We validated the LEAP setup in the Phoenix AMA by comparing simulated and observed energy generation in power plants grouped according to the fuel type during the years 2001-2018. For this aim, we provided LEAP with (i) the energy intensities reported in Appendix A, (ii) population estimates from ADWR (Janice and Guenther, 2010), (iii) annual water volume supplied by the different sources available from ADWR (Janice and Guenther, 2010), and (iv) annual water volume treated in WWTPs available from EPA (EPA, 2018). According to reports from PWCC (PWCC, 2018a) and SRP (SRP, 2020a), the capacity of most power plants remained constant during 2001-2018 and, only in some cases, it changed with time, i.e. it was added or retired. We incorporated this information in the definition of the power plant characteristics in LEAP. For the two power plants representing all solar and all wind power generating stations, we set their merit order to one and their capacity factors to 30% and 35%, respectively. These values were defined by minimizing the difference between simulated and historical energy generation of these types of power plants. We used LEAP to simulate the annual electricity generation needed to meet the demand plus transmission and distribution losses; we then compared these values with observations from EIA to build confidence in our model setup.

2.4.4. Future scenarios

2.4.4.1. Scenario description

Once tested, LEAP was used to explore three scenarios of energy supply developed for the period 2019-2060 (Table 2). All scenarios satisfy the same energy demand and were designed following the Integrated Resource Plans (IRPs) produced by APS (APS, 2017) and SRP (SRP, 2018), which provide information on distinct power plants that are currently scheduled to be retired in the future and where a set of possible future energy portfolios is explored through year 2032 (2037) for APS (SRP). In a "business as usual" (BAU) scenario, it was assumed that (i) all coal power plants will retire by 2045, (ii) the capacity of the nuclear plant will not change, and (iii) the renewable portfolio standard (RPS; the percent of energy generated by renewable sources) will reach 22% (50%) by 2030 (2060). These RPS targets will be achieved by adding solar plants with photovoltaic (PV) technology and wind turbines, which are the main renewable sources and technologies considered in the IRPs. The "Renewable" scenario is partly inspired by the time horizons of the RPSs of neighboring states of Nevada and California (Ballotpedia, 2018). It was assumed that (i) coal power plants will retire faster than in the BAU scenario (see Table 2), (ii) RPS will rise to 50% by 2030 with the same sources used in BAU, and (iii) natural gas power plants will retire in 2060 achieving carbon-free energy generation. Finally, the "Solar" scenario takes advantage of Arizona's highly productive solar potential (Hurlbut et al., 2012), and differs from the Renewable scenario by assuming that solar PV is the only added renewable technology. For all scenarios, in each year we (i) used the same nuclear generation capacity, and (ii) increased (decreased) the percentage of renewable sources (coal and natural gas) according to the distinct scenario goals for each year. These three scenarios assume that the availability of surface water supplies will be affected by the same climate variability observed in the past. To model the consequences of an extended period of drought, we also considered an additional BAU scenario, named “BAU-Shortage”, where the water supplied by CAP and SRP is reduced as a consequence of a multidecadal drought that resembles the ‘Medieval’ megadrought retrieved from paleo reconstruction data in the Colorado, Salt and Verde Rivers (Meko et al., 2012). We highlight that, given the inherent uncertainty of future projections, we have consulted local stakeholders to refine the assumptions adopted to create the scenarios through a series of workshops structured as described in White al. (White et al., 2015).

Table 2. Future scenarios of energy supply and associated goals. RPS is the renewable portfolio standard.

Scenario	Goals	Climate
Business as usual (BAU)	• No addition of new coal plants • Compliance with currently announced retirements • Retirement of all coal plants by 2045 • No addition or retirement of nuclear capacity • RPS of 22% by 2030 and 50% by 2060 • New renewable capacity from solar PV and wind	Conditions not affecting surface water availability
Renewable	• No addition of new coal plants • Compliance with currently announced retirements • Retirement of total coal capacity entitlement of APS by 2032 and SRP by 2037 and all gas-fueled plants by 2060 • No addition or retirement of nuclear capacity • RPS of 50% by 2030 • New renewable capacity from solar PV and wind • Carbon-free generation to be achieved by 2060	Conditions not affecting surface water availability
Solar	• New renewable capacity from solar PV • Achievement of all other goals of the Renewable scenario	Conditions not affecting surface water availability
BAU-Shortage	• Achievement of all goals of the BAU scenario	Megadrought

In the four scenarios, we forced LEAP with population projections of the Office of Economic Opportunity of the State of Arizona (Office of Economic Opportunity, 2018). We obtained estimates of future water volumes supplied by the different sources to each demand sector from Guan et al. (Guan et al., 2020), who recently applied the WEAP model (Yates et al., 2005) to the Phoenix AMA. These authors (i) derived future projections of water demand for each sector up to 2060 following the trends observed over the last 25 years, and (ii) applied WEAP to compute the annual water allocations from the four supply sources to the five demand sectors under both climate conditions that will not impact surface water resources variability and the multidecadal drought. To account for the uncertainty in climate variability, Guan et al. (Guan et al., 2020) (i) generated an ensemble of 1000 time series of water volumes provided by CAP and SRP through the stochastic approach of Gober et al. (Gober et al., 2016), and (ii) applied WEAP to simulate the allocation of water in the Phoenix AMA. Here, we forced LEAP in each scenario with the ensemble mean of the 1000 time series of water allocations simulated by WEAP. The projected annual water demand of the main sectors and the ensemble mean of simulated annual water allocations are reported in Figure 6.

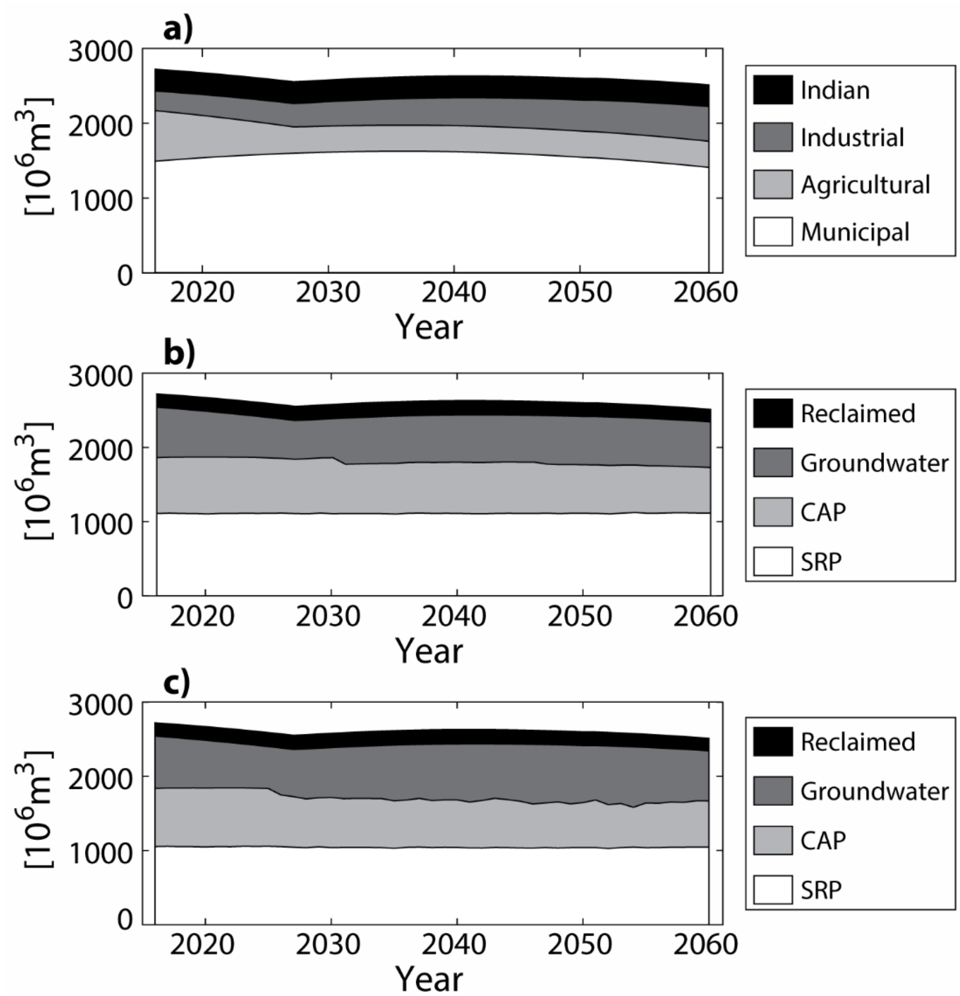

Figure 6. (a) Annual water demand for the municipal, agricultural, industrial and Indian sectors as defined by ADWR (Janice & Guenther, 2010). (b) Mean of annual water volume supplied by SRP, CAP, groundwater, and reclaimed water simulated by WEAP under the same climate variability observed in the past. (c) Same as (b) but under megadrought conditions. Figure adapted from (Guan et al., 2020).

2.4.4.2 Scenario comparison

We compared the future scenarios through variables characterizing the WEN interactions, environmental impacts, and cost. First, we used the energy consumptions of the water infrastructure components simulated by LEAP. Second, we computed the water withdrawals by power plants. For this aim, we used LEAP outputs of electricity generation and water withdrawal rates reported by EIA (EIA, 2018c). Third, we used CO_2 emissions simulated by LEAP using the IPCC Tier 1 default emission factors. Fourth, we estimated the cost of each scenario. This was done by considering four types of costs: (i) overnight costs, (ii) fixed operations and maintenance (O&M) costs, (iii) variable O&M costs, and (iv) fuel costs. Overnight costs quantify the building cost of new power plants assuming no interest during construction. Fixed O&M costs account for salaries and administrative expenses; these were computed annually for all existing capacities. Variable O&M costs depend on the actual electricity generated and incorporate expenses related to water disposal and power purchase, among other items. Fuel costs are expenses related to the purchase of coal, natural gas, and uranium. The calculation of these costs is reported in Appendix D.

2.5. Results

2.5.1. Historical simulations

2.5.1.1. Model validation

Prior to analyzing outputs of LEAP during the historical period, we first evaluated the reliability of the approaches proposed to estimate the sectoral electricity demand by comparing the estimated values with historical electricity sales to residential, commercial, and industrial customers in Arizona, which are available from 1990 to 2017 (EIA, 2018a). Results are presented in Figure 7. The estimated residential and commercial demands capture well the overall increasing trends (correlation coefficient, CC, equal to 0.99 in both cases; root mean square error, RMSE, equal to 0.4 TWh and 0.5 TWh, respectively). The electricity consumption of the industrial sector remained fairly constant, although with some minor fluctuations, which are largely captured by the multilinear regression model of equation (7) (p-value of the F-test <0.01, CC = 0.7 and RMSE = 0.9 TWh).

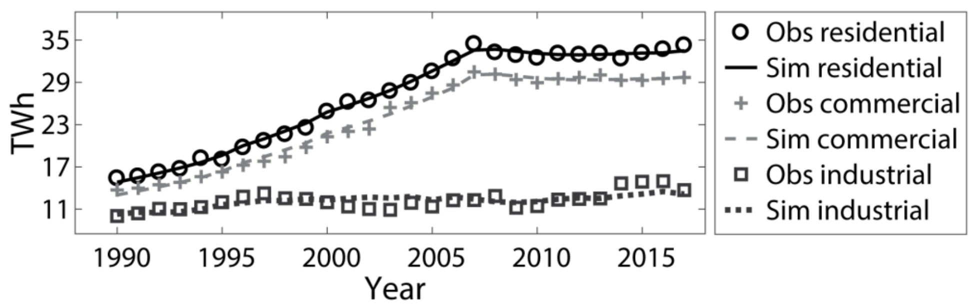

Figure 7**.** Comparison between (i) observed (obs) electricity sales to residential, commercial, and industrial customers in Arizona, and (ii) estimates (sim) of energy demand for each sector obtained through the approaches described in Section 4.2.1 and Appendix A. For this verification, we used the population estimates from the Office of Economic Opportunity (Office of Economic Opportunity 2018).

We applied the LEAP model to the Phoenix AMA during the years 2001-2018, when the energy generation in each power plant was available from EIA. We emphasize again that (i) we only considered the capacity entitlements of APS and SRP, and (ii) we computed the energy demand using population estimates for the Phoenix AMA, even if the population served by these utilities is slightly larger. Figure 8a shows the comparison between simulated and observed energy generated by natural gas, nuclear, coal, and renewable power plants. The total energy generated is reported along with the portion of each fuel type. Given the relatively smaller magnitude of the energy generated by renewable sources, we reported the values for hydroelectric, wind and solar in Figure 8b. We first notice from Figure 6a that the observed total energy generated exceeds the values simulated by LEAP by a maximum of 12%. This surplus is expected because of the larger population served by the two energy utilities and the exports towards other utilities. Since these exports dropped considerably from 2016 to 2018 (FERC, 2020), the simulated surplus is significantly lower in those years. The simulated generation from nuclear and renewable sources match very well the historical generation. The model underestimates instead the energy produced by coal-fired power plants, likely because coal power plants are located outside the borders of the Phoenix AMA and, thus, are serving customers residing both inside and outside of our study region. Figure 6b shows that LEAP captures very well the observed electricity generated by solar, wind, and hydropower sources, except for year 2013 when the simulated solar power generation is 3.5 times the observation. This overestimation is explained because we fully included a new solar power plant (named Solana) that started operating at the end of summer. Overall, these findings provide confidence on the ability of LEAP to capture the energy generation from different sources and its allocation to the different sectors in the Phoenix AMA, thus supporting our analyses of historical conditions and future scenarios presented next. To our knowledge, this is the first time that an energy model is tested with this level of detail at the metropolitan scale over an extended period of time.

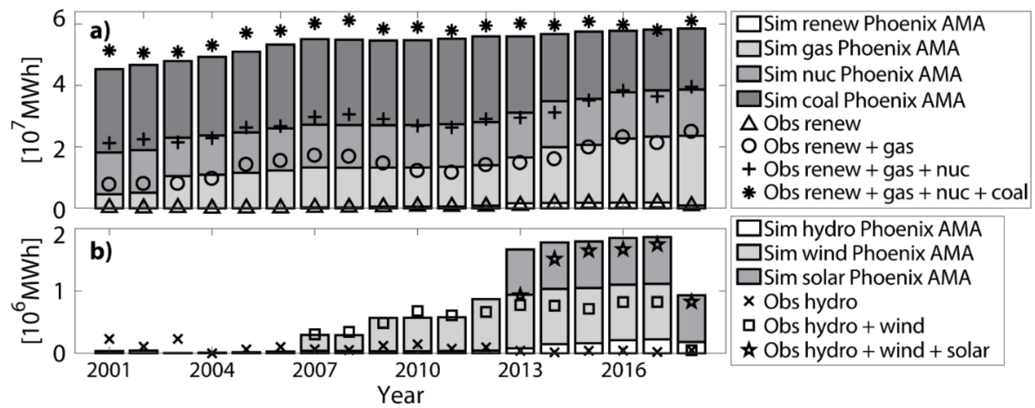

Figure 8. Comparison between simulated (sim) and observed (obs) electricity generation of power plants aggregated by fuel type during the historical period 2001-2018. The simulations are produced by running LEAP in the Phoenix AMA, while the observations are obtained from EIA considering the capacities of APS, SRP, and CAP power plants. Panel (a) shows results for renewable, natural gas, nuclear, and coal-fired power plants, while panel (b) reports results for each source of the renewable energy, including hydroelectric, solar and wind.

2.5.1.2. Quantification of the WEN interactions in historical conditions

The LEAP historical simulations were used to explore the water-energy interactions in the Phoenix AMA. These are visualized through the Sankey diagram presented in Figure 9a that shows the energy fluxes in TWh from each source to the final consumption referred to year 2009, chosen as an example. Energy originates as a primary resource from different fuel types and gets converted to electricity. Due to power plants efficiencies ranging from 26% to 46% (Table 10), a significant portion (104.3 TWh; labeled Unused energy) is lost largely during electricity generation. The electricity generated is used by the residential (21.0 TWh), commercial (18.8 TWh), and industrial (12.6 TWh) sectors either for water-related or water-unrelated activities (Other). The energy embedded in water (6.6 TWh) accounts for 13% of the total energy use (52.4 TWh). The breakdown of the uses is shown in Figure 7b (fluxes are in GWh). Water heating by residential and commercial customers is the largest use (4706 GWh), accounting for 71% of the total energy embedded in water. The rest of the energy is required to pump, move, and treat water (1950 GWh). The energy consumed by CAP (620 GWh) is more than two times the combined energy used to pump groundwater for potable use (GW; 122 GWh) and to pump groundwater and surface water for irrigation (AG; 176 GWh). The energy needed for water treatment and distribution (WTP; 651 GWh) is almost two times the energy requited to treat wastewater in WWTPs and WRFs (347 GWh).

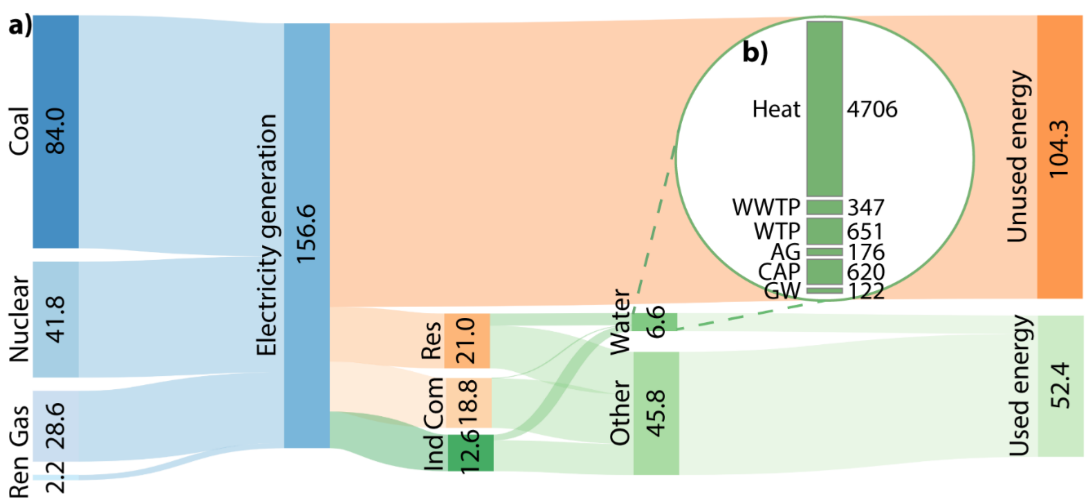

Figure 9. (a) Sankey diagram for the energy fluxes in TWh in the Phoenix active management area in 2009. Ren is renewable energy, Res is the residential sector, Com is the commercial sector, Ind is the industrial sector, Water is the energy embedded in water, Other is the energy consumed in activities unrelated to water. (b) Zoom on single activities where energy is embedded in water, with units in GWh. Differences in total values are due to rounding. Acronyms are defined in the main text.

2.5.2. Future projections

2.5.2.1. Future changes of the WEN interactions

The total energy demand adopted for the BAU, Renewable and Solar scenarios is projected to increase by 13 TWh over 42 years (Figure 10a). Results are substantially similar under the BAU-Shortage scenario simulating the megadrought (not shown). This increase is largely due to energy uses unrelated to water and to water heating, which are directly affected by population growth. In contrast, the energy embedded in water infrastructure is expected to slightly decline (by 210 GWh for BAU-Shortage and 174 GWh for the other scenarios), as a result of the temporal changes of water demand and supply (see Figure 6). To investigate further the changes in energy demand of water infrastructure, Figure 10b,c show the time series of energy required by each component under the two analyzed climate conditions. Under climate conditions that will not affect surface water availability, energy consumptions for transporting CAP water (CAP) and pumping water in irrigations districts (AG) are projected to decline by 120 GWh and 67 GWh over the simulation period, respectively (Figure 8b), mainly due to the decreasing water demand of the agricultural sector (see Figure 6a,b). The energy consumption of the other components (GW, WTP, and WWTP) remains instead fairly constant with time (Figure 10b) to satisfy the combined water demand of industrial, municipal and Indian sectors. The occurrence of a megadrought will reduce the availability of surface water from the gravity-fed SRP system that will be replaced by groundwater and, when available, CAP water (Figure 6c). Interestingly, the change of water supply sources in these extreme climate conditions results in net energy reductions as high as 7% on an annual basis (Figure 10c). This occurs because the additional energy required for groundwater pumping (maximum of additional 20 GWh annually) is offset by the lower energy needs for CAP water conveyance and potable water treatment (WTP) (maximum annual declines of 87 GWh and 68 GWh, respectively). The decrease of energy for WTPs is the result of groundwater requiring less treatment than surface water.

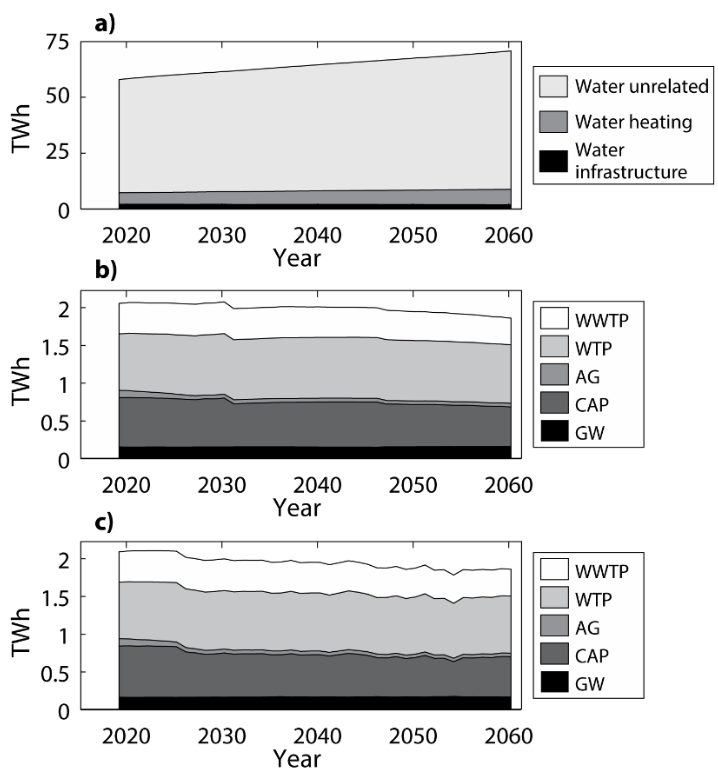

Figure 10. (a) Energy embedded in water infrastructure, energy for water heating, and energy for activities unrelated to water in all scenarios. (b) Energy embedded in water infrastructure in BAU. (c) Same as (b) but for BAU-Shortage. Acronyms are defined in the main text.

Turning the attention now to water needs for energy production, the simulations suggest that annual water withdrawals by power plants will decline from the initial value of 114 hm^3 (1 hm^3 = 1 million m^3) in 2018 following different trends that depend on the scenario (Figure 11a). In BAU conditions with current cooling technologies, water withdrawals drop in 2019, then remain relatively constant through 2040 and, then, gradually decrease to 70 hm^3 in 2060 (-39% from 2018). In the Renewable and Solar scenarios (note that they have the same water needs), the decline of water withdrawals begins in 2019 and continues at a relatively constant rate of about 4 hm^3/year, reaching 45 hm^3 in 2037, then slowly decreases to 36 hm^3 in 2060 (-68% from 2018). In year 2060, the Renewable and Solar scenarios will reduce water withdrawals by 34 hm^3 compared to the BAU scenario, which represent ~2% of the total water demand (Figure 6a). Finally, we highlight that water withdrawals in the BAU-Shortage scenario are similar to BAU since their total energy demand is almost the same.

2.5.2.2. CO_2 emissions

As found for water consumption, CO_2 emissions are also projected to decrease (Figure 11b). In the BAU scenario (results are the same for BAU-Shortage), emissions decline from 31 million metric tons of CO_2 in 2018 to 10 million metric tons of CO_2 in 2060 through a step-wise curve with abrupt drops of about 9 and 3 million metric tons of CO_2 in 2020, and 2042, respectively. In these years, in fact, coal power plants are expected to be retired; for instance, the Navajo generating station is scheduled to cease operations by the end of 2019 (Eden et al., 2011). In the Renewable scenario (results are the same for Solar), reductions are more significant: emissions fall at a relatively constant rate reaching 6 million metric tons of CO_2 in 2036 and, then, after all coal- and gas-fired power plants retire, they drop to zero in 2060, i.e. a total decarbonization.

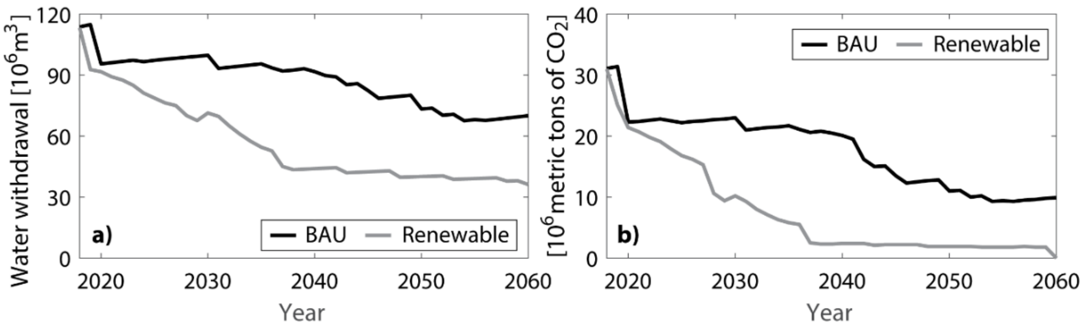

Figure 11. (a) Water withdrawals by all power plants in BAU and Renewable scenarios. (b) CO2 emissions in BAU and Renewable scenarios. Note that: (i) results for the BAU and BAU-Shortage scenarios are comparable because of the similar total energy demand, and (ii) results for Renewable and Solar scenarios are the same because their energy mix of carbon emitting sources is the same.

2.5.2.3. Economic assessment of future energy mixes

As a next step, we provided a first-level quantification of the structural and operational costs of the future energy mixes. The aggressive alteration of the energy portfolio in the Renewable and Solar scenarios results in more capacities added and retired as compared to the BAU scenario (Figure 12). As a consequence, overnight and fixed O&M costs of Renewable ($101 billion) and Solar ($104 billion) scenarios are higher than BAU ($59 billion). Differences in costs between Solar and Renewable scenarios originate from the use of solar PV technologies that have a higher overnight cost as compared to wind turbines (EIA, 2016). Despite the higher overnight and fixed

O&M costs, Renewable and Solar scenarios have lower fuel and variable O&M costs (EIA, 2016) (Figure 13). These expenses total $17 billion and $20 billion for Renewable and Solar scenarios, respectively, and are much lower than the $45 billion required in the BAU scenario, where more energy is generated by more expensive fossil fuel sources. Considering all four types of costs, the investments are $111, $121, and $127 billion in BAU, Renewable, and Solar scenarios, respectively. Under BAU conditions, the supply of natural gas is the largest expense accounting for $36 billion, while overnight costs of solar power plants are the highest cost item in the Renewable (Solar) scenario accounting for $53 billion ($74 billion). Finally, we point out that costs and capacity expansion of BAU and BAU-Shortage scenarios are the same, because of similar energy supply goals and demands.

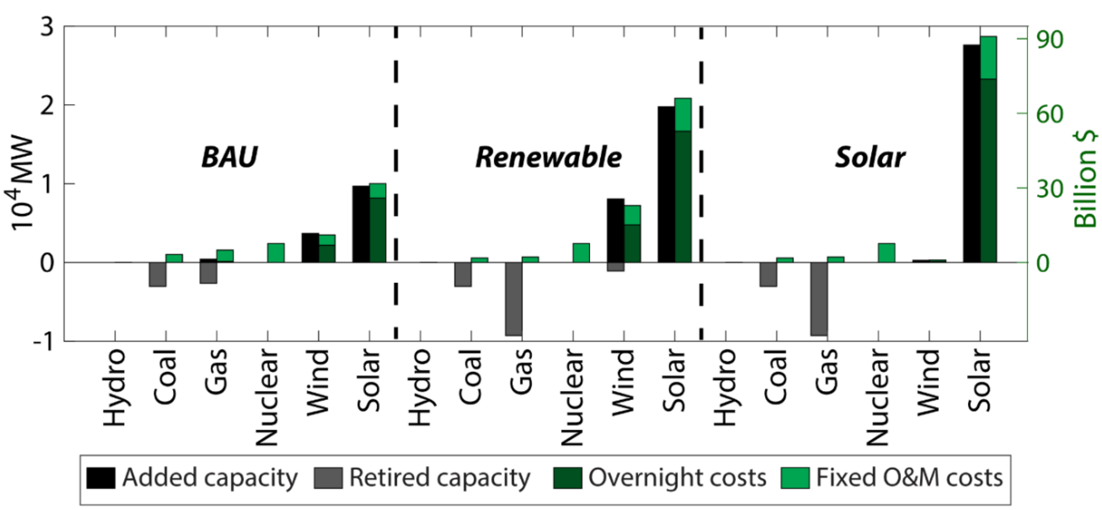

Figure 12. Added and retired capacities (left vertical axis) grouped by fuel type along with the associated overnight costs and the fixed operations and maintenance (O&M) costs (right vertical axis). Values are cumulated from 2019 to 2060.

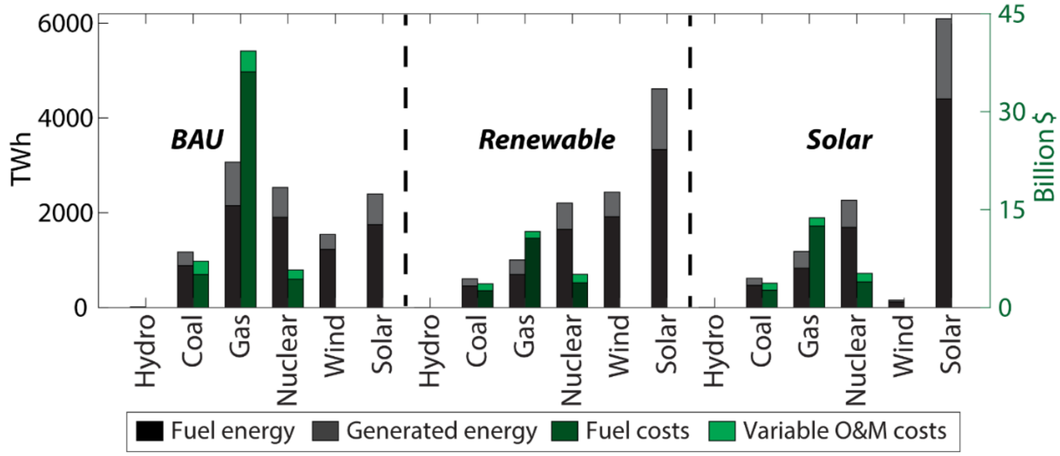

Figure 13. Fuel energy and generated electricity grouped by fuel type (left vertical axis), along with fuel and variable O&M costs (right vertical axis). Values are cumulated from 2019 to 2060.

2.6. Discussion

2.6.1. Implications for future planning

The simulations presented here provide a detailed quantification of the water-energy interactions at metropolitan scale that complete and address the limitations of the regional studies of Yates et al. (Yates et al., 2013), Bartos and Chester (Bartos and Chester, 2014), and Scott and Pasqualetti (Scott and Pasqualetti, 2010). In the Phoenix Metropolitan region, additional energy infrastructure will be needed to meet future energy demands that are expected to increase driven by population growth (Scott and Pasqualetti, 2010). We found that energy portfolios that transition more ambitiously to renewable energy generation have two main advantages as compared to the more conservative BAU portfolio relying more on fossil fuels. First, the operation of renewable energy power plants is projected to require less water (reduction of 1330 hm^3 or 35% throughout the simulation period): this is a crucial benefit in a region with limited water resources where the expansion of energy infrastructure is limited by complicated water rights and the goal of achieving aquifer safe-yield. Second, electricity generation from renewable sources will lead to significantly lower CO_2 emissions (reduction of 436 million metric tons of CO_2 or 57%). SRP has recently approved the target of reducing CO_2 emission rates to 0.33 ton/MWh by 2035 (SRP, 2018). The simulations indicate that this target would be achieved in 2031 in the BAU scenario and in 2022 in the Renewable scenario.

When considering costs, it is suggested that a more ambitious transition to renewable energy generation will require much higher structural costs but significantly lower operational costs than the more conservative BAU scenario. The total costs estimated over a time horizon of 42 years will be comparable. We highlight that our cost estimations are based on several simplifications, which should be addressed in future work. For example, (i) the delivery costs of electricity generated by the wind farms serving the Phoenix AMA, which are and will likely be mainly located in New Mexico (APS, 2017), have not been included in our assessment; (ii) the costs of Renewable and Solar scenarios do not account for battery storage expenses; and (iii) the overnight costs of energy technologies, especially renewables, have been assumed as constant, but they are expected to decrease over time because of the process of “technological learning” (Handayani et al., 2019).

2.6.2. WEN interactions and potential for synergies

In the Phoenix AMA, water-related energy uses account for about 13% of the total. Most of this energy (~71%) is required for water heating. Since future population growth will likely lead to increasing energy needs for water heating, programs targeting energy efficiency and water conservation at the residential level have the potential to induce important energy savings. For example, Bartos and Chester (Bartos and Chester, 2014) estimated that the potential of annual energy savings from residential water conservation measures in Arizona is, on average, 1.68 TWh, an important amount when compared to the 2.03 TWh currently consumed by the water infrastructure of the Phoenix AMA (Figure 9). The rest of water-related energy uses are needed to move and treat water (~4% of the total energy use, in line with the national average; EPRI, 2000). Most of this energy is needed to convey CAP water and for potable water treatment and distribution (~19%). Our future projections indicate that energy uses to move and treat water will decrease by 9% from 2018 to 2060, largely because of lower water needs for agriculture. The occurrence of an extreme drought is expected to induce slight energy savings of 1613 GWh or 2% over the simulation period, because less water will be conveyed through the CAP aqueduct and treated in WTPs. Somewhat surprisingly, this finding suggests that severe drought conditions may have minimal impacts on the energy sector. However, the larger use of groundwater resources will severely compromise the ability to achieve aquifer safe-yield; if policies restricting the use of these nonrenewable water resources will be adopted, the negative impacts on the energy sector could be significant.

2.6.3. Limitations and future work

The modeling approach adopted here is based on several simplifications that we plan to address in future work. First, we used an energy model with water allocations externally calculated by a water management model. This approach should be refined by capturing the two-way feedbacks between water and energy systems. For example, water withdrawals by power plants that are simulated by LEAP should be provided to the water management model as a demand input during the simulation. The water management model, in turn, should provide LEAP with water allocations from distinct supply sources of each power plant. Dale et al. (Dale et al., 2015) demonstrated the feasibility of this modeling strategy by coupling WEAP and LEAP in Sacramento, California. Second, we applied the LEAP model at an annual time resolution; to improve the accuracy of our simulations, we plan to adopt a monthly or weekly scale that will allow (i) capturing the seasonality in energy and water demand and supply, (ii) assessing the impact of short duration extreme events such as heat waves and high-intensity storms; and (iii) modeling more accurately the dispatch from renewable technologies. Finally, we are currently representing energy uses that are not related to water through a single energy intensity. To better assess water and energy conservation programs, we should disaggregate this value into single energy uses in the commercial and residential sectors (e.g., appliances, heating, ventilation and cooling) to be able to change these intensities over time according to the energy efficiency target of each technology.

2.7. Conclusions

The analyses presented in this study in the Phoenix metropolitan region show that the LEAP platform is able to simulate quite well historical observations of energy generation and consumption at the metropolitan scale. Water heating is by far the largest water-related energy consumer, followed by conveyance of Colorado River water through the CAP aqueduct and water treatment for potable use along with distribution. Future projections of energy demand through year 2060 indicate that energy needs for water heating will increase by 35% due to population growth, but the energy required to treat and move water will decrease by 9% mainly because of the declining water demand from the agricultural sector. Simulations of future electricity generation showed that energy mix solutions that transition faster to renewable sources will reduce significantly water needs for electricity generation (35%) and CO_2 emissions (57%) as compared to the BAU scenario. The occurrence of a megadrought will result in net energy savings because less water will be transported through the energy intensive CAP aqueduct, but it will likely compromise the ability to achieve the aquifer safe-yield. The infrastructure needed to achieve these energy supply portfolios will have higher structural costs and lower operational costs as compared to the more conservative business as usual scenario that relies more on fossil fuels. By quantifying WEN interactions at the metropolitan scale, this work complements and expands previous regional studies focused on southwestern U.S. and Arizona and, thus, supports policy discourse for integrated nexus governance.

CHAPTER 3

VALUE OF SPATIOTEMPORAL RESOLUTIONS AND FEEDBACK LOOPS IN WATER-ENERGY NEXUS MODELING

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3.1. Introduction

The water-energy nexus (WEN) is a term used to refer collectively to the dependencies and interdependencies between water and energy systems and resources (Rio Carrillo and Frei, 2009; Siddiqi and Anadon, 2011; U.S. DOE, 2014). For example, water is required for cooling purposes in thermal power plants and is directly used to produce electricity in hydropower plants. Energy is needed to pump, transport, and treat water. Depending on the region, each resource could use a significant amount of the other (Khan et al., 2017). For instance, in the U.S. power plants are estimated to be responsible for 13% of the total water consumption, while the energy required to pump, transport, treat, and heat water accounts for 13% of the total primary energy consumption (Dieter et al., 2018; Sanders and Webber, 2012). Due to the interdependencies between water and energy, climate and anthropogenic stressors (e.g., intense storms, heatwaves, droughts, terrorist attacks, etc.) acting on one system can cause cascading impacts on the other system, thus significantly compromising the security of both resources over both short (daily and sub-daily; de Amorim et al., 2018; Hatvani-Kovacs et al., 2016; Lubega and Stillwell, 2018; Su et al., 2020) and long (multiple years; Bartos and Chester, 2015; van Vliet et al., 2016a) time periods. The adoption of a nexus approach to operate and manage water and energy systems has then become increasingly pressing, especially considering the additional stresses that climate change, population growth, and urbanization will exert on these two resources (Dai et al., 2018; Rio Carrillo and Frei, 2009; Scott, 2011; Siddiqi and Anadon, 2011; van Vliet et al., 2016).

A key step for the adoption of a nexus perspective in policy- and decision-making is to quantify interactions in water-energy systems through numerical models (Khan et al., 2017). These allow identifying synergies and limiting tradeoffs both in current conditions and under possible scenarios of climate change, demand growth, and expansion of technologies and infrastructure. Given the broad scopes of WEN studies, models have been developed using several approaches (Hamiche et al., 2016). For instance, Schuck and Green (2002) relied on econometrics principles to quantify the potential of price variation to conserve water and energy resources. Grubert and Webber (2015) used a life-cycle assessment method to estimate future changes in water and energy interdependencies according to various policy choices. Stercke et al. (2020) set up a system dynamics model to explore global and local sustainable development goals that are related to the WEN. Khan et al. (2018) and Gjorgiev and Sansavini (2018) developed resource optimization models to simulate the impacts of changes in water temperature on power generation. The same goal was pursued by van Vliet et al. (2016b) combining a large-scale hydrologic model with a stream temperature and hydropower and thermoelectric models. Obringer et al. (2019) and Dale et al. (2015) investigated the implications of climate change for the WEN using statistical and simulation modeling, respectively. As summarized in a review study by Dai et al. (2018), WEN applications have been conducted at different temporal resolutions or time steps. These include sub-hourly real-time simulations of water distribution systems and power transmission networks (Khatavkar and Mays, 2018; Santhosh et al., 2014); and analyses at monthly and annual scales of infrastructure expansion, effects of policies, and environmental impacts (Jääskeläinen et al., 2018; Zhou et al., 2019). Moreover, WEN models have incorporated the physical components of water and energy systems with various levels of detail. For instance, simulations of electricity generation and water demands have been performed both at fine spatial resolution (or granularity), accounting for each power plant (e.g., Mu et al., 2020), and at a coarser resolution, aggregating the generating stations based on fuel type and cooling technologies (e.g., Zhou et al., 2019). In general, the adoption of given temporal resolution and spatial granularity depends on data availability, geographical extent of the study area (e.g., city, country, or transnational), and duration of the simulations (e.g., daily, annual, or multidecadal). In a recent review of current efforts and challenges in WEN modeling, Khan et al. (2017) noted that the increasing efforts devoted to capture finer resolutions should be carefully considered in terms of the gained simulation accuracy. However, very limited research has been dedicated to systematically investigate the importance of spatial and temporal resolutions on model accuracy in WEN applications.

Khan et al. (2017) also reported that most previous studies of integrated water and energy systems rely on a single model to simulate one system and process its outputs to infer information on the other system. In particular, these authors found that in most studies (e.g., Bouckaert et al., 2012; Faeth et al., 2014; Mounir et al., 2019), modeling tools are utilized to explicitly simulate the energy sector, and estimate its water requirements without including an appropriate representation of the water infrastructure, its internal dynamics, and the interactions with the energy components. Other work has applied water management models to simulate the water system and post-processed its outputs to estimate energy demand for water uses (e.g., Baki and Makropoulos, 2014; Guan et al., 2020). A more accurate representation of WEN interdependencies would instead require the use of models that explicitly simulate each system and are integrated by linking the computer codes (i.e., hard links) or exchanging data in real time (i.e., soft links). Currently, integrated or coupled WEN models that capture the feedback loops between the two systems have been adopted in a limited number of cases. These include both (i) the coupling with soft links of existing water and energy models (van Vliet, Wiberg, et al., 2016; Voisin et al., 2020), as done with the Water Evaluation and Planning (WEAP) and the Long-range Energy Alternatives Planning (LEAP) platforms (Dale et al., 2015; Lin et al., 2019; Liu et al., 2021); and (ii) the development of hard-linked water-energy optimization (Khan et al., 2018; Parkinson and Djilali, 2015) and integrated assessment (Liu et al., 2019; Miara et al., 2017) models. Despite these promising studies, their number is still limited and the added values of coupled simulations compared to simpler approaches based on single models and data postprocessing has not been yet properly quantified.

In this study, we contribute to addressing a number of the research gaps discussed above by investigating how the adoption of single and coupled models under different spatial and temporal resolutions affects the accuracy of WEN simulations. For this aim, we focus on long-term water allocations and energy dispatch in the metropolitan region of Phoenix, Arizona. This is a compelling study site for WEN studies for several reasons. First, it relies on limited water resources mainly provided by energy-intensive sources, including groundwater and the Central Arizona Project (CAP) that transfers water from the Colorado River to central and southern Arizona through a 541-km canal (Bartos and Chester, 2014; Mounir et al., 2019). Second, while renewable energy sources have been increasing (APS, 2017; SRP, 2018), electricity is largely generated by thermal power plants that heavily depend on water, including the largest nuclear generating station in the country, Palo Verde. Finally, the Phoenix metropolitan region has experienced, over the last three decades, one of the fastest population growth in the U.S. that was possible by converting agricultural land into urban areas (Bausch et al., 2015); this shift has caused a dramatic change in water and energy demands.

The work presented here is built upon our previous effort in the Phoenix metropolitan region where the WEAP platform has been applied to simulate food-energy-water dynamics under a set of future scenarios of water demand and supply (Guan et al., 2020), and the LEAP model has been used to quantify the implications of future energy mix alternatives on the WEN (Mounir et al., 2019). In both studies, WEAP and LEAP have been applied at an annual resolution for several decades. Here, we first improve the model configurations by (i) increasing the temporal resolution of both models from annual to monthly, (ii) expanding the WEAP network from a single water demand node representing all power plants to an explicit representation of all electricity generating stations, and (iii) coupling WEAP and LEAP through soft links. We then apply the models under different configurations using independent estimates of observed water and energy fluxes in the region as a reference over the period 2008-2017. First, we explore the importance of the temporal resolution by comparing simulations of the coupled WEAP-LEAP model applied with annual and monthly time steps, respectively. Second, we quantify the value of increased spatial granularity by contrasting simulations of WEAP-LEAP where the WEAP domain has either a single water demand node representing all power plants or multiple nodes each representing a distinct power plant. Finally, we investigate the added value of capturing two-way feedbacks between water and energy systems by comparing simulations with the coupled WEAP-LEAP model and a standalone approach based on the WEAP model plus a post-processing routine designed to calculate energy fluxes. After presenting results of these comparisons that are obtained for a specific study region and model type, we discuss a number of implications useful to address challenges of WEN modeling more generally.

3.2. Materials and Methods

To properly describe our methodology and case study, we initially define water and energy models. We refer to a *water model* as a tool that simulates allocation, treatment, and distribution of water from supply sources to demand nodes as a function of time. Similarly, we define an *energy model* as a tool that reproduces electricity generation and dispatch from different power plants to satisfy sectorial demands as a function of time. While some of the processes simulated in the water model require energy, these interactions are not explicitly captured and assumptions must be made on energy availability (e.g., energy is unlimited). A similar argument can be made for the energy model. Water and energy models can be coupled so that fluxes and information between the two systems are exchanged during the simulation. In the following, we first describe the study area (section 2.1) and provide a brief overview of the adopted water and energy models (section 2.2), along with their setup in the study region (section 2.3). Finally, we summarize the modeling configurations used for our analyses (section 2.4).

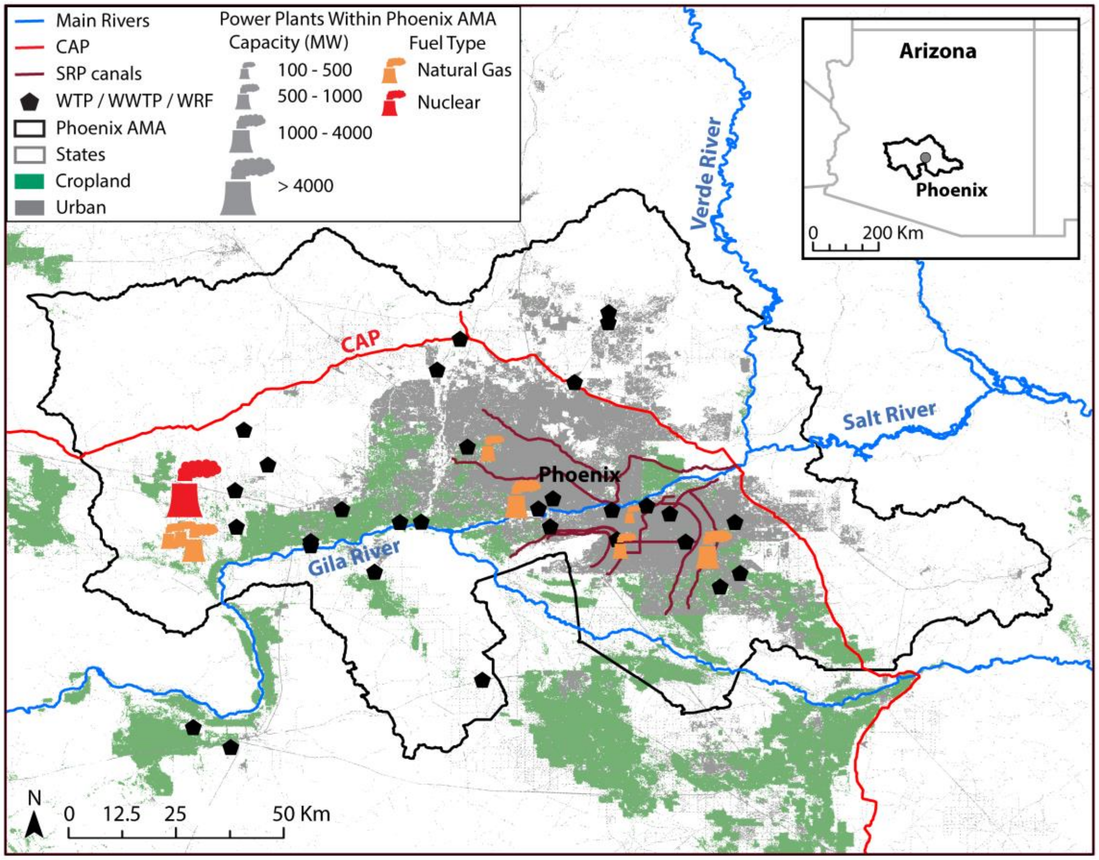

Figure 14. The Phoenix Active Management Area (AMA) in central Arizona, along with the location of power plants with the indication of fuel type and capacity; main water treatment plants (WTP), wastewater treatment plants (WWTP), and water reclamation facility (WRF); the Salt, Verde and Gila Rivers; the Central Arizona Project (CAP) aqueduct; canals of the Salt River Project (SRP); and cropland and urban areas of the Phoenix metropolitan region.

3.2.1. Study area

We apply the water and energy models to the Phoenix Active Management Area (AMA), an administrative region of 14,623 km^2 (Figure 14) managed by the Arizona Department of Water Resources (ADWR) and created after the approval of the Arizona Groundwater Management Act in 1980 to sustainably manage the regional aquifer. The

Phoenix AMA is located in central Arizona and entirely includes the Phoenix metropolitan area and several irrigation districts. The water and energy systems of this region are highly interdependent. Four main sources supply water to the different users, including (i) surface water from the Salt and Verde Rivers managed by the Salt River Project (SRP); (ii) surface water from the Colorado River transported from Lake Havasu to Southern Arizona through the Central Arizona Project (CAP) canal; (iii) groundwater (GW); and (iv) reclaimed water (RW). Over the last decade, these water sources delivered ~2,800 million m^3 annually satisfying the municipal (47% of the demand), agricultural (33%), Native American (11%, accounting for domestic and agricultural needs of the three largest communities in the region), industrial (5%), and power plant (4%) demands. To achieve this, energy is required to operate pumping stations, wells, water (WTPs) and wastewater (WWTPs) treatment plants, and water reclamation facilities (WRFs), totaling a demand of ~1,900 GWh per year (3.6% of the total electricity demand; Mounir et al., 2019). Energy supply for the region is largely provided by SRP and Arizona Public Service (APS) utilities, which operate eight natural gas generating stations and one nuclear power plant within the region boundary, along with 22 large power plants located outside of this area (Mounir et al., 2019). Electricity is needed to satisfy the residential (39% of the demand), commercial (35%), and industrial energy sectors (26%). The latter one includes the energy provided to the water infrastructure.

3.2.2. Overview of WEAP, LEAP, and coupled WEAP-LEAP modeling platforms

The Water Evaluation and Planning (WEAP; Yates et al., 2005) platform is used here as the water model. WEAP is designed to support water resources planning and management at different scales, by optimizing water allocations in a network linking supply sources to demand nodes under mass balance and user-specified constraints, including demand priorities and infrastructure operation rules, among others. Inputs for WEAP include fixed and time-varying variables characterizing water supply (e.g., aquifer properties, river discharge, water releases from reservoirs), demand nodes (e.g., population, water intensities), and management rules (e.g., canal and reservoir size). Outputs include several variables describing fluxes of water demand and supply in the network. In previous studies, WEAP has been applied at different time steps, ranging from annual (e.g., Guan et al., 2020), to monthly (e.g., Lévite et al., 2003) and weekly (e.g., Dale et al., 2015), and at national (e.g., Welsch et al., 2014), regional (e.g., Yates et al., 2013a, 2013b), and metropolitan (e.g., Guan et al., 2020) scales.

The Long-range Energy Alternatives Planning (LEAP; Heaps, 2020) system is used in this study as the energy model. LEAP is an integrated energy-economy-environment model designed to support energy resource planning and management. It simulates energy generation from diverse fuel types to satisfy demand from different end-users through simple dispatch rules. It requires inputs characterizing demand, including activity levels (e.g., population, water flow) and energy intensities (e.g., per capita or per unit volume energy consumption), and supply, such as characteristics of power plants (e.g., fuel type, capacity), percent of energy losses, and reserve margins. Depending on application and data availability, inputs can be constant or vary in time. LEAP outputs time series of energy demand from each end-user, as well as energy generation and greenhouse gas emissions at each power plant, among many other variables. In previous applications, this modeling tool has been applied at annual (e.g., Mounir et al., 2019), monthly (e.g., Javadifard et al., 2019), and weekly (e.g., Dale et al., 2015) time steps to simulate energy systems at continental (e.g., Ouedraogo, 2017), national (e.g., Aliyu et al., 2013), regional (e.g., Chang et al., 2017), and metropolitan (e.g., Mounir et al., 2019) scales. Both WEAP and LEAP have been used to model water and energy systems under present climate and infrastructural conditions, as well as to explore the impacts of future scenarios of demand and supply (e.g., Dale et al., 2015; Esteve et al., 2015; Guan et al., 2020; Gul and Qureshi, 2012; Mounir et al., 2019) and new policies (e.g., Handayani et al., 2017; Lévite et al., 2003).

Recently, the WEAP and LEAP platforms have been coupled to allow simulating the interactions of water-energy systems at each time step. The coupling is achieved through so-called "links" where: (i) LEAP reads variables from WEAP to determine energy demand for specific uses (e.g., groundwater pumping and desalination) and/or constrain hydropower generation; and (ii) WEAP reads variables from LEAP to estimate water requirements for thermal cooling and/or electricity generation in hydropower stations. These links allow both platforms to communicate iteratively at each time step. The coupled WEAP-LEAP modeling platform was applied by Dale et al. (2015) to investigate the impact of climate change on water and energy consumption in Sacramento, California, finding that electricity imports in the region may increase to 35% during hot dry years.

3.2.3. Set up of WEAP, LEAP, and coupled WEAP-LEAP in the Phoenix AMA

The WEAP and LEAP models are set up in our study region by improving the configurations adopted and validated by Guan et al. (2020) and Mounir et al. (2019), respectively, by increasing temporal resolution and spatial granularity, and by coupling the models. It is first noted that the words energy and electricity are used interchangeably in the rest of the paper, but our simulations involve only electricity. To investigate the effect of temporal resolution, we apply the models at an annual scale, as in the two studies mentioned above, and extend the setup also at monthly resolution. We derive the monthly SRP and CAP water allocations and estimate monthly water demands through the data sources provided in Table 1 and the assumptions described in the Appendix. The network representing the water system of the Phoenix AMA implemented in WEAP is exemplified in Figure 15a. Water from SRP, CAP, GW, and RW sources is directly distributed to the agricultural sector and is treated in WTPs prior to being delivered to the municipal, Native American, and industrial sectors; power plants receive water from all sources except for SRP. Water allocations from SRP are affected by management rules and natural flow in the Salt and Verde Rivers; CAP water deliveries depend on the entitlements of Colorado River water to the region; and RW is generated by treating municipal water in WRFs. All these rules and time-varying flows are implemented in the model, so that water supply is limited and constrained. Water demand is computed as a function of population and per capita water use for the municipal and industrial nodes, while it is directly inputted for the Native American node using data from ADWR (2018). For the power node, we adopt two configurations to investigate the effect of spatial granularity of the energy system. In the first, a single node represents collectively all power plants, as in Guan et al. (2020), while, in the second, nine nodes are used to simulate the distinct power plants located in the Phoenix AMA. The transmission links between water supply and demand nodes are set up to represent the physical constraints of infrastructure and water management rules. The two networks are presented in Figure 37 and Figure 38. More details are provided by Guan et al. (2020).

Table 3. Datasets used to set up, apply, and test WEAP and LEAP in the Phoenix AMA.

Model	Dataset	Purpose of use
LEAP	EIA (2019)	Estimates of electricity generation used as observations
	PWCC (2018); SRP (2020)	Capacities of the power plant
	EIA (2020a)	Annual capacity factors
	EIA (2018)	Rate of water withdrawals from power plants
	EIA (2019)	Determination of the monthly variability of capacity factors
	EIA (2020b)	Monthly variability of the load
WEAP	ADWR (2018)	Water supply and demand in the Phoenix AMA
	SRP (2020b)	Monthly variability of discharge in SRP canals
	CAP (2020)	Monthly variability of discharge in CAP
	CPWSD (2011)	Monthly variability of municipal, industrial, and power plant water demand
	Lahmers and Eden (2018)	Monthly variability of agricultural water demand

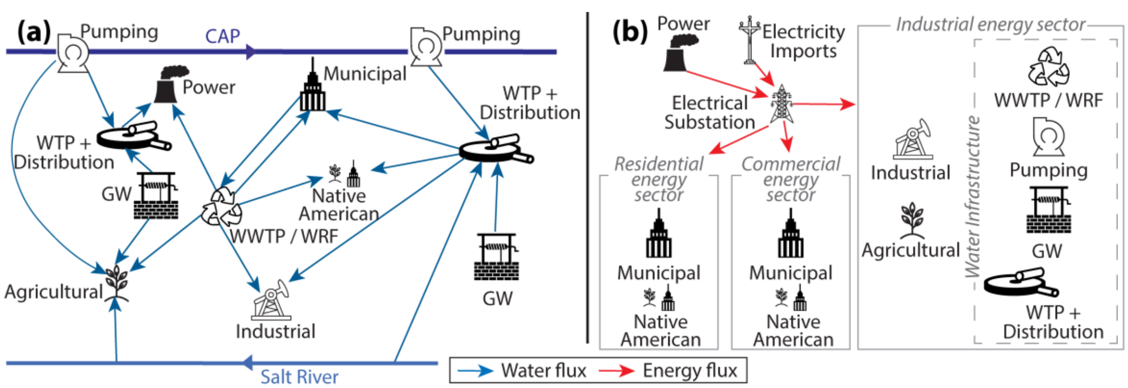

Figure 15. Schematic of (a) water and (b) energy systems in the Phoenix AMA. Acronyms are defined in the main text.

The energy system implemented in LEAP is summarized in Figure 15b. Energy supply is provided by nine power plants located within the Phoenix AMA and 22 outside of this region, fueled by coal, natural gas, uranium, and renewable resources (i.e., solar radiation, wind, and water). These 31 generating stations are selected because they are entirely or partially owned by SRP and APS, the main utilities satisfying electricity demand in the region (PWCC, 2018; SRP, 2020). Table 2 presents the fuel type, total capacity, SRP and APS capacity entitlement, mean annual electricity generation, and water source for the nine power plants located within the Phoenix AMA; note that, for the nine generating stations, water withdrawal is equal to water consumption (EIA, 2020a). For each of the 31 power plants, we input fuel type, capacity entitled to SRP and APS, merit (or dispatch) order, efficiency, and capacity factor. We also specify transmission and distribution losses of 5% and a planned reserve margin of 15%. The energy demand structure is designed to focus on water-energy interactions and facilitate the coupling with WEAP. It includes (i) residential and commercial sectors, which can be related to the municipal and Native American water nodes; and (ii) industrial energy sector, which is divided into subsectors that are linked to industrial and agricultural water nodes, as well as to water infrastructure components that rely on seven different energy intensities to treat, transport, pump and convey the different water sources. Based on this setup, the electricity demand of the Phoenix AMA is assumed to be fully satisfied by the power plant capacities entitled to SRP and APS. This implies that (i) energy is imported into the Phoenix AMA only from the 22 external power plants managed by SRP and APS, and (ii)

LEAP does not simulate the electricity exported outside of the Phoenix AMA boundaries associated with capacity entitlements of other energy companies. While we assume no limit in fuel availability at each power plant, the electricity generated is practically constrained by energy demand and water availability when WEAP is coupled to LEAP. Further details can be found in Mounir et al. (2019).

Table 4. Power plants located within the Phoenix AMA and their fuel type, total capacity, SRP and APS capacity entitlement, mean annual electricity generation, and water sources.

Power Plant	Fuel Type	Capacity [MW]	SRP+APS Capacity Entitlement [MW]	Electricity Generation [GWh]	Water Source	Reference
Palo Verde	Nuclear	3,875	1,822	31,532	RW, GW	(APS, 2017)
Red Hawk	Natural gas	1,060	984	4,132	RW	(ADWR, 2020; APS, 2017)
West Phoenix	Natural gas	1,207	997	1,938	RW, GW	(APS, 2017; PWCC, 2020)
Kyrene	Natural gas	523	523	804	CAP, GW	(ADWR, 2020; Stanley Consultants, 2021)
Santan	Natural gas	1,219	1,219	3,168	CAP, GW	(ADWR, 2020; Veolia Water Technologies, 2006)
Ocotillo	Natural gas	333.4	330	103	GW	(ADWR, 2020; APS, 2017)
Agua Fria	Natural gas	626	626	82	GW	(ADWR, 2020; APS, 2017)
Arlington Valley	Natural gas	580	580	1,419	GW	(ADWR, 2020; APS, 2017)
Gila River	Natural gas	1,650	1,100	4,705	GW	(ADWR, 2020; APS, 2017)

We investigate the effect of the coupling strategy by first simulating WEN interactions in a standalone mode, which is illustrated in Figure 16a. In this approach, we assume that WEAP is the only available model. Time series of water demand from the power plants are prescribed externally using estimates from ADWR (2018), and the energy needed for water-related uses is calculated by post-processing outputs of the water model. This involves multiplying the water fluxes from the supply sources simulated by WEAP by the corresponding energy intensities. We note that EIA provides data on water withdrawals and consumption for the power plants. These data are in good agreement with the ADWR estimates but incomplete for several years; we then utilize ADWR data to be consistent. In the second approach, we run the WEAP-LEAP model in coupled mode, as shown in Figure 16b. We create a first set of links to connect the nine power plants located within the Phoenix AMA implemented in LEAP with the water demand nodes (or node, depending on the spatial granularity) for power in WEAP. In each link, we provide the water withdrawal intensity (in m^3/kWh) obtained from the U.S. Energy Information Administration (EIA, 2018) for each power plant, multiplied by the ratio between the corresponding total capacity and the entitlement of SRP and APS. At each time step, LEAP simulates electricity generation in the system and WEAP uses these links to derive all water needs of each power plant. For instance, the electricity generation simulated by LEAP in the Palo Verde power plant to satisfy the demand of the Phoenix AMA is used by WEAP to quantify the water required for the full production (including exports) at this generating station. Similarly, we create a second group of links that connects the water fluxes simulated by WEAP in 31 transmission links with the energy demand structure in LEAP, and we input the energy intensities (in kWh/m^3) of each water infrastructure component obtained from Mounir et al. (2019). At each time step, the water fluxes simulated by WEAP are converted into energy required by the water infrastructure components implemented in the LEAP demand structure, by multiplying the water volumes by the corresponding energy intensity. For example, the water flow simulated by WEAP in the transmission link from CAP to the municipal demand node is used by LEAP to calculate the associated energy demand for conveyance and treatment.

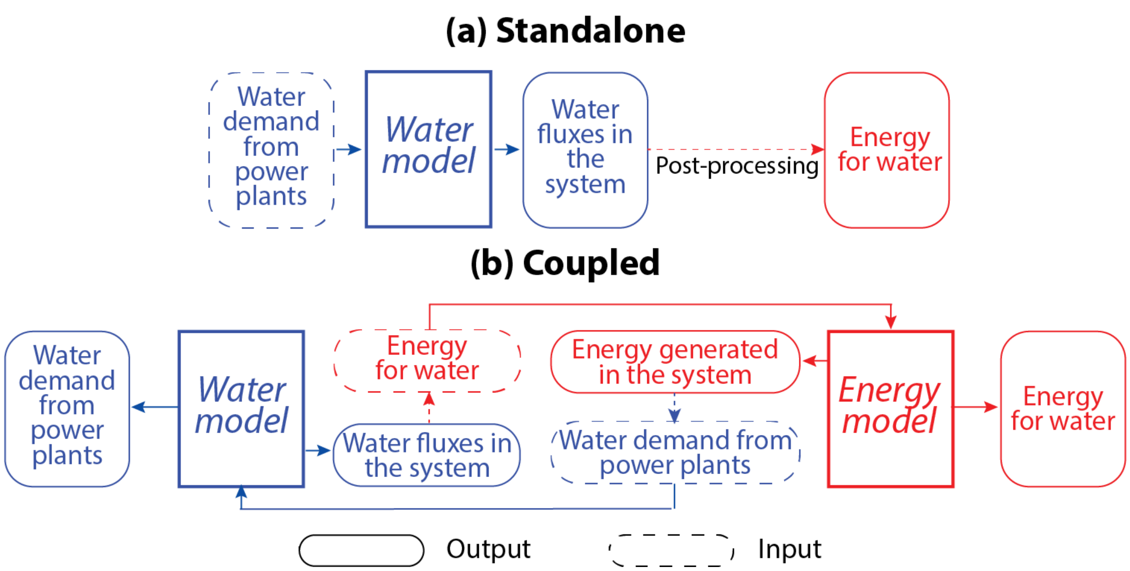

Figure 16. Modeling approaches of water and energy systems in (a) standalone and (b) coupled modes. See text for details.

3.2.4. Modeling configurations

We adopt four model configurations to investigate our research questions. They are summarized in Table 3. In two configurations, a single water demand node for power generation is used in WEAP and the coupled WEAP-LEAP models are applied at annual and monthly resolutions; these are labeled as 1A and 1M (1 power node, M = monthly, and A = annual time resolution), respectively. In an alternative configuration, labeled as 9M, nine demand nodes are implemented in the WEAP network to simulate the water demand of each power plant located within the Phoenix AMA, and the coupled WEAP-LEAP models are run at a monthly temporal resolution. Finally, the configuration called "standalone" is based on the WEAP model running at a monthly temporal resolution with nine power nodes plus a post-processing routine for the estimation of the energy embedded in water, as shown in Figure 16b. Simulations under 1A and 1M configurations are compared to test the effect of temporal resolution; those under 1M and 9M to evaluate the impact of spatial granularity; and those under 9M and standalone to assess the significance of the coupling approach. All simulations are performed from 2008 to 2017.

Table 5. Characteristics of modeling configurations.

Configuration name	**Temporal resolution**	**Granularity**	**Coupling**
1A	Annual	1 power node in WEAP	WEAP-LEAP
1M	Monthly	1 power node in WEAP	WEAP-LEAP
9M	Monthly	9 power nodes in WEAP	WEAP-LEAP
Standalone	Monthly	9 power nodes in WEAP	WEAP + post-processing

We investigate the accuracy of the modeling experiments in multiple ways. We compare historical simulations of (1) monthly electricity generation at distinct power plants with values reported by EIA; and (2) annual water allocations from supply sources to demand sectors, including power plants, with estimates from ADWR (Table 1). Comparison against historical observations is one of the four main strategies for evaluating integrated assessment models recently reported in the review of Wilson et al., (2021). To quantify differences between the time series, we compute correlation coefficient (CC), root mean square error (RMSE), and absolute percent error (APE). When contrasting 1A and 1M simulations, we present differences between the constant monthly value of several outputs derived under 1A with the time-varying values returned by monthly runs of 1M. Finally, we use Sankey diagrams to explore potential disagreements in allocations of water and embedded energy from supply sources to the power plants and to verify whether a given model configuration correctly represents water delivery dynamics.

3.3. Results

3.3.1. Effects of time resolution

We begin by presenting in Figure 17 the electricity generated in 2008-2017 in the three largest power plants located within the Phoenix AMA (see Table 2), as reported by EIA, and as simulated under 1A and 1M. The monthly means are also reported in the right panels. The electricity generation from EIA exhibits marked seasonality, with a summer peak at the two natural gas power plants, Santan and Redhawk (Figure 17a-d);

and winter and summer peaks at the Palo Verde nuclear generating station (Figure 17e-f). This seasonality and its interannual variability are well captured by 1M simulations (CC > 0.62 and RMSE < 0.2 TWh). In contrast, as expected, 1A simulations (plotted in Figure 17 by dividing the annual totals by 12) are not able to reproduce seasonal peaks, and, in turn, the associated peaks of water demand for energy production, as further described below. Despite this, the annual electricity generations returned by 1A each year are very close to the 1M simulations aggregated annually (APE between the two configurations relative to 1M and evaluated annually <2%).

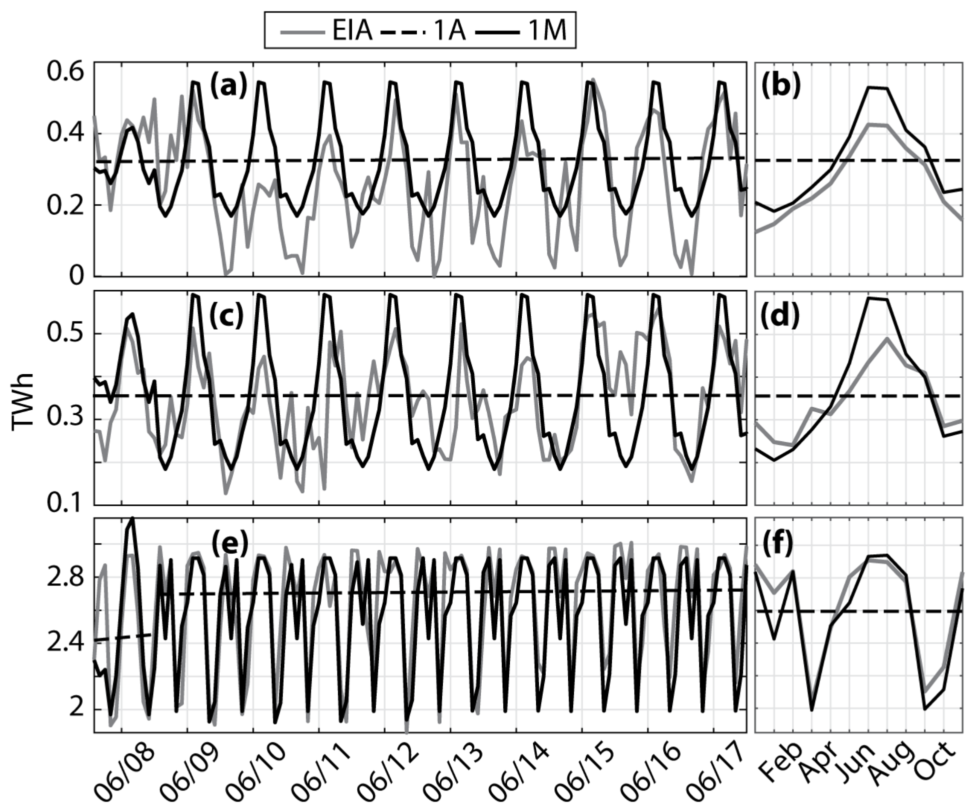

Figure 17. Monthly electricity generation in 2008-2017 (left panels) and monthly means across all years (right panels) reported by EIA (2019) and simulated by coupled WEAP-LEAP under the 1A and 1M configurations at (a)-(b) Santan, (c)-(d) Redhawk, and (e)-(f) Palo Verde power plants.

We now turn our attention to the water allocation for electricity generation (note that, for this variable, observations from ADWR are only available at annual resolution and aggregated for all power plants, while EIA provides data on water withdrawals only for 2014-2017 without detailed information on the water sources). In the domain with a single power node, WEAP allocates water to such node only from RW and GW sources. The corresponding mean monthly allocations simulated by 1M are shown in Figure 18a, while the single monthly averaged value produced by 1A is presented in Figure 18b. As suggested by the results on electricity generation of Figure 17, water volumes required by power plants are characterized by a lower winter and a more pronounced summer peak. This resource is largely provided by RW in summer (84% in August) and almost equally supplied by both sources in late winter and spring. As expected, annual simulations by 1A are unable to capture this variability in time and between the two water sources. For example, 1A underestimates results of 1M by 2.5 million m^3 (or 21%) in August and overestimates them by 2.2 million m^3 (or 33%) in November. We note that the increase of simulated RW is caused by a rise of municipal water demand in summer and is likely overestimated due to the assumption made in the WEAP setup of a constant water consumption rate of 70% for the municipal water demand (see Supporting Information of Guan et al. (2020) for details). This setup should be improved in the future if observed data on the monthly variability of RW will become available.

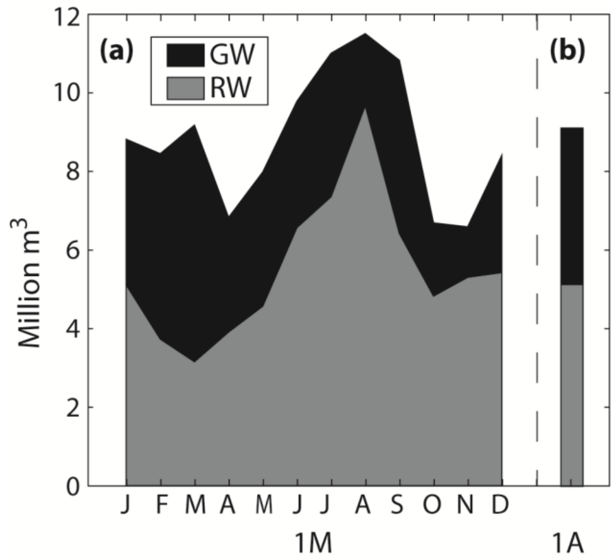

Figure 18. (a) Mean monthly water allocations from RW and GW to the power node simulated in the 1M configuration, and (b) single mean monthly value derived from the 1A setup.

As a next step, we analyze the differences between 1A and 1M in terms of annual water supply to all uses. In particular, we focus on water delivered by CAP, which is the most energy-intensive water source. The observed and simulated time series of annual water volume supplied by CAP to all demand nodes are displayed in Figure 19a, which shows that 1M simulations better capture the ADWR estimates, especially in early years when supply is lower. This finding can be explained by the 1M's ability to better represent key water allocation dynamics occurring within each year. To demonstrate this, we plot in Figure 19b,c the CAP monthly supplies to the municipal demand node for two representative years. To interpret these figures, we highlight that (i) CAP has the second-lowest allocation priority in the WEAP setup; (ii) there is a maximum water volume that CAP can distribute to each user due to allocation rights (44 million m^3 for the municipal user, plotted with a red line labeled “CAP Max” in Figure 19b,c); and (iii) when CAP allocations reach this maximum volume, an unmet demand exists that is satisfied by the next available water source. Simulations under 1A lead to constant monthly CAP water allocations, which could be either smaller than the maximum allocation (as in 2010; Figure 19b) or reach this value (as in 2012; Figure 19c) depending on water demand. In the former case, CAP allocations satisfy all water demand; in the latter case, another water source is used throughout the year to meet the unmet demand. When simulations are instead conducted under 1M, the water demand that CAP should satisfy (labeled “Demand” in Figure 19b,c) varies each month and the resulting allocations could be either smaller (e.g., August) or larger (e.g., December) than 1A. Similar to 1A, there are months when CAP allocations reach the maximum value, as in, e.g., January, November, and December of 2010. In this year, the annual water demand potentially requested to CAP is almost identical under both 1A and 1M. However, this demand is satisfied using solely CAP under 1A, while a supplementary source is required under 1M. Because of this difference, annual CAP allocations simulated in 2010 are larger under 1A and smaller under 1M, which is closer to the observation (Figure 19a).

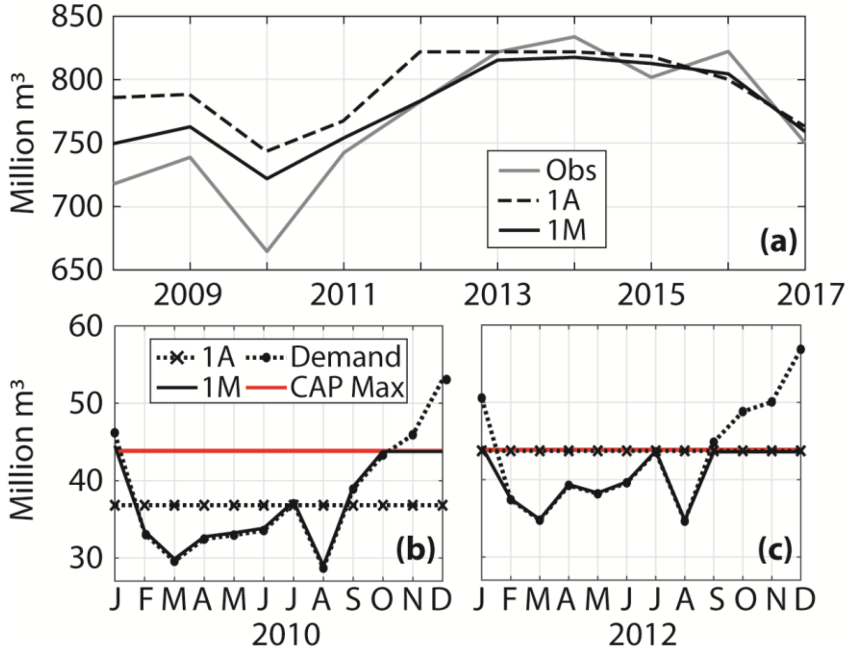

Figure 19. Water allocations from CAP. (a) Time series of CAP annual volumes to all demand nodes estimated by ADWR (2018) (Obs) and simulated under 1A and 1M configurations. (b)-(c) Monthly simulations of CAP supplies to the municipal node in 2010 and 2012, respectively (see main text for details on legend).

As a final note, the 1M's ability to better capture intra-annual dynamics of water allocations results also in significant differences in the estimation of energy required to transport and treat water. This is illustrated in Figure 20, which shows that, under 1M, this energy ranges from a peak of 173 GWh in July to a minimum of 117 GWh in February. Simulations at the annual scale suggest instead a constant value of ~150 GWh with differences of up to 19% with 1M. As found for electricity generation, when aggregated annually, the differences between 1A and 1M are instead small (<1.1%).

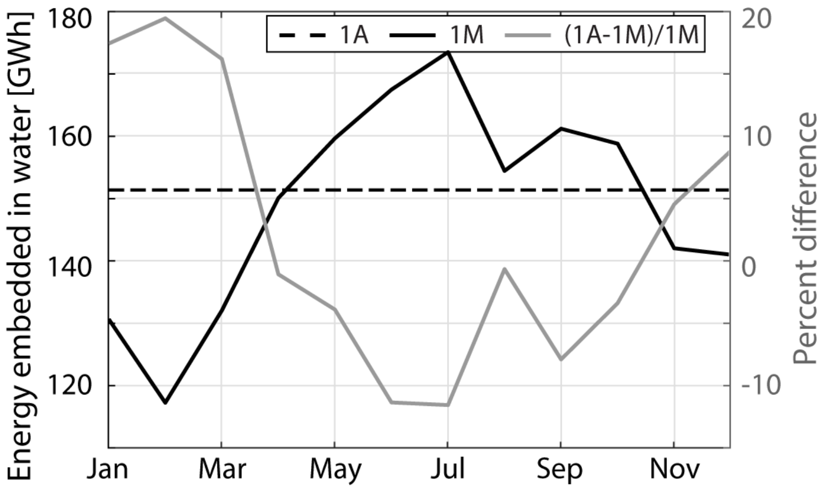

Figure 20. Monthly mean energy embedded in transporting and treating RW, SRP, GW, and CAP water simulated under 1A and 1M along with the percent difference.

3.3.2. Effects of spatial granularity

To investigate how the level of spatial details affects WEN simulations, we compare results of runs with monthly forcings and two WEAP networks with one (1M) and nine (9M) power nodes, respectively. The Sankey diagrams of Figure 21 display water allocations and embedded energy from supply sources to power demand nodes. We first focus on the monthly mean values (Figure 21a,b) and note that the total water use for power generation is practically identical in the two cases (~8.87 million m^3). However, the sources supplying water for power generation change depending on the spatial granularity. Under 1M, RW and GW are simulated as the only water sources that satisfy this demand (Figure 21a). When each power plant is instead represented in the WEAP network along with the connections to the associated water supply sources (9M), CAP is utilized as an additional water source (Figure 21b). In particular, CAP is the main water provider for Kyrene and Santan power plants (Table 2). The use of CAP water reduces GW and RW allocations when compared to 1M. This change results in an increase of 0.23 GWh (or 4%) of the annual energy demand for water because CAP is more energy-intensive (1.31 kWh/m^3, see the appendix in Mounir et al., 2019) than GW and RW (0.35 kWh/m^3 and 0.81 kWh/m^3, respectively).

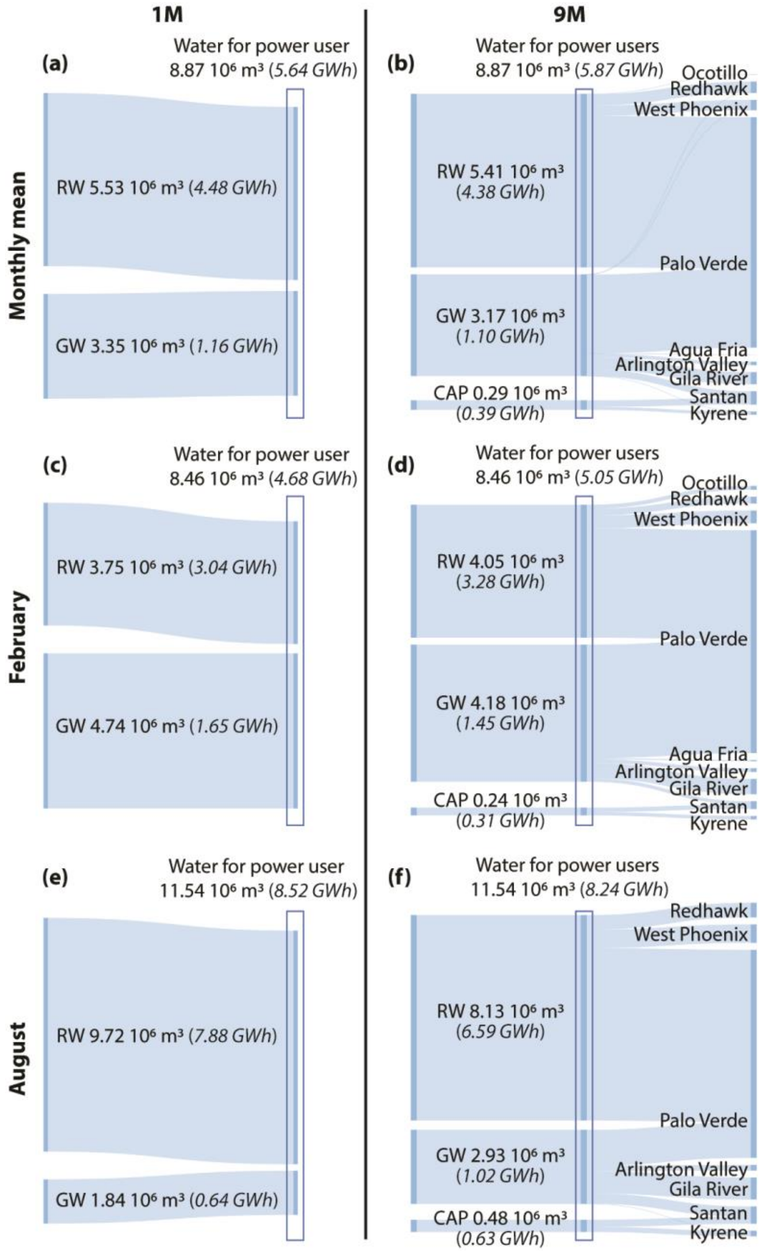

Figure 21. Sankey diagrams showing mean monthly water allocations from sources to power users simulated under (a)-(c)-(e) 1M and (b)-(d)-(f) 9M, along with embedded energy. Means are computed across (a)-(b) all months of all simulated years; (c)-(d) all Februarys; and (e)-(f) all Augusts.

We further investigate differences between water allocations and embedded energy by focusing on the months with the lowest (February; Figure 21c,d) and highest (August; Figure 21e,f) water needs for power generation. In February, simulations with one power node indicate GW to be the largest water provider for power. When the domain includes instead nine nodes, changes in water allocations caused by the use of CAP water result in similar volumes supplied by GW and RW. This redistribution leads, in turn, to an increase of energy for water treatment and distribution of 0.37 GWh (8%) as compared to the simulation under 1M (compare Figure 21c with Figure 21d). In August, the larger water use by the municipal sector increases the availability of RW (also due to the assumption made to set up WEAP, as discussed in the previous section), which is simulated as the major water source for energy generation in both configurations. However, the use of CAP under 9M leads to (i) lower RW and higher GW volumes compared to 1M, and (ii) a decrease of energy embedded in the water of 0.28 GWh or 3% (compare Figure 21e with Figure 21f).

3.3.3. Importance of coupling

The significance of representing two-way interactions in models of water and energy systems is evaluated by comparing simulations with the standalone and the coupled model configurations, which are both based on a WEAP network with nine power plants and monthly simulations. A key difference between standalone and coupled models relies on the monthly water volumes required by the power plants. In the coupled simulations, these fluxes are generated at each time step by converting the energy generated by each power plant simulated by LEAP into water volumes (Figure 16b). In the standalone configuration, these fluxes are instead provided as external inputs to WEAP (Figure 16a). In our study site, annual estimates of water withdrawals by all generating stations combined are available from ADWR (2018); thus, to conduct standalone simulations, assumptions are needed to disaggregate these volumes to each power plant and at monthly resolution. Details are provided in the Appendix.

Figure 22a-c show the water volumes required by the three largest generating stations, which are representative of results obtained across all power plants. In some cases (e.g., Santan; Figure 22a), the standalone simulations are very similar to the coupled model outputs, while in others they overestimate (e.g., Redhawk; Figure 22b) or underestimate (e.g., Palo Verde; Figure 22c) the coupled fluxes, with smaller and larger ranges between the maximum and minimum monthly values, respectively. The two configurations exhibit these same differences in terms of simulated electricity generation, as displayed in Figure 22d-f. This is expected since the water used for power generation and the electricity produced are linearly related through the water withdrawal intensities of the power plants (note that this is a model limitation that should be addressed to incorporate recent evidences of nonlinear behavior by Tidwell et al., 2019). More importantly, Figure 22d-f display also monthly estimates of electricity generation from EIA that can be used as a reference to assess the accuracy of the modeling approaches. It is apparent that simulations with the coupled models capture much better EIA observations than those obtained using the standalone mode, as quantified by RMSE being lower than 0.2 TWh and 0.8 TWh for the coupled and standalone runs, respectively.

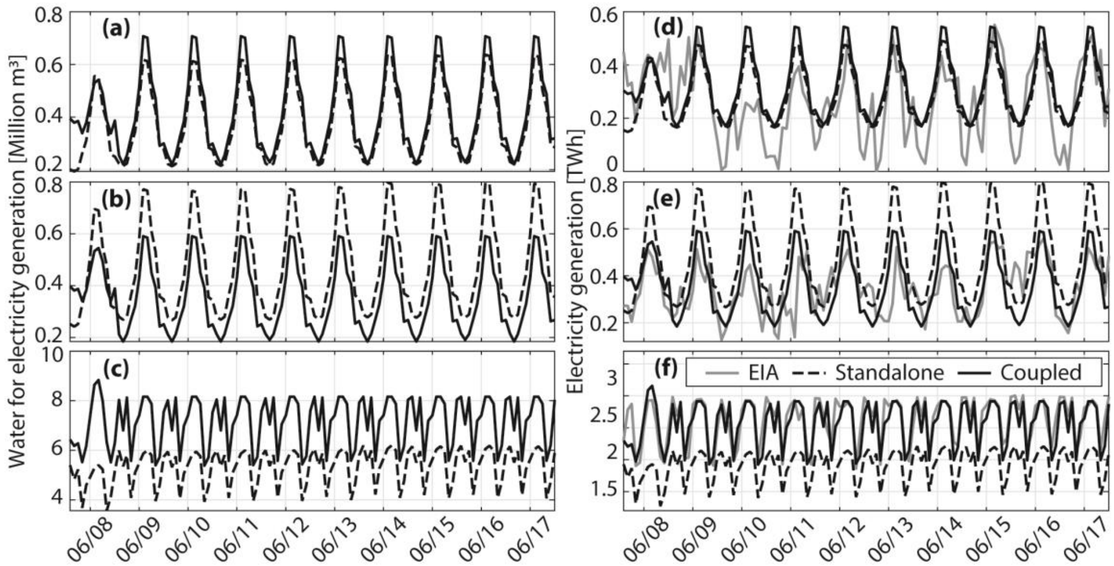

Figure 22. (a)-(c) Simulation of water allocations for power generation at (a) Santan, (b) Redhawk, and (c) Palo Verde power plants using standalone and coupled configurations. (d)-(f) Same as (a)-(c) but for electricity generation, along with estimates from EIA (2019).

The discrepancies between the water demand of power plants simulated with the two modeling approaches lead to differences in volumes supplied by CAP, GW, and RW to these users, along with the associated energy required for treatment and pumping. The mean monthly water fluxes from sources to individual power plants are compared in the Sankey diagrams of Figure 23. The total water used for power generation provided as input in the standalone configuration is slightly larger than the simulated value in the coupled runs (9.34 vs. 8.87 million m^3), resulting in higher embedded energy (6.08 vs. 5.87 GWh). To satisfy the water demand, the coupled models simulate a larger (smaller) fraction of RW (GW and CAP water) compared to the standalone case. Moreover, the two configurations predict different portfolios of water sources for some of the power plants. For example, (i) Redhawk and West Phoenix receive water only from RW in the standalone configuration, while they are also supplied by GW in the coupled mode; and (ii) Palo Verde is supplied by a much smaller fraction of GW in the standalone runs.

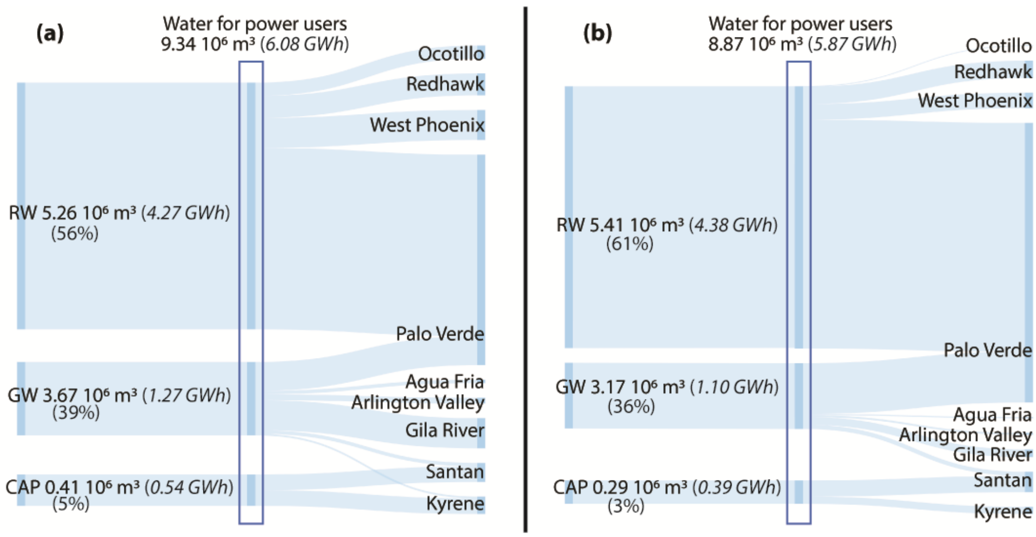

Figure 23. Sankey diagrams showing the mean monthly water supply from RW, GW, and CAP to the power users along with the energy embedded in treating and pumping these fluxes as simulated by the (a) standalone and (b) coupled models.

The water allocations from the three sources to the power plants exhibit also temporal differences. For instance, as illustrated in Figure 24a,b, the coupled runs simulate an increasing trend of CAP water allocations to all power plants from 2008 to 2017 that is not captured by the standalone configuration. Under this simpler modeling approach, constant annual allocations are predicted that result in an overestimation of CAP water throughout the simulation period. Both modeling types simulate an increasing trend of GW allocations from 2008 to 2015 and a decrease afterward (Figure 24c). However, simulations under standalone overestimate (underestimate) GW monthly fluxes simulated by the coupled models below (above) ~4.5 million m^3 (see scatterplot in Figure 24d), leading to lower variability of the monthly fluxes. The two modeling approaches simulate instead similar allocations of RW to all power plants (Figure 24e,f). Despite this, differences are found in terms of RW allocations to distinct generating stations. This is demonstrated in Figure 25, which shows that outputs of the coupled models are both overestimated (e.g., +104.7% in West Phoenix and +31.8% in Redhawk) and underestimated (e.g., -17.9% in Palo Verde) by the standalone runs.

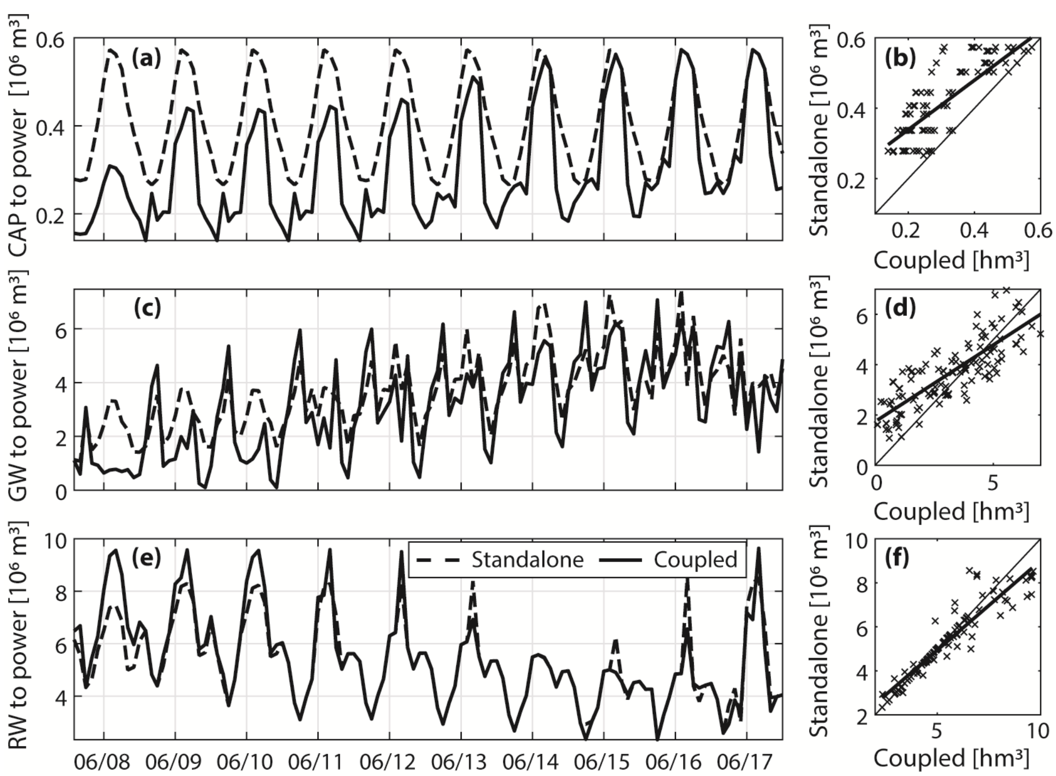

Figure 24. Simulations of (a)-(b) CAP, (c)-(d) GW, and (e)-(f) RW water allocations for power generation using the standalone and coupled models. For each water source, the monthly time series and scatterplots between the two estimates are shown. In the scatterplots, the thinner (thicker) line is the 1:1 line (linear regression).

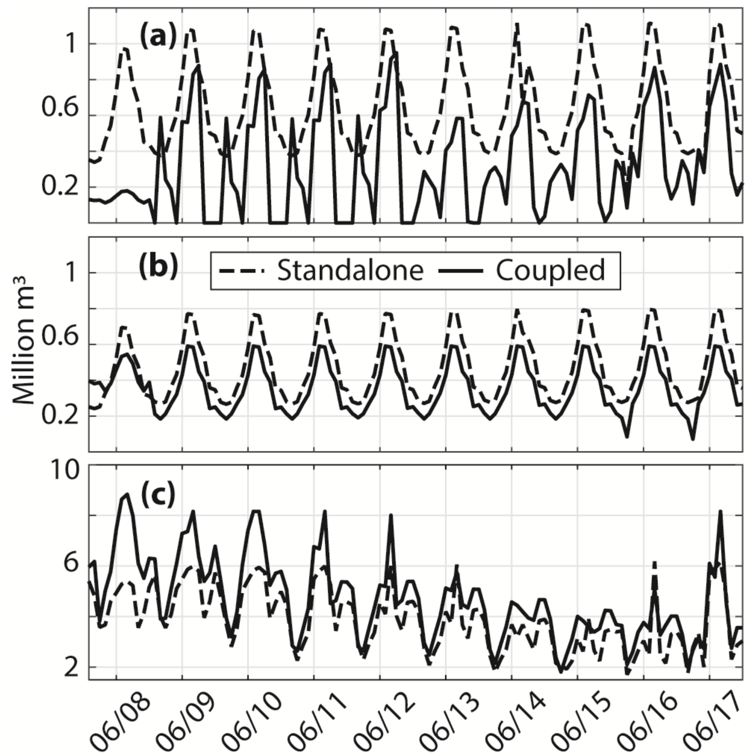

Figure 25. Simulation of RW water allocations to (a) West Phoenix, (b) Redhawk, and (c) Palo Verde power plants using standalone and coupled configurations.

3.4. Discussion and Summary

While obtained for a specific study site, our results provide useful information that could support WEN modeling efforts in other regions. In particular, our findings are relevant for models that simulate WEN dynamics over spatial extents of metropolitan regions or larger and at timescales larger than one day. They are less applicable to real-time simulations at sub-hourly resolutions of water distribution and power transmission networks at a city or neighborhood scale, as, e.g., in the 24-hour simulations conducted by Santhosh et al. (2014) and Khatavkar and Mays (2018).

3.4.1. Data availability and spatiotemporal disaggregation are key

As for all modeling exercises, increasing the spatial and temporal resolutions of WEN models leads to more complex model setups that require a larger amount of data. Focusing on the U.S., Chini and Stillwell (2017) recently highlighted that obtaining data on water and energy systems, demand, and supply is a challenging task. In particular, these authors reported that data on energy are available at higher time frequencies and finer spatial granularity than data on water. EIA reports the main characteristics of most power plants in the country and their monthly electricity generation, as well as energy consumption grouped by sectors at the state level. Hourly energy demands are also publicly available in numerous balancing areas, defined as regions where energy demand and supply must be balanced (FERC, 2020). Data from EIA have been crucial for our modeling study at the metropolitan scale (Table 1).

Considering instead water, EIA reports water withdrawals and consumption for the power plants. For other uses, the main efforts at the national scale are from the United States Geological Survey (USGS) and include Water Data for the Nation (USGS, 2016) and the National Water Use Information Program (USGS, 2010). The Water Data for the Nation initiative publishes almost in real-time streamflow data at daily or sub-daily resolution across the country. These data could be used to estimate water diversions from rivers at high temporal resolutions (up to daily), which are needed to apply water models. Data on water withdrawals from reservoirs, pumped volumes from wells, and allocations of reclaimed water are instead more difficult to obtain since they depend on policies on data sharing adopted by agencies and utilities managing these supply sources. The National Water Use Information Program reports every five years water use estimates at the county level, which are temporal and spatial resolutions often too coarse for WEN modeling studies. Currently, no agency has the mandate to collect national water data at the utility or city scale, as EIA does with energy (Chini and Stillwell, 2017). In our effort, we have been able to access a relatively extensive dataset on water, including estimates of annual water demand and supply data in the AMA by ADWR, daily water diversions from the closest reservoir to Phoenix published online by SRP, and monthly reports with water volumes allocated to different customers by CAP (see Table 1 and Appendix).

Even if data are partially available, as in our study region, they are very often provided at different resolutions and for limited time periods. Thus, assumptions are needed to disaggregate data temporally and spatially and to extrapolate them in time for their use in more detailed WEN simulations (Khan et al., 2017). Such assumptions could be supported by reports of local water and energy utilities and irrigation districts. In our effort, we have disaggregated annual estimates of municipal and agricultural water demand from ADWR (2018) to monthly scale through monthly fractions derived from a report published online by the City of Phoenix, which is one of the largest water providers (CPWSD, 2011), and from a recent report on irrigated agriculture in Arizona by Lahmers and Eden (2018), respectively. For the standalone simulations, we have also performed a spatial disaggregation of energy-related water demand from ADWR (2018) by combining power plant characteristics (i.e., capacity, capacity factor, and water withdrawal rate; see Appendix) available from EIA (2021). Alternatively, open record requests could be sent to utilities to obtain data, as done by Chini and Stillwell (2017, 2018) who contacted water utilities in 127 U.S. cities to conduct a utility-scale analysis of drinking water and wastewater flows along with the embedded energy. Despite this, these authors also warned about potential limitations of data provided by utilities in terms of accuracy (e.g., absence of data quality assurance and control) and low resolution (e.g., energy data is not collected at sub-monthly resolution).

3.4.2. Value of higher temporal resolution

In our study region, fluxes of water and energy systems are characterized by marked intra-annual variability largely due to higher demands in hot summers (see Figure 17, Figure 18, and Figure 22). Incorporating this higher temporal variability in simulations of water-energy interactions provides critical support for the identification of synergies between the two systems that can guide policy- and decision-makers in the two sectors. This is particularly true in regions where there are large fluctuations of demand for both resources and of surface water supply. For example, simulating the seasonal water availability for power generation provides detailed information on (i) which type of power plants is more convenient and sustainable to expand or retire in the future (APS, 2017; SRP, 2018); (ii) reservoir operations to optimize hydropower generation (Demertzi et al., 2014; Xuan et al., 2020); and (iii) planning of energy generation and, in turn, of imports and exports (FERC, 2020). Capturing the seasonality in water and energy demand and supply is also important to (i) identify optimal water conservation (energy efficiency) strategies that save energy (water) while being cost-effective (e.g., Bartos and Chester, 2014; Escriva-Bou et al., 2018; White and Fane, 2002); and (ii) model impacts of heat waves and low water flows on power production (Bartos and Chester, 2015; Gjorgiev and Sansavini, 2018; Harto and Yan, 2011; van Vliet et al., 2016).

Results of our work also suggest that adopting higher temporal resolutions increases the accuracy of WEN simulations. This is particularly true for water fluxes and less critical for energy fluxes. For instance, the use of annual or monthly temporal resolutions results in a difference of up to 5% in the simulated annual CAP water supply (Figure 19), but practically no difference in simulated annual electricity generation at each power plant. This finding can be explained considering that water systems are more rigid because there is a direct connection between demand nodes and their supply sources due to both infrastructural constraints and management rules. As a consequence, if simulations are performed at the monthly resolution, the contribution of each supply source to a given demand node can vary dramatically each month depending on water availability. Since these seasonal dynamics are not captured in annual simulations, there may be marked differences in the simulated water volumes provided by each water source throughout the year. Two main reasons can instead explain why the simulated annual energy supply is less sensitive to the model temporal resolution. The first is that electricity is not directly delivered from specific power plants to distinct users because of the presence of the electric grid; therefore, even if the overall demand changes monthly, electricity generations at individual power plants are not importantly affected by demand changes of each user. The second reason is that, in our study region, water infrastructure contributes only ~4% to the total energy demand (Mounir et al., 2019); thus, even if different water fluxes are simulated at the two resolutions, the difference in associated electricity demands is comparatively very small.

These outcomes obtained for the Phoenix AMA with thermoelectric power plants can be used as a reference to assess the value of temporal resolution in WEN modeling in other study areas. Water systems rely everywhere on relatively rigid allocation rules and infrastructure constraints. We then expect that the simulation of water allocations from supply sources to demand nodes, including power plants, will be ubiquitously impacted by the temporal resolution. Conversely, modeling energy supply will likely be less impacted by temporal resolution in several regions in the U.S., because the power grid is always present and the national average of the percentage of total energy use to pump and treat water is ~4%, as in the Phoenix AMA (EPRI, 2000). The sensitivity of simulated electricity generation to the WEN model temporal resolution is expected to increase in regions where water infrastructure is responsible for a substantial portion of the total energy consumption, such as in California, where this portion is ~10% (CPUC, 2010), and in areas greatly dependent on desalination, like the UAE where desalination uses up to 22% of its total electricity (Siddiqi and Anadon, 2011). However, increasing temporal resolution to monthly is most likely needed when hydropower represents a large share of the electricity generation, due to the need to model streamflow seasonality and reservoir operation, as also showed by Dale et al. (2015).

3.4.3. Value of higher spatial granularity

Our analyses show that, when the spatial granularity of the water model domain is increased, dynamics of water allocations for energy generation are simulated with higher accuracy. This suggests that, depending on the specific study site, a coarse representation of the energy system components in the water model domain may result in ignoring the contribution of distinct water sources for power generation. For example, in the Phoenix AMA, allocations of CAP water to power plants are only captured using the configuration where each power plant is explicitly represented in the water model (Figure 21). This modeling capability is important for both the electricity companies that manage the generating stations relying on such water supply and the regional management of water resources. While increasing the spatial resolution up to the granularity of single power plants enhances model accuracy, it also requires a larger amount of data and adds complexity to the model. Here, we show that this effort is valuable and achievable at the scale of a metropolitan region. As the spatial extent of the study region increases (e.g., states or countries), capturing the dynamics of water allocations to distinct power plants may become unfeasible and, in some cases, even unnecessary. For example, Yates et al. (2013a) coupled WEAP with the regional energy deployment system (ReEDS) to quantify water withdrawals by different users including the power system in Southwestern U.S., which encompasses our study site. In doing so, these authors aggregated power plants by technology type within balancing areas, thus using a much coarser description of the energy system than the one adopted in our study. However, the differences in CAP water supplies simulated in our study for the coarse and fine domains represent only 0.06% of the annual water withdrawals over the Southwestern U.S. As a result, the simplified modeling setup adopted by Yates et al. (2013a) is justified to simulate the WEN in such a large domain without causing any major loss of information. Finally, the need to disaggregate spatially and increase model complexity could be less critical if the main sources of electricity generation come from solar PV and wind turbines because these require very limited water volumes.

3.4.4. Utility of coupled simulations

In our study, coupled and standalone models are compared–to our knowledge for the first time–in the same WEN system. We find that the use of coupled models results in more accurate simulations of electricity generation and its water needs than estimations based on a standalone configuration where a water model is used to infer information on the energy system (Figure 22). This difference is explained by the assumptions made to generate energy-related inputs for the water model, which, as discussed above, are obtained by disaggregating annual estimates of water use for power generation from ADWR in space (to each power plant) and time (monthly). Under these assumptions, simulations of energy generation and water demand with the standalone and coupled models are similar at some power plants (e.g., Santan), but they diverge significantly at others, including a large underestimation of water withdrawn by the most water-consuming generating station, Palo Verde. Moreover, results from these two approaches differ in terms of (i) water allocations supplied from each source to the power plants (this may be a minor issue elsewhere if power plants are supplied by a single source), (ii) energy embedded in treating and pumping these water volumes, and (iii) intra-annual variability of the total water allocation from the different sources. These differences highlight the limitations of simpler approaches where a model is used to simulate one system (in our case, water) and infer information about the other system (energy). Clearly, the limitations of standalone simulations are less critical when there is enough information and confidence on the assumptions made to constrain the model (in our case, on the time series of water demand from power plants).

An additional advantage of coupled models is that they allow a more mechanistic representation of processes and characteristics of water and energy infrastructure. This has three important benefits. First, it facilitates the simulation of WEN systems characterized by different temporal and spatial scales, a process named synchronization by Khan et al. (2017). The case of the Phoenix AMA illustrates this point since the coupled model is capable to simulate electricity generation in all power plants supplying the study area, including those located outside of the geographical boundaries that contribute to satisfy the local energy demand. These external generating stations are instead not included in the standalone configuration because it is quite hard to make assumptions on their contribution. The second benefit of the higher mechanistic nature of integrated models is that they are (probably the most) accurate tool to simulate WEN systems under different future scenarios since they allow implementing, in a relatively easy fashion, changes of infrastructural components (e.g., number and type of power plants, construction or decommission of water infrastructure) and their management rules, new energy and water efficiency technologies, and modifications of water and energy demands in the different sectors, among other features. The value of this capability has been shown, for example, by Yates et al. (2013a), who used the coupled ReEDS-WEAP models to simulate capacity expansion and energy generation according to different future electricity mix scenarios, along with water allocations under drought conditions. Lastly, coupled models could be beneficial in data-scarce regions to simulate processes for which data are not available, provided that reliable assumptions are made on their parameterization through, e.g., values reported in literature or relations with population served.

3.5. Conclusions

The simulation of the interactions between water and energy systems is crucial to identify synergies and adopt a holistic management approach. In this study, we investigate how the accuracy of WEN simulations is affected by the spatiotemporal resolution and use of coupled models that capture two-way feedbacks between the systems. We do so by applying the WEAP and LEAP models in the Phoenix metropolitan region, where water resources are limited and energy-intensive. Our results can be summarized as follows:

(i) Increasing the temporal resolution from annual to monthly allows capturing the marked seasonality of electricity generation and the associated water requirements. While the use of both time steps leads to the simulation of similar annual electricity generations at each station, annual aggregates of water deliveries from each source vary with the temporal resolution. This difference in sensitivity to the model time step is explained by the presence of more rigid infrastructure constraints and allocation rules in water systems compared to energy systems.

(ii) The use of a finer spatial granularity by incorporating each power plant in the WEAP domain allows simulating the correct water portfolios of power plants, which the coarser configuration with a single water demand node for power is unable to capture. This leads to differences in simulated energy embedded in water for power generation. The accuracy achieved by refining the spatial granularity up to the single power plant can be unnecessary in studies applied to regions with a large spatial extent.

(iii) Simulations with the coupled models reproduce EIA observations of electricity generation better than the standalone approach. Simulations under the two modeling approaches differ in terms of magnitude and intra-annual variability of water allocations from distinct sources to each power plant, with relative differences exceeding 100%. By representing processes and characteristics of water and energy infrastructure in a more mechanistic fashion, coupled models facilitate the simulation of WEN systems with different temporal and spatial scales and under possible future scenarios. Once the spatial granularity and complexity of the domain are fixed and data have been collected, we believe that the adoption of coupled instead of standalone approaches is not limited by the scale of the problem, but rather by the current low availability of these integrated models.

CHAPTER 4

CONTRIBUTION OF RENEWABLE ENERGY TO GROUNDWATER SUSTAINABILITY IN THE PHOENIX METROPOLITAN REGION

4.1. Introduction

Groundwater (GW) abstraction has helped social and economic development while also mitigating the adverse effects of droughts in numerous drought-prone areas (Giordano and Villholth, 2007; Gleeson et al., 2010). However, significant volumes of GW extraction have caused water tables to fall in many regions of the world (Gleeson et al., 2010, 2020). GW depletion occurs when water abstraction and natural GW discharge exceed the natural and artificial recharge. Therefore, sustainable GW use could be achieved by increasing artificial recharge and/or reducing withdrawals (Scanlon et al., 2012). Given that electricity generation is estimated to be responsible for ~15% of global total water consumption (Qin et al., 2019), recent studies have investigated the utility of new methods to indirectly promote GW sustainability by reducing water demand in the power sector through the penetration of renewable energies. For instance, He et al. (2019) conducted state-level research in California to evaluate how solar and wind energy generation might be used to replace hydropower stations in order to reduce surface water usage. The authors determined that the surface water saved may be transferred to other demand sectors (e.g., agriculture irrigation) in lieu of GW. Moreover, in Saskatchewan, Canada, Wu et al. (2021) found that expanding wind power reduces GW use by 3.8%.

These promising studies suggest an urgent need to further investigate how the power sector, and especially the adoption of renewable technologies, could support GW sustainability. This is especially critical in water-limited desert regions, like Arizona.

Arizona is a semi-arid state in the southwestern United States that experienced a substantial drop in water tables in the 1970s (Gober et al., 2010; Jacobs and Holway, 2004). In 1980, the groundwater management act was passed to achieve "safe-yield" by 2025. The safe-yield concept was described as the amount of abstraction that balances natural and artificial recharge in the long term (Jacobs and Holway, 2004). It is noteworthy to mention that a more comprehensive definition accounts for natural GW discharges to springs, rivers, and wetlands (Zhou et al., 2019). Achieving this goal requires adopting programs that limit the demand for GW use (e.g., prohibiting high water use activities) and promote the use of other water sources. In the last three decades, Arizona water users have been relying on a variety of sources, including GW, Colorado River water, in-state rivers, and reclaimed water (RW). Arizona's water management initiatives have been effective since the state's dependency on GW has decreased dramatically (Jacobs and Holway, 2004) and the water table has been rising (Tillman and Leake, 2010). However, future access to Colorado River water will most likely decrease due to a reduction in runoff in the upper Colorado River basin and increasing competing demands from other states (USBR, 2021). In 2021, the U.S. Secretary of the Interior declared a Tier 1 shortage for Colorado River operations beginning in 2022, which will reduce Arizona’s supply of Colorado River water and place a strain on other water sources like GW (CAP, 2021).

Power utilities in Arizona have initiated efforts to support GW sustainability. For example, the Arizona Public Service (APS) has set a goal to reduce GW use by 75% between 2019 and 2035 (APS, 2020). APS is investigating different solutions to achieve this goal, including (i) reliance on renewable energy resources, (ii) an increase in surface and RW use, and (iii) surface water storage in subsurface storage facilities (APS, 2020; PWCC, 2018b). Further strategies could take place to limit the reliance of local power plants on GW without investing in new infrastructure components. Notably, power utilities could establish a GW withdrawal volume cap and rely on power plants with access to RW. However, due to the competition among water consumers, increased utilization of this water source for power generation may be impossible. Accordingly, power utilities would have to purchase electricity from the market to ensure a consistent supply of energy while limiting GW withdrawals. To understand the implications of these operational strategies, I will use a coupled water and energy model to investigate the possibility of a GW abstraction cap for the power plants located inside the Phoenix Metropolitan Area (PMA) considering different levels of penetration of renewables. I will also conduct a trade-off analysis between the GW use by the power plants that are located inside the PMA and the purchase of electricity from the market. Specifically, this chapter pursues the following research question: Will renewable energies be able to mitigate the trade-offs between GW sustainability and the dependence on purchased electricity in the PMA under future climate scenarios?

4.2. Materials and Methods

4.2.1. Study region and its future electricity generation mix

This chapter considers the same study site as the previous two chapters (the Phoenix active management area (AMA), see sections 2.2 and 3.2.1). The two power utilities supplying energy to this area are the Salt River Project (SRP) and the Arizona Public Service Company (APS) mentioned in Chapter 2, the future electricity generation mix of SRP and APS, which will satisfy the future energy demand, is uncertain and the Integrated Resource Plans (IRPs) produced by SRP (2018) and APS (2020) employ a scenario analysis approach to investigate various possibilities. Using a similar approach, in this chapter four scenarios are developed based on two plausible future renewable portfolio standards (RPS; the percent of the energy generated by renewable sources) and two future climate scenarios. The first set of scenarios of electricity mix is named "business as usual" (BAU) and includes the same characteristics presented in Chapter 2. Specifically, it is assumed that (i) the decommission of all coal power plants will occur by 2045, (ii) the Palo Verde nuclear power plant will not change, and (iii) the RPS will reach 40% by 2050 with the help of new solar PV plants and wind turbines. The second set of scenarios is named "Renewable" and includes characteristics similar to the electricity mix scenario developed in APS (2020) under the name "Accelerate". This scenario assumes an aggressive penetration of renewables; specifically: (i) a quicker retirement of coal power plants by 2031, (ii) an RPS that will rise to 45% by 2030 with the same sources used in BAU, and (iii) a total decommission of natural gas power plants in 2050, achieving a carbon-free energy generation. BAU and Renewable incorporate two future climate scenarios, which will affect water and energy demand and supply. Guan & Mascaro (2022) processed future scenarios of moderate and intense warming using outputs of 10 general circulation models (GCMs) for SSP2-4.5 and SSP5-8.5 for Coupled Model Intercomparison Project Phase 6 (CMIP6), with SSP being the Shared Socioeconomic Pathway (O’Neill et al., 2016). Out of the 10 GCMs, here the model named INM-CM4-8 is selected and used for the simulations because its temperature projections are closer to the ensemble mean (see the following section for the significance of the temperature variable for the energy system).

Table 6. Future scenarios of energy supply and associated goals.

Scenario	Goals	Climate
BAU-4.5	• No addition of new coal plants • Compliance with currently announced retirements • Retirement of all coal plants by 2045 • No addition or retirement of nuclear capacity • RPS of 40% by 2050 • New renewable capacity from solar PV and wind	SSP2-4.5
BAU-8.5	• Achievement of all goals of the BAU-4.5 scenario	SSP5-8.5
Renewable-4.5	• No addition of new coal plants • Compliance with currently announced retirements • Retirement of total coal capacity by 2031 and all gas-fueled plants by 2050 • No addition or retirement of nuclear capacity • 65% clean energy by 2030 with an RPS of 45% • New renewable capacity from solar PV and wind • Carbon-free generation to be achieved by 2050	SSP2-4.5
Renewable -8.5	• Achievement of all goals of the Renewable-4.5 scenario	SSP5-8.5

4.2.2. Development of a Water-Energy-Climate Nexus model in the Phoenix AMA

Recent studies started investigating the effects of climate on the WEN (e.g., Dale et al., 2015; Obringer et al., 2019; Pereira-Cardenal et al., 2014; Scott, 2011; Suo et al., 2021) using the so-called water-energy-climate nexus (WECN) models (Kraucunas et al. 2015; Scott 2011; Suo et al. 2021). A similar methodology is used in this chapter. Specifically, a modeling framework is developed based on the calibrated and validated coupled WEAP-LEAP configuration labeled as 9M in Chapter 3. This configuration is improved in this chapter to address the effects that climate imposes on the WEN as decribed next.

First, the effect of temperature on the residential/commercial energy demand is accounted for through the heating (*HDD*) and cooling (*CDD*) degree days. These varables are calculated as the difference between the daily mean temperature and a base temperature of 21°C. A negative (positive) value is then considered *HDD* (*CDD*). Daily absolute values of *HDD* and *CDD* are aggregated to obtain monthly values. Different linear and multilinear empirical regressions were tested to link energy demand to these temperature related variables and the best perfoming equation is:

$$Ln(E_{demand,t}) = \alpha_0 + \alpha_1 \cdot CDD_t + \alpha_2 \cdot HDD_t + \alpha_3 \cdot HDD_t^2, \qquad (1)$$

where E_{demand} is the residential or commercial energy demand per capita for the month *t* in MWH/person, α_0, α_1, α_2, and α_3 are regression coefficients, and CDD_t and HDD_t are the cooling and heating degree days in °C for the same month *t*, respectively. Because of the limited data availability of per capita energy demand in the Phoenix AMA, the regression coefficients are calculated for the entire state of Arizona, with the monthly values of climate variable being weighted by population densities. The datasets used for energy demand, population density, and temperature are presented in Table 7.

Second, the effect of temperature on the monthly water intensity of power plants is considered using the empirical equation (12) in Rutberg et al. (2011) and the datasets are included in Table 7:

$$I_{cw} = 3{,}600 \cdot \frac{(1-\eta_{net}-k_{os})(1-k_{sens})}{\eta_{net} \cdot \rho_w \cdot h_{fg}} \cdot \left(1 + \frac{1-k_{bd}}{n_{cc}-1}\right) + I_{proc}\ , \qquad (2)$$

where I_{cw} is the water consumption intensity in L/MWh, η_{net} is the net efficiency (EIA 2019b), k_{os} is the fraction of heat lost to other sinks (0.2 for combined-cycle; 0.12 for fossil steam-cycle; and 0 for nuclear steam-cycle), k_{sens} is the fraction of heat load rejected through sensible heat transfer (calculated using $k_{sens,t} = -0.000279 \cdot T_t^3 + 0.00109 \cdot T_t^2 - 0.345 \cdot T_t + 26.7$; T_t is the mean temperature in °C), ρ_w is the water density (1 kg/L), h_{fg} is the latent heat of vaporization of water (2.454 MJ/kg at 20 °C), k_{bd} is the fraction of blowdown water that is discharged back to the watershed, n_{cc} is the number of cycles of concentration (between 2 and 10), I_{proc} is the water consumption intensity of all non-cooling processes in L/MWh (200 L/MWh for oil/coal and 10 L/MWh for gas/nuclear).

Third, the effect of climate on the water availability in the SRP reservoir system, which is part of the Salt and Verde River Basins (see Figure 26), is considered. The streamflow is simulated in two USGS streamflow stations (i.e., “Verde River above Horseshoe Dam, AZ” and “Salt River Near Roosevelt, AZ”) located near the two most upstream reservoirs (i.e., Roosevelt and Horseshoe reservoirs) using the following linear regression equation:

$$Q_t = \alpha_0 + \alpha_1 \cdot P_t + \alpha_2 \cdot T_t + \alpha_3 \cdot Q_{t-1} + \alpha_4 \cdot P_{t-1} + \alpha_5 \cdot PS_t + \alpha_6 \cdot PS_{t-1}, \qquad (3)$$

where Q_t is the mean streamflow for the month *t* in m^3/s, P_t is the total liquid precipitation in mm, T_t is the mean temperature in °C, and PS_t is the total precipitation falling as snow in mm, which is calculated through equation 3 in Ellis et al. (2008) $PS_t =$

$(0.47 - 0.04 \cdot T_t) \cdot P_t$ (see Table 7 for the datasets of streamflow and climate variables). Water deliveries from the SRP system was then simulated based on the inflow to the reservoirs through the methodology developed by Guan et al. (2020).

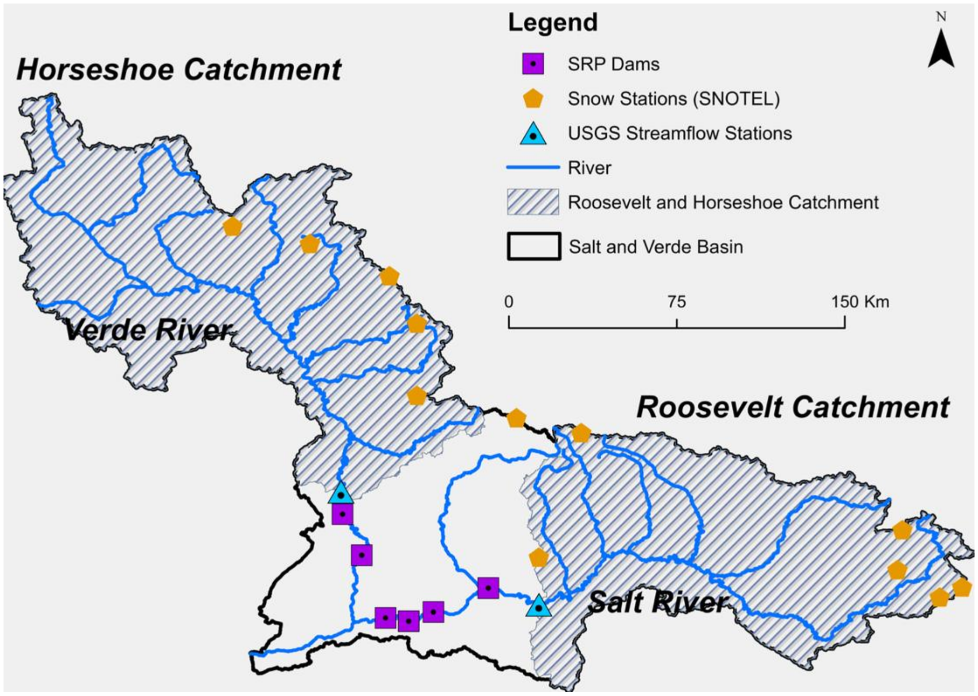

Figure 26. The Salt and Verde River basins with location of the reservoirs managed by SRP. The most upstream reservoirs are the Roosevelt and Horseshoe reservoirs on the Salt and Verde rivers, respectively. The map also shows the location of two USGS streamflow stations: “Verde River above Horseshoe Dam, AZ” and “Salt River Near Roosevelt, AZ”, which represent outlets to the Horseshoe and Roosevelt catchments and the location of 12 snow stations.

Finally, the water demand for crop irrigation in the Phoenix AMA was estimated by Guan & Mascaro (2022) through the crop model MABIA , which is embedded in the WEAP platform. The WEAP-MABIA methodology calculates the daily root-zone soil water balance through the following fluxes: effective precipitation, surface runoff, irrigation, actual crop evapotranspiration, capillary rise from the groundwater table, and deep percolation. This methodology uses daily precipitation, wind speed, minimum relative humidity, and reference evapotranspiration. The latter is calculated based on a simplified version of the Penman-Monteith equation, which requires daily minimum/mean/maximum temperature, solar radiation, mean relative humidity, and mean wind speed. The summary of modifications made to the coupled WEAP-LEAP modeling in this chapter to incorporate climate effects is illustrated in Figure 27.

Table 7. Datasets used to study the influence of climate variables on water and energy demand and supply.

Variable	Dataset	Description
Residential/Commercial electricity demand		
Observed demand	EIA (EIA, 2018f)	Monthly residential and commercial electricity sales data at the Arizona scale for the period 1990-2018
Population density	GPWv3 (CIESIN et al., 2005)	Arizona state population density gridded data at 0.0416° resolution for the years 1990 and 1995
	GPWv4 (CIESIN and University, 2018)	Arizona state population density gridded data at 0.0416° resolution for the years 2000, 2005, and 2010
	US Census (U.S. Census Bureau, 2021)	Annual population density data at the Arizona census tract scale for the period 2011-2018
Temperature	Livneh (Livneh, et al. 2013; Su et al., 2020)	Monthly temperature gridded data at the Arizona scale at 0.0625° resolution for the period 1990-2018
Water intensity of power plants		
Observed intensity	EIA (EIA, 2018g)	Monthly water intensity data for each power plant for the years 2014-2018
Temperature	Livneh (Livneh, et al. 2013; Su et al., 2020)	Monthly temperature gridded data at the Arizona scale at 0.0625° resolution for the period 2014-2018
Water availability (SRP system)		
Observed streamflow	USGS (USGS, 2016)	Monthly streamflow data for the years 1950-2013 reported in the two stream gages located upstream of Theodore Roosevelt Dam and Horseshoe Dam
Precipitation and temperature	Livneh (Livneh, et al. 2013; Su et al., 2020)	Monthly precipitation and temperature gridded data at the Arizona scale at 0.0625° resolution for the period 1950-2013

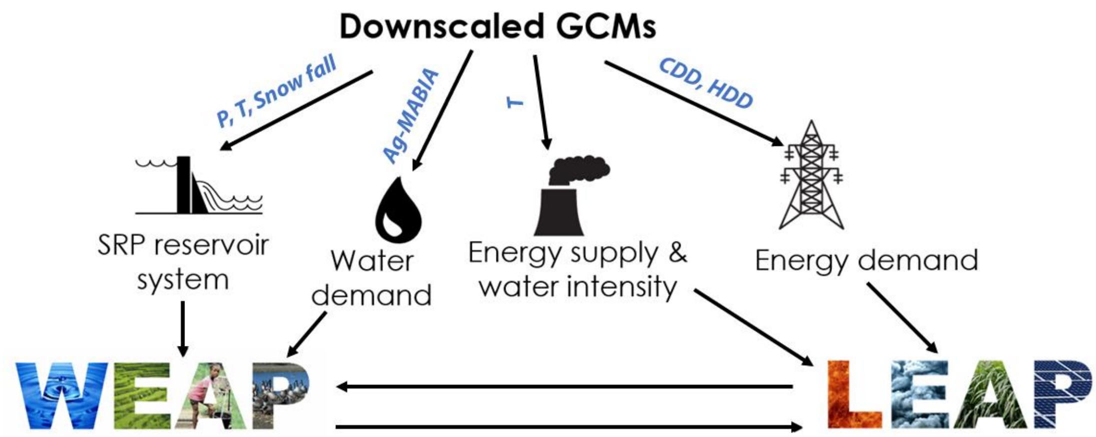

Figure 27. Integrated modeling of water, energy, and climate

4.2.3. Modeling configurations

The modeling framework is used under 20 configurations to simulate the period from 2020 to 2050 with a monthly time step. Table 8 provides a description of the modeling configurations. First, the configurations differ from each other as a function of the electricity generation system. Specifically, four sets of configurations, with names beginning with B4.5, B8.5, R4.5, and R8.5, follow the four future electricity generation mix scenarios BAU-4.5, BAU-8.5, Renewable-4.5, and Renewable-8.5, repectively (see Table 6). For example, the model configurations that are developed based on the generation mix of the BAU-4.5 scenario have names that begin with B4.5. Besides, the configurations belonging to the same set have the same electricity generation system. Second, four additional model configurations are included in each set of electricity generation mix scenarios. These configurations include GW withdrawal volume caps that range from 25% to 100% reductions. These caps are included in the names of each configuration as a hyphen followed by a one- or two-digit number, which refers to the percent of reduction. For instance, the configuration B4.5-25 includes a power system according to the BAU-4.5 scenario and assumes a 25% reduction by 2050. Similarly, the configuration R8.5-100 includes a power system according to the Renweable-8.5 scenario and assumes a 100% reduction by 2050. The percent reductions are estimated in reference to the first-year simulation (i.e., 2020) (Table 8).

Further, two population projections (obtained from U.S. EPA, 2009) are used in this chapter and are derived for each SSP. Additionally, since the energy demand is driven by climate (see the previous section) and population (see section 2.4.2.2), the configurations with the same climate scenario will have the same energy demand.

Table 8. Modeling configurations to study the GW sustainability vs. electricity purchases tradeoff.

		GW abstraction cap				
		0% reduction all years	**25% reduction by 2050**	**50% reduction by 2050**	**75% reduction by 2050**	**100% reduction by 2050**
Future energy supply scenario	**BAU-4.5**	B4.5-0	B4.5-25	B4.5-50	B4.5-75	B4.5-100
	BAU-8.5	B8.5-0	B8.5-25	B8.5-50	B8.5-75	B8.5-100
	Renewable-4.5	R4.5-0	R4.5-25	R4.5-50	R4.5-75	R4.5-100
	RenewaRle-8.5	R8.5-0	R8.5-25	R8.5-50	R8.5-75	R8.5-100

4.3. Results

The BAU and Renewable configurations differ in terms of water demand for power generation. Specifically, the Renewable configurations simulate a smaller demand compared to the BAU ones. This finding is expected as renewable technologies do not need water to produce electricity; hence lower water requirements from the energy system as already proven in Chapter 2 (see section 2.5.2.2.). The following sections will investigate the consequences of these lower water requirements in terms of GW and RW as well as in terms of purchased electricity.

4.3.1. Groundwater use for power generation

The simulations that are investigated in this section and in sections 4.3.2. and 4.3.3. assume a future climate scenario of moderate warming (SSP2-4.5). The effects of the intense warming scenario (SSP5-8.5) is investigated in section 4.3.4. As shown in Figure 28a, the simulated annual total GW use for power generation obtained from the configuration B4.5-0 remain fairly constant over the simulation period with some interannual fluctuations. GW use declines during the years marked by the addition of solar and/or wind generation capacities (e.g., the addition of ~3,000 MW of solar capacity in 2025 highlighted by a green arrow; APS, 2019; SRP, 2020a). Similarly, GW use increases during the years marked by the decommissioning of large power plants that are located outside the Phoenix AMA, which result in a larger reliance on local thermal power plants (e.g., the retirement of the coal power plant named Four Corners in 2031 highlighetd by the brown arrow; APS, 2017). Unlike B4.5-0, simulations of annual total GW use for power generation under R4.5-0 decrease by ~38% from 2020 to 2050 (Figure 28a). This means that the water savings achieved by the rapid adoption of renewables are partially translated to GW savings. Additional RW savings exist, please refer to the following section for additional detail (section 4.3.2.).

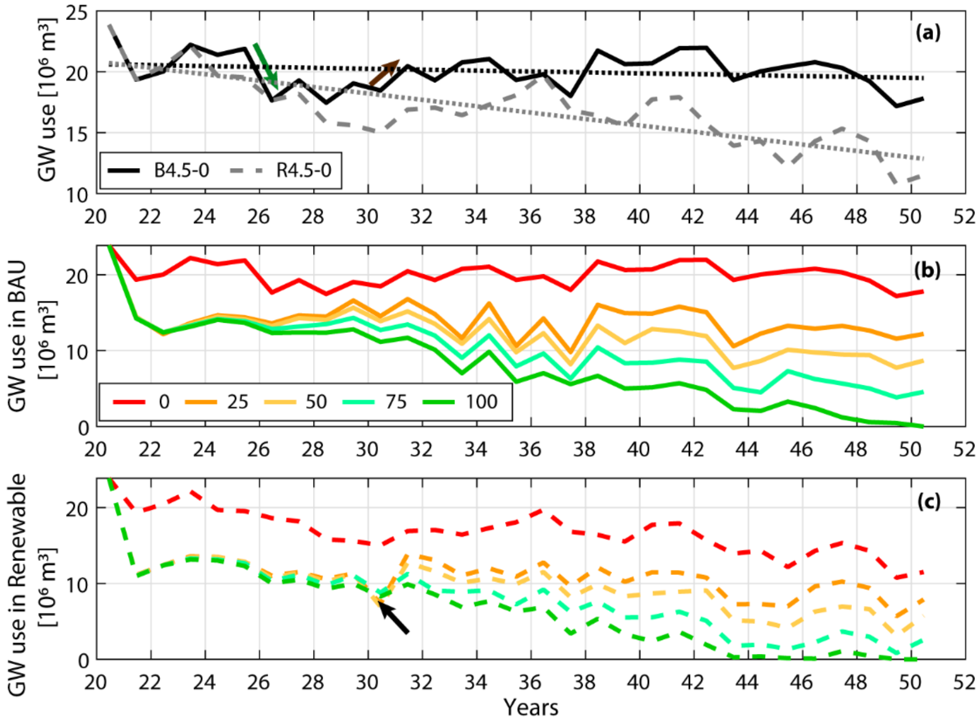

Figure 28. Total GW use for power generation in million m^3 using the model configurations (a) B4.5-0 and R4.5-0; (b) B4.5-0, B4.5-25, B4.5-50, B4.5-75, and B4.5-100; (c) R4.5-0, R4.5-25, R4.5-50, R4.5-75, and R4.5-100. The dotted lines in the top panel represent the linear regressions and the colors in the other two panels represent the various GW abstraction caps, shown as percentages in the legend in panel (b).

As expected, power generation requires smaller amounts of GW when considering GW abstraction caps (Figure 28b,c). In the BAU configurations, differences in GW use based on GW abstraction caps are noticeable since the year 2027 (Figure 28b), whereas these differences are noticed only after all coal power plants are retired in 2031 (black arrow in Figure 28c). This could be due to simulations of lower GW requirements of power plants in the Renewable configurations compared to the BAU ones.

4.3.2. Reclaimed water (RW) use

Turning the attention to RW use for power generation (Figure 29a), the configurations under BAU consume higher volumes compared to the Renewable scenarios. Consequently, the water conservation achieved by adopting renewable energy technologies is observed both in GW and RW (Figure 28a, Figure 29a). Additionally, severe GW abstraction caps result in higher RW use for power generation in the ten model configurations included in Figure 29a. For example, in 2050, B4.5-75 simulates ~1 million m^3 of RW more than B4.5-50, which in turm simulates ~3 million m^3 of RW more than B4.5-25. This suggests that limiting access to GW for power production generates higher demand for RW by power plants, which, in turn, affects the allocations of RW to other demand sectors. (Figure 29b). In particular, increasing GW abstraction caps leads to a decrease in RW consumption by the non-power users, which mainly consists of municipal and industrial water users accounting for ~42% and ~21% of total RW use, respectively. GW abstraction caps result in reductions in the amounts of RW used by the municipal sector, which are replaced with CAP (82% in B4.5-25) and GW (18% in B4.5-25). Similarly, reductions occur in the amounts of RW used by the industrial sector, which are replaced with CAP (~47% in B4.5-25) and GW (~53% in B4.5-25).

The amount of RW that is added for electricity generation because of GW abstraction caps balances the volume of RW allocated to the other users. For example, in 2050, the difference between RW use by the power sector simulated by R4.5-0 and R4.5-100 equals 9 million m^3, which is the exact difference observed in the other sectors considering the same configurations. In summary, all water users compete for a limited volume of RW and introducing GW abstraction caps causes the power sector to increase its share of RW. Furthermore, the added volume of RW is smaller than the GW savings presented in Figure 28. For example, in 2050, the difference between GW use by the power sector simulated by R4.5-0 and R4.5-100 equals 11.5 million m^3, which is larger than the RW increase of 9 million m^3. This might suggest a water shortage, given that power plants rely on GW and RW for water supply along with a negligible supply from surface water (i.e., CAP, see Figure 23 in Chapter 3). A water shortage would lead to a decrease in electricity generation within the AMA and the need to purchase electricity from the market as discussed in the following section.

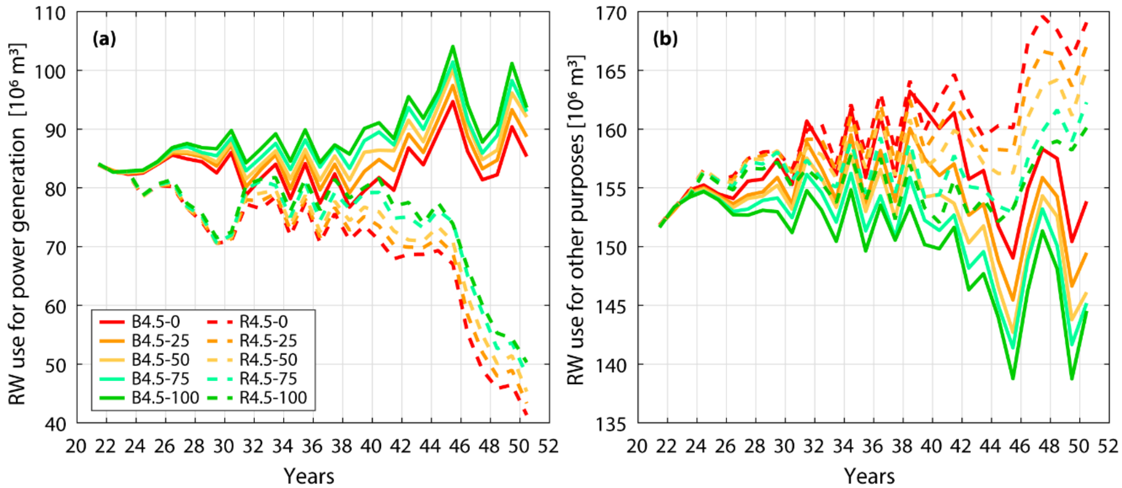

Figure 29. Simulations of RW use in million m^3 for (a) power generation and (b) other purposes.

4.3.3. Trade-offs between groundwater sustainability and the dependence on purchased electricity

As a next step, simulations of purchased electricity are compared with GW savings (Figure 30). Note that LEAP simulates purchased electricity each month in order to satisfy the energy demand that cannot be met using electricity generation. Additionally, GW savings are measured in reference to the outputs of B4.5-0 following the equation:

$$\Delta V_c = \sum_{t=2021}^{2050} (V_{c,t} - V_{B4.5-0,t}), \quad (4)$$

where ΔV_c is the total GW savings for the configuration c and $V_{c,t}$ and $V_{B4.5-0,t}$ are the GW use for power generation in the year t for the configuration c and B4.5-0, respectively. As presented in Figure 27, under B4.5-0 and R4.5-0, no electricity is purchased as the power system is not stressed by GW reductions and the difference between these two configurations is that R4.5-0 uses 102 million m^3 of GW than B4.5-0. When comparing the different GW abstraction caps, one can note the existence of a conflict between GW conservation and the need for purchasing electricity. In other words, conserving GW yields increased purchase of electricity, and vice-versa. Additionally, simulations from all renewable configurations are located in the lower right quadrant of Figure 30. This means that the rapid penetration of renewables decreases the purchase of electricity from the market while increasing GW savings when compared to the BAU configurations. This is a clear evidence that renewables can mitigate the trade-off between GW sustainability and the purchase of electricity. For example, if we consider the case of 25% GW abstraction cap, the adoption of renewable energy technology configuration allows saving 83% electricity purchases and 51% volume of GW compared to BAU conditions (compare R4.5-25 with B4.5-25).

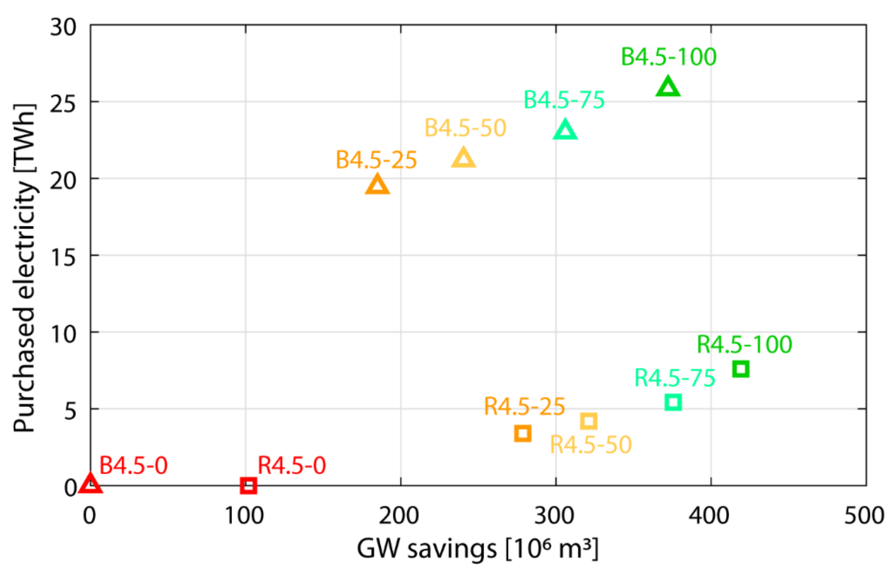

Figure 30. Simulations of total purchased electricity vs total GW savings under SSP2

As a final note, the monthly variability of the purchased electricity is investigated by comparing outputs of B4.5-25 and R4.5-25 (Figure 31). Under B4.5-25, electricity is mainly purchased in summer, especially in August, and to a lesser extent in winter, following the load shape of the region. On the other hand, simulations of R4.5-25 require the purchase of much lower amount of electricity in all months with small peaks in summer and winter. The BAU configuration has a large difference between summer and winter peaks compared to the Renewable configuration (e.g., the electricity purchased in January represents 17% and 60% of August purchases simulated in B4.5-25 and R4.5-25, respectively). This is explained by the fact that BAU configurations require a small amount of additional electricity in the winter season relative to the summer season because of the small peak in energy demand. However, Renewable configurations simulate purchased electricity in the winter season because of the small peak in energy demand as well as the limited availability of solar energy.

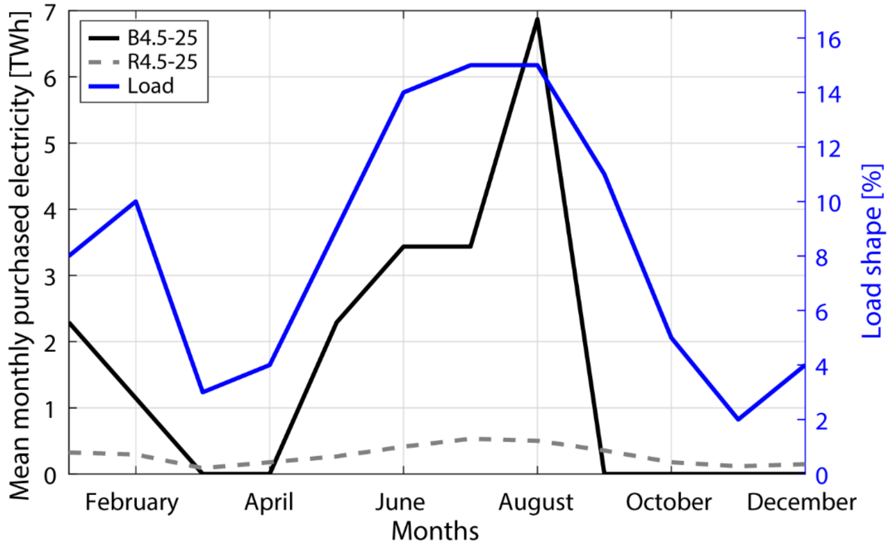

Figure 31. Mean monthly purchased electricity simulated under B4.5-25 and R4.5-25, aling with load shape (EIA 2020b).

4.3.4. Effects of climate

This section quantifies the simulation disparities resulting from the use of climate foricngs under the moderate (SSP2-4.5) and intense (SSP5-8.5) global warming scenarios. First, U.S. EPA (2009) projects a population that is growing much faster under SSP5-8.5 compared to projections under SSP2-4.5. In 2050, the two population projections differ by ~1.2 million (Figure 32a). Consequently, the energy demand is higher when using future climate scenarios of intense warming (Figure 32b). However, simulations of energy demand per capita are comparable between the configurations forced by SSP2-4.5 and those forced by SSP5-8.5 (Figure 32c). This means that the effect of temperature on energy demand is negligible compared to the effect of population projections.

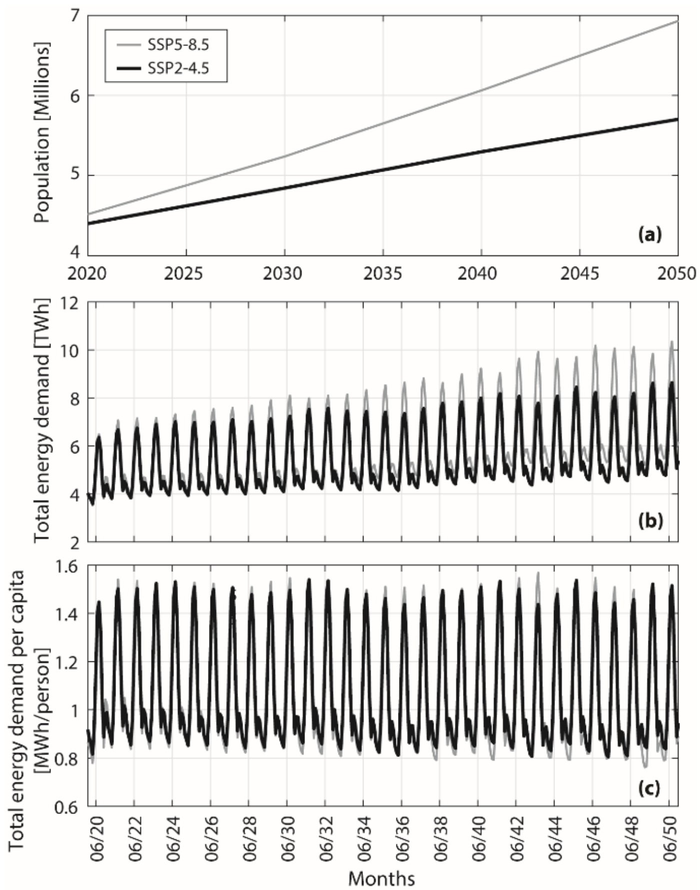

Figure 32. Population and energy demand according to SSP2-4.5 and SSP5-8.5. (a) Population projections in the Phoenix AMA; (b) Total energy demand; (c) Total energy demand per capita.

The differences in total energy demand that are caused by climate forcings lead to variations in GW and RW use for power generation. Figure 33 presents the scatterplot between total GW and RW allocated to the power sector for all 20 model configurations. The model configurations forced by SSP5-8.5 use more GW and RW compared to those forced by SSP2-4.5. This additional water consumption is due to the higher energy demands and therefore increased electricity generation. Besides, when considering the same GW abstraction cap, the Renewable configurations use less GW and RW than the BAU ones, independent of the climate forcing. For example, R4.5-25 and R8.5-25 simulate a amount of RW and GW for power generation that are smaller than B4.5-25 and B8.5-25. Further, the GW savings due to renewable energy are more pronounced when considering intense warming. For instance, while the GW use simulated by R4.5-100 represents a 16% decrease from B4.5-100, simulations of R8.5-100 represent a 21% decrease from B8.5-100.

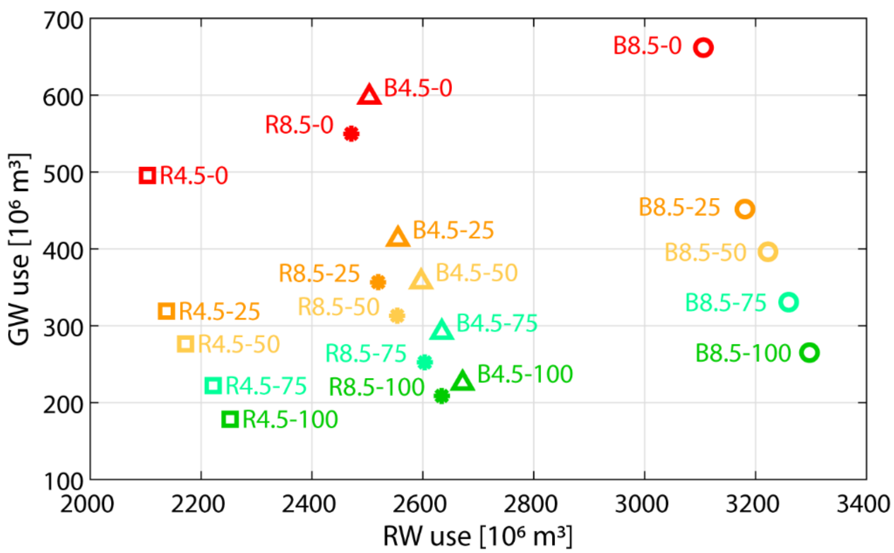

Figure 33. Total GW use for power generation vs total RW use for power generation.

Finally, simulations of purchased electricity are compared with GW savings assuming SSP5-8.5 forcings (Figure 34). Like Figure 30, B4.5-0 and R4.5-0 result in no purchased electricity. Moreover, the GW savings that are simulated by R8.5-0 with respect to B8.5-0, are higher than those simulated by R4.5-0 with respect to B4.5-0 (112 million m^3 > 102 million m^3). This finding is in line with the previously mentioned result regarding the GW savings due to renewable energy being more pronounced when considering intense warming. Further, RW is more available under SSP5-8.5 since it is generated by treating municipal water, which increases with higher projections of the population. Yet, the added RW quantities under SSP5-8.5 are unable to replace the GW savings. For example, simulations of purchased electricity in Figure 34 are higher than those included in Figure 30. In other words, the rate of increase in energy demands might be higher than the rate of increase in municipal water demand.

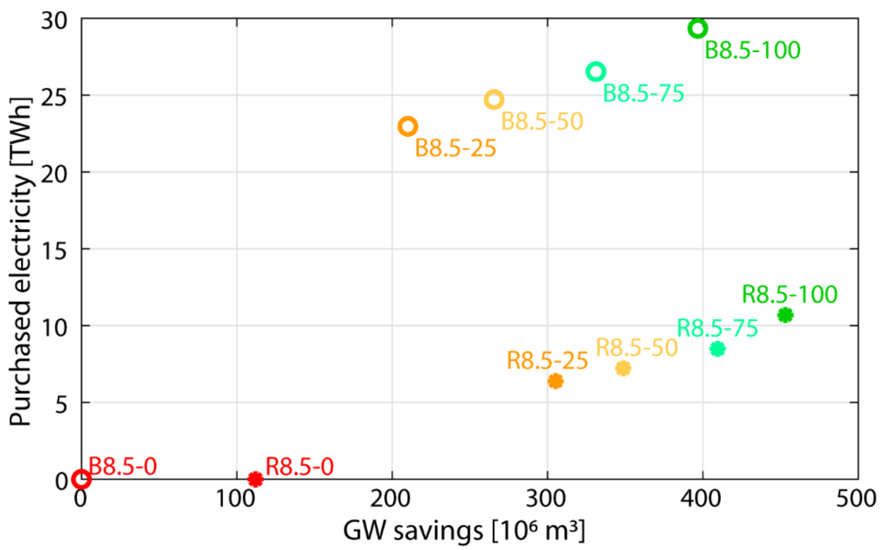

Figure 34. Simulations of total purchased electricity vs total GW savings under SSP5.

4.4. Discussion and Summary

4.4.1. Utility of the groundwater abstraction cap strategy

The introduction of the GW abstraction cap strategy highlights the potential GW savings of SRP's and APS' power plants assuming no water conservation measure other than adopting renewable technologies (e.g., storing surface water or changing water cooling technologies). This is illustrated through the example of R4.5-100 simulations that could save 11.5 million m^3 of GW and replace most of it with RW (9 million m^3) in 2050. In other words, the system could potentially reduce GW use by 9 million m^3 in 2050 without affecting electricity generation. Although water conservation could potentially generate the undesirable need for purchasing electricity from the market, managers may consider this negative outcome to be outweighted by the amount of GW savings. For example, B4.5-100 simulates a total GW conservation of 372 million m^3 (Figure 30), which represents ~62% of total GW use (Figure 33), but the total purchased electricity is 25.8 TWh (Figure 30), which represents ~1.3% of total electricity generation (Figure 32). Further, simulations of GW conservation from power utilities assumed that RW could be used as an alternative source. This assumption could hinder GW sustainability since RW is used to recharge the aquifer in this region. Therefore, future analyses should account for GW recharge for a more comprehensive study of GW sustainability.

4.4.2. Impacts of renewable energies on trade-off between groundwater sustainability and purchased electricity

Simulations of water requirements for electricity generation are considerably lower under the Renewable configurations compared to the BAU ones. These water savings translate to reductions in GW as well as RW. The future climate scenario of intense global warming result in higher simulations of GW and RW. However, this increased water use resulting from using SSP5-8.5 instead of SSP2-4.5 is not as substantial as the savings achieved by the rapid adoption of renewables, assuming the same level of GW abstraction caps. Additionally, renewable energies mitigate the trade-off between GW saving and purchasing electricity, which allows a great conservation of GW when also GW abstraction cap strategies are adopted with minor unmet energy demand that can only be satisfied by buying electricity. For example, (i) using only renewables (R4.5-0) can achieve GW savings of 102 million m^3 with no purchased electricity, (ii) using a GW reduction of 25% by 2050 without aggressively adopting renewables (B4.5-25) can achieve GW savings of 185 million m^3 while purchasing of 19.5 TWh of electricity, and finally, (iii) rapidly deploying renewable technologies and adopting a GW reduction of 25% by 2050 (R4.5-25) can achieve GW savings of 279 million m^3 while purchasing only 3.4 TWh of electricity (or 0.2% of the total electricity generation). Further, renewables have been demonstrated to better mitigate this trade-off under intense warming. This finding promotes the transition towards renewable energy sources to help achieve GW sustainability while producing electricity in near satisfactory quantities, especially if the intensity of climate change will not slow down.

4.5. Conclusions

The analyses presented in this chapter demonstrate that adopting renewable energies will reduce both RW and GW under future climate scenarios of moderate and intense warming. Moreover, GW abstraction cap strategies present a great potential for the power systems of SRP and APS to achieve GW savings (up to 372 million m^3 by B45-100). These reductions in GW use cause the RW demand for power generation to rise. However, the RW demand from other water users makes it hard to satisfy the increased RW need for power generation. Consequently, GW abstraction cap strategies create a conflict between GW conservation and the need for purchasing electricity, since high GW savings lead to the need to purchase electricity from the market. However, this tradeoff is reduced by renewables. For instance, R4.5-25 simulates 83% less purchased electricity than B4.5-25 and 51% more GW conservation. The adoption of renewable technologies has also been found to better mitigate this trade-off under intense global warming. These findings suggest that renewable energies can promote GW sustainability, especially when combined with other water conservation measures.

CHAPTER 5

CONCLUSIONS AND PERSPECTIVES

5.1. Conclusions and Implications

This dissertation has addressed two main goals: (1) it quantified the value of spatiotemporal resolutions and feedback loops in integrated WEN modeling; and (2) it investigatived the synergies generated by renewable energy technologies in the WEN of the Phoenix AMA. The summary, conclusions, and implications of Chapters 2, 3, and 4 are as follow:

(i) To evaluate the impacts of possible future electricity mix scenarios on the WEN of the Phoenix AMA, an energy model was developed based on the LEAP platform and tested against historical observations of electricity demand and generation. This model was first used to explore the energy embedded in the water infrastructure and services in the study area. It was found that water heating is the largest water-related energy consumer, followed by transfer of Colorado River water via the CAP aqueduct and by water treatment for potable use and distribution. Future energy demand projections through 2060 showed that energy requirements for water heating will increase by 35% owing to population growth, whereas energy needs for treating and moving water will drop by 9%, mostly due to decreased agricultural water use. Simulations of power production in the future revealed that energy mix options that transition quicker to renewable sources will considerably lower water demands for electricity generation (35%), as well as

CO_2 emissions (57%), when compared to the BAU scenario. Additionally, a megadrought will result in net energy savings since less water will be delivered through the energy-intensive CAP aqueduct, but it will certainly jeopardize the capacity to meet the aquifer safe-yield. The cost analysis demonstrated that the infrastructure required to achieve future energy supply for aggressive renewable portfolios will have greater structural costs and lower operational costs when compared to the more cautious business as usual scenario. These findings indicated that renewable energy technologies save water and greenhouse gas emissions with reasonable associated costs; therefore, they endorse policy discourse for integrated nexus governance.

(ii) The WEAP and LEAP platforms were used in the Phoenix AMA to examine how the the accuracy of WEN simulations is affected by adopting different spatiotemporal resolutions and by coupling the water and energy models to capture two-way feedbacks between the systems. When increasing the temporal resolution from yearly to monthly, simulations reproduced the marked seasonality of electricity production and the corresponding water demand. While the use of both annual and monthly time step lead to the simulation of the same annual energy generation at each power plant, the portfolio of water sourecs used to generate electricity at each station differed with the temporal resolution of the simulations. The differences in sensitivity to the model time step were explained by the more rigid infrastructure restrictions and allocation rules in the water system that require higher time resolutions to be fully captured. The ability to reproduce the dynamics of the more flexible energy system was less sensitive to the simulation time step. The use of greater spatial granularity by adding each power plant in the WEAP domain enabled modeling the right water portfolios of power plants, which the coarser setup with a single water demand node for power could not capture. This resulted in variations in the simulated energy embedded in water for power generation. In large scale studies, the precision gained by refining the spatial granularity up to the single power plant may be unneeded. Simulations using the integrated models better reproduced EIA observations of power generation than the standalone method. The magnitude and intra-annual variability of water supplies from separate sources to each power plant varied in simulations under the two modeling methodologies, with relative differences surpassing 100%. Coupled models can capture the dynamics in the energy infrastructure such as the dispatch of power plants that standalone approaches might not represent. Further, coupled models make it easier to simulate WEN systems with diverse temporal and geographical dimensions and under different future scenarios by capturing processes and features of water and energy infrastructure in a more mechanistic manner. Once the spatial granularity and complexity of the domain have been determined and data have been collected, the adoption of coupled rather than standalone methods is restricted not by the scope of the problem, but rather by the existing scarcity of these integrated models.

(iii) Under future climate scenarios of moderate and extreme warming, adopting renewable energies will lower both RW and GW. Furthermore, GW abstraction cap regulations gave a significant opportunity for SRP and APS power systems to achieve GW savings (up to 372 million m^3 by B45-100). Because of these decreases in GW usage, the demand for RW for power generation rose. However, these GW abstraction cap measures created a conflict between GW conservation and the requirement to purchase electricity from the market. In other words, high GW savings lead to the additional purchase of electricity. However, the electricity that was purchased (~1.3% of total electricity generation in B4.5-100) was low in comparison to the amount of GW that was saved (~62% of total GW use in B4.5-100). Furthermore, renewables decreased this tradeoff; for example, R4.5-25 simulated 83% less purchased electricity than B4.5-25 and 51% more GW conservation. These technologies have also been found to be more effective in mitigating this trade-off under intense warming. These results suggested that renewable energy, when coupled with other water conservation strategies, could increase GW sustainability.

5.2. Future Work

The analyses conducted in this dissertation focused on large power plants and did not account for the distributed generation, which brings the production of electricity closer to the site of its use. Currently, such systems are mostly considered as a supplement to existing centralized systems; however, the entire power system may become decentralized soon (NREL 2022). In such a case, the dependence of electricity generation on water would reduce if solar panels remain cost-efficient. Future investigations should quantify the potential decoupling of water and energy in a decentralized energy system.

The energy infrastructure operated by SRP and APS exports electricity to states that belong to the western U.S. electrical energy system as mentioned in section 2.5.1.1. However, most discussions included in this dissertation focused on the Phoenix AMA without investigating repercussions on areas importing the locally generated electricity. Studies such as Chini et al. (2018) and Ruddell et al. (2014) found that California outsources a portion of its water footprint of electricity production to Arizona. Future investigations should explore how renewables could achieve GW conservation while exporting electricity to other states.

The design and management of water and energy infrastructures require the consideration of climate uncertainty, which affects both the demand and supply of these two resources. While the impact of climate uncertainty on supply has been analyzed in several studies (Gjorgiev and Sansavini, 2018; Schaeffer et al., 2012), the effect on the demand side, especially water demand, has received less attention. In Chapter 4 of this dissertation, climate effects on agricultural water demand are accounted for but the effects on municipal water demand are disregarded. Several studies demonstrated that climate substantially affects this component of water consumption. For example, Hemati et al. (2016) estimated that 55% of the observed variance of urban water use in

Melbourne, Australia is explained by precipitation and temperature. The outdoor residential water use, especially landscape water needs, is the portion that is mostly affected by climate. In the city of Phoenix, about 74% of residential water use is for outdoor purposes (Balling and Gober, 2007). It is then natural for future analyses of the WEN of the Phoenix metropolitan region to incorporate the climate sensitivity of residential outdoor use. Furthermore, the land cover in residential areas is changing with a substantial increase in the percent occupied by xeric compared to mesic (Buyantuyev et al., 2010). Such dynamic changes will alter the future water demand in the area as the water requirements of xeric land covers are much smaller than those of mesic vegetation (Martin 2001). Future work should account for a suite of possible trajectories of residential land cover in the area. In general, there is a need to improve the generation of scenarios that represent demand with higher sophistication, whether it is through including the sensitivity of demand to climate and land cover as mentioned above or through better population projections and energy efficiencies (e.g., better representation of the age of buildings).

Most models derived the water and energy demand considering the effect of only temperature and precipitation with little to no regard to other climate variables. The importance of climate variables in modeling water and energy demand was illustrated by Obringer et al. (2019) who simulated water and energy demand in the Midwestern USA using statistical models that account for climate variables and ignore anthropogenic drivers. For this reason, understanding the impacts of climate variability on water and energy demand in different regions is key to improving WECN modeling (Emodi and Chaiechi 2018).

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APPENDIX A

COMPUTATION OF THE ENERGY DEMAND FOR EACH SECTOR AND SUBSECTORS OF THE LEAP MODEL

The energy demand structure for the Phoenix AMA implemented in the LEAP model is summarized in Table 1, which reports: (i) demand sectors, (ii) subsectors with different levels that may exist within a given sector, (ii) end-users, (iv) activity level of each end-user; and (v) energy intensities of each end-user. The computation of the energy demand for each sector and subsectors is described in the next sections.

A.1. Residential and commercial sectors

The activity level and energy intensity of the residential and commercial electricity demand are population and per capita demand, respectively. The residential and commercial per capita demand were estimated from data of historical electricity sales in Arizona to residential and commercial customers in years 1990-2017 (EIA 2018a). We found these values to increase from 1990 to 2007 and decrease subsequently. We used a linear regression to represent the linear growth and a negative exponential model to represent the asymptotic decline with time of the intensity of residential and commercial energy sectors:

$$y = a + bt \qquad \text{if } t < 2007, \tag{5}$$

$$y = a + b \cdot \exp(-ct) \qquad \text{if } t \geq 2007, \tag{6}$$

where y is the residential or commercial energy intensity in MWh/capita, t is the year, and a, b and c are regression coefficients. Values of a, b, and c are provided in Table A1. The coefficient of determination R^2 for all four regression ranges from 0.84 to 0.95.

We then computed the percent of the energy demands of the residential and commercial sectors embedded in water. Previous work found water heating to be the largest energy intensive activity in these two sectors (Bartos and Chester 2014; Kiov and Toode 2001; Ndoye and Sarr 2008; Swan, Ugursal, and Beausoleil-Morrison 2011). We then assumed that water heating to be the only water-related energy use and that this accounts for 22% (EIA 2018e) and 0.5% (EIA 2018b) of the total electricity use in the residential sector and commercial sectors, respectively. The rest of the electricity use was defined as uses unrelated to water in the model demand structure (Table 1).

Table 9. Values of the regression coefficients and the power transformation used in the determination of residential and commercial energy intensities.

Sector	**Years**	***a***	***b***	***c***
Residential	< 2007	-146.84	0.08	-
Residential	≥ 2007	4.6	$1.1 * 10^{87}$	0.1
Commercial	< 2007	-130.43	0.07	-
Commercial	≥ 2007	4.3	$1.1 * 10^{87}$	0.1

A.2. Industrial sector

The energy demand of the industrial sector was estimated through a top-down approach. First, we derived an equation to estimate the overall energy demand of the industrial sector as a function of population and electricity price, based on previous empirical evidence (Kamerschen and Porter 2004). The following multilinear regression was fitted to the log-transformed variables:

$$\ln(y) = 26.094 - 0.102 \ln(x_1) - 0.638 \ln(x_2), \quad (7)$$

where y is the industrial electricity demand in kWh, x_1 is population, and x_2 is the industrial electricity rate in ¢/kWh obtained from EIA and expressed in 2017 dollars to exclude inflation effects. The energy demand in the industrial water-unrelated subsector was set up as the difference between the total demand of the industrial sector provided by equation (7) and the energy demand of all water infrastructure subsectors.

The end-users of the water infrastructure subsectors are CAP, SRP, groundwater, and WWTPs (Table 1). For all end-users, the activity level is the annual water volume that is either transported, treated or pumped. Depending on the subsector, the end-users have different types of energy intensities. CAP is associated with two types of energy intensities, including water pumping and water treatment. SRP is gravity-based and only requires energy to treat water in WTPs. For the groundwater end-user, energy is needed to pump and treat water. In the agricultural subsector, all end-users utilize energy only to pump water since no treatment is required. In addition to the intensities previously described, in this subsector energy is also required to irrigate the fields from surface water sources. The computation of the energy intensities to (i) pump CAP water, (ii) pump groundwater, (iii) treat water in WTPs, WWTPs and WRFs, and (iv) pump surface water for irrigation is described in the next subsections.

A.2.1. Energy intensity of CAP water conveyance

The CAP aqueduct transports Colorado River water from lake Havasu to central and southern Arizona. Five pumping stations are required to move water to the Phoenix AMA. The energy intensity required by these pumping stations was estimated using the well-known equation $E = \frac{H\gamma}{3600*\eta}$, where E is the energy intensity for water pumping in kWh/m^3, H is the water lift height in m, γ is the specific weight of water (9.807 kN/m^3), and η is the overall pump efficiency. The latter is the product of the pump efficiency, η_p, the mechanical transmission efficiency, η_t, and the electric motor efficiency, η_m. We assumed the same efficiencies in all pumping stations and obtained their values from previous studies. Specifically, we assumed $\eta_p = 85\%$ (Cheng-Li 2002), $\eta_t = 100\%$ (Cheng-Li 2002; Yoon, Sauri, and Amorós 2018), and $\eta_m = 96\%$ (Kaya et al. 2008), yielding an overall efficiency $\eta = 82\%$. Using this overall efficiency and H = 250 m, we calculated an intensity of 0.83 kWh/m^3 in the Mark Wilmer pumping station (one of the five CAP pumping stations), which is close to previous estimates of 0.78 kWh/m^3 (Eden et al. 2011), 0.85 kWh/m^3 (Bartos and Chester 2014), and 0.81 kWh/m^3 (Hoover 2009).

A.2.2. Energy intensity of groundwater pumping

The energy intensity (in kWh/m^3) required to pump water from the aquifer depends on the discharge pressure (DP), the water pumping lift (H, distance from the pump to the groundwater level accounting for the drawdown), and the performance rating of the pumping plant (PR) (Martin et al. 2011). According to Martin et al. (Martin et al. 2011), a PR of 100% corresponds to a well maintained and designed pumping plant, which is known as the Nebraska Pumping Plant Performance Criteria (NPPPC). These authors also report that pumping plants often operate at PR ranging from 80% to 100% and, sometimes, exceeding 100% of the NPPPC. Martin et al. (Martin et al. 2011) provides a table that allows obtaining the energy intensity of a pumping station as a function of H, DP, and PR.

We considered two groups of wells in our study region, including (i) wells supplying drinking water and (ii) wells located in the irrigation districts, and calculated two distinct energy intensities. For each group, a time series of *H* for the period 2001-2018 was obtained by averaging the mean annual water depth in the corresponding wells (ADWR 2018a). For group 1, a DP of ~110 kPa (~11 m of hydraulic head) was considered, while, for group 2, DP was set to 240 kPa (~25 m of hydraulic head). This value accounts for the additional pumping lift required for irrigation purposes once the water is pumped at the surface level (see Section A.2.4). PR was assumed identical and constant in time in both groups. We estimated this value by using state-level data of dollar expenses for pumping groundwater for irrigation in 2003 and 2008 collected by USDA (USDA and NASS 2018). Assuming an electricity rate of 0.053 $/kWh in 2003 and 0.066 $/kWh in 2008, we first converted the expenses into energy intensities of 0.34 kWh/m^3 and 0.35 kWh/m^3, respectively, and, then, we computed the values of PR from the table of Martin et al. (Martin et al. 2011) using *H* of the corresponding year and DP = 240 kPa. We averaged these two values obtaining a PR of 96%. This leads to estimated energy intensities of 0.38 kWh/m^3 and 0.32 kWh/m^3 in 2003 and 2008, respectively, corresponding to a relative error of ~10% in both years. The adopted values of PR and DP for the wells located in irrigation districts lead to an energy intensity of 0.31 kWh/m^3 that matches very well the value reported by Burt and Soto (Burt and Soto 2008) for an irrigation district in California with a similar mean water depth of 46 m.

A.2.3. Energy intensity for treatment and distribution

The energy intensities of WTPs, WWTPs and WRFs were computed according to the methodology described in Pabi et al. (Pabi et al. 2013). This approach relies on typical treatment and distribution intensities in the U.S. that depend on the average flow rates and treatment processes used in WTPs, WWTPs and WRFs (see reference (CPRAS 2017) for treatment processes used in WTPs and WWTPs in Phoenix). In addition to the treatment processes, the energy intensities of WTPs include also the energy required to pump treated water into the pressurized distribution system, but neglect the energy consumed by additional booster pumps. To validate the use of this approach in our study region, we compared the estimated average intensity of five WTPs, two WWTPs and one WRF owned by the city of Phoenix with observed values (Figure 35). These were derived from the energy expenses of the city provided by WWRAC (WWRAC 2017) assuming a constant electricity rate of 0.075 $/kWh. As showed in Figure A1, the observed energy intensities do not vary significantly, thus supporting our assumption of energy intensities constant in time. The difference between estimated and observed intensities ranges from 1% to 8%.

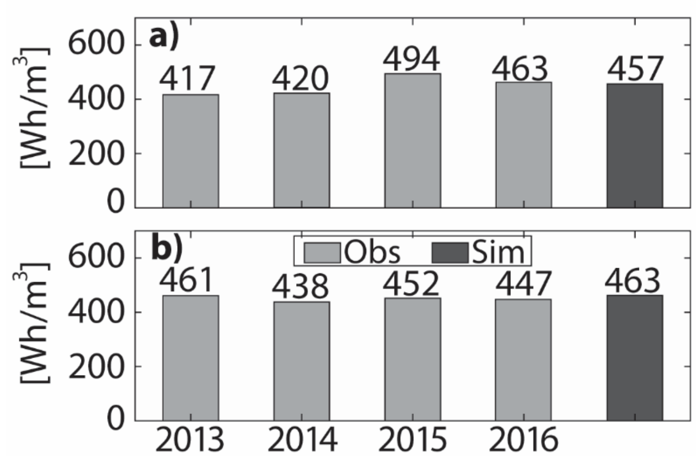

Figure 35. Observed (Obs) and simulated (Sim) electricity intensity in (a) the five WTPs and (b) the two WWTPs and the WRF owned by the city of Phoenix.

A.2.4. Energy intensity of surface water pumping for irrigation purposes

One of the energy intensities of the agricultural subsector is related to irrigation with surface water, i.e. water provided by CAP or SRP. This intensity varies depending on irrigation types, operating pressures, crop varieties, and field areas (Plappally and Lienhard V 2012). We assumed a constant surface water irrigation intensity of 0.1 kWh/m^3 obtained from the average electricity expenses in irrigation from surface water in Arizona (USDA and NASS 2018) and an electricity rate of 0.053 \$/kWh reported for 2003 (EIA 2019a).

APPENDIX B

INPUT DATA FOR THE PHOENIX AMA POWER SYSTEM

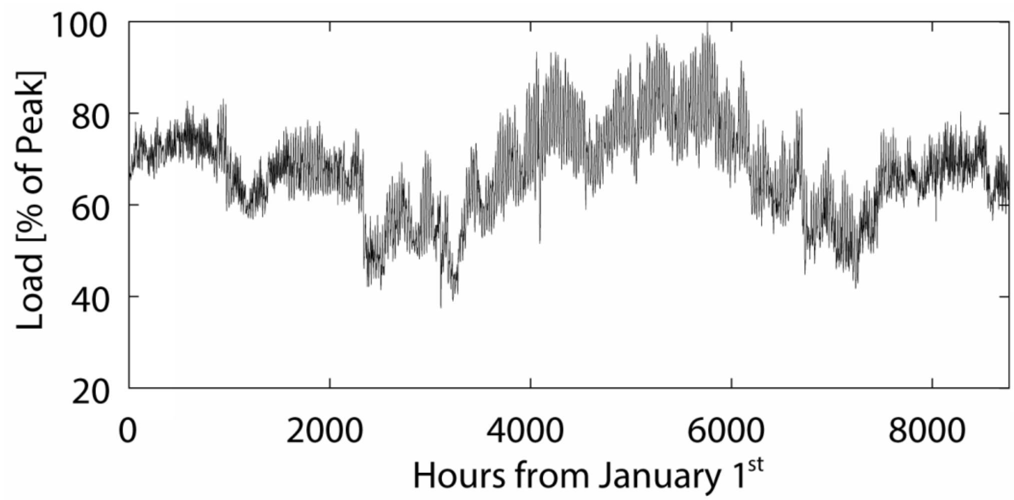

Figure 36. Annual load shape at hourly resolution of the Phoenix AMA power system (EIA 2018d).

Table 10. Characteristics of power plants generating electricity for SRP, APS, and CAP implemented in the LEAP model setup.

Primary fuel type	**Plant name** [(a)]	**Capacity [MW]** (PWCC, 2018a; SRP, 2020a)	**SRP capacity entitlement [MW]** (Casiraro, 2009)	**APS capacity entitlement [MW]** (PWCC, 2018a)	**Year of first generation** (EIA 2018c)	**Merit order** [(b)] (PWCC, 2018a)	**Efficiency [%]** (EIA 2019c)	**Capacity factor** [(c)] [%] (EIA 2020a)
Hydro	Horse Mesa Dam	149	149	-	1972	2	37	30
GAS	Agua Fria Generating Station (Units 1 and 3)	626	626	-	1957	3	28	30
	Kyrene Generating Station	523	523	-	1952	2	46	20
	Santan Generating Station	1219	1219	-	1974	1	44	40
	Desert Basin Generating Station	600	600	-	2001	1	45	40
	Ocotillo	333.4	-	330	1960	3	27	40
	Saguaro (Units 1 and 2)	184.5	-	110	1972	3	20	80
	Saguaro (Unit 3)	184.5	-	79	2002	3	20	40
	Sundance	605	-	420	2002	3	31	40
	West Phoenix	1207	-	997	1972	2	39	80

Primary fuel type	Plant name [(a)]	Capacity [MW] (PWCC, 2018a; SRP, 2020a)	SRP capacity entitlement [MW] (Casiraro, 2009)	APS capacity entitlement [MW] (PWCC, 2018a)	Year of first generation (EIA 2018c)	Merit order [(b)] (PWCC, 2018a)	Efficiency [%] (EIA 2019c)	Capacity factor [(c)] [%] (EIA 2020a)
	Redhawk	1060	-	984	2002	1	45	60
	Yucca (Units 1, 2, and 3)	264	-	93	1971	3	29	40
	Yucca (Units 5 and 6)	264	-	96	2008	3	29	40
	Coolidge Generating Station	575	575	-	2011	3	33	80
	Mesquite Generating Station Block 1	625	625	-	2013	3	46	80
	Gila River Power Plant (Blocks 1, 2 and 4)	1650	1650	-	2005	2	39	80
Nuclear	Palo Verde Generating Station	3875	676	1146	1986	1	33	94
Coal	Coronado Generating Station (Units 1 and 2)	785	785	-	1980	1	32	90

Primary fuel type	**Plant name** [a]	**Capacity [MW]** (PWCC, 2018a; SRP, 2020a)	**SRP capacity entitlement [MW]** (Casiraro, 2009)	**APS capacity entitlement [MW]** (PWCC, 2018a)	**Year of first generation** (EIA 2018c)	**Merit order** [b] (PWCC, 2018a)	**Efficiency [%]** (EIA 2019c)	**Capacity factor** [c] [%] (EIA 2020a)
	Navajo Generating Station	2250 [d]	488	315	1974	1	33	92 (Hurlbut et al. 2012)
	Craig Generating Station (Units 1 and 2)	856	248	-	1979	1	34	75
	Four Corners Power Plant	1480	148	970	1963	1	34	75
	Hayden Generating Station (Unit 2)	262	131	-	1976	1	31	75
	Springerville Generating Station (Unit 4)	385	385	-	2010	3	33	80
	Cholla	995	-	387	1962	1	31	90
Solar	Gila Bend, Foothills, and Solana	317	-	317	2013	1 [c]	37	30
Wind	Aragonne Mesa, High Lonesome,	289	-	289	2007	1 [c]	26	35 (Acker et al. 2007)

Primary fuel type	**Plant name** (a)	**Capacity [MW]** (PWCC, 2018a; SRP, 2020a)	**SRP capacity entitlement [MW]** (Casiraro, 2009)	**APS capacity entitlement [MW]** (PWCC, 2018a)	**Year of first generation** (EIA 2018c)	**Merit order** (b) (PWCC, 2018a)	**Efficiency [%]** (EIA 2019c)	**Capacity factor** (c) [%] (EIA 2020a)
	and Perrin Ranch Wind							
Total		19313	8828	6533				

(a) Plants having a capacity over 100 MW (>40 MW in the case of wind and solar power plants).

(b) 1st, 2nd, and 3rd merit orders in LEAP correspond to base load, load following, and peaking power plants, respectively.

(c) Value adjusted until plant simulated generation fits actual generation.

(d) CAP owns 24.3% of Navajo Generating Station, corresponding to a capacity of 547 MW (Eden et al., 2011).

APPENDIX C

DATA SOURCES

Table 11. Overview of datasets used to setup the LEAP model in the Phoenix AMA

Type of use	**Information**	**Agency**	**Source**
Determination of energy intensities	Water and wastewater treatment intensity	Water/Wastewater Rate Advisory Committee (WWRAC)	(WWRAC, 2017)
	Water treatment processes	City of Phoenix Rate Advisory Subcommittee	(CPRAS, 2017)
	WWTP average inflow and level of treatment	U.S. Environmental Protection Agency (EPA)	(EPA, 2018)
	Electricity expenses in irrigation	U.S. Department of Agriculture (USDA)	(USDA and NASS, 2018)
	Depth to groundwater	Arizona Department of Water Resources (ADWR)	(ADWR, 2018a)
	Water heating share in residential energy use	U.S. Energy Information Administration (EIA)	(EIA, 2018e)
	Water heating share in commercial energy use	EIA	(EIA, 2018b)
	Electricity sales to sectorial users	EIA	(EIA, 2018a)
	Electricity rate	EIA	(EIA, 2019a)
	Electricity sales per residential customer	Arizona Corporation Commission (ACC)	(ACC, 2018)
	Number of occupied housing units	U.S. Census Bureau	(U.S. Census Bureau, 2018)
LEAP input	Transmission losses	EIA	(EIA, 2018d)
	Capacity factor	EIA	(EIA, 2020a)
	APS load shape	EIA	(EIA, 2018c)
	Capacity entitlement of SRP	Salt River Project (SRP)	(SRP, 2020a)

Type of use	Information	Agency	Source
LEAP input	Planned reserve margins	Pinnacle West Capital Corporation (PWCC)	(PWCC, 2018a)
	Capacity entitlement of CAP	Central Arizona Project (CAP)	(U.S. DOE WAPA and CAWCD, 2016)
	Capacity entitlement of APS	Arizona Public Service Company (APS)	(APS, 2017)
	Electricity sales per residential customer	ADWR	(Janice and Guenther, 2010)
	Number of occupied housing units	Office of Economic Opportunity, State of Arizona	(Office of Economic Opportunity 2018)
LEAP validation	Power plant generation	EIA	(EIA 2018c)
Post-processing	Water withdrawals by power plants	EIA	(EIA 2018g)

APPENDIX D

COST ESTIMATION OF FUTURE ENERGY MIXES

The total costs C of future energy mixes are calculated in \$ as:

$$C = \sum_{f=1}^{6} \sum_{y=2016}^{2060} [O_f \cdot N_{f,y} + F_f \cdot E_{f,y} + V_f \cdot G_{f,y} + FU_{f,y} \cdot R_{f,y}], \tag{D1}$$

where O_f is the overnight cost rate in \$/kW, $N_{f,y}$ is the new capacity simulated by LEAP in kW, F_f is the fixed O&M cost rate in \$/kW, $E_{f,y}$ is the existing capacity in kW, V_f is the variable O&M cost rate in \$/kWh, $G_{f,y}$ is the generated electricity in kWh, $FU_{f,y}$ is the fuel cost rate in \$/kWh, $R_{f,y}$ is the energy in required fuels in kWh, f is an index referring to one of the six fuel types (including renewable sources), and y is the year. Values for O_f, F_f, V_f, and $FU_{f,y}$ were obtained from EIA (EIA 2016, 2019a), while $N_{f,y}$, $E_{f,y}$, $G_{f,y}$, and $R_{f,y}$ were simulated by LEAP. All costs are actualized to year 2016.

APPENDIX E

CONFIGURATION OF THE WEAP NETWORK

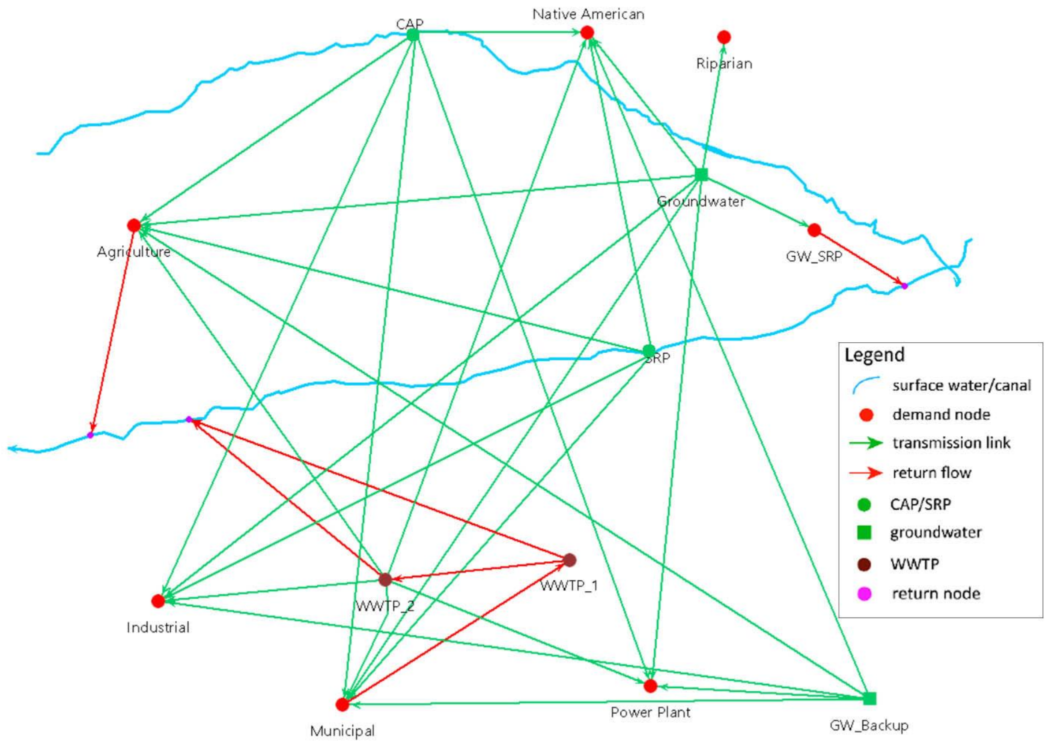

Figure 37. Configuration of the WEAP network simulating water allocation from supply sources to demand nodes in the Phoenix Active Management Area (AMA). This configuration includes one node representing water demand from all power plants combined. Note that, although GW_SRP is represented with a demand node, it practically acts as a source node that accounts for the groundwater pumped by SRP.

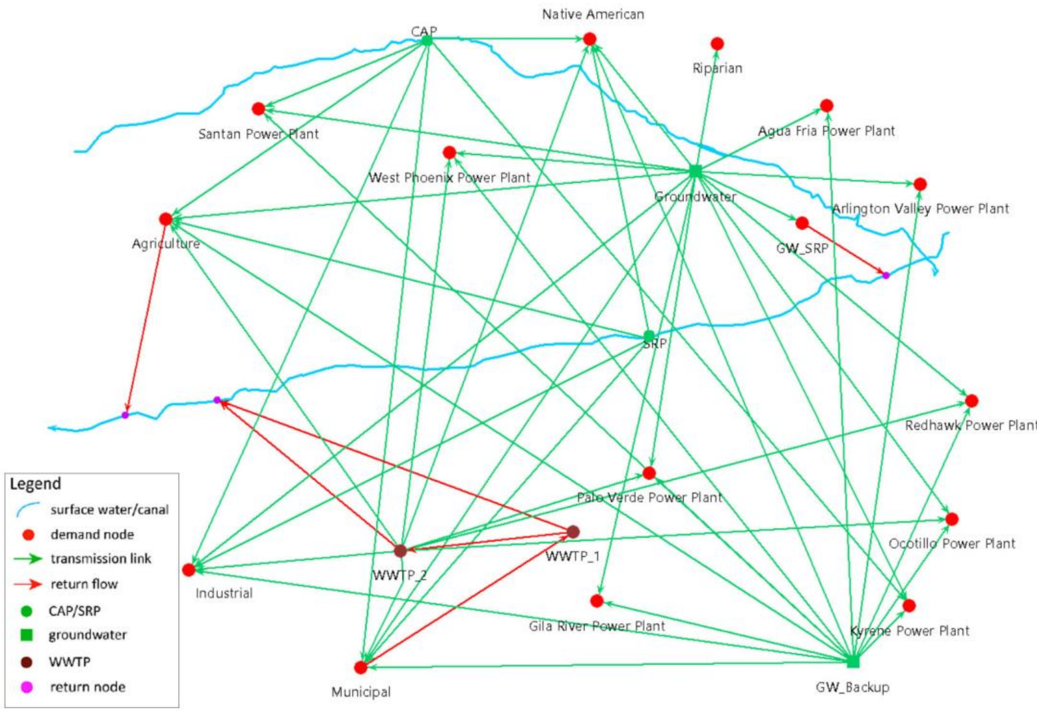

Figure 38. Configuration of the network in WEAP simulating the water allocation from the supply sources to the main demand nodes in the Phoenix AMA. This configuration includes nine nodes representing the water demands for power generation by each power plant located within the Phoenix AMA boundaries. Note that, although GW_SRP is represented with a demand node, it practically acts as a source node that accounts for the groundwater pumped by SRP.