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Investigating the value of spatiotemporal resolutions and feedback loops in water-energy nexus modeling

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ABSTRACT

Modeling the interactions between water and energy is crucial to managing holistically these resources. Here, we simulate water allocations and energy dispatch in the metropolitan region of Phoenix, Arizona in 2008–2017 using the WEAP and LEAP models under different spatiotemporal resolutions and coupling configurations. We find that increasing the temporal resolution from annual to monthly allows capturing seasonal demands, which improves the simulation of water allocations from supply sources to all demand nodes; the simulation of energy fluxes is instead less sensitive to the model time step. Representing the domain with higher spatial granularity enhances the ability to model the correct water portfolio of the power plants. Finally, coupling the models to capture two-way feedbacks between water and energy systems improves the simulations of electricity generation and, in turn, of water fluxes. While related to Phoenix, our findings provide useful insights to improve water-energy nexus modeling at other sites.

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. Department of Energy, 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., 2016a).

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.

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(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 et al., 2016b; 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.

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).

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 (Fig. 1) 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

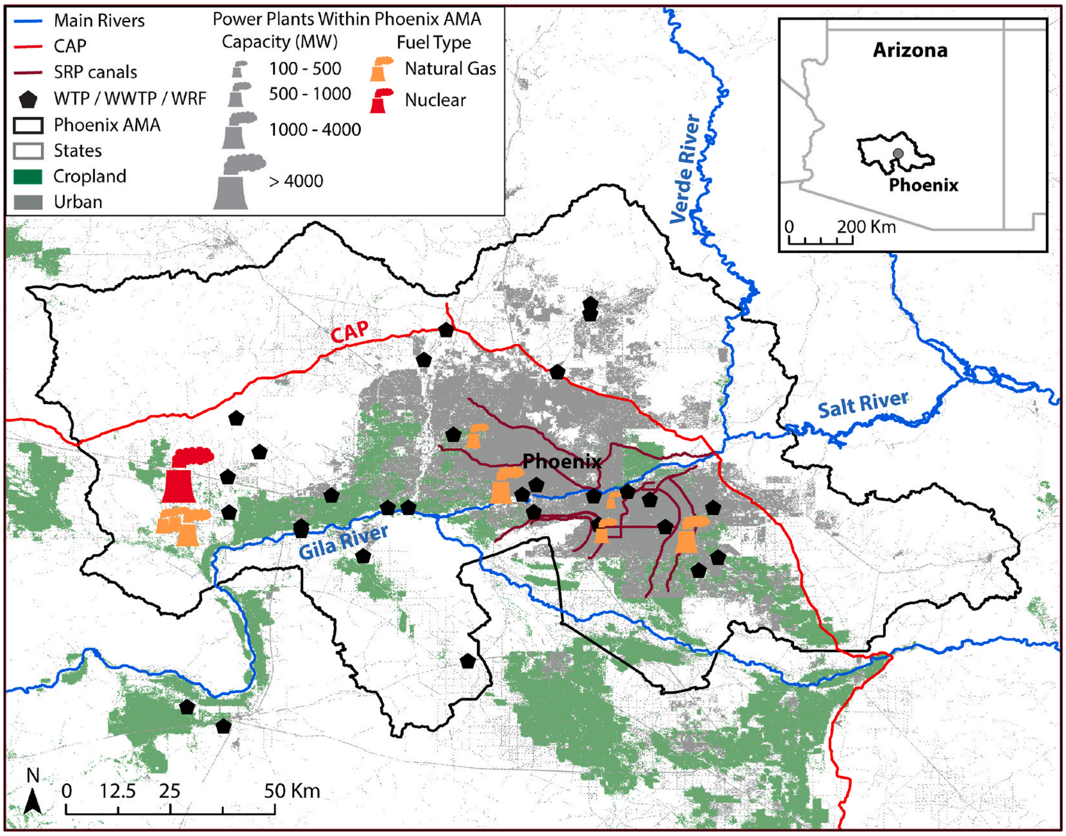

Fig. 1. The Phoenix Active Management Area (AMA) in central Arizona, along with the location of power plants with the indication of fuel type and capacity; main water treatment plants (WTP), wastewater treatment plants (WWTP), and water reclamation facility (WRF); the Salt, Verde and Gila Rivers; the Central Arizona Project (CAP) aqueduct; canals of the Salt River Project (SRP); and cropland and urban areas of the Phoenix metropolitan region.

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.

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.

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 Fig. 2a. 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 Figs. S1 and S2. More details are provided by Guan et al. (2020).

Table 1
Datasets used to set up, apply, and test WEAP and LEAP in the Phoenix AMA.

Model	Dataset	Purpose of use
LEAP	U.S. Energy Information Administration (EIA 2019)	Estimates of electricity generation used as observations
	Pinnacle West Capital Corporation (PWCC, 2018); SRP (2020a)	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
	City of Phoenix Water Services Department (CPWSD 2011)	Monthly variability of municipal, industrial, and power plant water demand
	Lahmers and Eden (2018)	Monthly variability of agricultural water demand

The energy system implemented in LEAP is summarized in Fig. 2b. 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, 2020a). 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 according to the U.S. Energy Information Administration (EIA, 2018, 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).

We investigate the effect of the coupling strategy by first simulating WEN interactions in a standalone mode, which is illustrated in Fig. 3a. 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 Fig. 3b. 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 EIA (2018, 2019) 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

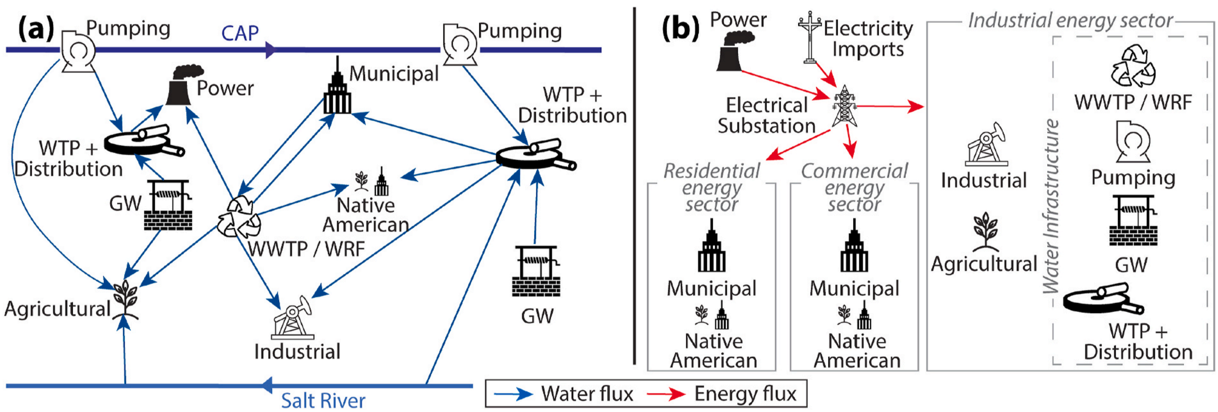

Fig. 2. Schematic of (a) water and (b) energy systems in the Phoenix AMA. Acronyms are defined in the main text.

Table 2
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]	Annual 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	(PWCC, 2018)
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)

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.

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 Fig. 3b. 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.

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.

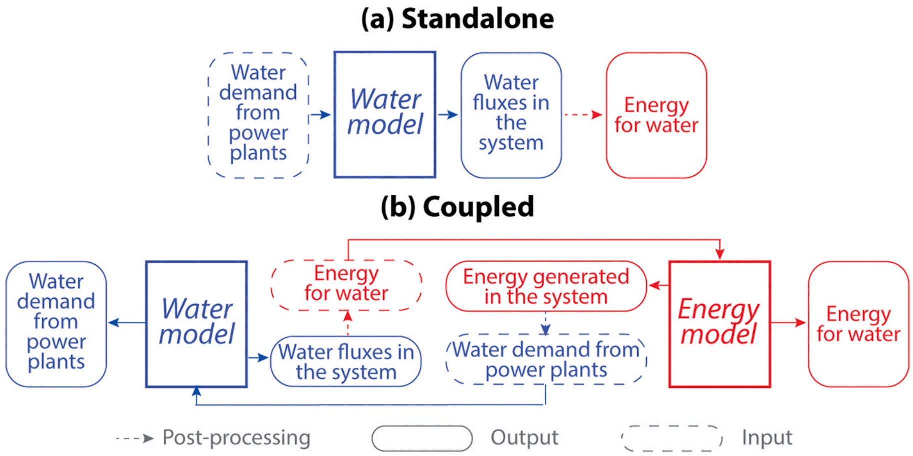

Fig. 3. Modeling approaches of water and energy systems in (a) standalone and (b) coupled modes. See text for details.

Table 3
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

3. Results

3.1. Effects of time resolution

We begin by presenting in Fig. 4 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 (Fig. 4a–d); and winter and summer peaks at the Palo Verde nuclear generating station (Fig. 4e and 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 Fig. 4 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%).

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 Fig. 5a, while the single monthly averaged value produced by 1A is presented in Fig. 5b. As suggested by the results on electricity generation of Fig. 4, 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

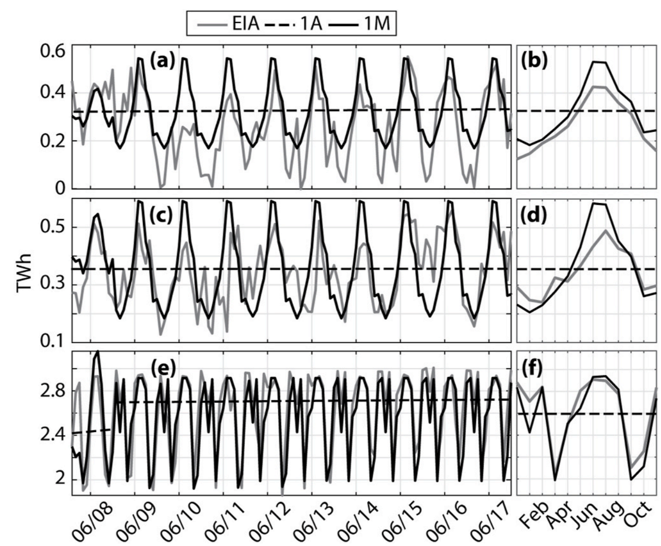

Fig. 4. Monthly electricity generation in 2008–2017 (left panels) and monthly means across all years (right panels) reported by EIA (2019) and simulated by coupled WEAP-LEAP under the 1A and 1M configurations at (a)–(b) Santan, (c)–(d) Redhawk, and (e)–(f) Palo Verde power plants.

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.

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 Fig. 6a, 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 Fig. 6b and 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

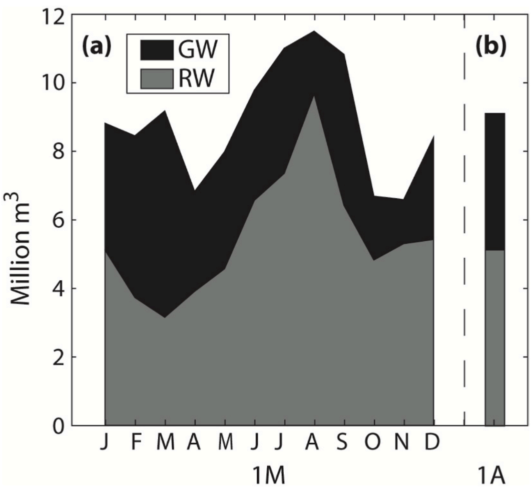

Fig. 5. (a) Mean monthly water allocations from RW and GW to the power node simulated in the 1M configuration, and (b) single mean monthly value derived from the 1A setup.

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 Fig. 6b and 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; Fig. 6b) or reach this value (as in 2012; Fig. 6c) 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 Fig. 6b and 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

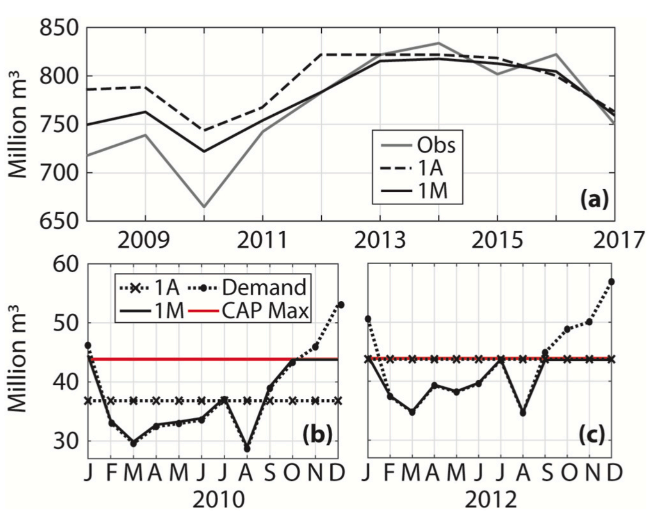

Fig. 6. Water allocations from CAP. (a) Time series of CAP annual volumes to all demand nodes estimated by ADWR (2018) (Obs) and simulated under 1A and 1M configurations. (b)–(c) Monthly simulations of CAP supplies to the municipal node in 2010 and 2012, respectively (see main text for details on legend).

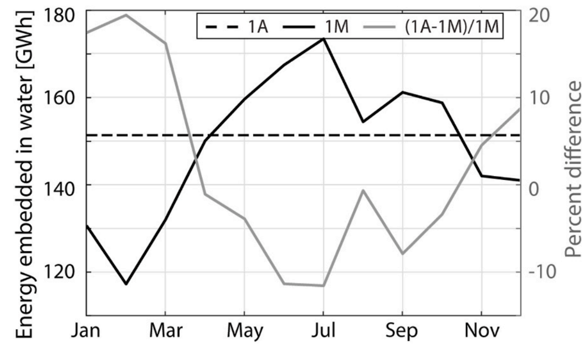

Fig. 7. Monthly mean energy embedded in transporting and treating RW, SRP, GW, and CAP water simulated under 1A and 1M along with the percent difference.

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 (Fig. 6a).

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 Fig. 7, 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%).

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 Fig. 8 display water allocations and embedded energy from supply sources to power demand nodes. We first focus on the monthly mean values (Fig. 8a and 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 (Fig. 8a). 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 (Fig. 8b). 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).

We further investigate differences between water allocations and embedded energy by focusing on the months with the lowest (February; Fig. 8c and d) and highest (August; Fig. 8e and 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 Fig. 8c with 8d). 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

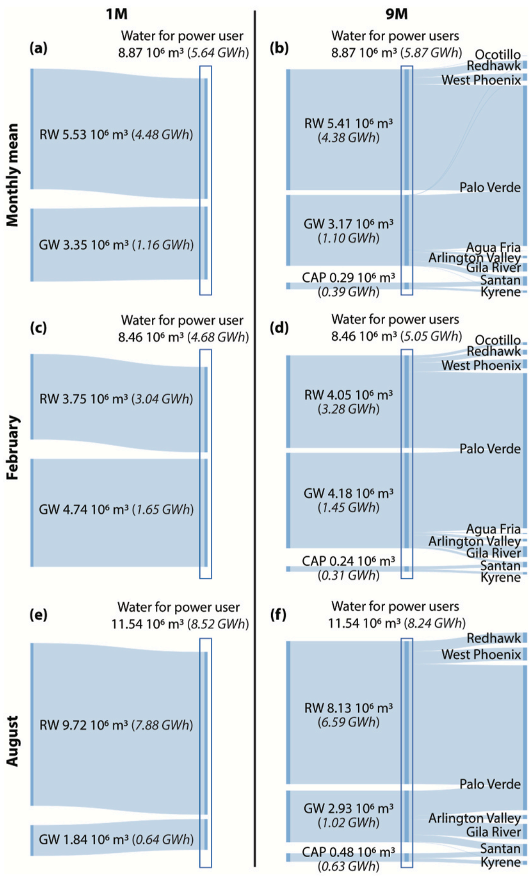

Fig. 8. Sankey diagrams showing mean monthly water allocations from sources to power users simulated under (a)-(c)-(e) 1M and (b)-(d)-(f) 9M, along with embedded energy. Means are computed across (a)–(b) all months of all simulated years; (c)–(d) all Februarys; and (e)–(f) all Augusts.

of energy embedded in the water of 0.28 GWh or 3% (compare Fig. 8e with 8f).

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 (Fig. 3b). In the standalone configuration, these fluxes are instead provided as external inputs to WEAP (Fig. 3a). 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.

Fig. 9a–c shows 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; Fig. 9a), the standalone simulations are very similar to the coupled model outputs, while in others they overestimate (e.g., Redhawk; Fig. 9b) or underestimate (e.g., Palo Verde; Fig. 9c) 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 Fig. 9d–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, Fig. 9d–f displays 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.

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 Fig. 10. 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.

The water allocations from the three sources to the power plants exhibit also temporal differences. For instance, as illustrated in Fig. 11a and 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 (Fig. 11c). However, simulations under standalone overestimate (underestimate) GW monthly fluxes simulated by the coupled models below (above) ~4.5 million m^3 (see scatterplot in Fig. 11d), leading to lower variability of the monthly fluxes. The two modeling approaches simulate instead similar allocations of RW to all power plants (Fig. 11e and f). Despite this, differences are found in terms of RW allocations to distinct generating stations. This is demonstrated in Fig. 12, 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.

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-h simulations conducted by Santhosh et al. (2014) and Khatavkar and Mays (2018).

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

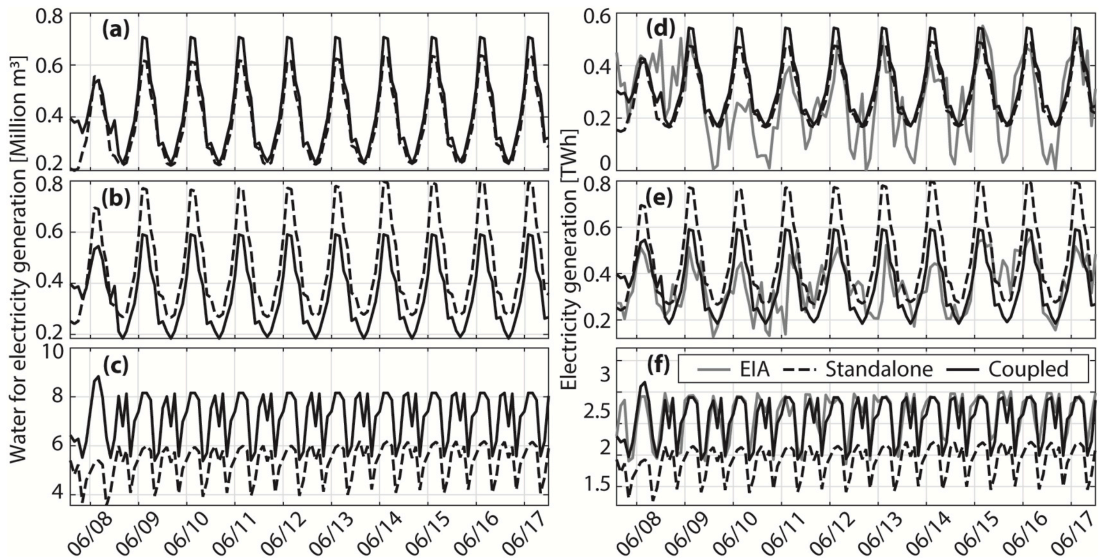

Fig. 9. (a)–(c) Simulation of water allocations for power generation at (a) Santan, (b) Redhawk, and (c) Palo Verde power plants using standalone and coupled configurations. (d)–(f) Same as (a)–(c) but for electricity generation, along with estimates from EIA (2019).

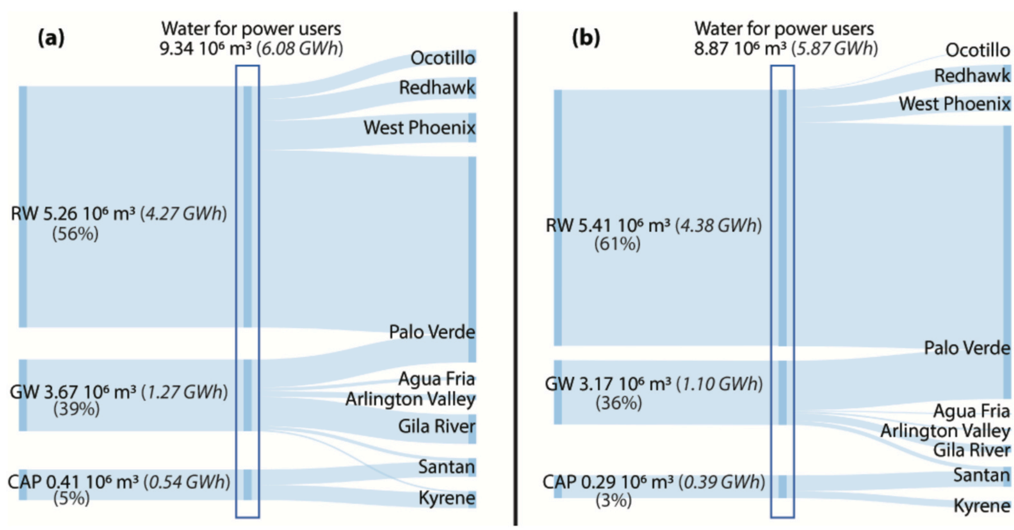

Fig. 10. Sankey diagrams showing the mean monthly water supply from RW, GW, and CAP to the power users along with the energy embedded in treating and pumping these fluxes as simulated by the (a) standalone and (b) coupled models.

(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 (Federal Energy Regulatory Commission, 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

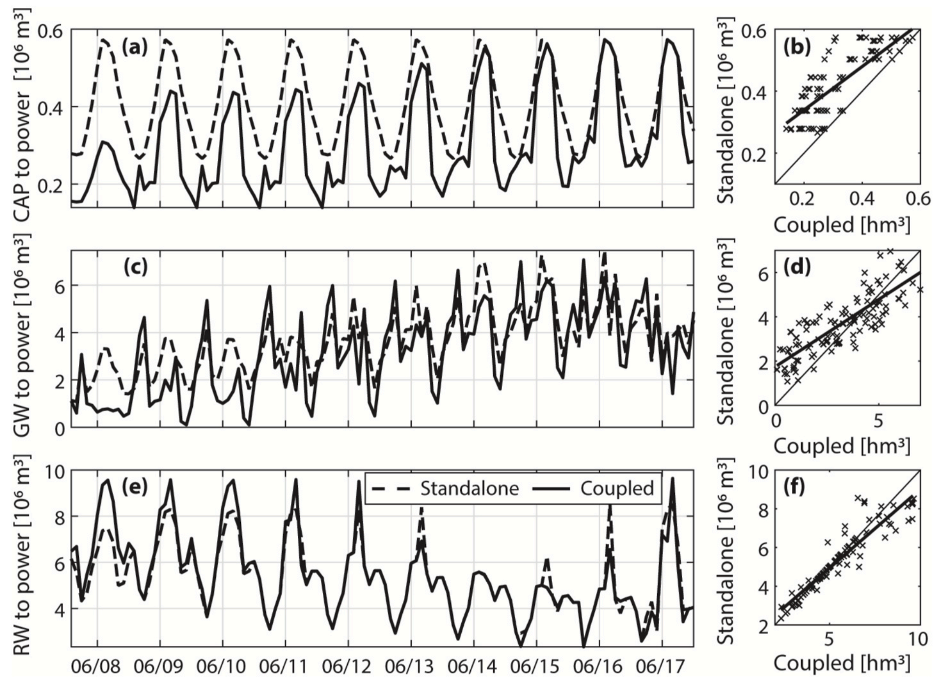

Fig. 11. Simulations of (a)–(b) CAP, (c)–(d) GW, and (e)–(f) RW water allocations for power generation using the standalone and coupled models. For each water source, the monthly time series and scatterplots between the two estimates are shown. In the scatterplots, the thinner (thicker) line is the 1:1 line (linear regression).

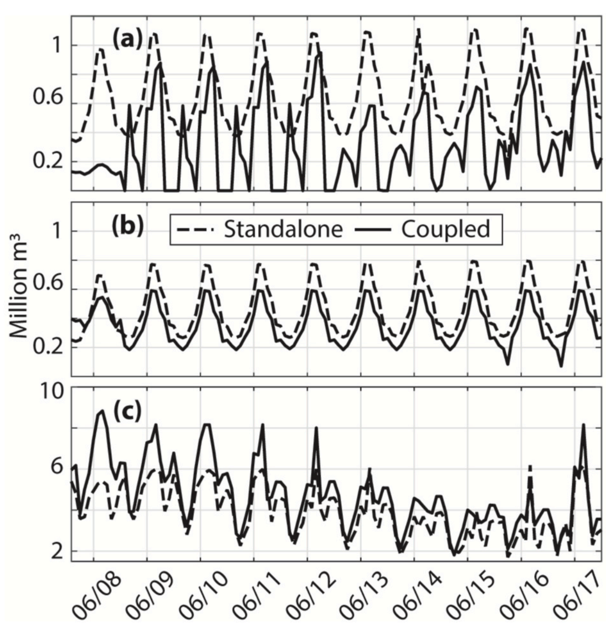

Fig. 12. Simulation of RW water allocations to (a) West Phoenix, (b) Redhawk, and (c) Palo Verde power plants using standalone and coupled configurations.

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 (2018, 2019). 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).

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 Figs. 4, 5, and 9). 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 (Federal Energy Regulatory Commission, 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., 2016a).

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 (Fig. 6), 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 (Electric Power Research Institute; 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% (California Public Utilities Commission; 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).

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 (Fig. 8). 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.

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 (Fig. 9). 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.

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.

Software and/or data availability

The software tools used in this paper are: (i) the Water Evaluation and Planning (WEAP), and (ii) the Long-range Energy Alternatives Planning (LEAP). Both tools are developed by the Stockholm Environment Institute (SEI; sei-international.org). The 2-year license for WEAP is free for non-profit, governmental or academic organization based in a developing country, and it ranges from \$250 to \$3000 depending on the user type. Pricing for the LEAP license is available by contacting SEI. Both platforms run in Windows machine. The data used to apply the software is publicly available and listed in Tables 1 and 2

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envsoft.2021.105197.

Appendix. Data sources used to spatially and temporally disaggregate the WEAP and LEAP models

The datasets used to set up and calibrate the LEAP and WEAP models are presented in detail in Mounir et al. (2019; their Table C1) and Guan et al. (2020; their Table 1). Table 1 presents a sample of these datasets as well as additional data sources used in this publication to determine the monthly variability in some variables.

To increase the temporal resolution of WEAP, we derive the monthly variability of SRP and CAP water allocations from the SRP's daily water report (SRP, 2020b) and CAP's monthly delivery report (CAP, 2020), respectively. We estimate the monthly water demands of municipal, industrial, and power plant sectors from the 2011 Water Plan of the City of Phoenix Water Services Department (CPWSD, 2011). To estimate the monthly agricultural water demand, we use data available for Yuma County, located in southwestern Arizona (Lahmers and Eden, 2018). We instead assume uniform demand for the Native American node because (i) its magnitude is comparatively much smaller, and (ii) we could not identify any valuable source to disaggregate it.

To increase the temporal resolution of LEAP, we assume the monthly variability of the capacity factors to match the observed monthly variability in the respective power plant electricity generation reported in EIA (2019). For the energy demand, the monthly variability is assumed identical to the variability in (i) the total load obtained from EIA (2020b) for the activities unrelated to water; and (ii) water demand as described for WEAP for the activities related to water. For example, the monthly variability of the energy required to pump CAP water to the municipal node is assumed identical to the monthly variability of the water demand by this node.

To conduct the standalone simulations and generate inputs for WEAP, we disaggregate spatially and temporally annual estimates of ADWR water allocations to all power plants. To disaggregate spatially, we multiply the total annual water volumes of the nine power plants by a weighting coefficient defined as $w_p = (C_p \cdot CF_p \cdot WR_p) / \sum_{p=1}^{9} (C_p \cdot CF_p \cdot WR_p)$, where C_p, CF_p, and WR_p are capacity, annual mean capacity factor, and water withdrawal rate of the *p*-th power plant, respectively. We use instead the variability in monthly capacity factors available from EIA (2019) for the temporal disaggregation.

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