Title
Crossed wires: Cross-sectoral dynamics of planning climate-resilient electricity systems

Author
Szinai, Julia

Publication Date
2021

Peer reviewed|Thesis/dissertation

Crossed wires: Cross-sectoral dynamics of planning climate-resilient electricity systems

by

Julia Katalin Szinai

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Energy and Resources

and the Designated Emphasis

in

Development Engineering

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Andrew Jones, Co-Chair
Professor Daniel Kammen, Co-Chair
Professor Isha Ray
Dr. David Yates

Summer 2021

Crossed wires: Cross-sectoral dynamics of planning climate-resilient electricity systems

by

Julia Katalin Szinai

Abstract

Crossed wires: Cross-sectoral dynamics of planning climate-resilient electricity systems

by

Julia Katalin Szinai

Doctor of Philosophy in Energy and Resources

Designated Emphasis in Development Engineering

University of California, Berkeley

Professor Andrew Jones, Co-Chair

Professor Daniel Kammen, Co-Chair

The impacts of climate change—including rising temperatures, changing precipitation patterns, declining snowpack, and more frequent extremes—are already occurring, and are projected to intensify, around the world. As both a source of greenhouse gas (GHG) emissions and an infrastructure system vulnerable to such climate change impacts, the electricity sector faces a dual mitigation and adaptation challenge: decarbonizing generation with renewable sources, while also adapting to changing resource availability and demands under climate change. Long-term electricity resource planning—which has historically focused on minimizing the cost of building and operating the grid to maintain reliability—must therefore shift to plan for climate resilience. Climate-resilient electricity systems are flexible, efficient, diverse, and redundant to be able to respond to climate stressors and maintain clean, reliable, cost-effective electricity. Further, climate change does not affect the electricity system in isolation. Failing to account for cross-sectoral interactions in planning may overlook cascading vulnerabilities, and lead to unintended consequences that jeopardize system resilience. Therefore, grid planners must also account for interactions with other sectors and their feedbacks on electricity supply and demand. However, methods for considering cross-sectoral interdependencies and resilience under climate change are both understudied in the literature and not part of electricity system planning in practice.

To address these challenges, in this dissertation I study the electricity systems of the Western United States (WUS), and the case of California—a state that is the world's sixth largest economy, the 12th largest source of GHG emissions, and one of North America's most "climate-challenged" regions in terms of impacts such as water stress and extreme heat. In my dissertation chapters, I focus on the cross-sectoral interactions between the electricity and transportation systems, and between the electricity and water systems. Grounded in systems thinking, I uniquely tie together transportation, water, and energy resource operations and planning methods, in consideration of sectoral differences in management and modeling. My research is informed by both academic literature and engagement with key stakeholders through co-production to improve the decision-relevance of the results. Overall, by evaluating how climate mitigation strategies, climate impacts, and adaptation measures across sectors affect grid

outcomes, I aim to demonstrate the value of, and necessity for, modernizations to the electricity system planning paradigm to increase climate resilience and account for cross-sectoral dynamics.

In Chapter 1, I analyze the interplay between electricity decarbonization and transportation electrification, otherwise known as vehicle-grid integration. These energy transitions require planners to consider how electric vehicle (EV) charging can complement, rather than challenge, grid operations. However, there is no consensus on the value and feasibility of EV charge management strategies for a highly renewable grid, such as that of California, because electricity markets and charging behaviors are often inadequately represented in the literature. Through a novel linkage of an agent-based mobility model and a high-resolution electricity dispatch model, this chapter quantifies the achievable benefits, in terms of avoided grid operating costs and renewable curtailment, of managed charging compared to the unmanaged charging alternative.

In Chapter 2, I study the interactions between electricity and water systems, commonly referred to as the energy-water nexus. Electricity is used to power all stages of the managed water cycle including water extraction, conveyance, treatment, distribution, use, and disposal. However, the implications of evolving water and electricity systems on the energy usage and GHG associated with California's water are not clear. Chapter 2 forecasts the energy and GHG footprint related to urban and agricultural water in California out to 2035, given recent trends in declining water demand, shifts to local water sources, and increasing renewable energy on the grid. By evaluating different water sector pathways, the analysis demonstrates the energy and GHG savings co-benefits of water conservation across different regions, which can help in achieving state climate mitigation goals.

Climate change is likely to stress the interactions between electricity and water resources highlighted in Chapter 2. However, the ways and extent that such cross-sectoral interdependencies may exacerbate or offset climate change impacts and related adaptation strategies are unclear. Chapter 3 synthesizes the fragmented literature and develops a generalized framework for understanding how climate change may affect the energy-water relationship. A case study of California by the end-century—when climate impacts on water supply, air-conditioning demand, and hydropower are expected to be greatest—finds that energy requirements of some water sector adaptation strategies may exceed the direct climate impacts on the energy system, demonstrating the value of cross-sectoral coordination to ensure efficient and reliable energy and water provision.

Despite the compounding risk of climate change on coupled energy-water systems shown in Chapter 3, most electricity planning models omit these interactions, which could result in future capacity shortfalls from unanticipated resource changes. Chapter 4 fills this gap with a novel model linkage that evaluates the range of climate impacts on water resources across the WUS, and how the buildout of the region's electricity system may subsequently need to change to account for, and maintain resilience in the face of, changes in hydropower availability and energy use related to water. The results quantify the additional redundancy and diversity, in terms of generation and transmission capacity resources, needed to make the grid resilient to both water-related climate change impacts and decarbonization.

While many benefits of coordination have been demonstrated in the literature, in the independently managed energy and water sectors, cross-sectoral interactions are still not typically or explicitly operationalized into decision-making. One possible explanation for this gap between the theory and practice of the nexus is that scientists working at the nexus may not be engaging directly with stakeholders to understand and adjust their research based on the kind of information, norms, and methods used by practitioners. Chapter 5 uses a co-production approach through a focus group and surveys with water managers to improve the decision-relevance of Chapter 4 modeling efforts. The results highlight the climate impacts of concern to WUS water managers for providing reliable water services, the explicit and implicit ways that energy interactions affect water management decisions, the diverse tradeoffs managers consider when weighing decisions, and the metrics they use to evaluate the tradeoffs.

I conclude the dissertation with a summary of ongoing work as well as recommendations for both policy-makers and researchers on ways to evaluate and plan for cross-sectoral dynamics and climate resilience for the electricity system.

Dedicated in memory of Anna Bruszt, who taught me that education is the one thing that can never be taken away

Table of Contents

Acknowledgements

This dissertation would not have been possible without a community of family, friends, colleagues, advisors, collaborators, and funders.

First and foremost, words cannot express how grateful I am to Eyal, who provided his love and support from the beginning and throughout the long and winding PhD road, even when it meant delays or sacrifices in other parts of our lives. Thank you for listening to and talking through my ideas, helping to debug my code countless times and patiently fixing my programming and database snafus, reviewing and editing my writing, being a practice audience for presentations, and of course cooking delicious meals. For these reasons alone you deserve an honorary PhD. Above all, thank you for being my rock and partner through the highs and lows of the process. I can't wait for our next adventure together. Thank you to my parents, Veronika and Istvan, who are always my role models for perseverance and hard work and who epitomize the term resilience that this whole dissertation is about. Thank you for your unwavering encouragement and for modeling and instilling in me a curiosity in the world around me. Thank you for everything you have done to provide me the opportunities to be here, to study at the best public university in the world, and to try to make a positive difference in the world. Thank you to Pista for your love, encouragement, and generosity throughout this process. Thank you Mimi for being like another grandmother to me, and sharing your humor and love of gardening to add to my appreciation of the wonders of nature. Thank you to Jutka for your loving support.

I am very grateful and privileged to have learned from and been guided by such an esteemed group of advisors and committee members. Thank you Dan for wholeheartedly supporting my goal of doing this PhD, for giving me confidence in my ideas, and for your guidance and enthusiasm in pursuing this work. Andy, I am so thankful for your mentorship and support of my research from the beginning, for believing in me and for finding a way to make it happen and fund me to carry out this cross-sectoral vision. I could not have done this work without you. I look forward to keeping this work going and growing as an interdisciplinary researcher with your guidance. David, it has been a great learning experience to work with you. Thank you for taking a chance on me, and going on this crazy ride of modeling the Western US water and energy systems. A large part of the dissertation wouldn't have happened without all of your tireless WEAP modeling work, and I really appreciate all of the time and care you have put into our project. Isha, thank you for taking me under your wing in the Water Group community. You have helped me to think more critically, to push myself to become a more rigorous researcher and interdisciplinary scholar, and to always ask: what is this a case of? I also want to thank Duncan Callaway and Paolo D'Odorico who were on my qualifying exam committee and asked the tough questions that prepared me to take on this research.

Navigating this non-linear grad school path (and the Berkeley campus) would not have been possible without the support of Kay Burns. Thank you for being equal parts advocate, confidante, and fairy godmother for so many of us at ERG. Thank you also to ERG faculty members David Anthoff, Margaret Torn, Lara Kueppers, and John Harte for being fantastic teachers and for your invaluable feedback, perspectives, and critiques during PhD seminars and coursework.

Of course, I owe a huge thanks to the special ERG community and the incredible peers and friends who became my chosen family. You all never ceased to inspire me! Thank you so much to the ERG newbies 2014 cohort, and especially Paty (for being a wonderful friend, research collaborator, optimization tutor, and travel buddy), Cecilia, Laney, MK, and Valeri for your friendships, study session help, gardening tips, and travel and Bay Area fun. Thanks to my adopted 2015 cohort for taking me in and sharing apple clouds and coffee at Strada. And thank you to the 2013 cohort and especially Kripa, Laura (for accepting me as an honorary Hilgard group member and sharing your love of plants, crafts, and good food), Chris (for being a workout and InFEWs buddy), Nikky (for giving me pep talks on my research and being a great neighbor and friend) and Noah (for always being a good confidante) for being fantastic friends and role models. I especially can't thank you enough Kripa, for your friendship and your invaluable mentorship. I owe you about a million dinners, not to mention BTS tickets in Seoul, for all the support and guidance you have helped me with. At least 3 chapters of this dissertation wouldn't have existed without your help! And thank you to other ERGie elders and friends (Ranjit, Grace, Pierce, Isa, Salma, Samira, Anna, and others) and the ERG community broadly.

This research is also a product of the thoughtful feedback from several lab and other research groups. Thank you to Water Group+, EMAC, RAEL, PhD seminar, and LBL colleagues.

Finally, none of this work would have been possible without my collaborators, mentors, and funders over the years. I would like to thank Merrian Borgeson at NRDC; Tim Lipman at TSRC; Peter Alstone, Mary Ann Piette, Jennie Potter, Colin Sheppard, Nikit Abhyankar, Anand Gopal, Amol Phadke, Ranjit Deshmukh, and Alan Rhoades at LBNL; Heather Cooley, Peter Gleick, and Sonali Abraham at the Pacific Institute; and Sarah Kurtz, Paty Hidalgo-Gonzalez, Pedro Sanchez-Perez, and Martin Staadecker from the CEC Long Duration Energy Storage project. I am very appreciative of research funding in particular from the HyperFACETS project, and through the NSF InFEWS Traineeship program.

I stand on the shoulders of giants. Thank you all for helping me along this dissertation journey!

Introduction

1. Background and motivation

The impacts of climate change—including rising temperatures, changing precipitation patterns, declining snowpack, earlier snowmelt, and more frequent and intense extremes—are already occurring, and are projected to intensify, around the world [1]. Coupled human and natural systems, or socio-ecological systems, are vulnerable because of their exposure, sensitivity, and limited resilience to such climate perturbations [2]. Decreasing anthropogenic greenhouse gas (GHG) emissions from fossil fuels used for energy generation, transportation, buildings, and industry is a key mitigation strategy to reduce or slow such climate change impacts [3]. At the same time, there is increasing recognition that even with ambitious mitigation efforts some impacts are unavoidable in the near term, thus responding to climate change also requires adaptation actions to reduce vulnerability to stressors occurring now and anticipated in the future [4]. Synthesized across many definitions and disciplines, adaptation can be broadly described as an adjustment in human or natural systems that alters the exposure, reduces the sensitivity, or increases the climate resilience of a system [5], [6].

Climate resilience is the ability of a system to adapt to, and cope with, such climate perturbations while continuing to provide or improve upon essential services [2], [7]–[9]. The goal of developing climate-resilient infrastructure systems is to reduce GHG emissions, while simultaneously having flexibility and redundancy to function under changes in both average and extreme weather [10], [11]. Incorporating these concepts of climate resilience into infrastructure planning has been gaining interest from governments, utilities, and other organizations concerned about being able to deliver the historical level of services with systems predicated on climate stationarity [12]–[14]. However, gaps in understanding and in practice remain on how best to account for the uncertainties of climate projections, impacts on infrastructure, and socio-economic conditions; the already aging and degrading state of many systems [15]; the long lead time, costs, and lifetimes of infrastructure [13]; and other non-climatic political or economic stressors [14].

An added complexity to this climate resilience planning challenge is that the infrastructure systems are often systems-of-systems comprised of multiple sectors that have feedbacks among them [16], [17]. These systems often also have disconnected governing institutions with different organizational objectives, scales, and information [18]–[20]. Despite these complexities, it is important to comprehensively consider these cross-sectoral dependencies because evaluating and adapting to climate impacts for individual sectors alone may underestimate climate risks [21], [22]. Ignoring interactions and feedbacks may lead to compounding impacts of climate change, and/or "maladaptation" if one sector's adaptation strategy inadvertently increases the climate vulnerability of another [21], [23], [24].

Incorporating cross-sectoral interactions and decision-relevant information for electricity system planning under climate change

This dissertation centers on the challenges of planning a climate-resilient electricity system. As both a source of GHG emissions from fossil fuel generation, and an infrastructure system vulnerable to climate change impacts, the electricity sector faces a dual mitigation and adaptation challenge: decarbonizing generation with renewable sources, while also adapting to changing resource availability and demands as well as risks to physical infrastructure, such as from sea level rise and wildfire (which itself could be exacerbated by grid infrastructure as a source of ignition) under climate change [25]–[28]. Rolling blackouts in response to recent extreme weather events across the United States, like in California during the West-wide 2020 heat storm [29], in Texas during the 2021 cold-snap [30], or in the Pacific Northwest's 2021 record-breaking heat wave [31], suggest that the current grid infrastructure, and by extension the electricity planning paradigm, is ill prepared to both mitigate and adapt the grid for climate resilience. Long-term electricity resource planning has historically focused on minimizing the cost of building and operating the grid to maintain reliability[32],[1] but in the context of climate change, resilient electricity systems must also be flexible, efficient, diverse, and redundant to be able to respond to climate stressors and maintain clean, reliable, cost-effective electricity [34].

Climate change also does not affect the electricity system in isolation [5]. Failing to account for cross-sectoral interactions in planning may overlook cascading vulnerabilities across time and geography, and lead to unintended consequences or missed opportunities that jeopardize grid resilience [16], [17], [22]. Risks may be exacerbated when adaptation actions in one sector are maladaptive and adversely impact the other, such as increasing energy use or reducing generation [23], [35]. Therefore, electricity system planners must account for interactions with other sectors that have typically been outside the grid planning process—but which are also responding to climate drivers—because their activities may now directly affect electricity supply and demand. In particular, the transportation and water are two sectors that will have increasing interaction with the electricity sector in the context of climate change. As a major source of GHG emissions, transportation electrification is a key strategy for mitigation, but one that could add massive new energy demands and operational challenges for grid operators in simultaneously integrating intermittent renewable resources [36]. The electricity sector must also account for potentially propagating impacts from the climate-vulnerable water sector, through interdependencies also known as the energy-water nexus, because water systems in many regions can have large energy demands and contribute to energy supply through hydropower [16], [37].

Despite recognition of the importance and benefit of considering such cross-sectoral dynamics, transportation and water system interactions under climate change have not been operationalized as part of standard grid planning practices [26]. One possible explanation for this gap between the theory and practice is that scientists working across sectors may not be engaging directly with stakeholders to understand and adjust their research based on the kind of information and methods that are used by practitioners on the ground [38]. Co-producing information jointly with scientists and practitioners can help make the information credible, legitimate, and salient for use in decision-making [39]. Such stakeholder engagement has been effective in revealing non-technical barriers to effective adaptation and coordination between sectors, and can augment technical modeling assumptions, scenario creation, and model design for decision-relevance and improved climate information usability [40]–[42].

[1] Reliability in electricity systems is defined in terms of both adequacy (ability of the system to supply energy to customers at all times, given scheduled and reasonably unexpected unscheduled outages), and operating reliability (ability of the system to withstand sudden disturbances such as an unanticipated loss of a generator, while avoiding cascading blackouts) [33].

2. Overall dissertation goals, research questions, and structure

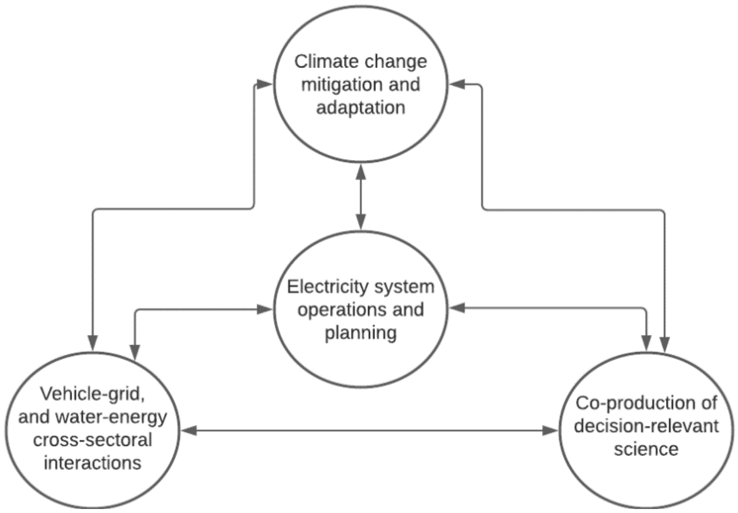


Figure 1. Dissertation main themes.

In this dissertation I aim to demonstrate the value of, and necessity for, modernizations to the electricity planning paradigm to increase climate resilience and account for cross-sectoral dynamics. I do this by evaluating how climate mitigation strategies, climate impacts, and adaptation measures across sectors affect grid outcomes. Overall, my goal is to advance understanding toward answering:

How can cross-sectoral linkages be accounted for in planning a climate-resilient electricity system?

Grounded in systems thinking, I uniquely tie together literature on 1) power systems operations and planning, 2) climate change impacts, mitigation, and adaptation, 3) cross-sectoral interactions between the electricity and transportation systems and between the electricity and water systems, and 4) co-production of decision-relevant science (Figure 1). In this dissertation, I develop and apply these methodologies to the Western US (WUS) where such complex challenges are playing out today, and where accounting for interactions with the transportation and water systems has become an operational imperative to planning an electricity system. Throughout this research, I have an emphasis on the case of California— a state that is the world's sixth largest economy, the 12th largest source of GHG emissions [36], and one of North America's most "climate-challenged" regions in terms of impacts such as water stress and extreme heat [7].

My dissertation spans the electricity, transportation, and water sectors and answers five specific research questions across a spectrum of climate change mitigation and adaptation approaches (Figure 2). Chapter 1 analyzes the impact of transportation electrification in California and how electric vehicle (EV) charge management may increase grid resilience by providing flexibility to balance intermittent renewables. In Chapters 2 through 5, I study linked electricity and water systems in California and the broader WUS. Chapter 2 evaluates the energy and GHG footprint of California's urban and agricultural water systems in the near term, given emerging trends in the state's water and energy supply and demand portfolios. Chapter 3 identifies cross-sectoral vulnerabilities and feedbacks of water and energy systems under climate change, looking ahead to the end of the century. Given these linkages, Chapter 4 evaluates the range of climate impacts on water resources in the WUS, and how the buildout of the region's electricity system may subsequently need to change to account for changes in hydropower availability and energy use related to water. Chapter 5 is an analysis of a focus group and surveys conducted through a co-production process with water planners to understand if and how they consider energy when deciding to adapt their water systems to climate change. I conclude the dissertation with a summary of ongoing work as well as recommendations for both policy-makers and researchers on ways to evaluate and plan for cross-sectoral interactions and climate resilience for the electricity system.

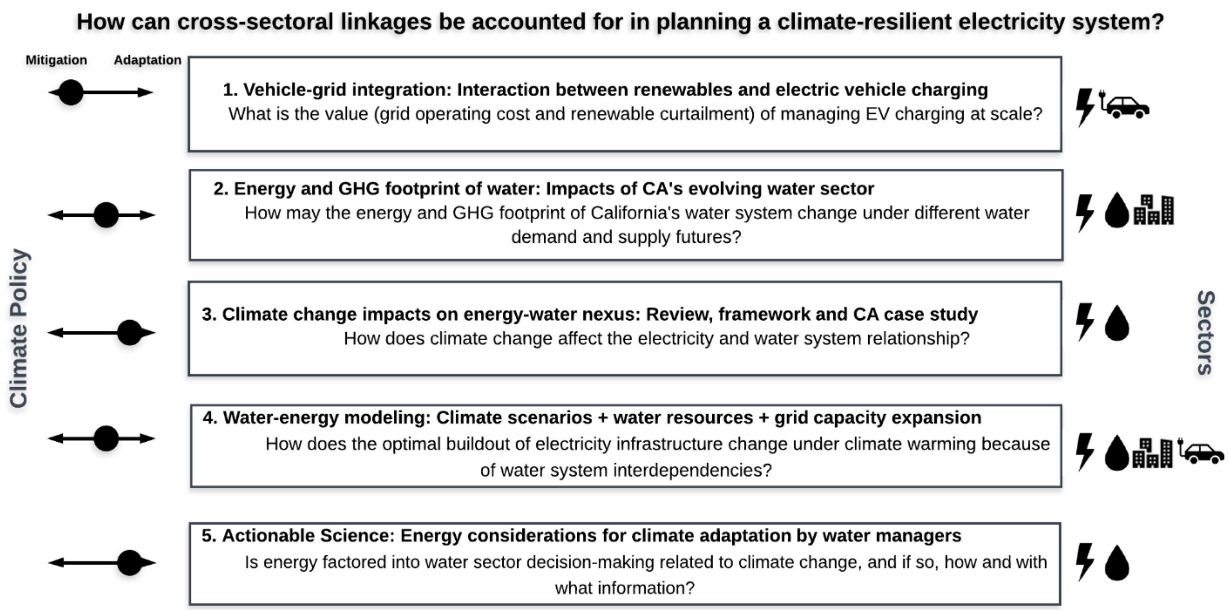


Figure 2. Dissertation chapter outline and research questions.

In the following sections of the introduction, I provide the background and motivation for these chapters, and how they support my overall research aim to demonstrate the value and necessity of a new electricity planning paradigm for increased climate resilience.

2.1 Chapter 1: Reduced grid operating costs and renewable energy curtailment with electric vehicle charge management

The transportation sector is the largest contributor to emissions in California (39% of GHG), and the state's climate mitigation strategy (to reduce overall emissions 40% by 2030 and 80% by 2050) has centered around electrification in parallel with decarbonization of generation resources (targets of 5 million EVs on the road by 2030, and 100% carbon-free generation by 2045). These energy transitions require electricity system planners to consider the cross-sectoral implications of how EV charging can complement, rather than challenge, grid operations increasingly dominated by intermittent solar and wind sources [43]. Prior research suggests that with high levels renewable energy, off-peak time-of-use (TOU) and smart charge management strategies can make EVs a complementary flexible grid resource [44]. However, there are gaps in evaluating the feasibility and value of these strategies at high vehicle and renewable adoption levels [45] because electricity market dispatch and drivers' charging behaviors are often inadequately represented [46]–[50]. Much of the literature either (1) has not included realistic charging behaviors which account for divers' mobility needs and charging infrastructure availability, or (2) has not evaluated charging demand in an electricity system operational model that can simulate dynamic grid dispatch [51]–[53], thereby estimating benefits which may not be achievable.

In Chapter 1, I build on these efforts with a novel linkage of a more robust and realistic simulation of the transportation sector (with an agent-based mobility model [46]) and the power sector (with a production cost model [27], [54]), to quantify the hourly impacts and annual wholesale market value and renewable energy curtailment that California policymakers can reasonably expect with large scale EV and renewable adoption.

2.2 Chapter 2: The future of California's Energy-Water-GHG Nexus

Energy is integral to all aspects of managing and using water in California. Prior studies have estimated that about 20 percent of California's total statewide electricity use, a third of non-power plant natural gas consumption, and 88 billion gallons of diesel consumption are related to water – from collection and treatment to use and wastewater management – with a large share associated with heating water [55]. However, many factors have since evolved in California's water demand and supply portfolio, and the implications of multiple, ongoing changes to the state's water resources on future energy use and GHG emissions are not well understood. California has experienced a dramatic decoupling between water use and economic growth over the last 40 years [56]. Urban water suppliers also are pursuing local water supply options [57], many of which are more energy-intensive than traditional water sources but still less energy-intensive than imported water [58]. While agricultural water use has remained relatively flat since the 1980s, it is particularly dependent on unsustainable groundwater extraction, and pumping has become increasingly energy-intensive as groundwater levels have fallen around the state [59]. Climate change, with impacts on water availability, quality, and demand, is accelerating these trends [60]. Water and energy changes in California also affect GHG emissions for the state. Electricity generation, the main energy source for the provision and treatment of water, is undergoing structural reform to decarbonize. There are also state programs to incentivize switching to electric water heating, which is the most energy-intensive end-use of water and is still largely done using natural gas water heaters.

Given this complex set of factors affecting the water and energy systems in the state, there is a need to update estimates of water-related energy and GHG footprints. Some prior studies are out-of-date and do not incorporate the decarbonizing electricity mix, both urban and agricultural water, the major energy use of water heating, or the entire state [55], [61]–[65]. Chapter 2 builds on these previous analyses to quantify the combined impact of emerging trends on California's water (including population growth, climate change, and policies to promote water efficiency and alternative water supplies) and electricity (including generation decarbonization) on the state's water-related energy and GHG footprints from 2015 to 2035. Based on the results of the analysis, the chapter includes recommendations for water and energy sector planners to find mutually beneficial strategies to lower energy use and GHG emissions.

2.3 Chapter 3: Evaluating cross-sectoral impacts of climate change and adaptations on the energy-water nexus: a framework and California case study

Chapter 2 demonstrates that electricity and water systems are inextricably linked through energy demands for using, moving, and treating water and wastewater. In California and worldwide, water is also a key input to electricity generation, for hydropower and cooling of thermoelectric power plants [37], [38], [66]–[68]. Climate change and the resulting shifts in the global hydrologic cycle [69], [70] may strengthen or strain these nexus connections in new and uncertain ways [71]. For example, higher temperatures and shifts in precipitation and snowpack could simultaneously increase irrigation water demand and energy for water pumping, while reducing surface water and hydropower availability [72], [73]. Further, as shown in Chapter 2, water sector measures commonly sought during long-term declines in surface water, including water recycling, desalination, or groundwater recharge and withdrawal, can be relatively energy-intensive [67], [74]–[77]. Some of these impacts have already occurred during recent droughts in California, foreshadowing how the state's energy-water nexus may fare under these impacts of climate change [21]. The drought response of the state's water sector transferred and compounded vulnerability to its electricity sector—increased groundwater pumping spiked electricity consumption, while hydropower deficits were replaced by GHG-emitting fossil generation [35], [78].

Because water and electricity system climate vulnerabilities and adaptations are often studied in isolation, there is limited understanding of how multiple interactive risks and feedbacks between them may propagate [16], [17], [21], [22]. Typically climate vulnerability analyses evaluate electricity [25], [72], [79] or water system [80] risks with the assumption that all else remains fixed, or assess climate-related changes to supplies or demands separately [72], [81]–[83]. Many studies that are focused on demonstrating how integrated energy and water systems' management improves efficiency, increases equitable resource access, and maximizes synergies [38] only characterize historical conditions [61], [84], [85]. The cross-sectoral tradeoffs of climate adaptation strategies, such as the energy footprint of alternative water supplies, are particularly understudied despite recognition that ignoring such externalities could lead to maladaptation, whereby one sector's adaptation strategies increase climate vulnerabilities in another [23], [85], [86].

In Chapter 3, I review and synthesize this fragmented literature and develop a generalized framework for understanding implications of climate change on the energy-water nexus. I apply this framework in a case study to quantify the range of end-century direct climate impacts on California's water and electricity resources and estimate the magnitude of the indirect cross-sectoral feedback of electricity demand from various water adaptation strategies.

2.4 Chapter 4: Planning for climate change impacts on electricity and water systems in the Western US with a cross-sectoral modeling approach

Chapter 3 finds that the main ways electricity and water systems are impacted by climate change in the WUS are through changing water supply availability, irrigation water demand, hydropower generation, and electric demand for cooling. Yet, there are few examples of grid planners considering such impacts of climate change or water system interactions in modeling efforts for future grid expansion, and existing examples only analyze select impacts [87], [88]. To inform their decision-making, electricity system planners traditionally use capacity expansion optimization models to decide what type of technology, where, and when to build new capacity that meets forecasted loads and operational constraints [89]. However, capacity expansion models that incorporate water linkages are uncommon and primarily have focused on water constraints on thermal power plant cooling. These constraints are less relevant in the WUS where there is a relatively minimal share of freshwater for thermoelectric cooling [90]–[92]; in California, for example, the dependency on cooling water is further decreasing as the generation mix is transitioning to renewable resources that do not require cooling water [90], [91]. Additionally, limited work has been done on incorporating climate impacts on both changes in "water-for-energy" (i.e. hydropower) as well as "energy-for-water" (i.e. changes to energy demand for groundwater pumping, conveyance, water treatment, etc.). Since climate change is projected to have significant impacts on both water supply availability as well as water demand, the energy usage related to supplying, transporting, treating, using, and disposing of water in the region will change correspondingly and affect the overall energy demand grid planners must plan to meet. These are key areas for further research given that grid infrastructure predicated on climate stationarity is unlikely to be resilient to future conditions.

I address these gaps in Chapter 4 by connecting a high-resolution grid capacity expansion model with a water resources model that combines climatically-driven physical hydrology and management of both water supply availability and demand allocation. The objective of this work is to evaluate the optimal buildout of Western Electricity Coordinating Council (WECC) electricity infrastructure in response to climate impacts and water sector interactions by 2050. This analysis (1) quantifies the climate impacts on hydropower and energy demand for water under a range of potential futures; and (2) quantifies the sensitivity of the electricity grid buildout and operations to climate impacts on hydropower and water-related energy demand.

2.5 Chapter 5: Assessing climate adaptation decisions at the energy-water nexus

Many energy-water nexus studies demonstrate how integrated systems' management improves efficiency, increases equitable resource access, and maximizes synergies [38]. There is also recognition in the literature [73], [93] of the importance of accounting for climate impacts on such linked energy and water systems, because the cross-sectoral interactions could exacerbate the effects of warming. Yet, in the two independently managed sectors, it appears that energy-water interactions are not typically or explicitly operationalized into decision-making [18], [94], and many ideas and tools of the nexus have remained conceptual [38]. Nexus challenges for climate adaptation in particular tend to not be in the forefront of decision criteria and are often considered outside the scope or jurisdiction for resource managers of individual sectors to evaluate [20]. One possible explanation for this gap between the theory and practice of the nexus is that scientists working at the nexus may not be engaging directly with stakeholders to understand and adjust their research based on the kind of information, frameworks, institutional norms, and analytical methods that are used by practitioners on the ground; only a small share of nexus literature includes stakeholder engagement and decision support methods [38].

Active scientist-stakeholder interaction and engagement are highlighted as ways to narrow this gap and make climate information more decision-relevant for adaptation planning [95], [96]. Participatory approaches, such as the workshops or focus groups, are effective methods to reveal non-technical barriers to effective adaptation and coordination between sectors, and can augment technical modeling assumptions, scenario creation, and model design for decision-relevance and improved climate information usability [40]–[42]. One form of scientist-stakeholder interaction is co-production, whereby information is jointly produced through the collaboration between scientists and stakeholders, and values and knowledge are incorporated from both communities [97]. In addition to addressing gaps in knowledge creation, co-production can help scientists conduct their analysis and present their results in consideration of the different facets of decision-making, including in institutional norms, local context, and specific costs and benefits [98].

Chapter 5 uses the collaborative process of co-production between scientists and stakeholders to improve the decision-relevance of energy-water nexus modeling. Through a focus group and surveys between researchers and water managers, the work aims (1) to co-produce research questions and scenarios to explore with energy-water nexus modeling described in Chapter 4; (2) to understand in fundamental ways how climate and energy information is currently used by water managers; and (3) to hear from managers and scientists on what scientific information about these interactions can potentially help inform the management context under future climates.

Chapter 1: Reduced grid operating costs and renewable energy curtailment with electric vehicle charge management

Chapter 1 focuses on climate change mitigation efforts and the cross-sectoral interactions between the electricity system and an electrified transportation system in California and the WUS. The analysis quantifies the value, in terms of avoided grid operating costs and renewable energy curtailment, of managed electric vehicle charging with a 50% renewable grid in California and electric vehicle adoption scenarios up to California's 5 million vehicle target. By integrating a detailed agent-based mobility model with a high-resolution power systems dispatch model, this analysis provides realistic estimates of the availability of managed charging services, and recommendations on targeted charging strategies that maximize benefits to a power system such as California's with a high share of renewable energy. The work in this chapter was published in the journal Energy Policy as an article titled, "Reduced grid operating costs and renewable energy curtailment with electric vehicle charge management," and is included in this dissertation with permission of my co-authors Colin Sheppard, Nikit Abhyankar, and Anand Gopal.

---

1. Introduction

The number of plug-in electric vehicles (PEVs) on the road, including both fully battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), has surpassed 3 million worldwide and is growing steadily [99]. Widespread PEV adoption can enable oil independence [100], save on fuel costs for drivers [101], and lower greenhouse gas (GHG) emissions [102], among other benefits. Increasing the share of renewable energy (RE) on the power grid in parallel with vehicle electrification generates a cleaner PEV fuel source and thus accelerates GHG emissions reductions [36].

However, shifts to a PEV-dominant vehicle fleet and decarbonized generation mix can challenge grid operations. PEV charging typically begins as soon as a driver arrives home from their evening commute and plugs in the vehicle [46], [103]. This charging load often coincides with the power system's peak demand [103] and increases ramping needs and costs through the dispatch of inefficient and expensive fossil generators. High penetrations of intermittent wind and solar photovoltaic (PV) sources may also increase the need for curtailment or require other strategies to mitigate imbalances between energy supply and demand [104]–[106].

California is an ideal region to study interactions between an electrified fleet and a high-RE grid because such transitions are already underway and will likely accelerate in the next decade. In 2012, the Governor set a state goal of 1.5 million zero emission vehicles (ZEVs)—which include hydrogen fuel cell electric vehicles (FCEVs)[2] and PEVs—by 2025, and the goal has since been extended to 5 million vehicles by 2030 [108], [109]. With about 500,000 PEVs currently on the road, California has about half of the U.S.'s PEVs and about 15% of the world's PEVs [99], [107]. The state has charging infrastructure investments [110]–[112], growing vehicle model options [113]–[115], and other policy support [116]–[118] to help achieve the

[2] We do not evaluate the impact of FCEVs in this report, because they comprise a much smaller share of ZEVs in California [107].

vehicle targets. For the power sector, through a Renewable Portfolio Standard (RPS), California mandated in 2015 that 50% of electricity consumption come from RE sources by 2030 [119]. In 2018, the 50% RPS requirement was accelerated to 2026, on the way to 60% RPS by 2030 and an ultimate goal of 100% zero-carbon resources by 2045 [120].

Prior research suggests that if PEV charging is managed, the vehicles could both alleviate peak loads and serve as a complementary grid resource to integrate more RE [43]. Time-of-use (TOU) charging and "smart" charging are two such managed charging strategies that have been commonly studied and piloted [43], [121], [122].[3] Under TOU charging, drivers are incentivized by a lower electricity rate to charge during off-peak hours, often pre-programming the start time through the charger or PEV. With smart charging, PEVs usually participate in a demand response program whereby an aggregator (utility or third-party) remotely controls active charging to be on or off through the charger or vehicle software. The aggregator shifts charging to times that provide most grid benefit, when prices are low and/or RE is abundant, bidding the total flexible load of many PEVs into the wholesale electricity market.

To plan for high adoption rates of both PEVs and RE, policymakers need an understanding of the impacts and benefits that managed charging, also known as Vehicle-Grid Integration (VGI), can realistically provide at scale. However, California's related policy guidance lacks consensus on the systemwide value of VGI, calling for improved quantification to inform program design, investments, and business models [45]. Accordingly, the purpose of this research is to assess the impacts on California's planned 2025 power system, including operating cost and RE curtailment, resulting from unmanaged, TOU, and smart charging at various PEV adoption levels. Because utilities are ahead of schedule to meet their 2030 RPS goal [126], and the targets have been since been expedited, we evaluate the California grid in 2025 with a 50% RPS.

Bulk power system impacts have been studied in numerous contexts, varying in results depending on a system's generation portfolio, PEV adoption level, and charging schemes [43]. For example, in several geographies, [44], [127], [52], [128], [129], [53], [130]–[135], [47], [48] compare outcomes of unmanaged and managed charging strategies, finding that overall, managed charging leads to lower costs, reduced emissions, and higher utilization of RE. [53], [128]–[131], [133], [135] use dispatch models to estimate generation with PEVs while [47], [53], [127], [129] also plan generation portfolios with consideration of PEV charging load profiles. [44], [128], [129], [53], [134], [135], [48], [136] examine the interaction between PEV charging and RE resources, showing that PEV charging schemes can lower RE curtailment. [132], [135] compare PEV flexibility value with that of stationary storage.

Although VGI has been analyzed widely, much of the existing literature has either simplified the representation of charging strategies or grid dispatch. Without first robustly accounting for mobility (i.e. drivers' travel demands), charging infrastructure, and drivers' preferences, the availability of grid services provided by managed PEVs could be overestimated [46]–[50]. For example, [52], [53], [127], [135] aggregate travel patterns inferred from travel surveys to characterize PEV charging. Because this approach cannot account for individuals' mobility constraints and assumes unlimited chargers, charging demands could be misrepresented.

[3] Vehicle-to-grid (V2G) charging is also a managed charging strategy. V2G allows for bi-directional power flow between the vehicle and grid such that the vehicle can both discharge energy to the grid and charge from the grid. We do not model bi-directional power flow from the vehicle to the grid (V2G) or participation in ancillary services [123], because of the low marginal benefits and greater complexity and transaction cost of these strategies relative to just one-directional charging [124], [125].

Previous work [46] demonstrates significant differences in timing and magnitude of loads when PEVs have access to unlimited chargers versus to the actual limited number of installed chargers; when chargers are abundant, charging is evenly distributed between morning and evening peaks, whereas charging occurs primarily in the evening with limited chargers. Studies including [44], [127], [135] assume PEVs park at certain locations and times, presuming they are plugged into a VGI-enabled charger [136], thereby potentially overestimating availability by ignoring actual charger scarcity. Secondly, neglecting to model PEV loads endogenously within the dispatch of a RE-dominated wholesale electricity market may skew the demand for, and therefore the value of their grid services. [44] uses a purely engineering input-output method to model the system, [52] conducts a macro-level supply-demand matching analysis, and [132] uses non-PEV loads and RE profiles as the only grid-related model inputs. These approaches may inflate VGI value by ignoring electricity market dynamics and competing sources of flexibility in the dispatch such as stationary storage and gas generation.

As a result, the existing literature lacks realistic estimates of managed charging services, and their value in a power system such as California's with a high share of RE. Building on other studies, we compare grid impacts from managed and unmanaged PEVs, while representing constrained infrastructure, mobility, and the dynamic electricity market. We first use a novel agent-based travel behavior model—Behavior, Energy, Autonomy, Mobility (BEAM) [46], [137]—that represents PEV drivers' charging choices given constrained infrastructure. Agent-based models are seen as best to capture neglected traveler behaviors [138], and are distinguished by: 1) simulating individual drivers (agents) in a virtual transportation system with a detailed road network and 2) dynamically representing agents' behavior contingent on the virtual environment and each other. Agents' choices are based on empirical studies of human behavior. We then link the outputs of BEAM with PLEXOS, a unit commitment and economic dispatch model, to simulate PEV charging within the grid at an hourly resolution. PLEXOS is an industry-standard software developed by Energy Exemplar and used by system operators worldwide [139] for simulating grid operations, including to model VGI [128], [129], [140], [141]. PLEXOS uses mixed integer optimization to minimize the cost of meeting load given physical (e.g. generator capacities, transmission limits) and economic (e.g. fuel prices, start-up costs) parameters. Through this integration of BEAM and PLEXOS, we compare unmanaged charging to smart and TOU charging under four scenarios of PEV adoption ranging from 0.95 million (4% of the current California automobile fleet) to 5 million PEVs (20% of the current fleet).

Section 2 describes the two models and their linkage, and the methodology and data for each PEV charging scenario. Sections 3 and 4 discuss the 2025 California hourly and annual results, conclusions, and policy implications.

2. Methodology, Data, and Scenarios

Figure 3 illustrates our VGI methodology, beginning with the BEAM mobility model, continuing with the scaling of individual PEVs' charging sessions to 2025 California-wide, and ending with the PLEXOS grid simulation with scenarios of PEV charging strategies and adoption.

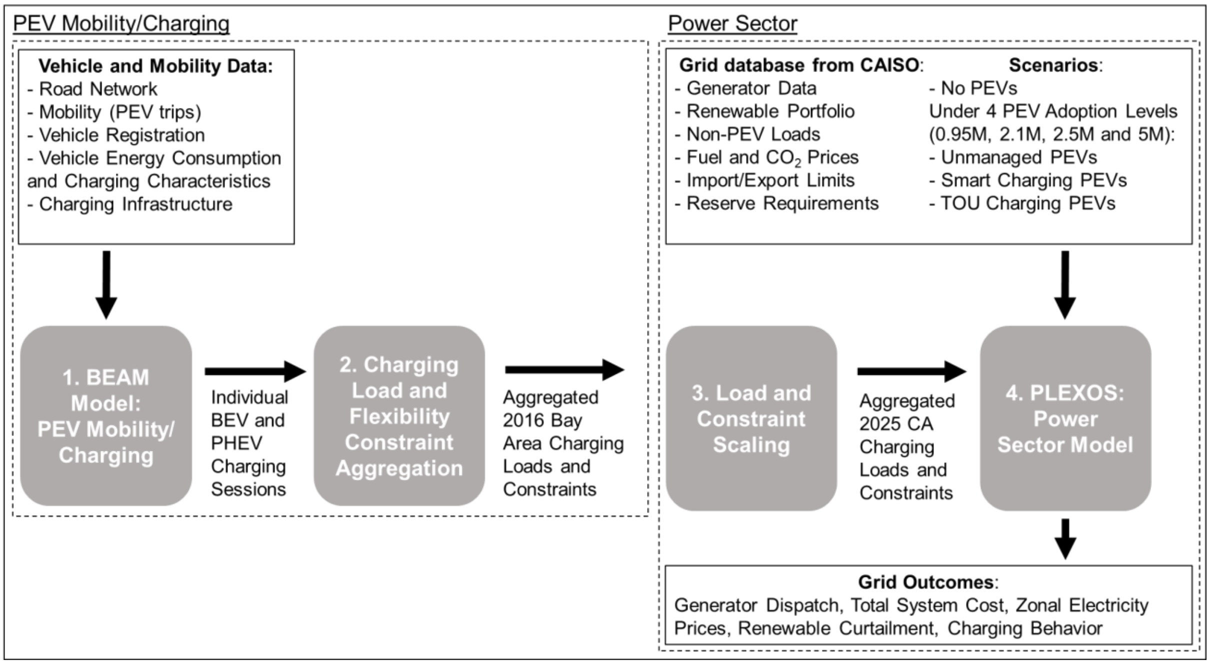


Figure 3. Vehicle-grid integration modeling framework and methodology. The approach links an agent-based mobility model (BEAM) with a unit commitment and economic dispatch model (PLEXOS) to evaluate grid outcomes of PEV charging.

2.1 BEAM: Agent-based PEV mobility and charging model

BEAM is an extension of the open source transportation systems modeling framework Multi-Agent Transportation Simulation (MATSim), which simulates individuals and their detailed interactions with the transportation system. Prior work describes MATSim and BEAM in depth [46], [137], [138]. BEAM simulates the daily travel patterns of individual drivers (where and when people drive between home, work, shopping mall, etc.) in their personal vehicles. These agents make their trips in a PEV and make charging-related decisions to maximize their utility by considering their battery's state of charge (SOC), their remaining mobility needs for the day, their location, the number of accessible chargers at a site, the level of chargers, the cost, and the distance to their next activity [46]. BEAM's charging behavior model contains terms that simulate the difference between PHEVs and BEVs; charging away from home provides less utility to PHEV drivers, reflecting a lower sense of urgency to top off their battery. The BEAM simulation outputs data from each PEV's charging sessions including: charging session start and end time, end time of active power delivery, charging location, charger level, energy delivered (kWh), and maximum power of the charger and vehicle's charge controller (kW). With these outputs we construct PEV charging scenarios (Section 2.3) for PLEXOS.

Table 1: Key assumptions used in BEAM modeling for the San Francisco Bay Area.

PEV Vehicles and Characteristics [A]						
Make/Model	Type	Battery capacity (kWh)	Fuel economy (kWh/mi)	L2 Charging limit (kW)	DCFC Charging limit (kW)	# Vehicles
NISSAN LEAF	BEV	45	0.30	7.0	50.0	16,598
CHEVROLET VOLT	PHEV	28	0.31	7.0	50.0	10,804
TESLA MODEL S	BEV	113	0.33	20.0	120.0	10,102
TOYOTA PRIUS PLUG-IN	PHEV	12	0.29	7.0	20.0	8,599
FIAT 500e	BEV	37	0.29	7.0	50.0	3,989
FORD FUSION	PHEV	11	0.34	3.3	-	4,168
FORD C-MAX	PHEV	11	0.35	7.0	-	3,490
BMW I3	BEV	50	0.27	7.4	50.0	2,721
GEM - Various Models	BEV	19	0.20	-	-	1,806
VOLKSWAGEN E-GOLF	BEV	36	0.29	7.2	50.0	1,516
FORD FOCUS	BEV	50	0.32	6.6	-	1,265
CHEVROLET SPARK EV	BEV	30	0.28	3.3	50.0	921
TOYOTA RAV4 EV	BEV	63	0.44	10.0	50.0	764
All other BEVs	BEV	*41*	*0.37*	varied	varied	888
All other PHEVs	PHEV	*17*	*0.47*	varied	varied	858
Electric Vehicle Miles Traveled [B]						
Vehicle Type	eVMT	Comments				
BEVs	11,000	Average annual electric vehicle miles traveled per vehicle. Used to scale electricity demand for aggregated fleet for whole year, and based on assumption that all batteries are 50% higher capacity in 2025 than they are in 2016.				
PHEVs	7,600					
Charging Infrastructure [C]						
Market Sector	Level	# Chargers	Charging limit (kW)			
Residential	L2	68,489	Typically 7 kW, up to 20 kW for some vehicles (see [A])			
Workplace	L1	330	1.92 kW			
Workplace	L2	4,900	Typically 7 kW, up to 20 kW for some vehicles (see [A])			
Workplace	DCFC	210	Typically 50 kW, up to 120 kW for some vehicles (see [A])			
Public	L1	130	1.92 kW			
Public	L2	900	Typically 7 kW, up to 20 kW for some vehicles (see [A])			
Public	DCFC	160	Typically 50 kW, up to 120 kW for some vehicles (see [A])			

Battery capacities are for 2025 (scaled 50% larger than 2016 levels). "All other BEVs" and "All other PHEVs" values represent weighted averages. Sources: A. Scenarios, Evaluation, Regionalization, and Analysis model by National Renewable Energy Laboratory, Original Equipment Manufacturer specifications, and U.S. Department of Energy fuel economy website; B. San Francisco Bay Area Metropolitan Transportation Commission and California Air Resources Board; C. U.S. Department of Energy Alternative Fuels Data Center and ChargePoint data.

BEAM simulates mobility and charging behaviors for the approximately 68,000 BEVs and PHEVs registered in the San Francisco Bay Area in 2016. The number of vehicles and their spatial distribution are based on ownership estimates from the Scenarios, Evaluation, Regionalization, and Analysis (SERA) model developed by the National Renewable Energy Laboratory (NREL) [142]. PEV attributes are based on Original Equipment Manufacturer (OEM) specifications and the U.S. Department of Energy (DOE) fuel economy website [143]. Driver mobility is from the San Francisco Bay Area Metropolitan Transportation Commission's (MTC) activity-based travel demand model [144], [145]. The drivers' charging preferences are calibrated to observed 2016 charging session data received from ChargePoint, the largest charging infrastructure provider in the United States (Ch. 1 Appendix Table D1). We assume San Francisco Bay Area driving behavior is representative of other parts of California. According to MTC, the daily per capita vehicle miles traveled (VMT) in the San Francisco Bay Area (24.8) are almost equivalent to that of Los Angeles (23.7) [146]. Congestion levels are also very similar; in 2017, drivers in both metropolitan areas spent 12% of total driving time in congestion

[147]. More explicitly modeling driving behavior across California is an area for future refinement.

The charging infrastructure is modeled in detail in BEAM to include the number of parking spaces with physical access to chargers, resulting in the formation of queues at occupied chargers. We assume all drivers have a charger at home [148] and include a relatively small share of other chargers based on Alternative Fuels Data Center and ChargePoint data; we model about 5,400 workplace chargers (Level 1, Level 2 and DC Fast chargers), 1,200 public chargers (Level 1, Level 2 and DC Fast chargers), and 68,000 residential chargers (Level 2) for the San Francisco Bay Area (Table 1) [149]. In two infrastructure sensitivity analyses, we assess potential impacts on our results of additional workplace chargers (Ch. 1 Appendix A), and different DC Fast charging assumptions (Ch. 1 Appendix B).

To reflect anticipated technology improvements and subsequently higher PEV utilization by our 2025 study year, we assume the PEV fleet has battery capacities—and therefore a driving range—1.5 times greater than that of the original 2016 fleet. For example, the Nissan Leaf's second-generation model (2017-present) has a range of 1.5 times the range of a 2016 Leaf. Evidence suggests that the electric vehicle miles traveled (eVMT) is strongly correlated to battery capacity and vehicle range [150], [151] and we therefore also scale the resulting charging load of the aggregated fleet to correspond to the larger batteries. While proportional scaling of aggregated load does not completely account for the timing and charging power associated with increased travel demand, this approximation maintains the temporal distribution of individual vehicle loads developed within BEAM. This adjustment corresponds to BEVs driving 11,000 electric-miles and PHEVs driving 7,600 electric-miles on average per vehicle owner, annually. Given the rapidly evolving PEV market, we evaluate the implications of an even greater share of high-range PEVs (Ch. 1 Appendix B).

There are several limitations of the BEAM version used in this analysis. BEAM is calibrated to charging behavior from 2016 ChargePoint data, which may differ by 2025. The calibration data also excludes Teslas, and therefore BEAM may over-represent the behavior of lower range vehicles, especially in the frequency of residential charging (although 961 residential chargers were included in the data). Additionally, PEV energy consumption in BEAM is derived from a simple calculation based on the average fuel economy of the vehicle and BEAM does not consider other forms of mobility, such as electrified ride-hailing.

2.2 PLEXOS: Power sector dispatch model

PLEXOS performs a unit-commitment and economic-dispatch simulation using mixed-integer programming and the Xpress-MP 28.01.13 mathematical solver [152] to minimize an objective function of operating costs, subject to constraints including imports, generator capacities, and a linearized DC optimal power flow [139] (Ch. 1 Appendix C). We populate PLEXOS with the scaled PEV loads and constraints from BEAM and data from a California stakeholder-validated database originally created by the California Independent System Operator (CAISO) for the state's 2024 grid planning process [153]–[155]. We use a version released in November 2016 that CAISO updated with a 50% RPS RE portfolio and 2025 loads [154], [155]. Additional information on the CAISO database is described in regulatory documents [153]–[156]. Several studies have been conducted with variants of the same database [104], [157]–[159].

The PLEXOS simulation covers the Western U.S. grid, or Western Electricity Coordinating Council (WECC) geography, and is a zonal model such that the transmission network is broadly represented as paths between utility zones and not as individual lines. There are 25 utility zones, including eight in California [153]. California loads and distributed rooftop solar PV estimates come from a California Energy Commission (CEC) forecast [154], [160]. The total annual 2025 load for the California utility zones, net of distributed solar PV and energy efficiency, is 298 TWh. We remove 6.1 TWh of PEV load[4] included in the original load forecast to avoid double-counting when adding the PEV loads from BEAM [162]. Non-California loads come from the WECC Transmission Expansion Planning Policy Committee (TEPPC).

The 125 TWh RE portfolio (Table 2) in this analysis is forecasted by CAISO to meet a 50% RPS mandate (based on [153], [154], [160], [163]). We set PLEXOS to curtail California in-state solar PV, wind, and solar thermal generation if electricity prices reach a -$150/MWh floor price, the lower limit for economic bids in the CAISO market [153], [164].

Table 2: RE capacity and available annual generation in 50% RPS scenario.

	Biogas	Biomass	Geothermal	Small Hydro	Large Solar PV	Small Solar PV	Solar Thermal	Wind	Total
Capacity (MW)	228	635	2,076	986	19,316	2,073	1,021	14,649	40,986
Energy (GWh)	1,511	4,120	15,775	3,104	53,611	4,995	2,412	39,779	125,307
% of RE	1.2%	3.3%	12.6%	2.5%	42.8%	4.0%	1.9%	31.7%	100%

RE generation and capacity values include RPS-eligible out-of-state capacity. Source: California Independent System Operator.

We model the conventional thermal and hydro generators as specified in the CAISO database, including several generic fossil generators that represent authorized new plants expected to be built by 2025 in California [153], [154], [165], and excluding California's remaining nuclear plant whose license expires by 2025 [166]. Generators are characterized in PLEXOS by start-up and shut-down times and costs, operations and maintenance (O&M) costs, heat rates, emissions rates, and energy limits for hydropower. Fuel prices vary by generator location, using natural gas price forecasts from the CEC for California and natural gas and coal prices from TEPPC for the rest of WECC [153], [154]. The GHG price we include from CAISO is $20.75/metric ton CO_2-eq, which is added to California fossil generators' variable generation cost [153]. Per the CAISO's methodology, for resources imported from outside California, except dedicated imports, a CO_2 cost adder is added to the transmission wheeling charge [153]. We also include 1,300 MW of stationary storage mandated in California [153], [167], and non-PEV demand response [153].

California's hourly net exports are constrained such that exports minus imports cannot exceed 2000 MW [156]. We also model dedicated imports to California entities, including from certain fossil and large hydropower resources, and 70% of out-of-state RPS-eligible RE [153]. Regulation and load-following reserve requirements are calculated by CAISO based on variability and forecast error in load and RE [168]. Renewable generators can provide up to half of their energy as downward load-following reserves, satisfying up to half the downward load-following requirement [154].

For each PEV scenario (Section 2.3), we run PLEXOS deterministically, one month at a time for a full year. Each run first optimizes over a month-long time horizon to accommodate generators with monthly energy limits, and then conducts daily chronological optimizations to

[4] The CEC generated this PEV load forecast based on their 2025 mid-case vehicle adoption scenario, assuming 75% of charging occurs 10pm to 6am [161].

balance load by dispatching generation for each hour. PLEXOS co-optimizes for energy and reserves provision to achieve a minimum cost result. The optimization is run to globally minimize costs across all generators in the WECC area, but our analysis focuses on results for California.

The PLEXOS solution for 2025 for each scenario includes hourly generator dispatch, RE curtailment, zonal prices, and California imports/exports. We calculate the California total system cost, often referred to as production cost, by summing costs of generation (from fuel, startup/shutdown, and variable O&M) and emissions (for CO_2) for all generators in California. Because the state is a net electricity importer from neighboring regions [153], we include the hourly import costs and export revenue (negative costs) by adding the product of net interstate power flows and the electricity price in the utility zone receiving the power [169]. Finally, we add the total system costs from out-of-state generators serving as dedicated exporters to California. Since our focus is on operational impacts of PEVs and we hold infrastructure fixed, our California total system cost calculation does not include capital costs, such as for building new generators. We also do not include distribution system costs. Even at higher PEV penetrations, distribution system upgrades are forecasted to contribute only a small component of California utilities' costs [170]. Lastly, our study's hourly resolution is standard for dispatch models, but could slightly underestimate ramping costs [171] and prevents study of intra-hour impacts of PEV charging for which more research is warranted.

2.3 PEV Adoption and Charging Strategy Scenarios

We run the PLEXOS optimization with constant grid parameters (Section 2.2) under 1 base case scenario with no PEVs included and under 12 PEV scenarios (Table 3) that each test a charging strategy at a range of California PEV adoption from a CEC forecast [172]. "Low" (0.95 million) and "High" (2.5 million) scenarios represent CEC's estimate if PEV prices remain more or less expensive than gasoline vehicles, and "Mid" (2.1 million) scenarios are CEC's estimate of "most likely compliance" with California's ZEV Program[5] [172], [173]. We add "Reach" scenarios (5 million) to estimate impacts of very aggressive PEV market transformation, which would achieve the Governor's extended target.

Table 3: Scenarios of 2025 California PEV adoption and energy.

PEV Adoption [A]				
	Low	Mid	High	"Reach"
Number of BEVs (60% of PEVs)	570,000	1,260,000	1,500,000	3,000,000
Number of PHEVs (40% of PEVs)	380,000	840,000	1,000,000	2,000,000
Total Number of PEVs	950,000	2,100,000	2,500,000	5,000,000
PEVs % of Current CA Auto Stock	4%	8%	10%	20%
Annual PEV Loads [B]				
	Low	Mid	High	"Reach"
Unmanaged charging load (GWh)	2,728	6,030	7,179	14,358
TOU charging load (GWh)	2,728	6,030	7,179	14,358
Smart charging load (GWh)	2,744	6,062	7,215	14,417
PEV Load as % of CA Load	1%	2%	2%	5%

A. Total Number of PEVs is from California Energy Commission (CEC) 2015 California Energy Demand Forecast for 2016–2026, assumed split 60% BEVs and 40% PHEVs. The Current Auto Stock assumed is 25.5 million registered automobiles from

[5] The California ZEV Program regulation (in place in some form since 1990) requires that each automaker hold a certain number of ZEV credits, which reflects the share of ZEVs produced out of the total number of cars the manufacturer sold in California each year. Each ZEV vehicle produced receives a number of credits based on its range, and automakers with surplus credits can bank or trade credits with other manufacturers [117]. The California Governor's executive orders setting 1.5 million and 5 million ZEV targets are complementary policies to accelerate ZEV adoption.

California Department of Motor Vehicles. B. Annual PEV Loads is the scaled load from BEAM. The PEV load as % of CA load is of 292 TWh of California load in the PLEXOS model, net of solar PV, energy efficiency and PEV loads. Smart charging total loads are <1% more than the unmanaged and TOU loads due to the load shifting efficiencies assumed for the smart charging storage resource in the PLEXOS dispatch.

Scenarios:

- *Base case scenario*: No PEVs included in California load.
- *Unmanaged charging scenarios*: Low (0.95 million), Mid (2.1 million), High (2.5 million), Reach (5 million) PEV adoption, all PEVs charging unmanaged.
- *Smart charging scenarios*: Low (0.95 million), Mid (2.1 million), High (2.5 million), Reach (5 million) PEV adoption, all PEVs participating in an aggregator-based smart charging program.
- *TOU charging scenarios*: Low (0.95 million), Mid (2.1 million), High (2.5 million), Reach (5 million) PEV adoption, all PEVs responding to a residential overnight off-peak TOU rate.

We do not forecast customer participation rates for any charging strategy because the scenarios are meant to characterize the maximum potential wholesale market value—under more realistic mobility, charging infrastructure, and grid assumptions—if all California PEVs participated in a given charging strategy. Therefore, our results are the foundation for future work to assess benefits of specific smart charging or TOU tariff designs. Sections 2.3.1 and 2.3.2 describe how the scenarios are constructed with BEAM and PLEXOS.

2.3.1 Modeling PEV charging strategy scenarios in BEAM

2.3.1.1 Unmanaged charging

Charging sessions are first simulated for individual vehicles in BEAM as unmanaged, such that a PEV starts charging as soon as it is plugged in, and we record the energy delivered during each session as the unmanaged load for an individual PEV.

2.3.1.2 Smart charging

We use outputs from the BEAM unmanaged charging simulation to construct individual vehicle energy and power constraints for smart charging, similar to the methodology of [47]. These constraints characterize a flexible resource to be dispatched by PLEXOS (Section 2.3.2.2). We assume smart charging PEVs are plugged-in at the same times as if unmanaged, but that the timing of active charging within those periods is flexible as long as the delivered energy is equivalent to that of the unmanaged case. Smart charging flexibility is thereby limited to within individual charging sessions, rather than across different sessions. We assume that 1) drivers' travel needs are too highly valued and their plans too inflexible to charge at entirely different times of the day because chargers are not universally available, 2) drivers do not unplug immediately after active charging ends unless there is a queue, and 3) drivers have sufficient foreknowledge and willingness to indicate their expected departure times for an aggregator to schedule active charging (similar to [174]). We do not model drivers leaving earlier than expected, but only 5% of BEV charging events in BEAM start with a critically low remaining range of 20 miles or less; these BEVs would only need to charge on average 36 uninterrupted minutes to reach a 20-mile minimum in case of unexpected early departure.

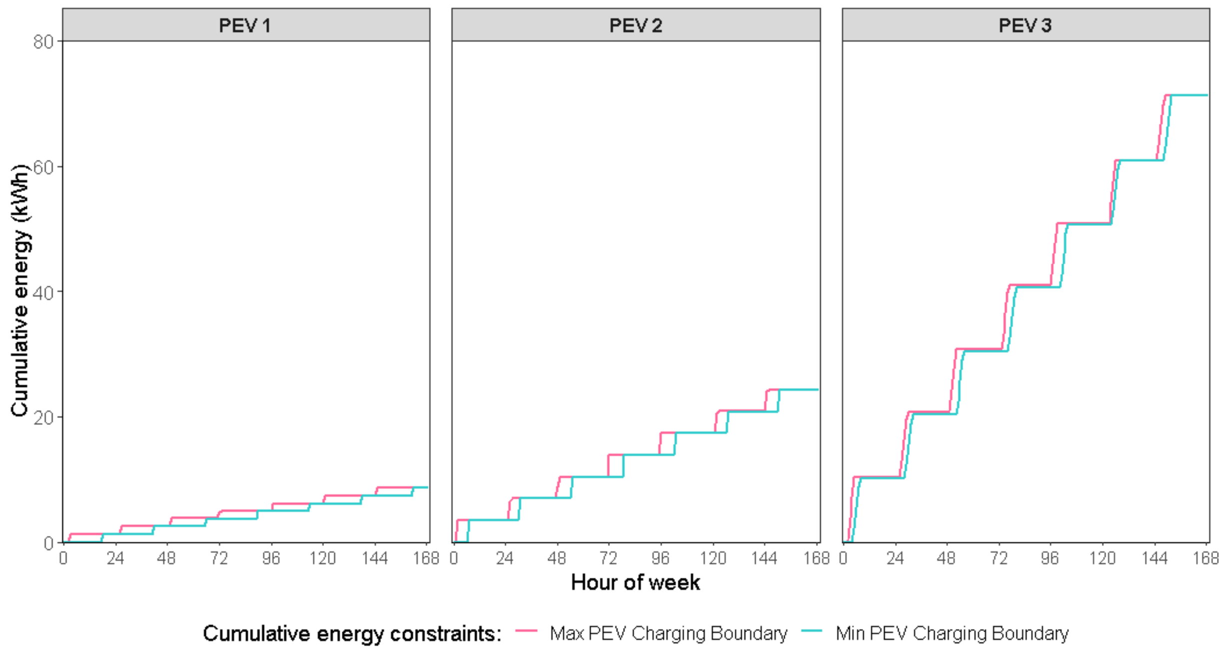


Figure 4. Illustrative sample smart charging constraints of 3 individual PEVs. Maximum (upper line) and minimum (lower line) cumulative energy constraints bound possible smart charging trajectories for three representative PEVs in the first week of the BEAM simulation.

The cumulative energy delivered for unmanaged charging is the maximum constraint, representing the earliest possible charge, for each smart session. The minimum cumulative energy constraint assumes that active charging is delayed until the last possible moment, while still delivering equivalent energy by the end of the session, as in [174]. For three representative PEVs, Figure 4 illustrates an example of the maximum (earliest) and minimum (latest) smart charging cumulative energy constraints for a week of the BEAM simulation. Within the area bounded by these curves, any monotonically increasing trajectory can be achieved with smart charging, subject to the target SOC and the maximum power of the PEV and charger. The curves meet between charging sessions. In BEAM, the probability that drivers charge at home each day is based on a distribution derived from ChargePoint data, in which the average residential charger was used 93% of the days.

2.3.1.3 Overnight time-of-use charging

We represent the response to TOU rates in a second BEAM simulation by forcing the charging sessions to begin at staggered times (to avoid inducing a sudden demand spike) between 10 PM and 2 AM—approximately the range of start times of California's current residential off-peak rate periods [175]–[177]—for those PEVs that would already be plugged in overnight at home if unmanaged. Within BEAM, we record the energy delivered during each PEV's TOU session. We do not explicitly model a TOU electric rate but assume the off-peak price would be sufficiently low to incentivize all drivers to pre-program charging for those times. PEV drivers enrolled in current California TOU rates are very responsive to off-peak periods, especially with a large peak/off-peak price differential [121], [178].

2.3.2 Representing PEV charging scenarios in PLEXOS

2.3.2.1 Aggregation of PEV charging loads and constraints

For the unmanaged and TOU charging scenarios we aggregate the loads, and for the smart charging scenarios we aggregate the constraints, across the individual vehicles in BEAM by summation [174]. For each scenario, we do this summation separately for BEVs and PHEVs for the San Francisco Bay Area. These aggregated loads and constraints from a typical weekday (the second day of a three-day BEAM run) are used to construct a full week based on observed ChargePoint charging data. This construction occurs by repeating the full day of hourly loads from BEAM seven times to create a week, and then scaling the profiles separately by charger location (residential, workplace, and public) to match the normalized daily average loads from ChargePoint by charger location. Weekend loads are adjusted to mimic the observed ChargePoint weekend load shapes. These weekly loads and constraints are repeated to create an annual data set for San Francisco Bay Area.

These aggregated San Francisco Bay Area loads and flexibility constraints produced by BEAM for the three charging strategies in 2016 are then increased linearly by vehicle type (BEV and PHEV) to represent the eight California utility zones modeled in PLEXOS in 2025. The scaling occurs in two parts: 1) first by the ratio of the current San Francisco Bay Area PEV stock to that of each California utility area from the California Vehicle Rebate Program (CVRP) data [116], and then 2) by the ratio of the current California-wide stock totaled from CVRP data compared to a CEC state forecast ranging from 0.95 million to 2.5 million PEVs for 2025, and a "Reach" adoption level of the Governor's targeted 5 million PEVs [179] (Section 2.3). Because the state forecast is reported for PEVs in aggregate, we assume that 60% of the 2025 stock will be comprised of BEVs and 40% of PHEVs, similar to trends found in the CVRP data [116]. Finally, the annual loads for the TOU cases are normalized to equal the annual unmanaged loads for each level of PEV adoption, allowing for results comparison across charging strategies. Implicit in this overall scaling process of PEV loads from the San Francisco Bay Area in 2016 to California in 2025 is that the state's charging infrastructure will continue to grow, such that the proportion of chargers to vehicles is the same as current levels. Given the planned large-scale infrastructure investments [110]–[112] and the Governor's goal of installing 250,000 additional chargers by 2025, we think this is a reasonable assumption [109]. The final loads for each PEV adoption scenario are shown in Table 3.

2.3.2.2 Incorporating PEVs into PLEXOS

For the unmanaged and TOU charging scenarios, for each utility zone we add the aggregated and scaled 2025 PEV load to the non-PEV load as a fixed load profile in PLEXOS. We model smart charging loads in PLEXOS as the sum of a fixed load plus net generation of a dispatchable storage resource. The fixed load is the unmanaged PEV load for each utility. The storage resource for each utility is dispatched as part of the PLEXOS WECC-wide optimization to either discharge energy during high priced times (equivalent to PEVs not charging when unmanaged vehicles would have otherwise charged) or consume energy during low priced times (equivalent to PEVs charging when unmanaged vehicles would not have charged). This represents load shifting a collection of PEVs by an aggregator in a smart charging program. The storage resource starts full at the beginning of each PLEXOS simulation, and if not dispatched by the optimization, the smart load equals the load of the unmanaged scenario.

We constrain the total size (in GWh) of the smart charging storage facility to be the largest difference between the maximum and minimum energy constraints of the aggregated PEVs in each utility zone (from Section 2.3.2.1). We limit the storage resource's SOC to be greater than the hourly difference between the maximum and minimum cumulative energy constraints of the aggregated vehicles. We enforce time-varying maximum power constraints on discharging the storage resource, corresponding to the unmanaged load. The time-varying maximum power constraint for charging the storage resource depends on the capacity of all grid-connected PEVs and available chargers in each hour under unmanaged charging. We set the round-trip efficiency of the storage resource to 99% (instead of 100%) so that PLEXOS first dispatches a zero-marginal-cost generator before the flexible smart charging load. Because the PLEXOS simulation runs one month at a time, we account for edge effects by constraining the storage resource to return to the starting SOC by the end of each month.

3. Results and Discussion

3.1 Hourly Grid Impacts

For the same level of PEV adoption, even with PEVs comprising 1% to 5% of total California loads (Table 3), the PLEXOS results show the choice of charging strategy noticeably impacts hourly grid operations, in terms of net load shapes, hourly RE curtailment, and wholesale electricity prices.

Figure 5 illustrates these key system outcomes averaged hourly across three seasonally representative months of grid operation with 2.5 million PEVs; results are similar with other adoption scenarios. The majority of the unmanaged PEV load occurs between 3pm and 11pm (row B), after the predominant commute home. Unmanaged charging yields higher prices (row D) and exacerbates the evening peak of the system's load net of solar PV, solar thermal, and wind generation (row A). TOU charging, by design, is concentrated overnight at home starting at 10pm and lasting until the early morning (row B). TOU charging creates smoother prices (row D), and avoids peak load times (row A) but also most RE curtailment (row C). In contrast, smart PEVs, as dispatched by PLEXOS, charge in the late morning and the late afternoon (row B) to reduce RE curtailment especially in spring (row C), surging again when prices drop around 11pm (row D). This pattern follows the timing of low-priced generation (row D) of solar PV during the day and wind plus baseload plants overnight.

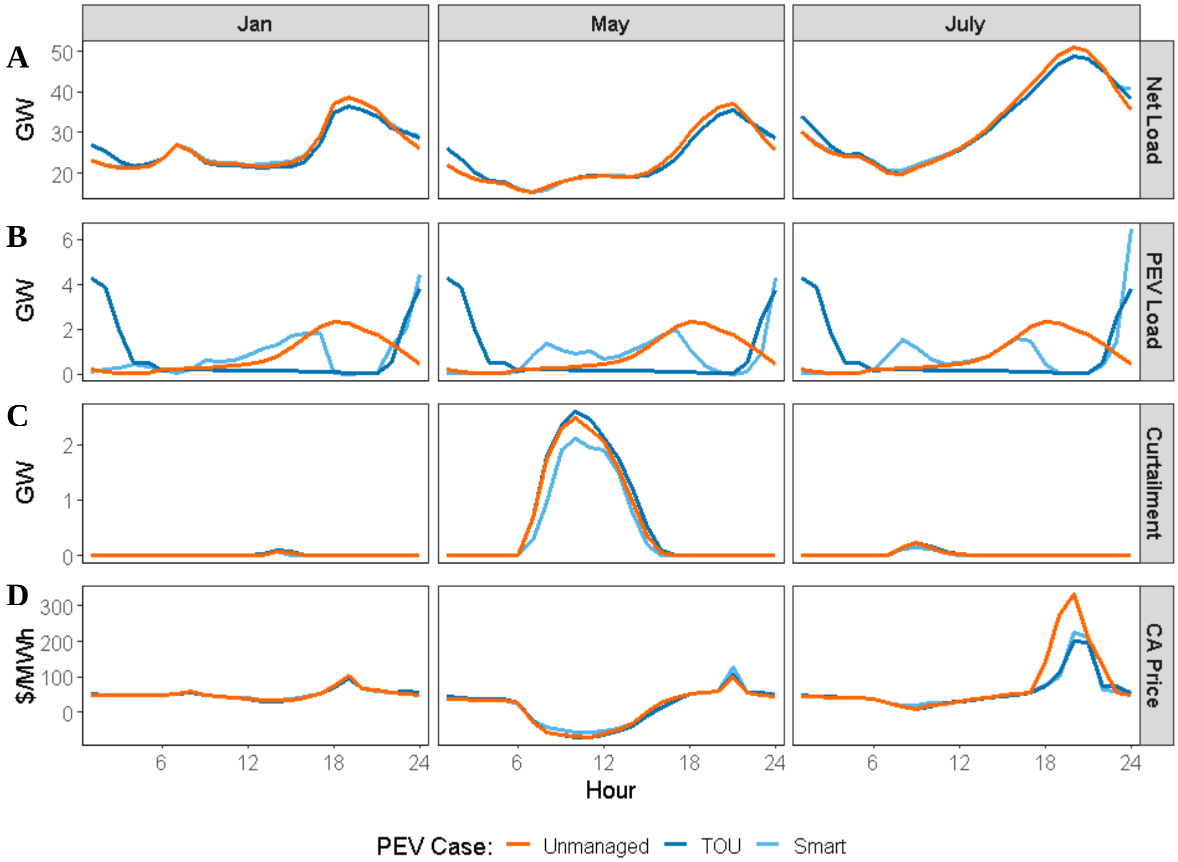


Figure 5. California net load, PEV charging, RE curtailment, and average prices with 2.5 M PEVs. These figures are for 2.5 million PEVs and outcomes averaged hourly across three seasonally representative months of grid operation; results are similar with other PEV scenarios. A. California system load net of solar PV, solar thermal, and wind generation; B. Unmanaged, TOU, and smart charging PEV loads; C. Curtailment of California solar PV, solar thermal, and wind generation; D. Load-weighted average price of California utility regions.

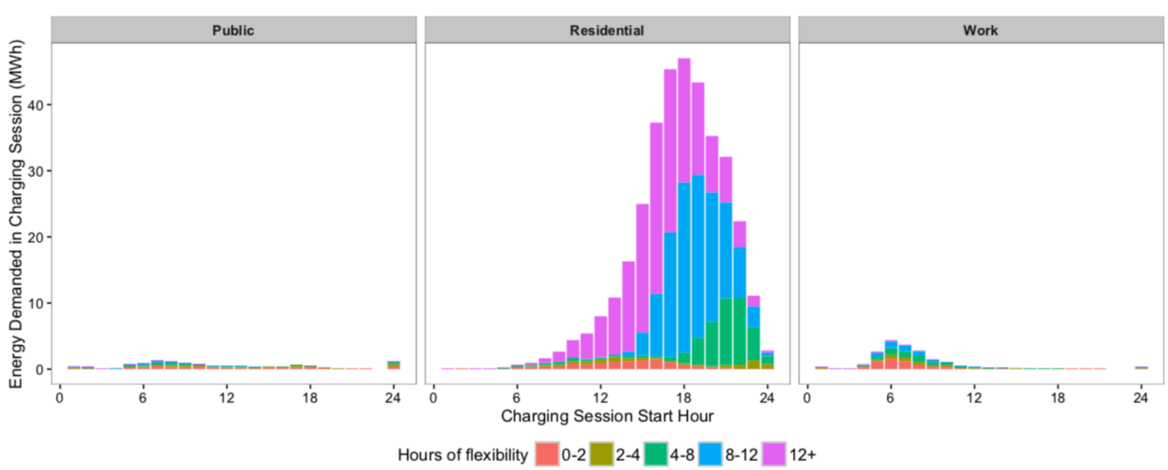


Figure 6. Weekday charging session flexibility duration and energy demanded by location and hour. The panels show for a typical weekday in the San Francisco Bay Area BEAM simulation (before scaling to California 2025 levels), the energy demanded by location and the hours of flexibility to shift load within charging sessions (based on the time between active charging and unplugging).

Figure 5 suggests smart charging is the most favorable strategy for California hourly grid operations because of its flexibility to lower net load peak, smooth prices, and reduce curtailment. Subsequently, this study's linked transportation model can identify when and where PEVs can supply such hourly flexibility to target VGI policies, subject to mobility needs and charger availability. For a typical weekday in the San Francisco Bay Area BEAM simulation (before scaling to California 2025 levels), Figure 6 shows the energy demanded in unmanaged charging sessions and the duration of availability flexibility, based on the time between the end of active charging and unplugging. Most charging sessions occur at home in the afternoon and during grid peak hours. These residential sessions have the greatest flexibility (12+ hours) to shift charging and therefore contribute most of the smart charging benefits we see in the hourly outcomes (Figure 5). In contrast, there are relatively few charging sessions at work or public locations, and those sessions, concentrated in the mid-morning hours, have much less flexibility since drivers are both parked for shorter times and have queues that require unplugging immediately after active charging. A sensitivity testing the addition of four and eight times more workplace chargers shows only a minor increase in energy demanded and hours of daytime flexibility (Ch. 1 Appendix A).

Together, these results suggest that in terms of location and timing, residential smart charging policies are the most efficient way to capture the majority of hourly grid flexibility. Even when there is remaining RE curtailment and negative pricing in the middle of the day (Figure 5)—which would be ideal times to shift additional PEV loads—the marginal value from increased smart charging at work or public chargers appears limited. These results appear robust to a higher buildout of DC Fast chargers: with a 20-fold increase in public DC Fast charging sessions, the number of charging-hours that can be shifted only decreases 3% and most flexibility still occurs at home (Ch. 1 Appendix B). Similarly, if the 2025 PEV fleet includes a greater share of high-range vehicles, we expect marginally less morning charging and slightly shorter duration evening flexibility but not a significant change to overall grid costs and curtailment (Ch. 1 Appendix B).

3.2 Annual Grid Impacts

The following section compares the annual total system cost and renewable curtailment impacts for California, resulting from hourly charging and grid interactions for each of the PEV scenarios.

Table 4: California annual total system costs and renewable curtailment results.

California total system costs [A]									
	Total system costs ($ Millions)					Avoided cost relative to Unmanaged ($ Millions)		Share of Incremental Cost Avoided (%)	
PEV Scenario	Base	Unmanaged	Smart	TOU		Smart	TOU	Smart	TOU
No PEVs	6,514	-	-	-		-	-	-	-
Low	-	6,711	6,592	6,620		119	91	60%	46%
Mid	-	6,946	6,738	6,778		208	168	48%	39%
High	-	7,024	6,783	6,829		241	195	47%	38%
Reach	-	7,792	7,104	7,244		688	548	54%	43%
California renewable energy curtailment [B]									
	Curtailment (GWh)					Curtailment relative to Unmanaged (GWh)		Curtailment relative to Unmanaged (%)	
PEV Scenario	Base	Unmanaged	Smart	TOU		Smart	TOU	Smart	TOU

No PEVs	1,347	-	-	-		-	-	-	-
Low	-	1,274	1,155	1,324		-119	50	-9%	4%
Mid	-	1,191	953	1,294		-238	103	-20%	9%
High	-	1,164	902	1,287		-262	123	-23%	11%
Reach	-	1,013	608	1,230		-405	216	-40%	21%

A. Total system costs reflects the grid operating cost and includes the cost of generation and emissions for power plants located within California and the out-of-state import cost and export revenue. Avoided cost relative to Unmanaged is the difference in cost between the Unmanaged and Smart (or TOU) cases. Share of Incremental Cost Avoided is the Avoided cost relative to Unmanaged divided by the cost increase between the Unmanaged and No PEV cases for each PEV adoption scenario. B. Curtailment is of California's solar PV, solar thermal, and wind generation. Curtailment relative to Unmanaged (GWh) is the difference in curtailment between the Unmanaged and Smart (or TOU) cases. Curtailment relative to Unmanaged (%) is the avoided curtailment divided by the curtailment under the Unmanaged case for each PEV adoption scenario.

3.2.1 Total System Cost

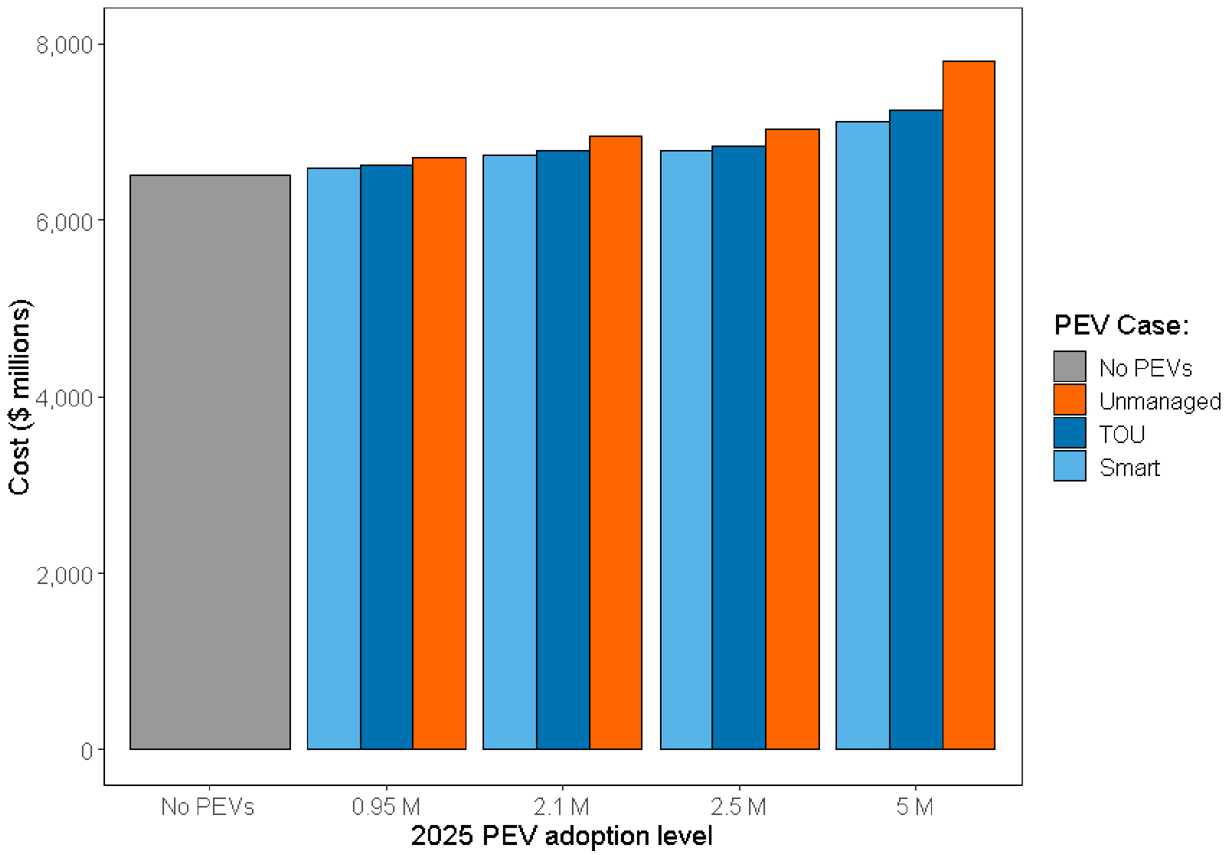


Figure 7. Annual California total system cost. Annual total system cost for California includes the grid operating cost from generation, emissions, and net imports.

When PEVs are added to the grid, California's annual total system costs (grid operating costs described in Section 2.2) increase in all scenarios because of additional generation used to meet load. However, for the same number of vehicles, the charging strategy significantly affects the degree to which costs increase. The difference in total system cost increases from smart or TOU charging compared to unmanaged charging are what we consider the value of a given managed charging strategy.

We find that smart charging provides the greatest annual value among the charging strategies tested. Smart charging avoids $120 to $690 million of California total system cost increases per year with 0.95 million to 5 million PEVs, compared with the same number of unmanaged vehicles (Figure 7, Table 4). Therefore, by managing PEVs with smart charging, California can save about 50% of the incremental cost of adding the new vehicle loads to the grid. Across the state, these savings are significant, on the order of 2% to 10% of California's total system costs with 0.95 to 5 million smart PEVs, respectively. While smart charging results in lower total system costs than with TOU charging, similar to the findings of [52], the difference in value between the two strategies is not large. Compared to unmanaged charging, TOU charging provides California $90 to $550 million in value per year. Consequently, these cost savings compared to unmanaged charging amount to 1% to 8% of California's annual total system cost with 0.95 to 5 million TOU charging PEVs.

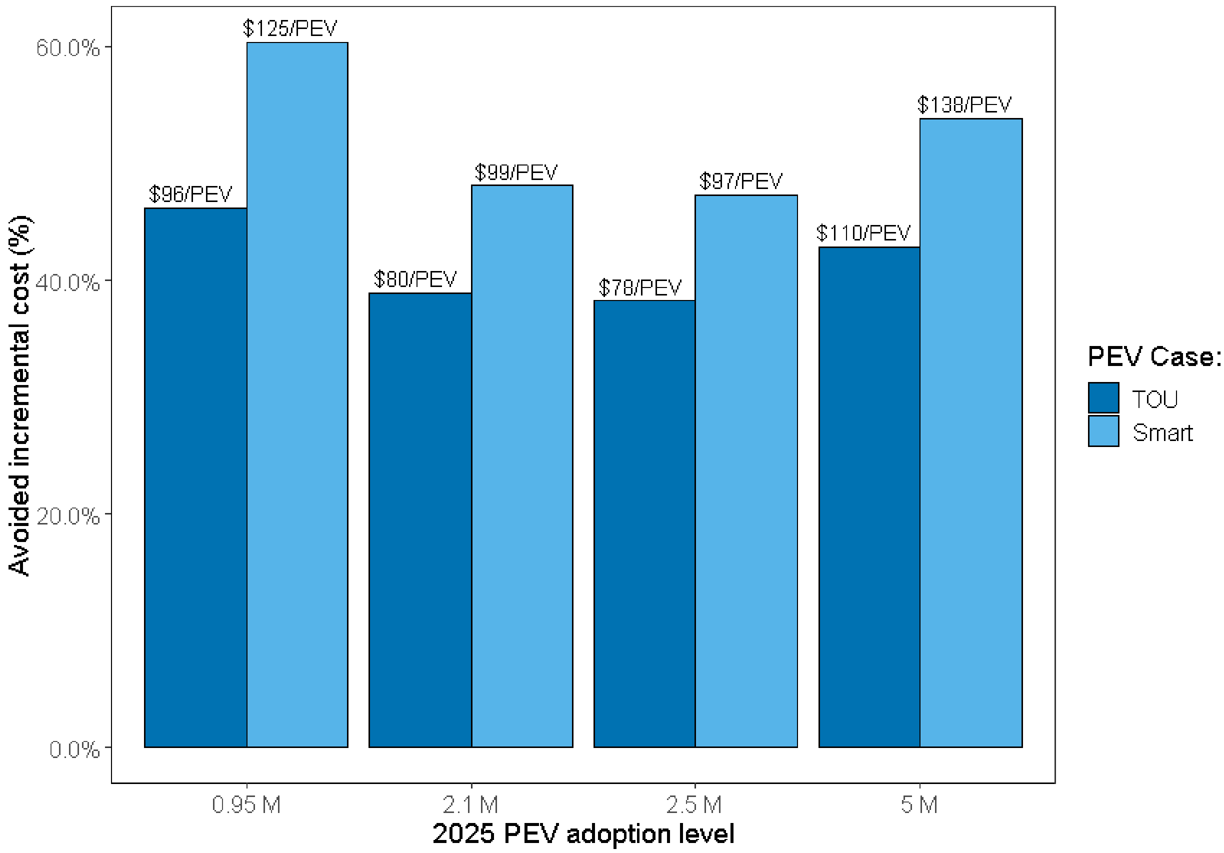


Figure 8. Avoided total system cost increases relative to Unmanaged PEVs. Avoided incremental cost percentage is the incremental cost from smart or TOU charging divided by the incremental cost of unmanaged charging. The per-PEV system cost savings from smart charging and TOU charging is the annual avoided incremental cost divided by the number of PEVs for each adoption scenario.

Across PEV adoption levels, smart charging incurs lower system costs relative to unmanaged charging because of lower peak loads (less expensive generators are used) and because more PEV load is served by RE (Ch. 1 Appendix Table D.2). TOU charging decreases system costs relative to unmanaged charging because of reduced load (Figure 5)—and thus reduced ramping primarily from natural gas generation—during evening peak demand hours. Under both managed charging strategies, the system dispatches less demand response to reduce peak loads and displaces some use of stationary storage (Ch. 1 Appendix Table D.2), increasing the option value, or the opportunity for future use, of these flexible resources for other grid needs.

With both managed strategies, the share of unmanaged charging costs that are avoided and the per PEV value are non-linearly related to increasing levels of PEV adoption. When divided by the number of PEVs assumed for each scenario, the total system cost savings are relatively low, averaging about $120/PEV per year with smart charging and about $90/PEV per year with TOU charging (Figure 8). We note, however, that this value would be spread more broadly across ratepayers and is not necessarily what would accrue directly to drivers; the driver savings from managed charging would also depend on factors including the enablement cost for demand response aggregators of smart charging and the particular level of TOU rates. Because this analysis takes the societal perspective and focuses on statewide wholesale market value, we do not simulate specific business models or rate designs to determine monetary benefits at the customer level. To fully evaluate the customer impacts, future research must also quantify additional value streams of managed charging, such as from avoided investment in infrastructure upgrades or distributed stationary storage, which also may make managed charging more financially attractive to drivers [180].

Consistent with [127], our results also show that at very high PEV levels, both smart and TOU charging strategies can defer capital costs for building new generating and transmission capacity. If 5 million PEVs are deployed, unmanaged PEV charging stresses the system peak to the point that about 2,500 MWh of load are unserved in California over two days in July, while smart or TOU charging PEVs can still be accommodated by existing generators without any unserved load. In our simulation, when there is not enough generation to meet load (within a utility zone or with imports), a zone's electricity price spikes, up to the level of a market ceiling price set at $2000/MWh. Because we calculate California's total system cost to include price times net imports into the region, the high total system cost for unmanaged charging with 5 million PEVs—and the greatest per PEV value for smart and TOU charging—is driven by the increased imports during spikes of California regional market prices around this price ceiling. These results show that without a charge management policy, California's grid as it is planned for 2025 may reach a saturation point at the state's 5 million PEV goal and require added resources to avoid unserved energy.

3.2.2 RE Curtailment

VGI policies that reduce RE curtailment are favorable because curtailment—although a reliable way to maintain grid stability—raises a system's operating cost and is an inefficient use of RE assets [10]. Curtailment is often invoked because of transmission congestion, but also occurs when must-run inflexible resources and minimal levels of thermal generation exceed load minus exports [181]. Lowering curtailment can increase investor confidence in developing future RE projects, and enable emissions reductions [182]. Our results show that smart charging is best able to shift load to times with excess RE, when power is priced negatively. With 0.95 to 5 million PEVs, compared with unmanaged vehicles, smart charging lowers annual RE curtailment by an additional 9% to 40%, or about 120 to 410 GWh, respectively (Figure 9, Table 4). Dividing the avoided curtailment by the annual PEV load, it is estimated that with smart charging about 4% of PEV load is served by RE energy that would have otherwise been curtailed if the vehicles were left unmanaged (Ch. 1 Appendix Table D.3). In contrast, across all PEV adoption scenarios TOU charging results in more curtailment than does unmanaged charging, because most of the RE generation, dominated by solar PV, does not coincide with overnight

PEV load. For TOU charging to reduce curtailment, off-peak periods may need to be augmented with more hours that overlap with solar generation.

Because utilities consequently deliver less RE to comply with regulations, curtailment also necessitates additional RE capacity or resources such as energy storage, quickly ramping generators, or flexible loads to compensate [105], [106], [164]. The additional monetary value of curtailment reductions therefore depends on the avoided capital cost of overbuilding RE plants and the cost of alternative curtailment-reduction measures. Although we find that annual curtailment even with unmanaged charging is only 1.4% to 1.1% of RE generation (Ch. 1 Appendix Table D.3), more study is needed of future higher RE levels when PEV charging may play a much more significant role in reducing curtailment and thus overall costs and emissions in California.

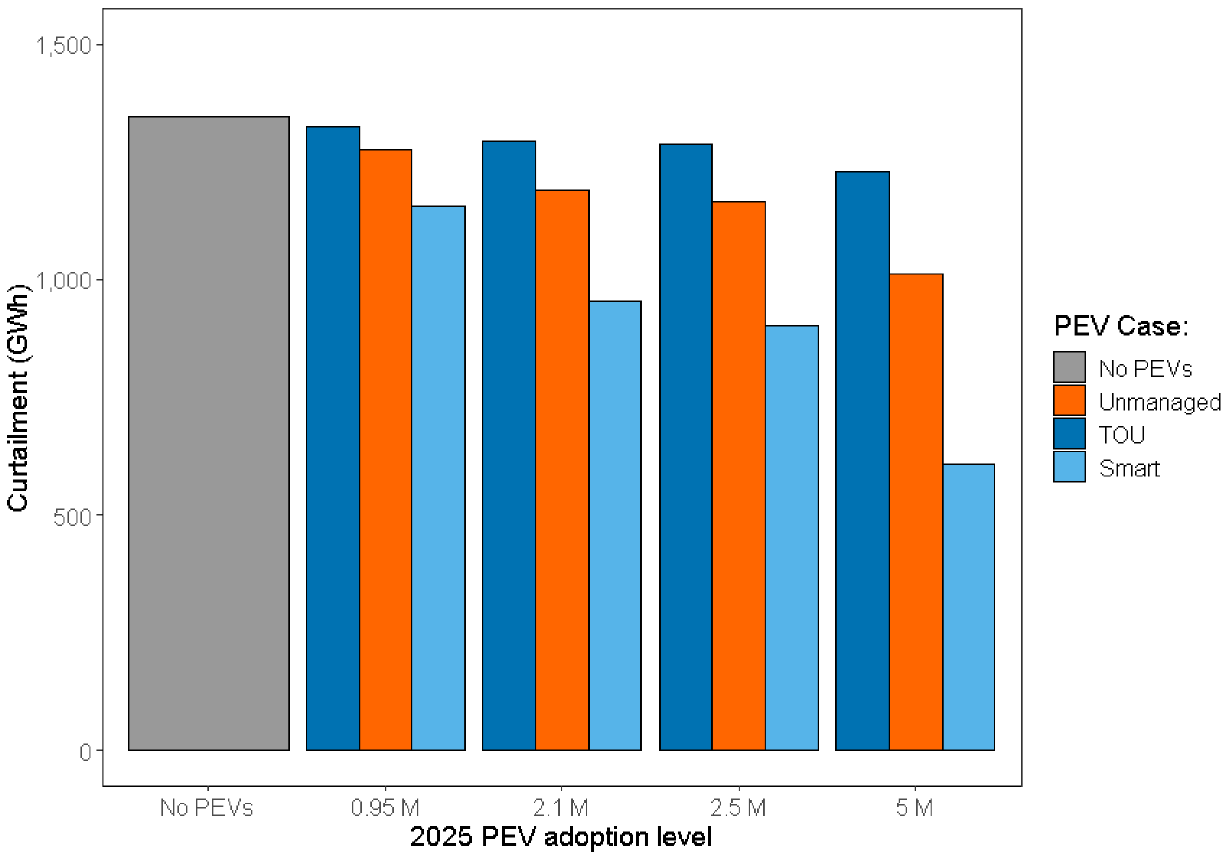


Figure 9. Annual California renewable energy curtailment. Annual curtailment of California in-state solar PV, solar thermal, and wind generation for each charging strategy and PEV adoption scenario.

4. Conclusions and Policy Implications

Previous literature, including [44], [127], [52], [128], [129], [53], [130], [132], shows managed charging can save on grid costs and reduce RE curtailment. However, most prior work does not fully account for constraints on mobility, charging infrastructure, and grid dispatch, thereby estimating benefits which may not be achievable. This study improves on these models through more robust and realistic simulation of both the transportation and power sectors, to represent the hourly impacts and annual wholesale market value and curtailment that California policymakers can expect with large scale PEV and RE adoption. We find unmanaged charging coincides with peak loads and yields higher prices, while smart charging occurs during low-priced times to avoid peaks and lower curtailment; TOU charging also reduces peak impacts. Annually, even with our more realistic assumptions, California can save between $120 to $690 million of grid operating costs by managing PEVs with smart charging, and $90 to $550 million with overnight TOU charging. The introduction of practical limitations further reduces the average per-vehicle value of these managed charging strategies to the order of $100 per PEV annually compared to the $100 to $300 per PEV range seen in previous studies [43]. Nonetheless, the aggregate VGI values still make a significant difference for the California system: comprising up to about 8% or 10% of the state's 2025 expected grid operating costs, making managed charging overall a beneficial policy for the state to pursue. Especially at the 5 million PEV penetration ultimately targeted by state, some form of charge management becomes essential to avoid new generation or transmission investments. Lastly, smart charging lowers the cost of achieving California's RE targets through curtailment reductions. Overnight TOU charging is counterproductive to RE integration efforts because it results in higher annual curtailment than even unmanaged PEVs.

In terms of hourly grid impacts, annual total system cost savings, and RE curtailment reductions, we find that smart charging is overall a more valuable managed charging policy for California. Our detailed mobility model demonstrates most flexibility exists at residential locations rather than at work or public locations. This residential flexibility contributes nearly all the smart charging value by avoiding evening peak times and utilizing solar generation. Therefore, smart charging targeted at residential customers, who typically already have home chargers, appears to be the biggest opportunity and most cost-efficient policy for the state. Many chargers available today can be upgraded for smart charging for about $100, and some PEV models have smart charging software onboard [132], [122]. However, for residential smart charging to be implemented at a large scale, careful consideration is needed to design programs that monetize multiple value streams [180], [183] to increase driver participation incentives and overcome other consumer adoption barriers including perceived restricted mobility, concerns about data privacy, and aversion to new technologies [47], [49], [184]–[186]. Smart charging pilots have highlighted the importance of customer education on RE benefits, and of guaranteeing minimum charge levels [122], [184], [187].

Overnight TOU rates achieve the majority of smart charging cost savings, have been effective among current adopters [121], and may have fewer customer acceptance barriers [188], however, our results show they are detrimental for RE integration. Given these tradeoffs, California might additionally consider a policy adjusting residential TOU off-peak periods to include some daytime hours and to establish daytime commercial TOU rates to capture a greater share of RE. Some utilities are moving towards these rates to produce curtailment reductions that cannot be achieved with overnight charging [189]. Further work on impacts of these new TOU rates is needed and on market segmentation for PEV flexibility to account for customer heterogeneity in desired levels of user involvement, financial subsidy, and environmental benefit [185], [190], [191].

These estimates of VGI value are California-specific and will also depend on the evolution of the generation mix (such as higher RE levels), curtailment-reduction policies (such as better coordination with neighboring areas), distributed energy resources (such as other "smart" loads), and flexible supply-side resources (such as stationary battery storage). However, the relative value of managed compared to unmanaged PEVs is applicable to other systems considering both high PEV and RE deployment. We conclude that regions with dual transportation electrification and grid decarbonization policies can benefit from hybrid smart charging and TOU strategies to avoid grid operating costs, RE curtailment, and capacity expansion.

Chapter 2: The future of California’s Energy-Water-GHG Nexus

Chapter 2 introduces the concepts of cross-sectoral interactions between the electricity system the water system, also known as the energy-water nexus. This analysis evaluates the combined impact of emerging trends on California’s water (including population growth, climate change, and policies to promote water efficiency and alternative water supplies) and electricity (including generation decarbonization) on the state’s water-related energy and GHG footprints from 2015 to 2035. The analysis builds on prior work that last evaluated the water sector’s state-wide energy footprint almost 20 years ago, and on regional or sectoral analyses that did not look at (1) both urban and agricultural water trends across all of California or (2) consider the widespread and connected nature of the state’s water infrastructure in aggregate. This analysis tests scenarios of future water demand and climate to evaluate the sensitivity of the energy and GHG footprints to conservation efforts and climate impacts. The work in this chapter includes selections of a technical report titled, “The Future of California’s Energy-Water-GHG Nexus” that I wrote with co-authors Sonali Abraham, Heather Cooley, and Peter Gleick. The report will be published by Next 10 in collaboration with the Pacific Institute in September 2021, and the copyright to the report is owned by Next 10. The chapter is included in this dissertation with permission from Next 10 and my co-authors.

---

1. Introduction

California's energy and water systems are closely connected. Water is a key input for energy production, and energy is integral to all aspects of water management and use in California. About 18% of California’s electricity generation has come from hydropower on average [192], and water is also used to cool thermoelectric power plants. Prior studies have estimated that in California nearly 20 percent of annual statewide electricity use, a third of non-power plant natural gas consumption, and 88 billion gallons of diesel fuel consumption are related to water – from collection and treatment to use (such as water heating) and wastewater management [55]. The State Water Project – which pumps water from Northern California to communities across the state including over the Tehachapi Mountains to Southern California – is the single largest electricity user in the state [193]. These interdependencies are commonly referred to as the water-energy nexus.

Many factors affect California’s water demand and supply portfolio, and the implications of multiple, ongoing changes to the state’s water resources on future energy use are not well understood. California’s urban water demand has been declining significantly with time, decoupling water use from population growth and economic output in the state [56]. At the same time, ongoing water-scarcity concerns and continued population growth are prompting water planners to pursue alternative, local water-supply options [57], many of which are more energy-intensive than traditional water sources, but still less energy-intensive than imported water [58]. Similarly, declining water quality and new contaminants are leading water suppliers to adopt more energy-intensive treatment options like UV purification, ozonation, and reverse osmosis. In the agricultural sector, water use has stayed relatively flat since the 1980s while the economic value of crop production has increased significantly [56]. However, groundwater pumping, heavily relied on by the agricultural sector, is increasingly energy-intensive as groundwater levels fall in many parts of the state [59]. Climate change, with impacts on water availability, quality, and demand [60], is likely to accelerate these trends.

Water and energy trends in California also affect greenhouse gas (GHG) emissions for the state. Shifts in water supplies and demands affect energy usage related to water and the GHG emissions associated with that energy usage. In California, electricity generation, the main energy source for the provision and treatment of water, is undergoing structural reform to decarbonize. The state has committed to reach 100% carbon-free electricity by 2045, including intermediate requirements of 50% renewable generation by 2026 and 60% renewable generation by 2030 [194, p. 100]. However, water heating is the most energy-intensive end-use of water and is still largely done using natural gas water heaters. Therefore, energy programs in the state have begun to provide incentives for switching natural gas water heaters to more efficient and less GHG-intensive electric heat pump water heaters [195]. These complex interactions between changing water supply and demand trends, grid decarbonization, and electrification of water heaters will affect California's water-related GHG emissions.

There are several options for reducing the energy and GHG footprint related to California's water. These include reducing water demand, adopting water sources with low energy requirements, and using renewable energy sources. For example, the East Bay Municipal Utility District's (EBMUD) wastewater treatment plant produces more renewable energy onsite than is needed to run the facility, selling excess energy back to the electrical grid. Some local water-supply strategies, such as Los Angeles' plans to source an increased share of water supplies from recycled water, are energy-intensive, but may offset even more energy-intensive imported water supplies. In the agricultural sector, there is an opportunity for energy savings with higher efficiency groundwater pumps, especially in Central Valley regions where the energy intensity of groundwater pumping may increase from current levels, at the proposed minimum thresholds allowed by the 2014 Sustainable Groundwater Management Act (levels of groundwater beyond which any reduction would cause undesirable effects in the basin).

There is a need to update prior estimates of the water-related energy and GHG footprint of the urban and agricultural sectors in California given the complex set of trends likely to affect water and energy systems in the coming decades. This study builds on previous studies [55], [61]–[65] to address this need.

First, we develop a comprehensive assessment of the energy and GHG footprint related to water in California. We examine statewide and regional trends in water supply and demand for the urban and agricultural sectors, and calculate associated energy use and GHG emissions under various future water scenarios. Second, we offer a set of policy recommendations drawn from the scenario analysis for reducing California's water-related GHG and energy footprint.

Section 2 of this chapter outlines the energy, GHG, and water data and analysis methodology. Section 3 presents results of the energy and GHG emissions associated with California's urban and agricultural water. Section 4 provides conclusions and recommendations.

2. Analysis methodology and data

Energy is required for all stages of the managed water cycle, from extraction or generation to conveyance, treatment, distribution, end-use, wastewater collection, and wastewater treatment (Figure 10). Our analysis of the energy and GHG emissions related to this managed water cycle is comprised of four steps: 1) identification of the energy intensities associated with each stage of this water management cycle, 2) calculation of the GHG intensity of each energy source related to water, 3) development of scenarios of future water supplies and demands for the urban and agricultural sectors, and 4) application of the energy and GHG intensities to historical water volumes and each scenario of future water volumes. Given data availability, we evaluate the urban and agricultural water sectors separately, and we analyze 2015 historical data and project future scenarios in 5-year intervals for 2020, 2025, 2030, and 2035. Each step of the analysis is described in detail below.

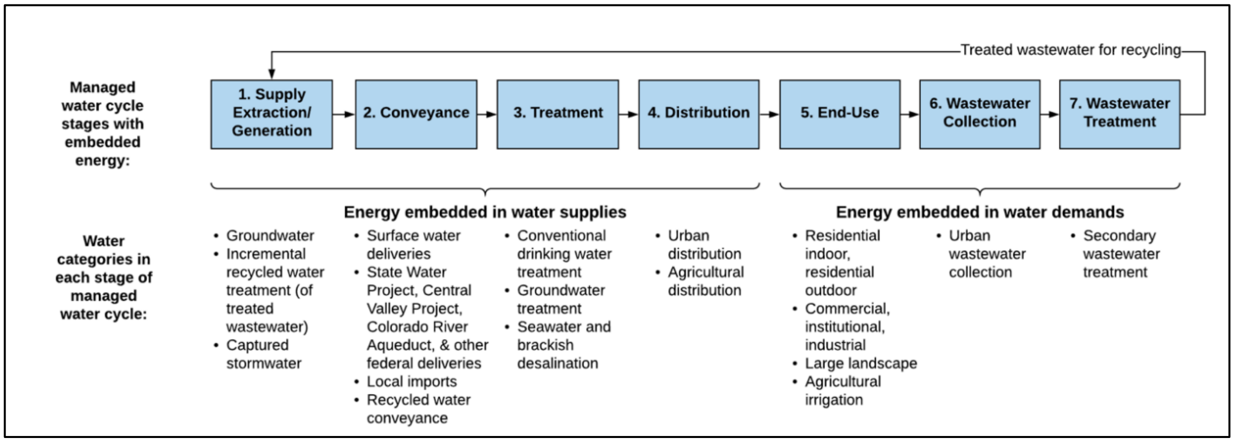


Figure 10. Stages of the water cycle with embedded energy.

2.1 Energy intensity of California's water

Following a similar approach to Cooley et al. (2012) and Diringer et al. (2019) [196], [197] to track the total embedded energy of the managed water system, energy intensity values (energy use per unit volume of water in units of kWh/acre-foot (AF) for electricity and MMBtu/AF for natural gas) are assigned for the extraction, conveyance, and treatment of historical and projected water sources, and for the distribution, end-use, wastewater collection, and wastewater treatment based on end-use sector (urban and agriculture) for each of California's 10 hydrologic regions.[6] These energy intensities are summed to calculate the total embedded energy in a particular water source and water demand category and for the system as a whole. We use data from Urban Water Management Plans (UWMP) and from the Department of Water Resources (DWR) to identify water source and demand categories for the urban and agricultural sectors, respectively (details in Section 2.3).[7]

[6] The 10 hydrologic regions are North Coast, San Francisco, Central Coast, South Coast, North Lahontan, Sacramento River, San Joaquin Valley, Tulare Lake, South Lahontan, and Colorado River.
[7] We are constrained by the "water supply" and "water demand" categories included in these urban and agricultural water datasets. In cases where supply categories cannot be attributed to a specific water source, we make assumptions as noted below.

2.1.1 Mapping Water Categories to Energy Use

We first map the urban and agricultural water supply and demand data to the relevant stages of the managed water cycle (Figure 10), starting with categories of water sources (Table 5) and then water demands (Table 6). We focus on electricity usage throughout each of the stages, and only evaluate natural gas usage for water-heating, which is the largest natural gas user related to California water [55]. The energy intensity of recycled water, which does not fit easily in this framework, is detailed at the end of Section 2.1.1.

Table 5. Energy intensity categories applied to water sources.

	Water Cycle Stages Related to Water Sources		
	1. Extraction or Generation	2. Conveyance	3. Treatment [a]
Water Sources			
Desalinated Water (Seawater)		Seawater Desalination Conveyance	Seawater Desalination Treatment
Desalinated Water (Brackish)	Groundwater pumping		Brackish Desalination Treatment
Exchanges		Local Imported Deliveries	Conventional Drinking Water Treatment
Groundwater	Groundwater pumping		Conventional Drinking Water Treatment
Other		Local Surface Water Deliveries	Conventional Drinking Water Treatment
Central Valley Project Deliveries		Central Valley Project Deliveries	Conventional Drinking Water Treatment
Colorado River Deliveries		Colorado River Deliveries	Conventional Drinking Water Treatment
Other Federal Deliveries		Local Imported Deliveries	Conventional Drinking Water Treatment
State Water Project Deliveries		State Water Project Deliveries	Conventional Drinking Water Treatment
Recycled Water (Indirect Potable Reuse)	Recycled Water (Potable) Treatment	Recycled Water Conveyance	Conventional Drinking Water Treatment
Recycled Water (Non- Potable)	Recycled Water (Non-potable) Treatment		
Captured Stormwater	Groundwater pumping		Conventional Drinking Water Treatment
Supply from Storage		Local Surface Water Deliveries	Conventional Drinking Water Treatment
Surface water		Local Surface Water Deliveries	Conventional Drinking Water Treatment
Local Imports		Local Imported Deliveries	Conventional Drinking Water Treatment
Transfers		Local Imported Deliveries	Conventional Drinking Water Treatment

[a] Energy intensity values for treatment of water supplies to drinking water standards are only applied to water supplies for the urban sector. We assume water used in the agricultural sector does not receive potable treatment.

1. Water Extraction or Generation: Following the framework of Cooley et al. (2012) [196], water supply extraction includes the energy required to pump groundwater from its source to Earth's surface. Energy intensities depend on the depth of groundwater relative to the surface and on the pump efficiency. We also apply the energy intensity for groundwater pumping to captured stormwater because in some cities, such as Los Angeles, stormwater is used to recharge aquifers and requires pumping for extraction [198]. We also add groundwater energy intensities for desalinated brackish water, which is typically pumped from aquifers before it is conveyed to a desalination treatment plant. Because of limited availability of detailed data, we assume that all groundwater pumps are electric. However, we note that this may slightly overestimate electricity use, and underestimate GHG emissions because a small portion of groundwater pumps in California use diesel or natural gas, which are both more GHG-intensive than California's current and projected electricity mix [199].[8]

This category also includes the energy to "generate" water supplies, namely the incremental treatment of wastewater to recycle it for either potable or non-potable reuse, which is described in more detail at the end of Section 2.1.1.

2. Water Conveyance: Energy for water conveyance includes the energy for pumping, lifting, and transporting raw or partially-treated water that is at the Earth's surface from its source to the drinking water treatment plant (for the urban sector) or directly to the distribution system (for the agricultural sector). The energy for water conveyance primarily depends on the lift (elevation) of the water pumped and on the pump efficiency. Conveyance energy is included for deliveries from the state's major inter-basin water transfers including the State Water Project (SWP), Central Valley Project (CVP), and Colorado River Aqueduct (CRA); local imports (water transferred by local water suppliers from other regions of California); and local surface water deliveries. For inter-basin conveyance projects (SWP, CVP, CRA) we use the energy intensity values for the furthest delivery point within a given hydrologic region. If there are multiple branches of a project within the same region, we calculate a volume-weighted average energy intensity across the delivery points in the region. In addition, average hydropower generation per unit of water volume on any conveyance project is subtracted from the energy intensity, to represent a net value of energy required [64, p. 1].[9] Supplies labeled as 'Other Federal Deliveries,' 'transfers' or 'exchanges' are assigned the same energy intensity as local imports, because the UWMP data do not typically include more detailed information about these categories. Supplies labeled as 'Other,' 'Supply from Storage,' or 'Return Flows' are similarly assigned the same energy intensity as local surface water. For potable recycled water, we also assign an energy-intensity for conveyance (pumping) from the wastewater treatment plant to the drinking water treatment plant [201], via an environmental buffer as detailed at the end of Section 2.1.1.[10] Finally, for desalinated seawater, we include the energy requirements for conveyance of ocean feedwater to the desalination plant.

3. Water Treatment: Water used in the urban sector is assumed to be treated to drinking water standards and is assigned a drinking water treatment energy. For all water sources (including deliveries from inter-basin water projects, local imports, and stormwater), an average energy intensity for conventional water treatment is assigned.[11]

---

[8] We believe our simplification is appropriate given that the 2018 Irrigation and Water Management Survey by the U.S. Department of Agriculture found that 90% of on-farm well pumps and other irrigation pumps are electric, and only 8% of on-farm well and other irrigation pumps are diesel in California. The remaining 2% of pumps are powered by natural gas or other fuels [200].

[9] Electricity generated from hydropower plants on SWP and CVP conveyance projects is also included in the calculation of the GHG intensity of California's total electricity generation, however, the contribution by conveyance project hydropower to statewide GHG intensity is nominal relative to the total emissions from all electricity in the state.

[10] We use a simplifying assumption of a uniform energy intensity for conveyance of treated potable water from the wastewater to the treatment plant across all hydrologic regions. However, the energy intensity may vary widely according to the terrain and decisions regarding buildout, which will affect the total energy requirements of recycled water.

[11] This assumption may overestimate the water treatment for groundwater sources, which in some cases may use a lower level of treatment (typically just disinfection, such as with chlorine) [202].

Desalination of seawater and brackish water is included under the Treatment category. It is assumed that the desalination technology used is reverse osmosis, which is most common worldwide and for existing and proposed plants in California [67]. The energy requirements for desalination to drinking water quality (<500 ppm salinity) are much higher with seawater (35,000 – 45,000 ppm salinity) than with brackish water (1,500 – 15,000). All desalted water in coastal hydrologic regions is assumed to come from seawater, and desalted water in inland hydrologic regions is assumed to come from brackish groundwater.

Supplies for the agricultural sector are assumed to not receive treatment to potable standards [201] and therefore have no treatment energy intensities assigned.

Table 6. Energy intensity categories applied to water demand sectors.

	Water Cycle Stages Related to Demand Sectors			
	4. Demand Distribution	5. Demand End-Use	6. Demand Wastewater Collection	7. Demand Wastewater Treatment
Demand Sectors				
Commercial	Urban Water Distribution	Urban Commercial Water Heating	Wastewater Collection	Wastewater Treatment (secondary)
Industrial	Urban Water Distribution	Urban Industrial Water Heating	Wastewater Collection	Wastewater Treatment (secondary)
Institutional/ Governmental	Urban Water Distribution	Urban Institutional Water Heating	Wastewater Collection	Wastewater Treatment (secondary)
Landscape	Urban Water Distribution			
Losses	Urban Water Distribution			
Other	Urban Water Distribution		Wastewater Collection	Wastewater Treatment (secondary)
Residential-Indoor	Urban Water Distribution	Urban Residential Indoor Water Heating	Wastewater Collection	Wastewater Treatment (secondary)
Residential-Outdoor	Urban Water Distribution			
Agricultural	Agricultural Water Distribution	Agricultural Irrigation		

4. Distribution: Urban water demand volumes are assigned a distribution system energy intensity to represent the energy required to pump and pressurize the water for delivery from the treatment plant to the end-user. This value varies by the distance and steepness of the terrain over which water is pumped (hilly areas require more energy to pump water) [203].

Agricultural water is assigned an energy intensity for pumping and distributing raw water from the primary conveyance or groundwater source to on-farm end-users.

5. End-use: We model energy for water heating in the residential, commercial, institutional, and industrial sectors as the primary urban end-uses, and for irrigation as the primary agricultural sector end-use.

Residential indoor water is assigned electric and natural gas energy intensities for water heating, calculated (Section 2.1.2.1) based on the water temperatures used by different appliances and state average saturation of electric or gas water heaters [204]–[206]. Residential outdoor water use is not assigned an energy intensity for the end-use category. The estimated indoor share of commercial, institutional, and industrial (CII) water volumes are also assigned electric and natural gas energy intensities based on the estimated water temperatures of CII end-use processes. Landscape water is not assigned an energy intensity.

Agricultural end-uses are assigned an average energy intensity for irrigation, which often requires pumping and pressurization. The energy intensity is calculated (Section 2.1.2.2) based on the average share of applied water by crop, the typical energy intensity by irrigation technology, and the average irrigation technology for each crop type.

6. Wastewater collection: Energy is required to collect and move untreated wastewater from end-users to the wastewater treatment plant [207]. As with water distribution, wastewater collection energy requirements depend on the terrain steepness and distance for pumping wastewater to the treatment facility. This energy intensity is assigned to all indoor residential, commercial, and industrial water volumes. Agricultural water is assumed to not require wastewater treatment, and therefore has no energy for wastewater collection.

7. Wastewater treatment: Urban wastewater is assumed to be treated to secondary levels.[12] The energy intensity assigned is an average of requirements across wastewater treatment plant capacities, technologies, and efficiencies for secondary treatment. Wastewater treatment energy intensities are applied to all indoor residential, commercial, and industrial water volumes. Agricultural water is assumed to not require wastewater treatment.

Recycled water: Recycled water does not fit neatly in the linear progression of the managed water cycle steps (Figure 10), because the "source" water for recycled water is treated wastewater. Therefore, the energy for incremental levels of treatment beyond standard, secondary wastewater treatment for recycled water for potable and non-potable reuse is included in the "extraction/generation" category.

Potable recycled water is assumed to be for indirect reuse, which is currently the only permitted form of potable recycled water in the state. With indirect potable reuse, treated recycled water is stored temporarily in either a reservoir (surface water augmentation) or in a groundwater aquifer, which serves as an environmental buffer before the water is conveyed to a conventional drinking water treatment plant and distributed to the end-user [208]. For potable recycled water we assume a treatment train following the Orange County Water District Groundwater Replenishment System, i.e., after secondary treatment at a wastewater treatment plant, water is treated with microfiltration, reverse osmosis, and UV/Advanced Oxidation Processes (AOP). Therefore, for potable recycled water we include conveyance energy to represent water transport to the environmental buffer and to the drinking water treatment plant from the environmental buffer in the "conveyance" category, as well as conventional water treatment in the "treatment" category (Table 5).[13]

Non-potable recycled water is typically reused for irrigation of food crops, non-food crops, and parks or golf courses; cooling; and other industrial uses [209]. The treatment level for non-potable recycled water depends on the use. For example, irrigation of food crops that have an edible part in contact with the recycled water require at least disinfected tertiary treatment,

[12] This energy intensity of wastewater treatment may be an underestimate because there are some treatment plants in the state which use more energy-intensive tertiary treatment.
[13] We note that the energy for pumping water from the groundwater environmental buffer to the surface is not captured in our calculation of the energy intensity of indirect potable recycled water.

whereas irrigation of food crops with the edible portion not in contact with the recycled water (or other uses such as freeway landscape, cemeteries, certain golf-courses) can use disinfected secondary treatment or undisinfected secondary treatment (including vineyards, orchards, not-fruit bearing trees) [209]. For this analysis, non-potable recycled water is assumed to receive disinfected tertiary treatment, and we aggregate the incremental energy requirements for tertiary treatment plus disinfection for its energy intensity value. We also include distribution energy to pump the non-potable recycled water to the end-user using the same energy intensity as for potable water distribution.

2.1.2 Literature review and estimation of energy intensities of California water cycle

We review academic literature and technical reports related to the energy usage of California's water system [55], [58], [61], [64], [65], [73], [202], [203], [207], [210], [211, p. 2] and collect the range of low-, mid-, and high-energy intensity values from each study for each process involved in the water cycle stages described in Section 2.1.1. We use data for each hydrologic region if available; otherwise, we use a statewide value. For all water cycle stages except for end-use, we average the energy intensity values across the studies for each hydrologic region and water cycle process. In this analysis, we use the averages of the "mid" energy intensity values. For both the urban and agricultural sectors, we calculate the energy intensity values for water end-uses as described below, because these data are not available directly from the literature. The final electricity and natural gas energy intensity values we use in this analysis, based on the literature and our calculations, are summarized by hydrologic region and water cycle stage in Table 8.

2.1.2.1 Urban end-use energy intensities

End-use energy intensity for water heating is calculated for residential indoor water use as the product of several parameters. First, we estimate the average fuel share of residential water heaters (approximately 32% electric, 64% natural gas based on Energy Information Administration surveys of the Pacific region [212]). Next, we calculate the energy intensity for water heating based on the specific heat formula, which estimates the thermal energy required to heat a unit of water a certain number of degrees. We calculate the degrees of heating for each end-use as the difference between the average water heater inlet temperature (58 °F) across California cities from a prior analysis [213], and outlet temperatures specific to each water end-use from [196], listed in Ch. 2 Appendix Table 35. For gas water heaters, we apply a typical water heater efficiency of 63% to the thermal energy required, and for electric water heaters we apply an efficiency of 90% to the thermal energy required.[14] We next collect data on the average share of residential indoor water for each end-use, summarized in the Ch. 2 Appendix Table 35 from [206]. Finally, we multiply the fuel share, energy intensity of the water heater for each end-use, and indoor water share for each end-use to estimate a total weighted average energy intensity that is applied to total residential indoor water use (6,800 kWh/AF for electric and 67 MMBtu/AF for natural gas water heaters).[15] The same value is used for residential indoor water

[14] The energy required to heat one 1 kg of water by 1 °C is calculated based on the specific heat formula: $Q = mc\Delta T$, where Q = thermal energy, m= mass of water, c = specific heat capacity of water (4200 Joules/kg/°C), ΔT = change in temperature, calculated as the difference between the California average inlet temperature (58 °F) and the typical temperature for each water end-use. The formula is multiplied by 1/efficiency of the water heater.

[15] We note that the energy requirements for natural gas water heaters are in "primary energy" terms, and therefore not directly comparable to electric water heaters which use "secondary energy" that is generated from primary fuel sources and is subject to generation and transmission efficiency losses.

volumes in all hydrologic regions. Residential outdoor water use is not assigned an energy intensity for the end-use category.

The water end-uses within the CII sectors vary significantly. Here, we focus on the energy requirements for water heating on average across all CII water uses. We first assume an average share of total CII water use in California among different types of processes (i.e., landscaping, laundry, kitchen, industrial process, restroom, cooling, other) based on Gleick et al. (2003), as shown in Table 7. Within each of these processes, we estimate the average share of water to different end-uses based on Gleick et al. (2003) as shown in Ch. 2 Appendix Table 36. Next, we assign temperatures to each end-use in the various process categories (Ch. 2 Appendix Table 36), and use the specific heat formula to calculate the energy intensity of heating to that temperature from the California average inlet temperature (as described for residential heating). We use fuel shares between electric and gas water heaters based on the electric and gas proportions of total commercial floor space that uses heating [214]. Finally, we multiply the process shares, end-use shares within each process, energy intensity of water heating for each process, and the fuel ratios. For electric water heaters, we use the same water heater efficiency value as for residential water heaters, and for natural gas water heaters, we calculate the energy requirements with higher efficiencies (68%) typical of average commercial water heaters [201]. The resulting average energy intensities used for CII water are about 5,200 kWh/AF for electric and 30 MMBtu/AF for natural gas water heating. The same value is used for CII indoor water volumes in all hydrologic regions.

Table 7. Estimated CII Water Use by Process from Gleick et al., 2003.

CII Sub-Sector	Percentage of CII Total Water Use
Landscaping	35%
Laundry	2%
Kitchen	6%
Process	17%
Other	9%
Cooling	15%
Restroom	16%

2.1.2.2 Agricultural end-use energy intensities

Irrigation is the primary agricultural end-use requiring energy. We estimate the average energy intensity for irrigation for each hydrologic region based the regional crop mix and typical irrigation technology by crop. First, we estimate the weighted average energy intensity of irrigation for each crop type, based on irrigation surveys about the typical irrigation technology used for each crop as shown in Ch. 2 Appendix Table 37 [215], and the average energy intensity for each irrigation technology (15 kWh/AF for gravity or flood irrigation, 284 kWh/AF for standard sprinklers, and 206 kWh/AF for drip/micro-irrigation [199]. We find the average applied water for each hydrologic region to each crop type between 1998 – 2002, based on available data on applied crop water from DWR's Agricultural Land and Water Use Estimates [216]. Finally, we multiply the weighted average energy intensity of irrigation by crop with the average applied water volumes by crop for each region to estimate an average energy intensity of irrigation by hydrologic region.

Table 8. California electricity (kWh/AF) and natural gas (MMBtu/AF) energy intensities by hydrologic region, by water cycle stage.

	North Coast	SF Bay	Central Coast	South Coast	Sacramento River	San Joaquin River	Tulare Lake	North Lahontan	South Lahontan	Colorado River
Electricity Energy Intensity (kWh/AF)										
1. Water Generation/Extraction										
Groundwater Pumping	343	453	479	647	350	365	450	320	433	494
Recycled (Indirect Potable) Treatment	1,218	1,218	1,218	1,218	1,218	1,218	1,218	1,218	1,218	1,218
Recycled (Non-potable) Treatment	543	543	543	419	508	508	508	508	508	508
2. Water Conveyance										
Local Surface Water Deliveries	110	110	118	128	118	118	118	110	118	128
Local Imported Deliveries	116	137	44	44	44	44	44	44	44	44
Central Valley Project Deliveries	225	650	726	225	225	334	196	NA	NA	NA
Colorado River Deliveries	NA	NA	NA	2,115	NA	NA	NA	NA	NA	225
State Water Project Deliveries	NA	1,031	2,043	3,280	238	501	2,158	NA	3,505	4,000
Seawater Desalination Conveyance	100	100	100	100	100	100	100	100	100	100
Recycled Water Conveyance	364	364	364	364	364	364	364	364	364	364
3. Water Treatment										
Conventional Drinking Water Treatment	237	237	237	227	235	235	235	235	235	235
Groundwater Drinking Water Treatment	70	70	70	70	70	70	70	70	70	70
Seawater Desalination Treatment	4,503	4,503	4,503	4,503	4,503	4,503	4,503	4,503	4,503	4,503
Brackish Desalination Treatment	1,593	1,593	1,593	1,593	1,707	1,707	1,707	1,593	1,593	1,593
4. Distribution										
Urban Water Distribution	501	977	501	501	54	54	54	54	501	54
Agricultural Water Distribution	144	144	144	488	19	19	389	144	389	488
5. End-Use										
Urban Residential Indoor Water Heating	6,830	6,830	6,830	6,830	6,830	6,830	6,830	6,830	6,830	6,830
Urban Commercial Water Heating	5,245	5,245	5,245	5,245	5,245	5,245	5,245	5,245	5,245	5,245
Urban Industrial Water Heating	5,245	5,245	5,245	5,245	5,245	5,245	5,245	5,245	5,245	5,245
Urban Institutional Water Heating	5,245	5,245	5,245	5,245	5,245	5,245	5,245	5,245	5,245	5,245
Agricultural Irrigation	98	154	175	181	78	116	121	84	91	98
6. Wastewater Collection										
Wastewater Collection	104	104	104	111	111	111	111	111	111	111
7. Wastewater Treatment										
Wastewater Treatment (Secondary)	716	716	716	687	697	697	697	697	697	697

	North Coast	SF Bay	Central Coast	South Coast	Sacra mento River	San Joaquin River	Tulare Lake	North Lahont an	South Lahont an	Color ado River
Natural Gas Energy Intensity (MMBtu/AF)										
5. End-Use										
Urban Residential Indoor Water Heating	67	67	67	67	67	67	67	67	67	67
Urban Commercial Water Heating	30	30	30	30	30	30	30	30	30	30
Urban Industrial Water Heating	30	30	30	30	30	30	30	30	30	30
Urban Institutional Water Heating	30	30	30	30	30	30	30	30	30	30

2.2 GHG intensity of California's water cycle

To calculate the total GHG emissions associated with California's water system, we first calculate the GHG intensity (emissions of carbon dioxide (CO_2) equivalent per unit of energy) of the energy sources powering the water system: electricity (metric tons CO_2 equivalent/MWh) and natural gas (metric tons CO_2 equivalent/MMBtu).

The GHG intensity of electricity depends primarily on the regional fuel mix of generation. Because of policy targets in California like the Renewable Portfolio Standard (RPS), which requires a certain percentage of electricity be generated from renewable sources like solar and wind, electricity generation in California has a relatively low GHG intensity compared to neighboring states. The state passed Senate Bill 100 (SB 100) in 2017, which accelerated existing RPS targets for electricity and now requires 60% of electricity generation from renewable sources by 2030, and 100% of electricity from zero-emissions sources by 2045 [194]. California does import electricity from outside the state to meet demands, however, because future GHG intensity projections for imported electricity were not available, in this analysis we assume that the electricity demand of California's water system is met entirely by in-state generation compliant with the SB 100 renewable targets.[16]

The GHG intensity of electricity also varies temporally. For example, during times of high electricity demand, electricity may be generated from "peaking" fossil generators that have high emissions, while for other times of day, electricity demand may be met primarily from renewable generators that produce no GHG emissions. For simplicity, we calculate the California annual average GHG intensity of electricity based on the total GHG emissions from in-state electric generators divided by the total annual electricity produced.

Because state policy would drive such substantial changes to the GHG emissions from electricity over the time horizon of our analysis, we track the historical and projected GHG intensities in our calculations. We use data from the California Air Resources Board on in-state emissions and annual electricity generation to calculate the historical annual average GHG intensity of electricity generation [217]. For future years, we use the GHG intensities projected in electricity system simulations prepared for policy discussions on pathways for California's 100% zero-emissions electricity by 2045 [218]. The GHG intensities for the intervening years between historical data and projections are linearly interpolated. The annual GHG intensity values used are summarized in Table 9, and decrease from 0.26 tons CO_2/MWh in 2015 to 0.10 tons

[16] In-state generation includes utilities within the California Independent System Operator (CAISO) region, as well as other municipal and irrigation district utilities such as Los Angeles Department of Water and Power and the Imperial Irrigation District.

CO_2/MWh by 2035. The GHG emissions from natural gas are assumed to be a constant 0.053 tons of CO_2/MMBtu [219].

Table 9. GHG Intensity of California Electricity Generation 2015 – 2035 (tons of CO_2 equivalent/MWh).[17]

	Historical observed					Interpolated					Projected from simulations				
	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2030	2035
In-state generation	0.26	0.21	0.18	0.20	0.19	0.19	0.19	0.19	0.18	0.18	0.18	0.17	0.17	0.13	0.10

2.3 Historical and future scenarios of water supply and demand

The third step of the analysis is to collect historical and develop future scenarios of water supply and demand volumes for the urban and agricultural water sectors in California. We conduct the analysis separately for the urban and agricultural sectors.

2.3.1 Urban water sector

For this analysis, we obtain historical and projected water demand and supply from Urban Water Management Plans (UWMPs) submitted by urban water suppliers. In California, water suppliers that provide more than 3,000 AF of water annually or serve more than 3,000 customers (referred to as urban water suppliers) are required to prepare a UWMP every five years and submit those plans to the California Department of Water Resources (DWR). Together, the population served by the UWMPs is about 90% of California's total population; we do not analyze the urban water demands not included in the UWMP data [220]. The first UWMPs were published in 1990, and the most recent plans as of 2020 are the 2015 UWMPs.[18] We extract actual and projected demand and supply and current population data from the 2015 UWMPs from DWR's public data portal, WUEdata [220]. Suppliers report their data in five-year increments. Therefore, our analysis is performed using actual data for 2015, and projected data for 2020, 2025, 2030, 2035.

UWMP data are available for a total of 401 water suppliers. We only used data related to retail operations for all water suppliers. However, we remove data for eight suppliers, which account for 0.4% of the total population reported in the UWMPs, from the analysis since their reported numbers are outliers and appear to be reporting errors.[19] Data for demand, supply, and population are joined with another dataset,[20] to match each supplier to its respective hydrologic region. Each of these compiled datasets is then grouped and aggregated by hydrologic region for further analysis.

2.3.1.1 Urban water demand data

Water demand data are extracted from "Table 4-1 Retail: Demands for Potable and Raw Water – Actual" and "Table 4-2 Retail: Demands for Potable and Raw Water – Projected." Population data are extracted from "Table 3-1 Retail: Population - Current and Projected." These data are joined with another dataset ("California Urban Water Use Map," n.d.), as referenced above, to assign each supplier to a hydrologic region. Population and each demand category are then respectively summed to give totals for each hydrologic region. The

[17] The low GHG intensity value in 2017 was due to an overall in renewable generation on the grid as well as to the large increase in hydroelectricity production that year, the wettest year on record.
[18] UWMPs for 2020 are under development and will be submitted to DWR in 2021.
[19] These suppliers are Calaveras County Water District, City of Corcoran, City of Exeter, Fruitridge Vista Water Company, City of Greenfield, City of Lemoore, South Feather Water and Power, and Truckee - Donner Public Utilities District.
[20] Based on data from the California Department of Public Health via Pacific Institute's California Urban Water Map [221]

UWMP data categorize residential end-use as "multifamily" and "single family." We separate the residential categories into "indoor" and "outdoor" using a ratio for each hydrologic region based on a six-year (2011-2016) annual average on indoor and outdoor demand from DWR's Water Balances data [222]. We then apply this ratio to the UWMP data and sum the respective categories to get total "indoor residential" and "outdoor residential" water demand for each hydrologic region. The final set of demand categories are residential indoor, residential outdoor, commercial, industrial, institutional/governmental, landscape, losses, and other. Per-capita demand is calculated based on population for the respective year.

2.3.1.2 Urban water supply data

Water supply data are extracted from "Table 6-8 Retail: Water Supplies – Actual" and "Table 6-9 Retail: Water Supplies – Projected." These data are joined with another dataset, as referred to above, to assign each supplier to a hydrologic region. Each supply category is then summed to give totals for each hydrologic region. The UWMPs combine all imported water sources into one category. For our study, we disaggregate this category into various imported sources of water, e.g., the Colorado River and the State Water Project, based on a six-year (2011-2016) average using data from DWR's Water Balances. The UWMPs combine all recycled water into one category, regardless of quality. Because of differences in the energy-intensity of recycled water for potable and non-potable applications, we split this category into potable and non-potable sources using Title 22 recycled water standards [209] and data from the 2015 UWMP "Table 6-4 Retail: Current and Projected Recycled Water Direct Beneficial Uses Within Service Area." We apply the percentage split between potable and non-potable categories by hydrologic region to the supply volumes labeled as "recycled water" in the UWMP data.[21]

[21] The final list of water source categories includes desalinated water (seawater and brackish), exchanges, groundwater, other, Central Valley Project deliveries, Colorado River Aqueduct deliveries, local imports, other federal deliveries, State Water Project deliveries, recycled water (potable), recycled water (non-potable), stormwater use, supply from storage, surface water, and transfers.

2.3.1.3 Urban water demand scenarios

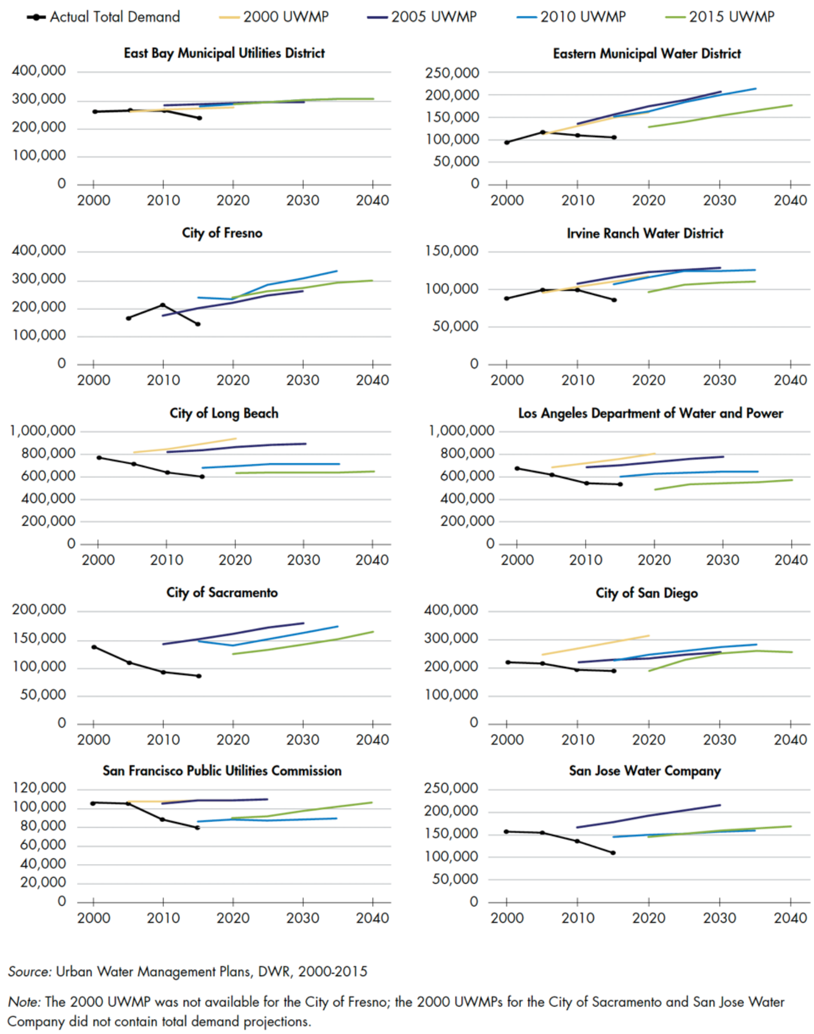


Figure 11. Actual and Projected Total Water Demands for Ten Selected Urban Water Suppliers (Acre-feet) from Abraham et al. 2020.

California's urban water demand has declined significantly over the last two decades [56]. A recent analysis of the state's 10 largest urban water suppliers, serving 25% of the population, finds that per-capita water demands declined by an average of 25% between 2000 and 2015 [223]. Further, the study shows that many water suppliers did not adequately account for these trends in their Urban Water Management Plans, and overestimated total demand in 98% of the cases examined (Figure 11). Such overestimates of future water demands can result in investment in unneeded infrastructure and new sources of supply [223].

In this analysis, we develop three scenarios of future water demand to study potential changes to California's water-related energy and GHG footprint:

i. *Water Supplier Projections Scenario (High-Case):* Total demand is maintained as reported in the 2015 UWMPs for 2020, 2025, and 2030. Given that future water supplies reported in the UWMP exceed future demand, water supplies are proportionally scaled down to match projected demand. This scenario represents the highest future water demands as envisioned by water suppliers and includes planned facilities (such as for desalination or water recycling), assumed future changes in per capita water demand, and water suppliers' projections of population growth.

ii. *2015 Constant Per-Capita Demand Scenario (Mid-Case)*: System-wide per-capita water demand (i.e., for all urban end-use sectors) from the 2015 UWMPs is held constant for every future year. Total demand is then estimated by multiplying 2015 per-capita demand by projected population for each hydrologic region from the UWMP data. Supplies are then adjusted proportionally from UWMP projections to match demand by year and hydrologic region. We note that 2015 was not a "historically typical" year because of a statewide drought from 2012 to 2016—during which there was a mandate to reduce urban water use by 25%. However, monthly water use data from the State Water Resources Control Board suggests that urban water use increased slightly after the drought but remains lower than pre-drought levels [56], [223].

iii. *Declining Per-Capita Demand Scenario (Low-Case)*: System per-capita demand is decreased by 2 percent annually, based on a 2020 Pacific Institute study which found a trend of such decreases among the 10 largest suppliers between the years 2000 to 2015 [223]. This percentage decline is calculated using 2015 per-capita demand as the base year. Total demand is then estimated by multiplying future per-capita demand by projected population for each hydrologic region. Supplies are adjusted proportionally to match the demand volumes. This scenario represents a future pathway with more aggressive conservation and efficiency efforts to reduce urban water usage, and therefore the lowest total water demand.

Table 10 shows how total residential per-capita demand (R-gpcd) and indoor residential per-capita demand (indoor R-gpcd) changes between 2015 and 2035 under each of these scenarios. Under the Water Supplier Projections Scenario, both the statewide average R-gpcd and indoor R-gpcd increase 20% between 2015 (83 R-gpcd, 46 indoor R-gpcd) and 2035 (102 R-gpcd total, 56 indoor R-gpcd). However, if historical conservation trends continue as is assumed under the Declining Per-Capita Demand Scenario, statewide average residential usage drops to 59 R-gpcd and 32 indoor R-gpcd, respectively. While low, this scenario is similar to the water use already achieved in high-efficiency homes equipped with Energy Star and WaterSense appliances and fixtures [224] and in some other regions of the world, such as Israel where households on average use 36 R-gpcd [56].

Table 10. Statewide volume-weighted average residential daily per capita water demand, by scenario (gallons per capita per day, R-gpcd and indoor R-gpcd).

Scenario	Residential segment	2015	2020	2025	2030	2035
Water Supplier Projections Scenario (High-case)	R-gpcd	83	101	102	102	102
	Indoor R-gpcd	46	56	56	56	56
2015 Constant Per-Capita Demand Scenario (Mid-case)[22]	R-gpcd	83	86	87	88	88
	Indoor R-gpcd	46	48	48	48	49
Declining Per-Capita Demand Scenario (Low-case)	R-gpcd	83	78	71	65	59
	Indoor R-gpcd	46	43	39	36	32

[22] Residential per-capita demand increases slightly under the 2015 Constant Per-Capita Demand Scenario, because we keep the residential share of total system demand the same as that of each year's share from the Water Supplier Demand Scenario. For example, under the Water Supplier Demand Scenario, in 2015 indoor residential water use was 34% of total urban demand (1,842,682/5,432,207 AF), but in 2035 the indoor residential water use share increased to 35% of total urban demand (2,723,160/7,815,382 AF).

2.3.2 Agricultural Water Sector

For this analysis, we obtain future water demand and supply delivery data from an analysis DWR conducted for its 2018 California Water Plan Update for the three hydrologic regions in Central Valley (Sacramento River, San Joaquin Valley, and Tulare Lake) under a number of population growth and climate-change scenarios [225]. The data are publicly available to download through a Tableau workbook [226]. These data are the results of simulations conducted with the integrated water supply and demand modeling platform called Water Evaluation and Planning (WEAP), which assessed future water conditions in the Central Valley for the urban and agricultural sectors under a combination of five urban growth scenarios and 20 climate scenarios from a base year of 2006 through 2100. The data include total demand, total supply delivered, and unmet demand (the difference between water demanded and actual supply delivered) for each year, Planning Area, and sector (we only analyze the agricultural sector results). To be consistent with the time horizon and geographic resolution of our urban analysis (described in Section 2.3.1), we limit our agricultural analysis to 2015, 2020, 2025, 2030, and 2035, and aggregate the data to the hydrologic region. For each of these years, we calculate a rolling 10-year average to smooth out the inter-annual variability from the climate projections. We focus the agricultural analysis only on California's Central Valley, which comprises about 80% of total state agricultural water use [222].

2.3.2.1 Agricultural Water Demand Data

We use the "supplies delivered" variable from DWR's WEAP simulation results to represent agricultural water demand in this analysis, to be consistent with our urban analysis where we balance demand and supply and because "supplies delivered" represents water use given supply availability to agricultural water users.[23]

The WEAP model simulates agricultural water conditions within the three hydrologic regions in Central Valley based on the effects of urban growth on agricultural land and climate change. The urban growth scenarios are a combination of a low-, mid-, or high-population growth rate, and a low-, central-, or high-level of population density.[24] In the DWR analysis, it is assumed that population growth in Central Valley urban areas will cause agricultural land to go out of production, thereby reducing agricultural water demand [225]. This effect on agricultural water increases with population growth and decreases with population density. The urban growth scenarios available in the results are listed in Table 11.

Table 11. Urban growth scenarios from DWR simulations, and effect on agricultural water use.

DWR Scenario Abbreviation	Scenario Description
CTP_CTD	Central population growth, current trends density → mid-level agricultural water use
CTP_HID	Central population growth, high density → mid-level agricultural water use
CTP_LOD	Central population growth, low density → mid-level agricultural water use
HIP_LOD	High population growth, low density → low-level agricultural water use
LOP_HID	Low population growth, high density → high-level agricultural water use

[23] We do not use the "water demand" variable from WEAP because it represents a theoretical "requested" water demand based on crop acreage and climate, which may not be met if there are insufficient supplies after the (user-specified) higher priority urban water demands are satisfied [225].

[24] The low, mid, and high population forecasts from the data we use for this agricultural analysis from DWR's California Water Plan are not necessarily consistent with the population forecasts that are used in the urban analysis, which are based on individual water supplier's projections for their service territories. The DWR report and individual UWMPs do not provide enough information to compare the population forecasts used.

The climate scenarios include results from 10 Global Circulation Models (GCMs), and two emissions scenarios (Representative Concentration Pathways or RCP 4.5 and RCP 8.5, which represent future radiative warming of 4.5 W/m^2 and 8.5 W/m^2, respectively), as recommended to capture the range of possible climate futures in California [227]. The list of GCMs and emissions scenarios are listed in Table 12. While the water supply availability and agricultural water demands are affected by changing temperature and precipitation patterns under each climate change scenario modeled in WEAP, the variation between climate scenarios (both GCMs and emission scenarios) is minimal within our near-term time horizon; the overall impact of climate change is expected to be more significant, and vary between GCMs and emissions scenarios, closer to the end-century period.[25]

Table 12. Climate change scenarios modeled in DWR analysis.

GCMs	Emissions scenarios
Access10	RCP 4.5
Access10	RCP 8.5
Canesm2	RCP 4.5
Canesm2	RCP 8.5
Ccsm4	RCP 4.5
Ccsm4	RCP 8.5
Cesm1_bgc	RCP 4.5
Cesm1_bgc	RCP 8.5
Cmcc_cms	RCP 4.5
Cmcc_cms	RCP 8.5

2.3.2.2 Agricultural Water Supply

The supply deliveries in the DWR WEAP analysis results are reported as a total volume and do not include the share of water deliveries by source. We obtained a separate dataset from DWR of historical water deliveries to the agricultural sector by hydrologic region and source for 1999 to 2016. For each hydrologic region, we calculate the historical average share of supply from each water source (Table 13) and multiply these shares by the total projected supply deliveries from each year of the WEAP analysis to estimate water supply by source. This is a simplifying assumption given available data and implies that the historical ratio of different supply sources will stay constant in the future.[26]

Table 13. Historical 1999 – 2016 average share of agricultural water supply by source, by hydrologic region.

Supply Sources	Sacramento Valley	San Joaquin Valley	Tulare Lake
State Water Project Deliveries	0.2%	0.3%	8.7%
Central Valley Project Deliveries	25%	16%	15%
Other Federal Deliveries	2.8%	0.2%	0.0%
Surface water	33%	33%	18%
Local Imports	0.4%	0.0%	0.0%
Return Flows	6.8%	11%	0.1%
Groundwater	32%	39%	58%
Colorado River Deliveries	0.0%	0.0%	0.0%

2.3.2.3 Agricultural Water Scenarios

For this analysis, we select combinations of urban growth and climate scenarios from DWR's WEAP simulations that together result in a set of (i) low, (ii) mid, and (iii) high

[25] We note that because all the scenarios rely on climate model data which can have small differences for the historical period, there are slight differences in the 2015 data between scenarios. We use this simulated WEAP data for 2015 despite these small differences to have a fully consistent dataset, rather than mixing data with historical data collected from another source.

[26] The historical agricultural water use categories in the DWR data we use do not include recycled water; however, we recognize that there is a small share of agricultural water-supplies that comes from recycled sources [228].

agricultural water use scenarios. We first select the three bounding scenarios among urban growth scenarios (High Population Growth + Low Density, Central Population Growth + Central Density, and Low Population Growth + High Density). For each of these urban growth scenarios, we find the climate scenario that produces the highest and lowest unmet demand across the study period (2015 – 2035) for the aggregate Central Valley region. The unmet demand is sensitive to effects of climate on both supply availability and irrigation demand and therefore captures the cumulative climate change impact on agriculture for a given urban growth scenario. For the (i) High Population Growth scenario, we select the climate scenario with the maximum unmet demand (greatest climate change impact), and for the (iii) Low Population Growth scenario we select the climate scenario resulting in minimum unmet demand (smallest climate change impact). For the (ii) Central Population Growth scenario, we select the climate scenario with maximum unmet demand. We note that these scenarios are largely driven by DWR's assumptions of how urban population growth will affect agricultural land and subsequently water use, and do not account for economic factors, such as crop values on domestic and international markets, federal and state agricultural policies, and other factors that may have even greater impacts on farmers' land and water use choices [225]. For example, while California's agricultural water use has remained relatively flat since the 1980s, during this time the economic value of crop production has grown significantly, by shifting to higher value crops and increased adoption of more water-efficient irrigation technologies, such as drip and micro-sprinkler systems [56].

i. *Low Agricultural Water Use Scenario*: HIP_LOD (lowest agricultural demand because of urban encroachment on agricultural land) with the maximum unmet demand (highest climate change impact) based on GCM: CMCC_CMS and emissions scenario: RCP 4.5.
ii. *Mid Agricultural Water Use Scenario*: CTP_CTD (central agricultural demand) with maximum unmet demand based on GCM: CMCC_CMS and emissions scenario: RCP 4.5
iii. *High Agricultural Water Use Scenario*: LOP_HID (highest agricultural demand because of least urban encroachment on agricultural land) with the minimum unmet demand (lowest climate change impact) based on GCM: GFdl_cm3 and emissions scenario: RCP 8.5

2.4 Total energy and GHG of urban and agricultural water scenarios

For both the urban and agricultural analyses, for each future water scenario, hydrologic region, and year, we calculate the total water-related energy use and associated GHG emissions. For all the relevant stages of the water cycle described in Section 2.1.1, the corresponding energy intensities described in Section 2.1.2 are multiplied by the water supply and demand volumes of the scenarios in Sections 2.3.1.3 and 2.3.2.3, and finally summed to estimate total water-related energy usage for the urban and agricultural sectors, respectively, in each hydrologic region and scenario. For each urban and agricultural water scenario, the GHG intensity by fuel is multiplied by the total energy usage of the fuel to calculate total GHG emissions.

3. Results and Discussion

3.1 Urban water results

Here we describe the projected demand, supply, energy, and GHG results of our analysis across scenarios for California in aggregate, by hydrologic region, by supply source and demand sector, and by water cycle stage for urban water. In each section, we include a high-level comparison across scenarios and detailed results for the "mid-case" 2015 Constant Per-Capita

Demand Scenario; detailed results for the "high-case" Water Supplier Projections Scenario and the "low-case" Declining Per-Capita Demand Scenario are in the Ch. 2 Appendix.

3.1.1 Urban water demand: historical and future scenarios

According to data reported by water suppliers in the UWMPs, which represent 90% of California's population, total urban water demand in 2015 was 5.4 million acre-feet (MAF). If per-capita water demand is held constant at 2015 levels according to our "mid-case" scenario, statewide total urban demand increases 24% (1.3 MAF) between 2015 and 2035 with population growth. We compare this result to water suppliers' projections ("high-case"), and our declining demand scenario ("low-case") that represents a continuation of historical conservation and efficiency trends in Table 14 and Figure 12.[27] Water suppliers project a 44% increase (2.4 MAF) in overall urban water demand between 2015 and 2035, about twice the rate of the 2015 Constant Per-Capita Demand Scenario. With increased conservation under the Declining Per-Capita Demand Scenario, statewide urban demand would fall by 17% (0.9 MAF) between 2015 and 2035.

Table 14. State urban water demand 2015 – 2035, by scenario (AF).

Scenario	2015	2020	2025	2030	2035	% Change 2015 - 2035	Change 2015 - 2035
Water Supplier Projections Scenario (High-case)	5,432,207	6,778,861	7,158,608	7,485,695	7,815,382	+44%	2,383,175
2015 Constant Per-Capita Demand Scenario (Mid-case)	5,432,207	5,751,547	6,075,776	6,396,138	6,727,985	+24%	1,295,778
Declining Per-Capita Demand Scenario (Low-case)	5,432,207	5,198,943	4,964,351	4,723,990	4,491,656	-17%	-940,550

Under the 2015 Constant Per-Capita Demand Scenario, the largest absolute and percentage change increases come from indoor residential water demand—which is also the most energy-intensive end-use sector—and from outdoor residential water demand, respectively (Table 15).[28] Across the hydrologic regions, (Figure 13), the largest absolute increases in residential water demand are in two regions with highly populated urban centers and the highest overall urban demands in the state: South Coast (about +456,000 AF) and Sacramento (about +175,000 AF).

Table 15. Annual urban water demand by sector (AF) – 2015 Constant Per-Capita Demand Scenario (Mid-case).

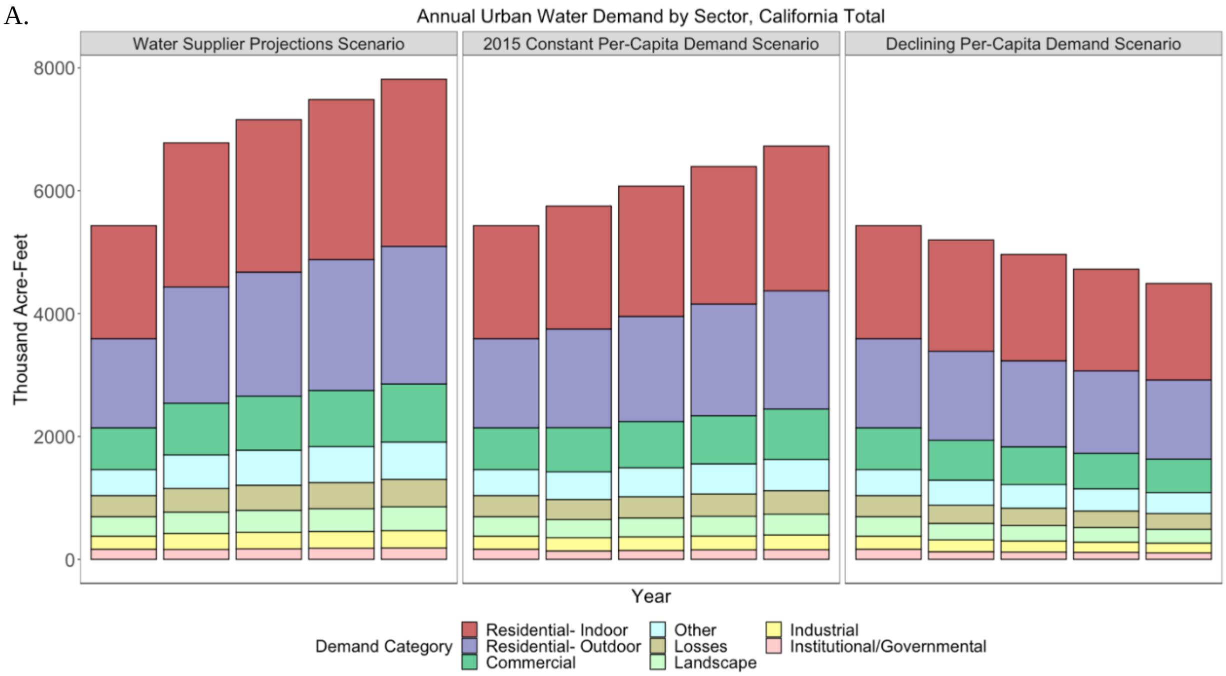
Demand Sector	2015	2020	2025	2030	2035	% Change 2015 - 2035	Change 2015 - 2035
Residential- Indoor	1,842,682	2,004,389	2,123,692	2,242,569	2,358,832	28%	516,151
Residential- Outdoor	1,448,045	1,603,035	1,709,520	1,816,070	1,922,994	33%	474,950
Commercial	682,261	720,403	753,573	785,961	821,041	20%	138,779
Industrial	216,065	217,743	223,731	227,876	240,385	11%	24,319
Institutional/ Governmental	162,886	133,502	142,866	152,689	156,521	-4%	-6,364
Landscape	315,900	296,957	306,808	321,261	338,634	7%	22,734

[27] See the Ch. 2 Appendix for detailed tables of water demand results for the Water Supplier Projections Scenario and Declining Per-Capita Demand Scenario.

[28] Because we do not have data on how water suppliers projected losses, we make a simplifying assumption that losses also scale proportionally with demand in our 2015 Constant Per-Capita Demand and Declining Per-Capita Demand Scenarios.

Losses	342,822	326,892	346,461	363,382	382,319	12%	39,497
Other	421,546	448,627	469,124	486,329	507,259	20%	85,713
Total	5,432,207	5,751,547	6,075,776	6,396,138	6,727,985	24%	1,295,778

A.



B.

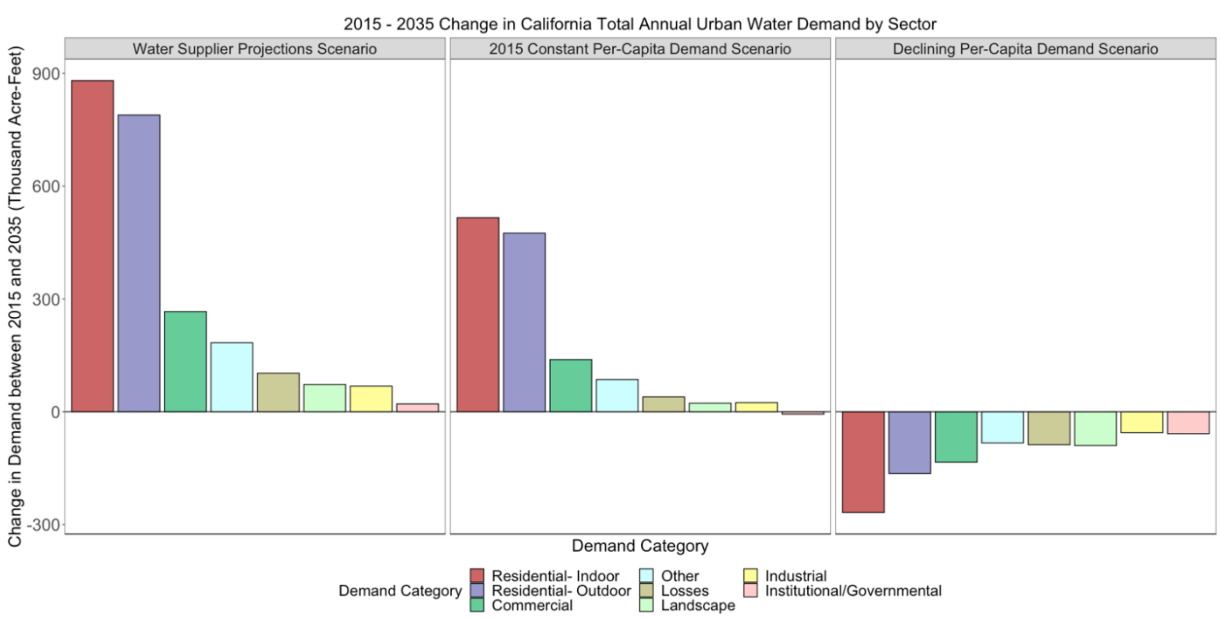
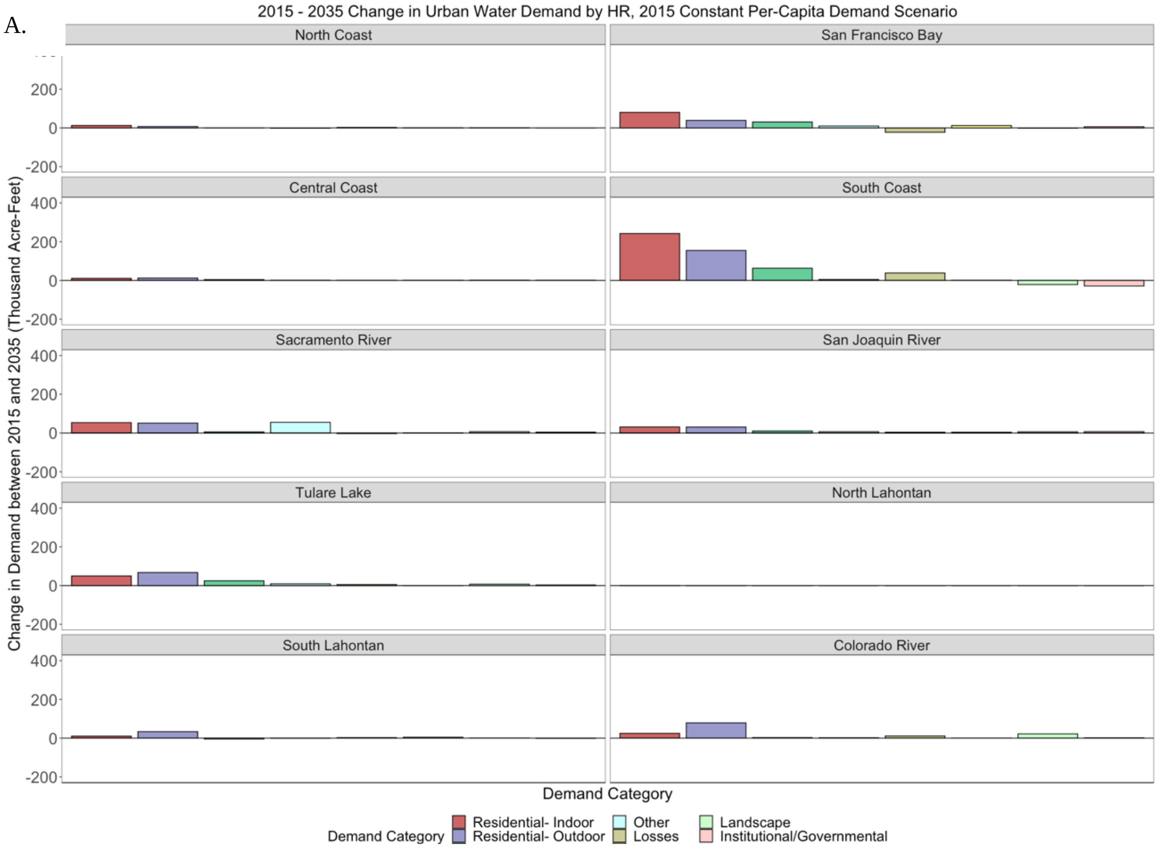


Figure 12. A. State urban water demand 2015 – 2035, by scenario. B. Change in state urban water demand between 2015 and 2035, by scenario.

A.



B.

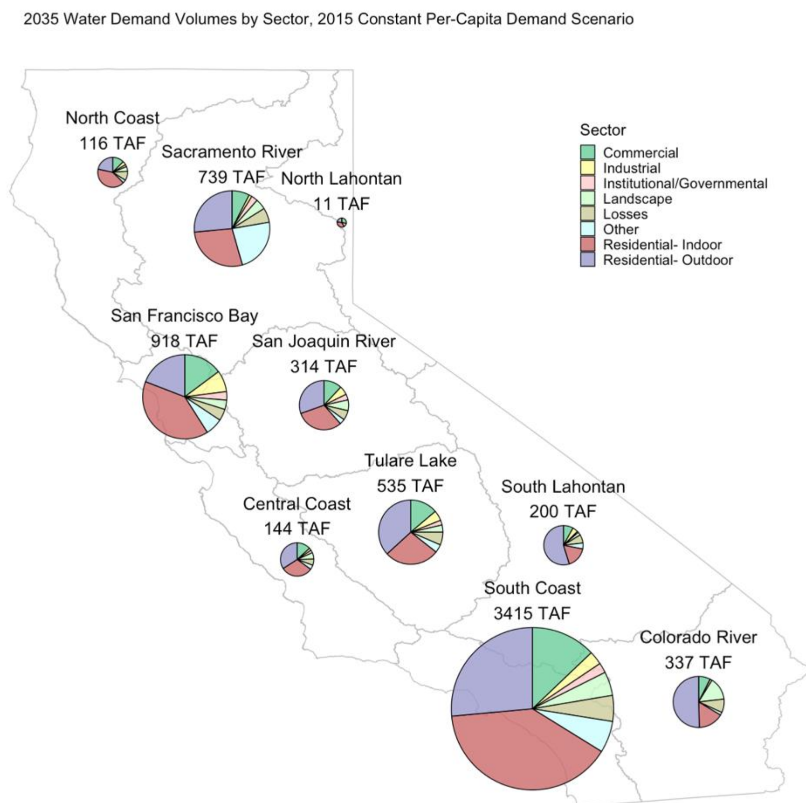


Figure 13. 2015 Constant Per-Capita Demand Scenario (Mid-case): A. Change in urban water demand between 2015 and 2035, by hydrologic region. B. 2035 Urban water demand, by hydrologic region.

3.1.2 Urban water supply: historical and future scenarios

To meet projected water demands under the "mid-case" 2015 Constant Per-Capita Demand Scenario, water supplies must increase by 1.3 MAF, or 24%, between 2015 (5.4 MAF) and 2035 (6.7 MAF).[29] This supply increase is largely met using traditional water sources (groundwater and surface water)[30] (Table 16), but there are also shifts in the supply mix from imported water toward local alternative water sources , which have important energy and GHG implications. The largest percentage increases in supplies between 2015 and 2035 are from brackish desalination (+7000% increase in supply), potable recycled water (+300% increase in supply), and captured stormwater (+19,000% increase in supply). Further, there are decreases in the statewide shares of imported water from the SWP and CRA from 13% to 12%, and 16% to 13% respectively, between 2015 and 2035. Although many alternative water sources are energy-intensive because of the combined energy use for associated supply extraction/generation, treatment, and conveyance, in many regions, their energy needs are typically lower than for imported water (Table 8).

Table 16. State annual urban water supply by source (AF) – 2015 Constant Per-Capita Demand Scenario (Mid-case).

Supply Source	2015	2020	2025	2030	2035	% Change 2015 - 2035	Change 2015 - 2035
Central Valley Project Deliveries	259,046	270,119	292,069	310,375	325,568	26%	66,522
Colorado River Deliveries	871,975	816,885	848,783	877,729	906,259	4%	34,283
Desalinated Water (Brackish)	205	3,495	7,206	10,860	14,595	7,013%	14,390
Desalinated Water (Seawater)	27,888	29,882	32,332	32,783	33,238	19%	5,350
Exchanges	2,216	3,858	1,162	1,083	1,169	-47%	-1,047
Groundwater	2,063,977	2,006,160	2,075,120	2,175,610	2,291,486	11%	227,509
Local Imports	365,972	350,455	367,474	383,598	400,499	9%	34,527
Other	98,094	196,039	200,210	212,057	219,965	124%	121,870
Other Federal Deliveries	28,565	26,593	29,107	31,143	32,428	14%	3,863
Recycled Water- Non Potable	287,519	346,256	403,475	454,109	495,238	72%	207,719
Recycled Water- Potable	17,010	29,555	61,305	63,599	68,653	304%	51,643
State Water Project Deliveries	716,384	687,402	723,632	754,014	784,892	10%	68,508
Stormwater Use	72	2,242	5,003	8,354	13,642	18,834%	13,569
Supply from Storage	14,329	24,266	24,801	25,456	26,155	83%	11,827
Surface water	648,056	943,758	988,764	1,036,668	1,094,451	69%	446,396
Transfers	30,898	14,583	15,333	18,699	19,748	-36%	-11,150
Total	5,432,207	5,751,547	6,075,776	6,396,138	6,727,985	+24%	1,295,778

Table 17. State urban water supply portfolio in 2015 and 2035 – 2015 Constant Per-Capita Demand Scenario (Mid-case).

Supply Source	% of 2015 Total Supply	% of 2035 Total Supply
Central Valley Project Deliveries	5%	5%
Colorado River Deliveries	16%	13%
Desalinated Water (Brackish)	0.004%	0.2%
Desalinated Water (Seawater)	1%	0.5%
Exchanges	0.04%	0.02%
Groundwater	38%	34%
Local Imports	7%	6%

[29] These water supply values are water production estimates and do not include conveyance losses, such as from the SWP.
[30] See the Ch. 2 Appendix for detailed tables of water supply results for the other scenarios.

Other	2%	3%
Other Federal Deliveries	1%	0.5%
Recycled Water- Non Potable	5%	7%
Recycled Water- Potable	0.3%	1%
State Water Project Deliveries	13%	12%
Stormwater Use	0.001%	0.2%
Supply from Storage	0.3%	0.4%
Surface water	12%	16%
Transfers	1%	0.3%
Total	100%	100%

There is significant variation in how these supply changes are distributed across hydrologic regions under the 2015 Constant Per-Capita Demand Scenario (Figure 14). The absolute largest increases in groundwater and non-potable recycled water are projected to occur in the South Coast, which also sees increases in potable recycled water. Although there are also large absolute increases in SWP and Colorado River imports to the South Coast, these sources decrease in their shares of the region's total supply (21% to 18% SWP, 29% to 25% Colorado River) between 2015 to 2035. Increases in surface water are dominant in the San Francisco Bay, Sacramento River, and Tulare Lake hydrologic regions.

Under the 'high-case' Water Supplier Projections Scenario, the increase in supply needed to meet the 44% projected demand between 2015 and 2035 primarily comes from surface water, groundwater, and non-potable recycled water (Figure 15). In the Declining Per-Capita Demand Scenario, which requires 17% less water by 2035 compared to 2015, the largest absolute reductions in supply deliveries come from groundwater, Colorado River water, and SWP, all of which are relatively energy-intensive water sources.

We note several limitations of these results. These results are driven in part by our simplifying assumption that increases or decreases in supply deliveries for each year under the 2015 Constant Per-Capita Demand Scenario and Declining Per-Capita Demand Scenario are divided among water sources in the same proportion as water sources for each year in the Water Supplier Projections Scenario. As discussed in Section 2.3.1.3, it is unclear whether urban water supplier projections of these supply source changes are physically, economically, ecologically, or legally possible; we take these estimates as given and make no assessment or adjustment of supplies for feasibility, but we note there are already serious constraints on existing supply options. In our two alternative demand scenarios, we also do not assume that water agencies would change how they prioritize which supply sources to increase or conserve, such as based on energy intensity or cost. We also note that projections of groundwater usage to 2035 are from the 2015 UWMP and do not account for the Sustainable Groundwater Management Act (SGMA), which was passed in 2014 and seeks to limit groundwater pumping by 2040. Additionally, what appears to be a statewide increase in CVP and SWP volumes from 2015 to 2035 may be a consequence of below-average deliveries from those sources in 2015 due to the 2012 – 2016 statewide drought.

A.

B.

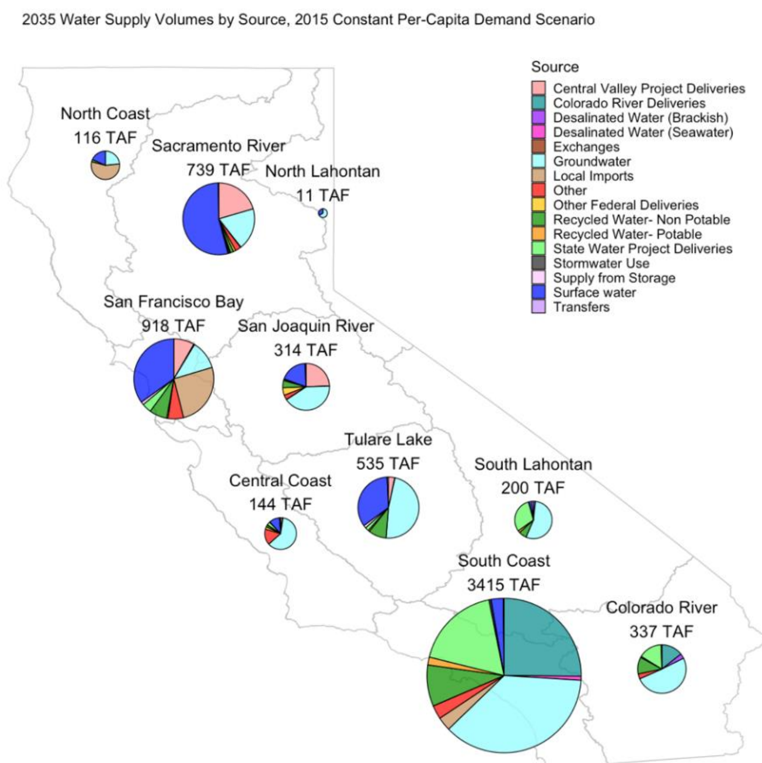
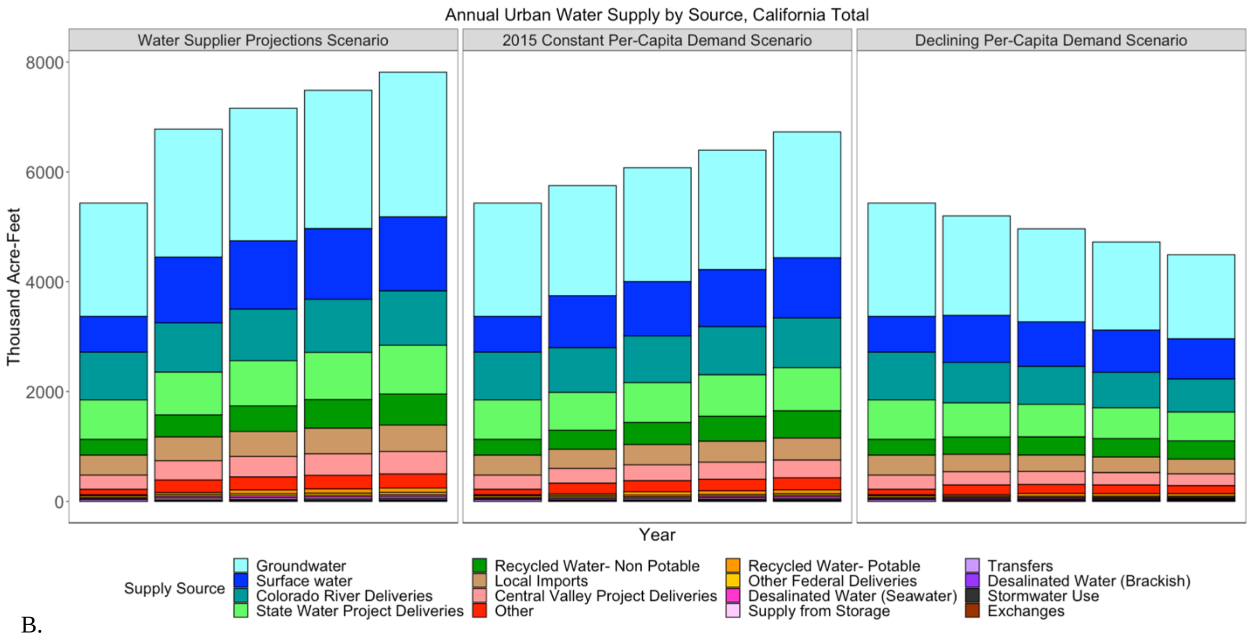


Figure 14. 2015 Constant Per-Capita Demand Scenario (Mid-case). A. Change in urban water supplies between 2015 and 2035, by hydrologic region. B. 2035 Urban water supplies, by hydrologic region.

A.



B.

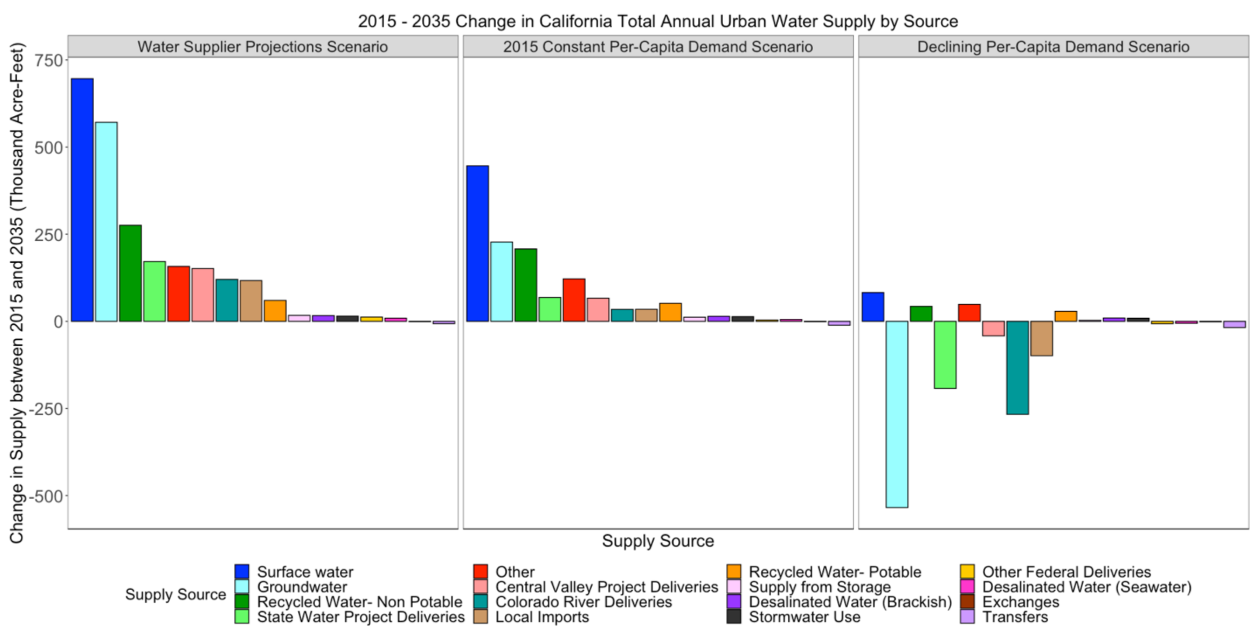


Figure 15. A. State total urban water supplies 2015 – 2035, by scenario. B. Change in state urban water supply between 2015 and 2035, by scenario.

3.1.3 Energy use for urban water: historical and future scenarios

The changing water demands and shifts in supply sources described in the previous sections can have significant effects on the urban water-related electricity footprint. Between 2015 and 2035, we find the total annual water-related electricity usage increases by about 21%, about 6,300 GWh annually, under the "mid-case" 2015 Constant Demand Scenario (Table 18). For context, California's total economy-wide annual electricity consumption (not only related to water) is currently about 300,000 GWh, suggesting that under this scenario projected increases in urban water demand could increase the state's overall annual electricity consumption by about 2% by 2035. If per-capita demand increases according to water supplier projections ("high-case"), annual electricity usage for urban water increases by about twice that amount (40% or 12,000 GWh) between 2015 and 2035 (Table 18, Figure 16).

In contrast, water conservation and efficiency improvements can lead to significant energy savings along the entire managed water cycle (Figure 10) from avoided water supply, conveyance, treatment, distribution, heating, and wastewater collection and treatment energy. The Declining Per-Capita Demand Scenario ("low-case") leads to a reduction in total electricity usage for urban water by 19% between 2015 to 2035, corresponding with an annual savings of 5,700 GWh (Table 18, Figure 16).

Table 18. State annual electricity use related to urban water, by scenario (GWh).

Scenario	2015	2020	2025	2030	2035	2015 - 2035 % Change	2015 - 2035 Change
Water Supplier Projections Scenario (High-case)	29,917	36,516	38,536	40,173	41,781	40%	11,864
2015 Constant Per-Capita Demand Scenario (Mid-case)	29,917	31,287	32,994	34,610	36,259	21%	6,342
Declining Per-Capita Demand Scenario (Low-case)	29,917	28,281	26,958	25,562	24,207	-19%	-5,710

In all scenarios, the largest share of statewide electricity use is from end-uses, followed by conveyance, distribution, and wastewater treatment energy (Figure 16). Under the 2015 Constant Per-Capita Demand Scenario (Table 19), between 2015 and 2035, the increase in electricity usage in absolute terms is also dominated by growing end-use electricity.[31]

Table 19. State annual electricity use related to urban water, by water cycle category (GWh) – 2015 Constant Per-Capita Demand Scenario (Mid-case).

Water Cycle Category	2015	2020	2025	2030	2035	2015 - 2035 % Change	2015 - 2035 Change
Supply Extraction or Generation	1,277	1,309	1,416	1,495	1,585	24%	308
Supply Conveyance	4,321	4,155	4,352	4,518	4,684	8.4%	363
Supply Treatment	1,308	1,382	1,459	1,529	1,604	23%	296
Demand Distribution	2,483	2,596	2,714	2,825	2,942	19%	459
Demand End-Use	18,152	19,312	20,381	21,436	22,500	24%	4,348

[31] See the Ch. 2 Appendix for detailed tables of energy results for the Water Supplier Projections Scenario and Declining Per-Capita Demand Scenario.

Demand Wastewater Collection	323	345	364	382	400	24%	77
Demand Wastewater Treatment	2,053	2,189	2,309	2,425	2,544	24%	491

While the total urban water-related electricity use increases in the "mid-case" scenario (and the "high-case" scenario), the statewide average energy intensity—the total electricity use divided by total water use—decreases 2% between 2015 and 2035 (Table 20).[32] This appears to be driven primarily by a reduced energy intensity of urban water in the South Coast region, which has California's highest total water-related electricity usage (Figure 17), due to its relatively high residential water demand (Figure 12) and energy-intensive water supply mix (Figure 14).[33] By 2035, under the 2015 Constant-Per Capita Demand Scenario, the South Coast has a reduced share of energy-intensive imported resources (21% to 18% of South Coast supplies from SWP, 29% to 25% of South Coast supplies from Colorado River, from 2015 to 2035) and an increase in local water sources (such as 1% to 2% potable recycled water, 6% to 9% non-potable recycled water, and 0 to 0.4% captured stormwater, between 2015 and 2035).

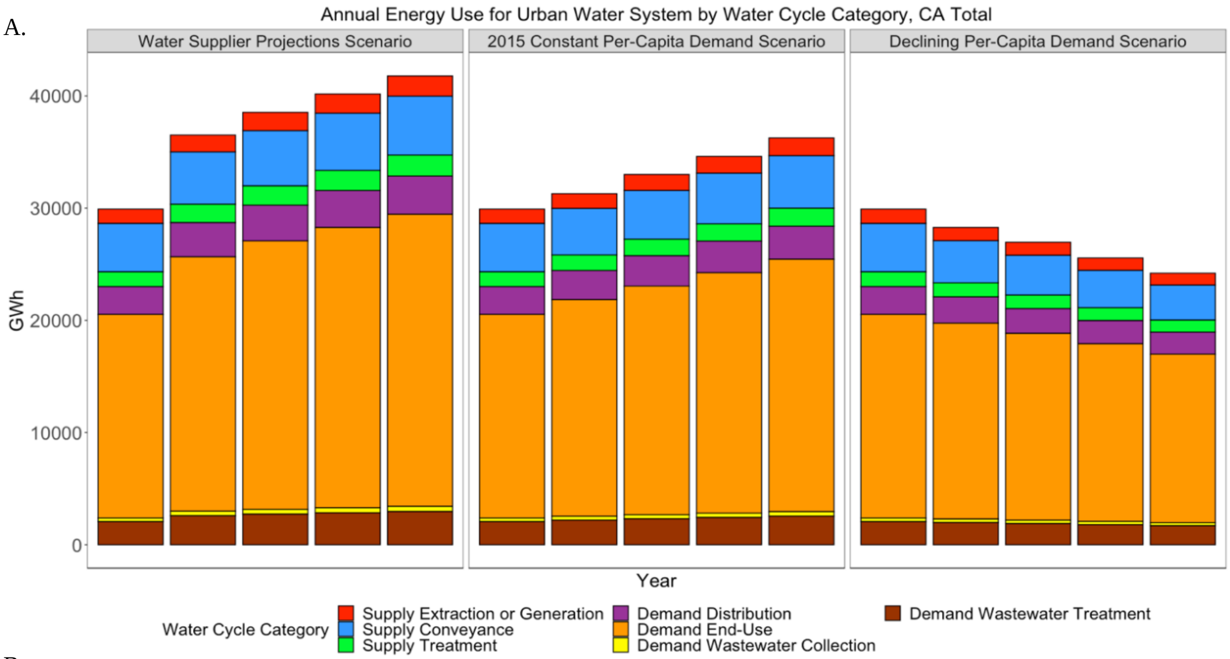
Local, alternative water sources have relatively high treatment energy requirements compared to traditional water sources; however, in regions like the South Coast, they are still typically lower than the energy requirements for conveyance of imported water (except for the most energy-intensive source, seawater desalination). For example, extraction, conveyance, and drinking water treatment requires about 350 kWh/AF for local surface water and 400 kWh/AF to 700 kWh/AF, depending on the region, for groundwater (Table 8). By comparison, extraction/generation, conveyance, and drinking water treatment requires 500 kWh/AF for non-potable recycled water, 700 kWh/AF for captured stormwater, 1,800 kWh/AF for indirect potable recycled water, 2,100 kWh/AF for brackish groundwater desalination, and 4,600 kWh/AF for seawater desalination. Energy requirements for SWP and Colorado River conveyance and treatment can reach up to 4,200 kWh/AF and 2,300 kWh/AF, respectively, depending on the region.

Table 20. Urban water system energy intensity (electricity) by hydrologic region (kWh/AF).

Hydrologic Region	2015	2035	2015 - 2035 % Change
Central Coast	4,639	4,638	0.0%
Colorado River	2,824	3,056	8.2%
North Coast	5,169	5,170	0.0%
North Lahontan	4,771	4,887	2.4%
Sacramento River	3,485	3,466	-0.5%
San Francisco Bay	5,886	6,104	3.7%
San Joaquin River	4,241	4,215	-0.6%
South Coast	6,356	6,274	-1.3%
South Lahontan	4,102	4,262	3.9%
Tulare Lake	4,101	4,011	-2.2%
State Volume-Weighted Average Urban Energy Intensity	5,507	5,389	-2%

[32] The energy intensity for each hydrologic region for a given year is the same across scenarios because we use the Water Supplier Projections Scenario proportions of energy supplies and demands per year and per hydrologic region for all scenarios.
[33] The San Francisco Bay and Sacramento hydrologic regions are the second and third highest overall electricity users, driven by high residential water demand. The San Francisco Bay, North Lahontan, South Lahontan, and Colorado River regions also all see an increase in energy intensity by 2035, and Tulare Lake has a decrease in energy intensity. The remaining regions (North Coast, Central Coast, Sacramento, and San Joaquin Valley) have negligible changes (+ or - < 1%) between 2015 and 2035.

A.



B.

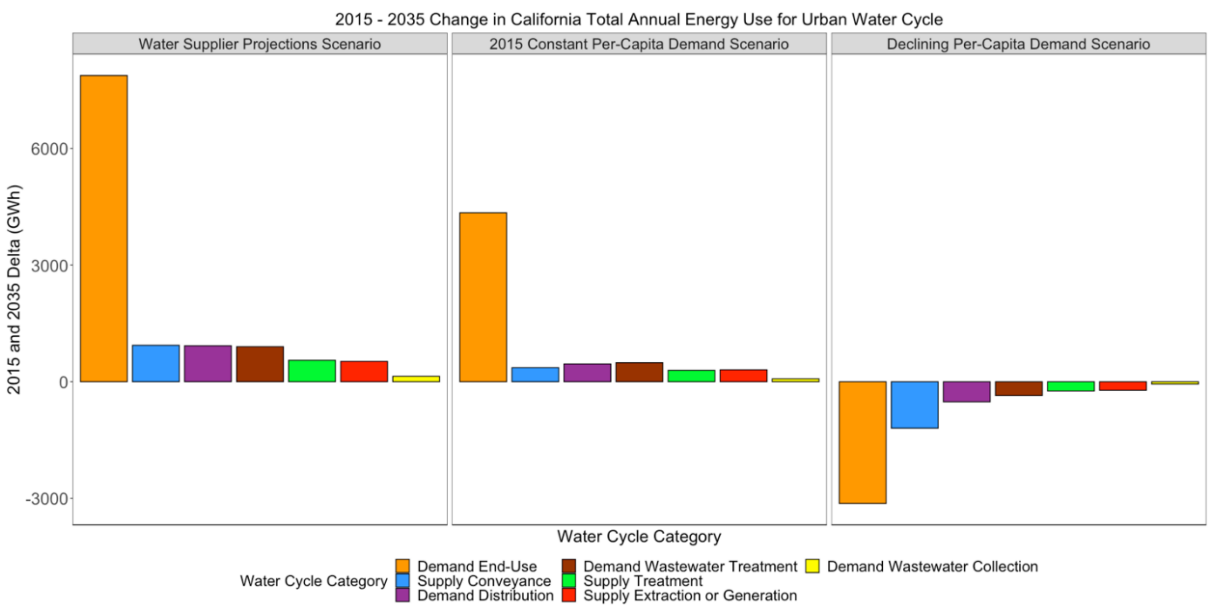
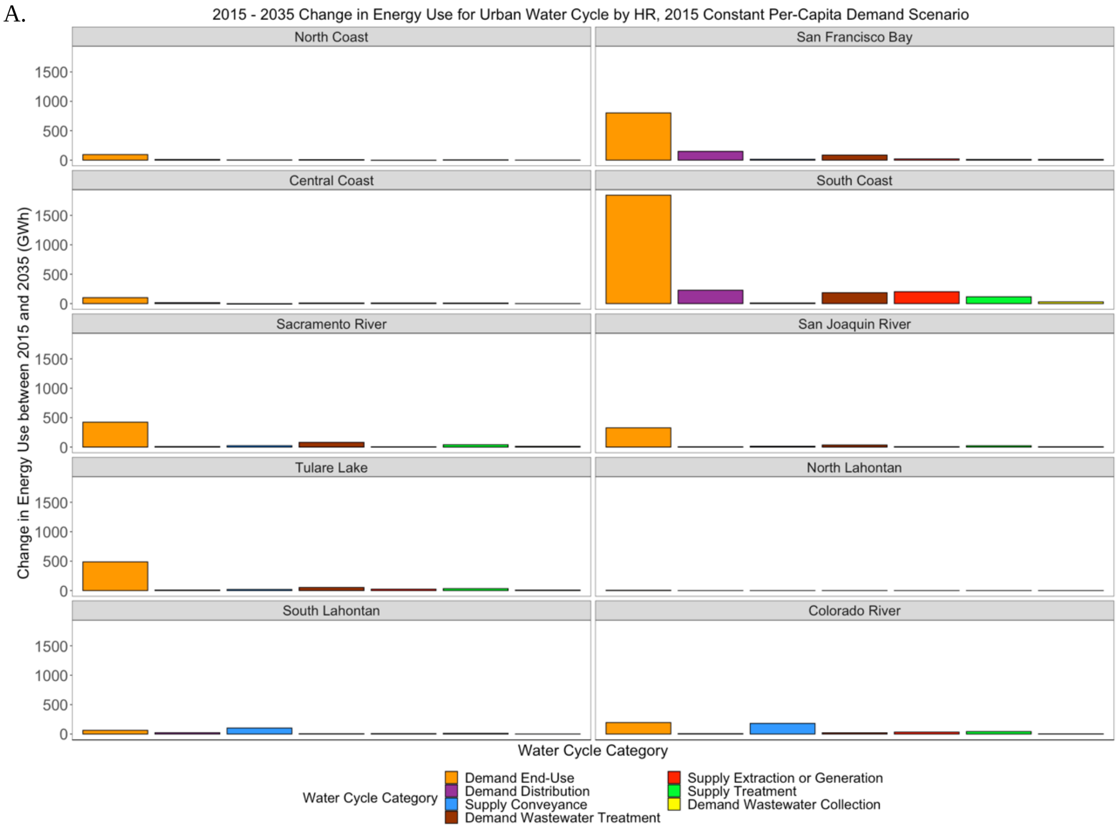


Figure 16. State urban water-related electricity use 2015 – 2035, by scenario. B. Change in state urban water-related electricity use between 2015 and 2035, by scenario.

As noted in Section 2.1.1, California currently does not allow for direct potable reuse because state regulators have not yet developed water quality and public health standards [229]. As a result, for potable applications, water suppliers are currently required to pump treated recycled water to an environmental buffer and then treat it a second time at a conventional drinking water treatment plant before distribution and use [208]. We estimate that this increases energy usage for indirect potable recycled water by approximately 580 kWh/AF. This would be higher in regions with hilly terrain where energy requirements for pumping between the wastewater treatment plant to the buffer and drinking water treatment plant are higher. While the regulatory requirements for direct potable reuse have not yet been established, this suggests that the energy footprint of potable recycled water could be substantially lower than indirect potable reuse because it avoids these additional steps.[34] Additionally, some energy-water research suggests that there are opportunities to lower the energy usage and/or shift the timing of energy demands to avoid peak times of some certain parts of the managed water cycle, such as at wastewater treatment plants, through demand response programs and the installation of variable speed drives [230]. It is unclear however, if typical treatment plants have the water storage capacity available to implement such programs.

[34] In this analysis we assume that proportion of non-potable to potable recycled water is as projected by water suppliers in the future which does not take possible change in legislation into account; the energy usage would be higher if a higher share of recycled water is treated to potable quality.

A.



B.

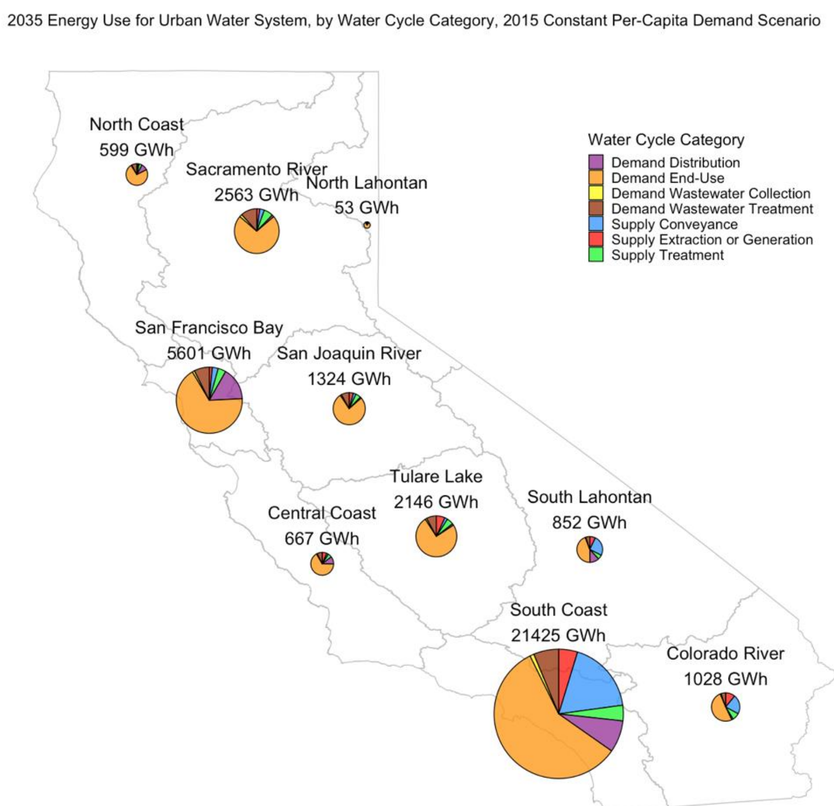


Figure 17. 2015 Constant Per-Capita Demand Scenario (Mid-case): A. Change in urban water-related electricity use between 2015 and 2035, by region. B. 2035 urban water-related electricity use, by region.

Increased water demand, especially for indoor residential uses, is expected to also raise natural gas usage. We find that between 2015 and 2035, natural gas usage for water heating in the residential and CII sectors increases 25% in the 2015 Constant Per-Capita Demand Scenario (from about 150,000,000 to 190,000,000 MMBtu), and 45% in the Water Supplier Projections Scenario (Table 21). As with electricity, the Declining Per-Capita Demand Scenario shows that water efficiency improvements save natural gas; annual water heating natural gas usage in 2035 is 16% lower (or about 25,000,000 MMBtu) than in 2015.

Table 21. State annual natural gas use by urban water heating end-uses, by scenario (MMBtu).

Scenario	2015	2020	2025	2030	2035	2015 - 2035 % Change	2015 - 2035 Change
Water Supplier Projections Scenario (High-case)	154,350,857	194,004,931	205,011,788	214,461,995	223,580,559	45%	69,229,701
2015 Constant Per-Capita Demand Scenario (Mid-case)	154,350,857	165,430,605	174,822,102	184,120,659	193,396,108	25%	39,045,251
Declining Per-Capita Demand Scenario (Low-case)	154,350,857	149,536,164	142,842,381	135,985,823	129,112,787	-16%	-25,238,070

3.1.4 GHG emissions related to urban water: Historical and future scenarios

Our results show that the decarbonization of California's electricity generation to meet SB 100 goals will reduce the GHG emissions associated with urban water-related electricity usage. Despite an overall increase in electricity use, GHG emissions decline by more than half (-52%) between 2015 and 2035 in the 2015 Constant Per-Capita Demand Scenario (Table 22) because of large reductions in in-state electricity GHG intensity (Table 9). The decrease in GHG emissions is more dramatic in the Declining Demand Scenario (-68%), but still substantial under Water Supplier Projections Scenario (-44%). We assume in this analysis that water-related electricity demand is met by in-state generation; if California meets water-related electricity demand by importing electricity from neighboring regions that have more GHG-intensive (fossil) generating portfolios, overall GHG emissions will be higher.

However, when we account for GHG emissions from natural gas water heating end-uses, we find total GHG emissions (from electricity plus natural gas) increase 2% in the Water Supplier Projections Scenario between 2015 and 2035 (Table 22). GHG emissions still decline under the 2015 Constant Per-Capita Demand Scenario and Declining Per-Capita Demand Scenario, but at more modest rates (-12% and -41%, respectively). In this analysis, we hold the electric share of water heaters in the residential and CII sectors constant at current levels (about 30% and 44%, respectively). However, with the state's energy policy moving in favor of electrification across the building sector, a greater share of water heaters may shift to electric from natural gas, which would have the effect of driving down overall GHG emissions from the water system.

Table 22. Urban water-related GHG emissions from in-state electricity, by scenario (million tons CO_2 equivalent).

Scenario	Fuel	2015	2020	2025	2030	2035	% Change 2015 - 2035	Change 2015 - 2035
Water Supplier Projections Scenario (High-case)	Electricity	7.7	7.0	6.8	5.3	4.3	-44%	-3
	Natural Gas	8.2	10.3	10.9	11.4	11.9	45%	4
	Total	15.9	17.3	17.7	16.7	16.2	2%	0.3

2015 Constant Per-Capita Demand Scenario (Mid-case)	Electricity	7.7	6.0	5.8	4.6	3.7	-52%	-4
	Natural Gas	8.2	8.8	9.3	9.8	10.3	25%	2
	Total	15.9	14.8	15.1	14.3	14.0	-12%	-2
Declining Per-Capita Demand Scenario (Low-case)	Electricity	7.7	5.4	4.7	3.4	2.5	-68%	-5
	Natural Gas	8.2	7.9	7.6	7.2	6.9	-16%	-1
	Total	15.9	13.4	12.3	10.6	9.3	-41%	-7

3.2 Agricultural water results

Here, we describe the projected agricultural demand, supply, energy, and GHG results of our analysis across scenarios for Central Valley in aggregate, by hydrologic region, and by supply source and demand sector.

3.2.1 Agricultural water demand: historical and future water scenarios

Under all three scenarios of future agricultural water (Table 23), total Central Valley water supply deliveries[35] decline between 2015 and 2035, decreasing by 3% (0.7 MAF) under the Low Ag Water Use Scenario, by 2% (0.3 MAF) under the Mid Ag Water Use Scenario, and by 5% (1.2 MAF) under the High Ag Water Use Scenario.[36] As noted in Section 2.3.2.3, these overall declining trends are largely driven by DWR's assumptions that urban population growth will reduce agricultural land and subsequently water use. However, these scenarios do not account for economic factors, such as crop values on domestic and international markets, federal and state agricultural policies, and other factors that affect farmers' land use choices [225]. Even with decadal averaging, differences in agricultural water deliveries between years are also affected by natural inter-annual variations in climatic conditions (temperature, precipitation, and evapotranspiration drive irrigation demands).[37] The overall effect of climate change across the scenarios appears to be minimal in this near-term time horizon.

Table 23. Central Valley agricultural water supply delivered, by scenario (AF).

Level of Ag use	Urban growth, climate scenarios	2015	2020	2025	2030	2035	% Change 2015 - 2035	Change 2015 - 2035
Low Ag water use	HIP_LOD, Cmcc_cms, RCP 4.5	23,342,447	23,863,569	23,775,521	23,223,430	22,618,405	-3%	-724,043
Mid Ag water use	CTP_CTD, Cmcc_cms,RCP 4.5	23,448,421	24,050,344	24,034,625	23,554,631	23,071,053	-2%	-377,368

[35] We use the "supplies delivered" variable from DWR's WEAP simulation results to represent agricultural water demand to be consistent with our urban analysis where we balance demand to equal supply, and because "supplies delivered" represents the actual water use given supply availability to agricultural water users in Central Valley. We do not use the "water demand" variable from WEAP because it represents a theoretical "requested" water demand based on crop acreage and climate, which may not be met if there are insufficient supplies after the (user-specified) higher priority urban water demands are satisfied [225].

[36] The 2015 values differ by scenario because they are all simulated data, even for the historical period, using simulated historical climate data from each GCM (climate model) which differ slightly. 2006 is the base year for DWR's WEAP simulations [225]. We use this simulated data for all years to maintain a consistent dataset across all scenarios, rather than mixing with historical observed data for 2015. For reference, observed data for 2015 from DWR Water Balance Data shows that the total Applied Crop Water across the three Central Valley Hydrologic regions was 24.3 MAF, about equivalent to the average between the "Low Ag water use" and "High Ag water use" scenarios (24.2 MAF) [222].

[37] The Low Ag water use and High Ag water use scenarios are based on DWR WEAP simulations with two different climate models, which may have different climate data for particular years and different patterns of underlying inter-annual variability. This results in the 2025 water supply deliveries in the High Ag water use scenario to be lower than in the Low Ag water use scenario, even though the trend is for the High Ag water use scenario to be higher in the remaining years of this analysis.

High Ag water use	LOP_HID, GFdl_cm3, RCP 8.5	25,084,130	24,300,280	23,479,049	24,275,013	23,877,242	-5%	-1,206,889

Across all three scenarios (Table 24), the Tulare Lake hydrologic region, which has the highest agricultural water demand among the Central Valley regions, experiences the largest percentage declines (up to -7%) in supply deliveries between 2015 and 2035. In contrast, the Sacramento River hydrologic region sees an increase in supply deliveries in all but the High Ag Water Use Scenario.

Table 24. Agricultural water supply deliveries (AF) by hydrologic region, by scenario.

Hydrologic Region	Level of Ag use	Urban growth, climate scenarios	2015	2020	2025	2030	2035	% Change 2015 - 2035	Change 2015 - 2035
Sacramento River	Low Ag water use	HIP_LOD, Cmcc_cms, RCP 4.5	7,791,897	8,124,773	8,281,018	8,054,964	7,926,691	2%	134,794
San Joaquin River			6,407,804	6,547,874	6,548,395	6,478,338	6,209,435	-3%	-198,369
Tulare Lake			9,142,747	9,190,922	8,946,108	8,690,128	8,482,279	-7%	-660,468
Sacramento River	Mid Ag water use	CTP_CTD, Cmcc_cms, RCP 4.5	7,827,603	8,188,157	8,372,529	8,170,778	8,084,196	3%	256,593
San Joaquin River			6,445,920	6,615,489	6,644,809	6,602,755	6,374,638	-1%	-71,282
Tulare Lake			9,174,898	9,246,698	9,017,288	8,781,097	8,612,219	-6%	-562,679
Sacramento River	High Ag water use	LOP_HID, GFdl_cm3, RCP 8.5	8,291,290	8,140,020	7,859,446	8,118,026	8,169,114	-1%	-122,177
San Joaquin River			6,912,865	6,640,439	6,403,358	6,671,952	6,501,189	-6%	-411,677
Tulare Lake			9,879,975	9,519,821	9,216,245	9,485,035	9,206,939	-7%	-673,036

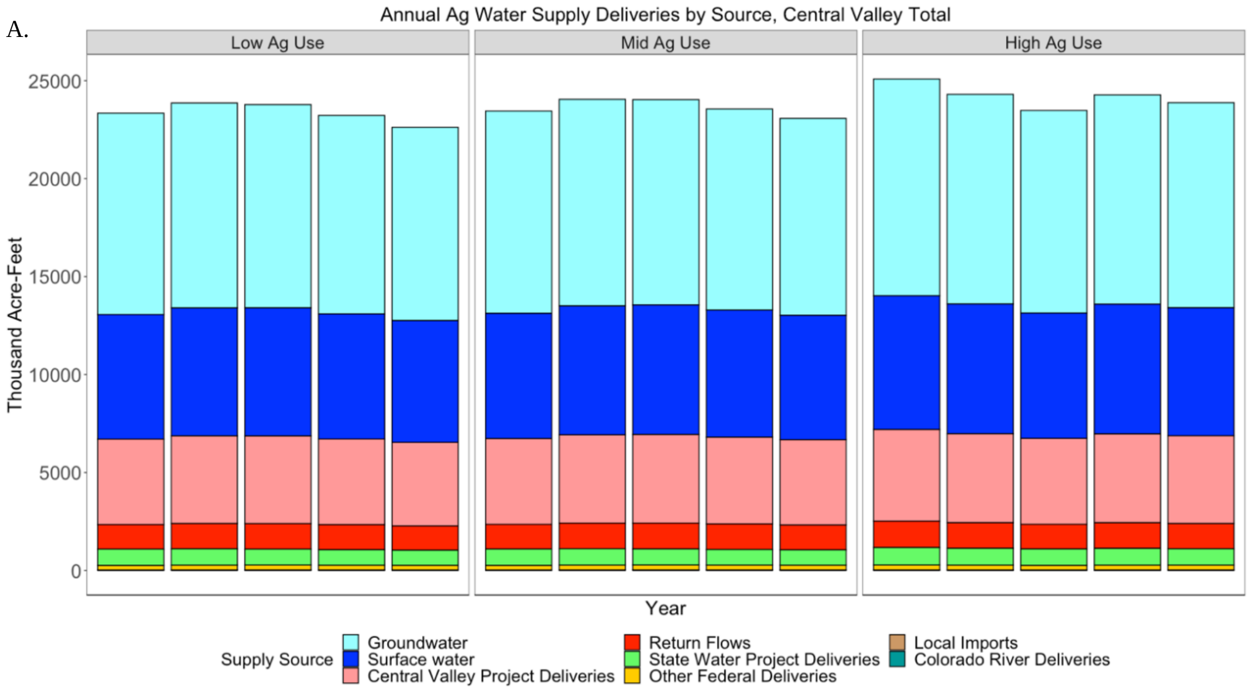
3.2.2 Agricultural water supply: historical and future water scenarios

We find that the largest absolute and percentage decreases in Central Valley agricultural water supplies come from SWP deliveries and groundwater, both of which are relatively energy-intensive water sources. Table 25 shows results for the Mid Ag Water Use Scenario, and Figure 18 compares differences between 2015 and 2035 supplies across scenarios. We note that these results would change if we do not assume that future agricultural water supplies maintain the historical proportion of sources. However, declines in SWP deliveries may be likely in the future due to climate change impacts [231], and decreased groundwater use is consistent with the goals of SGMA especially in regions with over-drafted basins, such as in Tulare Lake, where Figure 19 shows that supplies are dominated by groundwater use.

Table 25. Central Valley annual agricultural water supply by source (AF) – Mid Ag Water Use Scenario.

Supply Source	2015	2020	2025	2030	2035	% Change 2015 - 2035	Change 2015 - 2035
State Water Project Deliveries	827,354	834,614	815,022	794,036	778,624	-6%	-48,730
Central Valley Project Deliveries	4,384,778	4,513,291	4,529,638	4,436,782	4,352,714	-1%	-32,064
Other Federal Deliveries	233,993	244,505	249,760	243,989	241,072	3%	7,079
Surface water	6,386,804	6,575,142	6,604,000	6,480,093	6,345,748	-1%	-41,056
Local Imports	29,808	31,165	31,852	31,099	30,750	3%	942
Return Flows	1,261,943	1,305,528	1,321,200	1,302,645	1,270,991	1%	9,048
Groundwater	10,323,741	10,546,099	10,483,153	10,265,987	10,051,153	-3%	-272,588
Total	23,448,421	24,050,344	24,034,625	23,554,631	23,071,053	-2%	-377,368

A.



B.

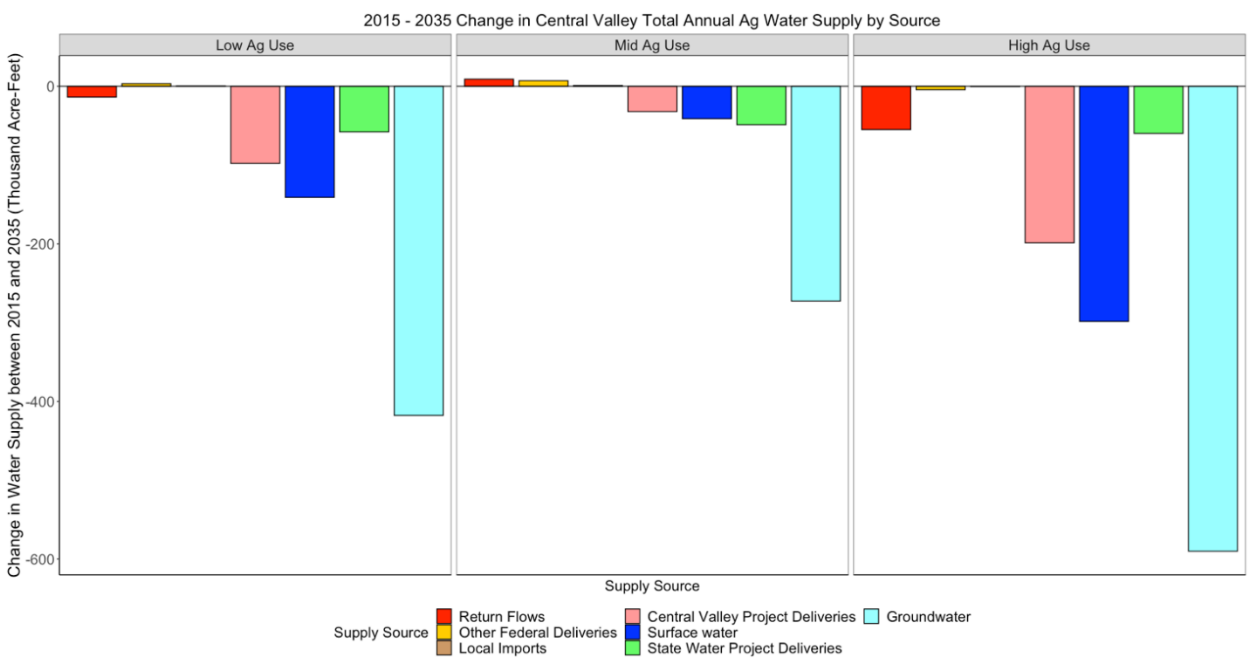


Figure 18. A. Central Valley agricultural water supply 2015 – 2035, by scenario. B. Change in total Central Valley agricultural water supply between 2015 and 2035, by scenario.

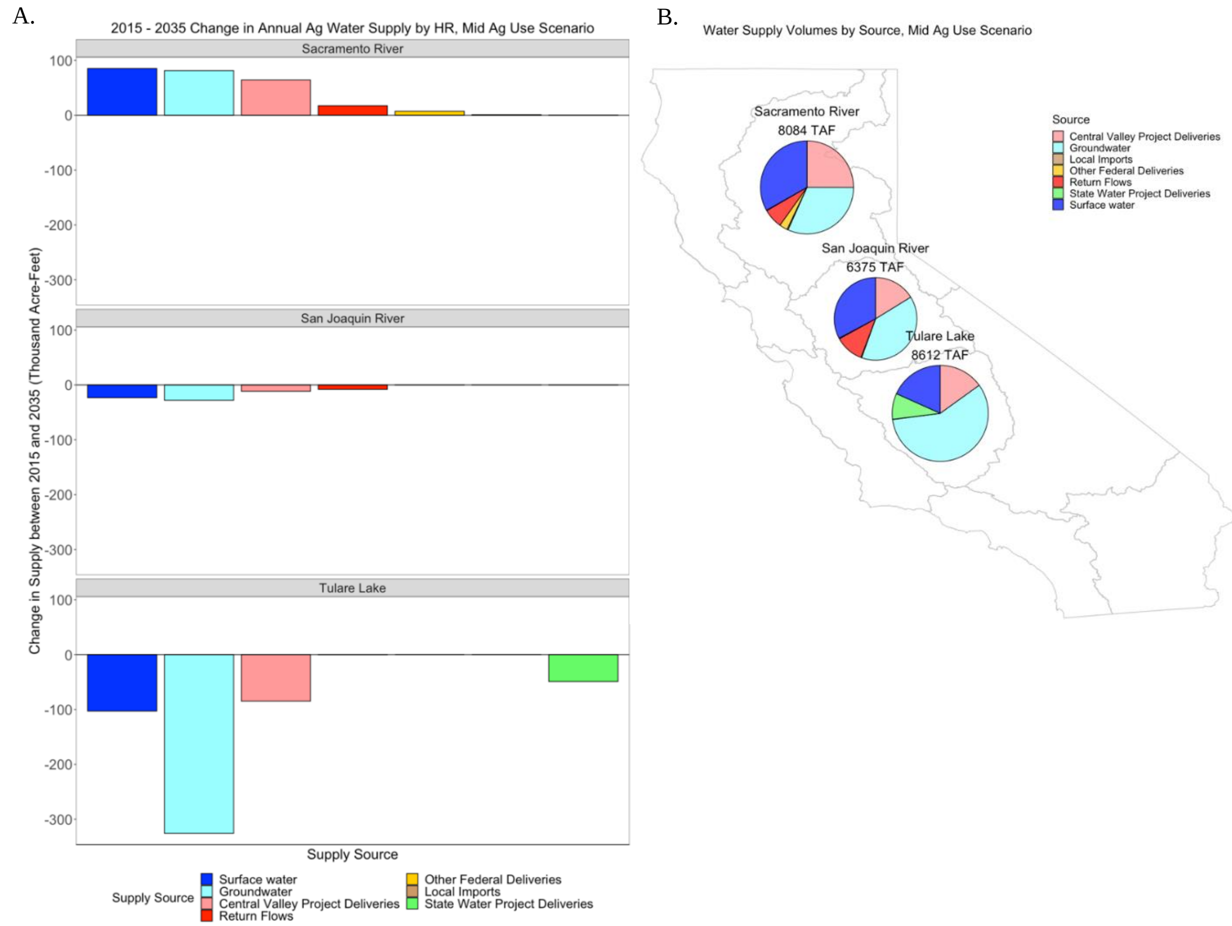


Figure 19. Mid Ag Use Scenario: A. Change in agricultural water supply by source between 2015 and 2035, by hydrologic region. B. 2035 Agricultural water supply volumes by source, by hydrologic region.

3.2.3 Energy use for agricultural water: historical and future scenarios

Despite almost double the water volumes, we find that water-related electricity use for agriculture in the Central Valley is about half that of California's urban areas (14,000 GWh in the Mid Ag water use scenario compared to 36,000 GWh in the urban mid-case scenario) in 2035. This relatively lower energy usage is due to much lower end-use energy use (compared to energy-intensive water heating), and the very limited, if any, energy requirements for water treatment, wastewater collection, and wastewater treatment within the agricultural sector. Declining supply deliveries over time in our scenarios further decrease electricity use related to agricultural water in the Central Valley. Across the three scenarios of agricultural water use, electricity use decreases from -5% (700 GWh) under the Low Ag Water Use Scenario to -6% (876 GWh) under the High Ag Water Use Scenario (Table 26). Among the water cycle categories (Figure 20), Central Valley-wide electricity use for agricultural is much more evenly split between supply extraction/generation, conveyance, distribution, and end-use than in urban areas.

Table 26. Central Valley electricity use related to agricultural sector, by scenario (GWh).

Level of Ag use	Urban growth, climate scenarios	2015	2020	2025	2030	2035	Change 2015 – 2035	% Change 2015 - 2035
Low Ag water use	HIP_LOD, Cmcc_cms, RCP 4.5	14,135	14,342	14,144	13,788	13,434	-701	-5%
Mid Ag water use	CTP_CTD, Cmcc_cms, RCP 4.5	14,193	14,444	14,282	13,964	13,678	-515	-4%
High Ag water use	LOP_HID, GFdl_cm3, RCP 8.5	15,230	14,714	14,228	14,684	14,354	-876	-6%

Electricity use is greatest in Tulare (Figure 21), not just because of high overall agricultural water use but also because of relatively high energy intensities for distribution (389 kWh/AF) and groundwater pumping (450 kWh/AF) compared to neighboring San Joaquin Valley (19 kWh/AF for distribution, 365 kWh/AF for groundwater pumping) and Sacramento River (19 kWh/AF for distribution, 350 kWh/AF for groundwater pumping). The 2035 energy intensity for Tulare's combined agricultural water supply and demands is 1,009 kWh/AF, about three times that in the Sacramento River (313 kWh/AF) and San Joaquin River (396 kWh/AF) (Table 27).

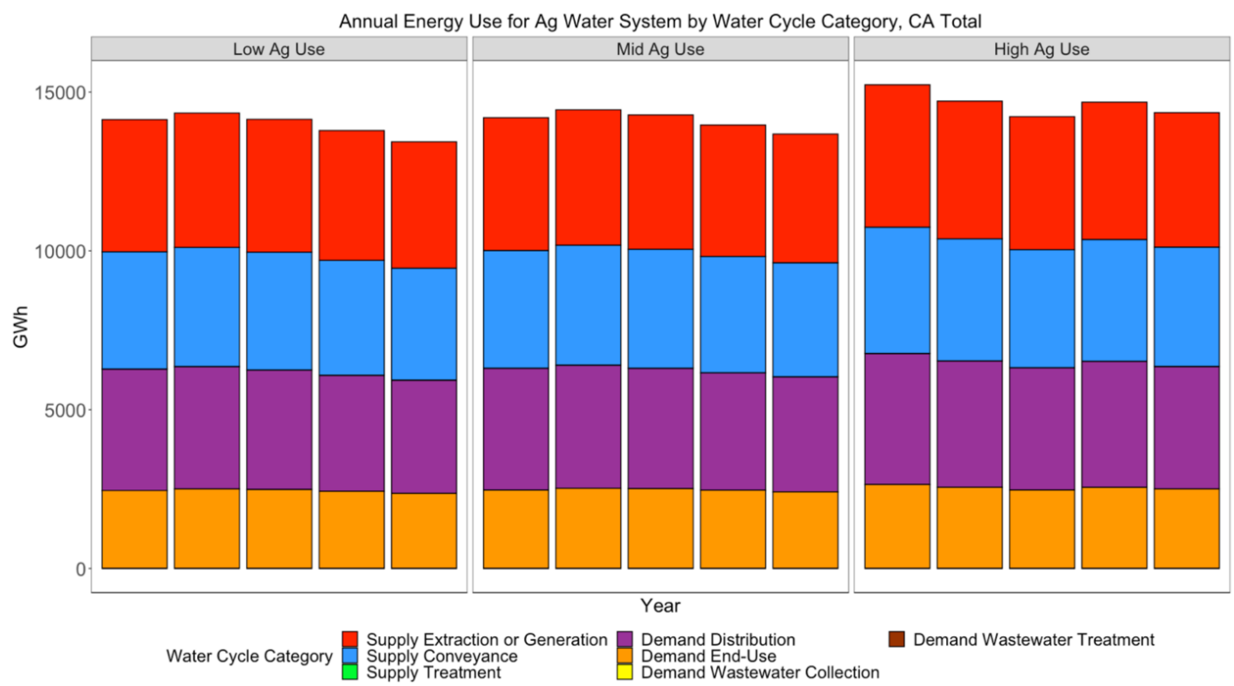
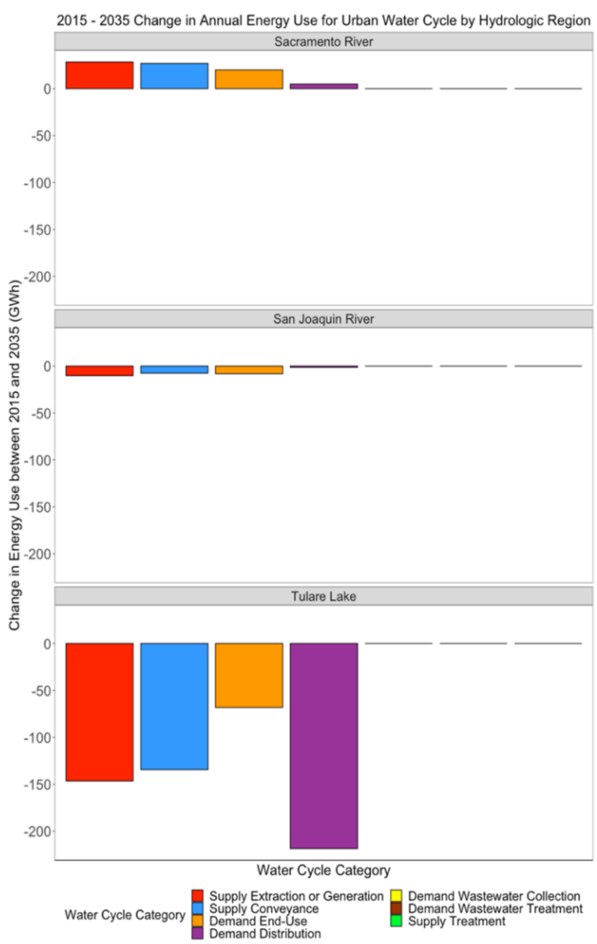


Figure 20. Central Valley electricity use by agricultural water system, by water cycle stage, by scenario.

Table 27. 2035 Agricultural water system energy intensity (electricity), by hydrologic region (kWh/AF).

Hydrologic Region	Energy intensity (kWh/AF)
Sacramento River	313
San Joaquin River	386
Tulare Lake	1,009
Central Valley Volume-Weighted Average Agricultural Energy Intensity	593

A.



B.

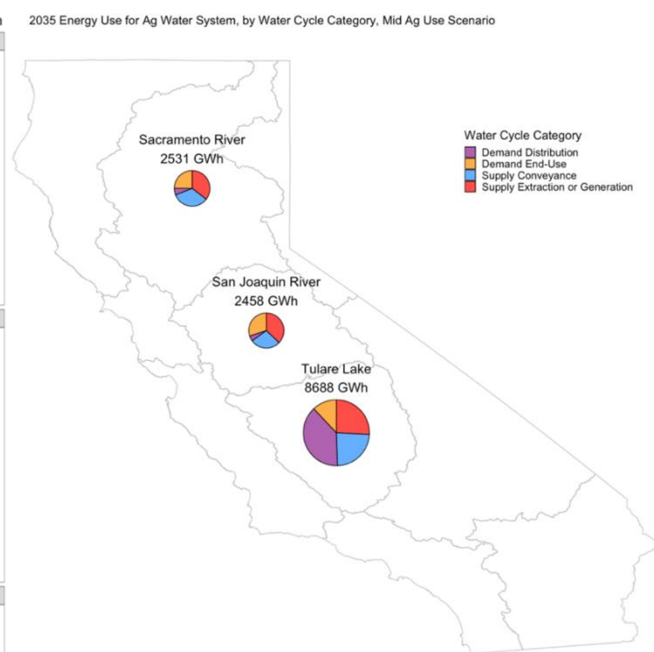


Figure 21. Mid Ag Water Use Scenario: A. 2015 and B. 2035 Electricity use by Central Valley agricultural water system, by water cycle stage, by hydrologic region.

3.2.4 GHG emissions related to agricultural water: historical and future scenarios

Across all scenarios, GHG emissions associated with Central Valley's agricultural water sector decrease by more than 60% (about 2 million tons) by 2035, due to the combined effect of lower electricity use and declining GHG intensity of California's electricity generating resources (Table 28). Since we do not include natural gas energy use for agriculture, this result captures the full effect of the decarbonization of California's electricity generation mix. In comparison, in urban California where natural gas GHG emissions are included (and total water demand is rising), total GHG increases by 1 million tons in the Water Supplier Projections Scenario. We also do not include any emissions from agricultural pumps that use diesel fuel in this analysis because of limited available data, but indications are that only a very small share of pumps are diesel powered in the state [200].

Table 28. Central Valley agricultural water-related GHG emissions from in-state electricity, by scenario (million metric tons CO2 equivalent).

Level of Ag use	Urban growth, climate scenarios	2015	2020	2025	2030	2035	Change 2015 - 2035	% Change 2015 - 2035

Low Ag water use	HIP_LOD, Cmcc_cms, RCP 4.5	3.65	2.75	2.49	1.82	1.38	-2.3	-62%
Mid Ag water use	CTP_CTD, Cmcc_cms, RCP 4.5	3.67	2.77	2.51	1.84	1.41	-2.3	-62%
High Ag water use	LOP_HID, GFdl_cm3, RCP 8.5	3.94	2.82	2.51	1.94	1.48	-2.5	-62%

4. Conclusions

In this analysis, we evaluate the combined impact of emerging pressures on California's water—including population growth, climate change, and policies to shift to water efficiency and alternative water supplies—and of electricity generation decarbonization on the energy and GHG footprints for urban and agricultural water from 2015 to 2035.

4.1 Urban

We find that if urban per-capita water demand is maintained at current (2015) levels, statewide urban water demand increases 24% (1.3 million acre-feet, or MAF) between 2015 and 2035 with population growth. This "mid-case" scenario would result in a 21% increase in water-related electricity use (from about 30,000 GWh to 36,000 GWh) and a 25% increase in natural gas use (from about 150,000,000 to 190,000,000 MMBtu). In contrast, if per-capita water demand increases to levels consistent with urban water suppliers' projections (a "high-case" scenario), urban water demand increases by 44% increase (2.4 MAF) between 2015 and 2035, resulting in a 40% and 45% increase in related electricity and natural gas use, respectively. As the state replaces fossil-fuel generators with more renewable resources, the GHG intensity of California's electricity is expected to decline, and consequently GHG emissions associated with urban water-related energy use (electricity and natural gas) is projected to decrease about 12% in our mid-case scenario. However, in the high-case scenario, GHG emissions increase 2% because growing natural gas use dampens the effect of decarbonization in the electricity sector.

We find that more comprehensive water conservation and efficiency efforts in urban California can *lower* water-related electricity usage by 19%, natural gas use by 16%, and GHG emissions by 41% between 2015 and 2035. Because indoor residential water use is the most energy-intensive subsector (driven by high energy requirements for end-use, treatment, and wastewater treatment), water conservation and efficiency improvements for this subsector could dramatically decrease the energy use and GHG emissions that would result from the mid- and high-case scenarios.

While the total annual electricity use related to urban water increases in the mid-case scenario, the average energy intensity of California's urban water—the total electricity used per unit of water used—decreases by 2% between 2015 and 2035. This decrease is driven in part by a shift in water supplies away from energy-intensive imports towards alternative sources, including brackish desalination, potable recycled water, and captured stormwater. While the shares of these alternative sources among the statewide urban water supply portfolio are still relatively very small, they have important implications for total energy use because, they are less energy-intensive than imported water in most regions of California, especially in the largest urban water region of South Coast. For example, Los Angeles' move to more local water with increased water recycling, and stormwater recharge, has reduced the overall increase in energy use compared to imported water. In 2035, the city plans to significantly reduce imported water and shift towards local sources, reducing energy use by 64% compared to 2015 values. Further, if the city shifted all imported sources to stormwater or direct potable reuse, energy use is estimated to further decrease between 27% and 40%.

4.2 Agricultural

Central Valley agricultural water use under the mid-case scenario (assuming central urban growth and density scenario) is projected to decline by 2%, or 0.3 MAF, between 2015 (23.4 MAF) and 2035 (23 MAF). This decline is driven only by DWR's projection that urban population growth will encroach on agricultural lands, not including any changes from crop prices, changes in agricultural markets, or other external factors that would also affect agricultural water use. Under this scenario, the associated electricity use decreases 4% (from 14,000 GWh to 13,600 GWh), and GHG emissions decrease about 60% (from 3.7 to 1.4 million tons CO_2).[38] The proportionally larger reduction in electricity usage compared to water use is due to expected reductions in supply from relatively energy-intensive water sources, i.e., groundwater (350 kWh/AF in Sacramento, 365 kWh/AF in San Joaquin, 450 kWh/AF in Tulare) and SWP deliveries (240 kWh/AF in Sacramento, 500 kWh/AF in San Joaquin, 2100 kWh/AF in Tulare). Likewise, the proportionally larger reduction in GHG emissions is due to statewide efforts to decarbonize its electricity generation. Climate change has minimal impacts on agricultural water use by 2035 in all three scenarios; however, changes in temperature, precipitation, and evapotranspiration are likely to have a much larger effect on both supply availability and irrigation water demand toward the end of century.

There are also large uncertainties in the future energy use of Central Valley agriculture because of its dependence on groundwater, which the state has mandated through SGMA to reach sustainable levels by 2040. In a case study, we evaluate the sensitivity of agricultural energy use in the San Joaquin Valley and Tulare regions to changing groundwater depths. If pumping volumes are maintained at current levels and groundwater depths drop to the minimum thresholds, overall agricultural water system energy intensity are projected to increase by 20% and 6% for the San Joaquin and Tulare regions, respectively. This would increase energy use in the San Joaquin and Tulare regions by about 16% in 2035. Permitting groundwater levels to rise can reduce the magnitude of the increase, as can improvements in pump efficiency. Likewise, shifting the timing of energy usage to coincide with times of renewable electricity generation could reduce the impact on GHG emissions.

4.3 Cross-cutting findings

Urban water efficiency improvements can have the largest statewide effect on California's water-related energy use and GHG emissions because urban water is much more energy-intensive than agricultural water. Even though Central Valley agricultural water use (~23 MAF) is projected to be about three times that of the urban sector (~7 MAF) by 2035, agriculture's water-related electricity usage is about half, primarily because irrigation end-uses are less energy-intensive than water heating for urban end-uses. By 2035 in the mid-case, the energy intensity and total GHG emissions related to urban water statewide are about 9 times that of Central Valley's agricultural water (5,400 kWh/AF and 14 million tons CO_2 for urban water, compared to 600 kWh/AF and 1.4 million tons CO_2 for agricultural water by 2035).

[38] GHG emissions are entirely from electricity because we do not calculate natural gas agricultural use.

Water-related GHG emissions are driven by the pace of California's electricity decarbonization and end-use electrification. With increased renewable resources on the grid, the GHG intensity of electricity generation is projected to decrease from 0.26 to 0.1 tons of CO_2 equivalent/MWh between 2015 and 2035. This decrease is estimated to effectively minimize the electricity component of the GHG emissions related to urban water. Natural gas usage, mostly for heating water in residential and non-residential settings, is projected to rise, causing urban GHG emissions to still increase overall. Therefore, there is an opportunity for water-energy partnerships to promote the electrification of water-end uses (water heaters) to reduce the state's GHG footprint.

We identify specific water policies that can play an important role in helping the state meet energy and GHG goals. We provide the following recommendations for energy- and GHG-conscious water policies for (1) reducing energy and GHG emissions associated with end-uses of water, (2) reducing energy and GHG emissions associated with the provision of water and wastewater services; and (3) supporting cross-sectoral collaborations.

4.4 Reducing water, energy, and GHG emissions associated with end-uses

4.4.1 Expand urban water conservation and efficiency efforts.

Urban water efficiency, for both indoor and outdoor uses of water and within the water distribution system, can save energy and avoid the associated GHG emissions for water extraction and generation, conveyance, treatment, and distribution. Indoor efficiency can further reduce end-use energy requirements and GHG emissions by avoiding, for example, water heating, as well as wastewater collection and treatment. Prior studies have shown there is significant urban conservation and efficiency potential in California—between 2.9 to 5.2 MAF per year [232]—through programs that cut water losses, encourage uptake of efficient devices and landscapes, and promote behavioral change through social norming [233]. One analysis found that water-efficiency programs during the most recent California drought saved as much energy as, and were cost-competitive with, the state's electric investor-owned utility efficiency programs during the same period [234]. Coordinating water and efficiency programs between water and energy suppliers can help both sectors meet water and energy goals and make these programs more cost-effective.

4.4.2 Accelerate water heater electrification.

Within the water management cycle, natural gas water heaters are the single largest emitters of GHGs. Electric heat pump water heaters are up to five times more thermally efficient than natural gas heaters [235] and can also provide significant GHG savings as the electricity system is decarbonized. However, the initial cost of electric heat pump water heaters is typically higher than natural gas heaters. Customer incentives that reduce the upfront cost of electric heaters can encourage more fuel-switching, lowering the state's overall GHG emissions. There is momentum at the state and local level to accelerate this transition. In 2020, the California Public Utilities Commission revised a previous policy preventing utilities from offering fuel-switching incentives and subsequently approved $45 million of the state's Self-Generation Investment Program budget to fund electric heat pump water heater rebates [195]. Further, several cities around California have passed regulations prohibiting natural gas in new housing developments [236], [237]. Together with water efficiency programs that lower hot water usage, incentives for electrification of water heaters can help lower the energy and GHG emissions from residential and non-residential water use.

4.4.3 Expand high-efficiency and more flexible groundwater pumps.

Maintaining groundwater levels above the minimum thresholds identified in Groundwater Sustainability Plans (GSPs) can reduce energy use, energy cost, and GHG emissions. More efficient pumps and variable frequency drives can provide additional reductions, and rebates can lower the upfront cost of these upgrades [238]. Through demand-response programs, farmers can also be compensated for operating their groundwater pumps to coincide with the timing of lower electricity prices and renewable electricity generation on the grid [239], and variable frequency drives can further be automated to adjust to grid needs [125]. This can help integrate renewable electricity and lower overall GHG emissions from electricity generation.

4.5 Reducing water, energy, and GHG emissions associated with the provision of water and wastewater services

4.5.1 Provide financial incentives and regulatory pathways for water suppliers to reduce the energy- and GHG-intensity of water systems.

California should make existing financial incentives and programs for energy efficiency and GHG reduction available to water suppliers for shifting to less energy-intensive water supplies. Energy- and GHG-related programs, such as the state’s cap-and-trade funds [240], or state bond money, such as a Climate Resilience Bond [241], are potential funding sources that could be provided to water suppliers for developing alternative local sources that save energy and reduce GHG emissions. It may also be possible to stack incentives across sectors, such as from electric investor-owned utility efficiency programs to account for the range of co-benefits of energy and GHG savings.

California should also prioritize creating regulatory pathways that enable water and wastewater services to reduce energy and GHG emissions. Guidance on direct potable reuse standards is expected to be issued from the State Water Resources Control Board by December 2023. Clear state guidelines and regulations allowing direct potable reuse may offer energy and GHG benefits over indirect potable reuse, as it could avoid energy, GHG emissions, and costs, from the additional conveyance and treatment that is currently required for indirect potable reuse. In addition, regulations that address challenges of co-digestion and resource recovery at wastewater treatment plants can lower GHG emissions, generate renewable energy, and divert organic waste from landfills with existing wastewater infrastructure. Coordination between electric and water utilities may provide opportunities to implement demand response programs at urban water and wastewater treatment plants to reduce or shift the timing of energy use. This could help alleviate stress on the electric grid from additional water-related energy use and allow energy demand to coincide with renewable generation to lower the overall GHG intensity related to water.

4.6 Water and energy data reporting and planning

4.6.1 Expand and standardize water data reporting and energy usage tracking

A unified set of projections of future water supply and demand portfolios for both urban and agricultural water suppliers is not publicly available, therefore we use different urban and agricultural datasets for this analysis. Such data - reported in a standardized way across water suppliers with harmonized assumptions (such as for population growth and climate change impacts) between urban and agricultural suppliers - is essential to understand future water system conditions. These data should also include mandatory reporting of energy usage and energy intensity of the water cycle stages for each water supplier. Ultimately the energy intensity of the water system must be tracked alongside other state environmental indicators to help California meet its energy and GHG goals.

4.6.2 Formalize coordination between water and energy regulatory agencies about forecasted energy demand changes

If water system energy demands grow as projected, California's electricity and natural gas systems will need to incorporate changes in their infrastructure planning to ensure that energy supply will reliably meet energy demand. Formal regulatory proceedings and reporting between water suppliers, state water agencies, electric and natural gas utilities, state energy regulators, and planning agencies can help facilitate coordinated cross-sectoral planning. For example, currently there is no explicit reporting of expected changes in water-related energy demand in California's Integrated Energy Policy Report and associated energy demand forecast [242]. As a result, it is unclear if the energy use growth anticipated based on water supplier projections has been factored into electricity and natural gas planning and procurement decisions. Improvements in coordination between agencies should lead to better integrated energy and water planning, reduced costs to consumers, and faster decarbonization of California's water system.

Chapter 3: Evaluating cross-sectoral impacts of climate change and adaptations on the energy-water nexus: a framework and California case study

Chapter 2 focuses on the near-term energy and GHG footprint related to water in California. Chapter 3 builds on this theme of cross-sectoral interactions and evaluates how climate change may affect the energy-water system relationship by the end-century. I review and synthesize the fragmented climate vulnerability and energy-water nexus literature to develop a generalized framework for understanding implications of climate change on the energy-water nexus. I apply this framework in a case study to quantify the range of end-century direct climate impacts on California's water and electricity resources and estimate the magnitude of the indirect cross-sectoral feedback of electricity demand from various water adaptation strategies. The work in this chapter was published in the journal Environmental Research Letters as an article titled, "Evaluating cross-sectoral impacts of climate change and adaptations on the energy-water nexus: A framework and California case study," and is included in this dissertation with permission of my co-authors Ranjit Deshmukh, Daniel Kammen, and Andy Jones.

1. Introduction

Water and energy[39] systems worldwide are, by design and necessity, interdependent: water is an input for hydropower generation and thermal power plant cooling, and electricity powers the conveyance, treatment, usage, and disposal of water. These connections have commonly been referred to as the "energy-water nexus" [37], [38], [66]–[68]. Climate change and the resulting shifts in the global hydrologic cycle [69], [70] may strengthen or strain these nexus connections in new and uncertain ways [71]. For example, temperature and precipitation changes could simultaneously increase irrigation water demand and energy for water pumping, while reducing surface water and hydropower availability [72], [73]. Further, water sector adaptation measures commonly sought during long-term declines in surface water, such as water recycling, desalination, or groundwater recharge and withdrawal, are energy-intensive [67], [74]–[77]. Ignoring such interactive climate impacts in planning reduces the reliability of both systems and increases the risk of cascading failures [17], [21], [26], [243], [244].

Climate impacts to energy and water sectors have been studied extensively, yet several gaps remain in the literature. On the one hand, many climate vulnerability studies evaluate risks to individual sectors but have not holistically assessed compounding climate risks, such as those inherent in the dynamic relationship between closely coupled electricity and water systems [16], [17], [21], [22]. Typically these analyses evaluate electricity [25], [72], [79] or water systems [80] in isolation assuming the other remains fixed, or assess climate-related changes to supplies or demands separately [72], [81]–[83], making it difficult to account for interdependent impacts within and across sectors. On the other hand, many energy-water "nexus" studies—focused on demonstrating how integrated systems' management improves efficiency, increases equitable resource access, and maximizes synergies [38]—characterize historical conditions without

[39] The terms "energy" and "electricity" are used interchangeably in this analysis; for simplicity, only electricity is considered an energy source for the water cycle even though there may be other fuels used (such as diesel or natural gas) by certain water sector processes.

climate change [61], [84], [85]. The cross-sectoral tradeoffs of climate adaptation strategies, such as the energy footprint of alternative water supplies, are particularly understudied despite recognition that ignoring such externalities could lead to maladaptation, whereby one sector's adaptation strategies increase climate vulnerabilities in another [23], [85], [86].

Given such complexity, a conceptual framework describing key system linkages and dynamics is essential to guide analysis [245]. In the first half of this paper, we integrate findings from the fragmented literature into a generalizable framework that catalogues how the relationship between electricity and water systems around the world may evolve under, and adapt to, climate change. This framework identifies the most critical cross-system climate impacts, adaptations, and feedbacks, to guide long-term planners on what to evaluate to comprehensively understand the scale and uncertainties of climate risks and adaptations of their resources. Because of regional variations in climate and infrastructure, in the second half of this paper we use a case study approach to apply the framework, focusing on the state of California.

As a semi-arid, populous, and agriculturally-intensive state, California's electricity and water systems are inextricably linked. On average 9% of California's electricity consumption is from water conveyance, treatment of drinking and wastewater, and agricultural pumping [61], and 10% of electricity consumption is from water end-uses [55]. The water sector is especially energy-intensive because of inter-basin transfers between the wet Northern and dry Southern regions [246]. Additionally, about 15% of in-state electricity generation comes from hydropower [192]. California, considered one of the most "climate challenged regions in the U.S,"[7] is projected to face temperature increases, more frequent droughts, and significant loss of snowpack (a major source of water storage) [93], [247], [248]. Recent droughts foreshadow how the state's energy-water nexus may fare under these impacts of climate change [21]. California's water sector's drought responses transferred and compounded vulnerability to its electricity sector—increased groundwater pumping spiked electricity consumption, while hydropower deficits were replaced by GHG-emitting fossil generation [35], [78]. In addition, the state has already seen several unprecedented climate-related impacts to the electricity grid, such as the August 2020 West-wide heat wave that triggered California's rolling blackouts [29].

In our case study, we quantify climate impacts by first synthesizing the range of individual water and electricity supply and demand changes projected by California-specific studies. Aggregating these projections, we estimate the overall change to the state's water and electricity annual resource balances due directly to climate impacts and indirectly to various potential climate adaptations by the end-century. We find that in the electricity sector, increased electricity demand for air-conditioning is the primary contributor to supply-demand imbalances. In the water sector, California's future water balance could span a wide range of shortage or surplus under climate change, driven mainly by large supply uncertainties. In the event of the worst-case water shortage, our results show that water-conserving adaptation measures provide large energy savings co-benefits, while other energy-intensive water adaptations may double the electricity resource imbalance caused by direct climate impacts alone. Through this analysis, we both quantify the compounding climate risks and demonstrate mutually beneficial adaptation opportunities that could arise with increased energy-water cross-sectoral coordination. We summarize the framework in Section 2, the California case study methodology in Section 3, and the case study results in Sections 4 and 5.

2. Electricity-Water Nexus Climate Change Adaptation Framework

The core objective of water and energy resource planners is to ensure adequate supplies to balance forecasted demands (subject to environmental, economic, and other constraints) [27], [32], [249]. Our framework (Figure 22) thus distills findings from across the literature on how climate change may affect these key metrics of annual supply and demand quantities, and subsequent resource balances, of regional energy and water systems (linkages $\boldsymbol{L_1}$ through $\boldsymbol{L_{15}}$). This framework provides a first-order, system-level assessment tool for identifying the biggest potential climate stressors, the range and order of magnitude of climate adaptation measures that may be needed, the possible compounding vulnerabilities due to cross-sectoral feedback effects, and key uncertainties and knowledge gaps for further analysis.

The framework centers (grey box) on the most relevant[40] projected climate change impacts—increased temperatures, reduced snowpack, changed precipitation patterns, and more frequent extremes. Across future emission scenarios, Global Circulation Models (GCMs) project climate change will increase surface temperatures worldwide [69]. Although there is uncertainty about future precipitation [82], [250], wetter regions, such as the northern high latitudes, are expected to become wetter, while some drier regions, such as the mid-latitudes, may become drier [250]–[252]. Higher temperatures will also shift precipitation towards rain, while reducing accumulation and speeding melt of snowpack, a natural slow-release reservoir that meets warm-season water demands [253]–[257], [83]. In many regions, the frequency and intensity of storms and droughts will also increase [69], [258], [259]. These climate impacts directly affect water supply (raw water availability, $\boldsymbol{L_1}$) and demand (irrigation water, $\boldsymbol{L_2}$), and electricity supply (transmission and generation efficiency, $\boldsymbol{L_3}$) and demand (air-conditioning, $\boldsymbol{L_4}$). There are subsequent feedbacks, e.g. water supply shifts ($\boldsymbol{L_1}$) affect electricity supply (hydropower generation, $\boldsymbol{L_5}$ and thermoelectric cooling, $\boldsymbol{L_6}$). In response to a resource imbalance, adaptation measures can reduce water demands ($\boldsymbol{L_7}$) or augment water supplies ($\boldsymbol{L_9}$), but may inadvertently affect electricity demand ($\boldsymbol{L_8}$, $\boldsymbol{L_{10}}$) and adaptations ($\boldsymbol{L_{13}}$). Electricity adaptation strategies can expand supply-side capacity ($\boldsymbol{L_{11}}$) and either reduce consumption through energy efficiency or increase consumption through electrification on the demand-side ($\boldsymbol{L_{12}}$). Decarbonization of centralized electricity supply can reduce thermal power plant cooling water demands ($\boldsymbol{L_{14}}$), and decentralized solar generation can power irrigation pumps and expand access to water supplies ($\boldsymbol{L_{15}}$). Population growth, urbanization, and policy change also affect energy and water systems.

[40] Because our focus is on long-term supply and demand balances, we omit climate impacts such as wildfires that primarily affect physical infrastructure and short-run reliability.

In the framework diagram, changes in electricity supply and demand quantities due to climate impacts are denoted with solid yellow linkages and water quantity changes are denoted with solid blue linkages. Dotted lines indicate supply and demand must balance in each system. Linkages that increase (decrease) quantities have + (-) and are green (red) if they increase (decrease) a system's supply-demand imbalance, i.e. difference between supply and demand. Linkages with both + and – indicate disagreement in literature or multiple strategies with different effects (e.g. electrification increases while energy efficiency decreases demand; both are electricity demand-side adaptations). These linkages are reviewed below.

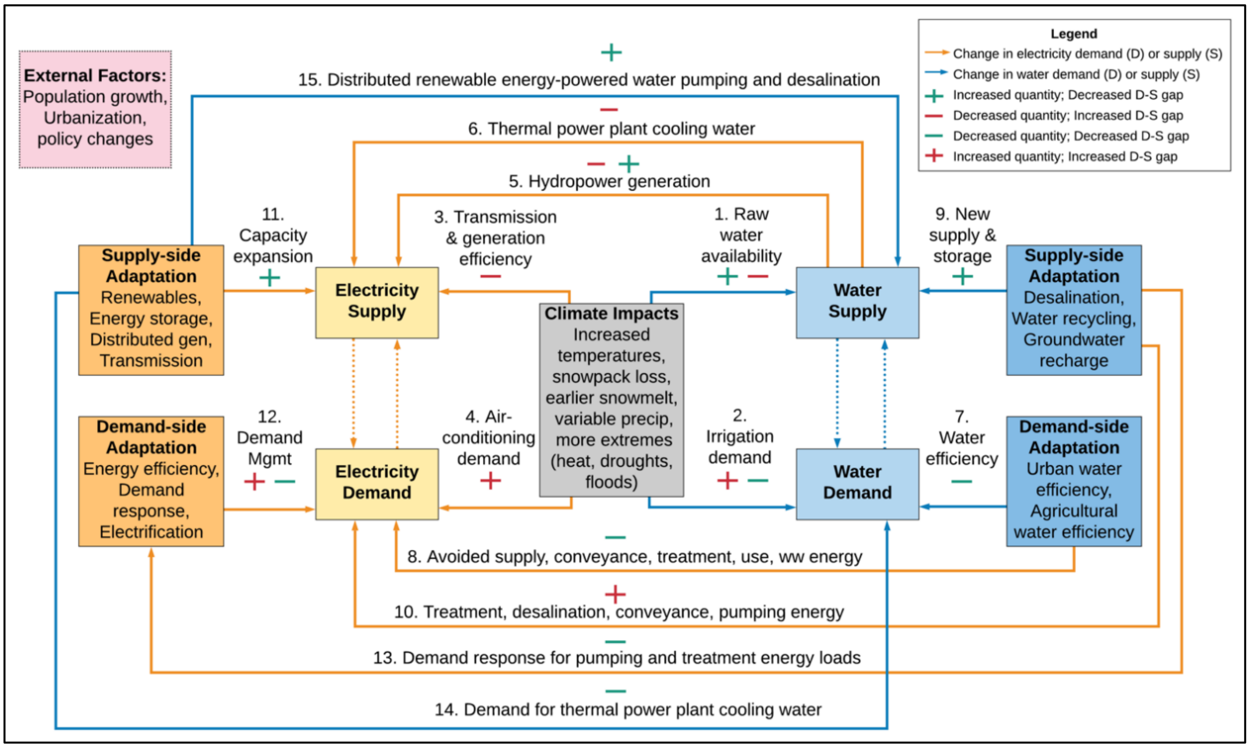


Figure 22. Electricity-Water Nexus Climate Change Adaptation Framework. Changes in electricity supply and demand quantities are denoted with solid yellow links. Water quantity changes are denoted with solid blue links. Dotted lines indicate supply and demand must balance. Impacts that increase (decrease) quantities have + (-) and are green (red) if they decrease (increase) a system's demand-supply imbalance, i.e. difference or gap between demand and supply. Links with + and – indicate disagreement in literature or multiple strategies with different effects (e.g. electrification increases while energy efficiency decreases demand; both are electricity demand-side adaptations).

2.1 Linkages $\boldsymbol{L_1} - \boldsymbol{L_6}$: Climate impacts on water and electricity supply and demand

Studies typically use GCM data and a hydrological model to simulate unimpaired runoff, which feeds into a water resource management model to estimate raw water availability, the water supply of a managed system ($\boldsymbol{L_1}$) [80], [260]. Such analyses find climate change will reduce or increase raw water availability primarily following the effect of regionally heterogenous precipitation patterns on runoff [82], [250]–[252], but results diverge due to GCM and hydrological model uncertainty [82], [250], [252]. For half the world's population dependent on snowpack for cold-season water storage [253], even with unchanged runoff volumes, raw water availability may decline if snowmelt timing shifts and reservoirs cannot store earlier inflows that coincide with the flood season, when empty reservoir space must be maintained [60], [83], [247], [254]–[256], [261].

Water demand for irrigated agriculture comprises 85% of global water consumption.[83] In many regions, climate change is projected to raise temperatures, decrease precipitation, and increase evapotranspiration (ET) [60], together affecting soil moisture and increasing irrigation water demand ($\boldsymbol{L_2}$) [81], [252], [262]–[264]. However, factors such as ET differ across hydrological models, GCMs, and observational data [250], [265]. For example, some studies account for increased atmospheric CO_2 causing plant stomata to reduce transpiration, thereby decreasing water demand [265]–[268]. Others contend that increased CO_2 fertilizes photosynthesis [264], [266], which could have an offsetting effect of speeding crop growth, enabling multiple plantings, and increasing annual irrigation requirements.

In the electricity sector, climate change could directly reduce supplies through increased transmission line losses and decreased generator efficiencies ($\boldsymbol{L_3}$). Resistive transmission losses increase as higher ambient temperatures lower radiative cooling of lines [72], [79], [269]–[271], requiring additional electricity generation to compensate [270], [272]. Higher ambient temperatures also lower both thermoelectric [79], [87], [273] and solar generating efficiencies [87], [274]; wind generation impacts are uncertain [25], [72], [79], [87].

Higher temperatures will raise electricity demand ($\boldsymbol{L_4}$) through more frequent usage (intensive effect) and new adoption (extensive effect) of air-conditioning [275]–[278]. In some regions, increases in demand may be partially offset by reduced heating, but demand is still projected to rise annually [72], [275], [278] and most significantly during summer peak times [28], [272], [279]. Electricity demand growth is especially pronounced in regions with both rising temperatures and incomes [276], [280].

Lastly, climate change affects electricity supply—hydropower ($\boldsymbol{L_5}$) and thermoelectric generation ($\boldsymbol{L_6}$)— through feedbacks of water supply changes ($\boldsymbol{L_1}$). Hydropower generation will change primarily according to raw water availability [25], [72], [79], [281], [282], and based on snowmelt dependence [25], [72], [253]. Hydropower reservoirs relying on snowpack storage [283], [284] and those with flood control objectives may have reduced summer and annual generation due to earlier snowmelt [72], [285], although larger reservoirs have greater operational flexibility and less sensitivity to these impacts [260], [284]. Meanwhile, with potentially reduced raw water availability and higher water temperatures, generation from thermoelectric plants relying on cooling water may decline [25], [72], [286]–[288]. The impact depends largely on the climate sensitivity of the cooling technology (once-through and recirculating) and water source (surface, groundwater, seawater, wastewater) [67], [282]. Dry-cooling systems use no water and are not sensitive to these water-related climate impacts, but because they are less effective at heat rejection compared to wet-cooling systems, switching to dry-cooling could reduce a thermoelectric generator's overall efficiency performance by 2-7% [67][67], [289].

2.2 Linkages $\boldsymbol{L_7} - \boldsymbol{L_{15}}$: Climate adaptations for water and electricity and their feedbacks

Traditional water supply management approaches, such as construction of reservoir storage or conveyance infrastructure, may be limited in the future by over-allocated rivers, social and ecological impacts, and costs [81], [232], [290], [291]. A combination of strategies reducing water demand ($\boldsymbol{L_7}$) and augmenting supplies with non-traditional sources ($\boldsymbol{L_9}$) may therefore be needed to adapt to climate-driven water imbalances [81], [292]. Urban demand-side adaptations include indoor savings from high-efficiency appliances, conservation, and leak repair [204], [290], [293]; and outdoor savings from drought-tolerant plants, reduced planted area, and optimized irrigation [204]. Agricultural demand-side adaptations include integrated crop water management (reducing evaporative soil moisture loss) [294], [295], irrigation efficiency [296] (although reducing return flows basinwide [297]), crop-switching [298]–[300], and land fallowing [232]. Groundwater recharge, water recycling, and desalination are common supply-side adaptations [301]. Groundwater recharge artificially infiltrates surface water (including flood or stormwater[232], [301]) into aquifers for withdrawal in dry years [302]. Treated wastewater can be reused for irrigation, or recycled further for potable use [290], [291], [293], [301]. Desalination treats seawater (35,000–45,000 ppm salinity) or brackish water (1,500–15,000 ppm salinity) to drinking water quality (< 500 ppm salinity) [67], [303].

These water sector adaptations have varying energy intensities (energy consumption per unit volume of water). Both urban and agricultural demand-side strategies save energy by avoiding water supply and conveyance ($\boldsymbol{L_8}$) [76]. Urban conservation further avoids energy from drinking water and wastewater treatment [293] and from water heating [290]. Conversely, supply-side water adaptations from unconventional sources tend to increase energy demand [58] ($\boldsymbol{L_{10}}$). Groundwater recharge programs require pumping to withdraw water from storage [74]. Water recycling uses advanced treatment to reach potable quality and pumps treated water into the distribution system (direct potable reuse) or into groundwater or reservoir storage (indirect potable reuse) [76], [201], [291]. Desalination, most commonly from reverse osmosis, is the most energy-intensive adaptation; by some estimates seawater desalination uses 25x more energy than groundwater pumping[67] and 2x more than recycling [293]. However, the impact of this energy consumption on the grid can be managed through electric utility programs that shift the timing of demand to coincide with renewable energy generation ($\boldsymbol{L_{13}}$) [67], [239].

Electricity sector adaptations, often primarily motivated by climate change mitigation, include supply expansion and decarbonization (through utility-scale renewable generation, storage, and transmission capacity, as well as distributed generation, $\boldsymbol{L_{11}}$), and demand management (energy efficiency, electrification of end-uses such as transportation, and demand response, $\boldsymbol{L_{12}}$). Supply-side strategies that transition from thermal to non-water-intensive solar and wind generation [36], [304], [305] decrease water demand for cooling ($\boldsymbol{L_{14}}$) [289], [306]. Distributed, off-grid generation from solar PV can also power irrigation pumps to expand access to surface or groundwater supplies and drip or sprinkler irrigation ($\boldsymbol{L_{15}}$) [307]–[309]. Small-scale, distributed solar-powered desalination has also been deployed to augment water supplies in several regions [67]**.**

2.3 External factors: Population growth, urbanization, policy drivers

Population growth, urbanization, and policy changes also compound or offset climate impacts on energy and water systems [21], [58], [81]. Population growth increases resource demand [82], [310], but impacts vary by density (urbanization). For example, if urban population growth creates sprawl and encroaches on agricultural lands, demand for more energy-intensive urban water displaces irrigation water demand [311]. Policy drivers, such as regulations limiting groundwater extraction, also affect a system's water supply portfolio and energy intensity [58], [312]. For electricity systems, decarbonization policies may increase reliance on climate-sensitive hydropower resources [281], [282].

3. Methods and Data: California case study

We apply our framework to California by: 1) synthesizing the range of climate impacts to linkages $\boldsymbol{L_1}$through $\boldsymbol{L_5}$ from existing studies 2) estimating the subsequent aggregate effect of climate change directly on both systems' annual resource balances, and 3) calculating energy consumption ($\boldsymbol{L_8}$, $\boldsymbol{L_{10}}$) tradeoffs of different water adaptation strategies ($\boldsymbol{L_7}, \boldsymbol{L_9}$) in the event of a worst-case water shortage.

We exclude changes to cooling water ($\boldsymbol{L_6}$ or $\boldsymbol{L_{14}}$) because California uses minimal freshwater[41], and must further reduce thermal generation (excepting small shares of biomass and solar thermal) to meet its 2045, 100% carbon-free energy goal [90], [91]. We also omit solar PV and wind generation losses in $\boldsymbol{L_3}$ because of uncertain end-century resources and nominal expected impacts (solar capacity declines <2%) [87]. Subsequent analysis is planned for $\boldsymbol{L_{11}}$ through $\boldsymbol{L_{13}}, \boldsymbol{L_{15}}$, and external factors.[42]

3.1 Synthesis of climate impacts on water and electricity resource balances

We review literature quantifying climate change impacts on California's energy and water supply and demands, excluding analyses with limited geographic coverage (apart from irrigation and hydropower which are typically analyzed regionally), and collect results from 18 studies for $\boldsymbol{L_1}$through $\boldsymbol{L_5}$. For each linkage, we cull the maximum and minimum of annual percentage changes to resources projected for end-century (2070 - 2100),[43] characterizing the combined uncertainty from different methodologies, GCMs, and emissions scenarios across studies (Ch. 3 Appendix A).

We standardize these ranges as absolute changes in water and energy volumes, applying the climate perturbation percentages to historical electricity and water stocks[44] (Table 29, Ch. 3 Appendix B). Finally, to calculate the overall bounding "worst-case" and "best-case" range of climate impacts on annual state water and energy balances, for each system the maximum of demand changes are subtracted from the minimum of supply changes, and the minimum of demand changes are subtracted from the maximum of supply changes, respectively; a positive resulting balance change indicates surplus, and a negative balance change indicates shortage. These sign conventions and method of calculation are appropriate to bound the systemwide worst-case and best-case because the climate impacts on demand and supply are coincident i.e. supply will decrease at the same time as demand will increase and vice versa.

---

[41] In 2018, thermal power plants in California withdrew and consumed approximately 0.02 Billion m^3 of freshwater, comprising 0.02% of average annual water supplies [313].

[42] Our analysis focuses on end-century climate impacts, however, in the nearer term, California's policies to electrify transportation, from internal combustion to electric vehicles (EVs), and buildings, from natural gas to electric space and water heating, may have a greater impact on increasing electricity demand than climate change ($\boldsymbol{L_{12}}$). One analysis for 2050 projects high levels of building electrification and high levels of EV adoption may each increase electricity demand as much as 3x times as climate increases the demand for air-conditioning [314]. However, given that end-century climate change impacts on air-conditioning could be 2x higher than in mid-century [8], [275], and the uncertainty of the future building stock and vehicle fleet by the end-century study period, we have not included these effects in our end-century analysis.

[43] The end-century is the time period for which we found the most studies across all the linkages. Ch. 3 Appendix Table 44 includes projections for mid-century where available.

[44] The literature we review projects average annual resource changes due to climate change. Therefore, we apply the percentage changes to average annual historical levels of water and electricity supplies and demands. However, there is significant inter-annual resource variability in the water sector (e.g. in a recent wet year, 2011, annual surface water supply in California was about 99 Billion m^3, about twice that of the 50 Billion m^3 supply during a drought year, 2015) [222]. Analysis of the impact of this inter-annual variability on energy and water balances under climate change is an area for future research.

Table 29: Calculations for climate change impacts on California annual water and electricity resource balances. L_1,and L_2 are calculated with 2002 – 2015 average urban and agricultural water balance data from the California Department of Water Resources in Billion cubic meters, Bm^3 [222]. Electricity linkages are calculated with residential and commercial building (L_4) and total (L_3) 2002-2018 average consumption data from the California Energy Commission [315], and hydropower generation data (L_5) averaged 2002-2018 from the Energy Information Administration [316] in terrawatt-hours. Irrigation demand changes (L_2) are calculated for the main agricultural regions (Sacramento Valley, San Joaquin Valley, and Tulare Lake) and hydropower changes are calculated by high- (>300m) and low-elevation generators (L_5).

Annual water supply changes	Annual water demand changes
L_1, Raw water availability $\Delta\,[Bm^3] =$ $(Total\ urban\ and\ agricultural\ water, 53\ Bm^3) * (\%\,\Delta)$	L_2, Irrigation water demand $\Delta\,[Bm^3] =$ $(Irrigation\ demand_{Sac}, 10\ Bm^3) * (\%\,\Delta_{Sac}) +$ $(Irrigation\ demand_{SJV}, 9\ Bm^3) * (\%\,\Delta_{SJV}) +$ $(Irrigation\ demand_{Tulare}\ 14\ Bm^3) * (\%\,\Delta_{Tulare}) +$
Total change in annual water balance	
Annual water balance $\Delta\,[Bm^3] = L_1 - L_2$: Worst-case water balance $\Delta\,[\mathrm{Bm}^3] = min(L_1) - max(L_2)$ Best-case water balance $\Delta\,[\mathrm{Bm}^3] = max(L_1) - min(L_2)$	
Annual electricity supply changes	**Annual electricity demand changes**
L_3, Supply impact of transmission losses $\Delta\,[TWh] =$ $(Total\ electricity\ consumption, 278\ TWh) * (\%\,\Delta)$ L_5, Hydropower generation $\Delta\,[TWh] =$ $= (Hydropower\ generation_{high-elev}, 20\ TWh) * (\%\,\Delta_{high-elev}) + (Hydropower\ generation_{low-elev}, 11\ TWh) * (\%\,\Delta_{low-elev})$	L_4, Air conditioning demand $\Delta\,[TWh] =$ $(Res.\,\&\ comm.\ building\ consumption, 190\ TWh) * (\%\,\Delta)$
Total change in annual electricity balance	
Annual electricity balance $\Delta\,[TWh] = (L_3 + L_5) - L_4$: Worst-case electricity balance $\Delta\,[TWh] = (min(L_3) + min(L_5)) - max(L_4)$ Best-case electricity balance $\Delta\,[TWh] = (max(L_3) + max(L_5)) - min(L_4)$	

3.2 Climate adaptations for water shortages and their energy tradeoffs

If the worst-case, upper end of the water shortage calculated in Section 3.1 is realized, significant application of adaptation measures that either augment water supplies or reduce water demands may be needed. We estimate the energy balance feedback ($\boldsymbol{L_8}$**,** $\boldsymbol{L_{10}}$) from residential water conservation, agricultural water conservation, groundwater banking, water recycling, and desalination adaptation measures ($\boldsymbol{L_7}, \boldsymbol{L_9}$) that could fill the maximum water shortage volume.

As shown in Table 30, we first calculate the net energy intensity ($NEI_{i,j}$) of each adaptation measure, by summing the average energy intensities of all processes required to implement the measure (i.e. treatment, pumping, etc.) [234] as EI_i, and subtracting EI_j, the energy intensity of the water source it may replace because of climate impacts [301].

$$NEI_{i,j} = EI_i - EI_j$$

where,

EI_i = Energy intensity of adaptation i, summing energy intensities of all associated processes in $\frac{kWh}{m^3}$, $i \in$ {Residential water conservation, agricultural water conservation, groundwater banking, water recycling, desalination}.

EI_j = Energy intensity of substituted water source j in $\frac{kWh}{m^3}$, $j \in$ {local surface water, California volume-weighted average water source, State Water Project deliveries}.

For example, if climate change effectively reduces deliveries via the energy-intensive State Water Project (SWP) inter-basin transfer, the $NEI_{i,j}$ of an adaptation measure is net of avoided SWP conveyance energy. Because of uncertainties in where and how much of each water source may be substituted, for each adaptation we test three EI_j sensitivities that each assume a single source of substituted water j—local surface water (0.09 kWh/m^3), a weighted average of all California water supplies (0.32 kWh/m^3), and SWP deliveries (1.55 kWh/m^3) (details on energy intensities in Ch. 3 Appendix A.b).

Table 30: Net energy intensity of water adaptations in California. Net energy intensity of a water adaptation measure ($NEI_{i,j}$) is the difference in energy intensity of the substituted water source EI_j and adaptation measure EI_i. EI_i is the sum of energy spent in implementing the measure, using statewide averages of associated processes listed in the table. Negative EI_i and $NEI_{i,j}$ values indicate energy savings, and positive values indicate energy consumption. EI_i of residential water conservation includes energy savings from avoided water treatment, urban distribution, water heating, and wastewater treatment. EI_i of agricultural water conservation includes energy savings from avoided agricultural distribution and irrigation. EI_i of groundwater banking include energy for groundwater pumping. EI_i of water recycling includes energy for incremental treatment above wastewater treatment for indirect potable reuse, and for distribution from the treatment plant for storage. EI_i of desalination includes energy for reverse osmosis treatment, averaged across seawater and brackish water, and for distribution from the treatment plant. Three EI_j are included: local surface water (0.09 kWh/m^3), California supply-weighted average (0.32 kWh/m^3), and the average across delivery points of the State Water Project conveyance system (1.55 kWh/m^3). EI_i references: [55], [58], [61], [64], [65], [73], [74], [76], [199], [207], [210], [215], [317]

Water adaptation measures i	Calculation of EI_i of adaptation measure [kWh/m^3]	EI_i of adaptation measure [kWh/m^3]	$NEI_{i,j}$ with EI_j of local surface water [kWh/m^3]	$NEI_{i,j}$ with EI_j of CA avg. water source [kWh/m^3]	$NEI_{i,j}$ with EI_j of State Water Project water [kWh/m^3]
L_7, Residential water conservation	$-(urban\ distribution\ energy, 0.27 + treatment\ energy, 0.17 + res. water\ heating\ energy, 3.16 + wastewater\ treat\ energy, 0.69)$	-4.29	-4.39	-4.62	-5.84
L_7, Agricultural water conservation	$-(ag. distribution\ energy, 0.21 + avg. irrigation\ energy, 0.09)$	-0.30	-0.39	-0.62	-1.84
L_9, Groundwater banking	$Avg. groundwater\ pump\ energy, 0.38$	0.38	0.28	0.05	-1.17
L_9, Water recycling for potable reuse	$Incremental\ treatment\ energy, 0.95 + recycled\ distribution\ energy, 0.27$	1.22	1.13	0.90	-0.32
L_9, Desalination	$Reverse\ osmosis\ energy, 2.55 + desal\ distribution\ energy, 0.29$	2.84	2.75	2.52	1.30

We then construct five corner case scenarios of each individual adaptation measure addressing 100% of the worst-case maximum water shortage volume, and four portfolio scenarios, ranging from most to least diversified, combining multiple measures capped at their feasible volume limits (Table 31). Portfolio 1 caps residential (indoor plus outdoor) water conservation at 1.8 Bm^3/year [204] and water recycling at 6.7 Bm^3/year [75], [76] with the remaining shortage equally satisfied by groundwater recharge, agricultural conservation, and desalination. Portfolios 2 through 4 cap residential conservation and recycling, and desalination meets the remaining volume.

Table 31: Scenarios of water sector climate adaptations. In corner case scenarios, the water shortage volume WSV_i is equal to 100% of the worst-case water shortage volume (18 Bm^3) calculated in Section 3.1. In portfolio scenarios, WSV_i contributions of several measures sum to address the worst-case water shortage. Water conservation and water recycling are capped at their limits, 1.8 Bm^3/year [204] and 6.7 Bm^3/year [75], [76], respectively.

Corner case scenarios	WSV_i filled by adaptation measures	Portfolio scenarios	WSV_i filled by adaptation measures
Corner case 1: 100% Residential water conservation	18 Bm^3	Portfolio 1: 10% Residential conservation 18% Agricultural conservation 18% Groundwater banking 37% Recycling 18% Desalination	 1.8 Bm^3 3.2 Bm^3 3.2 Bm^3 6.7 Bm^3 3.2 Bm^3
Corner case 2: 100% Agricultural water conservation	18 Bm^3	Portfolio 2: 10% Residential conservation 37% Recycling 53% Desalination	 1.8 Bm^3 6.7 Bm^3 9.5 Bm^3
Corner case 3: 100% Groundwater banking	18 Bm^3	Portfolio 3: 10% Residential conservation 90% Desalination	 1.8 Bm^3 16.2 Bm^3
Corner case 4: 100% Water recycling	18 Bm^3	Portfolio 4: 37% Recycling 63% Desalination	 6.7 Bm^3 11.3 Bm^3
Corner case 5: 100% Desalination	18 Bm^3		

Finally, for each combination of adaptation scenario s and substituted water source j, we calculate the overall energy balance impact, $EB_{s,j}$, as the sum-product of the $NEI_{i,j}$ of included adaptation measures and associated water volumes WSV_i from Table 31.

$$EB_{s,j} = \sum_{i=1}^{n} (NEI_{i,j}) * (WSV_i)$$

where,

$NEI_{i,j}$ = Net energy intensity for adaptation measure i for substituted water source j in $\frac{kWh}{m^3}$, $i \in$ {Residential water conservation, agricultural water conservation, groundwater banking, water recycling, desalination} and $j \in$ {local surface water, California volume-weighted average water source, SWP deliveries}.

WSV_i = Water shortage volume filled by adaptation measure i in m^3, $i \in$ {Residential water conservation, agricultural water conservation, groundwater banking, water recycling, desalination}.

4. Case Study Results and Discussion

For California's water system, we find that by end-century, climate change may cause an annual average imbalance ranging from an 18 Bm^3 shortage in the worst-case to a 24 Bm^3 surplus in the best-case (Table 32, Figure 23). This large range is dominated by widely differing estimates (25% decrease to 46% increase) of raw water availability ($\boldsymbol{L_1}$) [260], [318], [319]. Despite rich literature on California hydroclimatic phenomena and on subsets of its water system [75], [247], [320] we find relatively little research estimating changes in California's total managed water supply. Further, studies differ on the degree to which any increased November through March runoff under climate change could be captured for water supplies, due to concurrent reservoir flood control requirements [247], [260]. Increased irrigation water demand ($\boldsymbol{L_2}$) contributes the remaining imbalance; demands could decrease 2% or increase up to 31% within California's individual agricultural regions [262], [263], [300], [321], [322]. The variation reflects assumptions for ET and plant physiology [321], and regional differences in the share of water-intensive crops [262], [263].

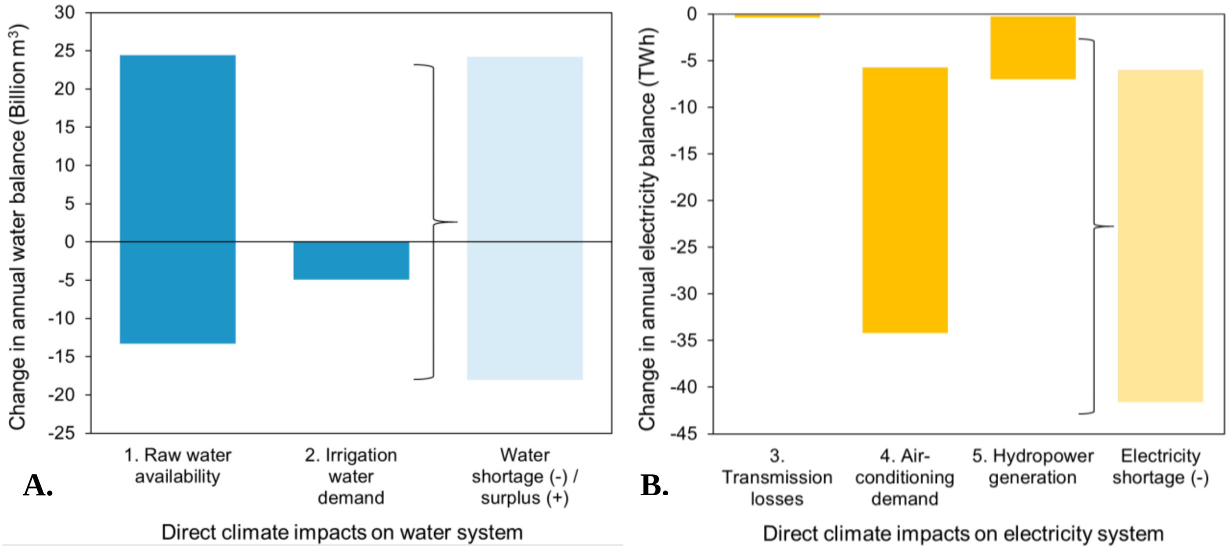


Figure 23: A. End-century climate impacts on California annual water balance. B. End-century climate impacts on California annual electricity balance. The upper and lower ends of the bars for each linkage show the maximum and minimum calculated absolute change as it affects the resource balance. The water and electricity shortage/surplus bars are respectively the sum of the supply and demand component changes and represent the aggregate worst-case and best-case changes in resource balances. Positive = surplus, negative = shortage.

In California's electricity system, climate change may create an annual imbalance ranging from a shortage of 6 TWh in the best-case up to a shortage of 42 TWh in the worst-case (Table 32, Figure 23). We find that higher electricity demand for air-conditioning ($\boldsymbol{L_4}$) is the largest contributor (3% increase to 18% increase) [8], [275], concurring with prior work [272]. During summer months, peak demand will increase more sharply (4% to 20% increase) than total annual demand [8], [271], [323]. The ranges reflect differences across studies in GCMs, spatial resolution, and inclusion of both extensive and intensive growth [275]. On the supply-side, California's annual average hydropower generation ($\boldsymbol{L_5}$) could decrease 27% or increase up to 14% by end-century, varying by region [283]–[285], [324]–[326]. Absolute declines are greatest for high-elevation hydropower (which contributes two-thirds of total average hydropower generation) and hot/dry GCM projections, worsening with droughts.[45] Despite disparities in annual estimates, studies agree seasonally—average hydropower generation (and spill) increases over winter and spring, and decreases up to 55% over summer, which exacerbates grid reliability planning challenges. Lastly, studies project a nominal 0.1% increase in transmission resistive losses ($\boldsymbol{L_3}$) [271], [328].

Table 32: Range of end-century annual climate change impacts on California electricity and water systems. Details on all studies referenced for each linkage are in Ch. 3 Appendix Table 44.

Linkage	End-century annual % Δ from literature (- decrease/ + increase)	Ref.	Calculated end-century annual absolute Δ

[45] For example, hydropower generation in 2015, the worst year of the recent 2012 – 2016 drought, decreased to about 50% of the 2002-2018 average level [192],[316]. Droughts are projected to become more frequent in California under climate change [327].

Supply-side L_1, Raw water availability	-25% to +46%	[260], [318], [319]	-13 to +24 Billion m^3
Demand-side L_2, Irrigation water demand	Sacramento Valley: -2% to +31% San Joaquin Valley: 0% to +7% Tulare Lake: +3% to +7%	[262], [263], [300], [321], [322]	+0.2 to +5 Billion m^3
Worst-case to best-case change in water balance (- shortage/+ surplus)			-18 to +24 Billion m^3
Supply-side L_3, Transmission energy losses	-0.14% to 0%	[271], [328]	-0.4 to 0 TWh
L_5, Hydropower generation	Low elevation: -27% High elevation: -20% to +14%	[283]–[285], [324]–[326]	-7 to -0.2 TWh
Demand-side L_4, Air-conditioning demand	+3% to +18%	[8], [275]	+6 to +34 TWh
Worst-case to best-case change in electricity balance (- shortage/+ surplus)			-42 to -6 TWh

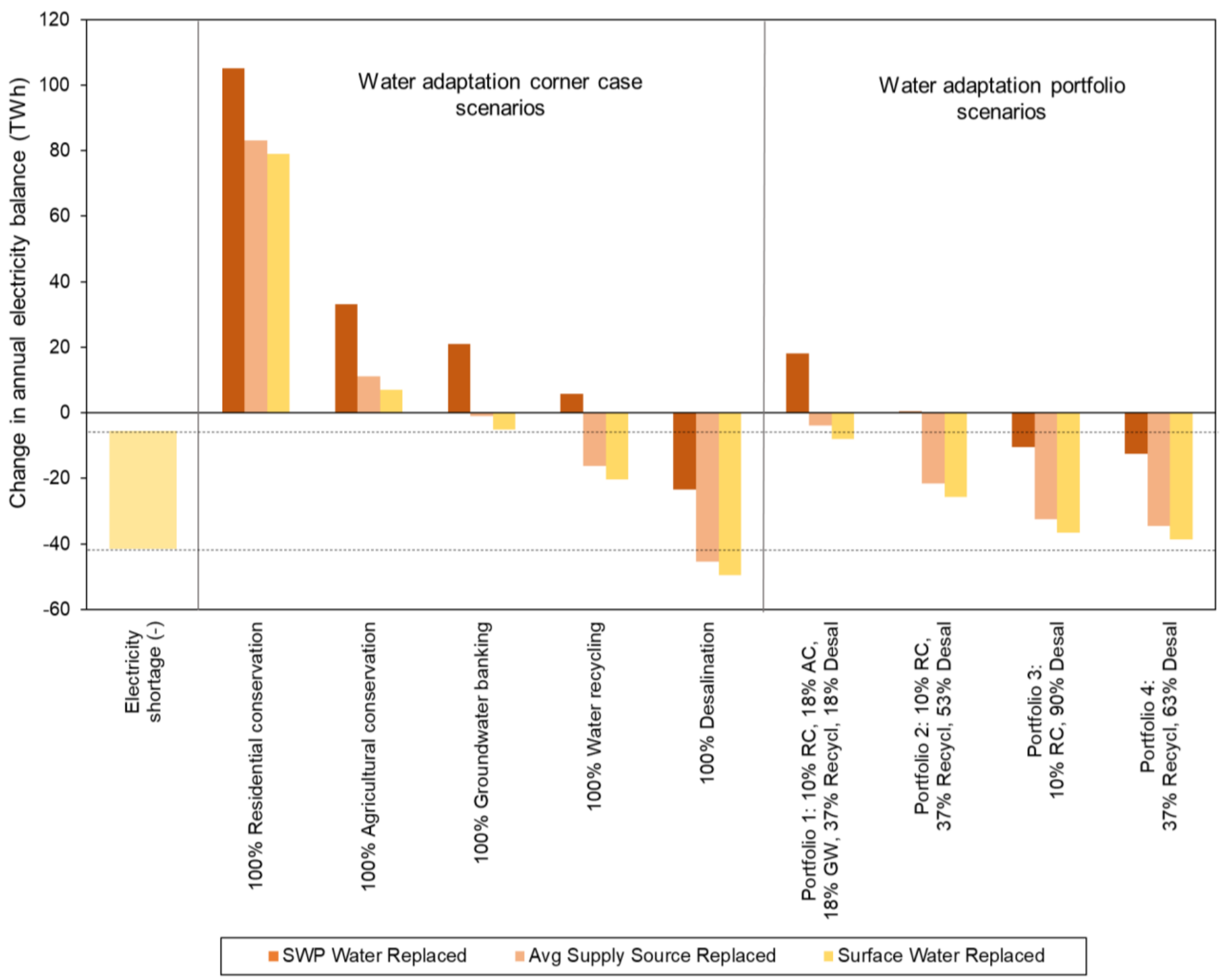


Figure 24. Energy impacts of water adaptations are comparable to direct climate impacts on electricity. Dotted lines indicate the range of the electricity shortage from direct climate change impacts. The panels on the right show energy consumption or savings of water adaptations to meet the 18 Bm^3 worst-case water shortage. Corner cases meet the full water shortage with a single adaptation; portfolios include combinations of measures, as indicated by the percentage share. RC = Residential conservation; AC = Agricultural conservation; GW = Groundwater recharge; Recylc = Water recycling for indirect potable reuse; Desal = Desalination. Colors indicate water sources replaced by adaptations. SWP = State Water Project. Positive indicates surplus, negative indicates shortage.

If climate change leads to water imbalances, our analysis finds that a wide range of energy impacts is possible from adaptations that meet the 18 Bm^3 worst-case supply shortage. Figure 24 shows that the energy balance ($EB_{s,j}$) impacts of several adaptation scenarios (including corner cases and portfolios), are on the same order of magnitude or even surpasses direct climate impacts on the energy system.

Among the adaptation corner case scenarios, consistent with prior studies [204], [234], [329]–[331], we find that strategies that rely strongly on conservation measures, particularly in urban areas, could substantially reduce energy requirements for water sector adaptation. Residential conservation saves the most energy (about 80 to 110 TWh saved) by avoiding energy-intensive end-uses, conveyance, and treatment. Conversely, if the water shortage is met entirely with desalinated water, the energy impact (20 to 50 TWh of additional demand) exceeds that of direct climate change induced shortages in the electricity sector, from hydropower generation, transmission losses, and air-conditioning combined.

Diversified portfolios of both demand-side and supply-side adaptations reduce overall energy impacts, while also overcoming some of the physical limits [67], [75], [76], infrastructure costs [290], public opinion [293], [301], and water pricing [293] implementation barriers that make relying on corner cases unrealistic. For example, with a mix of residential and agricultural conservation, groundwater recharge, water recycling, and desalination, we find that Portfolio 1's energy impact (ranging from 18 TWh saved to 8 TWh of additional demand) could completely or near completely offset direct climate impacts on the energy imbalance. Conversely, energy impacts increase with less diversified strategies relying primarily on supply-side measures [58]. Portfolios 2, 3, and 4 nearly double the energy imbalance, like the most energy-intensive corner cases, because of their high shares of desalination and water recycling. We find that the source of water substituted by an adaptation is nearly as important to the overall energy impact as the energy demand to implement the adaptation itself. All adaptation corner cases except for desalination save energy when substituting energy-intensive SWP water (using the average energy intensity across delivery points), whereas if a local or an "average" water source is replaced, groundwater banking, recycled water, and desalination would still create energy shortages. The most diverse Portfolio 1 saves energy if replacing SWP deliveries, while the replacement of average and local surface water supplies still adds to the energy shortage.

5. Summary and Conclusions

Previous analyses have characterized either current electricity and water system connections, or future climate change vulnerabilities of individual system components in isolation. This study unites these two threads of literature and presents a generalizable framework which can guide resource managers on evaluating climate impacts on the energy-water nexus for long-term planning. While this paper applies the framework to the California context, the overall concept can be broadly used by planners and researchers to conduct a first-order, aggregate assessment of cross-sectoral climate vulnerabilities and the tradeoffs among available adaptation technologies in regions with closely coupled electricity and water systems. The importance of particular linkages will differ by region based on hydroclimatic conditions and infrastructure. For example, generation losses depend on the share of thermoelectric plants that rely on cooling water, and water supply changes depend on region-specific snowpack storage, groundwater dependency, and reservoir operations. Further, the ability to realize co-benefits and minimize unintended energy impacts of water adaptations will also depend on a number of physical, institutional, environmental, and economic constraints [86] that are important criteria for future study and decision-making.

When applying this framework to California, we find that the range of potential climate-driven gaps in supply and demand are much larger for the water system (spanning both shortage and surplus) than the electricity system, reflecting large water supply uncertainties by end-century. To better support water and electricity planning efforts, subsequent research can explore in more detail how projected hydroclimatic variability and change interacts with constrained water infrastructure [25] in the nearer term, at more refined geographic and temporal scales, and during extreme events [269], [332]. For example, given available data, our estimates of annual average climate change impacts on energy and water resources in California potentially underestimate the severity of supply-demand imbalances during the summer months when several factors coincide (e.g., irrigation demand increases, raw water decreases, hydropower decreases, and air-conditioning increases).

Overall our findings imply that water sector adaptations could significantly compound the direct effect of climate change on the electricity system, suggesting the need for grid planning to incorporate not only direct impacts (such as future air-conditioning growth and hydropower reductions), but to also coordinate with water resource planners to prioritize energy considerations in decision-making and to anticipate water sector adaptations in electricity demand forecasts. Closer cross-sectoral adaptation planning could enable jointly funded R&D, customer incentives, and programs for water conservation, which would have the greatest mutual water and energy saving benefits and help ensure reliable services in both sectors. Climate change will bring new and uncertain challenges to strongly interdependent electricity and water systems. This analysis demonstrates the substantial benefits of coordinated climate adaptation planning between the electricity and water sectors to increase system resilience worldwide.

Chapter 4: Planning for climate change impacts on electricity and water systems in the Western US with a cross-sectoral modeling approach

Chapter 3 finds that the main ways electricity and water systems are impacted by climate change in the Western US are through changing water supply availability, irrigation water demand, hydropower generation, and electric demand for cooling. Yet, there are few examples of grid planners considering such impacts of climate change or water system interactions in modeling efforts for future grid expansion, and existing examples only analyze select impacts [87], [88]. I address these gaps in Chapter 4 by connecting a high-resolution capacity expansion model with a water model that combines climatically-driven physical hydrology and management of both water supply availability and demand allocation. This analysis evaluates the optimal buildout of Western US electricity infrastructure in response to climate impacts and water sector interactions by 2050. The work in this chapter is in preparation for submission to a journal, and is included in this dissertation with permission from co-authors David Yates, Patricia Hidalgo-Gonzalez, Martin Staadecker, Pedro Sanchez Perez, Daniel Kammen, and Andy Jones.

---

1. Introduction

Electricity and water systems are closely connected in the semi-arid Western United States (WUS). Electricity use for water services including long-distance conveyance, agricultural groundwater pumping, drinking water treatment, and wastewater treatment comprises 6-7% of total electricity consumption across the WUS states [61]. Hydropower is also a key source of electricity generation, comprising 17%, 37%, 68%, 74%, and 77% of electricity generation on average from 1990 – 2019 in California, Montana, Oregon, Washington, and Idaho respectively, but with significant year-to-year variability [333].

Both systems are each vulnerable to the impacts of climate variability and change. Across the region, climate models project higher temperatures and changes to the hydrologic cycle including snowpack loss, earlier snowmelt, and more variable precipitation [247], [334]–[336]. One study suggests that the threat of such climate change impacts to water resources in the WUS is unparalleled anywhere else in the country [335], affecting water supply availability and timing, and water demands for agriculture and urban outdoor uses [337]. Because of the inherently interconnected nature of the two systems, changing surface water availability affects hydropower generation, and in combination with increased water demand, raises associated energy use, such as for groundwater pumping [59], [284]. The electricity system further faces the compounding threat of higher demands for cooling, especially in the summer months [28], [338]. A US grid reliability agency has warned that electricity supplies in several regions including the WECC and California in particular are vulnerable this summer (2021) because of high temperature forecasts [339].

While the electricity system must adapt to such climate change impacts, it is also working to decarbonize the generation portfolio with zero-emissions resources because it is one of the largest sources of GHG, and it is widely held that simultaneously electrifying end-uses is a cost-effective strategy to also reduce emissions across the primarily non-electric transportation and building sectors. California has set targets for 100% carbon-free generation resources by 2045

[120, p. 100] and a bill requiring Oregon to reach 100% carbon-free energy by 2040 passed both legislative houses and is expected to be signed into law [340]. President Joe Biden's election campaign and proposed infrastructure plan is also targeting a carbon-free power sector across the US by 2035 [341]. Reaching such zero emissions targets and integrating renewables will be more difficult and more expensive if there is a decrease in carbon-free, dispatchable, and flexible resources like hydropower [342], alongside an increase in energy demand related to water. For example, in prior California droughts, hydropower generation declined to about half its historical level and was replaced by expensive and emitting natural gas generation [192], while energy use for groundwater pumping increased as surface water was replaced [35]. As the second year of a another drought takes hold in 2021, similar impacts are occurring again, with hydropower in California at 7% of state generation, down from a 17% average from 2016 to 2020 [333], [343].

Despite recognition in the literature [71], [73], [93], [244] of the importance of climate impacts and cross-sectoral linkages to the electricity system, most long-term planning processes in the WUS have not explicitly incorporated the three-way interactions between climate change, electricity, and water to evaluate how electricity capacity needs may be affected [18]. A number of studies have analyzed the impacts of climate change on electricity supply (ie. hydropower or thermal power plant cooling) or demand (ie. from increased air conditioning) in the WUS or sub-regions/states [87], [275], [284], but have not completed the next step to see how those changes would subsequently affect the optimal grid buildout. Other analyses focus on how climate change impacts grid operations but hold the generation mix and transmission infrastructure fixed at their current states [338], [344], which does not account for the very different operating requirements of a future grid envisioned by policy that is dominated by intermittent renewable generation [345]. If climate-driven changes in demand and supply resources are not holistically incorporated in long-term planning processes and modeling, the electricity system may not have sufficient redundancy or flexibility to maintain reliability and resilience [25], [34].

Electricity system planners traditionally use capacity expansion optimization models to decide what type of technology, where, and when to build new capacity that meets forecasted loads and operational constraints [89]. Some of these expansion models account for uncertainty in future costs or load forecasts [346], but there are only a few examples of studies that include additional uncertainty from climate change [87], [88], [347]. These planning models also typically consider the grid in isolation, without incorporating cross-sectoral interactions [348]; analyses incorporating water linkages are still relatively uncommon and primarily focus on water constraints on thermal power plant cooling [349]. These constraints are less relevant in the WUS where there is relatively minimal freshwater use for thermoelectric cooling [90]–[92]; in California, the dependency on cooling water is further decreasing as the generation mix transitions to wind and solar resources that do not require cooling water [90], [91], and we expect this trend to apply to other WUS areas with decarbonization. Further, limited work has been done on incorporating climate impacts on both "water-for-energy" (i.e. hydropower) as well as "energy-for-water" (i.e. energy demand for groundwater pumping, conveyance, water treatment, etc.). Because climate change is projected to have significant impacts on both water supply availability as well as water demand, the energy usage related to supplying, transporting, treating, using, and disposing of water in the region would change correspondingly and affect the overall energy demand grid planners must plan to meet.

The objective of this paper is to evaluate the optimal buildout of a decarbonized WUS electricity system, while also adapting to climate impacts and water sector interactions by 2050.

To our knowledge there is no existing linked electricity capacity expansion and water management analysis that quantifies climate impacts and feedbacks on both water-for-energy and energy-for-water on a zero-emissions grid. We address these gaps by connecting a high-resolution grid capacity expansion model of the Western Coordinating Council (WECC) area with a water model that combines climatically-driven physical hydrology and management of both water supply and demand over the same WUS geographic area. We evaluate these connected models with the downscaled climate projections of an ensemble of 15 Global Circulation Models (GCM) that have been selected for skill in characterizing the regionally relevant hydroclimatic phenomenon. We assume a baseline scenario wherein the WECC region reaches carbon-free generation by 2050. In this analysis, we (1) quantify the climate impacts on hydropower and energy demand for water in the WUS under a range of potential climate futures; and (2) quantify the sensitivity of the electricity grid buildout and operations to climate impacts on hydropower and water-related energy demand. Such large-scale models also enable us to evaluate regional interdependencies and the propagation of climate impacts in one location to another because of the connected nature of water and electricity infrastructure through long-distance water conveyance and electricity transmission networks across the WECC.

We describe the climate scenarios in Section 2.1, the methodology and data for the water model in Section 2.2, the electricity model in Section 2.3 and the model integration in Section 2.4, and the results, discussion, and conclusions in Sections 3 and 4.

2. Methods

Figure 25 illustrates our climate-water-energy model integration methodology. We start with downscaled GCM climate projections, which are inputs into the water resources model, WEAP. We then link energy-related WEAP outputs with the electricity planning model, SWITCH, which optimizes the generation and transmission expansion of the WECC grid out to 2050.

The analysis brings together different modeling paradigms: SWITCH is a cost-minimizing model that optimizes future investment to meet demand forecasts, while WEAP uses a rule-based priority system to allocate climatically-driven available water supply to demands given fixed infrastructure. This approach reflects key differences in the two sectors, with the operations and investment of the electricity sector being more centralized and market-based, and the operations of the water sector being driven by a legal system of water rights for which WEAP's prioritization scheme is a proxy. In future work, this model coupling will also enable us to explore different policies and adaptation strategies in the water sector through a scenario approach in WEAP, and to look at their implications for the optimal grid buildout in SWITCH. Each step of this analysis is summarized below and detailed in the Chapter 4 Appendix.

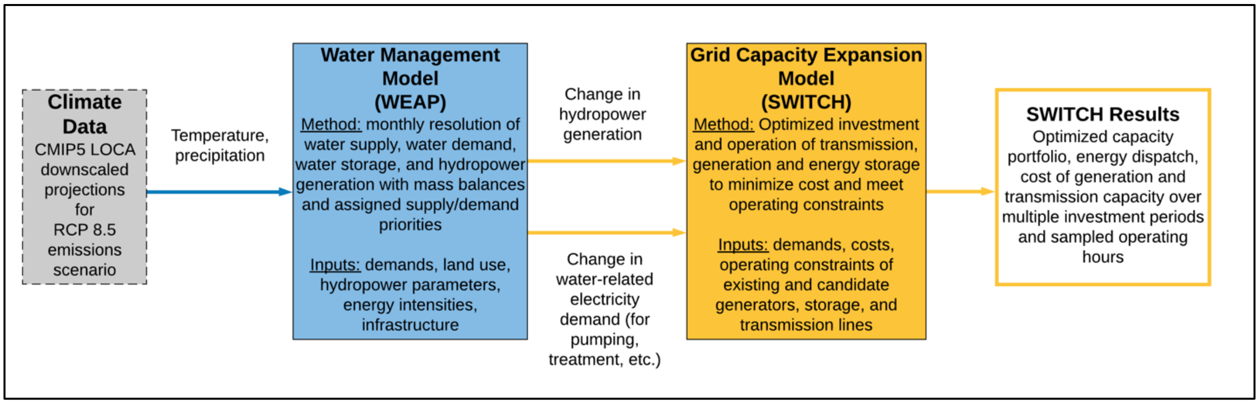


Figure 25. Climate-Water-Energy Integrated Modeling Schematic. This schematic describes the integrated modeling methodology. Temperature and precipitation data from CMIP5 LOCA downscaled climate projections for the RCP 8.5 emissions scenarios are inputs into the WEAP model, which then simulates the monthly water supply available and allocates water to demands and hydropower generation. The changes in hydropower generation and water-related electricity demand under the climate scenarios compared to the Reference scenario are inputs into the SWITCH model. SWITCH optimizes the investment and operations of generation and transmission with adjusted hydropower and energy demands from WEAP, and produces the optimal portfolio, dispatch and cost of generation and transmission by load zone and investment period.

2.1 Climate scenarios and data

We run the WEAP model with monthly average Temperature [ºC] and Precipitation [mm] variables for each watershed from 2015 – 2055 climate projections of 15 GCMs from the Coupled Model Intercomparison Project 5 (CMIP5) ensemble compared to a Reference scenario of historical climate.[46] All climate scenarios use the Representative Concentration Pathway (RCP) 8.5 emissions scenario, which represents a scenario with 8.5 W/m^2 of warming by 2100. We only use the RCP 8.5 scenario because during our study's mid-century time horizon the projections from the other emissions scenarios are very similar, and the majority of the uncertainty comes from differences in GCMs [350].

Using a group or ensemble of different GCMs is currently the best practice to account for this model uncertainty [351]. We run WEAP with 15 GCMs selected for their skill in simulating the climate of our study region as part of a screening process conducted by a Climate Change Technical Advisory group for California's Department of Water Resources (DWR) [227]. The DWR model selection process culled the original set of 31 models to 10 GCMs based on historical performance over three geographies and metrics: for the global scale using results from the IPCC AR5 [352] and model "genetics", for the Southwest region using metrics and methodology from Rupp et al. [353], and for the state of California. Because our study area comprises the whole WUS, we have added back in the five models to our ensemble which performed well for the Southwest region but which DWR had removed for their performance for California-specific metrics. Of the final 15 models, nine of the models are also in the top 15 GCMs for their performance in the Pacific Northwest region, where much of the WUS hydropower is located, based on an evaluation by Rupp et al [353].[47] The GCM projections have been statistically downscaled based on the Locally Constructed Analog (LOCA) method, which

[46] Relative humidity and wind speeds are assumed to remain constant across the climate scenarios.
[47] Two of the remaining top performing GCMs for the Pacific Northwest were not available with the given downscaling method, and 1 model was removed because of similar model genetics to that of others in the ensemble.

was the recommended downscaling method in the DWR analysis [227]. The Reference scenario is based on historical 1980 – 2010 climate data [354].

Compared to historical climate data, the ensemble average of the “raw” daily GCM data for 2020 - 2060, before downscaling and bias corrections, show drying is concentrated is the Southern half of the WUS, while the Pacific Northwest sees increases in precipitation (Figure 26 A). Temperatures rise across the entire WUS, but at a higher rate in the Inter-Mountain West, and to a lesser extent in coastal areas (Figure 26 B). Across the downscaled and bias-corrected GCMs, from 2020 – 2050, the projections range from -8% to +12% (-3.6 mm to +5.4 mm) of average change in monthly precipitation across the WUS, and -0.1% to +1.2% (-0.3 ºC to +3.5 ºC) of average change in monthly temperature (Table 33).

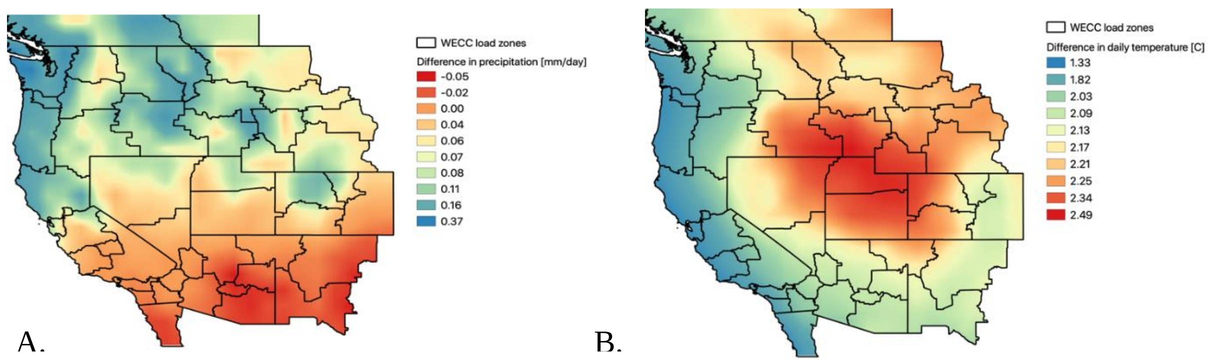


Figure 26. Ensemble difference in A. average daily precipitation [mm/day] and B. average daily temperature [ºC] from historical average. The ensemble values are annual average values of daily precipitation and temperature for 2020 – 2060 across all 15 GCMs, and these are subtracted from annual average values from Livneh 1980 – 2010 historical data at the 1º resolution. These maps have been resampled to a higher resolution using a nearest neighbors approach for the purposes of illustration.

Table 33. Summary decadal precipitation and temperature deltas compared to historical data across WUS domain area. The projections are based on the LOCA downscaled data from 15 GCMs, and the data is averaged across each 10 year period starting from 2015 to 2055, corresponding to the decadal investment periods of the SWITCH model. The table shows differences between these decadal average projections compared to the 1980 – 2010 historical average data of the Reference scenario in WEAP.

GCM	Change in average monthly temperature relative to 1980-2010 [ºC]				Change in total WUS monthly precipitation relative to 1980-2010 [mm]			
	2020	2030	2040	2050	2020	2030	2040	2050
ACCESS-1.0	1.6	1.9	2.4	3.1	-2.5 mm; -5.4%	-2.5 mm; -5.4%	-2.8 mm; -6.1%	-3.1 mm; -6.7%
CCSM	1.4	1.7	2.5	2.9	-1.3 mm; -2.9%	-2.2 mm; -4.7%	0.8 mm; 1.8%	-1.7 mm; -3.6%
CESM-BGC	1.1	1.8	1.9	2.6	0.2 mm; 0.4%	3.1 mm; 6.6%	1.3 mm; 2.7%	5.4 mm; 11.6%
CMCC-CMS	1.1	1.4	1.8	2.7	0.3 mm; 0.6%	-0.6 mm; -1.3%	4 mm; 8.5%	-1.9 mm; -4%
CMCC-CM	1.2	1.4	2.0	3.0	-1.4 mm; -3%	0.4 mm; 0.8%	3.8 mm; 8.1%	-3.6 mm; -7.7%
CESM-CAM5	1.6	2.0	2.4	3.1	-3.1 mm; -6.7%	3 mm; 6.4%	1.1 mm; 2.4%	4.7 mm; 10.1%
CNRM-CM5	1.1	1.6	1.7	2.3	-2.4 mm; -5%	-0.4 mm; -0.8%	2.3 mm; 4.9%	0.2 mm; 0.4%
CanESM	1.7	2.2	2.7	3.5	-1.4 mm; -2.9%	1.9 mm; 4.1%	0.7 mm; 1.6%	1.1 mm; 2.4%
GFDL-CM3	1.5	1.9	2.6	3.2	2.1 mm; 4.4%	3.3 mm; 7.1%	1.2 mm; 2.6%	3.1 mm; 6.7%
GFDL-ESM2M	0.8	1.0	1.2	1.9	0.3 mm; 0.7%	0.9 mm; 2%	3.7 mm; 7.9%	1.2 mm; 2.6%
HadGEM2-CC	1.4	1.8	2.8	3.1	0.5 mm; 1.1%	-2.8 mm; -5.9%	-1 mm; -2.1%	1 mm; 2.2%
HadGEM2-ES	1.5	2.0	2.4	3.3	-0.2 mm; -0.5%	-0.6 mm; -1.2%	-2.4 mm; -5.1%	3.2 mm; 7%
MIROC5	1.2	1.7	2.2	2.8	0.4 mm; 0.9%	0.3 mm; 0.7%	-0.9 mm; -2%	-2.9 mm; -6.2%
MPI-ESM-LR	1.2	1.5	2.2	2.5	-1.9 mm; -4.1%	2.1 mm; 4.4%	-0.5 mm; -1.2%	1.2 mm; 2.5%
bcc-csm1-1	1.5	1.9	2.2	2.8	-1.9 mm; -4.1%	1.8 mm; 3.8%	-3.3 mm; -7.1%	1.1 mm; 2.4%

Ensemble Mean	1.3	1.7	2.2	2.8	-0.8 mm; -1.8%	0.5 mm; 1.1%	0.5 mm; 1.1%	0.6 mm; 1.3%

2.2 WEAP model and data

WEAP is a hybrid water resources management and watershed hydrology tool, built by the Stockholm Environmental Institute. WEAP can test different climate inputs, land uses, and demands and policies [355], and separately accounts for irrigated agriculture, urban indoor water use based on per-capita use and population, and urban outdoor use [92]. Numerous studies have used WEAP to assess climate impacts on water management, including on energy-water linkages [38], [356]. In each timestep WEAP solves a series of simultaneous equations for a mass-balance that partitions precipitation into rain or snow (a main source of WUS water supplies), and runoff or groundwater infiltration based on land cover, temperature, and soil moisture for each of the sub-catchments at various elevations, subsequently calculating available water supply and irrigation water demand [92], [355]. With a linear program, WEAP then allocates the calculated available supplies to demands, in order of user-specified priorities and supply preferences. With the rainfall-runoff hydrological modeling capabilities underlying a representation of the water system infrastructure and uses of the region, the WEAP model is ideally suited to evaluate vulnerability and water management responses under climate change [92]. The mathematical formulations of the mass balance and other model components are documented in detail in a prior WEAP publication [355]. The WEAP data are summarized in the following section and more detail on the data, model, and calibration are in the Ch. 4 Appendix.

2.2.1 Geographic and temporal resolution

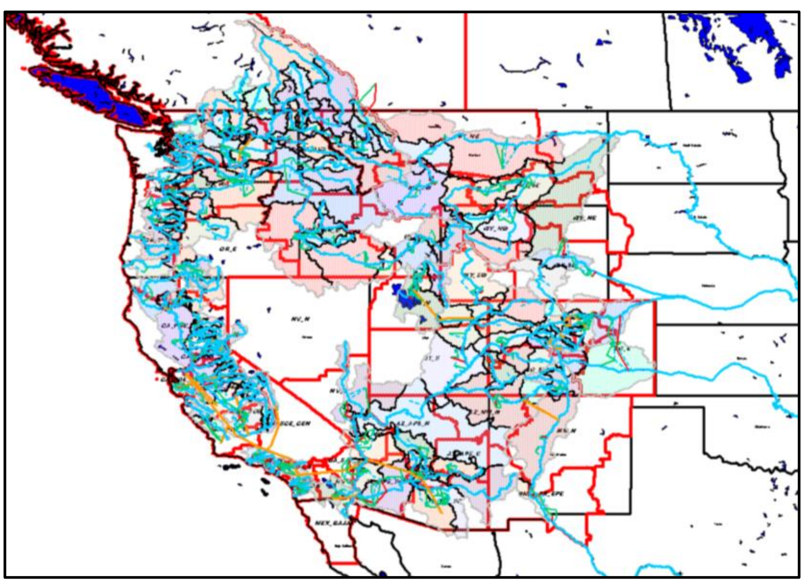


Figure 27. Schematic of WEAP model study area. Blue lines are rivers, orange lines are conveyance, green lines are transmission links between demands and supply sources, and the color shaded areas are the various catchments. Red boundaries indicate the SWITCH load zone areas.

For this analysis we build a new WEAP model covering the same region as the WECC region of the electricity expansion model (Figure 27).[48] The WEAP study area includes the

[48] The Canadian and Mexican regions of WECC are only partially included because of limited data availability.

watershed regions of the Columbia River, Snake River, Missouri River, Colorado River, Platte River, Salt River, Sacramento River, Feather River, and San Joaquin, among many others. The WEAP model also includes built infrastructure such as long-distance conveyance for inter-basin water transfers (such as the State Water Project, Central Valley Project, Colorado River Aqueduct, and Central Arizona Project), and major reservoirs and hydropower generators.

The model is run at a monthly time step, for the 2010 - 2060 time horizon, with the first and last 5 years of the simulation discarded to account for any artifacts or edge effects of model spin-up and end. The model has been calibrated for the historical period of 1980 – 2010 for key hydrologic metrics using observational US Geological Survey (USGS) gauge data for streamflows and/or reservoir outflows (see Ch. 4 Appendix) [91], [92], [349].

2.2.2 Demand priorities and supply preferences

Two user-defined priority systems are used to determine monthly allocations from supplies to demand sites, and for instream environmental flow requirements, reservoir storage, and hydropower generation [355]. Competing demand sites and flow requirements are allocated water according to their demand priorities and sites can share the same priority. These are useful in representing water rights, and are also important during a water shortage, in which case higher priorities are satisfied as fully as possible before lower priorities are considered. If priorities are the same, shortages will be equally shared. Typically, highest priorities are for critical demands that must be satisfied during a shortfall, such as an urban water supply. When demand sites are connected to more than one supply source, their supply preferences may also be ranked. These are attached to transmission links. Using the supply preferences and demand priorities, WEAP determines the allocation order to follow when allocating the water. The allocation order represents the actual calculation order used by WEAP for allocating water.

In this analysis, with 1 being the highest priority, we have assigned demand priorities as follows: 1) environmental flows, 2) urban indoor, 3) urban outdoor, 3) agriculture, 4) reservoir storage, and 5) hydropower. We have assigned supply preferences as follows: 1) reuse (when available), 2) surface water, 3) groundwater.

2.2.3 Catchment delineation and groundwater

We use WEAP's built-in "Catchment Delineation" tool to delineate catchments and rivers in the WUS, and to calculate land area disaggregated by 1000-meter elevation bands and by land use-land cover (LULC) categories (Agriculture, Forest, Grass and Shrub, Other, Urban, or Water) from digital elevation data [357]. Many of the catchments are delineated with major reservoirs as the outlet points of associated rivers, because a large focus of this analysis is on hydropower generation. The catchment delineation process results in 147 rivers and 311 catchments. Climate data is used for each combination of catchment and elevation band. These catchments characterize the hydrology of the land area to calculate runoff, agricultural irrigation demand, and urban outdoor irrigation demand. These catchments, along with associated groundwater aquifers, provide the source of water supply to meet water demands.

2.2.4 Water use and water infrastructure

For each of 50 load zones in SWITCH, we model an urban indoor and an urban outdoor water demand node in WEAP. For each urban indoor demand node, total water demand is modeled as the product of a water use rate per-capita by sector (either Domestic or Commercial and Industrial, C&I) * regional population. Per-capita rates[49] are calculated based on historical USGS population and water use data by sector and county [358], and this county-level data are aggregated and assigned to WEAP demand nodes based on population-density weighting. Because Domestic water data from USGS include both indoor and outdoor water use, we parse out the indoor portion based on per-capita indoor water use data collected for specific cities in our study area, ranging from 41 (San Francisco) to 68 (Sacramento) gallons per-capita per day (Ch. 4 Appendix). For cities for which we cannot find per-capita indoor use, we assign the indoor per-capita value from the nearest city with data. The remainder of the water use is assigned to the outdoor urban demand nodes, for the urban land-cover areas. For C&I water, we make a simplifying assumption that the demand is only for indoor use from the commercial, industrial, mining, livestock, aquaculture, and thermoelectric sectors as categorized by USGS [358]. We calculate a per-capita C&I water demand as the total water use from these sectors divided by population.[50]

Water demand for irrigated agriculture is modeled for the irrigated land area, which is the agricultural land area multiplied by irrigated fraction for each catchment (IrrigFrac). $IrrigFrac$ is calculated as the irrigated land area from the 2017 (MODIS) Irrigated Agriculture Datasets for the Conterminous United States [359], divided by the total agricultural area from the 2016 National Land Cover Database [360]. For the irrigated land area, the water use is calculated as part of the mass-balance equation using a Penman-Monteith formulation of evapotranspiration (ET), an average representative crop coefficient, and soil moisture thresholds.

2.2.4.1 Reservoirs, diversions, desalination, and reuse

We include 132 major reservoirs in the WEAP model of the WUS, which together provide 260 Billion m^3 of available storage capacity. Reservoir storage is divided into four management zones, including conservation, buffer, and inactive pools from top to bottom [355]. The conservation and buffer pools, together, constitute the reservoir's active storage. WEAP will ensure that the flood-control zone is always kept vacant, i.e., the volume of water in the reservoir cannot exceed the top of the conservation pool. WEAP allows the reservoir to freely release water from the conservation pool to fully meet withdrawal and other downstream requirements. Once the storage level drops into the buffer pool, the release will be restricted according to the buffer coefficient, to conserve the reservoir's dwindling supplies. Water in the inactive pool is not available for allocation, although under extreme conditions evaporation may draw the reservoir into the inactive pool. Parameters to characterize reservoir storage capacity and volume-area relationship are from National Inventory of Dams data and state and local water resource databases [361]. We also account for evaporation from the surface of the reservoirs for each climate scenario, based on the climate data of the catchment where the reservoir is located.

Major conveyance projects or diversions are included in WEAP. For California, these include the State Water Project (California Aqueduct and Coastal, East, and West Branches), Central Valley Project, Friant Kern Canal, Los Angeles Aqueduct, Colorado River Aqueduct, and the All American Canal; in Arizona, the Central Arizona Project; in Utah, the Central Utah Project; in Colorado, the Roberts Tunnel, Moffat Tunnel, Frying Pan-Arkansas and the Colorado-Big Thompson Projects. For the State Water Project and Central Valley Project

[49] Future research will simulate changes in per-capita water use rates as part of conservation programs.
[50] In reality, these C&I water uses are likely to change by other rates, i.e. production, square footage, electricity use, but because we do not have such sectoral data, we make a simplifying assumption that it also changes along with population growth. This is an area for future research.

diversions, releases are constrained based on available volumes determined by a water year categorization, calculated based on a river index of the Pit and Feather Rivers' streamflow. A monthly pattern of maximum releases is also imposed based on historical allocations. Water deliveries are driven by monthly demand and constrained by contracted annual volumes.

We include one desalination plant in Carlsbad, California [362] which provides water to San Diego, and also model non-potable reuse to the urban outdoor demand use up to 5% of return flows of urban indoor demand nodes in the drier Southwest states (California, Arizona, and Nevada).

2.2.5 Hydropower generators

We include 194 individual hydropower generators in the WEAP model, which together provide 48 GW of capacity. In the US portion of the WECC, these are all the generators greater than 30 MW, the threshold used by California for its Renewable Portfolio standard to denote "large hydro." Only one generator is included in Canada, because of limited data available for calibration. Hydropower generators are either modeled without storage (as run-of-river) or with reservoir storage. Power is generated as the WEAP model releases water from the reservoir, or as water flows through the run-of-river turbines, based on the supply and demand priorities discussed above. The generators are parameterized based on head, tailwater elevation, and max turbine flow. To match the SWITCH baseline hydropower generation as closely as possible, the WEAP hydropower is further calibrated to adjust generation to meet the historical average monthly pattern, the annual average generation levels, and the annual average capacity factors, per the equations and Ch. 4 Appendix. Data is based on EIA net generation, NID dam data, and USBR dam and powerhouse data, and filled in as much as possible from other documentation from FERC filings, utility websites [361], [363]–[365].

2.2.6 Energy demand for water

Electricity powers all stages of the managed water cycle, including groundwater pumping, long-distance conveyance, treatment, use, wastewater treatment, reuse, and desalination. In the WEAP model, we track this embedded energy by applying energy intensity values (energy use per unit of water, kWh/m^3) associated with the water volumes calculated in WEAP throughout the stages of the managed water cycle (Figure 28). Energy intensity values are either derived from endogenous model data (i.e. groundwater pumping based on water depth), calculated from input data (distribution energy, water heating energy, agricultural energy), or based on averages from the literature (desalination, treatment, wastewater treatment, reuse) as described below and in Ch. 4 Appendix equations.

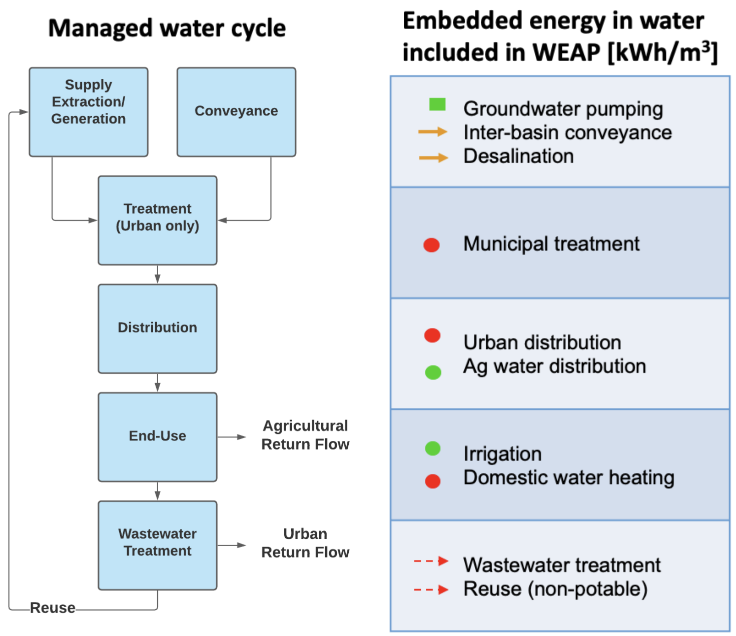


Figure 28. Schematic of managed water cycle and WEAP tracking of energy intensity embedded in each stage of water cycle. The diagram on the left shows the stages of the water cycle starting from supply extraction/generation, namely for groundwater pumping or desalination, or from conveyance of surface water. Urban water is then treated to potable quality (agricultural water assumed not be treated). Water is then distributed to end-users, for irrigation or urban residential or CII uses. Agricultural water is then runoff without wastewater treatment, while urban wastewater is treated and then returned to the environment or treated for reuse. The panel on the right shows the embedded energy we include in WEAP along each stage of this cycle, and the icons reflect how they are illustrated in WEAP. Water for environmental use that is left in streams is not included in this schematic because it has no embedded energy.

Groundwater pumping energy is calculated based on the lift, pump efficiency, and volumetric flow rate. For each groundwater object, the lift in meters is the aquifer water depth resulting from the WEAP model for each month. For all groundwater pumping, we assume an average pump efficiency of 49% based on [199], [366]. Energy for water conveyance, typically for inter-basin water transfers, is calculated based on the lift, pump efficiency, and volumetric flow rate. For each conveyance object, the lift in meters is the height that water needs to be raised for the specific project (Ch. 4 Appendix). We assume a pump efficiency of 57% (the highest pump efficiency in [199]). Gravity- fed conveyance projects, such as the Los Angeles Aqueduct, are assumed to consume no energy. Energy for desalination is assumed to be from seawater, averaged from literature [55], [58], [61], [64, p. 1], [65, p. 2], [73], [76], [207].

Water treatment energy, which we assume is with conventional drinking water treatment, is applied for all urban demands (domestic indoor and outdoor, and CII). We use an average value from the literature [55], [58], [61], [64, p. 1], [65, p. 2], [73], [76], [207]. Water distribution energy is the energy required to pump and distribute water from the treatment plant to the end-user, and is also applied for all urban demands. Distribution energy increases with steeper terrain, and we therefore calculate the average slope-length of each urban demand node area based on the topography of the urban land areas [357], [360]. We rank and categorize the demand nodes based on their slope-length values with the top third assigned hilly, middle third assigned moderate, and bottom third assigned flat distribution energy intensity values (0.79, 0.41, 0.04 kWh/m^3 respectively) [203].

Energy for agricultural water use includes the energy intensity for local surface water deliveries (averaged from [55], [58], [61], [64, p. 1], [65, p. 2], [73], [76], [207]) and for irrigation (pumping and pressurization). The energy intensity for irrigation is calculated as a weighted average based on California data for the historical average applied water by crop [216], typical irrigation technology installed by crop [215], and the energy intensity for each irrigation technology [199] (0.01 kWh/m^3, 0.23 kWh/m^3 for standard sprinklers, and 0.17 kWh/m^3 for micro/drip irrigation). Energy for Domestic[51] water heating is tracked and is calculated as the product of the average electric water heater saturation by state [367, p. 8], the average hot water share in typical residential homes (33.2%) [206], and the specific heat of water ($Q = mc\Delta T/\eta$) based on typical water heater characteristics (90% efficiency, about 44 degrees C of warming based on average 10 C inlet and 54 C outlet temperatures).

Energy for wastewater treatment applied to return flows from all urban indoor water, is assumed to be for secondary treatment, and is averaged from literature [55], [58], [61], [64, p. 1], [65, p. 2], [73], [76], [207]. Runoff from agricultural and urban outdoor water use is assumed to not receive wastewater treatment. For water non-potable reuse, we apply an energy intensity for incremental treatment above secondary wastewater treatment.

2.2.7 Calibration

The catchment parameters in WEAP are adjusted based on a calibration of modeled streamflows compared to observed gauge data for USGS gauging locations on rivers and diversions. Typically, managed flow is calibrated, including on the Columbia River below Grand Coulee Dam, Snake River below Hells Canyon Dam, Missouri River below Fort Peck Dam, inflows to Lake Powell, and Sacramento Delta outflow. Figure 29 is a summary of goodness-of-fit statistics including correlation and bias across key hydrologic points that are simulated in the WEAP model across the WUS.

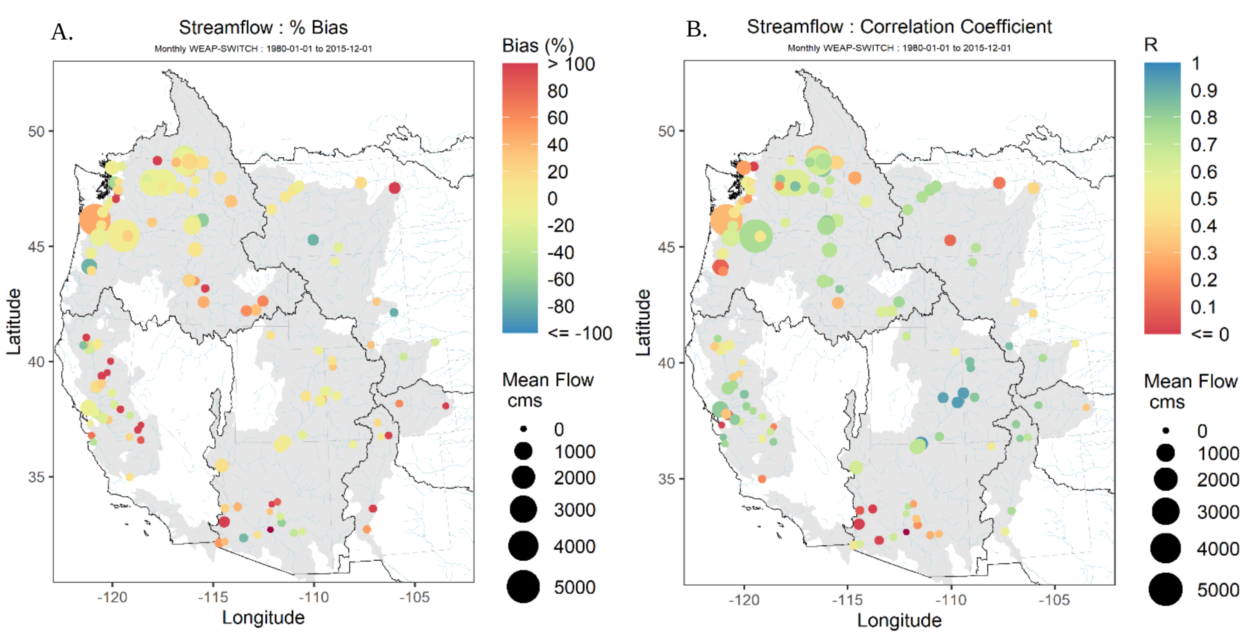
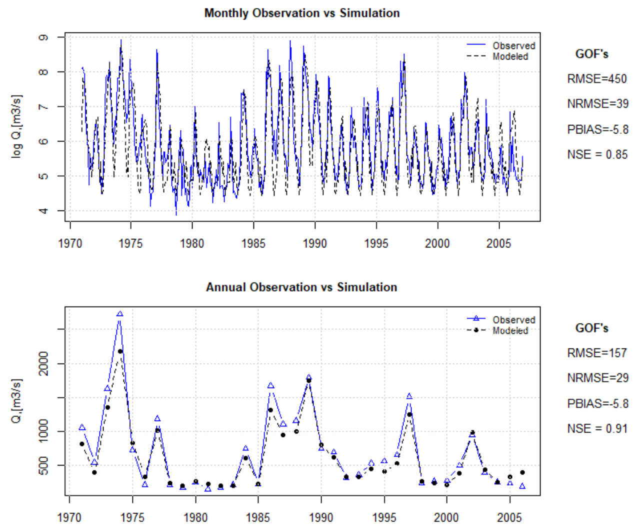


Figure 29. A. Percent bias of simulated vs. observed monthly flows for key USGS gauging locations across the WUS, where the size of the dot is monthly average flow for the given location. B. Correlation coefficient of simulated vs. observed monthly flows for key USGS gauging locations across the WUS, where the size of the dot is monthly average flow for the given location.

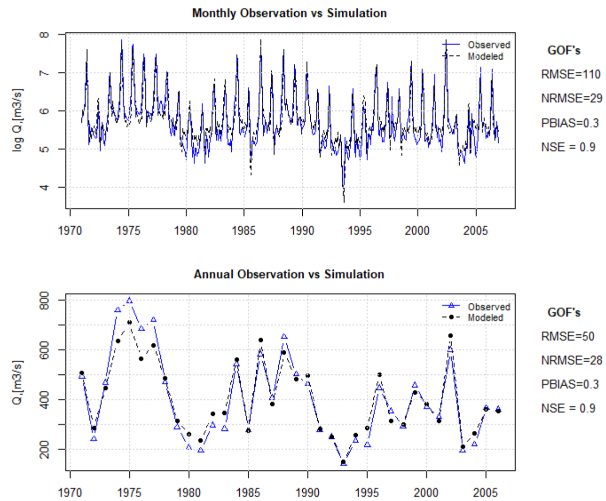
[51] We do not track energy use for commercial and industrial water heating because of lack of available data on hot water shares of such a diverse set of water end-uses.

Figure 30 shows examples of simulated and observed monthly and annual flow time series for the Sacramento-San Joaquin Delta outflow, the Colorado inflows to Lake Powell, and the Columbia River below Grand Coulee Dam, respectively. Together, Figure 29 and Figure 30 demonstrate that the WEAP model is generally skillful at reproducing the large scale hydrologic characteristics across the WUS, while there is generally more error in regions with lower flow magnitudes such as the headwater regions of the Sierra Nevada of California and the generally low flows of rivers such as the Gila River in Arizona. More details on the final catchment parameters after calibration are in the Ch. 4 Appendix.

A. Sacramento Delta Outflows



B. Colorado River Inflows into Lake Powell



C. Columbia River below Grand Coulee Dam

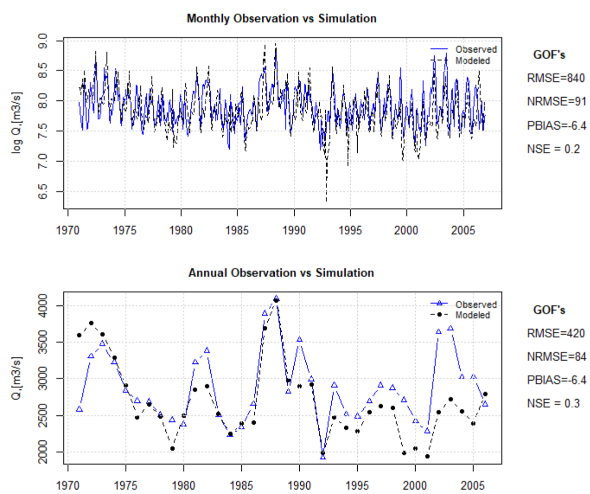


Figure 30. Monthly (top) and annual (bottom) A. outflows of the Sacramento-San Joaquin Delta of California, B. Colorado River inflows into Lake Powell, and C. Columbia river flows below Grand Coulee Dam. Each figure has several goodness-of-fit (GOF) statistics including Root Mean Square Error (RMSE), Normalized Root Mean Square Error (NRMSE), percent bias (PBIAS), and Nash-Sutcliffe Efficiency (NSE).

We compare water supply deliveries from the WEAP Reference case to historical 2000 – 2010 average reported water use at the state level (Table 34). We compare with 2 sources: USGS data [358] and data collected from individual state water resources websites [368]–[376], which were available for some, but not all, of the years as the USGS data.

Table 34. Comparison of observational water use data and WEAP Reference, Avg. 2000 - 2010 (Million Acre-Feet/ Year).

	Agricultural					Urban				
State	USGS Data	State-level Data	WEAP 2000 - 2010 Average	WEAP 2000 - 2010 Min	WEAP 2000 - 2010 Max	USGS Data	State-level Data	WEAP 2000 - 2010 Average	WEAP 2000 - 2010 Min	WEAP 2000 - 2010 Max
California	24.00	34.55	32.05	27.81	35.88	7.65	9.07	8.29	7.51	8.90
Arizona	4.39	5.61	3.99	3.63	4.46	1.32	1.90	1.45	1.29	1.56
New Mexico[A]	2.60	3.10	0.91	0.78	1.11	0.39	0.58	0.52	0.47	0.56
Nevada[A]	1.66	NA	0.36	0.29	0.40	0.89	NA	0.93	0.77	1.05
Utah[A]	3.83	3.84	1.31	0.98	1.53	0.77	0.98	0.35	0.31	0.38
Colorado[B]	11.32	13.27	5.33	3.86	6.92	1.31	1.19	0.74	0.66	0.81
Oregon	5.86	NA	6.05	5.10	6.88	1.33	NA	2.10	1.93	2.26
Washington	3.26	NA	12.64	11.47	13.57	1.94	NA	1.66	1.53	1.77
Idaho	15.87	18.50	12.31	10.22	14.11	2.96	3.25	2.41	2.18	2.65
Montana	8.90	NA	12.69	10.85	14.25	0.42	NA	0.33	0.29	0.38
Wyoming[B]	4.49	6.02	1.64	1.21	2.00	0.36	0.47	0.28	0.24	0.33

[A] The watersheds and water use in New Mexico, Nevada, Utah are not modeled for the full state areas, respectively. [B] The water accounting in Colorado is of applied water deliveries, but the WEAP model accounts for return flows and their reuse.

As part of the calibration process, we also match WEAP hydropower generation results from the Reference scenario (no climate change) as closely as possible to the SWITCH baseline scenario (no climate change) before applying the climate change factors when integrating the models forward in time. We manually calibrate the average monthly WEAP hydropower generation by generator to match the historical observed average generation from the EIA 2004 - 2018 [364], which is used for the SWITCH baseline scenario, based on the R^2 values of each generator and the average generation-weighted R^2 across all generators (Ch. 4 Appendix). After this calibration, the final generation-weighted R^2 across all generators is 0.82.

2.3 SWITCH model and data

To optimize long-term energy system buildout under climate scenarios and given water sector adaptations, we use the capacity expansion model SWITCH. SWITCH is an open-source model with high spatial and temporal resolution designed to plan a system with high levels of renewable resources [377], and has been used to evaluate system expansion in several case studies of the Western U.S. [88], [304], [378]. We build on the SWITCH 2.0 (Python) version from a recent study [377], and use an academic license of the Gurobi solver [379], to evaluate the optimal generation and transmission capacity expansion and operations decisions for the WECC region out to 2050. The objective function minimizes the expected value of the total net present value of generation and transmission operations and investment. The key decision variables include investment in generation and transmission capacity (MW of capacity built of each generator and transmission line for each investment period among the set of available candidate generators and transmission lines), and dispatch (hourly generation and transmission line flows for each generator and transmission line online in that period). It is a linear energy transport model where transmission flows (a decision variable) between zones are constrained by line limits which are an aggregation of the limits of individual lines between regions.

The optimization is subject to a number of constraints, including limits on capacity investments in generation and transmission to not exceed available capacity, energy balance requirements for hourly load in each zone to equal generation and net imported energy transmitted into and out of the zone, the dispatch of generation and transmission flows limited to available capacity and line limits net of outages or derating factors, and specific dispatch constraints specific to variable generators (solar and wind), hydropower, and battery storage. There are also planning reserve constraints, which require the total available capacity of generators and imports meet or exceed a percentage above peak annual load (a reserve margin) in each "reserves area." In addition to the above operational and investment constraints, we impose two main policy constraints on the model for each investment period: a renewable portfolio standard requiring a percentage of annual load to come from renewable sources, and a cap on carbon emissions from generation. Below we describe the key data inputs into this SWITCH analysis; the data, assumptions, objective function, and key constraints are described in more detail in the Ch. 4 Appendix. A complete full mathematical formulation of the SWITCH model is described in a prior paper [377].

2.3.1 Geographic and temporal resolution

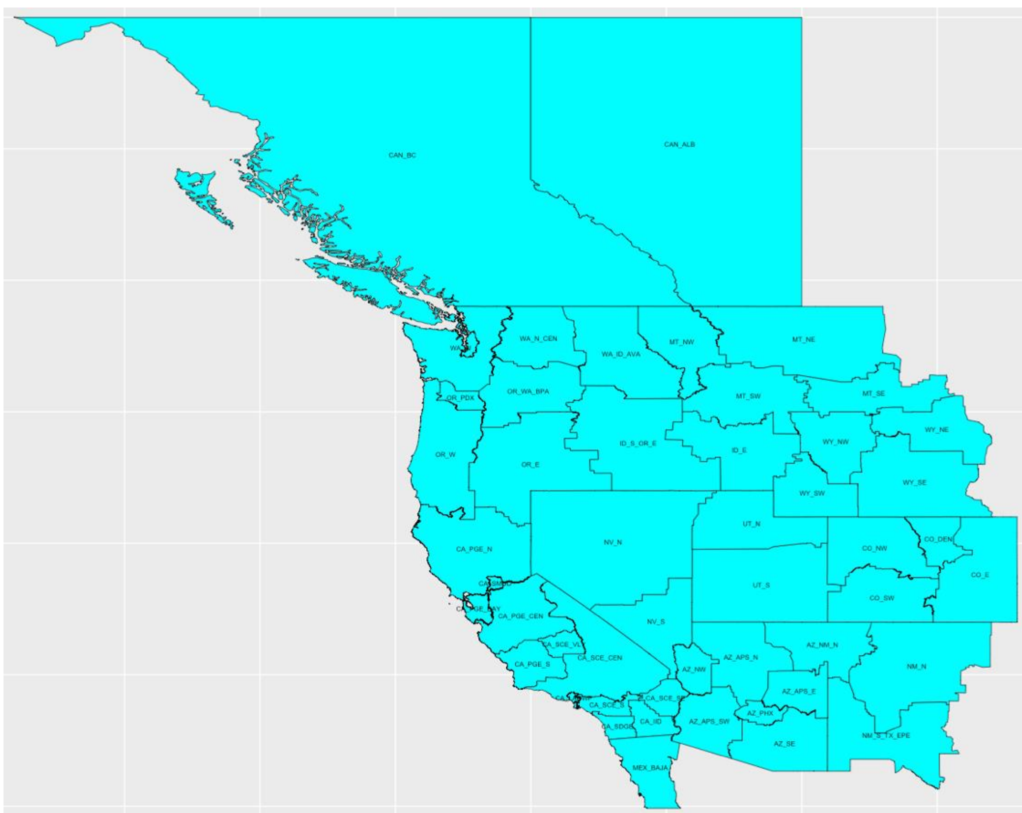


Figure 31. WECC study area and SWITCH load zone boundaries.

The WECC study area of this analysis is divided up into 50 "load zone" regions [304], [378] (Figure 31), covering all of parts of Washington, Oregon, California, Arizona, Nevada, New Mexico, Utah, Idaho, Montana, Wyoming, Colorado, and Texas in the US; British Columbia and Alberta in Canada; and the northern portion of Baja California in Mexico. The temporal resolution of the analysis includes four investment periods, each of a decadal duration: 2020 (covering 2016 – 2025), 2030 (covering 2026 - 2035), 2040 (covering 2036 – 2045), and

2050 (covering 2046 – 2055). The duration of these investment periods reflect the typical planning horizon of a utility, and the length of time often needed to plan and build generation and transmission infrastructure. Because of computation limitations on simulating both investment and detailed hourly operations, a sample of hours is selected to represent the typical grid dispatch for each investment period. In total, 576 hours are simulated (4 periods x 1 year/period x 12 months/year x 2 days (median and peak day)/month x 6 hours/day = 576 hours). The SWITCH dispatch results (i.e. costs, generation, transmission flows, emissions, etc.) from these sampled hours are scaled to calculate the typical annual or investment period value (i.e. annual operating cost, generation, transmission flow, emissions, etc.).

2.3.2 Generators

As inputs into SWITCH, we include the list of individual generators that are existing and/or are planned for the WECC region. For the US portion of WECC, we extract the list of currently operating generators and their characteristics (such as location, fuel source, generating technology, online year, and retirement year if any) from the Energy Information Administration (EIA) Form 860 [363]. For thermal generators, use the historical monthly generation and fuel use from EIA Form 923 to calculate heat rate (MMBtu/MWh) for the available years 2004 - 2018 [364]. In the baseline scenario (no climate change), hydropower generators are constrained to generate at their average historical monthly capacity factor and above a minimum generating level for each hour [304], calculated over the years 2004 – 2018 from the EIA Form 923 and repeated for all future investment periods of the SWITCH simulation (from 2020 – 2050). The existing generators for the Canadian and Mexican load zones are used from the data previously compiled for prior SWITCH-WECC analysis [88], [304].

One of the key decision variables in SWITCH is the capacity investment of generation, out of a set of candidate generators with specific generating technologies and fuel sources, load zone locations, and other physical and financial generating characteristics. Candidate generators include solar PV, wind (on- and off-shore), concentrating solar power, geothermal, biomass (liquid, solid, and gas), gas, coal, and battery storage technologies. We use the dataset of candidate generators that was previously compiled in prior SWITCH-WECC analyses [304], with some technology values (natural gas combined cycle, natural gas turbine, battery, wind, solar PV, solar CSP, and geothermal) updated based on NREL’s 2020 Annual Technology Baseline [380]. Details on the physical characteristics, and the available capacity of existing and candidate generators are in the Ch. 4 Appendix.

2.3.3 Transmission

The SWITCH optimization includes the construction of new transmission lines and the operations of existing and new transmission as decision variables. The model includes a set of 105 existing aggregated transmission lines between load areas within the WECC, based on a prior SWITCH analysis that aggregated the thermal limits of individual high-voltage lines between load areas [304]. New transmission capacity may be added to existing transmission corridors or constructed between 21 adjacent load zone pairs where there is currently no transmission. For both existing and newly constructed transmission lines, the maximum power transfer on each line is the thermal limit multiplied by an efficiency factor and a derating factor, which is meant to capture the combined effect of loop flows, voltage concerns, power factors less than unity, and overloading of individual transmission lines within the bundle, that are difficult to model in detail in the linear model [304].

2.3.4 Costs

The SWITCH optimization includes several types of costs in the decision to invest and/or operate in generation. Costs for candidate generators include overnight capital cost (applied to the built capacity), fixed O&M costs per year of operations, and variable O&M costs per hour of operation. Mature technologies (biomass, coal, gas cogeneration, gas steam turbine) are assumed to have their real costs stay constant over time, whereas other technologies are assumed to decrease costs over time with technology improvements and economies of scale. Capital, fixed O&M, and variable O&M costs by generator technology type originate primarily from Black & Veatch estimates for the mature technologies [304], [381]. For technologies with changing costs over time (battery, solar PV, solar CSP, wind, geothermal, gas CCGT, gas CT), we compile cost data from NREL's 2020 Annual Technology Baseline database [380]. For wind and solar, we also account for lower overnight costs in the first investment period from the Production Tax Credit and Investment Tax Credit, respectively [382], [383]. For battery storage, we separate out the capital costs into $/MW (balance of system battery cost) and $/MWh (battery pack cost which would be multiplied by the storage duration hours) costs [380]. The costs we use assume a four-hour duration battery. The average costs by decadal investment period, energy source, and technology are in Ch. 4 Appendix. Capital costs for existing generators are considered sunk costs and we do not include them in the total system costs; they do not affect future investment decisions. Variable O&M costs for existing generators are set to be the same as for candidate generators. In addition to capital costs for the construction of the generator itself, for candidate generators we also add a connection cost to reflect the expense of connecting to the existing grid [304].

Fuel costs are applied to non-renewable generators (natural gas, coal, fuel oil, uranium) and originate from the EIA's Annual Energy Outlook (AEO) [88]. Gas costs differ by load zone based differences in regional market prices and the wellhead price [304] (Ch. 4 Appendix). The fuel costs for bio solid generators are based on supply curves derived based on estimates of the economically feasible volumes of biomass feedstock available by load zone and different fuel price tiers [304].

The cost of building new transmission lines is calculated as the product of a line length, a base $960/MW-km cost [384], a terrain multiplier that reflects the topography differences that make a line more expensive to construct, and an economic multiplier [384] that represents differences in labor, permitting, and other "soft" costs between WECC load zones. Transmission lines also have a fixed O&M cost applied to reflect upkeep costs for lines.

2.3.5 Load

The future load assumed in this analysis was developed in a prior study and represents a case of high energy efficiency and building electrification, as well as increased adoption of Zero Emissions Vehicles (ZEVs), primarily from electric vehicles [88]. Hourly demand profiles from 2006 (consistent with the weather-year used for calculating solar and wind capacity factors) from FERC Form 714 and a dataset procured from ITRON were used as a base from which demand projects (residential, commercial, industrial, transportation) were created and scaled by sector to meet policy targets and reflect population growth [385]. Electric vehicles are assumed to charge in an "unmanaged" way (without smart charging or time-of-use rates), based on charging profiles developed with an agent-based mobility model BEAM [46], [386].

2.3.6 Policies

We assume that the load zones in the WECC region must meet a planning reserve margin of 15%, that is, the model is required to build capacity to meet 115% of the peak load. All generator technologies are assumed to be eligible to provide capacity towards meeting the planning reserve requirement (details in Ch. 4 Appendix). Future work will evaluate the sensitivity of the results to different planning reserve requirements as well as eligibility for reserves provision.

We include existing state Renewable Portfolio Standard (RPS) policies in SWITCH as constraints for each period requiring a fraction of electricity demand be generated by renewable generators. In addition, we impose a constraint on carbon emissions from generators by investment period. In this analysis, for the SWITCH Baseline scenario we assume a decline of carbon emissions to 0 by the 2050 investment period for all load zones in WECC, following the targets in California [120, p. 10], Oregon, and Biden's campaign and administration's policy goals to reach carbon-neutral electricity generation by 2035 (Ch. 4 Appendix) [341]. To measure compliance with this constraint, SWITCH tracks the emissions from each generator and aggregates to the load zone, based on carbon emissions intensity for each fuel source. Future research will test alternative Baseline scenarios without a zero-emissions carbon cap to isolate the effect of population growth and decreasing technology costs on the buildout of the grid infrastructure, before decarbonization policies are imposed.

2.4 Model "Handshake"

Changes in hydropower generation and energy use related to water are the two WEAP results that are connected with SWITCH, as described below.

2.4.1 Hydropower

We use the results from WEAP on hydropower generation under climate scenarios to adjust the hydropower generation availability in SWITCH. We first calculate a Reference monthly generation for each generator, $WEAP\ AvgGen_{g,m,Ref}$ by averaging the WEAP generation for each month 2016 – 2055 under the Reference climate scenario. Then for each climate scenario and for each generator we calculate $WEAPAvgGen_{g,m,Ref}$, the monthly average WEAP generation for each decade corresponding with the SWITCH investment periods. Finally, we calculate the "Delta ratio" $CC\ DeltaHydro_{g,m,d}$ by dividing these monthly average generation levels for each decade by the monthly average reference generation for each generator. We average these delta ratios for each decade across the generators in each load zone.

To complete the "handshake" with SWITCH, we multiply these monthly Delta ratios for each decade from WEAP with $SWITCH\ AvgGen_{g,m,Ref}$, the monthly average power and minimum power parameters by generator in SWITCH. For generators that are not modeled in WEAP (greater than 30 MW), we use the load zone average delta fractions for each generator in that load zone. If there are load zones in SWITCH with no hydropower generators included in WEAP, we use the load zone average Delta fractions from the nearest neighboring load zone. We also adjust the reserve capacity value that each hydropower generator can provide by calculating the new capacity factor (monthly average power/max capacity limit) with the Delta ratio-adjusted monthly average power values.

$$CC\ DeltaHydro_{g,m,d} = \frac{WEAP_{g,m,d}}{WEAP\ AvgGen_{g,m,Ref}}$$

$$SWITCH\ CC\ Gen_{g,m,d} = CC\ DeltaHydro_{g,m,d} * SWITCH\ AvgGen_{g,m,Ref}$$

where g is each hydropower generator greater than 30 MW, m is month, and d is the decade of the climate projection.

2.4.2 Energy demand related to water

We link the changes in electricity use related to water from WEAP with the total electricity demand by load zone in SWITCH. We first sum up the monthly energy use by category (water heating, treatment, distribution, groundwater pumping, ag water use, conveyance, wastewater treatment, reuse, and desalination) and by load zone across all the WEAP objects (urban indoor, urban outdoor, agricultural catchments, transmission links, and diversions). We calculate the decadal average monthly energy use for each energy category under the WEAP Reference scenario and under each climate scenario in WEAP. For each category and load zone, we calculate the absolute monthly delta for each decade as the difference between WEAP energy use under the climate scenario and under the Reference.

Next, we allocate the monthly deltas by energy category and load zone to corresponding hourly deltas to match the temporal resolution of SWITCH. We assign each energy category a daily "load shape," which determines the share of a day's total energy that is used in each hour (Figure 32), based on a study of 24-hour patterns of water use of different water sector components[52] [387], and a mapping of water sectors and processes included in the WEAP model (Ch. 4 Appendix). Finally, we multiply that hourly share $W_{e,h}$ with 1/number of days in each month and the monthly deltas for each energy use type and load zone. We sum the resulting hourly deltas across all energy types for each load zone $CC\ DeltaE_{lz,h,d}$ and add those to the Baseline SWITCH hourly load $SWITCH\ RefLoad_{lz,h,d}$ to calculate the new total hourly load under each climate scenario in SWITCH.

$$CC\ DeltaE_{lz,h,d} = \sum_{e \in lz} (WEAP\ E_{e,m,d} - WEAP\ E_{e,m,Ref} * W_{e,h} * 1/d_m)$$

$$SWITCH\ CC\ Load_{lz,h,d} = CC\ DeltaE_{lz,h,d} + SWITCH\ RefLoad_{lz,h,d}$$

where *lz* is each SWITCH load zone, *e* is the category of water use or energy demand demand (i.e. groundwater pumping, distribution, etc.), *h* is the hour, and *d* is the decade of each climate projection.

[52] We make a simplifying assumption that the energy use associated with each water sector category follows the same 24-hour pattern as the water use.

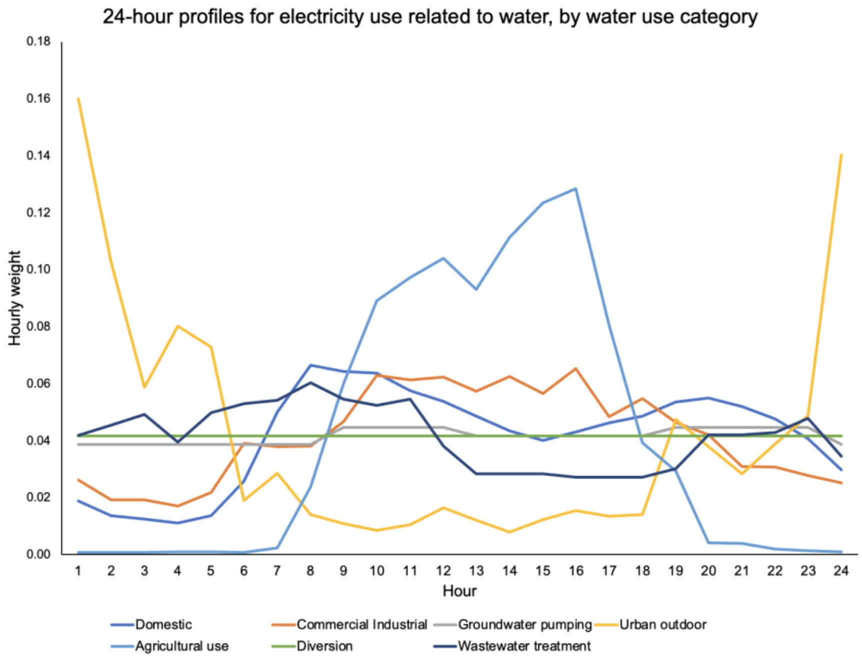


Figure 32. Daily 24-hour profiles of energy use for water services. The profiles show the hourly weight that is assigned for each day, based on the type of water use or supply category. These hourly weights are then multiplied by a day weight per month to allocate the WEAP monthly total energy use associated with each water category to an hourly interval for SWITCH.

3. Results and Discussion

We first present the results from WEAP related to water supply deliveries, hydropower generation, and energy use related to water under the WEAP Reference Scenario (no climate change) compared to the climate scenarios.[53] Secondly, we highlight key findings from SWITCH on capacity buildout, generation, transmission flows, and cost, that incorporate the changes in hydropower generation and water-related energy use from WEAP under the climate scenarios compared to the SWITCH Baseline Scenario (no climate change).

[53] Additional WEAP water system results that are not directly related to energy are detailed in a forthcoming companion paper.

3.1 WEAP Results

3.1.1 Water supplies delivered by sector, and by source

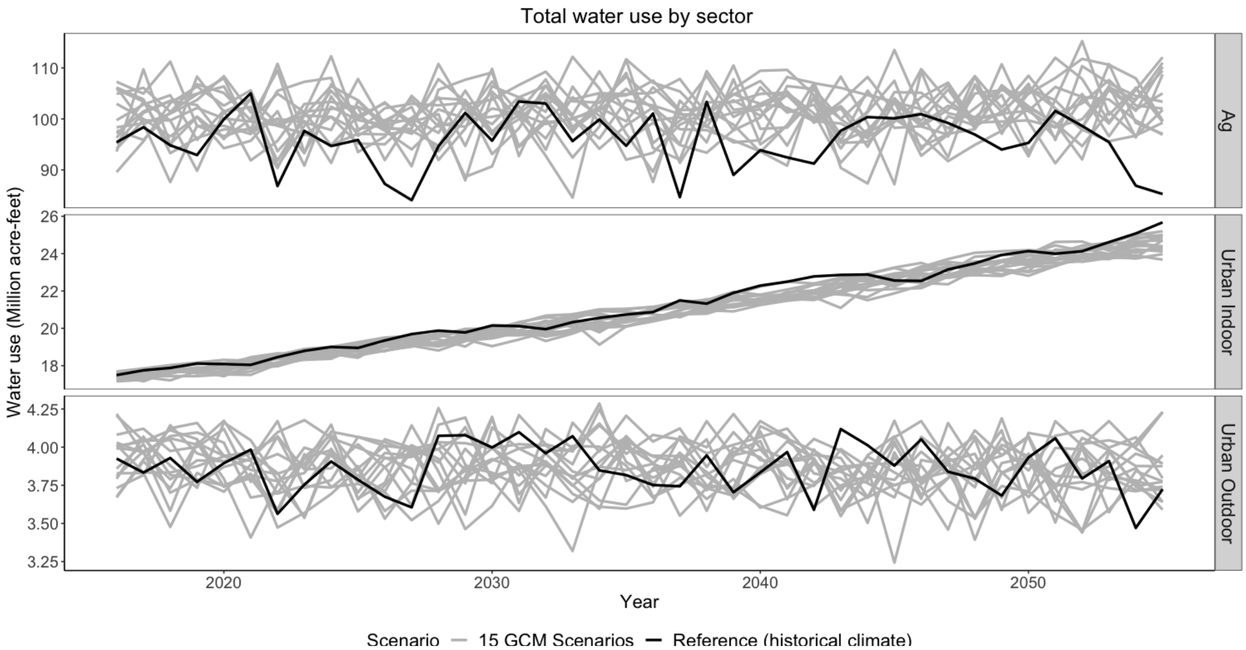


Figure 33. Total water supplies delivered to Agricultural, Urban Indoor, and Urban Outdoor sectors across the WUS region, 2016 - 2055, for climate scenarios (all GCMs in gray) compared to Reference scenario (black).

Across the WUS, water supplies delivered to the agricultural sector, the largest water user across the region (80% of supply deliveries), increases significantly under climate warming (Figure 33). Across the GCMs, the average annual irrigation water over the study period increases by +2% to +8% (+2 km^3 to +9km^3), compared to the "no climate change" Reference scenario. The lack of significant precipitation trends across the GCMs over this period suggest that the increase in irrigation water use is driven by temperature increases and soil moisture loss.

In the urban indoor sector, there is minimal change relative to the reference under the climate scenarios, which is expected because indoor use is not sensitive to climate warming. The overall increasing trend for all scenarios is from the population growth rate assumption we have imposed (Figure 33). Changes relative to the reference under climate warming, ranging from -3% to +0.2% (-0.7 km^3 to +0.1 km^3), are due to endogenous or forced conservation in the model when demands cannot be met with available supplies, depending on demand and supply priorities and operational or physical constraints. Decreased urban indoor water use, especially in the Domestic sector, saves energy because of avoided conveyance, treatment, distribution and wastewater treatment, as well energy-intensive water heating.

Urban outdoor use, the smallest of the three sectors, does not have the same increase as agricultural use across the climate scenarios because the ensemble warming and drying is very pronounced in the Colorado River basin, leading to all the urban water supplies there to be constrained. Deliveries to the Los Angeles basin from the SWP are also constrained, and together these limit the deliveries to urban outdoor supply, which is a lower priority than indoor, even though water demand for outdoor urban uses increases due to warming. Future work will evaluate the sensitivity of these results to the underlying assumptions of population growth, priority levels, and crop coefficients, as well as test scenarios of conservation programs in the urban and agricultural sectors.

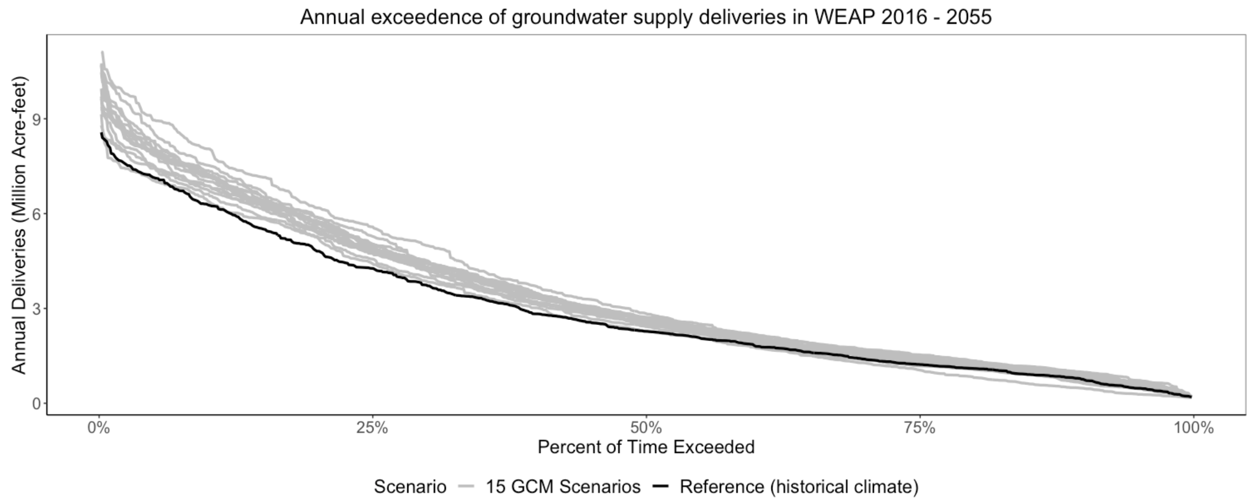


Figure 34. Annual exceedance of total groundwater supply deliveries to all sectors, 2016 – 2055, for climate scenarios (all GCMs in gray) compared to Reference scenario (black). The figure indicates the percentage of years that certain levels of annual groundwater supply deliveries are exceeded under each scenario.

The supply source of water deliveries also changes under climate warming. Groundwater remains constrained based on the assumptions imposed for the historic period simulations, with groundwater representing from 30 to 60% of annual supply delivery for agricultural uses, and a lower supply preference than that of surface water. Therefore, the model will delivery surface water up to its constrained limit, and then use groundwater up to its constrained limit. Under the climate scenarios, with increasing demand and surface water supplies hitting their limits, a growing share of overall water use is being met by groundwater. In all but two GCM climate scenarios, groundwater use exceeds that of the Reference case 100% of the years of the analysis (Figure 34). Groundwater pumping has a higher energy intensity than local surface water sources, thus this increasing trend has implications for energy use.

3.1.2 Hydropower

Under climate warming, there is a declining trend in total annual hydropower generation across the WUS. Annual generation is lower than the Reference Scenario 75% - 100% of the time for all but three GCMs (Figure 36). With an overall "flattening" of the trend, there are also no GCMs that produce annual generation levels at the high end of the range (from 170 to 220 TWh) seen in the Reference.

In addition to declines in generation, climate warming causes a damaging seasonal shift in hydropower generation, with declines over the summer months and increases in the spring months in nearly all GCMs by the 2050 decade (Figure 35). This seasonal shift exacerbates grid challenges under climate warming, when we expect increasing loads for air-conditioning during peak times over summer months, and curtailment of solar generation over the spring months when load is lower and solar production is relatively high. Increases in air-conditioning demand have not been included in this analysis but are planned for inclusion as part of future work.

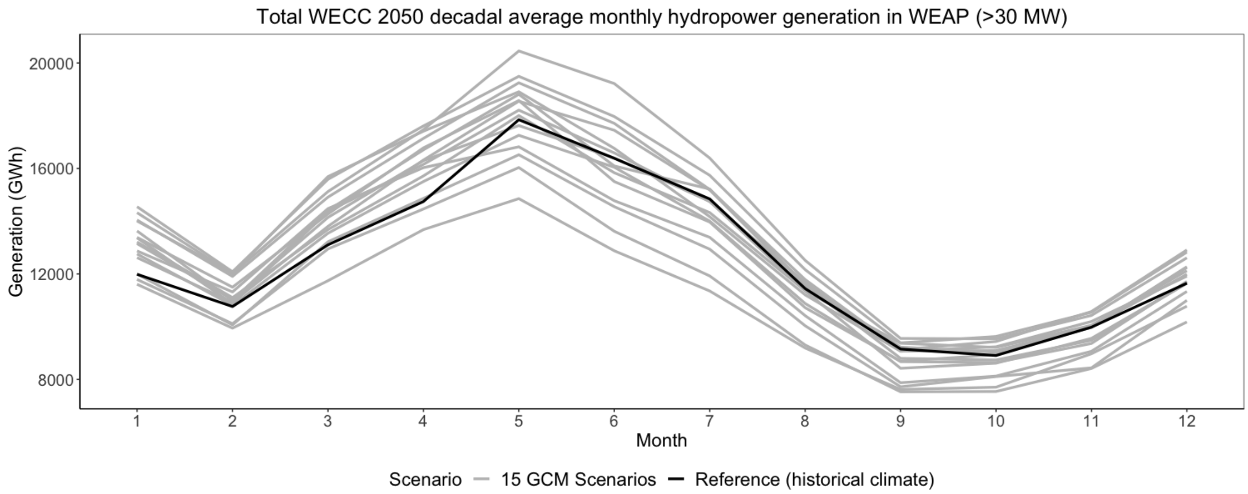


Figure 35. Average monthly total WECC hydropower generation in WEAP in 2050 decade (2046 – 2055), with the climate scenarios (all GCMs in gray) compared to the Reference scenario (black). The generation is the sum across all hydropower generators included in WEAP, which have a nameplate capacity greater than 30 MW.

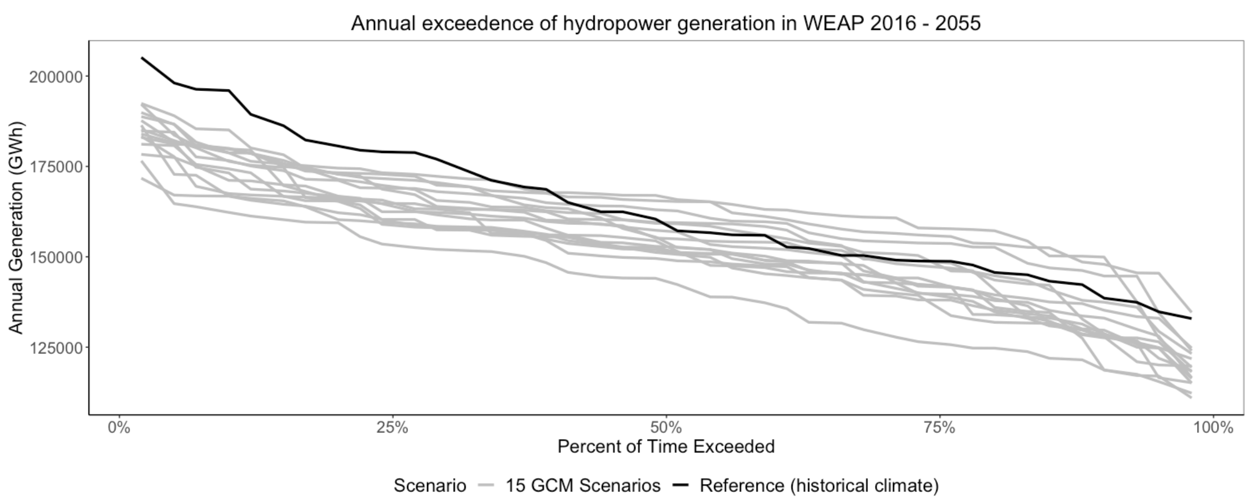


Figure 36. Annual exceedance percentages of hydropower generation WECC-wide, 2016 – 2055, for climate scenarios (all GCMs in gray) compared to Reference scenario (black). The figure indicates the percentage of years that certain levels of annual groundwater supply deliveries are exceeded under each scenario.

3.1.3 Energy demand for water

The strongest signal in climate impacts on energy demand related to water comes from increased electricity use related to groundwater pumping, especially in the agricultural sector. All scenarios but two have a strong upward trend in electricity use for groundwater pumping and increase significantly (more than 2x) relative to 2020 by the end of the 2050 period (Figure 37).

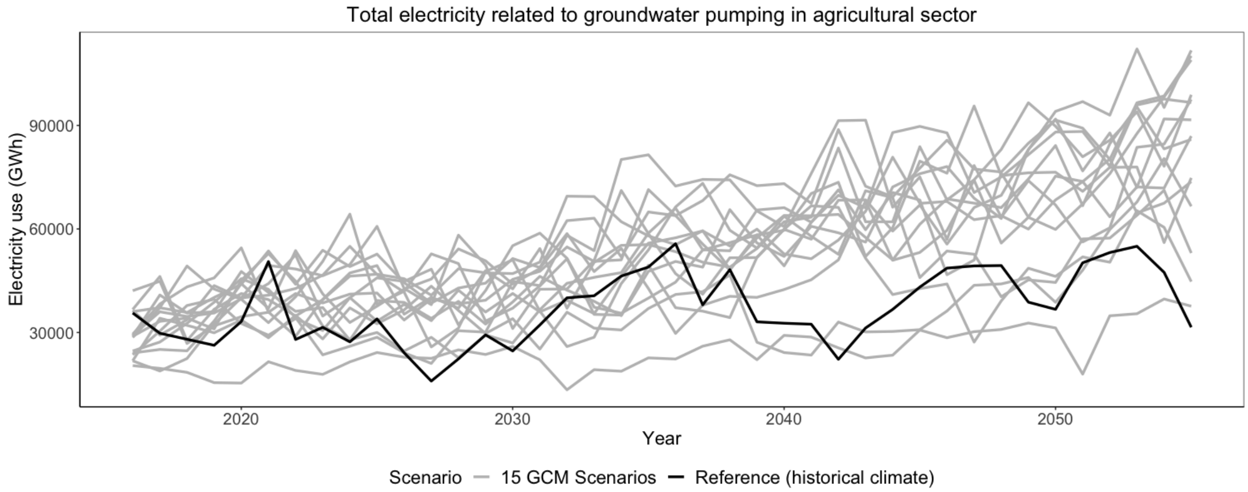


Figure 37. Total WEAP electricity use related to groundwater pumping in the agricultural sector, 2016 – 2055, with the climate scenarios (all GCMs in gray) compared to the Reference scenario (black).

3.1.4 Change in the aggregate energy balance

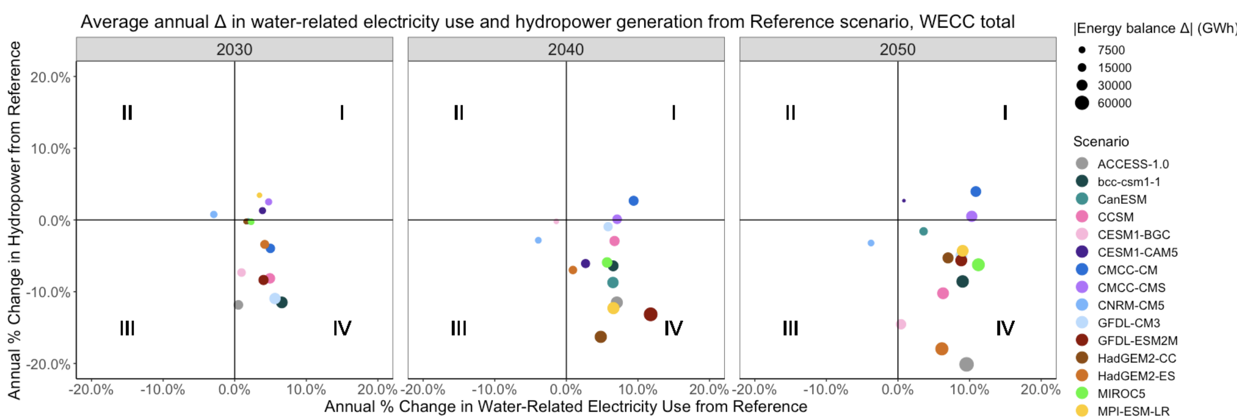


Figure 38. Average annual WECC-wide change in water-related electricity use, hydropower generation, and overall energy balance compared to Reference scenario. Roman numerals label each quadrant. Quadrant I includes scenarios with an increase in water-related electricity use, and an increase in hydropower generation. Quadrant II includes scenarios with a decrease in water-related electricity use, and an increase in hydropower generation, representing the offsetting effect that climate warming could have on the water sector. Quadrant III includes scenarios with a decrease in water-related electricity use, and a decrease in hydropower generation. Finally, Quadrant IV includes scenarios with both an increase in water-related electricity use, and an increase in hydropower generation, representing the compounding effect of climate warming on the water sector.

For each climate scenario, we calculate annual percent changes in hydropower and water-related energy use from WEAP as well an aggregate absolute “energy balance” metric to quantify the combined annual energy impact of climate change from WUS water resources. Decadal average annual changes in hydropower (energy supply) are subtracted from changes in water-related energy use (energy demand) to indicate whether climate change results in a net energy shortage or surplus, and the overall magnitude of changes that may either exacerbate or offset each other [337]. Figure 38 maps the changes in energy balances over time and across the different GCMs, with the size of the points varying by the absolute value of the change of energy balance, and their placement within the four quadrants depending on increases or decreases in both electricity use related to water and hydropower generation.

Between 2030 and 2050 the energy balances shift to concentrate in the “worst case” Quadrant IV (Figure 38), with compounding impacts from both increasing electricity usage related to water and decreasing hydropower generation that cause higher overall energy (im)balances. These effects are likely to be compounding seasonally, with lower hydropower generation and higher energy demand related to water in the summer months. By 2050, no climate scenario is in the “best case” Quadrant II, with decreasing energy use related to water, and increased hydropower. There is also a shift in relative position between models across the decades, highlighting the natural inter-annual climate variability and the non-linearity of climate signals and management responses across the models.

3.2 SWITCH results

3.2.1 WECC-wide generation, transmission, and storage capacity buildout and dispatch

To meet climate change mitigation targets through WECC-wide decarbonization by 2050 and meet forecasted load and operating constraints, under the SWITCH Baseline scenario the region sees about a three-fold increase in generating capacity online between 2020 – 2050, from about 330 GW to 960 GW (Figure 39 A). The greatest share of generation (43%) comes from solar PV by 2050, followed by wind (23%), battery storage (18%), and hydropower (12%) (Figure 39 B).

Increasing electricity use related to water under climate change increases WECC-wide total load up to 3% relative to the Baseline scenario (Figure 40). This increasing load, coupled with declining hydropower, is replaced in large part by storage, which increases total generation WECC-wide up to 5%, depending on the climate scenario. Overall, to simultaneously adapt to climate impacts on hydropower and energy use related to water, the WECC region must have an additional +0.2% to +7% (+2 GW to +65 GW) more generating capacity online by 2050 compared to the Baseline scenario (Figure 39 C). For reference, California’s peak demand forecasted for the summer of 2021, which has already seen two record-breaking heat waves by early July, is about 55 GW [339]. This suggests that in the worst-case, climate change could require building as much generating capacity across the WECC as is currently needed to meet demand in California (now a 30% share of WECC demand [388]) by 2050. Across the climate scenarios, the largest share of additional capacity comes from solar generation, followed by battery storage. However, there is significant variability in the overall magnitude of capacity additions needed between GCMs compared to the baseline (Figure 39 C). In the worst-case climate scenario, projected by the ACCESS-1.0 GCM, online capacity in 2050 is 65 GW greater than the Baseline, compared to only 2 GW for the best-case scenario CESM1-CAM5.

Decreases in hydropower generation annually and increases in energy demand can be seen as driving the capacity additions needed in each investment period (Figure 39 D). Decreased hydropower generation is replaced by a mix of generation sources, dominated by solar and complemented by battery storage and geothermal. Battery storage and geothermal resources, which are both flexible, are needed to replace the dispatchable hydropower, balance intermittent solar, and comply with a zero-carbon cap. For example, in ACCESS-1.0, solar generation and battery discharge both increase 10% compared to the Baseline by 2050.

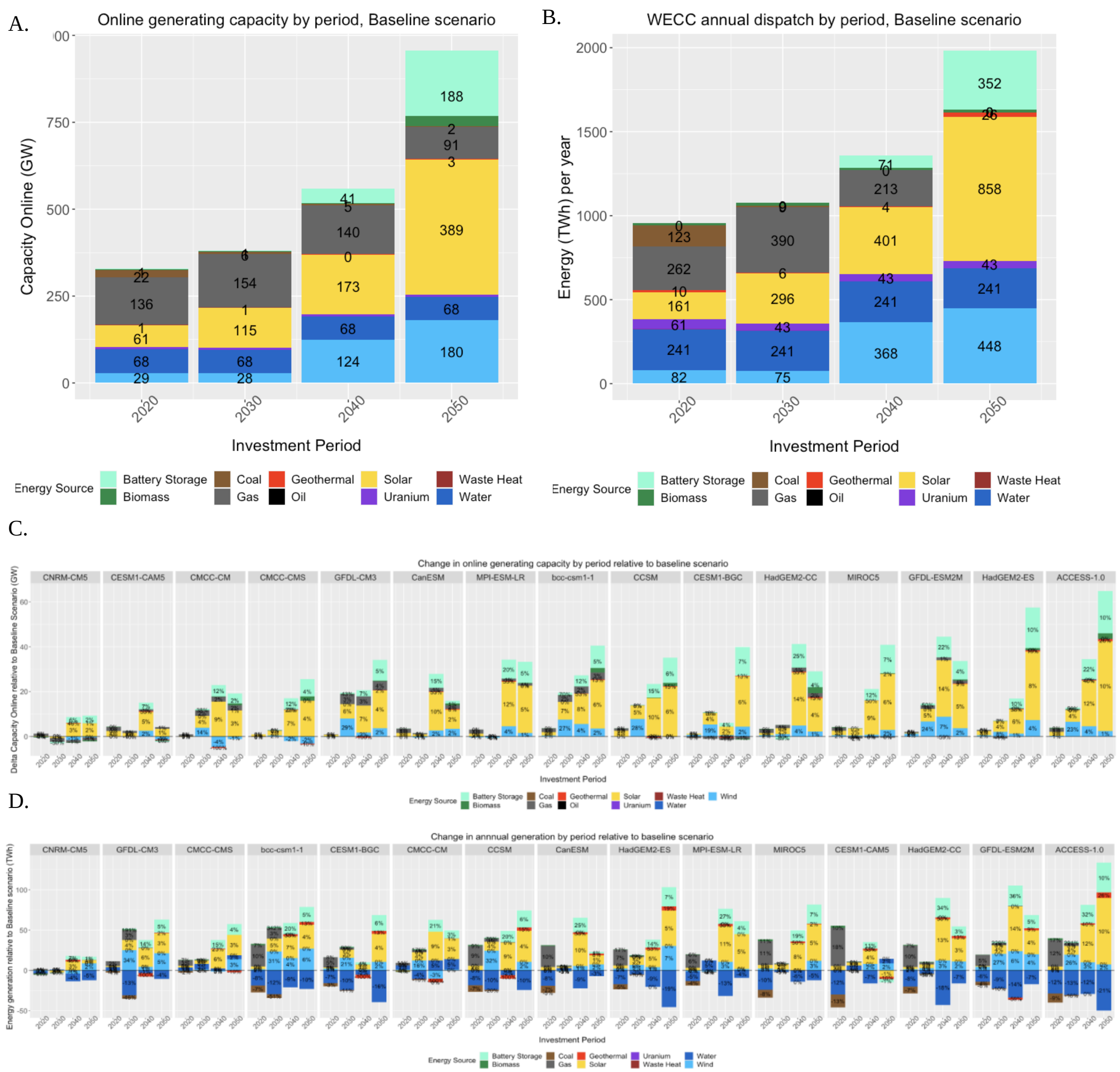


Figure 39. WECC total A. Baseline scenario online generating capacity by energy source for each investment period. B. Baseline scenario annual generation by energy source for each investment period. C. Difference in online generating capacity for each climate scenario (GCM) compared to Baseline scenario by energy source for each investment period. D. Difference in annual generation for each climate scenario (GCM) compared to Baseline scenario by energy source for each investment period.

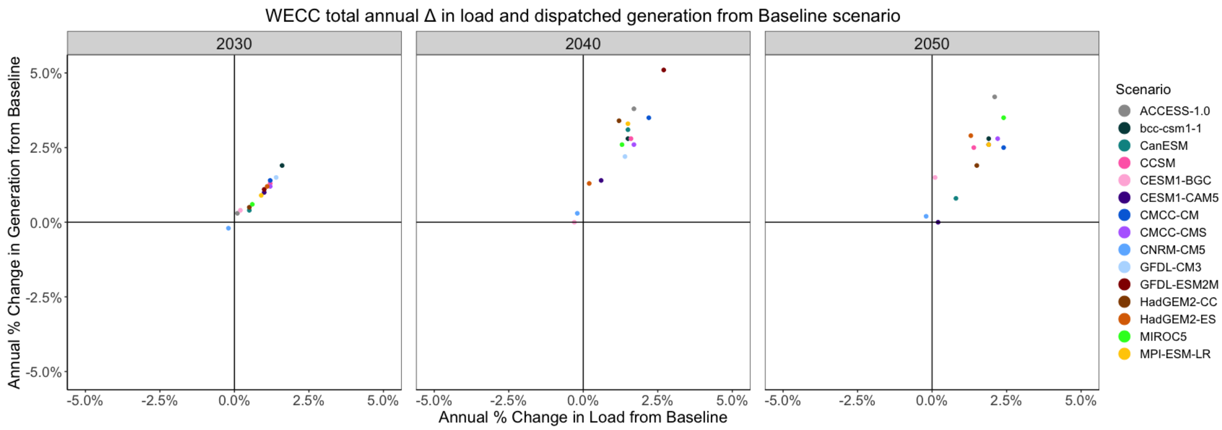


Figure 40. WECC-wide total annual percent change in load and dispatched generation for climate scenarios relative to Baseline scenario. The x-axis is the percentage difference in total annual load across the WECC (including both water-related and non-water-related) for each climate scenario compared to the Baseline SWITCH scenario without climate change. The y-axis is the percentage difference in total annual generation for each climate scenario compared to the SWITCH Baseline without climate change. Each panel includes the result from the sampled year of each decadal investment period.

Storage buildouts notably increase under the climate scenarios compared to the baseline (Figure 41). In addition to added capacity overall, the ratio of energy capacity online to power capacity online, in other words, the duration of storage, increases over 2020-2050 from about 4 to 6.25 on average across the climate scenarios (although the duration is constrained by the daily energy balance requirement). Climate warming, and the resulting decrease in flexible hydropower generation, requires longer duration storage to balance a greater share of intermittent solar PV and wind generation.

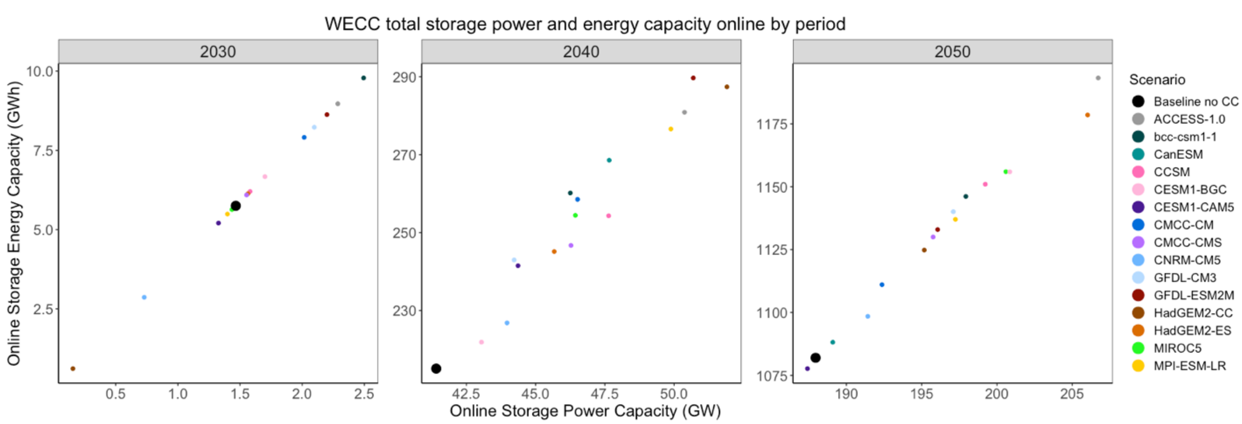


Figure 41. WECC total storage power capacity (GW) and energy capacity (GWh) online for Baseline scenario (black) and climate scenarios (all GCMs denoted by color) for each investment period. The ratio of the energy capacity to the power capacity represents the average duration of energy storage, which in this analysis is assumed to be from lithium ion battery technologies.

3.2.2 Climate impacts on regional interdependencies

Results aggregated across the WECC can obscure how climate change may stress regional interdependencies in such a closely linked region. Figure 42 highlights the spatial distribution of decarbonization-related changes from 2020 to 2050 (A, B; D, E), compared to impacts of adaptation to the ACCESS-1.0 climate scenario in 2050, which is the worst-case in terms of additional capacity needed under climate warming (C; F). Under the Baseline scenario between 2020 and 2050, large investments in solar (+330 GW online), wind (+150 GW online), and storage (+190 GW online), push out coal (-20 GW) and gas (-45 GW) generation, with solar capacity additions concentrated in the Southwest, and wind and transmission capacity additions in Canada and the Inter-Mountain West. Further, there are large investments in transmission (+240 GW) over the 2020 – 2050 time frame, especially between British Columbia, Alberta, Montana, Wyoming, and Colorado, and within the Southwest, enabling imports/exports of growing wind generation in the regions.

Compared to the structural changes in capacity and dispatch from decarbonization, the climate change adaptations are comparatively small even in the worst-case scenario. However, there are important shifts in sub-regions of the WECC under climate warming, and these changes can be seen in better detail by load zone in Figure 43. In the 2050 period, hydropower generation decreases compared to the Baseline are concentrated in the load zones of the Pacific Northwest region, in British Columbia, Washington, Oregon, and Idaho (-25% in CAN_BC, -11% in OR_WA_BPA, -25% in WA_ID_AVA, -19% in WA_N_CEN), as well as in the Lower Colorado basin (-63% AZ_APS_N) in Arizona where warming and drying is concentrated (Figure 43). These changes propagate to connected load zones that have historically relied on imports. To make up for hydropower shortfalls, generation increases from other sources, notably from geothermal in Oregon (by 6700 GWh in OR_E), from solar PV and battery storage in Northern California (by 7500 GWh in CA_PGE_BAY and CA_PGE_N), and from wind, solar PV, and storage in Arizona (by 16,000 GWh in AZ_APS_N, AZ_PHX, AZ_APS_SW, and AZ_SE) and Southern California (by 19,000 GWh in CA_IID and CA_SCE_SE). In some load zones, increases in generation or imports are driven by increased load under warming, such as in California's Central Valley (load increases by 24,000 GWh in CA_PGE_CEN and CA_SCE_VLY), which has significant growth of groundwater pumping demand. This underscores the importance of including changes in both hydropower and energy demands related to water when evaluating the comprehensive effect that climate change may have on energy-water linkages.

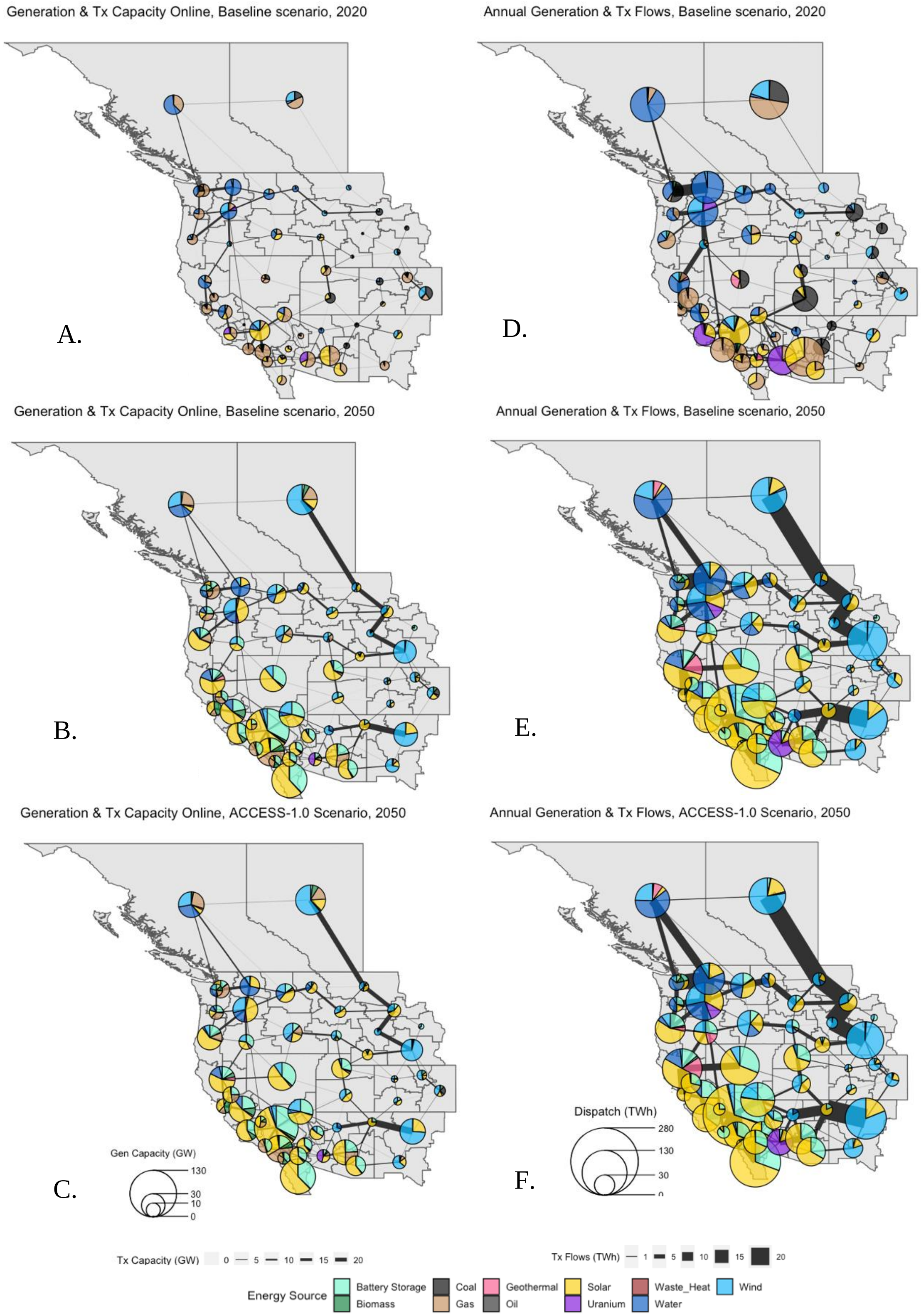


Figure 42. Generation and transmission capacity and annual generation and transmission dispatch by load zone of Baseline scenario in 2020 period (A, D) and in 2050 period (B, E); and of ACCESS-1.0 Scenario in 2050 period (C, F). The circle size indicates total capacity or energy, and the line thickness indicates total capacity or transmission flow. A comparison of panels A with B, and D with E shows the effect of decarbonization policies to reach zero-carbon generation across the WECC by 2050. A comparison of panels B with C and E with F shows the additional capacity and generation needed to adapt to the worst-case climate scenario (in terms of additional capacity needed).

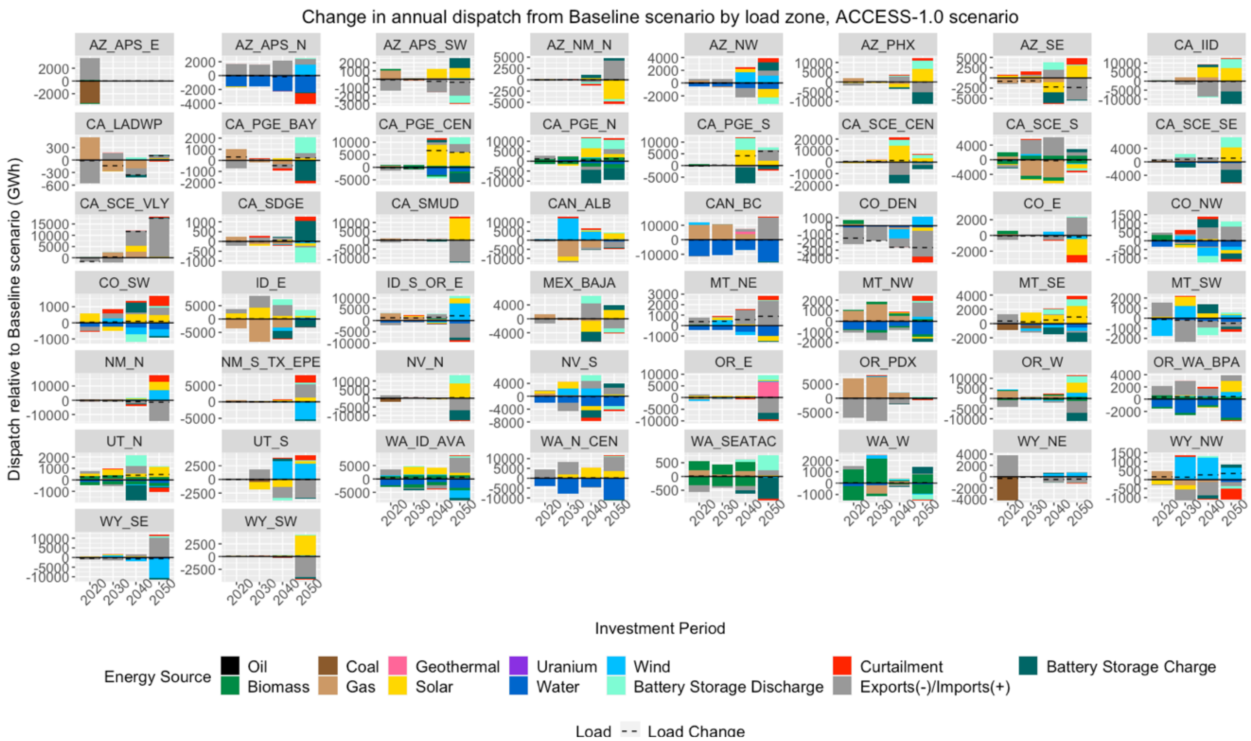


Figure 43. Change in annual dispatch in ACCESS-1.0 climate scenario relative to Baseline scenario for each load zone, by investment period and energy source. The dotted line indicates changes in load for each load zone. Exports/Imports are negative if they are exports and positive if imports. Battery storage charge is negative because it is a "load" that is matched by battery storage discharge that is counted as generation. The first two letters of each load zone name indicates the state where the zone is located (or the state with the greatest share of that zone's area if it spans more than one state). The map of load zones by name is in Section 2.3.1.

3.2.3 Costs

A. B.

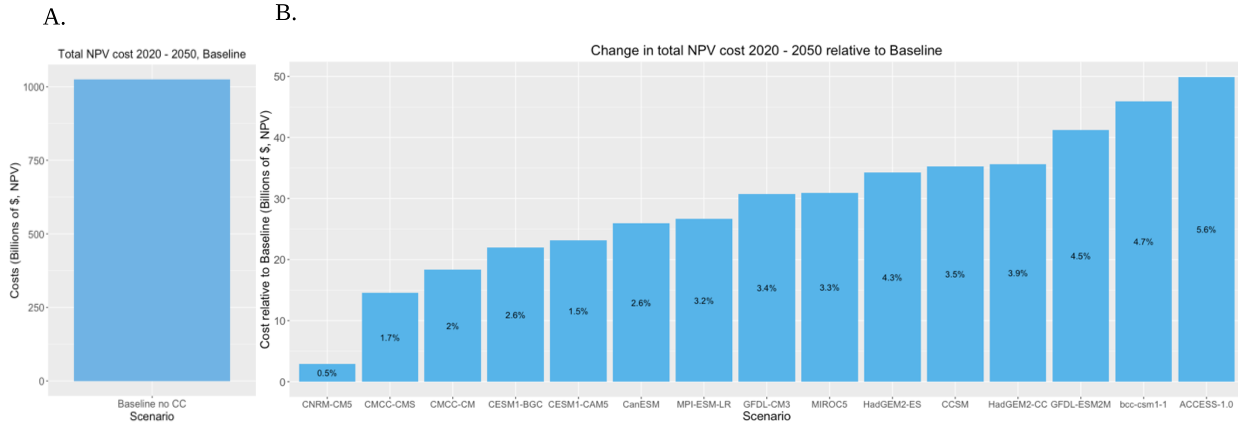


Figure 44. WECC total cost 2020 – 2050 in Net Present Value (NPV) terms for A. Baseline scenario. B. Difference in NPV cost for each climate scenario relative to Baseline scenario. NPV discounting uses a discount rate of 5% and the lifetime of the investments, as detailed in the Chapter 4 Appendix.

SWITCH finds that reaching the Baseline scenario of a zero-carbon grid by 2050 costs about $1000 Billion in Net Present Value (NPV) terms over the 2020 – 2050 timeframe across the WECC region, including the cost of transmission and generation capacity, fuel costs, and variable and fixed O&M costs (Figure 44 A). Adapting to the impacts of climate warming and building a more resilient electricity grid further increases costs to the WECC power system. Climate warming could incur additional costs of $5 Billion to $50 Billion in NPV terms over 2020 – 2050, which reflect a 1% to 6% increase above the Baseline (Figure 44 B). Most of the cost increases come from additional generation, storage, and transmission capacity needed to replace declining hydropower and meet increasing load.

4. Summary and Conclusion

Electricity and water systems are closely linked in the WUS, and are both vulnerable to the impacts of climate change. However, most electricity planning processes and models do not explicitly consider climate impacts or feedbacks from water sector interactions. We address these gaps by building a water resources model, WEAP, of the WUS that simulates infrastructure and water management within a physical hydrology model responsive to climate change. We calibrate WEAP to historical observed streamflow, state-level water deliveries, and generator-level monthly hydropower generation, and then simulate the water system under climate scenarios from an ensemble of 15 GCMs selected for their regional performance. WEAP tracks changes in hydropower and water-related energy use, and we link these results for each GCM relative to a no-climate-change Reference scenario to the electricity system expansion model SWITCH. Over four investment periods, SWITCH optimizes the generation and transmission buildout and operations to reach 0 carbon emissions across the WECC region by 2050 under a Baseline scenario and 15 climate scenarios that include WEAP results. Through this work we quantify 1) the climate impacts on water resources in the WUS, 2) the energy implications (in terms of hydropower and electricity use related to water) of such climate impacts to water resources, 3) and the climate sensitivity in terms of capacity, generation, and cost of the connected WECC electricity system.

WEAP results show that temperature increases are the strongest signals from the GCM projections, which drive an increase in irrigation water use in the agricultural sector, and subsequently a rise in energy-intensive groundwater pumping. Under nearly all the climate scenarios annual hydropower generation levels are lower than in the Reference scenario. There are also important seasonal shifts, with hydropower generation decreasing in the summer months when most needed to meet peak electricity demand, and increasing in the spring months when there is already an oversupply of renewable generation. Overall, by 2050, nearly all GCMs show both an increase in energy demand related to water and a decrease in hydropower generation, creating an energy imbalance or shortfall that has implications for capacity needs of the grid. When connected with SWITCH, we find that adapting to these water-related climate impacts, such as increase in total load by up to 3%, requires an additional 0.2% to 7% (+2 GW to +65 GW) of generating capacity online by 2050 across the WECC, relative to the Baseline scenario. At the upper end of this range, the capacity addition exceeds California's current peak demand. Adapting to climate change with this added capacity increases the total cost of grid infrastructure by 1% to 6% in the WECC. The results show the added difficulty of meeting mitigation goals with the decrease in a carbon-free, flexible resource like hydropower. Shortfall are made up for by over-building solar and wind capacity, and building additional flexible resources like geothermal and battery storage. We also see the ways that climate impacts can have cascading impacts in connected regions of the WECC grid. Declines in Pacific Northwest and Colorado River hydropower affect the capacity, generation, and transmission flows of neighboring load zones, and increases in electricity demand for groundwater pumping in the Central Valley of California increases electricity imports from connected regions.

We recognize that there are many areas for further research to better support the planning of a climate resilient grid. Future analysis will include the impact of climate warming on electricity use for air-conditioning, in addition to the already included changes in water-related electricity use. Additionally, it will be important to test the sensitivity of water resources to assumptions on crop coefficients (agricultural water use), population growth and per-capita water demand, and the energy intensity related to water. Subsequent research will also evaluate how changes in water sector policies and climate adaptation measures could affect the grid buildout. For example, because of stressed groundwater resources, water managers may need to replace declining surface water with alternative supplies to maintain reliable deliveries [260], [318], [326]. There are limited remaining low-energy-intensive water supplies [207], therefore, many water adaptation strategies (including desalination, water recycling, and groundwater recharge)[67], [74], [75] may also add to electricity capacity needs [75], [76]. Reservoir managers may also adjust their operations to maximize water supply storage, which could affect hydropower generation patterns. Finally, more study is also needed of how climate extremes, such as extended and more intense droughts, could compound the water and electricity systems.

Overall, our findings support the literature that climate change impacts mediated through the water system will have important implications in future grid expansion. In the WUS, where the fates of the water and electricity systems are already closely tied, these climate impacts affect the timing, magnitude, and spatial distribution of optimal future generation and transmission investment and operation. These results suggest that there are benefits to explicitly incorporating water sector interactions and climate scenarios into grid expansion models to help ensure a climate-resilient grid of the future.

Chapter 5: Assessing climate adaptation decisions at the energy-water nexus

An important aim of my research is to produce useful results that inform the development of climate resilient infrastructure in practice. This is to counter a major critique of energy-water nexus literature, and climate adaptation literature more broadly, that analyses are often disconnected from resource management decisions and therefore are not actionable. To improve the decision-relevance and usability of my research, I developed and refined the climate-energy-water nexus framework from Chapter 3 based not only on a synthesis of literature, but also through engagement with key water and energy stakeholders. I met with and presented to water planners in different divisions of the California Department of Water Resources, and participated in and observed workshops at the California Public Utilities Commission as part of the regulatory proceeding on climate adaptation of the electricity sector. Through interactions with, and feedback from, various energy and water stakeholders, organizations, and fora, I sought to have a better understanding of the most important climate-related concerns for decision-makers, and to ensure that my framework captured all the cross-sectoral feedbacks they considered most critical.

These engagements with stakeholders improved my understanding of challenges faced by practitioners beyond the theory and led me to pursue a co-production approach to develop the modeling efforts of Chapter 4. The goal of using co-production was to refine the Chapter 4 model, research questions, and scenarios to reflect decisions, scales, and information needs of decision-makers for their management contexts. In this final dissertation chapter, I discuss the focus group and surveys conducted with a group of water managers in the WUS to that end. The discussion of initial results with water managers ultimately centered less on the specific results and methodology, and instead illuminated the broader ways of when and how energy factors into water decisions, often in hidden or implicit ways. This chapter describes the findings of the first of several planned focus groups with resource managers and is an area of ongoing work. The analysis in this chapter will be prepared for submission to a journal and is included in this dissertation with permission from co-authors Kripa Jagannathan, Smitha Buddhavarapu, David Yates, and Andy Jones.

---

1. Introduction

In arid regions like the Western United States (WUS), energy and water systems are closely tied, with about 7% of total electricity use related to water [90], and hydropower comprising 17%, 37%, 68%, 74%, and 77% of average electricity generation in California, Montana, Oregon, Washington, and Idaho, respectively [333]. These interdependencies are often referred to as the “energy-water nexus” [389]. In addition to cross-sectoral linkages, both the electricity and water systems of the WUS are large-scale infrastructure networks unto themselves, engineered to overcome the spatial and temporal mismatch between resource supply availability and demand across the region. For example, seven states import water from the Colorado River, and on the grid, California imports the most electricity (25%) out of any US state to meet its demand [390]. The two systems are also vulnerable to climate change, with climate impacts on WUS water resources in particular unparalleled elsewhere in the country [335]. Because they are intricately connected, cascading impacts could occur if changes in one system have feedbacks on the other [71], [244]. Additionally, climate adaptation actions in one sector could transfer vulnerability to the other, ie. be maladaptive, if cross-sectoral interactions are not considered [23], [35].

Many energy-water nexus studies demonstrate how integrated systems' management improves efficiency, increases equitable resource access, and maximizes synergies [38]. There is also recognition of the importance of accounting for climate impacts on such linked energy and water systems, because the cross-sectoral interactions could exacerbate the effects of warming [21], [73], [93]. Yet, in the two independently managed sectors, it appears that energy-water interactions are not typically or explicitly operationalized into decision-making [18], [94], and many ideas and tools of the nexus have remained conceptual [38]. Nexus challenges for climate adaptation in particular tend to not be in the forefront of decision criteria and are often considered outside the scope or jurisdiction for resource managers of individual sectors to evaluate [20]. One possible explanation for this gap between the theory and practice of the nexus is that scientists working at the nexus may not be engaging directly with stakeholders to understand and adjust their research based on the kind of information, frameworks, institutional norms, and analytical methods that are used by practitioners on the ground; only a small share of nexus literature incorporates stakeholder engagement and decision support methods [38].

Collaborative and participatory approaches may help address this gap, making energy-water nexus analyses more actionable in practice through better identification of cross-sectoral interactions and the values and needs of stakeholders. In this work, we aim to use the collaborative process of co-production between researchers and stakeholders to improve the decision-relevance of an ongoing energy-water nexus modeling effort. We do so by bringing together scientists and water managers, and eliciting information on the extent to which energy interactions play a part in current water sector decisions, and whether and how impacts of climate change on the energy system may have feedbacks or complications for these specific water sector decisions. We seek to address the following questions:

Is energy factored into water sector decision-making related to climate change?

If so, how does energy enter into decisions, and what information is used?

Through focus group discussions and follow-up surveys with water managers across the WUS, we identify the often invisible, implicit ways in which energy considerations underlie major water sector decisions—such as those related to financial planning, reservoir operations, and drought management—and how these considerations are affected by climate change. Our work provides scholars and practitioners looking at adaptive water management a framework to examine (1) the critical climate impacts that are compounded due to water-energy interactions, (2) the specific management decisions that may be impacted due to consideration of these interactions, and (3) the tradeoffs that water managers may need to plan for under climate change. These findings on what is most important to stakeholders regarding the nexus and climate change, and how they do or do not factor energy considerations into their decisions, can be helpful for targeting other needed research efforts beyond the original water-energy modeling work directly motivating this project.

2. Examining energy-water interactions using co-production

Co-production is a collaborative process whereby knowledge is jointly produced through interactions between scientists and stakeholders, and values and knowledge are incorporated from both communities [97]. The process is often iterative, involving multiple interactions, such as through focus groups, workshops, or interviews, between scientists and stakeholders to work on framing research questions, analyzing findings, or deciding on a research approach [391]. The interactions are typically facilitated by "boundary" individuals, organizations, or objects who convene, translate, and mediate the exchange of ideas between the different groups involved [392], [393]. The literature suggests that co-production of knowledge helps make the resulting information more accepted and used by decision-makers [391] because it increases the credibility, salience, and legitimacy of the information [39], aligns the scale of the analysis to specific decision contexts [391], and allows for a better fit with norms and existing information of institutions [98]. Co-production has also been found to be an effective method to reveal non-technical barriers to effective adaptation and coordination between sectors, and can augment technical modeling assumptions, scenario creation, and model design for decision-relevance [40]–[42].

For this work, we use the co-production approach to understand how water managers in the WUS consider energy-water interactions and decisions under climate change, with the goal of narrowing the gap between conceptual energy-water nexus ideas and findings and their implementation in practice. Through a series of iterative focus groups, surveys and other formal and informal interactions, we bring together water managers from across the WUS with scientists who are in the process of developing a set of integrated water and energy models of the region. The scientists present the overall motivation, methods, and preliminary results of the ongoing modeling work, and aim to use the following discussion to gather feedback on the method and approach, future scenarios to run, and any results of interest. In addition to helping the scientists adjust their research for policy and decision-relevance and improve their understanding of underlying systems, another objective of the co-production process is to share insights with stakeholders who may not typically consider the cross-sectoral feedbacks under climate change.

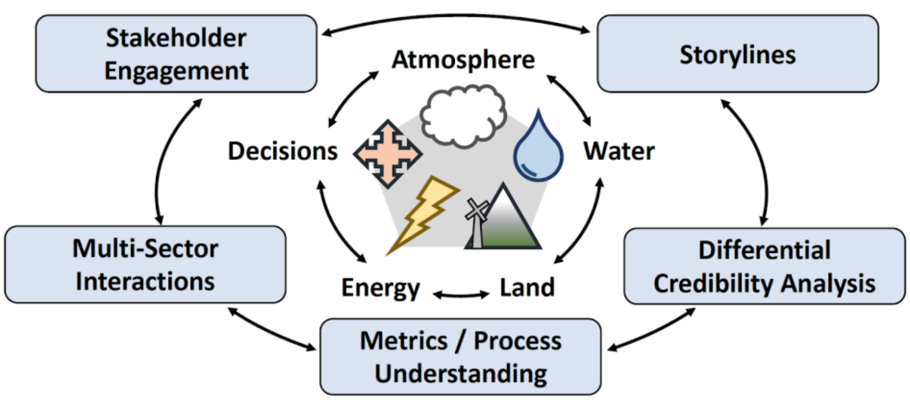


Figure 45. A graphical depiction of the topics being studied in HyperFACETS (inner loop) and different project elements (outer loop). The effort described here uses stakeholder engagement to improve the understanding of multi-sector interactions, specifically between the energy and water sectors and their related management decisions.

This effort is one part of the much larger HyperFACETS project (Figure 45), which aims to conduct climate modeling for management-relevant outcomes and analyze critical multi-sector interactions [394]. The HyperFACETS project applies principles of co-production to achieve these aims, whereby information is jointly produced through collaborations between an interdisciplinary group of scientists across nine research institutions and resource managers from 12 water management agencies and one electric utility, representing several major watersheds in the US, including the Sacramento/San Joaquin and Upper Colorado in the WUS. Facilitated by dedicated boundary spanners whose primary role is to mediate the scientist-stakeholder boundary, the HyperFACETS stakeholders and scientists have been participating in a number of focus groups to co-develop science and metrics, and share feedback on ongoing research projects to be more decision-relevant [395]. The co-production effort we describe in this work is specifically with scientists and stakeholders who are part of the Multi-Sector Interactions working group of the HyperFACETS project.

3. Methods

We conducted a focus group with seven water and one energy resource managers from across the WUS, in Eastern and Western Colorado, Utah, and Southern and Northern California who were part of the HyperFACETS project.[54] The focus group discussion followed the presentation by scientists of a climate-energy-water nexus framework they developed [337], and the preliminary results of their ongoing research linking climate projections with a water resources model and an energy planning model of the WUS. The linked models, from a forthcoming paper[55], evaluate the impact of climate change on the water system and how the optimal buildout of the grid subsequently changes when incorporating climate impacts and water system interactions. The models cover the major rivers, watersheds, built infrastructure, and urban and agricultural water demands across the entire WUS, and the electricity system of generation and transmission of the corresponding Western Electric Coordinating Council (WECC) region of the grid.[56] The scientists presented preliminary results on climate projections used from an ensemble of Global Circulation Models (GCM), water supply deliveries by sector (urban indoor, urban outdoor, agriculture), hydropower generation (annual and monthly), energy demand related to water (for groundwater pumping), and the electricity generation and transmission capacity buildout and dispatch by region.

The focus group was facilitated by two boundary-spanners (including two of the authors), who asked questions from the stakeholders and moderated the discussion. A 30-minute discussion with resource managers followed each of two presentations by scientists (including another two of the authors) on the motivation, methodology, and preliminary results of the integrated water resources and electricity planning models of the WUS, along with an additional 20-minute concluding open discussion. After the focus group, stakeholders were asked to fill out a survey asking what their main takeaways were, what they learned, and reiterating the main ways they think about energy and water sector interactions in their management contexts. In addition to questions about the decision-relevance of the particular modeling effort, the facilitators also asked broader questions about how the resource managers think about cross-sectoral questions and adaptation decisions. Using the qualitative data collected from the focus

[54] We base our analysis only on comments from the water managers and not the energy manager to be consistent and not skew the results.

[55] Szinai, Julia, David Yates, et al. *Planning for Climate Change Impacts on Electricity and Water Systems in the Western US with a Cross-Sectoral Modeling Approach*. Manuscript in preparation. 2021.

[56] Some of the discussion included feedback on the specifics of the modeling and its usability, but we do not describe that here.

group discussion and surveys, we conduct a thematic analysis and identify the key ideas that emerge.

We recognize the limitations to the generalizability of this work due to the size and nature of the sample. Because of their involvement in the HyperFACETS project, these resource managers are not a random selection of stakeholders across the region, but a self-selected group with interest and awareness of climate impacts on water and energy resources. However, even with a small group, the sample includes a diverse set of resource managers spanning multiple jurisdictional levels (including federal, state, regional, and local), watersheds, organizational sizes, and functions (including operations, planning, managing water quality and water supply, flood control, and power generation) across their agencies. Nonetheless, in order to strengthen the findings and reach convergence on key themes, we plan to conduct additional follow-up focus group discussions. Future discussions are planned with the same group of stakeholders, and the scientists will present updated modeling results that have been adjusted in response to initial feedback. We may also expand the sample to additional stakeholders in the region if time and resources permit.

4. Results and Discussion

The process of co-production between stakeholders and scientists led to a number of key themes, which emerged even as the discussion deviated from the original, more targeted questions regarding the preliminary results of the energy-water models. The focus group and survey responses moved away from the specifics of the models and instead facilitated a rich and much broader discussion on the important concerns around climate adaptation and the nexus. The presentation of the climate-water-energy nexus framework and preliminary modeling results acted as a boundary object for the scientists and water managers, and enabled the identification of key climate change impacts at the energy-water nexus, specific adaptation decisions faced by water managers as a result of these climate impacts, tradeoffs that management agencies face as they consider these adaptation decisions, and the metrics that help evaluate these tradeoffs (Figure 46). Here we describe the key themes that emerged from the co-production process.

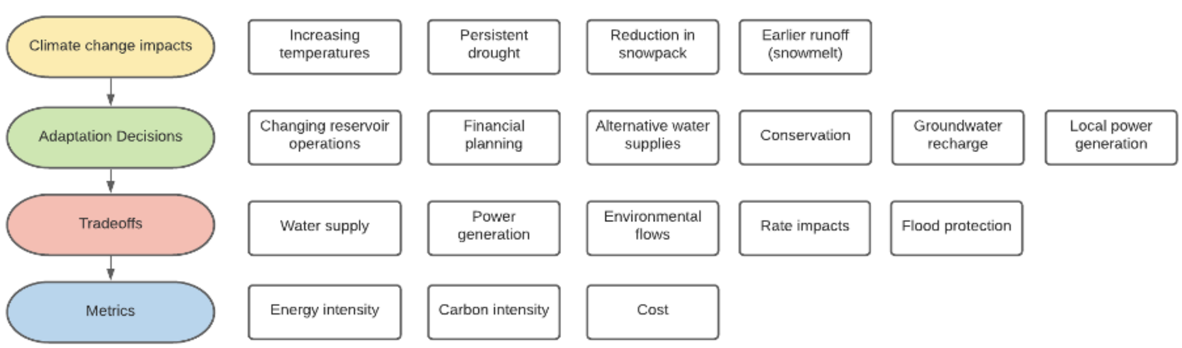


Figure 46. Key themes of climate impacts at the energy-water nexus, adaptation decisions, tradeoffs, and metrics.

4.1 Climate change impacts relevant to energy-water interactions

WUS water managers focused on increasing temperatures, persistent drought, reduction in snowpack, and earlier runoff (from snowmelt) as the key climate impacts of concern for their systems. They highlighted droughts and low snowpack years as particularly difficult to manage, for two underlying reasons that emerged from the discussion. These climate impacts tend to 1) simultaneously decrease water supply and increase water demand, and 2) to also affect connected energy supply and demand in ways that compound water management challenges. Some of these indirect effects are driven by structural dependencies on the energy system. While not immediately obvious, these energy interactions appear to be core factors underlying the water sector's climate vulnerabilities, with one manager even noting in a survey following the discussion:

> *"Power and water are even more interrelated than I had previously thought."*

Declining hydropower generation was the most prominent example of how periods of water scarcity during droughts could be exacerbated because of energy-water dependencies. When hydropower generation decreases and/or shifts to less profitable times of the year, there is a resulting loss of revenue from power production for agencies that operate hydropower, at the same time as a drop in revenue from water sales and an increase in energy costs for replacement power that must be procured in the energy market during high-priced times. This "double whammy," as one water manager called it, can have a destabilizing effect on the business model and rate structure of water suppliers, especially those that depend on power generation profits to keep water affordable for customers, particularly agricultural users. Reduced hydropower can also lead to reductions in water supply reliability, as one water manager remarked:

> *"Water supply reliability and power reliability are inseparable. Climate impacts to hydropower generation have a direct impact on some utility's ability to provide clean drinking water."*

Further, during such times when reservoir levels are low and drought reserve water supplies are needed, water agencies have less flexibility in operating their systems, such as in prioritizing lower energy-intensive pumps and treatment plants, driving up energy demand and related costs. Alongside these higher energy costs from less efficient operations, water managers were also concerned about the increase in electricity demanded from supplemental water sources during times of shortage, such as water recycling and desalination, which tend to be more energy-intensive.

Across the discussion of climate impacts of concern, the theme of regional interdependencies of both energy and water systems was also prevalent. Several stakeholders expressed concern about climate impacts that were correlated in time across different parts of the WUS, making it difficult to rely on neighboring regions to import water or hydropower generation. Similarly, there was a concern that climate impacts in one area could have (literal) downstream effects in another, because the system was designed with such a reliance on moving energy and water such long distances. Local resilience, self-sufficiency, distributed generation, and energy storage, were proposed by managers to adapt to these imminent climate threats of compounding vulnerabilities across space and time.

4.2 Adaptation decisions

From the focus group and survey responses, we identify a number of specific decisions that water managers are considering to adapt to these climate impacts of concern, including changes to financial planning, increased local power generation, changing reservoir operations, alternative water supplies, conservation, and groundwater management.

While the literature has largely focused on methods for including climate projections into water resources models, managers highlighted the need to also incorporate climate information into water agency financial planning and analyses. Because of the extent that droughts can affect water utilities on both sides of their balance sheet (from less revenue from water sales and lower hydropower production, alongside higher energy demands and costs), several managers mentioned the need to adapt both short-term and long-term financial forecasts to proactively account for climate risks. One organization is moving to use longer planning horizons along with climate scenarios to better anticipate and prepare for changing finances for the utility and its customers during droughts. Another manager also mentioned using climate projections in long-term rate design and the calculation of repayment terms for infrastructure costs, instead of predicating analyses on historical climate, because:

> *"...we're getting into situations that the power authorities didn't expect or we didn't model for them because we're using more of a climatology [historical average climate] and not a skillful 10-year projection [projections of climate change]."*

Changing reservoir operations was another key decision area discussed by several water agency stakeholders. Water managers emphasized that their first adaptation priority is to maximize the operations of their existing assets, before adding expensive new infrastructure that can take decades to plan and build. With the overall goal of better managing water storage, some water managers have already begun to incorporate improved short-term forecasts of large atmospheric river storm events, through Forecast Informed Reservoir Operations (FIRO), to optimize the timing and magnitude of water releases and adapt the buffer needed for flood control. Several managers are also investigating how reservoir operations may also need to adapt so that hydropower generation can be used for balancing an increasing share of intermittent renewable generation on the grid.

As an adaptation to declining hydropower generation across the WUS under climate change, some managers are thinking of investing in other forms of local power generation, energy storage, or micro-hydropower to ensure more reliable power (and water) supplies. This is consistent with the recurrent focus by managers on increasing local resilience by lowering regional interdependencies on imported water and energy supplies, and mitigating cascading failures that could result from the propagation of climate impacts across energy and water networks.

While some managers highlighted the risks from regional interdependencies, others viewed the linkages as an opportunity for adaptation by optimizing the timing and location of groundwater recharge across a wider, climatically diverse area. Recharging and banking groundwater during times and in locations of high rainfall (and lower energy prices), could save both water and energy. One manager remarked:

> *"We should be taking advantage of those moments when energy is plentiful instead of relying on large surface water storage projects. The ground could be our most cost-effective opportunity moving forward."*

In addition, water conservation was mentioned in 88% of respondents as an adaptation strategy currently being pursued.

Lastly, water managers mentioned alternative water supplies to use especially as a last resort during drought times. 75% of the survey respondents mentioned water recycling, but desalination was only mentioned as an option under consideration by 2 out of 8 (25%) of water managers polled.

4.3 Decision tradeoffs

The discussion of adaptation decisions raised the complicated tradeoffs water managers consider—including costs, power supply, water supply, environmental flows, and flood protection—and which are exacerbated under water scarcity conditions perpetuated by climate change. Many of these tradeoffs confirm existing water resources literature on multi-objective optimization and integrated resource planning, but here we also identify the implicit and less visible energy considerations underlying several tradeoffs of water system adaptation.

For example, some alternative water sources that may be called upon during scarcity conditions to augment supplies have relatively high energy usage and associated GHG emissions. So much so, that one manager remarked that their board members "want assurance that additional supplies are absolutely necessary and no other option is available." Similarly, during drought conditions, some water managers described having to resort to more energy-intensive equipment or processes to maintain water supply reliability. Providing flood protection by leaving a buffer in reservoirs may also limit the amount of water storage and hydropower generation available. Another manager mentioned that environmental flow and water temperature requirements imposed during a recent drought also meant less water storage in reservoirs and hydropower generation from bypassing turbines.

Some utilities are actively trying to reduce/optimize energy usage tradeoffs through various measures like water conservation, optimizing energy use with grid conditions, installing solar power on properties, producing hydropower, reducing waste, and using water to cool/heat their own buildings:

> *"These decisions are made both from a cost saving standpoint, as well as because there is a strong environmental ethic and realization that climate change directly impacts the ability to fulfill the mission of delivering safe and reliable water."*

However, increased awareness of such tradeoffs to the energy system of certain water sector decisions do not necessarily mean that water organizations will change their behavior. While recognizing that it may not be optimal for the needs of the electric grid, one water manager emphasized that they will continue to prioritize their water system operations to meet their core objectives of supplying water to meet demands and protect the environment:

> *"While good to know, the fact that by 2050 hydropower generation is expected to peak in the spring (when not as needed) and decline in summer (when needed to meet peak electricity demand) is unlikely to change operations because water agencies will strive to prioritize serving our water customers and acting as stewards for the environment."*

4.4 Energy-water metrics

Managers of water systems that are closely tied to energy systems highlighted several metrics they use to evaluate the tradeoffs of climate adaptation decisions: energy intensity, carbon intensity, and cost (which also affects customer rates). Notably, several managers distinguished energy and carbon intensity as evaluation metrics for alternative water supplies, and how these may change under drought conditions because of the coincident declining share of hydropower generation in the energy supply mix on the grid. Several managers pointed out that under such water scarcity conditions, the carbon intensity of energy tends to increase precisely during the times that water managers may rely on more energy-intensive projects, compounding the impact.

> *"We do really want to consider energy intensity metrics in evaluating new projects. Something that's going to be important for us if we have more energy-intensive projects, is where this energy is going to come from."*

Cost and energy and carbon intensity also factor into evaluations of water conservation for some water agencies, in terms of seasonal energy, cost, and carbon emissions savings. Another water manager mentioned the purchase of carbon offsets for their energy usage, which also affects the agencies' costs.

Some agencies are not yet fully or explicitly considering energy intensity of their operations, but expressed interest and think it will play a role in the future. Despite the interconnected nature of the water sector throughout the WUS and the reliance on energy-intensive inter-basin water transfers in many sub-regions, other water managers shared that they do examine the energy intensity of their local systems, but do not necessarily consider the regional context. Finally, one manager showed an interest in using cost as an evaluation metric to understand and weigh the "costs of doing nothing."

5. Conclusion

Through a co-production process consisting of focus group discussions and follow-up surveys with water managers across the WUS, we identify specific climate-energy-water interactions and feedback loops that impact operations and planning for water agencies. In doing so, we find that energy connections are more prevalent than previously thought, and we characterize these often invisible or overlooked drivers of water management decisions, such as financial planning for water supply, shifting to alternative water supplies during droughts, and modifying reservoir operations. This work also identifies specific tradeoffs that water managers might face while dealing with cross-sectoral interactions under climate change. Overall, our work highlights the importance of identifying and evaluating critical cross-sectoral connections across the climate-energy-water nexus and how this can lead to mutually beneficial, specific adaptation decisions for water and energy institutions. These results can guide energy-water modeling efforts on developing decision-relevant science.

It was the exploratory process of co-production with preliminary research results that enabled us to gain insights indirectly on water adaptation decisions, main concerns about climate impacts, and overall what energy interactions were or were not important to the WUS water managers. Despite the presentations being about the specific models, methods, and data used, the managers cared much more about how the scientists and their work could shed light on broad-brush issues and trends, directions of change, and drivers of change. In these early stages of research, the precise findings were less useful to the managers than the fact of seeing the cross-sectoral interactions at all, and also allowed for scientists to understand what was truly meaningful to decision-makers. The direction of the discussion suggested that the process to getting to results is as important to stakeholders as the results themselves, corroborating the importance of co-production of knowledge to close the gap between theory and practice for climate adaptation decision-making related to the energy-water nexus.

Conclusion

Long-term electricity resource planning has historically focused on minimizing the cost of the grid to maintain reliability, but in the context of climate change, electricity systems must also be climate-resilient: *flexible, efficient, diverse*, and *redundant* to be able to respond to climate stressors and maintain *clean, reliable, cost-effective* electricity. Further, electricity system operations and planning cannot ignore the compounding effects on grid outcomes of *cross-sectoral interactions* that may be exacerbated by climate change impacts, mitigation efforts, or adaptation strategies. The five chapters of my dissertation bring together these constructs, and I conclude here with a summary of the key findings, areas for ongoing and future work, and recommendations for planning a climate-resilient electricity system based on this research.

1. Summary of findings

EVs can help or hurt in decarbonizing the grid, depending on if the timing, location, and magnitude of their charging is flexible and responsive to grid needs. However, modeling efforts often oversimplify either vehicle mobility or electricity market dynamics, making it difficult to evaluate the fidelity of any estimates of the value of cross-sectoral coordination. Chapter 1 links high-resolution models of mobility and power systems and quantifies the demand *flexibility* and resulting cost savings and avoided renewable curtailment that managed EV charging can realistically achieve, compared to the unmanaged charging alternative that ignores transportation-electricity system interdependencies. The results show that smart charging can provide the greatest grid benefit, and has the most potential at residential locations, while unmanaged charging exacerbates peak loads.

Like EV charging, water resources and their use can also save or add to electricity demand, depending on the type of use, location, and source of water. Chapter 2 forecasts the energy usage and GHG footprint related to urban and agricultural water in California out to 2035, given recent trends in declining water demand, shifts to local supply sources, and increasing renewable energy on the grid. The findings demonstrate that if per-capita water demand continues to decline according to historical trends, there are significant energy and GHG savings co-benefits from the water conservation across different regions, which also increase the *efficiency* of both systems and may provide *redundancy* during drought periods that are expected to become more frequent under climate warming. Alternatively, if state water demand grows according to water supplier projections, energy and GHG emissions could increase and make California's climate goals more difficult to achieve.

Given the long lifetimes and planning times of infrastructure, it is important to also think about how the energy-water dynamics studied in Chapter 2 may evolve in the long term, when climate change is likely to play an even larger role. However, the ways and extent that cross-sectoral interdependencies may exacerbate climate change impacts and related adaptation strategies are unclear. Chapter 3 joins the fragmented literature and develops a generalized framework for understanding how climate change may affect the energy-water relationship. In the case of California—where climate impacts on water supply, air-conditioning demand, and hydropower are expected to be greatest—the findings show that energy requirements of certain water sector adaptation strategies may even exceed the direct climate impacts on the energy system, highlighting the importance of coordination to ensure *efficient* and *reliable* energy and water provision.

Despite recognition in literature and practice of the climate impacts and water dependencies highlighted in Chapter 3, most electricity planning models omit these aspects, which could result in future capacity shortfalls from unanticipated demand or supply changes. Chapter 4 fills this gap with a novel model linkage that evaluates the impact of climate change on water resources in the WUS, and the subsequent effects of changes in hydropower generation and water-related electricity use on the optimal buildout of the grid. The results quantify the additional *redundancy* and *diversity*, in terms of generation and transmission capacity resources, needed to make the grid resilient to both water-related climate change impacts and decarbonization.

While many benefits of coordination have been demonstrated in the literature, in the independently managed energy and water sectors, cross-sectoral interactions are still not typically or explicitly operationalized into decision-making. Chapter 5 uses a co-production approach through a focus group and surveys with water managers, to improve both the decision-relevance of Chapter 4 efforts and the fundamental understanding of critical energy and climate interactions for water management. The co-production process indicates that droughts and snowpack loss are the primary climate impacts of concern to WUS water managers for providing *reliable* water services. The findings show that energy connections are more prevalent than previously thought because water managers often implicitly consider energy as part of several water management decisions, including those related to financial planning, reservoir operations, and drought operations. There are several tradeoffs that managers consider when weighing decisions, such as water supply, power generation, cost, and water quality. Energy and carbon intensity are among the metrics they use to evaluate these tradeoffs.

Together, this dissertation research demonstrates the value and necessity of considering interdependencies of the electricity system with the transportation and water systems under the stressors of climate change. While some of the planning challenges and climate impacts are specific to the institutions, sectors, and geography of California and the WUS, many are generalizable to other regions that face challenges with stressed water and energy resources, increasing transportation electrification efforts, and decarbonization goals.

2. Areas of future research

Co-production for decision-relevant electricity and water planning

The insights gained from an initial co-production effort in Chapter 5 highlighted how critical continued stakeholder interaction will be to improve modeling efforts, like those in Chapter 4, and to ensure the overall development of actionable science. The focus group and surveys were just the starting point that already illuminated often hidden ways that energy factors into water sector decisions, and how that may evolve under climate change. Additional focus groups are planned with practitioners to fully understand how the "nexus" is viewed by different institutions and under different climate futures, what climate impacts and tradeoffs are important to resource managers, if and how energy is considered in water management decisions, and the type and form of climate information that is useful for such decisions. The outcomes of such work are essential to inform both improved modeling efforts and infrastructure planning in practice. Iterative feedback between stakeholders and scientists can help ensure that underlying cross-sectoral feedbacks are comprehensively considered in decisions and that they are adequately represented in related decision-support tools for the development of climate-resilient systems.

The stakeholder discussions from Chapter 5 also pointed to several specific modeling areas that would be useful for climate adaptation decision-making at the energy-water nexus. The directions for this future research are summarized below.

Extreme events and uncertainties

The dissertation analyses focused on changes to climate conditions at the mean, but water managers in Chapter 5 expressed that extreme events like droughts were a far greater concern. Future research will evaluate the effect of extended droughts on water and energy system operations and planning in the WEAP and SWITCH models. Another important area relates to uncertainties within and across climate models and emissions scenarios, as well as within sectoral management models. Such uncertainties are further propagated and potentially increased when coupling models across sectors. Therefore, an improved characterization of the sources, magnitudes, and reinforcing or offsetting nature of uncertainties across the analysis chain is needed to inform decision-making. Part of this effort includes additional analysis of the sensitivity of WEAP and SWITCH results to Reference/Baseline scenario assumptions, including population growth rates, crop coefficients and cropped area, generation technology cost and operating assumptions, and carbon emission policies.

Water adaptation and grid scenarios

Chapter 3 highlights that water sector adaptation strategies in the event of climate change-related scarcity have varying energy use or savings implications that may have compounding or offsetting effects on the grid. Therefore, future scenarios with the coupled WEAP and SWITCH models from Chapter 4 may also test the grid buildout in the WECC under several water sector adaptation strategies, including changing reservoir operations, which emerged as top water manager priority from the focus group discussion, and water conservation, which Chapter 2 and 3 highlighted for energy saving co-benefits. Additional adaptation strategies to test in WEAP include groundwater recharge, water recycling for potable reuse, and desalination. Ultimately, future work is planned to include an additional Baseline scenario without climate change or decarbonization policies to systematically decompose the effects of (1) climate policies, (2) direct impacts of climate warming on electricity use and supply via water interactions, and (3) the electricity impacts of water sector adaptation strategies.

Changing role of hydropower

Evaluating the potentially changing role of hydropower in a decarbonizing grid is an important area of future research. Decarbonization efforts relying on intermittent wind and solar resources have created a growing need for long-duration energy storage technologies. Hydropower generators may be repurposed to fill some of these long-duration storage gaps, or could be used more exclusively for short-term load-following operations, as discussed in Chapter 5. Future SWITCH analyses may evaluate the tradeoffs and benefits of different modes of operation for hydropower compared to alternative long- and short-duration energy storage.

3. Recommendations

While several areas for future study remain, this dissertation supports concrete recommendations for policy-makers and researchers on considering and modeling climate change mitigation and adaptation with cross-sectoral dynamics to comprehensively plan a more climate-resilient electricity system.

3.1 Policy recommendations

Transportation electrification and EV charge management in support of renewable integration

Transportation electrification alongside decarbonization is a key strategy to lower economy-wide GHG emissions. However, it is important that the added electricity demand from vehicle charging does not exacerbate grid operations. In terms of hourly grid impacts, annual total system cost savings, and renewable curtailment reductions, smart charging EVs at residential locations provide the greatest benefit, are relatively cost-effective, and can be implemented with current technology. However, overnight time-of-use (TOU) rates can achieve a large share of smart charging cost savings as well, have demonstrated efficacy among current adopters, and may have fewer customer acceptance barriers. Grid planners should consider a policy adjusting residential TOU off-peak periods to include some daytime hours and to establish daytime commercial TOU rates to capture a greater share of renewable energy. Overall a hybrid smart and TOU charge management approach can maximize the grid benefits, while avoiding costs, capacity investments, and stress on the grid from unmanaged charging behavior.

Reducing water, energy, and GHG emissions associated with water end-uses

Urban water efficiency, for both indoor and outdoor uses of water and within the water distribution system, can save energy and avoid the associated GHG emissions for water extraction and generation, conveyance, treatment, and distribution. Indoor efficiency can further reduce end-use energy requirements and GHG emissions by avoiding, for example, water heating, as well as wastewater collection and treatment. Prior studies have shown there is significant urban conservation and efficiency potential in California and that water-efficiency programs during the most recent drought saved as much energy as, and were cost-competitive with, the state’s electric investor-owned utility efficiency programs during the same period. Coordinating water and efficiency programs, including sharing program funding for incentives and administration, between water and energy suppliers can help both sectors meet water and energy goals and make these programs more cost-effective.

Within the water management cycle, natural gas water heaters are the single largest emitters of GHGs. Electric heat pump water heaters are up to five times more thermally efficient than natural gas heaters and can also provide significant GHG savings as the electricity system is decarbonized. However, the initial cost of electric heat pump water heaters is typically higher than natural gas heaters. Together with water efficiency programs that lower hot water usage, customer incentives that reduce the upfront cost of electric water heaters can help lower the energy and GHG emissions from residential and non-residential water use.

In the agricultural sector, more efficient groundwater pumps and variable frequency drives can provide energy, cost, and GHG reductions, and rebates can lower the upfront cost of these upgrades. Through demand-response programs offered by electric utilities, farmers can also be compensated for operating their groundwater pumps to coincide with the timing of lower electricity prices and renewable electricity generation on the grid, and variable frequency drives can further be automated to adjust to grid needs. This can help integrate renewable electricity and lower overall GHG emissions from electricity generation.

Formalize coordination between water and energy regulatory agencies about forecasted energy demand changes

If water system energy demands grow as projected in California and elsewhere in the WUS, electricity and natural gas systems will need to incorporate changes in their infrastructure planning to ensure that energy supply will reliably meet energy demand. Formal regulatory proceedings and reporting between water suppliers, state water agencies, electric and natural gas utilities, state energy regulators, and planning agencies can help facilitate coordinated cross-sectoral planning. For example, currently there is no explicit reporting of expected changes in water-related energy demand in California's energy demand forecast. As a result, it is unclear if the energy use growth anticipated based on water supplier projections has been factored into electricity and natural gas planning and procurement decisions. Improvements in coordination between agencies should lead to better integrated energy and water planning, reduced costs to consumers, and faster decarbonization of the water system.

3.2 Research recommendations

Include climate change data and scenarios in electricity planning models

Most electricity capacity expansion models used to help grid planners determine the least-cost portfolio of generation and transmission investments do not include climate change or cross-sectoral interactions. However, by omitting these considerations in modeling, the future grid capacity may not be sufficient, optimally located, or cost-effective to cope with climate impacts and resulting water-related changes in energy supply and demand. In 2020, this already occurred in the WUS and California, where rolling blackouts were caused when temperatures across the region peaked and there was not enough capacity or available imports to meet demand. Grid regulators are warning of similar shortfalls in 2021 with the WUS-wide drought shrinking hydropower generation and heat waves increasing air-conditioning use.

Instead of reacting to record-breaking weather forecasts with expensive and inefficient backstop approaches in the short-term, grid planners and modelers should proactively include climate change scenarios related to growing electricity use for air-conditioning, changes in hydropower, and increases in water-related electricity demand into long-term grid expansion models. These scenarios are critical to include alongside other analyses that affect future supply and demand, such as different levels of electrification of transportation and buildings. An ensemble of climate scenarios should be used with detailed modeling of individual hydropower generators and regional dependencies, to understand how climate impacts in one area and sector could further compound issues in another. Such modeling is an important complement to other electricity system planning efforts for climate adaptation that have largely focused on physical infrastructure hardening and vulnerabilities (such as from wildfire, sea level rise, and heat), but less so on equally important changes to the generation portfolio and the magnitude and shape of electricity demand.

Continued stakeholder interaction to support modeling efforts

Many energy-water nexus studies have highlighted the benefits of closer coordination, but it remains rare for energy or water managers to explicitly incorporate such cross-sectoral considerations in decision-making. This may be in part because of differences in institutional mandates or constraints, or because the researchers have not engaged directly with decision-makers to understand their management context. Participatory methods between scientists and stakeholders, such as through co-production or other forms of engagement, will be increasingly important to overcome this gap between theory and practice. Such interactions can help modelers understand specific decisions faced by stakeholders, key concerns and constraints, informal or unspoken institutional knowledge, and what truly is important in particular decision contexts. Deliberate collaboration between scientists and decision-makers to design, understand, and communicate actionable research will be crucial for planning climate-resilient electricity systems that also account for cross-sectoral interactions.

References

[1] Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, and S. MacCracken, P.R. Mastrandrea, and L.L. White, "Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change," IPCC, 2014. [Online]. Available: https://www.ipcc.ch/site/assets/uploads/2018/02/WGIIAR5-PartA_FINAL.pdf

[2] G. C. Gallopín, "Linkages between vulnerability, resilience, and adaptive capacity," *Glob. Environ. Change*, vol. 16, no. 3, pp. 293–303, Aug. 2006, doi: 10.1016/j.gloenvcha.2006.02.004.

[3] IPCC 2014, "Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change," IPCC, 2014. [Online]. Available: https://www.ipcc.ch/site/assets/uploads/2018/02/ipcc_wg3_ar5_full.pdf

[4] Burkett, V.R., A.G. Suarez, M. Bindi, C. Conde, R. Mukerji, M.J. Prather, A.L. St. Clair, and G.W. Yohe, "Point of departure. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change," IPCC, 2014. [Online]. Available: https://www.ipcc.ch/site/assets/uploads/2018/02/WGIIAR5-Chap1_FINAL.pdf

[5] W. Neil Adger, N. W. Arnell, and E. L. Tompkins, "Successful adaptation to climate change across scales," *Glob. Environ. Change*, vol. 15, no. 2, pp. 77–86, Jul. 2005, doi: 10.1016/j.gloenvcha.2004.12.005.

[6] B. Smit and J. Wandel, "Adaptation, adaptive capacity and vulnerability," *Glob. Environ. Change*, vol. 16, no. 3, pp. 282–292, Aug. 2006, doi: 10.1016/j.gloenvcha.2006.03.008.

[7] L. Bedsworth, Dan Cayan, Guido Franco, Leah Fisher, and Sonya Ziaja, "Statewide Summary Report. California's Fourth Climate Change Assessment," California Governor's Office of Planning and Research, Scripps Institution of Oceanography, California Energy Commission, California Public Utilities Commission, SUM-CCCA4-2018-013, 2018. [Online]. Available: https://www.energy.ca.gov/sites/default/files/2019-11/Statewide_Reports-SUM-CCCA4-2018-013_Statewide_Summary_Report_ADA.pdf

[8] G. Franco and A. H. Sanstad, "Climate change and electricity demand in California," *Clim. Change*, vol. 87, no. 1, pp. 139–151, Mar. 2008, doi: 10.1007/s10584-007-9364-y.

[9] C. Folke, "Resilience: The emergence of a perspective for social–ecological systems analyses," *Glob. Environ. Change*, vol. 16, no. 3, pp. 253–267, Aug. 2006, doi: 10.1016/j.gloenvcha.2006.04.002.

[10] C. Kennedy and J. Corfee-Morlot, "Past performance and future needs for low carbon climate resilient infrastructure– An investment perspective," *Energy Policy*, vol. 59, pp. 773–783, Aug. 2013, doi: 10.1016/j.enpol.2013.04.031.

[11] S. Tyler and M. Moench, "A framework for urban climate resilience," *Clim. Dev.*, vol. 4, no. 4, pp. 311–326, Oct. 2012, doi: 10.1080/17565529.2012.745389.

[12] T. Giordano, "Adaptive planning for climate resilient long-lived infrastructures," *Util. Policy*, vol. 23, pp. 80–89, Dec. 2012, doi: 10.1016/j.jup.2012.07.001.

[13] S. Hallegatte, "Strategies to adapt to an uncertain climate change," *Glob. Environ. Change*, vol. 19, no. 2, pp. 240–247, May 2009, doi: 10.1016/j.gloenvcha.2008.12.003.

[14] R. Leichenko, “Climate change and urban resilience,” *Curr. Opin. Environ. Sustain.*, vol. 3, no. 3, pp. 164–168, May 2011, doi: 10.1016/j.cosust.2010.12.014.

[15] “ASCE’s 2021 American Infrastructure Report Card | GPA: C-,” *ASCE’s 2021 Infrastructure Report Card* |, Jan. 11, 2017. https://infrastructurereportcard.org/ (accessed Jul. 25, 2021).

[16] R. Warren, “The role of interactions in a world implementing adaptation and mitigation solutions to climate change,” *Philos. Trans. R. Soc. Math. Phys. Eng. Sci.*, vol. 369, no. 1934, pp. 217–241, Jan. 2011, doi: 10.1098/rsta.2010.0271.

[17] V. Huber *et al.*, “Climate impact research: beyond patchwork,” *Earth Syst. Dyn.*, vol. 5, no. 2, pp. 399–408, Nov. 2014, doi: https://doi.org/10.5194/esd-5-399-2014.

[18] D. D. White, J. L. Jones, R. Maciejewski, R. Aggarwal, and G. Mascaro, “Stakeholder Analysis for the Food-Energy-Water Nexus in Phoenix, Arizona: Implications for Nexus Governance,” *Sustainability*, vol. 9, no. 12, Art. no. 12, Dec. 2017, doi: 10.3390/su9122204.

[19] A. Bhaduri, C. Ringler, I. Dombrowski, R. Mohtar, and W. Scheumann, “Sustainability in the water–energy–food nexus,” *Water Int.*, vol. 40, no. 5–6, pp. 723–732, Sep. 2015, doi: 10.1080/02508060.2015.1096110.

[20] C. Howarth and I. Monasterolo, “Understanding barriers to decision making in the UK energy-food-water nexus: The added value of interdisciplinary approaches,” *Environ. Sci. Policy*, vol. 61, pp. 53–60, Jul. 2016, doi: 10.1016/j.envsci.2016.03.014.

[21] L. Clarke *et al.*, “Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II: Chapter 17 Sector Interactions, Multiple Stressors, and Complex Systems,” U.S. Global Change Research Program, 2018. Accessed: Jun. 26, 2020. [Online]. Available: https://nca2018.globalchange.gov/chapter/17/

[22] P. A. Harrison, R. W. Dunford, I. P. Holman, and M. D. A. Rounsevell, “Climate change impact modelling needs to include cross-sectoral interactions,” *Nat. Clim. Change*, vol. 6, no. 9, pp. 885–890, Sep. 2016, doi: 10.1038/nclimate3039.

[23] J. Barnett and S. O’Neill, “Maladaptation,” *Glob. Environ. Change*, vol. 20, no. 2, pp. 211–213, May 2010, doi: 10.1016/j.gloenvcha.2009.11.004.

[24] F. Piontek *et al.*, “Multisectoral climate impact hotspots in a warming world,” *Proc. Natl. Acad. Sci.*, vol. 111, no. 9, pp. 3233–3238, Mar. 2014, doi: 10.1073/pnas.1222471110.

[25] M. T. Craig *et al.*, “A review of the potential impacts of climate change on bulk power system planning and operations in the United States,” *Renew. Sustain. Energy Rev.*, vol. 98, pp. 255–267, Dec. 2018, doi: 10.1016/j.rser.2018.09.022.

[26] A. K. Gerlak, J. Weston, B. McMahan, R. L. Murray, and M. Mills-Novoa, “Climate risk management and the electricity sector,” *Clim. Risk Manag.*, vol. 19, pp. 12–22, Jan. 2018, doi: 10.1016/j.crm.2017.12.003.

[27] S. Pfenninger, A. Hawkes, and J. Keirstead, “Energy systems modeling for twenty-first century energy challenges,” *Renew. Sustain. Energy Rev.*, vol. 33, pp. 74–86, May 2014, doi: 10.1016/j.rser.2014.02.003.

[28] E. Vine, “Adaptation of California’s electricity sector to climate change,” *Clim. Change*, vol. 111, no. 1, pp. 75–99, Mar. 2012, doi: 10.1007/s10584-011-0242-2.

[29] L. Sommer, “Climate Change Lesson From California’s Blackouts: Prepare For Extremes,” *NPR.org*, Aug. 19, 2020. Accessed: Sep. 26, 2020. [Online]. Available: https://www.npr.org/2020/08/19/903910770/climate-change-lesson-from-californias-blackouts-prepare-for-extremes

[30] J. Diaz and S. Neuman, "Texas Power Outages: Winter Storm Shocks Texas, Northern Mexico : Live Updates: Winter Storms 2021 : NPR." Accessed: Jul. 03, 2021. [Online]. Available: https://www.npr.org/2021/02/16/968230163/millions-without-power-in-texas-northern-mexico-as-blackouts-and-bitter-cold-con

[31] N. K. Geranios, "Rolling blackouts hit Pacific Northwest as cities swelter in record-breaking heat wave," *Los Angeles Times*, Jun. 29, 2021. Accessed: Jul. 03, 2021. [Online]. Available: https://www.latimes.com/world-nation/story/2021-06-29/rolling-blackouts-us-northwest-heat-wave

[32] B. F. Hobbs, "Optimization methods for electric utility resource planning," *Eur. J. Oper. Res.*, vol. 83, no. 1, pp. 1–20, May 1995, doi: 10.1016/0377-2217(94)00190-N.

[33] E. National Academies of Sciences, *Enhancing the Resilience of the Nation's Electricity System*. 2017. doi: 10.17226/24836.

[34] L. Molyneaux, L. Wagner, C. Froome, and J. Foster, "Resilience and electricity systems: A comparative analysis," *Energy Policy*, vol. 47, pp. 188–201, Aug. 2012, doi: 10.1016/j.enpol.2012.04.057.

[35] J. Christian-Smith, M. C. Levy, and P. H. Gleick, "Maladaptation to drought: a case report from California, USA," *Sustain. Sci.*, vol. 10, no. 3, pp. 491–501, Jul. 2015, doi: 10.1007/s11625-014-0269-1.

[36] J. H. Williams *et al.*, "The Technology Path to Deep Greenhouse Gas Emissions Cuts by 2050: The Pivotal Role of Electricity," *Science*, vol. 335, no. 6064, pp. 53–59, Jan. 2012, doi: 10.1126/science.1208365.

[37] H. Hoff, "Understanding the Nexus. Background Paper for the Bonn2011 Conference: The Water, Energy and Food Security Nexus," Stockholm Environment Institute, Stockholm, 2011. [Online]. Available: https://mediamanager.sei.org/documents/Publications/SEI-Paper-Hoff-UnderstandingTheNexus-2011.pdf

[38] T. R. Albrecht, A. Crootof, and C. A. Scott, "The Water-Energy-Food Nexus: A systematic review of methods for nexus assessment," *Environ. Res. Lett.*, vol. 13, no. 4, p. 043002, 2018, doi: 10.1088/1748-9326/aaa9c6.

[39] D. Cash, W. Clark, F. Alcock, N. M. Dickson, N. Eckley, and J. Jäger, "Salience, Credibility, Legitimacy and Boundaries: Linking Research, Assessment and Decision Making," 2003, doi: 10.2139/ssrn.372280.

[40] C. P. Weaver, R. J. Lempert, C. Brown, J. A. Hall, D. Revell, and D. Sarewitz, "Improving the contribution of climate model information to decision making: the value and demands of robust decision frameworks," *Wiley Interdiscip. Rev. Clim. Change*, vol. 4, no. 1, pp. 39–60, Jan. 2013, doi: 10.1002/wcc.202.

[41] A. Voinov and F. Bousquet, "Modelling with stakeholders," *Environ. Model. Softw.*, vol. 25, no. 11, pp. 1268–1281, Nov. 2010, doi: 10.1016/j.envsoft.2010.03.007.

[42] A. G. Bhave, D. Conway, S. Dessai, and D. A. Stainforth, "Water Resource Planning Under Future Climate and Socioeconomic Uncertainty in the Cauvery River Basin in Karnataka, India," *Water Resour. Res.*, vol. 54, no. 2, pp. 708–728, 2018, doi: 10.1002/2017WR020970.

[43] D. B. Richardson, "Electric vehicles and the electric grid: A review of modeling approaches, Impacts, and renewable energy integration," *Renew. Sustain. Energy Rev.*, vol. 19, pp. 247–254, Mar. 2013, doi: 10.1016/j.rser.2012.11.042.

[44] H. Lund and W. Kempton, “Integration of renewable energy into the transport and electricity sectors through V2G,” *Energy Policy*, vol. 36, no. 9, pp. 3578–3587, Sep. 2008, doi: 10.1016/j.enpol.2008.06.007.
[45] California Independent System Operator, “California Vehicle-Grid Integration (VGI) Roadmap: Enabling vehicle-based grid services,” California Independent System Operator, Feb. 2014. [Online]. Available: https://www.caiso.com/Documents/Vehicle-GridIntegrationRoadmap.pdf
[46] C. Sheppard, R. Waraich, A. Campbell, A. Gopal, and A. Pozdnukov, “Modeling plug-in electric vehicle charging demand with BEAM, the framework for behavior energy autonomy mobility,” Lawrence Berkeley National Laboratory, LBNL-2001018, May 2017. [Online]. Available: https://eta.lbl.gov/publications/modeling-plug-electric-vehicle
[47] M. Wolinetz, J. Axsen, J. Peters, and C. Crawford, “Simulating the value of electric-vehicle–grid integration using a behaviourally realistic model,” *Nat. Energy*, vol. 3, no. 2, pp. 132–139, Feb. 2018, doi: 10.1038/s41560-017-0077-9.
[48] D. Dallinger and M. Wietschel, “Grid integration of intermittent renewable energy sources using price-responsive plug-in electric vehicles,” *Renew. Sustain. Energy Rev.*, vol. 16, no. 5, pp. 3370–3382, Jun. 2012, doi: 10.1016/j.rser.2012.02.019.
[49] B. K. Sovacool, L. Noel, J. Axsen, and W. Kempton, “The neglected social dimensions to a vehicle-to-grid (V2G) transition: a critical and systematic review,” *Environ. Res. Lett.*, vol. 13, no. 1, p. 013001, 2018, doi: 10.1088/1748-9326/aa9c6d.
[50] Y. Xu, S. Çolak, E. C. Kara, S. J. Moura, and M. C. González, “Planning for electric vehicle needs by coupling charging profiles with urban mobility,” *Nat. Energy*, p. 1, Apr. 2018, doi: 10.1038/s41560-018-0136-x.
[51] A. Foley, B. Tyther, P. Calnan, and B. Ó Gallachóir, “Impacts of Electric Vehicle charging under electricity market operations,” *Appl. Energy*, vol. 101, pp. 93–102, Jan. 2013, doi: 10.1016/j.apenergy.2012.06.052.
[52] T. P. Lyon, M. Michelin, A. Jongejan, and T. Leahy, “Is ‘smart charging’ policy for electric vehicles worthwhile?,” *Energy Policy*, vol. 41, no. Supplement C, pp. 259–268, Feb. 2012, doi: 10.1016/j.enpol.2011.10.045.
[53] A. Weis, P. Jaramillo, and J. Michalek, “Estimating the potential of controlled plug-in hybrid electric vehicle charging to reduce operational and capacity expansion costs for electric power systems with high wind penetration,” *Appl. Energy*, vol. 115, pp. 190–204, Feb. 2014, doi: 10.1016/j.apenergy.2013.10.017.
[54] A. J. Wood, B. F. Wollenberg, and G. B. Sheblé, *Power Generation, Operation, and Control*, 3rd edition. Hoboken, New Jersey: Wiley-Interscience, 2013.
[55] G. Klein, M. Krebs, V. Hall, T. O’Brien, and B. B. Blevins, “California’s Water – Energy Relationship,” California Energy Commission, CEC-700-2005-011-SF, Nov. 2005. [Online]. Available: http://large.stanford.edu/courses/2012/ph240/spearrin1/docs/CEC-700-2005-011-SF.PDF
[56] H. Cooley, “Urban and Agricultural Water Use in California, 1960-2015,” Pacific Institute, Jun. 2020. [Online]. Available: https://pacinst.org/wp-content/uploads/2020/06/PI_Water_Use_Trends_June_2020.pdf
[57] R. G. Luthy, J. M. Wolfand, and J. L. Bradshaw, “Urban Water Revolution: Sustainable Water Futures for California Cities,” *J. Environ. Eng.*, vol. 146, no. 7, p. 04020065, Jul. 2020, doi: 10.1061/(ASCE)EE.1943-7870.0001715.

[58] J. Stokes-Draut, M. Taptich, O. Kavvada, and A. Horvath, “Evaluating the electricity intensity of evolving water supply mixes: the case of California’s water network,” *Environ. Res. Lett.*, vol. 12, no. 11, p. 114005, Oct. 2017, doi: 10.1088/1748-9326/aa8c86.

[59] T. Moran, J. Choy, and C. Sanchez, “The Hidden Costs of Groundwater Overdraft,” *Water in the West | Stanford Woods Institute for the Environment*, 2014. http://waterinthewest.stanford.edu/groundwater/ (accessed Feb. 07, 2021).

[60] J. Anderson *et al.*, “Progress on incorporating climate change into management of California’s water resources,” *Clim. Change*, vol. 87, no. 1, pp. 91–108, Mar. 2008, doi: 10.1007/s10584-007-9353-1.

[61] V. C. Tidwell, B. Moreland, and K. Zemlick, “Geographic Footprint of Electricity Use for Water Services in the Western U.S.,” *Environ. Sci. Technol.*, vol. 48, no. 15, pp. 8897–8904, Aug. 2014, doi: 10.1021/es5016845.

[62] E. Porse *et al.*, “Energy use for urban water management by utilities and households in Los Angeles,” *Environ. Res. Commun.*, vol. 2, no. 1, p. 015003, Jan. 2020, doi: 10.1088/2515-7620/ab5e20.

[63] A. Zohrabian and K. T. Sanders, “The Energy Trade-Offs of Transitioning to a Locally Sourced Water Supply Portfolio in the City of Los Angeles,” *Energies*, vol. 13, no. 21, Art. no. 21, Jan. 2020, doi: 10.3390/en13215589.

[64] GEI Consultants/Navigant Consulting, “Embedded Energy in Water Studies Study 1: Statewide and Regional Water-Energy Relationship,” Prepared for California Public Utilities Commission, Aug. 2010. [Online]. Available: ftp://ftp.cpuc.ca.gov/gopher-data/energy%20efficiency/Water%20Studies%201/Study%201%20-%20FINAL.pdf

[65] GEI Consultants/Navigant Consulting and GEI Consultants/Navigant Consulting, “Embedded Energy in Water Studies Study 2: Water Agency and Function Component Study and Embedded Energy-Water Load Profiles,” Prepared for California Public Utilities Commission, Aug. 2010. [Online]. Available: ftp://ftp.cpuc.ca.gov/gopher-data/energy%20efficiency/Water%20Studies%202/Study%202%20-%20FINAL.pdf

[66] P. D’Odorico *et al.*, “The Global Food-Energy-Water Nexus,” *Rev. Geophys.*, vol. 56, no. 3, pp. 456–531, 2018, doi: 10.1029/2017RG000591.

[67] P. Rao, R. Kostecki, L. Dale, and A. Gadgil, “Technology and Engineering of the Water-Energy Nexus,” *Annu. Rev. Environ. Resour.*, vol. 42, no. 1, pp. 407–437, Oct. 2017, doi: 10.1146/annurev-environ-102016-060959.

[68] A. Endo, I. Tsurita, K. Burnett, and P. M. Orencio, “A review of the current state of research on the water, energy, and food nexus,” *J. Hydrol. Reg. Stud.*, vol. 11, pp. 20–30, Jun. 2017, doi: 10.1016/j.ejrh.2015.11.010.

[69] G. Flato *et al.*, “2013: Evaluation of Climate Models. Climate Change 2013: The Physical Science Basis,” Intergovernmental Panel on Climate Change, Cambridge, United Kingdom and New York, NY, USA, 2013. Accessed: May 06, 2019. [Online]. Available: https://www.ipcc.ch/report/ar5/wg1/evaluation-of-climate-models/

[70] N. W. Arnell, “Climate change and global water resources,” *Glob. Environ. Change*, vol. 9, pp. S31–S49, Oct. 1999, doi: 10.1016/S0959-3780(99)00017-5.

[71] U.S. Department of Energy Office of Energy Policy and Systems Analysis, “The Water-Energy Nexus: Challenges and Opportunities,” U.S. Department of Energy, Jun. 2014. [Online]. Available: https://www.energy.gov/downloads/water-energy-nexus-challenges-and-opportunities

[72] R. Schaeffer *et al.*, “Energy sector vulnerability to climate change: A review,” *Energy*, vol. 38, no. 1, pp. 1–12, Feb. 2012, doi: 10.1016/j.energy.2011.11.056.
[73] Q. Liu, J. Morales, M. Correa, A. Schwartz, and J. Lin, “Connecting the Dots between Water, Energy, Food, and Ecosystems Issues for Integrated Water Management in a Changing Climate,” Climate Change Program, California Department of Water Resources, Feb. 2017. [Online]. Available: https://cawaterlibrary.net/wp-content/uploads/2017/10/QLf2017FinalWhitePaper_jta_edits_fk_format_2.pdf
[74] A. K. Plappally and J. H. Lienhard V, “Energy requirements for water production, treatment, end use, reclamation, and disposal,” *Renew. Sustain. Energy Rev.*, vol. 16, no. 7, pp. 4818–4848, Sep. 2012, doi: 10.1016/j.rser.2012.05.022.
[75] B. Tarroja, A. AghaKouchak, R. Sobhani, D. Feldman, S. Jiang, and S. Samuelsen, “Evaluating options for Balancing the Water-Electricity Nexus in California: Part 1 – Securing Water Availability,” *Sci. Total Environ.*, vol. 497–498, pp. 697–710, Nov. 2014, doi: 10.1016/j.scitotenv.2014.06.060.
[76] B. Tarroja, A. AghaKouchak, R. Sobhani, D. Feldman, S. Jiang, and S. Samuelsen, “Evaluating options for balancing the water–electricity nexus in California: Part 2—Greenhouse gas and renewable energy utilization impacts,” *Sci. Total Environ.*, vol. 497–498, pp. 711–724, Nov. 2014, doi: 10.1016/j.scitotenv.2014.06.071.
[77] A. M. Hamiche, A. B. Stambouli, and S. Flazi, “A review of the water-energy nexus,” *Renew. Sustain. Energy Rev.*, vol. 65, pp. 319–331, Nov. 2016, doi: 10.1016/j.rser.2016.07.020.
[78] E. Hardin *et al.*, “California drought increases CO2 footprint of energy,” *Sustain. Cities Soc.*, vol. 28, pp. 450–452, Jan. 2017, doi: 10.1016/j.scs.2016.09.004.
[79] T. K. Mideksa and S. Kallbekken, “The impact of climate change on the electricity market: A review,” *Energy Policy*, vol. 38, no. 7, pp. 3579–3585, Jul. 2010, doi: 10.1016/j.enpol.2010.02.035.
[80] S. Vicuna and J. A. Dracup, “The evolution of climate change impact studies on hydrology and water resources in California,” *Clim. Change*, vol. 82, no. 3–4, pp. 327–350, Jun. 2007, doi: 10.1007/s10584-006-9207-2.
[81] X. Wang *et al.*, “Adaptation to climate change impacts on water demand,” *Mitig. Adapt. Strateg. Glob. Change*, vol. 21, no. 1, pp. 81–99, Jan. 2016, doi: 10.1007/s11027-014-9571-6.
[82] J. Schewe *et al.*, “Multimodel assessment of water scarcity under climate change,” *Proc. Natl. Acad. Sci.*, vol. 111, no. 9, pp. 3245–3250, Mar. 2014, doi: 10.1073/pnas.1222460110.
[83] Y. Qin *et al.*, “Agricultural risks from changing snowmelt,” *Nat. Clim. Change*, vol. 10, no. 5, Art. no. 5, May 2020, doi: 10.1038/s41558-020-0746-8.
[84] D. Wichelns, “The water-energy-food nexus: Is the increasing attention warranted, from either a research or policy perspective?,” *Environ. Sci. Policy*, vol. 69, pp. 113–123, Mar. 2017, doi: 10.1016/j.envsci.2016.12.018.
[85] G. Rasul and B. Sharma, “The nexus approach to water–energy–food security: an option for adaptation to climate change,” *Clim. Policy*, vol. 16, no. 6, pp. 682–702, Aug. 2016, doi: 10.1080/14693062.2015.1029865.
[86] K. M. Ernst and B. L. Preston, “Adaptation opportunities and constraints in coupled systems: Evidence from the U.S. energy-water nexus,” *Environ. Sci. Policy*, vol. 70, pp. 38–45, Apr. 2017, doi: 10.1016/j.envsci.2017.01.001.

[87] M. D. Bartos and M. V. Chester, “Impacts of climate change on electric power supply in the Western United States,” *Nat. Clim. Change*, vol. 5, no. 8, pp. 748–752, Aug. 2015, doi: 10.1038/nclimate2648.
[88] M. Wei *et al.*, “Building a Healthier and More Robust Future: 2050 Low-Carbon Energy Scenarios for California.,” California Energy Commission, CEC-500-2019-033., 2017. [Online]. Available: https://www.energy.ca.gov/2019publications/CEC-500-2019-033/CEC-500-2019-033.pdf
[89] L. Gacitua *et al.*, “A comprehensive review on expansion planning: Models and tools for energy policy analysis,” *Renew. Sustain. Energy Rev.*, vol. 98, pp. 346–360, Dec. 2018, doi: 10.1016/j.rser.2018.08.043.
[90] V. C. Tidwell, M. Bailey, K. M. Zemlick, and B. D. Moreland, “Water supply as a constraint on transmission expansion planning in the Western interconnection,” *Environ. Res. Lett.*, vol. 11, no. 12, p. 124001, Nov. 2016, doi: 10.1088/1748-9326/11/12/124001.
[91] D. Yates, J. Meldrum, and K. Averyt, “The influence of future electricity mix alternatives on southwestern US water resources,” *Environ. Res. Lett.*, vol. 8, no. 4, p. 045005, 2013, doi: 10.1088/1748-9326/8/4/045005.
[92] D. Yates *et al.*, “A water resources model to explore the implications of energy alternatives in the southwestern US,” *Environ. Res. Lett.*, vol. 8, no. 4, p. 045004, 2013, doi: 10.1088/1748-9326/8/4/045004.
[93] California Natural Resources Agency, “Safeguarding California Plan: 2018 Update California’s Climate Adaptation Strategy,” California Natural Resources Agency, Jan. 2018. [Online]. Available: http://resources.ca.gov/docs/climate/safeguarding/update2018/safeguarding-california-plan-2018-update.pdf
[94] J. Liu *et al.*, “Challenges in operationalizing the water–energy–food nexus,” *Hydrol. Sci. J.*, vol. 62, no. 11, pp. 1714–1720, Aug. 2017, doi: 10.1080/02626667.2017.1353695.
[95] M. C. Lemos, C. J. Kirchhoff, and V. Ramprasad, “Narrowing the climate information usability gap,” *Nat. Clim. Change*, vol. 2, no. 11, pp. 789–794, Nov. 2012, doi: 10.1038/nclimate1614.
[96] N. Mimura *et al.*, “Adaptation planning and implementation. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects,” 2014. [Online]. Available: https://www.ipcc.ch/site/assets/uploads/2018/02/WGIIAR5-Chap15_FINAL.pdf
[97] D. W. Cash, J. C. Borck, and A. G. Patt, “Countering the Loading-Dock Approach to Linking Science and Decision Making: Comparative Analysis of El Niño/Southern Oscillation (ENSO) Forecasting Systems,” *Sci. Technol. Hum. Values*, vol. 31, no. 4, pp. 465–494, Jul. 2006, doi: 10.1177/0162243906287547.
[98] A. Dewulf, N. Klenk, C. Wyborn, and M. C. Lemos, “Usable environmental knowledge from the perspective of decision-making: the logics of consequentiality, appropriateness, and meaningfulness,” *Curr. Opin. Environ. Sustain.*, vol. 42, pp. 1–6, Feb. 2020, doi: 10.1016/j.cosust.2019.10.003.
[99] International Energy Agency, “Global EV Outlook 2018: Towards cross-modal electrification,” International Energy Agency, 2018. [Online]. Available: https://webstore.iea.org/download/direct/1045?filename=global_ev_outlook_2018.pdf
[100] M. Kintner-Meyer, K. Schneider, and R. Pratt, “Impacts Assessment of Plug-in Hybrid Vehicles on Electric Vehicles and Regional U.S. Power Grids, Part 1: Technical

Analysis," Pacific Northwest National Laboratory (PNNL), Richland, WA (US), Nov. 2007. [Online]. Available: https://www.ferc.gov/about/com-mem/5-24-07-technical-analy-wellinghoff.pdf
[101] J. Dumortier *et al.*, "Effects of providing total cost of ownership information on consumers' intent to purchase a hybrid or plug-in electric vehicle," *Transp. Res. Part Policy Pract.*, vol. 72, pp. 71–86, Feb. 2015, doi: 10.1016/j.tra.2014.12.005.
[102] S. Ramachandran and U. Stimming, "Well to wheel analysis of low carbon alternatives for road traffic," *Energy Environ. Sci.*, vol. 8, no. 11, pp. 3313–3324, Oct. 2015, doi: 10.1039/C5EE01512J.
[103] M. Muratori, "Impact of uncoordinated plug-in electric vehicle charging on residential power demand," *Nat. Energy*, vol. 3, no. 3, pp. 193–201, Mar. 2018, doi: 10.1038/s41560-017-0074-z.
[104] J. H. Nelson and L. M. Wisland, "Achieving 50 Percent Renewable Electricity in California: The Role of Non-Fossil Flexibility in a Cleaner Electricity Grid," Union of Concerned Scientists, Aug. 2015. [Online]. Available: www.ucsusa.org/California50RPSanalysis.
[105] California Independent System Operator, "CAISO Fast Facts: What the duck curve tells us about managing a green grid," California Independent System Operator, 2016. [Online]. Available: https://www.caiso.com/Documents/FlexibleResourcesHelpRenewables_FastFacts.pdf
[106] L. Bird, J. Cochran, and X. Wang, "Wind and Solar Energy Curtailment: Experience and Practices in the United States," National Renewable Energy Laboratory, NREL/TP-6A20-60983, Mar. 2014. [Online]. Available: http://www.nrel.gov/docs/fy14osti/60983.pdf
[107] "Advanced Technology Vehicle Sales Dashboard," *Alliance of Automobile Manufacturers*. https://autoalliance.org/energy-environment/advanced-technology-vehicle-sales-dashboard/ (accessed May 09, 2018).
[108] Edmund G. Brown Jr., Governor of the State of California, *Executive Order B-16-2012*. 2012. Accessed: Sep. 23, 2016. [Online]. Available: https://www.ca.gov/archive/gov39/2012/03/23/news17472/index.html
[109] "Governor Brown Takes Action to Increase Zero-Emission Vehicles, Fund New Climate Investments – Governor Edmund G. Brown Jr.," *Office of the Governor, Edmund G. Brown, Jr.* https://www.ca.gov/archive/gov39/2018/01/26/governor-brown-takes-action-to-increase-zero-emission-vehicles-fund-new-climate-investments/index.html (accessed May 09, 2018).
[110] E. F. Merchant, "California Regulators Approve Landmark Utility EV-Charging Proposals," *Greentech Media*, May 31, 2018. Accessed: Jun. 06, 2018. [Online]. Available: https://www.greentechmedia.com/articles/read/california-cpuc-approves-landmark-ev-charging-proposals
[111] "Volkswagen California ZEV Investment Plan: Cycle 1 - Electrify America," Volkswagen, Group of America, Mar. 2017. [Online]. Available: https://elam-cms-assets.s3.amazonaws.com/inline-files/California%20ZEV%20Investment%20Plan%20Cycle%201.pdf
[112] A. C. Mulkern, "California Utility Wants to Install Huge Number of Electric Car Chargers," *Scientific American*, Aug. 26, 2016. Accessed: Apr. 20, 2017. [Online]. Available: https://www.scientificamerican.com/article/california-utility-wants-to-install-huge-number-of-electric-car-chargers/

[113] B. Vlasic and N. E. Boudette, “G.M. and Ford Lay Out Plans to Expand Electric Models,” *The New York Times*, Oct. 02, 2017. Accessed: Oct. 06, 2017. [Online]. Available: https://www.nytimes.com/2017/10/02/business/general-motors-electric-cars.html
[114] “Luxury carmakers unveil electric plans,” *BBC News*, Sep. 07, 2017. Accessed: Oct. 06, 2017. [Online]. Available: http://www.bbc.com/news/business-41179332
[115] “EV Showroom | GoElectricDrive - Accelerate the Good, Powered by EDTA,” *Go Electric Drive*. https://www.goelectricdrive.org/you-buy/ev-showroom (accessed May 07, 2018).
[116] “CVRP Rebate Statistics,” *Clean Vehicle Rebate Project*, 2016. https://cleanvehiclerebate.org/eng/rebate-statistics
[117] “Zero Emission Vehicle (ZEV) Program,” *California Air Resources Board*. https://arb.ca.gov/msprog/zevprog/zevprog.htm (accessed Dec. 04, 2017).
[118] “Carpool Stickers | California Air Resources Board,” *Carpool Stickers*. https://ww2.arb.ca.gov/carpool-stickers (accessed Dec. 21, 2018).
[119] K. D. León, *SB-350 Clean Energy and Pollution Reduction Act of 2015*, vol. Chapter 547, Statutes of 2015. 2015.
[120] K. De León, *SB-100 California Renewables Portfolio Standard Program: emissions of greenhouse gases*. 2018.
[121] “Load Research Report Compliance Filing of San Diego Gas & Electric Company (U 902-M), Southern California Edison Company (U 338 - E), and Pacific Gas and Electric Company (U 39E) Pursuant to Ordering Paragraph 2 of D.16-06-011,” California Public Utilities Commission, Dec. 2017. [Online]. Available: http://www.cpuc.ca.gov/WorkArea/DownloadAsset.aspx?id=6442455828
[122] S. Kaluza, D. Almeida, and P. Mullen, “BMW i ChargeForward: PG&E’s Electric Vehicle Smart Charging Pilot,” BMW Group and PG&E, 2017. [Online]. Available: http://www.pgecurrents.com/wp-content/uploads/2017/06/PGE-BMW-iChargeForward-Final-Report.pdf
[123] W. Kempton and J. Tomić, “Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy,” *J. Power Sources*, vol. 144, no. 1, pp. 280–294, Jun. 2005, doi: 10.1016/j.jpowsour.2004.12.022.
[124] S. B. Peterson, J. F. Whitacre, and J. Apt, “The economics of using plug-in hybrid electric vehicle battery packs for grid storage,” *J. Power Sources*, vol. 195, no. 8, pp. 2377–2384, Apr. 2010, doi: 10.1016/j.jpowsour.2009.09.070.
[125] P. Alstone *et al.*, “Final Report on Phase 2 Results, 2025 California Demand Response Potential Study: Charting California’s Demand Response Future,” Lawrence Berkeley National Laboratory, Energy and Environmental Economics, and Nexant, Mar. 2017. [Online]. Available: http://www.cpuc.ca.gov/WorkArea/DownloadAsset.aspx?id=6442452698
[126] “California Energy Commission Tracking Progress: Renewable Energy,” California Energy Commission, Dec. 2017. [Online]. Available: https://www.energy.ca.gov/data-reports/tracking-progress/renewable-energy
[127] J. Kiviluoma and P. Meibom, “Methodology for modelling plug-in electric vehicles in the power system and cost estimates for a system with either smart or dumb electric vehicles,” *Energy*, vol. 36, no. 3, pp. 1758–1767, Mar. 2011, doi: 10.1016/j.energy.2010.12.053.

[128] A. Foley, B. Tyther, P. Calnan, and B. Ó Gallachóir, “Impacts of Electric Vehicle charging under electricity market operations,” *Appl. Energy*, vol. 101, pp. 93–102, Jan. 2013, doi: 10.1016/j.apenergy.2012.06.052.
[129] P. Calnan, J. P. Deane, and B. P. Ó Gallachóir, “Modelling the impact of EVs on electricity generation, costs and CO2 emissions: Assessing the impact of different charging regimes and future generation profiles for Ireland in 2025,” *Energy Policy*, vol. 61, pp. 230–237, Oct. 2013, doi: 10.1016/j.enpol.2013.05.065.
[130] D. Madzharov, E. Delarue, and W. D’haeseleer, “Integrating electric vehicles as flexible load in unit commitment modeling,” *Energy*, vol. 65, pp. 285–294, Feb. 2014, doi: 10.1016/j.energy.2013.12.009.
[131] R. Loisel, G. Pasaoglu, and C. Thiel, “Large-scale deployment of electric vehicles in Germany by 2030: An analysis of grid-to-vehicle and vehicle-to-grid concepts,” *Energy Policy*, vol. 65, pp. 432–443, Feb. 2014, doi: 10.1016/j.enpol.2013.10.029.
[132] J. Coignard, S. Saxena, J. Greenblatt, and D. Wang, “Clean vehicles as an enabler for a clean electricity grid,” *Environ. Res. Lett.*, vol. 13, no. 5, p. 054031, 2018, doi: 10.1088/1748-9326/aabe97.
[133] S. Babrowski, H. Heinrichs, P. Jochem, and W. Fichtner, “Load shift potential of electric vehicles in Europe,” *J. Power Sources*, vol. 255, no. Supplement C, pp. 283–293, Jun. 2014, doi: 10.1016/j.jpowsour.2014.01.019.
[134] D. Dallinger, S. Gerda, and M. Wietschel, “Integration of intermittent renewable power supply using grid-connected vehicles – A 2030 case study for California and Germany,” *Appl. Energy*, vol. 104, pp. 666–682, Apr. 2013, doi: 10.1016/j.apenergy.2012.10.065.
[135] K. E. Forrest, B. Tarroja, L. Zhang, B. Shaffer, and S. Samuelsen, “Charging a renewable future: The impact of electric vehicle charging intelligence on energy storage requirements to meet renewable portfolio standards,” *J. Power Sources*, vol. 336, pp. 63–74, Dec. 2016, doi: 10.1016/j.jpowsour.2016.10.048.
[136] P. Eser, N. Chokani, and R. S. Abhari, “Impacts of battery electric vehicles on renewable integration within the 2030 European power system,” *Int. J. Energy Res.*, vol. 42, no. 13, pp. 4142–4156, Oct. 2018, doi: 10.1002/er.4161.
[137] “BEAM - the Modeling Framework for Behavior, Energy, Autonomy, and Mobility,” *BEAM - the Modeling Framework for Behavior, Energy, Autonomy, and Mobility*. http://beam.lbl.gov/ (accessed Apr. 21, 2017).
[138] N. Daina, A. Sivakumar, and J. W. Polak, “Modelling electric vehicles use: a survey on the methods,” *Renew. Sustain. Energy Rev.*, vol. 68, pp. 447–460, Feb. 2017, doi: 10.1016/j.rser.2016.10.005.
[139] “Energy Market Modelling,” *Energy Exemplar*. https://energyexemplar.com/ (accessed Apr. 13, 2017).
[140] A. Gopal, Maggie Witt, Nikit Abhyankar, Colin Sheppard, and Andrew Harris, “Battery electric vehicles can reduce greenhouse gas emissions and make renewable energy cheaper in India,” Lawrence Berkeley National Laboratory, LBNL-184562, Jun. 2015.
[141] L. Wagner and L. Reedman, “Modeling the deployment of plug-in hybrid and electric vehicles and their effects on the Australian National Electricity Market,” in *2010 IEEE Conference on Innovative Technologies for an Efficient and Reliable Electricity Supply*, Sep. 2010, pp. 165–170. doi: 10.1109/CITRES.2010.5619871.

[142] "Scenario Evaluation, Regionalization & Analysis (SERA) | Open Energy Information." http://en.openei.org/wiki/Scenario_Evaluation,_Regionalization_%26_Analysis_(SERA) (accessed Jun. 13, 2017).
[143] "FuelEconomy.gov, the official U.S. government source for fuel economy information.," *U.S. Department of Energy*, Aug. 2016. https://www.fueleconomy.gov/
[144] M. T. Commission and I. Parsons Brinckerhoff, *Travel Model Development: Calibration and Validation*. 2012. [Online]. Available: http://mtcgis.mtc.ca.gov/foswiki/pub/Main/Documents/2012_05_18_RELEASE_DRAFT_Calibration_and_Validation.pdf
[145] A. Horni, K. Nagel, and K. W. Axhausen, *The Multi-Agent Transport Simulation*. London: Ubiquity Press, 2016. [Online]. Available: http://www.matsim.org/the-book
[146] "Daily Miles Traveled | Vital Signs," *Vital Signs: Metropolitan Transportation Commission*. http://www.vitalsigns.mtc.ca.gov/daily-miles-traveled (accessed Nov. 09, 2017).
[147] Inrix Research, "2017 Global Traffic Scorecard," Inrix Research, Feb. 2018. [Online]. Available: http://inrix.com/press-releases/scorecard-2017/
[148] "Charging Plug-In Electric Vehicles at Home," *Alternative Fuels Data Center*. https://afdc.energy.gov/fuels/electricity_charging_home.html (accessed Dec. 21, 2018).
[149] "Electric Vehicle Charging Station Locations," *Alternative Fuels Data Center, U.S. Department of Energy*. https://www.afdc.energy.gov/fuels/electricity_locations.html (accessed Oct. 11, 2017).
[150] "California's Advanced Clean Cars Midterm Review: Appendix E: Zero Emission Vehicle Complementary Policies in California and Section 177 ZEV States," California Air Resources Board, Jan. 2017. [Online]. Available: https://ww3.arb.ca.gov/msprog/acc/mtr/appendix_e.pdf
[151] Barney Carlson, Idaho National Laboratory, "Electric Vehicle Mile Traveled (eVMT): On-road Results and Analysis," presented at the 2015 DOE Vehicle Technologies Program Annual Merit Review, Jun. 09, 2015. [Online]. Available: https://energy.gov/sites/prod/files/2015/07/f24/vss171_carlson_2015_p.pdf
[152] *Xpress Solver | FICO®*. FICO. Accessed: Dec. 14, 2018. [Online]. Available: https://www.fico.com/en/products/fico-xpress-solver
[153] S. Liu, "Phase I.A. Direct Testimony of Dr. Shucheng Liu on Behalf of the California Independent System Operator Corporation R.13-12-010." Before the Public Utilities Commission of the State of California, Aug. 13, 2014. [Online]. Available: https://www.caiso.com/Documents/Aug13_2014_InitialTestimony_ShuchengLiu_Phase1A_LTPP_R13-12-010.pdf
[154] S. Liu, "A Bulk Energy Storage Resource Case Study updated from 40% to 50% RPS: 2015-2016 Transmission Planning Process." California Independent System Operator, 2016. [Online]. Available: http://www.caiso.com/Documents/BulkEnergyStorageResource-2015-2016SpecialStudyUpdatedfrom40to50Percent.pdf
[155] "2015-2016 ISO Transmission Plan," California Independent System Operator, Mar. 2016. [Online]. Available: http://www.caiso.com/Documents/Board-Approved2015-2016TransmissionPlan.pdf
[156] M. Picker, *California Public Utilities Commission Rulemaking 13-12-010: Assigned Commissioner's Ruling Adopting Assumptions and Scenarios for Use in the California*

Independent System Operator's 2016-17 Transmission Planning Process and Future Commission Proceedings. 2016.
[157] J. Eichman, P. Denholm, J. Jorgenson, and Udi Helman (Helman Analytics), "Operational Benefits of Meeting California's Energy Storage Targets," National Renewable Energy Laboratory, NREL/TP-5400-65061, Dec. 2015.
[158] J. Jorgenson, P. Denholm, and M. Mehos, "Estimating the Value of Utility Scale Solar Technologies in California Under a 40% Renewable Portfolio Standard," National Renewable Energy Laboratory, NREL/TP-6A20-61685, May 2014. [Online]. Available: http://www.nrel.gov/docs/fy14osti/61685.pdf
[159] A. Abrams *et al.*, "Energy Storage Cost-effectiveness Methodology and Preliminary Results," DNV KEMA Energy & Sustainability for the California Energy Commission, Jun. 2013.
[160] "California Energy Demand 2015-2025 Final Forecast - LSE and Balancing Authority Forecasts," *California Energy Commission*. https://www.energyarchive.ca.gov/2014_energypolicy/documents/demand_forecast_cmf/LSE_and_BA/ (accessed Nov. 11, 2017).
[161] C. Kavalec *et al.*, "California Energy Demand 2014–2024 Final Forecast, Volume 1: Statewide Electricity Demand, End-User Natural Gas Demand, and Energy Efficiency," California Energy Commission, Electricity Supply Analysis Division, CEC-200-2013-004-V1-CMF, Jan. 2014. [Online]. Available: http://www.energy.ca.gov/2013publications/CEC-200-2013-004/CEC-200-2013-004-V1-CMF.pdf
[162] "California Energy Demand 2015-2025 Final Forecast - Mid-Case Final Baseline Demand Forecast Forms." https://www.energyarchive.ca.gov/2014_energypolicy/documents/demand_forecast_cmf/Mid_Case/ (accessed Apr. 01, 2019).
[163] "RPS Calculator Home Page," *California Public Utilities Commission*. http://www.cpuc.ca.gov/RPS_Calculator/ (accessed Aug. 01, 2017).
[164] R. Golden and B. Paulos, "Curtailment of Renewable Energy in California and Beyond," *Electr. J.*, vol. 28, no. 6, pp. 36–50, Jul. 2015, doi: 10.1016/j.tej.2015.06.008.
[165] *California Public Utilities Commission Rulemaking 12-03-014: Decision Authorizing Long-term Procurement for Local Capacity Requirements*. 2013.
[166] I. Penn and S. Masunaga, "PG&E to close Diablo Canyon, California's last nuclear power plant," *Los Angeles Times*, Jun. 21, 2016. Accessed: Apr. 14, 2017. [Online]. Available: http://www.latimes.com/business/la-fi-diablo-canyon-nuclear-20160621-snap-story.html
[167] *California Public Utilities Commission Rulemaking 10-12-007: Order Instituting Rulemaking Pursuant to Assembly Bill 2514 to Consider the Adoption of Procurement Targets for Viable and Cost-Effective Energy Storage Systems: Decision Adopting Energy Storage Procurement Framework and Design Program*. 2013.
[168] "Integration of Renewable Resources: Technical Appendices for California ISO Renewable Integration Studies, Version 1," California Independent System Operator, Oct. 2010.
[169] G. Brinkman, J. Jorgenson, A. Ehlen, and J. H. Caldwell, "Low Carbon Grid Study: Analysis of a 50% Emission Reduction in California," National Renewable Energy Laboratory and Center for Energy Efficiency and Renewable Technologies, NREL/TP-6A20-64884, Jan. 2016.

[170] "California Transportation Electrification Assessment: Phase 2: Grid Impacts," Prepared by ICF International and E3, Oct. 2014. [Online]. Available: https://drive.google.com/file/d/0B6luZ_sq22LbMkQxZjN3QTNJdUk/view
[171] J. P. Deane, G. Drayton, and B. P. Ó Gallachóir, "The impact of sub-hourly modelling in power systems with significant levels of renewable generation," *Appl. Energy*, vol. 113, pp. 152–158, Jan. 2014, doi: 10.1016/j.apenergy.2013.07.027.
[172] C. Kavalec, N. Fugate, C. Garcia, and A. Gautam, "California Energy Demand 2016-2026, Revised Electricity Forecast, Volume 1: Statewide Electricity Demand and Energy Efficiency," California Energy Commission, CEC-200-2016-001-V1, Jan. 2016.
[173] A. Bahreinian *et al.*, "Staff Draft Report, Transportation Energy Demand Forecast, 2016-2026," California Energy Commission, CEC-200-2015-008-SD, Feb. 2016. [Online]. Available: https://efiling.energy.ca.gov/GetDocument.aspx?tn=210539
[174] Z. Xu, W. Su, Z. Hu, Y. Song, and H. Zhang, "A Hierarchical Framework for Coordinated Charging of Plug-In Electric Vehicles in China," *IEEE Trans. Smart Grid*, vol. 7, no. 1, pp. 428–438, Jan. 2016, doi: 10.1109/TSG.2014.2387436.
[175] "Electric Vehicle (EV) rate plans: Making sense of the rates," *Pacific Gas & Electric*. https://www.pge.com/en_US/residential/rate-plans/rate-plan-options/electric-vehicle-base-plan/electric-vehicle-base-plan.page (accessed Apr. 16, 2017).
[176] "EV Rates," *San Diego Gas & Electric*. https://www.sdge.com/clean-energy/ev-rates (accessed Oct. 06, 2017).
[177] "Electric Vehicle Rates," *Southern California Edison*. https://www.sce.com/wps/portal/home/residential/electric-cars/residential-rates (accessed Oct. 06, 2017).
[178] J. Cook, C. Churchwell, and S. George, "Final Evaluation for San Diego Gas & Electric's Plug-in Electric Vehicle TOU Pricing and Technology Study," Submitted by Nexant, Inc. to San Diego Gas & Electric, Feb. 2014. [Online]. Available: https://www.sdge.com/sites/default/files/SDGE%20EV%20%20Pricing%20%26%20Tech%20Study.pdf
[179] "Top 10 DMV Facts," *California Department of Motor Vehicles Statistics*. https://www.dmv.ca.gov/portal/wcm/connect/fafd3447-8e14-4ff6-bb98-e85f3aa9a207/ca_dmv_stats.pdf?MOD=AJPERES&CVID=
[180] E. Niesten and F. Alkemade, "How is value created and captured in smart grids? A review of the literature and an analysis of pilot projects," *Renew. Sustain. Energy Rev.*, vol. 53, pp. 629–638, Jan. 2016, doi: 10.1016/j.rser.2015.08.069.
[181] R. Golden and B. Paulos, "Curtailment of Renewable Energy in California and Beyond," *Electr. J.*, vol. 28, no. 6, pp. 36–50, Jul. 2015, doi: 10.1016/j.tej.2015.06.008.
[182] Jaquelin Cochran, National Renewable Energy Laboratory *et al.*, "Flexibility in 21st Century Power Systems," 21st Century Power Partnership, NREL/TP-6A20-61721, May 2014. [Online]. Available: https://www.nrel.gov/docs/fy14osti/61721.pdf
[183] F. Kley, C. Lerch, and D. Dallinger, "New business models for electric cars—A holistic approach," *Energy Policy*, vol. 39, no. 6, pp. 3392–3403, Jun. 2011, doi: 10.1016/j.enpol.2011.03.036.
[184] C. Will and A. Schuller, "Understanding user acceptance factors of electric vehicle smart charging," *Transp. Res. Part C Emerg. Technol.*, vol. 71, pp. 198–214, Oct. 2016, doi: 10.1016/j.trc.2016.07.006.

[185] J. Bailey and J. Axsen, “Anticipating PEV buyers’ acceptance of utility controlled charging,” *Transp. Res. Part Policy Pract.*, vol. 82, pp. 29–46, Dec. 2015, doi: 10.1016/j.tra.2015.09.004.
[186] J. Axsen, B. Langman, and S. Goldberg, “Confusion of innovations: Mainstream consumer perceptions and misperceptions of electric-drive vehicles and charging programs in Canada,” *Energy Res. Soc. Sci.*, vol. 27, pp. 163–173, May 2017, doi: 10.1016/j.erss.2017.03.008.
[187] F. Schmalfuß *et al.*, “User responses to a smart charging system in Germany: Battery electric vehicle driver motivation, attitudes and acceptance,” *Energy Res. Soc. Sci.*, vol. 9, pp. 60–71, Sep. 2015, doi: 10.1016/j.erss.2015.08.019.
[188] E. Dütschke and A.-G. Paetz, “Dynamic electricity pricing—Which programs do consumers prefer?,” *Energy Policy*, vol. 59, pp. 226–234, Aug. 2013, doi: 10.1016/j.enpol.2013.03.025.
[189] California Public Utilities Commission, *Decision 17-08-030 Adopting Revenue Allocation and Rate Design for San Diego Gas & Electric Company: Application of San Diego Gas & Electric Company (U902E) for Authority to Update Marginal Costs, Cost Allocation and Electric Rate Design (Application 15-04-012)*. 2017. [Online]. Available: http://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M194/K599/194599448.PDF
[190] H. C. Curtius, K. Künzel, and M. Loock, “Generic customer segments and business models for smart grids,” *Markt*, vol. 51, no. 2, pp. 63–74, Aug. 2012, doi: 10.1007/s12642-012-0076-0.
[191] J. Axsen and K. S. Kurani, “Connecting plug-in vehicles with green electricity through consumer demand,” *Environ. Res. Lett.*, vol. 8, no. 1, p. 014045, 2013, doi: 10.1088/1748-9326/8/1/014045.
[192] P. H. Gleick, “Impacts of California’s Five-Year (2012-2016) Drought on Hydroelectricity Generation,” Pacific Institute, Apr. 2017. [Online]. Available: https://pacinst.org/wp-content/uploads/2018/07/pi_impacts_of_california_s_five-year__2012-2016_drought_on_hydroelectricity_generation.pdf
[193] “Producing and Consuming Power,” *California Department of Water Resources*. http://water.ca.gov/What-We-Do/Power (accessed Feb. 14, 2021).
[194] K. De Leon and N. Skinner, *SB-100 California Renewables Portfolio Standard Program: emissions of greenhouse gases*. 2017.
[195] J. Gerdes, “California Moves to Tackle Another Big Emissions Source: Fossil Fuel Use in Buildings,” *Greentech Media*, Feb. 04, 2020. Accessed: Feb. 15, 2021. [Online]. Available: https://www.greentechmedia.com/articles/read/california-moves-to-tackle-another-big-emissions-source-fossil-fuel-use-in-buildings
[196] H. Cooley, M. Heberger, L. Allen, and R. Wilkinson, “The Water-Energy Simulator (WESim): User Manual,” WateReuse Foundation, Pacific Institute, UC Santa Barbara for California Energy Commission, 2012. [Online]. Available: https://pacinst.org/wp-content/uploads/2013/02/user_manual3.pdf
[197] S. Diringer, A. Thebo, H. Cooley, M. Shimabuku, R. Wilkinson, and M. Bradford, “Moving Toward a Multi-Benefit Approach for Water Management,” Pacific Institute and Bren School of Environmental Science and Management, University of California, Santa Barbara, Apr. 2019. [Online]. Available: https://pacinst.org/wp-content/uploads/2019/04/moving-toward-multi-benefit-approach.pdf

[198] Geosyntec Consultants *et al.*, “Los Angeles Stormwater Capture Master Plan,” Los Angeles Department of Water and Power, Aug. 2015. [Online]. Available: https://www.ladwp.com/cs/idcplg?IdcService=GET_FILE&dDocName=OPLADWPCCB421767&RevisionSelectionMethod=LatestReleased
[199] C. Burt, D. Howes, and G. Wilson, “California Agricultural Water Electrical Energy Requirements,” Prepared by Irrigation Training and Research Center for the California Energy Commission, ITRC Report No. R 03-006, Dec. 2003. [Online]. Available: https://digitalcommons.calpoly.edu/cgi/viewcontent.cgi?referer=https://www.google.com/&httpsredir=1&article=1056&context=bae_fac
[200] “2018 Irrigation and Water Management Survey.” https://www.nass.usda.gov/Publications/AgCensus/2017/Online_Resources/Farm_and_Ranch_Irrigation_Survey/index.php (accessed May 03, 2021).
[201] K. T. Sanders and M. E. Webber, “Evaluating the energy consumed for water use in the United States,” *Environ. Res. Lett.*, vol. 7, no. 3, p. 034034, Sep. 2012, doi: 10.1088/1748-9326/7/3/034034.
[202] EPRI, “Water & Sustainability (Volume 4): U.S. Electricity Consumption for Water Supply & Treatment - The Next Half Century,” 1006787, 2002. [Online]. Available: https://www.circleofblue.org/wp-content/uploads/2010/08/EPRI-Volume-4.pdf
[203] C. McDonald *et al.*, “Water/Energy Cost-Effectiveness Analysis,” Prepared for California Public Utilities Commission, Navigant Reference No.: 169145, Oct. 2014. [Online]. Available: https://www.cpuc.ca.gov/WorkArea/DownloadAsset.aspx?id=5360
[204] P. H. Gleick *et al.*, “Waste Not, Want Not: The Potential for Urban Water Conservation in California,” Pacific Institute, Nov. 2003. Accessed: Dec. 03, 2019. [Online]. Available: https://pacinst.org/wp-content/uploads/2003/11/waste_not_want_not_full_report.pdf
[205] KEMA, Inc., “2009 California Residential Appliance Saturation Study Volume 2,” California Energy Commission, CEC- 200-2010-004, 2010. [Online]. Available: http://web.archive.org/web/20190602112012/https://www.energy.ca.gov/2010publications/CEC-200-2010-004/CEC-200-2010-004-V2.PDF
[206] William B. DeOreo, Peter Mayer, Benedykt Dziegielewski, and Jack Kiefer, “Residential End Uses of Water, Version 2,” Water Research Foundation, PDF Report #4309b, 2016.
[207] H. Cooley and R. Wilkinson, “Implications of Future Water Supply Sources on Energy Demands,” WateReuse Foundation, Pacific Institute, UC Santa Barbara for California Energy Commission, 2012. [Online]. Available: https://pacinst.org/wp-content/uploads/2012/07/report19.pdf
[208] Environmental Protection Agency and CDM Smith, “2017 Potable Reuse Compendium,” Environmental Protection Agency, 2017. [Online]. Available: https://www.epa.gov/sites/production/files/2018-01/documents/potablereusecompendium_3.pdf
[209] *State Water Resources Control Board Regulations Related to Recycled Water*. 2018. [Online]. Available: https://www.waterboards.ca.gov/drinking_water/certlic/drinkingwater/documents/lawbook/RWregulations_20181001.pdf
[210] “California Water Plan Update 2013, Volume 3 - Resource Management Strategies,” California Department of Water Resources. [Online]. Available: https://water.ca.gov/-/media/DWR-Website/Web-Pages/Programs/California-Water-Plan/Water-Plan-Updates/Files/Update-2013/Water-Plan-Update-2013-Volume-3.pdf

[211] B. Tarroja, A. AghaKouchak, R. Sobhani, D. Feldman, S. Jiang, and S. Samuelsen, “Evaluating options for balancing the water–electricity nexus in California: Part 2—Greenhouse gas and renewable energy utilization impacts,” *Sci. Total Environ.*, vol. 497–498, pp. 711–724, Nov. 2014, doi: 10.1016/j.scitotenv.2014.06.071.
[212] “Residential Energy Consumption Survey (RECS) Table HC1.1 Fuels used and end uses in U.S. homes by housing unit type, 2015,” *Energy Information Administration (EIA)*. https://www.eia.gov/consumption/residential/data/2015/hc/php/hc8.8.php (accessed Apr. 25, 2021).
[213] “WeCalc: Your Home Water-Energy-Climate Calculator,” *WeCalc: Your Home Water-Energy-Climate Calculator*. http://www.wecalc.org/ (accessed Apr. 27, 2021).
[214] Itron, Inc., “California Commercial End-Use Survey (CEUS),” California Energy Commission, CEC-400-2006-005, Mar. 2006. Accessed: Mar. 30, 2016. [Online]. Available: http://web.archive.org/web/20190112033409/https://www.energy.ca.gov/2006publications/CEC-400-2006-005/CEC-400-2006-005.PDF
[215] “Statewide Irrigation Systems Methods Surveys.” http://water.ca.gov/Programs/Water-Use-And-Efficiency/Land-And-Water-Use/Statewide-Irrigation-Systems-Methods-Surveys (accessed May 13, 2019).
[216] “Agricultural Land & Water Use Estimates.” http://water.ca.gov/Programs/Water-Use-And-Efficiency/Land-And-Water-Use/Agricultural-Land-And-Water-Use-Estimates (accessed May 13, 2019).
[217] California Air Resources Board, “California Greenhouse Gas Inventory for 2000-2018 — by Sector and Activity,” California Air Resources Board, Oct. 2020. [Online]. Available: https://ww3.arb.ca.gov/cc/inventory/data/tables/ghg_inventory_sector_sum_2000-18.pdf
[218] California Energy Commission, California Public Utilities Commission, California Air Resources Board, “Draft 2021 SB 100 Joint Agency Report,” Dec. 2020. [Online]. Available: https://efiling.energy.ca.gov/GetDocument.aspx?tn=235848&DocumentContentId=68803
[219] “Carbon Dioxide Emissions Coefficients,” *U.S. Energy Information Administration (EIA)*. https://www.eia.gov/environment/emissions/co2_vol_mass.php (accessed Jan. 28, 2021).
[220] “WUEdata - Water Use Efficiency Data,” *California Department of Water Resources, WUEdata - Public Portal*. https://wuedata.water.ca.gov/ (accessed Jan. 28, 2021).
[221] “California Urban Water Use Map,” *Pacific Institute*. https://pacinst.org/gpcd/map/ (accessed Apr. 29, 2021).
[222] “Water Portfolios,” *California Department of Water Resources Water Portfolios*. http://water.ca.gov/Programs/California-Water-Plan/Water-Portfolios (accessed May 13, 2019).
[223] S. Abraham, S. Diringer, and H. Cooley, “An Assessment of Urban Water Demand Forecasts in California,” Pacific Institute, Aug. 2020. [Online]. Available: https://pacinst.org/wp-content/uploads/2020/08/Pacific-Institute-Assessment-Urban-Water-Demand-Forecasts-in-CA-Aug-2020.pdf
[224] W. B. DeOreo, “Analysis of Water Use in New Single Family Homes,” Salt Lake City Corporation and US EPA, Jan. 2011. [Online]. Available: https://energy.mo.gov/sites/energy/files/3-deoreo-%282011%29-analysis-of-water-use-in-new-single-family-homes.pdf

[225] M. Rayej, S. Kibrya, P. Shipman, and M. Correa, "Future Scenarios of Water Supply and Demand in Central Valley, California through 2100: Impacts of Climate Change and Urban Growth," California Department of Water Resources, Jun. 2019.
[226] "WEAP Future Scenarios," *Tableau Software*. https://public.tableau.com/views/WEAP_Scenarios/DemandSupplyMultiClimate?%3Aembed=y&%3AshowVizHome=no&%3Adisplay_count=y&%3Adisplay_static_image=y&%3AbootstrapWhenNotified=true&%3Alanguage=en&:embed=y&:showVizHome=n&:apiID=host0#navType=0&navSrc=Parse (accessed Jan. 28, 2021).
[227] E. Lynn, A. Schwarz, J. Anderson, and M. Correa, "Perspectives and Guidance for Climate Change Analysis," California Department of Water Resources, Climate Change Technical Advisory Group, Aug. 2015. [Online]. Available: https://water.ca.gov/-/media/DWR-Website/Web-Pages/Programs/All-Programs/Climate-Change-Program/Climate-Program-Activities/Files/Reports/Perspectives-Guidance-Climate-Change-Analysis.pdf
[228] "Volumetric Annual Reporting: Recycled Water Policy | California State Water Resources Control Board." https://www.waterboards.ca.gov/water_issues/programs/water_recycling_policy/volumetric_annual_reporting.html (accessed Mar. 04, 2021).
[229] "Regulating Direct Potable Reuse in California | California State Water Resources Control Board." https://www.waterboards.ca.gov/drinking_water/certlic/drinkingwater/direct_potable_reuse.html (accessed Mar. 01, 2021).
[230] A. Zohrabian, S. L. Plata, D. M. Kim, A. E. Childress, and K. T. Sanders, "Leveraging the water-energy nexus to derive benefits for the electric grid through demand-side management in the water supply and wastewater sectors," *WIREs Water*, vol. 8, no. 3, p. e1510, 2021, doi: https://doi.org/10.1002/wat2.1510.
[231] M. Selmon, A. Schwartz, and P. Coombe, "Climate Change Action Plan, Phase 3: Climate Change Vulnerability Assessment," California Department of Water Resources, Feb. 2019. [Online]. Available: https://water.ca.gov/-/media/DWR-Website/Web-Pages/Programs/All-Programs/Climate-Change-Program/Climate-Action-Plan/Files/CAP-III-Vulnerability-Assessment.pdf?la=en&hash=7DF13A5B51C4B4FA808166C596F7EAE67ED58AC5
[232] P. Gleick, H. Cooley, K. Poole, and E. Osann, "Issue Brief: The Untapped Potential of California's Water Supply: Efficiency, Reuse, and Stormwater," Pacific Institute and Natural Resources Defense Council, Issue Brief IB:14-05-C, Jun. 2014. [Online]. Available: https://pacinst.org/wp-content/uploads/2014/06/ca-water-capstone-1.pdf
[233] E. Lede, R. Meleady, and C. R. Seger, "Optimizing the influence of social norms interventions: Applying social identity insights to motivate residential water conservation," *J. Environ. Psychol.*, vol. 62, pp. 105–114, Apr. 2019, doi: 10.1016/j.jenvp.2019.02.011.
[234] E. S. Spang, A. J. Holguin, and F. J. Loge, "The estimated impact of California's urban water conservation mandate on electricity consumption and greenhouse gas emissions," *Environ. Res. Lett.*, vol. 13, no. 1, p. 014016, Jan. 2018, doi: 10.1088/1748-9326/aa9b89.
[235] "Product Finder — ENERGY STAR Certified Water Heaters." https://www.energystar.gov/productfinder/product/certified-water-heaters/results?page_number=0 (accessed Mar. 01, 2021).

[236] I. Ivanova, “Cities are banning natural gas in new homes, citing climate change,” *CBS News*, Dec. 06, 2019. Accessed: Mar. 07, 2021. [Online]. Available: https://www.cbsnews.com/news/cities-are-banning-natural-gas-in-new-homes-because-of-climate-change/

[237] A. C. Mulkern, “California Is Closing the Door to Gas in New Homes,” *Scientific American*, Jan. 04, 2021. https://www.scientificamerican.com/article/california-is-closing-the-door-to-gas-in-new-homes/ (accessed Mar. 07, 2021).

[238] “Get Big Rebates For Small Agricultural Pumps | PG&E.” https://www.pge.com/en/mybusiness/save/smbblog/article/get_big_rebates_for_small_agricultural_pumps.page?WT.mc_id=SMBNewsletter_ag_email_20160407_phase_link-small-pump&redirect=yes (accessed Mar. 01, 2021).

[239] A. Aghajanzadeh, M. Sohn, and M. Berger, “Water-Energy Considerations in California’s Agricultural Sector and Opportunities to Provide Flexibility to California’s Grid,” Jun. 2019, Accessed: Jun. 25, 2019. [Online]. Available: https://escholarship.org/uc/item/2qx647xg

[240] “California Climate Investments | California Air Resources Board.” https://ww2.arb.ca.gov/our-work/programs/california-climate-investments (accessed Mar. 01, 2021).

[241] J. Cart, “Bonds on the ballot: Will billions of dollars help California cope with climate change?,” *CalMatters*, Jan. 22, 2020. https://calmatters.org/environment/2020/01/bonds-on-the-ballot-will-billions-of-dollars-help-california-cope-with-climate-change/ (accessed Mar. 07, 2021).

[242] C. E. Commission, “Integrated Energy Policy Report - IEPR,” *California Energy Commission*, current-date. https://www.energy.ca.gov/data-reports/reports/integrated-energy-policy-report (accessed Mar. 01, 2021).

[243] F. Kesicki and M. Walton, “Water Energy Nexus: Excerpt from the World Energy Outlook 2016,” International Energy Agency, 2016. [Online]. Available: https://www.iea.org/publications/freepublications/publication/WorldEnergyOutlook2016ExcerptWaterEnergyNexus.pdf

[244] M. R. Allen *et al.*, “Global warming of 1.5°C: An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty, Summary for Policymakers,” World Meteorological Organization, Geneva, Switzerland, 2018. [Online]. Available: https://www.ipcc.ch/site/assets/uploads/2018/10/SR15_SPM_version_stand_alone_LR.pdf

[245] J. W. Forrester, “System dynamics, systems thinking, and soft OR,” *Syst. Dyn. Rev. Wiley*, vol. 10, no. 2/3, pp. 245–256, Summer/Fall ///Summer/Fall1994 1994, doi: 10.1002/sdr.4260100211.

[246] California Department of Water Resources, “State Water Project,” *California Department of Water Resources State Water Project*. http://water.ca.gov/Programs/State-Water-Project (accessed Jun. 29, 2020).

[247] K. Hayhoe *et al.*, “Emissions pathways, climate change, and impacts on California,” *Proc. Natl. Acad. Sci.*, vol. 101, no. 34, pp. 12422–12427, Aug. 2004, doi: 10.1073/pnas.0404500101.

[248] E. Lynn, “California Climate Science and Data for Water Resources Management,” California Department of Water Resources, Jun. 2015. [Online]. Available: https://cawaterlibrary.net/wp-content/uploads/2017/06/CA_Climate_Science_and_Data_Final_Release_June_2015.pdf
[249] D. P. Loucks and E. van Beek, “Water Resources Planning and Management: An Overview,” in *Water Resource Systems Planning and Management: An Introduction to Methods, Models, and Applications*, D. P. Loucks and E. van Beek, Eds. Cham: Springer International Publishing, 2017, pp. 1–49. doi: 10.1007/978-3-319-44234-1_1.
[250] S. Hagemann *et al.*, “Climate change impact on available water resources obtained using multiple global climate and hydrology models,” *Earth Syst. Dyn.*, vol. 4, no. 1, pp. 129–144, May 2013, doi: https://doi.org/10.5194/esd-4-129-2013.
[251] P. C. D. Milly, K. A. Dunne, and A. V. Vecchia, “Global pattern of trends in streamflow and water availability in a changing climate,” *Nature*, vol. 438, no. 7066, Art. no. 7066, Nov. 2005, doi: 10.1038/nature04312.
[252] I. Haddeland *et al.*, “Global water resources affected by human interventions and climate change,” *Proc. Natl. Acad. Sci.*, vol. 111, no. 9, pp. 3251–3256, Mar. 2014, doi: 10.1073/pnas.1222475110.
[253] M. Huss *et al.*, “Toward mountains without permanent snow and ice,” *Earths Future*, vol. 5, no. 5, pp. 418–435, 2017, doi: 10.1002/2016EF000514.
[254] I. T. Stewart, “Changes in snowpack and snowmelt runoff for key mountain regions,” *Hydrol. Process.*, vol. 23, no. 1, pp. 78–94, 2009, doi: 10.1002/hyp.7128.
[255] J. I. López-Moreno *et al.*, “Different sensitivities of snowpacks to warming in Mediterranean climate mountain areas,” *Environ. Res. Lett.*, vol. 12, no. 7, p. 074006, Jun. 2017, doi: 10.1088/1748-9326/aa70cb.
[256] M. Beniston, “Climatic Change in Mountain Regions: A Review of Possible Impacts,” *Clim. Change*, vol. 59, no. 1, pp. 5–31, Jul. 2003, doi: 10.1023/A:1024458411589.
[257] J. S. Mankin, D. Viviroli, D. Singh, A. Y. Hoekstra, and N. S. Diffenbaugh, “The potential for snow to supply human water demand in the present and future,” *Environ. Res. Lett.*, vol. 10, no. 11, p. 114016, Nov. 2015, doi: 10.1088/1748-9326/10/11/114016.
[258] J. Sillmann, V. V. Kharin, F. W. Zwiers, X. Zhang, and D. Bronaugh, “Climate extremes indices in the CMIP5 multimodel ensemble: Part 2. Future climate projections,” *J. Geophys. Res. Atmospheres*, vol. 118, no. 6, pp. 2473–2493, 2013, doi: 10.1002/jgrd.50188.
[259] J. Sheffield and E. F. Wood, “Projected changes in drought occurrence under future global warming from multi-model, multi-scenario, IPCC AR4 simulations,” *Clim. Dyn.*, vol. 31, no. 1, pp. 79–105, Jul. 2008, doi: 10.1007/s00382-007-0340-z.
[260] S. K. Tanaka *et al.*, “Climate Warming and Water Management Adaptation for California,” *Clim. Change*, vol. 76, no. 3–4, pp. 361–387, Jun. 2006, doi: 10.1007/s10584-006-9079-5.
[261] M. C. Mateus and D. Tullos, “Reliability, Sensitivity, and Vulnerability of Reservoir Operations under Climate Change,” *J. Water Resour. Plan. Manag.*, vol. 143, no. 4, p. 04016085, Apr. 2017, doi: 10.1061/(ASCE)WR.1943-5452.0000742.
[262] B. A. Joyce, V. K. Mehta, D. R. Purkey, L. L. Dale, and M. Hanemann, “Modifying agricultural water management to adapt to climate change in California’s central valley,” *Clim. Change*, vol. 109, no. 1, pp. 299–316, Dec. 2011, doi: 10.1007/s10584-011-0335-y.

[263] B. A. Joyce, V. K. Mehta, D. R. Purkey, L. L. Dale, and M. Hanemann, "Climate Change Impacts on Water Supply and Agricultural Water Management in California's Western San Joaquin Valley, and Potential Adaptation Strategies," CEC-500-2009-051-F, Mar. 2009. [Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.444.673&rep=rep1&type=pdf
[264] Y. Wada *et al.*, "Multimodel projections and uncertainties of irrigation water demand under climate change," *Geophys. Res. Lett.*, pp. 4626–4632, Jul. 2015, doi: https://doi.org/10.1002/grl.50686.
[265] G. G. Katul, R. Oren, S. Manzoni, C. Higgins, and M. B. Parlange, "Evapotranspiration: A process driving mass transport and energy exchange in the soil-plant-atmosphere-climate system," *Rev. Geophys.*, vol. 50, no. 3, 2012, doi: 10.1029/2011RG000366.
[266] R. A. Betts *et al.*, "Projected increase in continental runoff due to plant responses to increasing carbon dioxide," *Nature*, vol. 448, no. 7157, Art. no. 7157, Aug. 2007, doi: 10.1038/nature06045.
[267] P. C. D. Milly and K. A. Dunne, "Potential evapotranspiration and continental drying," *Nat. Clim. Change*, vol. 6, no. 10, Art. no. 10, Oct. 2016, doi: 10.1038/nclimate3046.
[268] S. P. Long, E. A. Ainsworth, A. Rogers, and D. R. Ort, "Rising atmospheric carbon dioxide: plants FACE the future," *Annu. Rev. Plant Biol.*, vol. 55, pp. 591–628, 2004, doi: 10.1146/annurev.arplant.55.031903.141610.
[269] M. Panteli and P. Mancarella, "Influence of extreme weather and climate change on the resilience of power systems: Impacts and possible mitigation strategies," *Electr. Power Syst. Res.*, vol. 127, pp. 259–270, Oct. 2015, doi: 10.1016/j.epsr.2015.06.012.
[270] D. M. Ward, "The effect of weather on grid systems and the reliability of electricity supply," *Clim. Change*, vol. 121, no. 1, pp. 103–113, Nov. 2013, doi: 10.1007/s10584-013-0916-z.
[271] J. A. Sathaye *et al.*, "Estimating impacts of warming temperatures on California's electricity system," *Glob. Environ. Change*, vol. 23, no. 2, pp. 499–511, Apr. 2013, doi: 10.1016/j.gloenvcha.2012.12.005.
[272] D. C. Steinberg *et al.*, "Decomposing supply-side and demand-side impacts of climate change on the US electricity system through 2050," *Clim. Change*, vol. 158, no. 2, pp. 125–139, Jan. 2020, doi: 10.1007/s10584-019-02506-6.
[273] X. Ke, D. Wu, J. Rice, M. Kintner-Meyer, and N. Lu, "Quantifying impacts of heat waves on power grid operation," *Appl. Energy*, vol. 183, pp. 504–512, Dec. 2016, doi: 10.1016/j.apenergy.2016.08.188.
[274] E. Skoplaki and J. A. Palyvos, "On the temperature dependence of photovoltaic module electrical performance: A review of efficiency/power correlations," *Sol. Energy*, vol. 83, no. 5, pp. 614–624, May 2009, doi: 10.1016/j.solener.2008.10.008.
[275] M. Auffhammer, "Climate Adaptive Response Estimation: Short and Long Run Impacts of Climate Change on Residential Electricity and Natural Gas Consumption Using Big Data," California Energy Commission, 2018. [Online]. Available: https://www.energy.ca.gov/sites/default/files/2019-11/Energy_CCCA4-EXT-2018-005_ADA.pdf
[276] L. W. Davis and P. J. Gertler, "Contribution of air conditioning adoption to future energy use under global warming," *Proc. Natl. Acad. Sci.*, vol. 112, no. 19, pp. 5962–5967, May 2015, doi: 10.1073/pnas.1423558112.

[277] P. Dowling, “The impact of climate change on the European energy system,” *Energy Policy*, vol. 60, pp. 406–417, Sep. 2013, doi: 10.1016/j.enpol.2013.05.093.

[278] G. S. Eskeland and T. K. Mideksa, “Electricity demand in a changing climate,” *Mitig. Adapt. Strateg. Glob. Change*, vol. 15, no. 8, pp. 877–897, Dec. 2010, doi: 10.1007/s11027-010-9246-x.

[279] M. Auffhammer, P. Baylis, and C. H. Hausman, “Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the United States,” *Proc. Natl. Acad. Sci.*, vol. 114, no. 8, pp. 1886–1891, Feb. 2017, doi: 10.1073/pnas.1613193114.

[280] B. J. van Ruijven, E. De Cian, and I. Sue Wing, “Amplification of future energy demand growth due to climate change,” *Nat. Commun.*, vol. 10, Jun. 2019, doi: 10.1038/s41467-019-10399-3.

[281] S. W. D. Turner, M. Hejazi, S. H. Kim, L. Clarke, and J. Edmonds, “Climate impacts on hydropower and consequences for global electricity supply investment needs,” *Energy*, vol. 141, pp. 2081–2090, Dec. 2017, doi: 10.1016/j.energy.2017.11.089.

[282] M. T. H. van Vliet, D. Wiberg, S. Leduc, and K. Riahi, “Power-generation system vulnerability and adaptation to changes in climate and water resources,” *Nat. Clim. Change*, vol. 6, no. 4, pp. 375–380, Apr. 2016, doi: 10.1038/nclimate2903.

[283] K. Madani and J. R. Lund, “Estimated impacts of climate warming on California’s high-elevation hydropower,” *Clim. Change*, vol. 102, no. 3–4, pp. 521–538, Oct. 2010, doi: 10.1007/s10584-009-9750-8.

[284] K. Madani, M. Guegan, and C. B. Uvo, “Climate change impacts on high-elevation hydroelectricity in California,” *J. Hydrol.*, vol. 510, pp. 153–163, Mar. 2014, doi: 10.1016/j.jhydrol.2013.12.001.

[285] S. Vicuña, J. A. Dracup, and L. Dale, “Climate change impacts on two high-elevation hydropower systems in California,” *Clim. Change*, vol. 109, no. 1, pp. 151–169, Dec. 2011, doi: 10.1007/s10584-011-0301-8.

[286] M. T. H. van Vliet, S. Vögele, and D. Rübbelke, “Water constraints on European power supply under climate change: impacts on electricity prices,” *Environ. Res. Lett.*, vol. 8, no. 3, p. 035010, 2013, doi: 10.1088/1748-9326/8/3/035010.

[287] M. T. H. van Vliet, J. R. Yearsley, F. Ludwig, S. Vögele, D. P. Lettenmaier, and P. Kabat, “Vulnerability of US and European electricity supply to climate change,” *Nat. Clim. Change*, vol. 2, no. 9, p. 676, Sep. 2012, doi: 10.1038/nclimate1546.

[288] A. Miara, J. E. Macknick, C. J. Vörösmarty, V. C. Tidwell, R. Newmark, and B. Fekete, “Climate and water resource change impacts and adaptation potential for US power supply,” *Nat. Clim. Change*, vol. 7, no. 11, p. 793, Nov. 2017, doi: 10.1038/nclimate3417.

[289] J. Macknick, S. Sattler, K. Averyt, S. Clemmer, and J. Rogers, “The water implications of generating electricity: water use across the United States based on different electricity pathways through 2050,” *Environ. Res. Lett.*, vol. 7, no. 4, p. 045803, Dec. 2012, doi: 10.1088/1748-9326/7/4/045803.

[290] H. Cooley, R. Phurisamban, and P. Gleick, “The cost of alternative urban water supply and efficiency options in California,” *Environ. Res. Commun.*, vol. 1, no. 4, p. 042001, May 2019, doi: 10.1088/2515-7620/ab22ca.

[291] C. E. Scruggs and B. M. Thomson, “Opportunities and Challenges for Direct Potable Water Reuse in Arid Inland Communities,” *J. Water Resour. Plan. Manag.*, vol. 143, no. 10, p. 04017064, Oct. 2017, doi: 10.1061/(ASCE)WR.1943-5452.0000822.

[292] P. H. Gleick, “Water management: Soft water paths,” *Nature*, vol. 418, no. 6896, Art. no. 6896, Jul. 2002, doi: 10.1038/418373a.
[293] S. B. Grant *et al.*, “Taking the ‘Waste’ Out of ‘Wastewater’ for Human Water Security and Ecosystem Sustainability,” *Science*, vol. 337, no. 6095, pp. 681–686, Aug. 2012, doi: 10.1126/science.1216852.
[294] J. Mitchell *et al.*, “No-tillage and high-residue practices reduce soil water evaporation,” *Calif. Agric.*, vol. 66, no. 2, pp. 55–61, Apr. 2012.
[295] J. Jägermeyr, D. Gerten, S. Schaphoff, J. Heinke, W. Lucht, and J. Rockström, “Integrated crop water management might sustainably halve the global food gap,” *Environ. Res. Lett.*, vol. 11, no. 2, p. 025002, Feb. 2016, doi: 10.1088/1748-9326/11/2/025002.
[296] J. Jägermeyr, D. Gerten, J. Heinke, S. Schaphoff, M. Kummu, and W. Lucht, “Water savings potentials of irrigation systems: global simulation of processes and linkages,” *Hydrol. Earth Syst. Sci.*, vol. 19, no. 7, pp. 3073–3091, Jul. 2015, doi: https://doi.org/10.5194/hess-19-3073-2015.
[297] F. A. Ward and M. Pulido-Velazquez, “Water conservation in irrigation can increase water use,” *Proc. Natl. Acad. Sci.*, vol. 105, no. 47, pp. 18215–18220, Nov. 2008, doi: 10.1073/pnas.0805554105.
[298] K. F. Davis, A. Seveso, M. C. Rulli, and P. D’Odorico, “Water Savings of Crop Redistribution in the United States,” *Water*, vol. 9, no. 2, p. 83, Feb. 2017, doi: 10.3390/w9020083.
[299] K. F. Davis, M. C. Rulli, A. Seveso, and P. D’Odorico, “Increased food production and reduced water use through optimized crop distribution,” *Nat. Geosci.*, vol. 10, no. 12, p. 919, Dec. 2017, doi: 10.1038/s41561-017-0004-5.
[300] V. K. Mehta, V. R. Haden, B. A. Joyce, D. R. Purkey, and L. E. Jackson, “Irrigation demand and supply, given projections of climate and land-use change, in Yolo County, California,” *Agric. Water Manag.*, vol. 117, pp. 70–82, Jan. 2013, doi: 10.1016/j.agwat.2012.10.021.
[301] J. G. Hering, T. D. Waite, R. G. Luthy, J. E. Drewes, and D. L. Sedlak, “A Changing Framework for Urban Water Systems,” *Environ. Sci. Technol.*, vol. 47, no. 19, pp. 10721–10726, Oct. 2013, doi: 10.1021/es4007096.
[302] B. R. Scanlon, R. C. Reedy, C. C. Faunt, D. Pool, and K. Uhlman, “Enhancing drought resilience with conjunctive use and managed aquifer recharge in California and Arizona,” *Environ. Res. Lett.*, vol. 11, no. 3, p. 035013, Mar. 2016, doi: 10.1088/1748-9326/11/3/035013.
[303] M. A. Eltawil, Z. Zhengming, and L. Yuan, “A review of renewable energy technologies integrated with desalination systems,” *Renew. Sustain. Energy Rev.*, vol. 13, no. 9, pp. 2245–2262, Dec. 2009, doi: 10.1016/j.rser.2009.06.011.
[304] A. Mileva, J. Johnston, J. H. Nelson, and D. M. Kammen, “Power system balancing for deep decarbonization of the electricity sector,” *Appl. Energy*, vol. 162, pp. 1001–1009, Jan. 2016, doi: 10.1016/j.apenergy.2015.10.180.
[305] M. Fürsch, S. Hagspiel, C. Jägemann, S. Nagl, D. Lindenberger, and E. Tröster, “The role of grid extensions in a cost-efficient transformation of the European electricity system until 2050,” *Appl. Energy*, vol. 104, pp. 642–652, Apr. 2013, doi: 10.1016/j.apenergy.2012.11.050.

[306] S. Clemmer, J. Rogers, S. Sattler, J. Macknick, and T. Mai, "Modeling low-carbon US electricity futures to explore impacts on national and regional water use," *Environ. Res. Lett.*, vol. 8, no. 1, p. 015004, Jan. 2013, doi: 10.1088/1748-9326/8/1/015004.
[307] R. R. Hernandez *et al.*, "Techno–ecological synergies of solar energy for global sustainability," *Nat. Sustain.*, vol. 2, no. 7, Art. no. 7, Jul. 2019, doi: 10.1038/s41893-019-0309-z.
[308] S. Agrawal and A. Jain, "Sustainable deployment of solar irrigation pumps: Key determinants and strategies," *WIREs Energy Environ.*, vol. 8, no. 2, p. e325, 2019, doi: 10.1002/wene.325.
[309] T. Shah, A. Rajan, G. P. Rai, S. Verma, and N. Durga, "Solar pumps and South Asia's energy-groundwater nexus: exploring implications and reimagining its future," *Environ. Res. Lett.*, vol. 13, no. 11, p. 115003, Nov. 2018, doi: 10.1088/1748-9326/aae53f.
[310] C. J. Vörösmarty, P. Green, J. Salisbury, and R. B. Lammers, "Global Water Resources: Vulnerability from Climate Change and Population Growth," *Science*, vol. 289, no. 5477, pp. 284–288, Jul. 2000, doi: 10.1126/science.289.5477.284.
[311] M. Rayej, R. Juricich, D. Groves, and D. Yates, "Scenarios of Future California Water Demand through 2050: Growth and Climate Change," *World Environ. Water Resour. Congr. 2011*, pp. 4423–4432, doi: 10.1061/41173(414)460.
[312] "SGMA Groundwater Management." http://water.ca.gov/Programs/Groundwater-Management/SGMA-Groundwater-Management (accessed Feb. 11, 2020).
[313] "EIA Electricity data browser - Plants for multiple sectors, California, multiple fuel types," *EIA Electricity Data Browser, Water Data*. https://www.eia.gov/beta/electricity/data/browser/#/topic/1?agg=2,0,1&fuel=vtvv&pt=&pm=&sec=vvo&geo=000000000004&wd=&ws=&wsn=&wt=&freq=A&datecode=2018&tab=water-intensity&start=200101&end=201710&ctype=linechart&ltype=pin&maptype=0&rse=0&pin= (accessed Jul. 01, 2020).
[314] A. Mahone *et al.*, "Deep Decarbonization in a High Renewables Future: Updated Results from the California PATHWAYS Model," California Energy Commission, CEC-500-2018-012, Jun. 2018. [Online]. Available: https://www.ethree.com/wp-content/uploads/2018/06/Deep_Decarbonization_in_a_High_Renewables_Future_CEC-500-2018-012-1.pdf
[315] "California Energy Commission database on Electricity Consumption by Entity." http://www.ecdms.energy.ca.gov/elecbyutil.aspx (accessed Dec. 01, 2019).
[316] "U.S. Energy Information Administration (EIA) - Open Data," *EIA Open Data*. https://www.eia.gov/opendata/qb.php?category=902935 (accessed Dec. 01, 2019).
[317] A. Siddiqi and S. Fletcher, "Energy Intensity of Water End-Uses," *Curr. Sustain. Energy Rep.*, vol. 2, no. 1, pp. 25–31, Mar. 2015, doi: 10.1007/s40518-014-0024-3.
[318] J. Herman, M. Fefer, M. Dogan, M. Jenkins, J. Medellín-Azuara, and J. Lund, "Advancing Hydro-Economic Optimization to Identify Vulnerabilities and Adaptation Opportunities in California's Water System," California Natural Resources Agency, CCCA4-CNRA-2018–016, 2018. [Online]. Available: https://www.energy.ca.gov/sites/default/files/2019-12/Water_CCCA4-CNRA-2018-016_ada.pdf
[319] T. Zhu, M. W. Jenkins, and J. R. Lund, "Estimated Impacts of Climate Warming on California Water Availability Under Twelve Future Climate Scenarios," *JAWRA J. Am.*

Water Resour. Assoc., vol. 41, no. 5, pp. 1027–1038, 2005, doi: 10.1111/j.1752-1688.2005.tb03783.x.

[320] S. Vicuna, E. P. Maurer, B. Joyce, J. A. Dracup, and D. Purkey, "The Sensitivity of California Water Resources to Climate Change Scenarios1," *JAWRA J. Am. Water Resour. Assoc.*, vol. 43, no. 2, pp. 482–498, Apr. 2007, doi: 10.1111/j.1752-1688.2007.00038.x.

[321] J. W. Hopmans and E. P. Maurer, "Impact of Climate Change on Irrigation Water Availability, Crop Water Requirements and Soil Salinity in the SJV, CA," *Univ. Calif. Water Resour. Cent.*, Jun. 2008, Accessed: Nov. 14, 2018. [Online]. Available: https://escholarship.org/uc/item/0g21p5hs

[322] D. R. Purkey *et al.*, "Robust analysis of future climate change impacts on water for agriculture and other sectors: a case study in the Sacramento Valley," *Clim. Change*, vol. 87, no. 1, pp. 109–122, Mar. 2008, doi: 10.1007/s10584-007-9375-8.

[323] N. L. Miller, K. Hayhoe, J. Jin, and M. Auffhammer, "Climate, Extreme Heat, and Electricity Demand in California," *J. Appl. Meteorol. Climatol.*, vol. 47, no. 6, pp. 1834–1844, Jun. 2008, doi: 10.1175/2007JAMC1480.1.

[324] V. K. Mehta *et al.*, "Potential impacts on hydrology and hydropower production under climate warming of the Sierra Nevada," *J. Water Clim. Change Lond.*, vol. 2, no. 1, pp. 29–43, Mar. 2011, doi: http://dx.doi.org/10.2166/wcc.2011.054.

[325] S. Vicuna, R. Leonardson, M. W. Hanemann, L. L. Dale, and J. A. Dracup, "Climate change impacts on high elevation hydropower generation in California's Sierra Nevada: a case study in the Upper American River," *Clim. Change*, vol. 87, no. 1, pp. 123–137, Mar. 2008, doi: 10.1007/s10584-007-9365-x.

[326] J. Medellín-Azuara *et al.*, "Adaptability and adaptations of California's water supply system to dry climate warming," *Clim. Change*, vol. 87, no. S1, pp. 75–90, Mar. 2008, doi: 10.1007/s10584-007-9355-z.

[327] N. S. Diffenbaugh, D. Swain, and D. Touma, "Anthropogenic warming has increased drought risk in California," *Proc. Natl. Acad. Sci.*, vol. vo. 112, no. No. 13, Mar. 2015, [Online]. Available: http://www.pnas.org/content/112/13/3931.full.pdf?with-ds=yes

[328] J. Sathaye *et al.*, "Estimating Risk to California Energy Infrastructure from Projected Climate Change," California Energy Commission, CEC-500- 2012-057, Jul. 2012. [Online]. Available: https://www.energy.ca.gov/2012publications/CEC-500-2012-057/CEC-500-2012-057.pdf

[329] California Energy Commission (CEC), "2005 Integrated Energy Policy Report.," California Energy Commission, Sacramento, California, 2005. [Online]. Available: https://ww2.energy.ca.gov/2005publications/CEC-100-2005-007/CEC-100-2005-007-CMF.PDF

[330] M. D. Bartos and M. V. Chester, "The Conservation Nexus: Valuing Interdependent Water and Energy Savings in Arizona," *Environ. Sci. Technol.*, vol. 48, no. 4, pp. 2139–2149, Feb. 2014, doi: 10.1021/es4033343.

[331] E. Porse *et al.*, "Energy use for urban water management by utilities and households in Los Angeles," *Environ. Res. Commun.*, vol. 2, no. 1, p. 015003, Jan. 2020, doi: 10.1088/2515-7620/ab5e20.

[332] A. T. D. Perera, V. M. Nik, D. Chen, J.-L. Scartezzini, and T. Hong, "Quantifying the impacts of climate change and extreme climate events on energy systems," *Nat. Energy*, vol. 5, no. 2, Art. no. 2, Feb. 2020, doi: 10.1038/s41560-020-0558-0.

[333] "Net Generation by State by Type of Producer by Energy Source (EIA-906, EIA-920, and EIA-923)," *EIA Detailed State Data*. https://www.eia.gov/electricity/data/state/ (accessed Jun. 23, 2021).

[334] T. P. Barnett *et al.*, "Human-Induced Changes in the Hydrology of the Western United States," *Science*, vol. 319, no. 5866, pp. 1080–1083, Feb. 2008, doi: 10.1126/science.1152538.

[335] M. Dettinger, B. Udall, and A. Georgakakos, "Western water and climate change," *Ecol. Appl.*, vol. 25, no. 8, pp. 2069–2093, 2015, doi: 10.1890/15-0938.1.

[336] A. M. Rhoades, A. D. Jones, and P. A. Ullrich, "The Changing Character of the California Sierra Nevada as a Natural Reservoir," *Geophys. Res. Lett.*, vol. 45, no. 23, p. 13,008-13,019, 2018, doi: 10.1029/2018GL080308.

[337] J. K. Szinai, R. Deshmukh, D. M. Kammen, and A. D. Jones, "Evaluating cross-sectoral impacts of climate change and adaptations on the energy-water nexus: A framework and California case study," *Environ. Res. Lett.*, 2020, doi: 10.1088/1748-9326/abc378.

[338] S. W. D. Turner, N. Voisin, J. Fazio, D. Hua, and M. Jourabchi, "Compound climate events transform electrical power shortfall risk in the Pacific Northwest," *Nat. Commun.*, vol. 10, no. 1, pp. 1–8, Jan. 2019, doi: 10.1038/s41467-018-07894-4.

[339] North America Electric Reliability Corporation, "2021 Summer Reliability Assessment," May 2021. [Online]. Available: https://www.nerc.com/pa/RAPA/ra/Reliability%20Assessments%20DL/NERC%20SRA%202021.pdf

[340] E. Holbrook, "Oregon May Become 8th US State to Go 100% Clean Energy," *Environment + Energy Leader*, Jun. 29, 2021. https://www.environmentalleader.com/2021/06/oregon-poised-to-become-8th-us-state-to-go-100-clean-energy/ (accessed Jul. 09, 2021).

[341] S. Waldman, "Biden's Infrastructure Plan Would Make Electricity Carbon-Free by 2035," *Scientific American*, Apr. 01, 2021. Accessed: Jun. 19, 2021. [Online]. Available: https://www.scientificamerican.com/article/bidens-infrastructure-plan-would-make-electricity-carbon-free-by-2035/

[342] B. Tarroja, A. AghaKouchak, and S. Samuelsen, "Quantifying climate change impacts on hydropower generation and implications on electric grid greenhouse gas emissions and operation," *Energy*, vol. 111, pp. 295–305, Sep. 2016, doi: 10.1016/j.energy.2016.05.131.

[343] "California drought cuts hydropower, boosts natgas prices," *Reuters*, May 21, 2021. https://www.reuters.com/business/energy/california-drought-cuts-hydropower-boosts-natgas-prices-2021-05-21/ (accessed May 24, 2021).

[344] N. Voisin *et al.*, "Impact of climate change on water availability and its propagation through the Western U.S. power grid," *Appl. Energy*, vol. 276, p. 115467, Oct. 2020, doi: 10.1016/j.apenergy.2020.115467.

[345] Z. Khan *et al.*, "Impacts of long-term temperature change and variability on electricity investments," *Nat. Commun.*, vol. 12, no. 1, p. 1643, Mar. 2021, doi: 10.1038/s41467-021-21785-1.

[346] A. J. Conejo, L. B. Morales, K. Jalal, and A. S. Siddiqui, *Investment in Electricity Generation and Transmission: Decision Making under Uncertainty*. Springer International Publishing, 2016. Accessed: Jul. 10, 2019. [Online]. Available: https://www.springer.com/gp/book/9783319294995

[347] S. C. Parkinson and N. Djilali, “Robust response to hydro-climatic change in electricity generation planning,” *Clim. Change*, vol. 130, no. 4, pp. 475–489, Jun. 2015, doi: 10.1007/s10584-015-1359-5.
[348] A. K. Gerlak, J. Weston, B. McMahan, R. L. Murray, and M. Mills-Novoa, “Climate risk management and the electricity sector,” *Clim. Risk Manag.*, vol. 19, pp. 12–22, Jan. 2018, doi: 10.1016/j.crm.2017.12.003.
[349] S. Sattler, J. Macknick, D. Yates, F. Flores-Lopez, A. Lopez, and J. Rogers, “Linking electricity and water models to assess electricity choices at water-relevant scales,” *Environ. Res. Lett.*, vol. 7, no. 4, p. 045804, 2012, doi: 10.1088/1748-9326/7/4/045804.
[350] E. Hawkins and R. Sutton, “The Potential to Narrow Uncertainty in Regional Climate Predictions,” *Bull. Am. Meteorol. Soc.*, vol. 90, no. 8, pp. 1095–1108, Aug. 2009, doi: 10.1175/2009BAMS2607.1.
[351] W. S. Parker, “Predicting weather and climate: Uncertainty, ensembles and probability,” *Stud. Hist. Philos. Sci. Part B Stud. Hist. Philos. Mod. Phys.*, vol. 41, no. 3, pp. 263–272, Sep. 2010, doi: 10.1016/j.shpsb.2010.07.006.
[352] G. Flato *et al.*, “2013: Evaluation of Climate Models. Climate Change 2013: The Physical Science Basis,” Intergovernmental Panel on Climate Change, Cambridge, United Kingdom and New York, NY, USA, 2013. Accessed: May 06, 2019. [Online]. Available: https://www.ipcc.ch/report/ar5/wg1/evaluation-of-climate-models/
[353] D. E. Rupp, J. T. Abatzoglou, K. C. Hegewisch, and P. W. Mote, “Evaluation of CMIP5 20th century climate simulations for the Pacific Northwest USA,” *J. Geophys. Res. Atmospheres*, vol. 118, no. 19, p. 10,884-10,906, 2013, doi: https://doi.org/10.1002/jgrd.50843.
[354] B. Livneh *et al.*, “A Long-Term Hydrologically Based Dataset of Land Surface Fluxes and States for the Conterminous United States: Update and Extensions,” *J. Clim.*, vol. 26, no. 23, pp. 9384–9392, Dec. 2013, doi: 10.1175/JCLI-D-12-00508.1.
[355] D. Yates, J. Sieber, D. Purkey, and A. Huber-Lee, “WEAP21—A Demand-, Priority-, and Preference-Driven Water Planning Model,” *Water Int.*, vol. 30, no. 4, pp. 487–500, Dec. 2005, doi: 10.1080/02508060508691893.
[356] M. Howells *et al.*, “Integrated analysis of climate change, land-use, energy and water strategies,” *Nat. Clim. Change*, vol. 3, no. 7, pp. 621–626, Jul. 2013, doi: 10.1038/nclimate1789.
[357] “HydroSHEDS.” https://www.hydrosheds.org/ (accessed Jul. 08, 2021).
[358] “USGS Water Data for the Nation,” *USGS National Water Information System Web Interface*. https://waterdata.usgs.gov/nwis (accessed Jun. 30, 2021).
[359] M. S. Pervez and J. F. Brown, “Mapping Irrigated Lands at 250-m Scale by Merging MODIS Data and National Agricultural Statistics,” *Remote Sens.*, vol. 2, no. 10, pp. 2388–2412, Oct. 2010, doi: 10.3390/rs2102388.
[360] C. Homer, “Remote Sensing Shrub/Grass National Land Cover Database (NLCD) Back-in-Time (BIT) Products for the Western U.S., 1985 - 2018.” U.S. Geological Survey, 2020. doi: 10.5066/P9C9O66W.
[361] “National Inventory of Dams (NID) - Home,” *US Army Corps of Engineers*. https://nid.sec.usace.army.mil/ords/f?p=105:1::::: (accessed Jul. 08, 2021).
[362] “Carlsbad Desal Plant,” *Carlsbad Desal Plant*. https://www.carlsbaddesal.com/ (accessed Jul. 11, 2021).

[363] “Form EIA-860 detailed data with previous form data (EIA-860A/860B).” https://www.eia.gov/electricity/data/eia860/ (accessed May 28, 2021).
[364] “Form EIA-923 detailed data with previous form data (EIA-906/920).” https://www.eia.gov/electricity/data/eia923/ (accessed May 28, 2021).
[365] “Bureau of Reclamation.” https://www.usbr.gov/projects/ (accessed Jul. 08, 2021).
[366] W. Green and G. Allen, “Irrigation pump efficiency – the evolving essentials.” n, Center for Irrigation Technology, California State University, Fresno; REDtrac, LLC, Bakersfield, California. [Online]. Available: https://ucanr.edu/sites/calasa/files/287377.pdf
[367] “Residential Energy Consumption Survey (RECS) Table HC8.8 Water heating in homes in the South and West regions, 2015,” *Energy Information Administration*. https://www.eia.gov/consumption/residential/data/2015/hc/php/hc8.8.php (accessed Jul. 09, 2021).
[368] “California DWR Workbook: Water_Balance,” *CA DWR California Water Plan*. https://tableau.cnra.ca.gov/t/DWR_Planning/views/Water_Balance/HRButterflyChart?iframeSizedToWindow=true&%3Aembed=y&%3AshowAppBanner=false&%3Adisplay_count=no&%3AshowVizHome=no (accessed Jul. 10, 2021).
[369] Arizona Department of Water Resources, “Arizona Water Atlas: Volume 1, Executive Summary,” Arizona Department of Water Resources, 2010. [Online]. Available: https://infoshare.azwater.gov/docushare/dsweb/Get/Document-10426/Atlas_Volume_1_web.pdf
[370] “Water Use and Conservation - NM Office of the State Engineer.” https://www.ose.state.nm.us/WUC/wuc_waterUseData.php (accessed Jul. 10, 2021).
[371] J. King, “STATEWIDE GROUNDWATER PUMPAGE INVENTORY, CALENDAR YEAR 2015,” Nevada Department of Conservation and Natural Resources, Nov. 2017. [Online]. Available: http://water.nv.gov/documents/Nevada_Groundwater_Pumpage_2015.pdf
[372] “Water Uses | Colorado Water Knowledge | Colorado State University.” https://waterknowledge.colostate.edu/water-management-administration/water-uses/ (accessed Jul. 10, 2021).
[373] Oregon Water Resources Department, “2015 Statewide Long-Term Water Demand Forecast: Oregon’s Integrated Water Resources Strategy,” Dec. 2015. [Online]. Available: https://www.oregon.gov/owrd/wrdpublications1/OWRD_2015_Statewide_LongTerm_Water_Demand_Forecast.pdf
[374] Idaho Water Resource Board, “State of Idaho Water Resource Inventory 2010,” Idaho Water Resource Board, 2010. [Online]. Available: https://idwr.idaho.gov/files/iwrb/2010/2010-Water-Resource-Inventory.pdf
[375] Montana Department of Natural Resources and Conservation, “Montana State Water Plan: A Watershed Approach to the 2015 Montana State Water Plan,” Dec. 2014. [Online]. Available: http://dnrc.mt.gov/divisions/water/management/docs/state-water-plan/2015_mt_water_plan.pdf
[376] “Wyoming State Water Plan Framework Plan Data Tables,” *Wyoming Water Development Office*. https://waterplan.state.wy.us/plan/statewide/tables/tables.html (accessed Jul. 10, 2021).
[377] J. Johnston, R. Henriquez-Auba, B. Maluenda, and M. Fripp, “Switch 2.0: A modern platform for planning high-renewable power systems,” *SoftwareX*, vol. 10, p. 100251, Jul. 2019, doi: 10.1016/j.softx.2019.100251.

[378] J. Nelson *et al.*, “High-resolution modeling of the western North American power system demonstrates low-cost and low-carbon futures,” *Energy Policy*, vol. 43, pp. 436–447, Apr. 2012, doi: 10.1016/j.enpol.2012.01.031.
[379] “Gurobi - The fastest solver,” *Gurobi*. https://www.gurobi.com/ (accessed May 28, 2021).
[380] National Renewable Energy Laboratory (NREL), “Data | Electricity | 2020 Annual Technology Baseline | NREL,” *Annual Technology Baseline*. https://atb.nrel.gov/electricity/2020/data.php (accessed Jun. 13, 2021).
[381] Black & Veatch, “Cost and Performance Data for Power Generation Technologies, Prepared for the National Renewable Energy Laboratory,” Feb. 2012. [Online]. Available: https://refman.energytransitionmodel.com/publications/1921
[382] “WINDExchange: Production Tax Credit and Investment Tax Credit for Wind,” *DOE Office of Energy Efficiency and Renewable Energy*. https://windexchange.energy.gov/projects/tax-credits (accessed Jun. 14, 2021).
[383] “Residential and Commercial ITC Factsheets,” *Energy.gov*. https://www.energy.gov/eere/solar/articles/residential-and-commercial-itc-factsheets (accessed Jun. 14, 2021).
[384] W. Cole *et al.*, “Regional Energy Deployment System (ReEDS) Model Documentation: Version 2019,” National Renewable Energy Lab. (NREL), Golden, CO (United States), NREL/TP-6A20-74111, Mar. 2020. doi: 10.2172/1606151.
[385] “Form No. 714 - Annual Electric Balancing Authority Area and Planning Area Report | Federal Energy Regulatory Commission.” https://www.ferc.gov/industries-data/electric/general-information/electric-industry-forms/form-no-714-annual-electric/data (accessed Jun. 14, 2021).
[386] J. K. Szinai, C. J. R. Sheppard, N. Abhyankar, and A. R. Gopal, “Reduced grid operating costs and renewable energy curtailment with electric vehicle charge management,” *Energy Policy*, vol. 136, p. 111051, Jan. 2020, doi: 10.1016/j.enpol.2019.111051.
[387] Andrew Funk and William B. DeOreo, “Embedded Energy in Water Studies Study 3: End-use Water Demand Profiles,” Prepared for the California Public Utilities Commission, Apr. 2011.
[388] “Western Electricity Coordinating Council: Demand,” *Western Electricity Coordinating Council*. https://www.wecc.org/epubs/StateOfTheInterconnection/Pages/Demand.aspx (accessed Jul. 29, 2021).
[389] H. Hoff, “Understanding the Nexus. Background Paper for the Bonn2011 Conference: The Water, Energy and Food Security Nexus,” Stockholm Environment Institute, Stockholm, 2011. [Online]. Available: https://mediamanager.sei.org/documents/Publications/SEI-Paper-Hoff-UnderstandingTheNexus-2011.pdf
[390] “California was the largest net electricity importer of any state in 2019 - Today in Energy.” https://www.eia.gov/todayinenergy/detail.php?id=46156 (accessed Jul. 13, 2021).
[391] A. M. Meadow, D. B. Ferguson, Z. Guido, A. Horangic, G. Owen, and T. Wall, “Moving toward the Deliberate Coproduction of Climate Science Knowledge,” *Weather Clim. Soc.*, vol. 7, no. 2, pp. 179–191, Apr. 2015, doi: 10.1175/WCAS-D-14-00050.1.
[392] D. W. Cash, J. C. Borck, and A. G. Patt, “Countering the Loading-Dock Approach to Linking Science and Decision Making: Comparative Analysis of El Niño/Southern Oscillation (ENSO) Forecasting Systems,” *Sci. Technol. Hum. Values*, vol. 31, no. 4, pp. 465–494, Jul. 2006, doi: 10.1177/0162243906287547.

[393] K. A. Goodrich, K. D. Sjostrom, C. Vaughan, L. Nichols, A. Bednarek, and M. C. Lemos, "Who are boundary spanners and how can we support them in making knowledge more actionable in sustainability fields?," *Curr. Opin. Environ. Sustain.*, vol. 42, pp. 45–51, Feb. 2020, doi: 10.1016/j.cosust.2020.01.001.
[394] "Project HyperFACETS." https://climate.ucdavis.edu/hyperfacets/index.php (accessed Jul. 16, 2021).
[395] K. Jagannathan, A. D. Jones, and I. Ray, "The making of a metric: Co-producing decision-relevant climate science," *Bull. Am. Meteorol. Soc.*, vol. 1, no. aop, pp. 1–33, Feb. 2020, doi: 10.1175/BAMS-D-19-0296.1.
[396] E. C. Evarts, "EVgo launches first public 350-kw fast charger," *Green Car Reports*. https://www.greencarreports.com/news/1120518_evgo-launches-first-public-350-kw-fast-charger (accessed Apr. 16, 2019).
[397] K. Fehrenbacher, "California's great electric vehicle charging build-out," *GreenBiz*, Oct. 03, 2018. https://www.greenbiz.com/article/californias-great-electric-vehicle-charging-build-out (accessed Apr. 16, 2019).
[398] "PLEXOS Wiki - Concise Modelling Guide." https://wiki.energyexemplar.com/index.php?n=Article.ConciseModellingGuide (accessed Apr. 09, 2019).
[399] P. Sullivan, J. Colman, and E. Kalendra, "Predicting the Response of Electricity Load to Climate Change," National Renewable Energy Laboratory, NREL/TP-6A20-64297, Jul. 2015. [Online]. Available: https://www.nrel.gov/docs/fy15osti/64297.pdf
[400] B. Boehlert *et al.*, "Climate change impacts and greenhouse gas mitigation effects on U.S. hydropower generation," *Appl. Energy*, vol. 183, pp. 1511–1519, Dec. 2016, doi: 10.1016/j.apenergy.2016.09.054.
[401] "Western Wind Data Set," *National Renewable Energy Laboratory*. https://www.nrel.gov/grid/western-wind-data.html (accessed Jun. 11, 2021).
[402] G. C. Wu, M. S. Torn, and J. H. Williams, "Incorporating Land-Use Requirements and Environmental Constraints in Low-Carbon Electricity Planning for California," *Environ. Sci. Technol.*, vol. 49, no. 4, pp. 2013–2021, Feb. 2015, doi: 10.1021/es502979v.
[403] "System Advisor Model (SAM)," *National Renewable Energy Laboratory*. https://sam.nrel.gov/ (accessed Jun. 11, 2021).
[404] A. Milbrandt, "A Geographic Perspective on the Current Biomass Resource Availability in the United States," National Renewable Energy Laboratory, NREL/TP-560-39181, 2005. [Online]. Available: https://www.nrel.gov/docs/fy06osti/39181.pdf
[405] "Assumptions to the Annual Energy Outlook 2017," U.S. Energy Information Administration, Jul. 2017. [Online]. Available: https://www.eia.gov/outlooks/aeo/assumptions/pdf/0554(2017).pdf
[406] "State Renewable Portfolio Standards and Goals," *National Conference of State Legislatures*. https://www.ncsl.org/research/energy/renewable-portfolio-standards.aspx (accessed Jun. 15, 2021).
[407] "Are you efficient with your indoor water use?," *Residential | Denver Water*. https://www.denverwater.org/residential/efficiency-tip/are-you-efficient-your-indoor-water-use (accessed Oct. 15, 2020).
[408] Candice Hasenyager, Eric Klotz, and Todd Adams, "2009 Residential Water Use: Survey Results and Analysis of Residential Water Use for Seventeen Communities in Utah," Utah

Department of Natural Resources, 2010. [Online]. Available: https://water.utah.gov/wp-content/uploads/2019/08/2009-Residential-Water-Use.pdf
[409] William B. DeOreo *et al.*, “California Single Family Water Use Efficiency Study,” Sponsored by California Department of Water Resources, 2011. [Online]. Available: http://water.cityofdavis.org/Media/PublicWorks/Documents/PDF/PW/Water/Documents/California-Single-Family-Home-Water-Use-Efficiency-Study-20110420.pdf
[410] C. Mini, T. S. Hogue, and S. Pincetl, “Estimation of residential outdoor water use in Los Angeles, California,” *Landsc. Urban Plan.*, vol. 127, pp. 124–135, Jul. 2014, doi: 10.1016/j.landurbplan.2014.04.007.
[411] San Francisco Public Utilities Commission, “Water Resources Division Annual Report, Fiscal Year 2016 - 2017,” San Francisco Public Utilities Commission, Nov. 2017. [Online]. Available: https://sfwater.org/modules/showdocument.aspx?documentid=11472
[412] Brenda Estrada and Charles Duncan, “City of Sacramento 2015 Urban Water Management Plan,” Jun. 2016. [Online]. Available: https://www.cityofsacramento.org/~/media/Corporate/Files/DOU/Reports/City%20of%20Sacramento%20Final%202015%20UWMP%20June%202016.pdf
[413] Prepared by Aquacraft, Inc., Water Engineering and Management, “Seattle Public Utilities Study of Market Penetration of Water Efficient Fixtures,” Seattle Public Utilities, 2004. [Online]. Available: https://aquacraft.com/wp-content/uploads/2015/10/Conservation-Potential-Water-Use-Assessment.pdf
[414] “How Does Your Water Use Stack Up?,” *Arizona Municipal Water Users Association*. http://www.amwua.org/blog/how-does-your-water-use-stack-up (accessed Oct. 15, 2020).
[415] “Indoor Water Efficiency | The City of Portland, Oregon,” *Portland Water Bureau*. https://www.portlandoregon.gov/water/51031 (accessed Oct. 15, 2020).
[416] P. W. Mayer, “Water Research Foundation Study Documents Water Conservation Potential and More Efficiency in Households,” *J. AWWA*, vol. 108, no. 10, pp. 31–40, 2016, doi: 10.5942/jawwa.2016.108.0160.

Appendices

Chapter 1 Appendix

A. Sensitivity analysis of added workplace charging infrastructure

We assess the opportunity for expanding workplace chargers to increase the supply of load shifting flexibility of PEV charging. We do this by simulating BEAM in the San Francisco Bay Area with two workplace charger sensitivities on our base scenario of charging infrastructure (Table 1). The first sensitivity introduces 14,700 additional Level 2 chargers, sited at drivers' workplace locations in the San Francisco Bay Area model. The chargers are sited in proportion to the spatial density of these existing workplace locations. This 4X sensitivity results in four times more Level 2 workplace chargers than in the base scenario. An additional 8X sensitivity is created using the same technique but with 34,300 new chargers, resulting in eight times more Level 2 workplace chargers than in the base scenario.

We then process the charging sessions and analyze the change in charging flexibility from the base scenario (Figure A.1). As in Figure 6 of the main text, these charging sessions represent a typical weekday in the San Francisco Bay Area and are not shown scaled to California 2025 levels. We find that dramatic increases in workplace charging infrastructure increases the charging load in the workplace sector, but not proportionally with the number of added chargers. The morning peak workplace charging load only increases by 63% and by 99% for the 4X and 8X sensitivities, respectively. For short duration flexibility (0-2 hours), the peak morning workplace load increases by 57% from the base to the 8X sensitivity. For longer period flexibility, the peak morning load only increases by 123% with the 8X sensitivity.

With both workplace charging sensitivities, overall, residential charging still dominates the load profile and the opportunity for charging flexibility. Even in the 8X sensitivity, there is still eight times more energy demanded at home than at the workplace, and a much higher fraction of this load is of long-duration flexibility. These sensitivities support a focus on residential smart charging, because of the relatively small marginal increase in daytime load and flexibility from added workplace chargers.

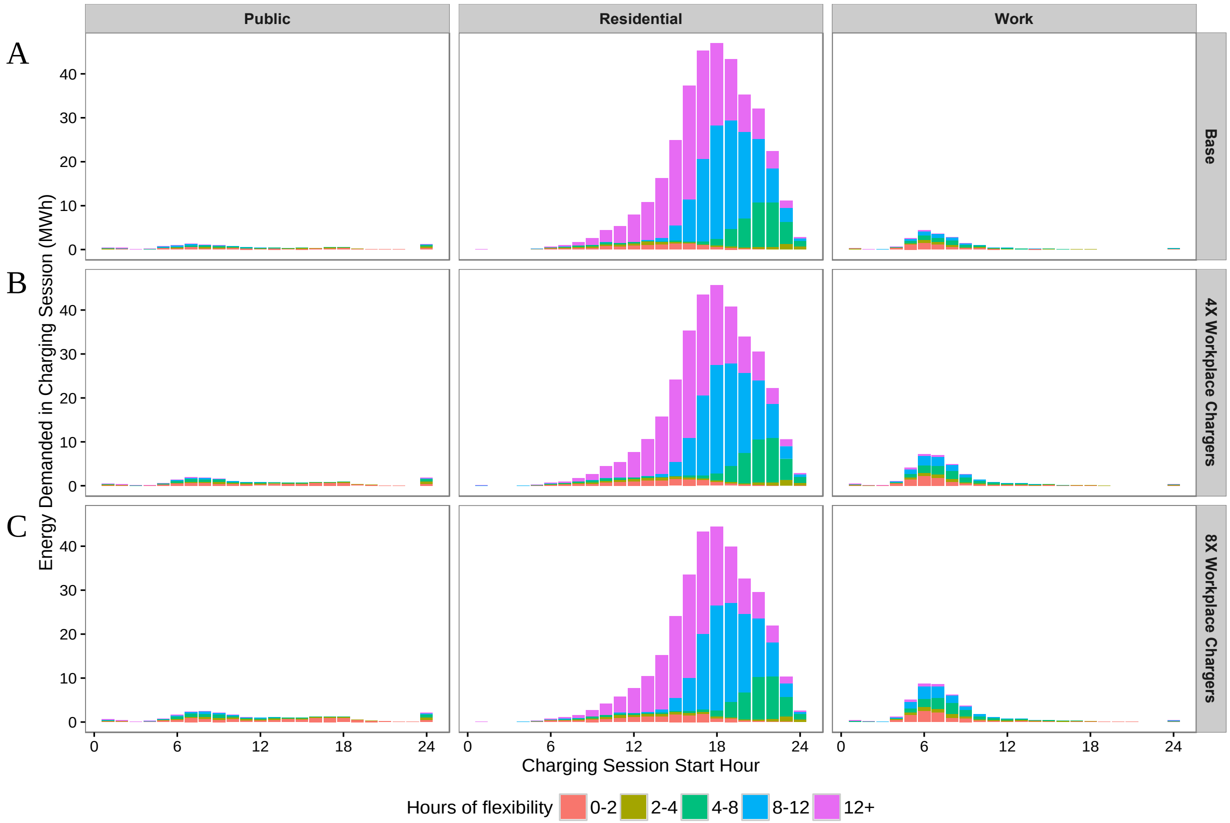


Figure A.1: Weekday charging session flexibility duration and energy demanded by location and hour for three workplace infrastructure scenarios.

The panels show for a typical weekday in the San Francisco Bay Area BEAM simulation (before scaling to California 2025 levels), the energy demanded by location and the hours of flexibility to shift load within charging sessions (based on the time between active charging and unplugging). Each row of panels represents a different workplace charging infrastructure scenario where progressively more workplace chargers are sited. A. Base case with original number of chargers assumed in the analysis. B. 4X sensitivity with four times number of workplace chargers as base case. C. 8X sensitivity with eight times the number of workplace chargers as base case.

B. Sensitivity analyses of vehicle range and fast charging infrastructure

The PEV market is quickly evolving and battery capacities in new vehicle models are already much larger than the 2016 fleet [116]. While we assume in our baseline analysis that by our 2025 study year every vehicle will have 1.5X larger battery capacity than a 2016 vehicle, even this assumption may be an underestimate. In addition to battery capacity, DC Fast charger technology is also advancing, with chargers rated as high as 350kW entering the market [396]. Furthermore, with increased availability of DC Fast chargers in general [397], PEV driver behavior in the future may differ from our assumed behavioral patterns which were based on 2016 utilization of DC Fast chargers in the San Francisco Bay Area. In these sensitivity analyses, we deduce how our flexibility results may potentially change by post-processing the charging sessions from our BEAM baseline scenario (Table 1, Figure 6) to mimic higher range and faster charging futures.

In Figure B.1 we disaggregate the flexibility result in the baseline BEAM scenario for the San Francisco Bay Area by low- and high-range vehicles using the medians of 126 miles for BEVs and 31 miles for PHEVs, respectively, as the dividing points. We observe subtle differences between low- and high-range vehicles in the time of day and the relative duration of load shift capacity. With BEVs, the low-range vehicles have slightly more of the longest duration flexibility (12+ hours), while the high-range vehicles have more 8 to 10-hour duration flexibility. For PHEVs, the low-range vehicles provide more flexibility during the morning hours compared to the high-range PHEVs. Consequently, we deduce that increased numbers of high-range PEVs may result in marginally lower cost savings and curtailment reductions, but not a significant overall change from our baseline results.

In Figure B.2 we present the same flexibility analysis for the San Francisco Bay Area but for several scenarios that vary the amount and rate of DC Fast charging that occurs in the simulation. We replace a share of slow charging (Level 2) sessions in the baseline scenario BEAM output with a representative DC Fast charging session that occurs at approximately the same time and delivers approximately the same amount of energy, but at a higher rate. In these sensitivities, we increase the number of fast charging sessions by a factor of 20, to 6% of all sessions from 0.3% of all sessions originally in the baseline scenario. We also increase the rate of DC Fast charging across the scenarios from 50 kW to 350 kW. We find that including more public DC Fast chargers moves some charging away from home and to the morning (between 6am to 12pm). The added DC Fast chargers also decrease the flexibility in those hours; the overall amount of temporal flexibility (the number of hours into which load can be shifted) decreases by 3% between the baseline and the DC Fast sensitivities. This implies that if DC Fast chargers comprised a greater share of infrastructure, there may be slightly lower curtailment reductions (and cost savings) that could be achieved by smart charging in the morning hours than indicated by our baseline results. However, even with a 20-fold increase in DC Fast chargers, we expect this decrease to be relatively small and overall the bulk of load flexibility to still occur at home with slow chargers in the evening. Our sensitivities also show no difference in flexibility between the three fast charger rates, because in all cases we have assumed that PEVs unplug immediately at the end of active charging during fast charging sessions. Overall, we expect that across increasing rates of DC Fast chargers the shape of the charging load would be different, and a greater installation of faster chargers might allow for more utilization over slow charging, but that the impact of charging rate on total load flexibility (and therefore costs and curtailment) would be marginal.

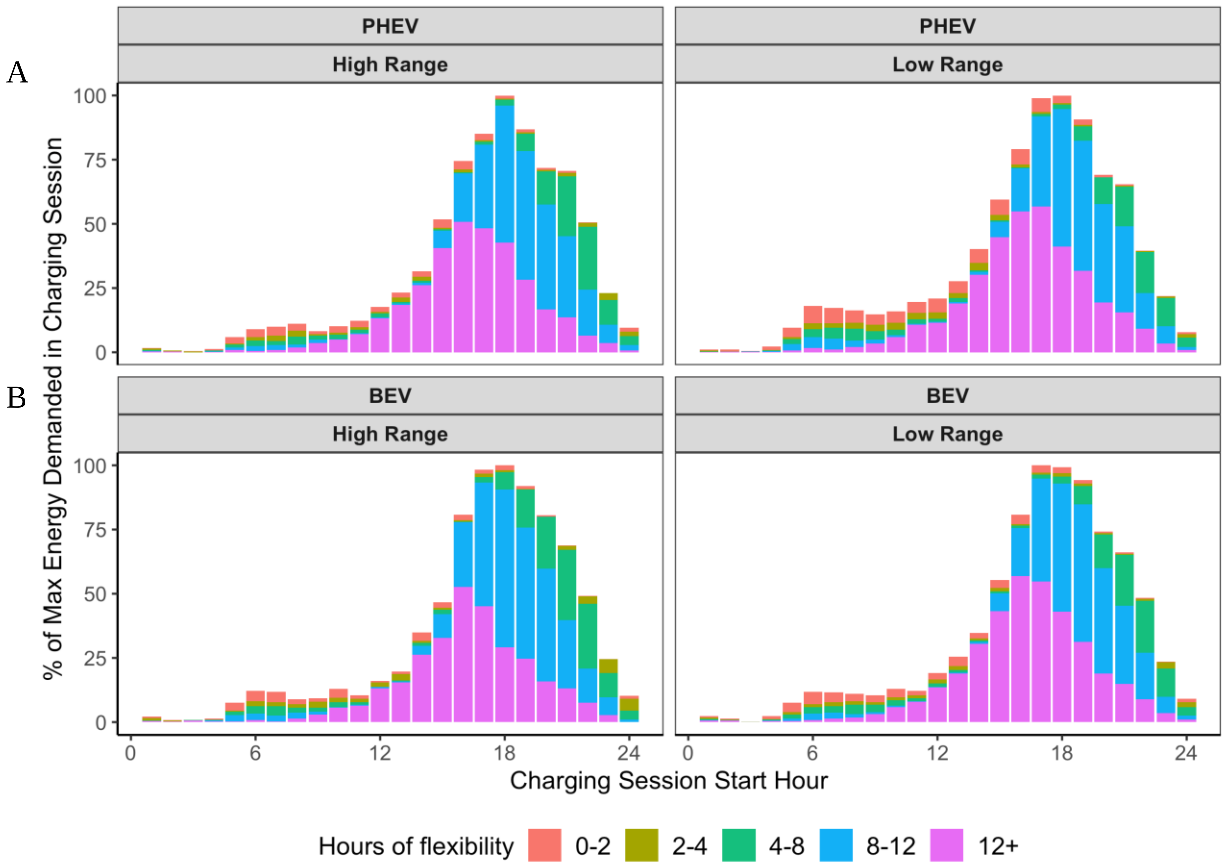


Figure B.1: Weekday charging session flexibility duration and energy demanded by BEV and PHEV, by high- range and low-range battery sizes.

The panels show for a typical weekday in the San Francisco Bay Area BEAM simulation (before scaling to California 2025 levels), the percent of maximum energy demanded and the hours of flexibility to shift load within charging sessions (based on the time between active charging and unplugging) by high- and low-range battery sizes. Each row of panels represents a vehicle type, either BEV or PHEV. A. High- and Low-Range PHEVs, split by the median 31-mile PHEV range in the baseline analysis. B. High- and Low-Range BEVs, split by the median 126-mile BEV range in the baseline analysis.

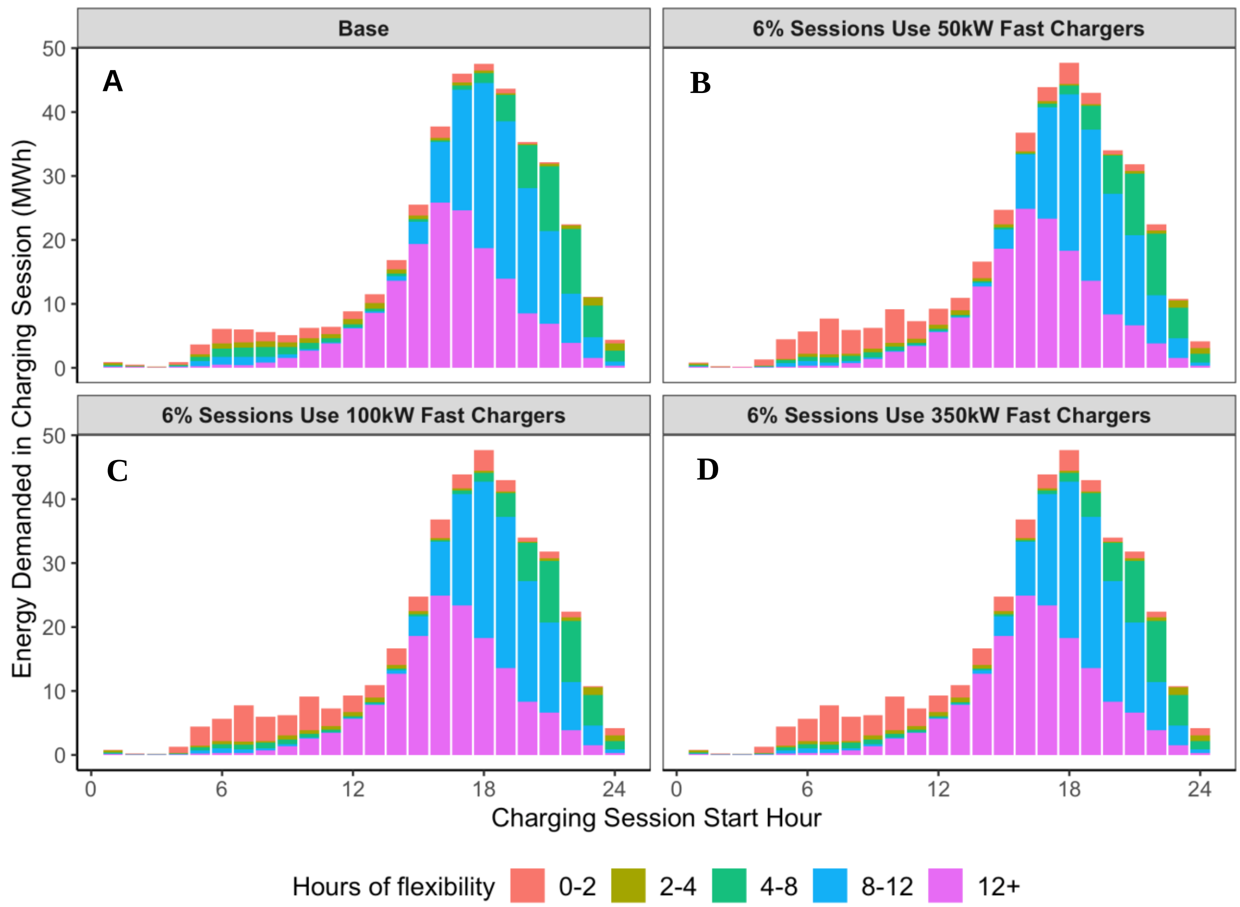


Figure B.2: Weekday charging session flexibility duration and energy demanded in Base case (0.3% DC Fast charging sessions) and sensitivities (6% DC Fast charging sessions) with 50 kW to 350 kW DC Fast chargers.

The panels show for a typical weekday in the San Francisco Bay Area BEAM simulation (before scaling to California 2025 levels), the energy demanded (MWh) and the hours of flexibility to shift load within charging sessions (based on the time between active charging and unplugging) by high- and low-range battery sizes. Each plot represents a different percent of charging sessions by DC Fast chargers, and a particular rate of DC Fast chargers. A. Base case with 0.3% of charging sessions at DC Fast chargers, at 50 kW. B. Sensitivity with 6% of charging sessions at DC Fast chargers, at 50 kW. C. Sensitivity with 6% of charging sessions at DC Fast chargers, at 100 kW. D. Sensitivity with 6% of charging sessions at DC Fast chargers, at 350 kW.

C. PLEXOS Unit Commitment and Economic Dispatch Optimization

In this analysis we use the unit commitment and economic dispatch model PLEXOS, a commercial optimization software created by Energy Exemplar. This Appendix presents the main characteristics and high-level model outline of the optimization used in this analysis, and not a comprehensive mathematical model. More detail on the mathematical model is available in PLEXOS documentation from Energy Exemplar [398]. Additionally, [128], [129], [140], [141] provide examples of other studies which have used PLEXOS for similar types of analyses.

PLEXOS constructs the objective function and constraints based on parameters provided in the input database. The specific PLEXOS database we use in this analysis for the WECC region (containing generator, load, network data, and constraints) was obtained from and originally created by the California Independent System Operator (CAISO) for state grid planning processes, and more information on the database is described in regulatory documents [153]–[156] and prior studies using variants of the same database [104], [157]–[159].

The objective function for each day of the optimization in our WECC-wide analysis can broadly be simplified to:

Eq.(C.1):

$$\min \sum_{i,t} GenerationCost_{i,t} + \sum_{t} TransmissionCharge_{t} + \sum_{j,t} VoLL_{j} * UnservedEnergy_{j,t} - \sum_{j,t} PriceofDumpEnergy_{j} * DumpEnergy_{j,t}$$

subject to several types of operational constraints, which are described further below.

The objective function has several main components defined as follows:

i indexes each of the generators, which are in specific utility zones (j) within the WECC region and could be thermal (natural gas, coal, nuclear, other) or renewable. There are several thousand generators included in WECC.

t indexes each hour in the optimization. The optimization is conducted for hourly intervals, at daily timesteps, one month at a time for a complete year.

j indexes each utility zone in the optimization. This analysis has 25 total zones in WECC, including eight in California.

$GenerationCost_{i,t}$ is the operating cost of generator i at hour t, including the fuel costs ($FC_{i,t}$), operations and maintenance costs ($O\&M_{i,t}$), start/shutdown costs of thermal units ($SC_{i,t}$) and the emissions costs of fossil units ($EC_{i,t}$).

Eq.(C.2): $$GenerationCost_{i,t} = FC_{i,t} + O\&M_{i,t} + SC_{i,t} + EC_{i,t}$$

Each component of $GenerationCost_{i,t}$ is defined as follows:

Eq.(C.3): $$FC_{i,t} = FuelPrice_{i} \times HeatValue_{i} \times HeatRate_{i} \times Generation_{i,t}$$

$FC_{i,t}$ is the fuel cost (applicable only for natural gas, coal, nuclear, and biomass generators).

$FuelPrice_{i}$ and $HeatValue_{i}$ are the price and heating value of the fuel used by generator i.

$HeatRate_i$ is the rate of electricity output given a unit of fuel input, and could be modeled as a function (linear or non-linear) depending on the generation level.

$Generation_{i,t}$ is the instantaneous electricity production from generator i in hour *t*. It is one of the main decision variables of the optimization.

Eq.(C.4): $O\&M_{i,t} = Generation_{i,t} * VO\&M_i$

$O\&M_{i,t}$ is the cost for operations and maintenance for each generator, based on its variable $VO\&M_i$ cost per unit of $Generation_{i,t}$.

Eq.(C.5): $SC_{i,t} = StartCost_i \times UnitsStarted_{i,t} + ShutdownCost_i \times UnitsShutdown_{i,t}$

$SC_{i,t}$ is the cost to start and shutdown a generator and is typically applicable only for thermal generators depending on the number of $UnitsStarted_{i,t}$ or $UnitsShutdown_{i,t}$ during the period, which are integer decision values that are part of the unit commitment decision.

Eq.(C.6): $EC_{i,t} = EmissionsPrice \times EmissionsRate_i \times Generation_{i,t}$

$EC_{i,t}$ is the emissions cost for CO_2 emissions based on each fossil plant's $EmissionsRate_i$ per MWh times its $Generation_{i,t}$ and the exogenously set $EmissionsPrice$ per unit of CO_2. The emissions cost is applied in this way directly to fossil generators within California, and added to the transmission $WheelingCharge_{jk}$ with an assumed $EmissionsRate$ to out-of-state generators which produce "unspecified" imports (not dedicated fossil or RE imports from a known origin).

Eq.(C.7): $TransmissionCharge_t = \sum_{j,k} WheelingCharge_{jk} \times LineFlow_{jk,t}$

$TransmissionCharge_t$ reflects a Transmission Access Charge [153] for net hourly flow on the transmission paths between each zone j and all the connected utility zones k, based on the $WheelingCharge_{jk}$ per MWh for each set of connected zones j and k and the hourly $LineFlow_{jk,t}$ decision variables in the reference flow direction.

$VoLL_j * UnservedEnergy_{j,t}$ is the cost of load shedding. The $VoLL_j$ sets a maximum price in each zone above which there is $UnservedEnergy_{j,t}$. If there is not enough generation to meet load, the electricity market price will reach the $VoLL$. $PriceofDumpEnergy_j$ is a price below which generators shutoff rather than $DumpEnergy_{j,t}$ or over-generate. If generation exceeds load, the electricity market price reaches the $PriceofDumpEnergy$, which is typically negative.

Generator unit commitment and dispatch is subject to the following selected constraints:

For each utility zone *j* there is an energy balance constraint such that total generation of all generators within the zone j (minus any over-generation $DumpEnergy_{j,t}$) plus total power $Inflows_{j,t}$ from connected zones minus total power $Outflows_{j,t}$ to connected zones must match the $Load_t$ in zone j, which is the total electricity demanded in hour t (minus any under-generation $UnservedEnergy_{j,t}$):

Eq.(C.8): $\sum_i Generation_{i,t} - DumpEnergy_{j,t} + Inflows_{j,t} - Outflows_{j,t} = Load_t - UnservedEnergy_{j,t}$

Where:

Eq.(C.9): $Outflows_{j,t} = \sum_k LineFlow_{jk,t}$

Eq.(C.10): $Inflows_{j,t} = \sum_k LineFlow_{kj,t}$

jk indicates power flow from zone j to zone k, and kj indicates power flowing from zone k to zone j.

Selected generator constraints:

Instantaneous energy from any generator must be less than or equal to its max capacity:

Eq.(C.11): $MaxCapacity_i \geq Generation_{i,t}$

All thermal generators must abide by their ramping constraints:

Eq.(C.12): $|Generation_{i,t} - Generation_{i,t-1}| \leq RampRate_i$

Hydropower generators have monthly energy budgets (based on the amount of water they can allocate that month) as well as minimum and maximum flows. PLEXOS first optimizes for the monthly budget through a monthly scheduling process. There are also particular constraints for other generator types or demand-side resources that are not described here, such as pumped storage, battery storage, and demand response. RE generation is included as a "fixed dispatch" with a $VO\&M_i$ set to -\$150/MWh such that generation is curtailed when the market price reaches that level. The method for modeling PEVs and their constraints are described in Section 2.3.2.

Overall, the optimization is a mixed integer program including a unit commitment decision (1 or 0 whether a generator is on or off) and an economic dispatch decision (how much a generator generates). The following are the main unit commitment related constraints:

Eq.(C.13): $UnitOn_{i,t} = UnitOn_{i,t-1} + UnitStarted_{i,t} - UnitShutdown_{i,t}$

There are also constraints specific to the unit commitment problem for minimum stable levels, minimum up time, and minimum down time:

Eq.(C.14): $Generation_{i,t} \geq UnitOn_{i,t} * MinStableLevel_i$

When a generator is committed ($UnitOn_{i,t} = 1$), it must operate at or above its $MinStableLevel_i$.

$MinUpTime_i$ is the minimum number of hours a generator unit must be on if committed (primarily applies to thermal generators).

$MinDownTime_i$ is the minimum number of hours a generator unit must be off if shut down (primarily applies to thermal generators).

Selected transmission and reserves constraints:

The optimization solves a linearized DC power flow which follows Kirchhoff's Laws, and flows between utility zones j and k must not exceed $LineLimits_{jk}$ and $LineLimits_{kj}$.

For California there are some additional import and export constraints that are included in this analysis, per CAISO's assumptions [156], [153]. For example, for the set of utility zones j which are part of the CAISO region (PG&E Valley, PG&E Bay, SCE, SDG&E), there is a 2000 MW limit on its total hourly total net exports:

Eq.(C.15): $\sum_j Outflows_{j,t} - \sum_j Inflows_{j,t} \leq 2000 \; \forall \, j \; \in$ $\{PG\&E\ Valley, PG\&E\ Bay, SCE, SDG\&E\}$

There are also hourly reserve requirements (load-following, regulation, spinning, and non-spinning) as estimated by CAISO that must be met for utility zones throughout the WECC. Constraints specify that certain generator types can provision different types of reserves, and the provision of reserves is determined as part of a co-optimization with the unit commitment and dispatch of generators to provide energy.

Solution algorithm:

We set the Mixed Integer Program (MIP) gap, the percentage difference between the best integer solution and the best bound (through the Branch and Bound algorithm) to be 0.01%, and set the optimization to stop solving for each day's optimum when it reaches this MIP gap or a time limit of 4000 seconds.

D. Supplementary Tables

Table D.1: Charging sessions by location included in ChargePoint calibration data.

Charging Session Location	Number of Charging Sessions
Education	17,824
Fleet	10,165
Government	4,239
Healthcare	10,295
Hospitality	6,340
Multifamily Commercial	12,579
Multifamily Home Service	1,256
Municipal	84,517
Parking	17,920
Parks and Rec	3,729
Retail	34,093
Single family residential	40,901
Workplace	607,239

To calibrate the charging profiles from BEAM, we used data obtained from ChargePoint, the largest charging provider in the U.S. The number of charging sessions by location type is described in the table. The data covered charging sessions from the last 2 months of 2016 and included 961 residential charging locations in addition to commercial charging locations.

Table D.2: Annual California generation by fuel source (GWh).

Fuel Category	Scenario	Unmanaged	Smart [G]	TOU
Biomass/Biogas	Low	5,285	5,285	5,285
Geothermal	Low	15,381	15,381	15,381
Hydro	Low	37,166	37,166	37,166
Natural Gas [A]	Low	96,363	96,372	96,520
Net Imports [B]	Low	48,526	48,384	48,412
Demand Response [C]	Low	22	15	16
Distributed Generation-Behind the Meter	Low	9,156	9,156	9,156
Other [D]	Low	1,586	1,586	1,586
Hydro Pumped Storage	Low	4,617	4,583	4,613
Battery Storage	Low	1,402	1,303	1,370
Uncurtailed Large PV [E]	Low	51,073	51,073	51,073
Uncurtailed Small PV [E]	Low	4,972	4,972	4,972
Uncurtailed Solar Thermal [E]	Low	2,286	2,286	2,286
Uncurtailed Wind [E]	Low	33,519	33,519	33,519
Solar and Wind Capacity Curtailed [E]	Low	-1,274	-1,155	-1,324
Pump Load/Storage Charging Load [F]	Low	-6,617	-6,448	-6,570
Biomass/Biogas	Mid	5,285	5,285	5,285
Geothermal	Mid	15,381	15,381	15,381
Hydro	Mid	37,166	37,166	37,166
Natural Gas [A]	Mid	99,003	98,876	99,467
Net Imports [B]	Mid	49,097	48,979	48,765
Demand Response [C]	Mid	33	15	16
Distributed Generation-Behind the Meter	Mid	9,156	9,156	9,156
Other [D]	Mid	1,588	1,586	1,586
Hydro Pumped Storage	Mid	4,628	4,591	4,713
Battery Storage	Mid	1,413	1,231	1,341
Uncurtailed Large PV [E]	Mid	51,073	51,073	51,073
Uncurtailed Small PV [E]	Mid	4,972	4,972	4,972
Uncurtailed Solar Thermal [E]	Mid	2,286	2,286	2,286
Uncurtailed Wind [E]	Mid	33,519	33,519	33,519
Solar and Wind Capacity Curtailed [E]	Mid	-1,191	-953	-1,294
Pump Load/Storage Charging Load [F]	Mid	-6,643	-6,368	-6,669
Biomass/Biogas	High	5,285	5,285	5,285
Geothermal	High	15,381	15,381	15,381
Hydro	High	37,166	37,166	37,166
Natural Gas [A]	High	99,957	99,722	100,495

Net Imports [B]	High	49,257	49,249	48,877
Demand Response [C]	High	38	15	18
Distributed Generation-Behind the Meter	High	9,156	9,156	9,156
Other [D]	High	1,588	1,586	1,586
Hydro Pumped Storage	High	4,625	4,636	4,716
Battery Storage	High	1,414	1,213	1,336
Uncurtailed Large PV [E]	High	51,073	51,073	51,073
Uncurtailed Small PV [E]	High	4,972	4,972	4,972
Uncurtailed Solar Thermal [E]	High	2,286	2,286	2,286
Uncurtailed Wind [E]	High	33,519	33,519	33,519
Solar and Wind Capacity Curtailed [E]	High	-1,164	-902	-1,287
Pump Load/Storage Charging Load [F]	High	-6,641	-6,409	-6,666
Biomass/Biogas	Reach	5,285	5,285	5,285
Geothermal	Reach	15,381	15,381	15,381
Hydro	Reach	37,166	37,166	37,166
Natural Gas [A]	Reach	105,754	105,195	107,392
Net Imports [B]	Reach	50,426	50,719	49,254
Demand Response [C]	Reach	105	16	24
Distributed Generation-Behind the Meter	Reach	9,156	9,156	9,156
Other [D]	Reach	1,595	1,587	1,586
Hydro Pumped Storage	Reach	4,643	4,762	5,089
Battery Storage	Reach	1,443	1,146	1,387
Uncurtailed Large PV [E]	Reach	51,073	51,073	51,073
Uncurtailed Small PV [E]	Reach	4,972	4,972	4,972
Uncurtailed Solar Thermal [E]	Reach	2,286	2,286	2,286
Uncurtailed Wind [E]	Reach	33,519	33,519	33,519
Solar and Wind Capacity Curtailed [E]	Reach	-1,013	-608	-1,230
Pump Load/Storage Charging Load [F]	Reach	-6,703	-6,503	-7,248

A. Natural Gas generation includes energy from both combined-cycle generators as well as combustion turbine (peaking) generators. B. Net Imports represent imports into California minus exports out of California. It is the sum of unspecified net imports and dedicated imports (including out-of-state renewable energy, and energy from other contracted resources). C. Demand response (DR) in this table only refers to traditional peak shedding DR, and does not include the smart charging PEV DR. The marginal cost of this DR can cost up to $1000/MWh. D. The Other category includes generation from fuel cells, oil, coal, petroleum coke, and waste heat. E. Generation from Large PV, Small PV, Solar Thermal, and Wind plants is listed in the table before curtailment (gross available energy), and their aggregated curtailment is listed separately. We report curtailment across these sources in aggregate because, absent any transmission constraint, if generators from more than one of these sources are generating at the same time, the model randomly chooses which one to curtail. F. Pump Load is the sum of the pumping load from pumped storage hydropower generators and the charging load of battery storage. We do not include PEV smart charging load shifting. G. The Smart column does not list the "charging" load or the "discharging" generation from the PLEXOS dispatch of the storage generator that represents PEV load shifting, and which together accounts for the differences in the total generation and charging load between Smart and the other charging cases.

Table D.3: California annual solar PV, solar thermal, and wind generation and curtailment.

	Generation, Net of Curtailment (GWh) [A]			Curtailment (GWh) [B]			% Curtailed of Available Energy [C]			Curtailment Reduction from Smart % of PEV load [D]	
PEV Scenario	Unman.	Smart	TOU	Unman.	Smart	TOU	Unman.	Smart	TOU	PEV Load (GWh)	%
Low	90,576	90,695	90,526	1,274	1,155	1,324	1.4%	1.3%	1.4%	2,744	4%
Mid	90,660	90,897	90,557	1,191	953	1,294	1.3%	1.0%	1.4%	6,062	4%
High	90,687	90,948	90,564	1,164	902	1,287	1.3%	1.0%	1.4%	7,215	4%
Reach	90,837	91,242	90,621	1,013	608	1,230	1.1%	0.7%	1.3%	14,417	3%

A. Generation, Net of Curtailment includes the generation of solar PV, solar thermal and wind plants located within California after accounting for curtailed energy. B. Curtailment is only of in-state California solar PV, solar thermal, and wind plants. C. % of Curtailed Available Energy is the curtailment divided by the available energy from in-state solar PV, solar thermal and wind (before curtailment). D. Curtailment Reduction from Smart % of PEV load is the avoided curtailment by smart charging relative to unmanaged charging in GWh, as a share of the smart PEV load in GWh for each PEV adoption level. This represents the percent of PEV load that is met by renewable energy that would have otherwise been curtailed without smart charging.

Chapter 2 Appendix

A. Data for calculation of end-use energy intensities

These tables provide more detailed data and assumptions for calculation of urban and agricultural end-use energy intensities, as described in Chapter 2 Sections 2.1.2.1 and 2.1.2.2.

Table 35. Hot Water Shares and Temperatures of Residential Indoor Water End-Uses.

Water End-Use	Avg. Daily Hot Water Use (gphd)	Avg. Daily Cold Water Use (gphd)	Indoor Total (gphd)	Share of residential indoor water use (%)	Hot water share of end-use (%)	Hot water share of total residential indoor use (%)	Outlet temperature ºF	Outlet temperature ºC
	[B]	[C]	[D] = [B] + [C]	[A]	[E] = [B] / [D]	[F] = [A] * [E]		
Faucets	15	12	27	20%	57%	11%	80	27
Toilets	0	33	33	25%	0%	0%	58 (same as CA average inlet temperature)	15 (same as CA average inlet temperature)
Showers + Bath	20	11	31	24%	65%	14%	103	40
Dishwashers	2	0	2	2%	100%	1%	139	59
Clothes washers	4	18	22	17%	20%	3%	78	26
Leaks	2	16	18	13%	12%	1%	91.4 (average of all other temperatures)	33 (average of all other temperatures)
Total	44.5	88.4	132.9	100%				

Table 36. Estimated Average CII Water End-Uses for each Process from Gleick et al., 2003.

End-Use Category in CII Process	Total Share of End-Use Category in CII Water	End-uses within Category	Share of End-Use Category (%)	Estimated Outlet temperature ºC
Restroom	16%	Showers	7%	41
		Faucets	4%	27
		Urinals	17%	15 (same as CA average inlet temperature)
		Toilets	72%	15 (same as CA average inlet temperature)
Cooling	15%	Cooling	100%	15 (same as CA average inlet temperature)
Kitchen	6%	Pre-Rinsing	14%	49
		Pot Cleaning	17%	41
		Dishwashing	24%	82
		Ice Making	19%	15 (same as CA average inlet temperature)
		Food Preparation	9%	27
		Other	17%	27
Process	17%	Hospitals	2%	27
		High-Tech	13%	49
		Dairy	1%	49
		Meat Processing	2%	49
		Fruits and Vegetables	12%	49

		Beverages	6%	49
		Laundries	0%	26
		Refining	8%	49
		Paper	5%	49
		Textiles	6%	27
		Metals	3%	49
		Unexplained	42%	27 (assumed same as faucet flow)
Laundry	2%	Laundry	100%	26
Other	9%	Other	100%	27 (assumed same as faucet flow)
Landscaping	35%	Turf	70%	15 (same as CA average inlet temperature)
		Other Vegetation	30%	15 (same as CA average inlet temperature)

Table 37. Energy Intensity and Acreage Share of Irrigation Technologies, by Crop Type.

Energy Intensities by Irrigation Technology (kWh/AF)					
	Flood/Gravity[a]	Standard sprinklers	Drip/micro irrigation (low volume)	Other[b]	
Energy intensity	15	284	206	168	
Acreage Share by Irrigation Technology, by Crop Type (%)					
Crop Type	Flood/Gravity (% acres)	Standard sprinkler (% acres)	Drip/micro irrigation (low volume) (% acres)	Other (% acres)	Weighted Average Energy Intensity of Irrigation by Crop (kWh/AF)
Almonds & Pistachios	13%	14%	71%	1%	190.8
Vineyards	20%	2%	75%	2%	168.3
Alfalfa	77%	18%	3%	3%	71.6
Grains	79%	13%	3%	5%	63.8
Other Deciduous	31%	27%	40%	1%	166.7
Corn	78%	1%	7%	14%	52.0
Other Vegetables	24%	41%	35%	0%	191.3
Subtropical Trees	6%	15%	76%	4%	205.3
Pasture	69%	26%	0%	6%	92.9
Other Field Crops	69%	15%	14%	2%	84.5
Cotton	73%	7%	15%	4%	70.6
Beans (dry)	67%	21%	12%	0%	95.6
Safflower	54%	44%	0%	1%	136.3
Sugar beets	86%	3%	12%	0%	45.0
Cucurbit	51%	11%	39%	0%	117.7
Onions & Garlic	19%	39%	42%	0%	200.1
Potatoes	2%	81%	17%	0%	265.4
Tomatoes (fresh)	44%	11%	45%	0%	131.3
Tomatoes (process)	33%	4%	63%	0%	145.6
Rice[3]	100%	0%	0%	0%	15.0

[a] "Flood" energy intensity averaged across energy intensity values for irrigation 'with 10ft lift' and 'without on-farm lift' from Burt et al. 2003. [b] "Other" averaged from flood, sprinklers, and micro irrigation. [3] Rice was assumed to be grown with flood irrigation.

B. Additional results

Table 38. Annual urban water demand by sector (AF) – Water Supplier Projections Scenario (High-case).

Demand Sector	2015	2020	2025	2030	2035	% Change 2015 - 2035	Change 2015 - 2035
Residential- Indoor	1,842,682	2,346,592	2,486,350	2,608,215	2,723,160	48%	880,479
Residential- Outdoor	1,448,045	1,890,643	2,015,650	2,127,849	2,237,118	54%	789,073
Commercial	682,261	843,602	883,116	914,963	948,601	39%	266,340
Industrial	216,065	262,013	268,868	271,775	284,293	32%	68,228
Institutional/ Governmental	162,886	160,091	170,735	180,749	183,696	13%	20,810
Landscape	315,900	345,831	357,317	371,382	388,154	23%	72,253
Losses	342,822	386,752	409,464	426,604	445,402	30%	102,580
Other	421,546	543,337	567,108	584,157	604,959	44%	183,413
Total	5,432,207	6,778,861	7,158,608	7,485,695	7,815,382	44%	2,383,175

Table 39. Annual urban water demand by sector (AF) – Declining Per-Capita Demand Scenario (Low-case).

Demand Sector	2015	2020	2025	2030	2035	% Change 2015 - 2035	Change 2015 - 2035
Residential- Indoor	259,046	244,166	238,641	229,233	217,352	-16%	(41,695)
Residential- Outdoor	871,975	738,400	693,517	648,263	605,025	-31%	(266,950)
Commercial	205	3,159	5,887	8,021	9,744	4649%	9,539
Industrial	27,888	27,011	26,417	24,213	22,190	-20%	(5,698)
Institutional/ Governmental	2,216	3,487	950	800	780	-65%	(1,436)
Landscape	2,063,977	1,813,410	1,695,524	1,606,838	1,529,814	-26%	(534,162)
Losses	365,972	316,784	300,253	283,314	267,376	-27%	(98,595)
Other	98,094	177,203	163,586	156,619	146,850	50%	48,756
Total	28,565	24,038	23,783	23,001	21,649	-24%	(6,916)

Table 40. Annual urban water supply by source (AF) – Water Supplier Projections Scenario (High-case).

Supply Source	2015	2020	2025	2030	2035	% Change 2015 - 2035	Change 2015 - 2035
Central Valley Project Deliveries	259,046	350,136	375,196	394,433	410,515	58%	151,469
Colorado River Deliveries	871,975	897,972	939,342	968,188	992,388	14%	120,413
Desalinated Water (Brackish)	205	4,952	8,981	12,829	16,653	8016%	16,447
Desalinated Water (Seawater)	27,888	33,442	36,344	36,707	36,957	33%	9,069
Exchanges	2,216	4,642	1,391	1,277	1,359	-39%	-857
Groundwater	2,063,977	2,329,289	2,413,785	2,518,323	2,635,035	28%	571,058
Local Imports	365,972	435,704	452,953	466,949	483,001	32%	117,029
Other	98,094	229,528	236,425	248,140	255,471	160%	157,376
Other Federal Deliveries	28,565	34,123	37,124	39,364	40,801	43%	12,235
Recycled Water- Non Potable	287,519	398,667	465,113	520,297	563,031	96%	275,512
Recycled Water- Potable	17,010	33,454	69,555	72,039	77,177	354%	60,168
State Water Project Deliveries	716,384	778,044	824,510	857,330	887,842	24%	171,458
Stormwater Use	72	2,466	5,713	9,406	15,163	20946%	15,091
Supply from Storage	14,329	30,372	30,701	31,022	31,464	120%	17,135
Surface water	648,056	1,198,034	1,242,554	1,286,390	1,344,440	107%	696,384
Transfers	30,898	18,037	18,921	22,999	24,086	-22%	-6,812
Total	5,432,207	6,778,861	7,158,608	7,485,695	7,815,382	+44%	2,383,175

Table 41. Annual urban water supply by source (AF) – Declining Per-Capita Demand Scenario (Low-case).

Supply Source	2015	2020	2025	2030	2035	% Change 2015 - 2035	Change 2015 - 2035
Central Valley Project Deliveries	259,046	244,166	238,641	229,233	217,352	-16%	-41,695
Colorado River Deliveries	871,975	738,400	693,517	648,263	605,025	-31%	-266,950
Desalinated Water (Brackish)	205	3,159	5,887	8,021	9,744	4649%	9,539
Desalinated Water (Seawater)	27,888	27,011	26,417	24,213	22,190	-20%	-5,698
Exchanges	2,216	3,487	950	800	780	-65%	-1,436
Groundwater	2,063,977	1,813,410	1,695,524	1,606,838	1,529,814	-26%	-534,162
Local Imports	365,972	316,784	300,253	283,314	267,376	-27%	-98,595
Other	98,094	177,203	163,586	156,619	146,850	50%	48,756
Other Federal Deliveries	28,565	24,038	23,783	23,001	21,649	-24%	-6,916
Recycled Water- Non Potable	287,519	312,988	329,668	335,391	330,625	15%	43,106
Recycled Water- Potable	17,010	26,715	50,090	46,972	45,833	169%	28,824
State Water Project Deliveries	716,384	621,357	591,260	556,892	524,000	-27%	-192,384
Stormwater Use	72	2,026	4,088	6,170	9,107	12541%	9,035
Supply from Storage	14,329	21,934	20,265	18,801	17,462	22%	3,133
Surface water	648,056	853,082	807,892	765,651	730,664	13%	82,609
Transfers	30,898	13,182	12,528	13,811	13,184	-57%	-17,714
Total	5,432,207	5,198,943	4,964,351	4,723,990	4,491,656	-17%	-940,550

Table 42. State annual electricity use related to urban water, by water cycle category (GWh) – Water Supplier Projections Scenario (High-case).

Water Cycle Category	2015	2020	2025	2030	2035	2015 - 2035 % Change	2015 - 2035 Change
Supply Extraction or Generation	1,277	1,501	1,628	1,711	1,801	41%	524
Supply Conveyance	4,321	4,674	4,927	5,103	5,259	22%	938
Supply Treatment	977	1,253	1,330	1,383	1,437	47%	460
Demand Distribution	2,483	3,059	3,194	3,299	3,409	37%	927
Demand End-Use	12,614	15,812	16,699	17,459	18,196	44%	5,582
Demand Wastewater Collection	323	406	428	446	465	44%	141
Demand Wastewater Treatment	2,053	2,584	2,723	2,840	2,957	44%	904

Table 43. State annual electricity use related to urban water, by water cycle category (GWh) – Declining Per-Capita Demand Scenario (Low-case).

Water Cycle Category	2015	2020	2025	2030	2035	2015 - 2035 % Change	2015 - 2035 Change
Supply Extraction or Generation	1,277	1,183	1,157	1,104	1,058	-17%	-219
Supply Conveyance	4,321	3,756	3,556	3,337	3,127	-28%	-1,194

Supply Treatment	977	959	921	872	825	-16%	-151
Demand Distribution	2,483	2,346	2,217	2,087	1,964	-21%	-518
Demand End-Use	12,614	12,183	11,631	11,067	10,504	-17%	-2,109
Demand Wastewater Collection	323	312	297	282	267	-17%	-56
Demand Wastewater Treatment	2,053	1,979	1,886	1,791	1,698	-17%	-355

Chapter 3 Appendix

A. California literature on climate change impacts on water and energy used in case study

Table 44 summarizes the key aspects of each study reviewed for framework linkages in California, including geographic coverage, climate assumptions (GCM and emissions scenarios used), time horizon for study, and the annual percentage change result. The maximum and minimum annual percent changes across all the studies for each linkage are presented in the table by mid-century and end-century time horizons.

Table 44: Summary of literature reviewed on climate change impacts on California energy and water systems.

Framework Linkage	Paper	Geographic coverage	Climate data (GCM, emissions scenario)	Time Horizon	Annual % Δ
L_1, Raw water availability	1. Herman et al., 2018. [318]	Major water supply storage and conveyance facilities in CA,	1. RCP 4.5 2. RCP 8.5; 10 GCMs and additional sensitivities	2070-2100	1. -6% to +35% 2. -7% to +46%
	2. Tanaka et al., 2006. [260]	Major water supply storage and conveyance facilities in CA	1. PCM B06.06, dry warming 2. HCM2 run 1, wet warming	A. 2050-2079 B. 2080-2099	A. 1-2. -13% to +7% B. 1-2. -25% to +12%
	3. Zhu, T., Jenkins, M.W., Lund, J.R., 2005. [319]	Inflows to CA's entire water system	1. HadCM, wet warming 2. PCM, dry warming Additional sensitivities of temperature and precipitation changes	A. 2025 B. 2065 C. 2090	A. 1-2. -6% to +11% B. 1-2. -13% to +7% C. 1-2. -25% to +12%
	Max and min of all papers	Across all CA	Across all GCMs and emissions scenarios	Mid-century	-13% to +7%
	Max and min of all papers	Across all CA	Across all GCMs and emissions scenarios	End-century	-25% to +46%
L_2, Irrigation water demand	1. Mehta, V. et. al, 2013. [300]	Yolo County, Sacramento Valley, CA	1. B1 2. A2 with GFDL (warm-dry)	A. Mid-century B. until 2099	A. 1-2. +21% to +24% B. 1-2. +27% to +31%
	2. Joyce et al, 2011. [262]	Sacramento Valley, CA San Joaquin Valley, CA Tulare Lake, CA	1. B1 2. A2 with 6 GCMs (CM3, CM2.1, MIROC 3.2, ECHAM5, CCSM3.0, PCM1)	A. Mid-century B. End-century	Sacramento Valley: A. 1-2. +6% to +6% B. 1-2. +6% to +9% San Joaquin Valley: A. 1-2. +3% to +3% B. 1-2. +4% to +6% Tulare Lake: A. 1-2. +3% to +3% B. 1-2. +4% to +6%
	3. Joyce, et al, 2009. [263]	Sacramento Valley, CA	1. B1 2. A2 with 6 GCMs (CM3,	A. 2035-2064 B. 2065-2099	Sacramento Valley:

		San Joaquin Valley, CA Tulare Lake, CA	CM2.1, MIROC 3.2, ECHAM5, CCSM3.0, PCM1)		A 1-2. +1% to +6% B 1-2. +3% to +12% San Joaquin Valley: A 1-2. +1% to +5% B 1-2. +3% to +7% Tulare Lake: A 1-2. +1% to +5% B 1-2. +3% to +7%
	4. Hopmans and Maurer, 2008. [321]	San Joaquin Valley, CA	1. B1 2. A2 3. A1fi with 2 GCMs (HadCM3 and PCM)	2100	~0%
	5. Purkey et al., 2008. [322]	Sacramento Valley, CA	1. B1 2. A2 with 2 GCMs (GFDL and PCM)	2070-2099	1-2 -2% to +9%
	Max and min of all papers	Across all studies Sac. Valley SJ Valley Tulare Lake	Across all GCMs and emissions scenarios	Mid-century	0% to +24% +1% to +24% 0% to +5% +1% to +5%
	Max and min of all papers	Across all studies Sac. Valley SJ Valley Tulare Lake	Across all GCMs and emissions scenarios	End-century	-2% to +31% -2% to +31% 0% to +7% +3% to +7%
L_3, Transmission losses	1. Sathaye et al., 2013. [271]	All California, using illustrative typical 230 kV transmission line	1. B1 2. A2 with 3 GCMs (GFDL, PCM1, CNRM)	2070-2099	0.14% change during summer
	2. Sathaye et al., 2012. [328]	All California, using illustrative typical 230 kV transmission line	1. B1 2. A2 with 3 GCMs (GFDL, PCM1, CNRM)	2070-2099	0.14% change during summer
	Max and min of all papers	Across all CA	Across all GCMs and emissions scenarios	End-century	0% to +0.14%
L_4, Air-conditioning demand (annual)	1. Auffhammer, M., 2018. [275]	80% of CA population	1. RCP 4.5 2. RCP 8.5	A. 2020-2039 B. 2040-2059 C. 2060-2079 D. 2080-2099	A. 1-2. +1% to +1% B.1-2. +3% to +4% C.1-2. +4% to +9% D.1-2. +5% to +15%
	2. Sullivan, P. et al., 2015. [399]	All CA (and rest of US)	RCP 4.5	2050	+0.5% to +2%

	3. Franco, G., & Sanstad, A. H., 2008. [8]	CAISO (most of CA)	1. B1 2. A2 3. A1Fi	A. 2005-2034 B. 2035-2064 C. 2070-2099	A.1-3. +1% to +3% B.1-3. +2% to +8% C.1-3. +3% to +18%
	Max and min of all papers	Across all CA	Across all GCMs and emissions scenarios	Mid-century	+1% to +9%
	Max and min of all papers	Across all CA	Across all GCMs and emissions scenarios	End- century	+3% to +18%
L_4, Air-conditioning demand (summer peak)	1. Sathaye et al., 2013. [271]	All California	1. B1 2. A2 with 3 GCMs (GFDL, PCM1, CNRM)	2070-2099	August peak loads: 1-2. +10% to +20%
	2. Franco, G., & Sanstad, A. H., 2008. [8]	CAISO (most of CA)	1. B1 2. A2 3. A1Fi	A. 2005-2034 B. 2035-2064 C. 2070-2099	Peak load: A. 1-3 +1% to +5% B. 1-3. +2% to +11% C.1-3. +4% to +20%
	3. Miller et al., 2008. [323]	All CA, and specific values for major urban areas	1. B1 2. A2 3. A1Fi with 3 GCMs (PCM, GFDL, HadCM3)	A. 2035-2064 B. 2070-2099	Residential peak load: A. 1-3. +3% to +10% B. 1-3. +4% to 19%
	Max and min of all papers	Across all CA	Across all GCMs and emissions scenarios	Mid-century	Peak demand change: +2% to +11%
	Max and min of all papers	Across all CA	Across all GCMs and emissions scenarios	End-century	Peak demand change: +4% to +20%
L_5, Hydropower generation	1. Tarroja et al., 2016. [342]	All CA (13 representative reservoirs)	1. RCP 4.5 2. RCP 8.5	2050	1. -3% 2. +1%
	2. Boehlert et al., 2016. [400]	All CA (part of 500 largest facilities across all US)	1. 3.7 W/m2 by 2100 2. 4.5 W/m2 by 2100 3. BAU, similar to RCP 8.5	A. 2025 B. 2050	A.1-3. 0% to +3% B.1-3. 0% to +3%
	3. Madani et al., 2014. [284]	137 High-elevation plants in CA Sierra Nevada	1. Dry Warming - GFDL-A2 2. Wet Warming - PCM-A2	2070-2099	1-2. -20% to +6%
	4. Vicuña et al., 2011. [285]	2 High-elevation systems: Upper American River system and Big Creek System	1. B1 2. A2 with 6 GCMs (CNRMCM3, GFDL CM21, NCAR PCM1, MIROC32MED, MPIECHAM5, NCARCCSM2)	A. 2011 – 2040 B. 2041 - 2070 C. 2071 - 2011	A. -2% to -1% B. -8% to -8% C. -12%. to -10%
	5. Mehta et al. 2011. [324]	36 hydropower plants in Cosumnes, American, Bear and Yuba watersheds (high-elevation)	1. 2ºC increase 2. 4ºC increase 3. 6ºC increase	2100	1. -5% 2. -15% 3. -20%

	6. Madani and Lund, 2010. [283]	137 High-elevation plants in CA Sierra Nevada	1. Dry-warm - GFDL-A2 2. Wet - PCM-A2 3. Warming only - A2 (same annual runoff but different seasonal timing of flows at each elevation)	2070-2099	1. -20% 2. +6% 3. -1%
	7. Vicuña et al., 2008. [325]	11 reservoirs in Sacramento Municipal Utilty District (Upper American River Basin)	1. B1 2. A2 with 2 GCMs (PCM, GFDL)	2070-2099	1. -10% to +10% 2. -12% to +14%
	8. Medellín-Azuara et al., 2008. [326]	Hydropower at major reservoirs in CA	Dry-warm - GFDL-A2	2085	-27%
	Max and min of all papers	Across all hydropower Low elev. (< 300 m), large rim reservoirs High elev. (> 300 m), small reservoirs	Across all GCMs and emissions scenarios	Mid-century	-8% to +3% -3% to +3% -8%
	Max and min of all papers	Across all hydropower Low elev. (< 300 m), large rim reservoirs High elev. (> 300 m), small reservoirs	Across all GCMs and emissions scenarios	End-century	-27% to +14% -27% -20% to +14%

B. Details on California case study methodology

This Appendix section provides more detail on the case study data sources and calculations of absolute water and energy impacts and energy intensities of water climate adaptations.

a. Climate impacts on water and electricity balances

To compare supply and demand changes in common units, for each linkage, we apply the climate perturbation percent changes to corresponding historical electricity and water stocks and approximate the range of possible absolute changes.

Table 29 summarizes the calculations to estimate the range of California's climate-driven changes in supply, demand, and system balance for water and electricity, respectively. Percentage changes from our review for change in raw water availability ($\boldsymbol{L_1}$) were applied to the historical average total applied water for the urban and agricultural irrigation users (53 Billion m^3) from the California Department of Water Resource (DWR) 2002 – 2015 state total water balance data. [222] For irrigation water demand ($\boldsymbol{L_2}$), in our review we primarily find percentage changes for the three major agricultural sub-regions of California (Sacramento Valley, San Joaquin Valley, Tulare Lake) and apply these to the 2002 – 2015 average applied agricultural water by region (10 Billion m^3, 9 Billion m^3, 14 Billion m^3 respectively) [222]. For the remaining agricultural water in California we apply the overall minimum and maximum percentage changes across all the regional estimates. We only estimate changes in agricultural irrigation water (80% of total water demand) rather than in urban irrigation water. Finally, we aggregate climate-driven changes in supply ($\boldsymbol{L_1}$) and in demand ($\boldsymbol{L_2}$) to calculate the overall bounding “worst-case” and “best-case” range of climate impacts on annual state water balances. The maximum demand changes ($\boldsymbol{L_2}$) are subtracted from the minimum supply changes ($\boldsymbol{L_1}$), and the minimum demand changes ($\boldsymbol{L_2}$) are subtracted from the maximum supply changes ($\boldsymbol{L_1}$); a positive resulting balance change indicates surplus, and a negative balance change indicates shortage.

To estimate the added electricity supply needed to make up for transmission line resistive losses ($\boldsymbol{L_3}$), we apply the same loss rate year-round to the total annual average 2001-2018 California electricity consumption level (278 TWh) [315]. To calculate changes in air-conditioning electricity demand ($\boldsymbol{L_4}$), we apply the percent changes of electricity demand growth to the sum of California residential and commercial building electricity consumption (190 TWh) averaged across 2001-2018 [315]. The range of percentage changes include estimates for both intensive and extensive changes in air conditioning use. The hydropower studies we reviewed for California largely focused on either high or low elevation hydropower, thus we first categorize all the hydropower generators in California as high elevation if situated at 300m or above, and low elevation if below 300m (the threshold used by Madani et al [284]). We then apply percentage changes to 2002-2018 average total high (20 TWh total) and low elevation (11 TWh total) hydropower generation [316] separately ($\boldsymbol{L_5}$). We aggregate the maximum and minimum climate-driven changes in supply ($\boldsymbol{L_3}$ and $\boldsymbol{L_5}$) and demand ($\boldsymbol{L_4}$) impacts for the electricity system to calculate the aggregate worst-case and best-case statewide imbalances. The maximum demand changes ($\boldsymbol{L_4}$) are subtracted from the minimum supply changes ($\boldsymbol{L_3}$ + $\boldsymbol{L_5}$), and the minimum demand changes ($\boldsymbol{L_4}$) are subtracted from the maximum supply changes ($\boldsymbol{L_3}$ + $\boldsymbol{L_5}$); a positive resulting balance change indicates surplus, and a negative balance change indicates shortage.

b. Climate adaptations for water shortages and their energy tradeoffs

In the final step, we estimate the energy balance impact ($EB_{s,j}$) related to water sector adaptations ($\boldsymbol{L_7}$ and $\boldsymbol{L_9}$) based on a review of energy intensities for different adaptation strategies and the maximum worst-case water shortage volume calculated from Section 3.1. The energy intensities EI_i of the adaptation measures are calculated by summing the statewide average energy intensities of all the relevant water cycle processes (Table 45) required to implement the measures, which are described below.

The energy intensities EI_i of both demand-side conservation adaptations (from residential and agricultural sectors) are negative because of avoided energy across the entire water supply chain. We calculate the energy intensity of residential water conservation by summing statewide average energy intensities of conventional water treatment (0.17 kWh/m^3), urban distribution (0.27 kWh/m^3) and wastewater treatment (0.69 kWh/m^3) processes [55], [61], [65], [73], [76], [207] plus avoided hot water end-uses (3.17 kWh/m^3). We calculate the 3.16 kWh/m^3 energy intensity of water heating assuming: 50% indoor water use out of total residential water [222], 25%[57] electric share of water heaters [205], an average electric water heater efficiency [74] of 55 kWh/m^3, and a weighted average hot water share of 47% across residential indoor water uses (estimating that hot water comprises 50% of faucet and 100% of clothes washer, dishwasher, and

[57] Because of uncertainties in how much decarbonization policies may shift water heating from gas to electric in California, we use the current 25% share.

shower water, which make up 19%, 14%, 1%, and 22% of indoor water use respectively).[204] For the energy intensity of agricultural water conservation, we sum the avoided energy from irrigation (0.09 kWh/m^3) and agricultural water distribution (0.21 kWh/m^3) [65, p. 2]. Consistent with literature [76], we assume agricultural water foregoes drinking water and wastewater treatment. We estimate the weighted average energy for irrigation based on surveys that indicate typical irrigation technology by crop (43% of acres with gravity/flood, 15% with standard sprinklers, 38% with drip/micro-irrigation, and 3% with other),[215] the average share of irrigation water for each crop across California [216], and the average energy intensity for each irrigation technology (0 kWh/m^3 for gravity/flood, 0.23 kWh/m^3 for standard sprinklers, 0.17 kWh/m^3 for drip/micro-irrigation) [199].

Supply-side strategies have positive EI_i energy intensity values from treatment and/or conveyance required. For groundwater recharge, we average the energy intensity of groundwater pumping statewide to estimate the energy for extraction from aquifer storage (0.38 kWh/m^3) [55], [58], [64], [65], [73], [74], [199], [210], [302]. For water recycling, we average the energy for incremental treatment beyond tertiary wastewater treatment for potable quality across plant size and technology (0.95 kWh/m^3) [58], [64], [65], [207]. Because we assume indirect potable reuse (based on current state regulations) [207], we add energy for distributing the recycled water from the wastewater treatment plant to surface or groundwater temporary storage (0.27 kWh/m^3) [55], [61], [73], [207]. For desalination, we assume reverse osmosis technology, and estimate an average energy intensity (2.55 kWh/m^3) across plant size, salinity of feedstock (seawater and brackish water), and flow rates to capture the range of facilities [55], [58], [64], [65], [67], [73], [76], [199], [207]. We add the energy to pump the desalinated water back to the water distribution system (0.29 kWh/m^3) [73], [207].

Table 45: California Water Cycle Average Energy Intensities. Energy intensities are averaged across all the hydrologic regions in California from these sources: [55], [58], [61], [64], [65], [73], [74], [76], [199], [207], [210], [215], [317].

Water Cycle Process	Average Energy Intensity [kWh/m^3]	2002 – 2015 Average Share of CA Supply
Water Supply and Conveyance		
Local Water		
Local Surface Water Deliveries	0.09	40%
Groundwater Pumping	0.38	22%
Recycled Water (treatment + deliveries)	1.22	0.3%
Desalination (treatment + deliveries)	2.84	0.0%
Reuse	0.09	18%
Imported Water		
Local Imported Deliveries	0.37	2%
Colorado River Deliveries	1.63	6%
Central Valley Project Deliveries	0.31	8%
State Water Project Deliveries	1.55	3%
Volume-Weighted Average EI of Supply/Conveyance	0.32	100%
Drinking Water Treatment		
Urban Water Treatment	0.17	
Water Distribution		
Urban Water Distribution	0.27	
Agriculture Water Distribution	0.21	
Water End-Use		
Urban Residential Water Heating	3.16	
Agriculture Irrigation	0.09	
Wastewater Treatment		
Urban Wastewater Treatment	0.69	

The total net energy impact of a water adaptation i is contingent on its EI_i energy intensity (as calculated above) minus the energy intensity of the water source j replaced in the system EI_j. The literature we review here is too course to indicate where and how much of each water source may be substituted because of climate change, nor precisely where adaptation strategies should be implemented. Thus, for each adaptation measure i we test three sensitivities of EI_j that each assume all substituted water j comes from the same source—local surface water with an energy intensity of 0.09 kWh/m^3, California supply-weighted average energy intensity of 0.32 kWh/m^3, and the average energy intensity across delivery points of the State Water Project conveyance system of 1.55 kWh/m^3. These energy intensities EI_j are subtracted from the energy intensity of the adaptation measure EI_i to calculate a net energy intensity $NEI_{i,j}$.

We assess both corner case scenarios and more realistic adaptation portfolio scenarios that combine multiple demand-side and supply-side measures. In the five corner cases we assume than an individual adaptation measure addresses 100% of the worst-case annual water shortage volume WSV_i, whereas in the more realistic cases we evaluate four portfolios that fully address the maximum WSV_i with different combinations of individual strategies. In Portfolio 1 we cap the strategies at their maximum potential limits (urban indoor plus outdoor water conservation at 1.8 Bm^3/year [204] and water recycling at 6.7 Bm^3/year [75], [76]) and assume the remainder of the water imbalance to be equally satisfied by groundwater recharge, agricultural conservation, and desalination. For Portfolios 2 – 4 we also cap conservation and recycling at their limits and assume desalination to fill the remainder. For each combination of adaptation scenario s and substituted water source j, we calculate the overall energy balance impact, $EB_{s,j}$, as the sum-product of the $NEI_{i,j}$ of included adaptation measures and associated water volumes WSV_i from Table 31.

Chapter 4 Appendix

A. SWITCH Model, Data, and Assumptions

To optimize long-term energy system buildout under climate scenarios and given water sector adaptations, we use the capacity expansion model SWITCH. SWITCH is an open-source model with high spatial and temporal resolution designed to plan a system with high levels of renewable resources [377], and has been used to evaluate system expansion in several case studies of the Western U.S. [88], [304], [378]. We build on the SWITCH 2.0 (Python) version from a recent study [377], and use an academic license of the Gurobi solver [379], to evaluate the optimal generation and transmission capacity expansion decisions for the Western Interconnect or Western Electricity Coordinating Council (WECC) region out to 2050. SWITCH makes investment and operations decisions for four time periods and a sample of hours per period between 2020 and 2050. The objective function minimizes the expected value of the total net present value of generation and transmission operations and investment. We describe the objective function and main constraints of the optimization model [377], as well as the input data and assumptions used for the analysis below. A detailed description and full mathematical formulation of the SWITCH model is described in a prior paper and accompanying Supplemental Materials [377].

a. Objective function

In this analysis we use a deterministic linear formulation of SWITCH to optimize the investment and operations of generation and transmission capacity. The objective function is the total net present value (NPV) cost of the power system (investment and operations). The key decision variables include investment in generation and transmission capacity (BuildGen and Build Tx, in MW of capacity built of each generator and transmission line, respectively for each investment period among the set of available candidate generators and transmission lines), and dispatch (DispatchGen and DispatchTx, hourly generation and transmission line flows for each generator and transmission line online in that period). In addition, the model decides the energy capacity for building battery storage (BuildStorageEnergy in MWh), and when and how much batteries charge and discharge (ChargeStorage). Transmission flows between load zones are represented as a simple “transport” model, where flows (a decision variable) between zones are constrained by line limits which are an aggregation of the limits of individual lines between regions. This simplification maintains a linear model, rather than including a representation of non-linear and computationally expensive AC power-flow.

$$\min \sum_{p \in P} d_p \left\{ \sum_{c^f \in C^{fixed}} c_p^f + \sum_{t \in T_p} w_t^{year} \sum_{c^v \in C^{var}} c_t^v \right\}$$

Where:

$d_p =$ discounting factor, which first converts annual payments into a lump sum equivalent at the beginning of an investment period, and then converts all costs into net present value (NPV) terms. In this analysis we use an interest rate *r* of 5%, reflecting the general decrease in US interest rates in recent years, and all costs have a *baseyear* of 2018. The formula for the factor is below, where y_p is the number of years in each period (10 years in this analysis), and st_p is the start year of each period.

$$\mathrm{d_p} = \frac{1-(1+\mathrm{r})^{-\mathrm{y_p}}}{\mathrm{r}} * (1+\mathrm{r})^{-(\mathrm{st_p}-\mathrm{baseyear})}$$

C_{fixed} = is the set of fixed costs components indexed for each period c_p^f, which include capital costs (overnight cost to construct generation, transmission, and storage capacity) and fixed operations and maintenance (O&M) for online generators. These costs are in $/MW-year.

w_t^{year} is the weight in the period of each sampled time point *t*.

$C_{variable}$ is the set of variable costs indexed for each time point c_t^v, including fuel costs for generators and variable O&M costs, in $/MWh (non-discounted real dollars).

The optimization is subject to a number of constraints, including the main ones listed below.

b. Investment-related constraints

Capacity investments in generation, for each generator and period $K_{g,p}^G$, cannot exceed cumulative limits on available capacity $\bar{k}_g^G$ dfor that particular generator:

$$K_{g,p}^G \leq \bar{k}_g^G$$

Additional constraints track the level of existing capacity, cumulative installed capacity over subsequent periods, and retired capacity. Fixed costs for generator capacity (overnight, connection, and fixed O&M costs) are calculated based on $K_{g,p}^G$.

Costs for transmission capacity built are calculated based on the $K_{l,p}^L$, the cumulative transfer capacity of each line, capital costs per MW per km, length of each line, and cost multipliers that account for varying terrain and economic costs along each transmission corridor.

c. Operations-related constraints

In each load zone, power withdrawals $p_{z,t}^w$ (from electricity demand, charging storage, and exports to other load zones) must equal power injections $p_{z,t}^i$ (from generation, discharging storage, and imports from other zones) for each time point:

$$\min \sum_{\mathrm{p} \in \mathrm{P^{inject}}} \mathrm{p_{z,t}^i} = \sum_{\mathrm{p} \in \mathrm{P^{withdraw}}} \mathrm{p_{z,t}^w}$$

At each time point, the dispatch of generation $P_{g,t}$ cannot exceed available capacity $K_{g,t,p}$ given forced outage rates η_g, and transmission flows $F_{l,t}$ cannot exceed available line limits given available transmission capacity in that period and transmission efficiency derating factors ($\eta_l * K_{l,p}$):

$$0 \leq \mathrm{P_{g,t}} \leq \eta_\mathrm{g} \mathrm{K}_{g,tp}$$

$$0 \leq \mathrm{F_{l,t}} \leq \eta_\mathrm{l} \mathrm{K_{l,p}}$$

There are special dispatch constraints specific to different generator types:

1) Solar PV and Wind: hourly generation cannot exceed the exogenously determined hourly capacity factor

$$0 \leq \mathrm{P_{g,t}} \leq \eta_\mathrm{g,t} \eta_\mathrm{g} \mathrm{K_{g,t,p}}$$

2) Hydropower: average generation across all the time points of a day must match historical average generation $p_{g,s}^{h,avg}$ of that month, and exceed the minimum generation $p_{g,s}^{h,min}$ of that month (in our analysis we sample 4 timepoints for each day-long timeseries):

$$\mathrm{P_{g,t}} \geq \mathrm{p_{g,s}^{h,min}}$$

$$\frac{1}{\mathrm{num_s}} * \sum_{\mathrm{t \in T_s}} \mathrm{P_{g,t}} = \mathrm{p_{g,s}^{h,avg}}$$

3) Battery storage: charging $C_{g,t}$ and the state of charge $Z_{g,t}$ are limited by installed capacity (in MW as with other generators and in MWh, $K_{g,p}^{S}$ and charging rates relative to maximum power output rate r_g^{max}, and batteries must balance charging and discharging over a given time period, subject to round-trip charging efficiency η_g. In this analysis we assume the battery must be balanced over the course of a day, the round-trip efficiency is 75%, and the charging rate is equal to the maximum power output ($r_g^{max} = 1$).

$$0 \leq \mathrm{C_{g,t}} \leq \mathrm{r_g^{max}} * \mathrm{P_{g,t}}$$

$$0 \leq \mathrm{Z_{g,t}} \leq \mathrm{K_{g,p}^{S}}$$

$$0 \leq \mathrm{Z_{g,t}} = \mathrm{Z_{g,t-1}} + \left(\eta_{\mathrm{g}}\mathrm{C_{g,t}} - \mathrm{P_{g,t}}\right)\delta_{\mathrm{t}}^{\mathrm{T}}$$

To maintain grid reliability, SWITCH includes a planning reserve requirement. During the peak load hour of the year, the total available capacity must meet or exceed a percentage k_π (defaults to 15%) above peak load $\mathrm{l_{z,t}}$ in a given "reserves zone." To contribute towards this reserve requirement $r_{\pi,t}^{r}$, capacity $r_{\pi,t}^{c}$ is credited to generators based on their installed capacity, and to battery storage based on the expected discharging output available at the peak hour in the reserves zone. Imports across transmission lines into the reserves zone are credited similarly to storage, based on the expected flows during the peak hour. We define reserves zones as the set of load zones for the same utility (i.e. all the load zones comprising the SCE service territory).

$$\mathrm{r_{\pi,t}^{r}} = (1 + \mathrm{k_\pi}) * \mathrm{l_{z,t}}$$

$$\sum_{\mathrm{r^c \in R^{cap}}} \mathrm{r_{\pi,t}^{c}} \geq \sum_{\mathrm{r^r \in R^{req}}} \mathrm{r_{\pi,t}^{r}}$$

d. Policy-related constraints

SWITCH includes constraints to represent state Renewable Portfolio Standard (RPS) requirements for each period, whereby a mandated percentage (rps_p) of annual load must be met with generation from renewable sources over the year $P_{g,t}w_t^{period}$(from non-fuel sources and renewable fuels). All generation from renewable sources is summed and must equal or equal or exceed the RPS requirement times the annual load for each zone:

$$\sum_{\mathrm{g \in G_r}} \sum_{\mathrm{t \in T_{g,p}}} \mathrm{P_{g,t}w_t^{period}} \geq \sum_{\mathrm{t \in T_p}} \sum_{\mathrm{z \in Z}} \mathrm{l_{z,t}\, w_t^{period}}$$

Annual carbon emissions ($AnnualEmissions_p$) calculated based on the dispatch, fuel use rate in MMBtu/h and emissions intensity of fuel in tCO_2/MMBtu ξ_f, must not exceed the specified carbon cap in tons of CO_2/year for that investment period (cap_p). A carbon cap is specified for California and for all the WECC region.:

$$\text{AnnualEmissions}_p = \sum_{g\in G^F} \sum_{f\in \varepsilon_g^F} \sum_{t\in T_g \cap T_p} \delta_t R_{g,t,f} \, x \, (\xi_f)$$

e. Geographic and temporal resolution

The WECC study area of this analysis is divided up into 50 “load zone” regions (Figure 31), covering all of parts of Washington, Oregon, California, Arizona, Nevada, New Mexico, Utah, Idaho, Montana, Wyoming, Colorado, and Texas in the US; British Columbia and Alberta in Canada; and the northern portion of Baja California in Mexico. Load zone boundaries were used from prior SWITCH-WECC analyses [304], [378], which constructed the regions based on state lines, North American Electric Reliability Corporation (NERC) control areas, utility service territory boundaries, and high-population metropolitan areas. Some utility service territories were divided into multiple zones if there was a large amount of high-voltage transmission connectivity existing within the same service territory (i.e. CA PGE BAY, CA PGE CEN, CA PGE S, CA PGE N for PG&E). The boundaries were also constructed to represent zones that are unlikely to have transmission congestion within the zone (since only transmission between zones is included), and between which there has historically been transmission congestion (reflecting pathways where additional transmission may be needed).

The temporal resolution of the analysis includes four investment periods, each of a decadal duration: 2020 (covering 2016 – 2025), 2030 (covering 2026 - 2035), 2040 (covering 2036 – 2045), and 2050 (covering 2046 – 2055). The duration of these investment periods reflect the typical planning horizon of a utility, and the length of time often needed to plan and build generation and transmission infrastructure. Because of computation limitations on simulating both investment and detailed hourly operations, a sample of 72 hours is selected to represent the typical grid dispatch for each investment period. For one year per period, for 2 days of each of 12 months, a 4-hour duration time slice is sampled every four hours (6 times per day). The hours are sampled from the peak and median load day of each month. In total, 576 hours are simulated (4 periods x 1 year/period x 12 months/year x 2 days/month x 6 hours/day = 576 hours). The SWITCH dispatch results (i.e. costs, generation, transmission flows, emissions, etc.) related to each of these sampled hours is multiplied with an hourly weight, the share of all hours in the year that is represented by that hour, to calculate the typical annual value (i.e. annual operating cost, generation, transmission flow, emissions, etc.). The hours sampled from the peak day of each month have a “day” weight of 1, while the hours sampled from the median day have a “day” weight of the number of days of the month minus 1. This sampling strategy is adopted from prior SWITCH WECC studies which conducted a “dispatch verification” analysis that tested the sensitivity of results compared to hourly simulations (where 8760 hours per year were simulated), finding that the buildout of the grid was still robust and did not violate constraints on peak and average days [378].

f. Generators

i. Existing generators

As inputs into SWITCH, we include the list of individual generators that are existing and/or are planned for the WECC region. For the US portion of WECC, we extract the list of generators and their characteristics (such as location, fuel source, generating technology, online year, and retirement year if any) from the Energy Information Administration (EIA) Form 860 [363]. At the time of the data collection (in late 2019/early 2020), the latest complete year of data was the 2018 EIA Form 860. We include generators from this form that are flagged with any of these statuses: operating, standby/backup, new unit under construction, cold standby, out of service but will be returned to service, construction complete but not yet in commercial operation, not under construction but site prep underway, and under construction. Generators are assigned to load zones based on their latitude and longitude.

The EIA Form 860 also includes planned retirement years for generators, if known. Generators are not allowed to operate beyond their expected lifetime, and therefore planned retirement years are used to calculate the lifetime of the plant to be included in the SWITCH runs. Monthly data was used from more recent Form 860 data to confirm that there were no additional planned retirements. For generators with no known retirement years, we assign a maximum lifetime based on the generating technology (Table 47).

For thermal generators, we join the list of generators from Form 860 with the monthly generation and fuel use from the EIA Form 923, for the available years 2004 – 2018 [364]. We use the historical monthly generation and fuel use from Form 923 to calculate the second-best (or second-lowest) heat rate (MMBtu/MWh) for each generator, avoiding any outliers from the best heat rate. The heat rate is used in the SWITCH dispatch optimization to calculate the fuel use and associated variable cost and emissions from dispatching thermal generators.

Hydropower generators are constrained to generate at their average historical monthly capacity factor [304]. We extract the monthly generation by generator from 2004 – 2018 (the most recent complete data at the time of the analysis) from the Form 923. For each generator, we calculate the average power for each month (monthly generation/hours in month) and estimate that the proxy for minimum flows for each generator is the power generated at half the average monthly level. For the SWITCH base case (without climate change), for each generator we calculate the average monthly power (and minimum flow power) over the years 2004 – 2018. These average values are repeated for all future investment periods of the SWITCH simulation (from 2020 – 2050). Monthly hydropower capacity factors by generator for the Canadian load zones (British Columbia and Alberta) are used from the prior SWITCH database, based on data from Statistics Canada Tables [304].

The existing generator set for the Canadian and Mexican load zones are used from the data previously compiled for prior SWITCH-WECC analysis, originally from the WECC Transmission Expansion Planning Policy Committee database of generators, and were not updated for this study [88], [304].

ii. Candidate generators

One of the key decision variables in SWITCH is the capacity investment of generation, out of a set of candidate generators with specific generating technologies and fuel sources, load zone locations, and other physical and financial generating characteristics. We use the dataset of candidate generators that was previously compiled in prior SWITCH-WECC analyses [88], [304], [378].

Candidate onshore and offshore wind generators were derived based on wind power output from a gridded 3TIER Western Wind and Solar Integration Study dataset [401] and a gridded Canadian wind developer dataset, and a selection of prime sites based on criteria including high wind energy density, and proximity to transmission [304]. A portion of candidate generators were screened out in California if they were in “Category 3, high environmental risk” locations, which include areas legally excluded for development, protected areas with ecological or social value, conservation regions, and prime agricultural land [402].

Candidate solar generators include Residential PV (rooftop PV on homes), Commercial PV (rooftop PV on commercial buildings), Central PV (utility-scale), and Concentrating Solar Power with and without storage (solar thermal trough systems with or without thermal energy storage). Distributed Residential and Commercial PV candidate generation had been derived based on a gridded population density dataset, solar insolation data from NREL’s (now deprecated) Solar Prospector tool, and assumptions on rooftop area and solar cell characteristics [304]. Available land and capacity for Central PV and Concentrating Solar Power candidate generators were screened based on land exclusion criteria (including national parks, wildlife areas, and steep terrain), solar insolation from the System Advisor Model from the National Renewable Energy Laboratory [403], and assumptions on the solar technology characteristics [304].

To simulate the dispatch of wind and solar generators, we use an exogenous dataset of hourly capacity factors by generator that had been constructed in prior SWITCH analyses [304], [378]. For wind generators, hourly capacity factors for the candidate generator set were calculated from the 3TIER Western Wind and Solar Integration Study wind speed dataset [401] using idealized turbine power curves. For solar generators, hourly capacity factors for the candidate generator set are calculated from the System Advisor, using data from 2006 (consistent with the base weather year underlying the load profiles) [403]. Central PV and onshore wind generators with capacity-weighted average capacity factors below the 75th percentile for their technology were screened out to only have the candidate set among a computationally tractable, and commercially viable, set of higher-quality resource sites [304]. For existing solar and wind generators, we average the hourly capacity factors for all solar and wind generators, respectively, in each load zone, and assign all the generators in that load zone the average capacity factor for the given technology.

Biogas (from landfill, wastewater treatment plants, and manure) candidate generator availability is derived from an assessment of the technical resource/feed stock availability [404]. Bioliquid generators are allowed to be reinstalled in their current locations but no new bioliquid plants are assumed. No new biomass (bio solid) candidate generators are assumed, but cogeneration bio solid generation is allowed to be reinstalled at the end of its lifetime [304]. Candidate geothermal generators are based on the current locations and capacity of existing plants that may be reinstalled after retirement [304]. We assume there is no candidate hydropower generation.

Natural gas combined cycle generators and combustion turbines do not have imposed maximum capacity limits. Coal generators are not allowed to be installed in California but are otherwise allowed to expand without capacity limits. Cogeneration plants (with gas combined cycle or combustion turbine plants) are given the option to be reinstalled at current locations after reaching their maximum age, at current capacity limits. We assume that there is no nuclear generation available for new, candidate generation.

Battery storage is available for installation in all load zones and investment periods, without capacity limits. An AC-DC-AC storage efficiency of 75%, a lifetime of 10 years, and a variable O&M cost of 0 is assumed, consistent with prior SWITCH analyses [304].

Table 46 summarizes the maximum capacity available for the set of candidate generators, and the capacity installed for existing generators.

Table 46. WECC total available capacity of existing and candidate generation.

Existing or Candidate Generator	Energy Source	Generation Technology	Capacity Limit (GW)
Existing Generator	Biogas	Biogas	0.2
		Biogas Internal Combustion Engine	0.3
		Biogas Internal Combustion Engine Cogen	0.2
		Biogas Steam Turbine	0.1
	Bio Liquid	Bio Liquid Steam Turbine Cogen	0.4
	Bio Solid	Bio Solid Steam Turbine	0.6
		Bio Solid Steam Turbine Cogen	0.5
	Coal	Coal Steam Turbine	42.2
		Coal Steam Turbine Cogen	0.3
	Distillate Fuel Oil	Distillate Fuel Oil Combustion Turbine	0.4
		Distillate Fuel Oil Internal Combustion Engine	0.4
	Electricity	Battery Storage	1.1
	Gas	CCGT	54.8
		CCGT Cogen	7.7
		Gas Combustion Turbine	23.6
		Gas Combustion Turbine Cogen	4.3
		Gas Internal Combustion Engine	1.1
		Gas Internal Combustion Engine Cogen	0.4
		Gas Steam Turbine	16.0
		Gas Steam Turbine Cogen	0.3
		Other Turbine	0.0
	Geothermal	Geothermal	4.5
	Residual Fuel Oil	Gas Combustion Turbine	0.2
	Solar	Central PV	22.0
		Concentrating Solar Power Trough, No Storage	0.4
		Steam Turbine	1.4
	Uranium	Nuclear	7.7
	Waste Heat	Other Turbine	0.0
		Steam Turbine	0.2
	Water	Hydropower	63.3
		Pumped Storage	4.3
	Wind	Onshore Wind	27.3
	Total		286.0
Candidate Generators	Biogas	Biogas	0.0
		Biogas Internal Combustion Engine Cogen	0.1
	Bio Liquid	Bio Liquid Steam Turbine Cogen	0.3
	Bio Solid	Bio Solid Steam Turbine Cogen	0.4
	Coal	Coal Integrated Gasification Combined Cycle (IGCC)	Not limited, except not allowed in CA
		Coal Steam Turbine	Not limited, except not allowed in CA
		Coal Steam Turbine Cogen	0.7
	Electricity	Battery Storage	Not limited
	Gas	Combined Cycle Gas Turbine (CCGT)	Not limited
		CCGT Cogen	6.9
		Gas Combustion Turbine	Not limited
		Gas Combustion Turbine Cogen	4.6

		Gas Internal Combustion Engine Cogen	0.1
		Gas Steam Turbine Cogen	0.3
	Geothermal	Geothermal	11.1
	Solar	Central PV	3,270.2
		Commercial PV	52.7
		Concentrating Solar Power Trough, 6 hours storage	3,695.3
		Concentrating Solar Power Trough, No Storage	5,362.5
		Residential PV	125.3
	Wind	Offshore Wind	6.4
		Onshore Wind	521.4
	Total		13,058.2

iii. Technology assumptions on lifetime, capacity factors, efficiencies

For all existing generators and candidate generators, we assume the following default technology assumptions based on the generating technology and fuel source (Table 47), primarily based on the technology and cost assumptions from Black & Veatch [381] and a CEC Cost of Generation Report collected in the prior SWITCH analyses [88], [304] and converted to $2018, with some technology values (natural gas combined cycle, natural gas turbine, battery, wind, solar PV, solar CSP, and geothermal) updated based on NREL's 2020 Annual Technology Baseline [380]. For existing generators with known planned retirement years, a specific lifetime is calculated.

Table 47.Technology assumptions for existing and candidate generators.

Fuel Source	Generating Technology	Lifetime (Years)	Forced Outage Rate (%)	Scheduled Outage Rate (%)
Biogas	Biogas	20	4%	6%
	Biogas Internal Combustion Engine	20	4%	6%
	Biogas Internal Combustion Engine Cogen	20	11%	4%
	Biogas Steam Turbine	20	13%	9%
Bio Liquid	Bio Liquid Steam Turbine Cogen	40	13%	9%
Bio Solid	Bio Solid Steam Turbine	20	4%	6%
	Bio Solid Steam Turbine Cogen	40	13%	9%
Coal	Coal IGCC	40	8%	12%
	Coal Steam Turbine	40	4%	6%
	Coal Steam Turbine Cogen	40	6%	10%
Distillate Fuel Oil	Distillate Fuel Oil Combustion Turbine	40	4%	6%
	Distillate Fuel Oil Internal Combustion Engine	20	4%	6%
Electricity	Battery Storage	10	2%	1%
Gas	CCGT	40	4%	6%
	CCGT Cogen	20	4%	6%
	Gas Combustion Turbine	40	4%	6%
	Gas Combustion Turbine Cogen	20	3%	5%
	Gas Internal Combustion Engine	20	4%	6%
	Gas Internal Combustion Engine Cogen	20	3%	5%
	Gas Steam Turbine	60	4%	6%
	Gas Steam Turbine Cogen	40	13%	9%
	Other Turbine	40	4%	6%
Geothermal	Geothermal	20	0%	0%
Residual Fuel Oil	Gas Combustion Turbine	40	4%	6%
Solar	Central PV	20	0%	0%
	Commercial PV	20	0%	0%
	Concentrating Solar Power Trough 6h Storage	20	6%	0%
	Concentrating Solar Power Trough No Storage	20	0%	0%
	Residential PV	20	0%	0%
	Steam Turbine	20	4%	6%
Uranium	Nuclear	80	4%	6%

Waste Heat	Other Turbine	40	4%	6%
	Steam Turbine	40	4%	6%
Water	Hydropower	200	5%	5%
	Pumped Storage	200	5%	5%
Wind	Offshore Wind	20	5%	1%
	Onshore Wind	20	0%	0%

g. Transmission

The SWITCH optimization includes the construction of new transmission lines and the operations of existing and new transmission as decision variables. The model includes a set of 105 existing aggregated transmission lines between load areas within the WECC, based on a prior SWITCH analyses that aggregated the thermal limits of individual high-voltage lines between load areas from a Ventyx purchased dataset and Federal Energy Regulatory Commission (FERC) data [304]. New transmission capacity may be added to existing transmission corridors or constructed between 21 adjacent load zone pairs where there is currently no transmission. The line length assumed is 1.3 times the straight-line distance between the largest substations in each load zone, based on a prior analysis that calculated this as the average ratio between line length and straight-line distance between transmission substations in WECC [304]. For every 100 miles of distance, a 1% efficiency loss is assumed, based on typical losses for high-voltage transmission [384]. For both existing and newly constructed transmission lines, the maximum power transfer on each line is the thermal limit multiplied by a derating factor. The derating factor is from a prior SWITCH analysis and is meant to capture the combined effect of stability concerns, loop flows, voltage concerns, power factors less than unity, and overloading of individual transmission lines within the bundle, that are difficult to model in detail in the linear model. The factors are 0.59 for alternating current (AC) lines, and 0.91 for direct current (DC) lines, of which there are only two in our analysis [304].

h. Costs

i. Overnight capital cost, variable O&M cost, fixed O&M cost

The SWITCH optimization includes several types of costs in the decision to invest and/or operate in generation. Costs for candidate generators include overnight capital cost (applied to the built capacity), fixed O&M costs per MW-year of operations, and variable O&M costs per MWh of operation. Mature technologies (biogas, bioliquid, biosolid, coal, gas cogeneration, gas steam turbine) are assumed to have their real costs stay constant over time, whereas other technologies are assumed to decrease costs over time with technology improvements and economies of scale. Capital, fixed O&M, and variable O&M costs by generator technology type originate primarily from Black & Veatch estimates for the mature technologies [304], [381]. For technologies with changing costs over time (battery, solar PV, solar CSP, wind, geothermal, gas CCGT, gas CT), we compile cost data from NREL's 2020 Annual Technology Baseline database using the "Moderate Scenario" which is based on the of median projections from the literature [380]. For wind and central solar PV, we also account for lower overnight costs in the first investment period from the Production Tax Credit and Investment Tax Credit, respectively [382], [383]. For battery storage, we separate out the capital costs into $/MW (balance of system battery cost) and $/MWh (battery pack cost which would be multiplied by the storage duration hours) costs [380]. The costs we use assume a four-hour duration battery. The average costs by decadal investment period, energy source, and technology are in Table 48. Capital costs for existing generators are considered sunk costs and we do not include them in the total system costs; they do not affect future investment decisions. Variable O&M costs for existing generators are set to be the same as for candidate generators.

Table 48. Average capital, fixed O&M, and variable O&M costs by investment period for candidate generation ($2018).

Energy Source	Generation Technology	Investment Period	Overnight capital cost ($/MW)	Fixed O&M cost ($/MW-year)	Variable O&M cost ($/MWh)
Bio Gas	Bio Gas	2020	2,118,354	64,380	9.20
		2030	2,118,354	64,380	9.20
		2040	2,118,354	64,380	9.20
		2050	2,118,354	64,380	9.20
	Bio Gas Internal Combustion Engine Cogen	2020	1,588,766	48,285	16.00
		2030	1,588,766	48,285	16.00
		2040	1,588,766	48,285	16.00
		2050	1,588,766	48,285	16.00
Bio Liquid	Bio Liquid Steam Turbine Cogen	2020	3,225,737	80,012	16.80
		2030	3,225,737	80,012	16.80
		2040	3,225,737	80,012	16.80
		2050	3,225,737	80,012	16.80
Bio Solid	Bio Solid Steam Turbine Cogen	2020	3,225,737	80,012	16.80
		2030	3,225,737	80,012	16.80
		2040	3,225,737	80,012	16.80
		2050	3,225,737	80,012	16.80
Coal	Coal Integrated Gasification Combined Cycle (IGCC)	2020	4,503,135	34,924	7.34
		2030	4,503,135	34,924	7.34
		2040	4,503,135	34,924	7.34
		2050	4,503,135	34,924	7.34
	Coal Steam Turbine	2020	3,245,403	25,828	4.57
		2030	3,245,403	25,828	4.57
		2040	3,245,403	25,828	4.57
		2050	3,245,403	25,828	4.57
	Coal Steam Turbine Cogen	2020	2,434,058	19,371	4.20
		2030	2,434,058	19,371	4.20
		2040	2,434,058	19,371	4.20
		2050	2,434,058	19,371	4.20
Electricity	Battery Storage	2020	414,708	32,043	0.0
		2030	150,026	20,982	0.0
		2040	126,912	17,749	0.0
		2050	113,216	15,834	0.0
Gas	CCGT	2020	1,115,074	11,708	4.50
		2030	981,532	12,863	4.50
		2040	947,742	12,863	4.50
		2050	924,780	12,863	4.50
	CCGT Cogen	2020	1,035,945	5,314	4.12
		2030	1,035,945	5,314	4.12
		2040	1,035,945	5,314	4.12
		2050	1,035,945	5,314	4.12
	Gas Combustion Turbine	2020	914,407	10,297	2.16
		2030	896,544	11,395	2.16
		2040	864,990	11,395	2.16
		2050	844,878	11,395	2.16
	Gas Combustion Turbine Cogen	2020	548,292	4,430	33.58
		2030	548,292	4,430	33.58
		2040	548,292	4,430	33.58
		2050	548,292	4,430	33.58
	Gas Internal Combustion Engine Cogen	2020	565,136	4,430	33.58
		2030	565,136	4,430	33.58
		2040	565,136	4,430	33.58

		2050	565,136	4,430	33.58
	Gas Steam Turbine Cogen	2020	418,841	26,717	4.46
		2030	418,841	26,717	4.46
		2040	418,841	26,717	4.46
		2050	418,841	26,717	4.46
Geothermal	Geothermal	2020	7,753,680	143,173	0.0
		2030	7,658,660	173,766	0.0
		2040	7,237,757	173,105	0.0
		2050	6,970,164	173,105	0.0
Solar	Central PV	2020	1,088,245	22,665	0.0
		2030	876,956	10,270	0.0
		2040	758,373	8,882	0.0
		2050	702,651	8,229	0.0
	Commercial PV	2020	1,550,322	20,415	0.0
		2030	1,089,723	7,813	0.0
		2040	910,568	6,529	0.0
		2050	819,995	5,879	0.0
	CSP Trough 6h Storage	2020	6,845,931	63,634	3.59
		2030	4,915,309	54,132	3.59
		2040	4,205,950	52,447	3.59
		2050	4,023,815	52,447	3.59
	CSP Trough No Storage	2020	5,074,725	56,149	0.0
		2030	4,661,582	56,149	0.0
		2040	4,248,663	56,149	0.0
		2050	3,937,151	56,149	0.0
	Residential PV	2020	2,078,361	25,068	0.0
		2030	1,256,559	9,424	0.0
		2040	984,462	7,384	0.0
		2050	884,353	6,633	0.0
Wind	Offshore Wind	2020	3,959,165	112,298	0.0
		2030	2,744,489	112,298	0.0
		2040	2,401,870	112,298	0.0
		2050	2,226,776	112,298	0.0
	Onshore Wind	2020	1,393,460	47,047	0.0
		2030	1,247,480	38,867	0.0
		2040	1,120,978	35,883	0.0
		2050	1,042,433	33,692	0.0

ii. Connection costs

In addition to capital costs for the construction of a generator itself, for candidate generators we also add a connection cost to reflect the expense of connecting to the grid. This connection cost originally derived from EIA data and compiled in a prior SWITCH analysis [304] is either a “generic” cost if the generator is not located at a specific site (for gas, coal, biosolid, biogas, or battery storage), or is calculated for a specific site (for onshore wind, offshore wind, geothermal, central PV, and CSP with and without storage). The “generic” cost includes the cost of building a substation ($80,000/MW in $2018) and a small transmission line to the substation ($31,000 in $2018). Site specific connection costs include a transmission line cost of $1,200 per MW per km based on the distance from the site to the substation, and the cost of the substation. The cost for underwater cable for offshore wind is $6000 per MW per km. There is no connection cost applied for existing generation.

iii. Fuel costs and Emissions

Fuel costs are applied to non-renewable generators (natural gas, coal, fuel oil, uranium) and originate from the EIA’s Annual Energy Outlook (AEO) compiled from a prior WECC analysis [88]. Gas costs differ by load zone based differences in regional market prices and the wellhead price [304]. Table 49 shows the average costs for each decadal investment period, across all the load zones, in $2018. The fuel costs for bio solid generators are based on supply curves derived based on estimates of the economically feasible volumes of biomass feedstock available by load zone and different fuel price tiers [304].

Table 49. Average fuel costs across load zones, by investment period ($/MMBtu in $2018).

Fuel Source	2020	2030	2040	2050
Bio Liquid	0.01	0.01	0.01	0.01
Coal	2.13	2.17	2.27	2.33
Distillate Fuel Oil	18.55	22.89	25.34	27.64
Gas	4.32	5.17	5.39	6.34
Residual Fuel Oil	11.88	16.34	18.30	20.44
Uranium	0.68	0.88	1.15	1.53

iv. Transmission costs

The cost of building new transmission lines is calculated as the product of a line length, a base $/MW/km cost, a terrain multiplier that reflects the topography differences that make a line more expensive to construct, and an economic multiplier that represents differences in labor, permitting, and other "soft" costs between WECC load zones.

We assume a base $960/MW-km cost, which is the cost for constructing a 500 kV line in the WECC from the ReEDS capacity expansion model database ($1,347/MW-mile in $2010 dollars, converted to $/MW-km and $2018 dollars) [384]. For the economic multiplier, for all lines within California we use a factor of 2.25, between California and other WECC load zones we use a factor of 1.125, and within other WECC load zones we use a factor of 1 (keeping the base cost as it is) from the the ReEDS documentation [384]. Steeper terrain and urban land area increase transmission construction costs. Terrain multipliers come from a prior SWITCH GIS analysis that overlaid the transmission line paths over a gridded dataset of terrain-dependent transmission costs, that had been derived from the slope and the land cover in the WECC region [304]. The multipliers range from 0.7 to 3.4. Transmission lines also have a fixed O&M cost applied to reflect upkeep costs for lines, which is assumed to be 3% of capital costs from the prior SWITCH analysis.

i. Load

The future load assumed in this analysis was developed in a prior study and represents a case of high energy efficiency and building electrification, as well as increased adoption of Zero Emissions Vehicles (ZEVs), primarily from electric vehicles [88]. The load forecast achieves a doubling of the rate of energy efficiency by 2030 in California, compliant with the state's SB 350 legislative targets, aggressive building electrification starting in 2020, growing industry electrification, and high levels of electric vehicle adoption. Hourly demand profiles from 2006 (consistent with the weather-year used for calculating solar and wind capacity factors) from FERC Form 714 and a dataset procured from ITRON were used as a base from which demand projects (residential, commercial, industrial, transportation) were created and scaled by sector to meet states' policy targets and reflect population growth [385]. Where detailed state/province-level load forecasts with state efficiency, electrification, and population estimates were available (including California, Washington, Oregon, British Columbia, and Alberta) load zone forecasts were scaled to those projections; otherwise forecasts were scaled to the EIA's Annual Energy Outlook projections in the prior SWITCH analysis [88], [405]. In the 2017 Annual Energy Outlook Electric projections used, population growth across the U.S. is on average 0.6%

annually, based on the U.S. Census Bureau's mid-case projections at the time [405]. Electric vehicles are assumed to charge in an "unmanaged" way (without smart charging or time-of-use rates), based on charging profiles developed with an agent-based mobility model BEAM [46], [386].

j. Planning reserves

We assume that the load zones in the WECC region must meet a planning reserve margin of 15%, that is, the model is required to build capacity to meet 115% of the peak load in each reserve area. The reserve requirement is applied by reserve area; utilities like Southern California Edison (SCE) and Pacific Gas & Electric (PG&E) that span multiple load zones have a combined reserve requirement across their total region. All generator technologies are assumed to be eligible to provide capacity towards meeting the planning reserve requirement. Thermal generators contribute their nameplate capacity, solar and wind generators contribute as much as their capacity factor during the peak hour, hydropower generators contribute as much as their monthly capacity factors for all hours of that month, battery storage contributes as much as it discharges during the peak hour, and net transmission imports contribute as much as the flows during the peak hour. the discharge capacity.

k. Policies

i. Renewable Portfolio Standards

We include state Renewable Portfolio Standard (RPS) policies in SWITCH as a constraint requiring a fraction of electricity demand be generated by renewable generators. Qualifying RPS-eligible technologies include solar PV and CSP, wind, geothermal, biogas, bio solid, bio liquid, and hydropower. We include the annual schedule of RPS requirements by state [406]. Because of computational tractability, the RPS constraint is calculated as a WECC-wide load-weighted average requirement (total RPS-eligible generation annually must equal or exceed the sum-product of annual load for each load zone and the RPS percentage requirement for that load zone), rather than accounting for the stocks, flows, and transmission imports of renewable power from specific generators.

ii. Carbon cap

A constraint on carbon emissions from generators can be imposed in SWITCH by load zone and investment period. In this analysis, for the base case we assume a decline of carbon emissions to 0 by the 2050 investment period for all load zones in WECC, following the mandate already set in California by SB 100 legislation [120, p. 10], and Biden's campaign and administration's policy goals to reach carbon-neutral electricity generation by 2035 (Table 50) [341]. We separately track the carbon cap for California because of SB 100 legislation, and the 2020 carbon cap accounts for the levels of observed emissions for electricity generation 2016 – 2018 (the first three years of the 2020 investment period)[217]. To measure compliance with this constraint, SWITCH tracks the emissions from each generator and aggregates to the load zone, based on emissions intensity for each fuel source [219] (Table 51).

Table 50. WECC-wide and California Carbon Cap Average by Investment Period.

Investment Period	WECC Carbon Cap (tCO_2/year)	CA Carbon Cap (tCO_2/year)
2020	222,591,762	57,699,000
2030	149,423,303	36,292,500
2040	76,328,672.3	11,400,000
2050	0	0

Table 51. Emissions Intensity of Fuel-based Energy Sources (tons CO2/BTU).

Fuel	CO_2 Intensity of Fuel
Coal	0.09552
Distillate Fuel Oil	0.07315
Gas	0.05306
Residual Fuel Oil	0.0788

B. WEAP Model, Data, and Assumptions

WEAP is a hybrid water resources management and watershed hydrology tool, built by the Stockholm Environmental Institute. WEAP can test different climate inputs, land uses, and demands and policies [355], and separately accounts for irrigated agriculture, urban indoor water use based on per-capita use and population, and urban outdoor use [92]. Numerous studies have used WEAP to assess climate impacts on water management, including on energy-water linkages [38], [356]. In each timestep WEAP solves a series of simultaneous equations for a mass-balance that partitions precipitation into snow or rain, and runoff or groundwater infiltration based on land cover, temperature, and soil moisture for each of the sub-catchments at various elevations, calculating the available supply and irrigation water demand [92], [355]. With a linear program, WEAP then allocates the calculated available supplies to demands, in order of user-specified priorities and supply preferences. With the rainfall-runoff hydrological modeling capabilities, embedded within a representation of the water system infrastructure and uses of the region, the WEAP model is ideally suited to evaluate climate sensitivity and water management responses under climate change. The mathematical formulations of the mass balance and other model components are documented in detail in a prior WEAP publication [355].

a. Geographic and temporal resolution

For this analysis we build a new WEAP model covering the same region as the WECC region of the electricity expansion model (Figure 27, Figure 31).[58] The WEAP study area includes the watershed regions of the Columbia River, Snake River, Missouri River, Colorado River, Platte River, Salt River, Sacramento River, Feather River, and San Joaquin, among many others. In addition to including the major rivers of the region, the WEAP model also includes built infrastructure such as long-distance conveyance for inter-basin water transfers (including the State Water Project, Central Valley Project, Colorado River Aqueduct, and Central Arizona Project), and major reservoirs and hydropower generators.

The model is run at a monthly time step, for the 2010 - 2060 time horizon, with the first and last 5 years of the simulation discarded to account for any artifacts or edge effects of model spin-up and end. The model has been calibrated for the historical period of 1980 – 2010 for key hydrologic metrics using observational US Geological Survey (USGS) gauge data for streamflows and/or reservoir outflows [91], [92], [349].

b. Water supply: catchment delineation and groundwater objects

We use WEAP's built-in "Catchment Delineation" tool to delineate catchments and rivers and to calculate land area disaggregated by 1000-meter elevation bands and by land use-land cover (LULC) categories (Agriculture, Forest, Grass and Shrub, Other, Urban, or Water)

[58] The Canadian and Mexican regions of WECC are only partially included because of limited data availability.

from digital elevation data [357]. Many of the catchments are delineated with major reservoirs as the outlet points of associated rivers, because a large focus of this analysis is on hydropower generation. The catchment delineation process results in 147 rivers and 311 catchments. Climate data is used for each combination of catchment and elevation band. These catchments characterize the hydrology of the land area to calculate runoff and agricultural irrigation demand, or characterize the urban outdoor irrigation demand. These catchments, along with associated groundwater aquifers, provide the water supply to meet water demands.

c. Water use and water infrastructure

i. Urban water demand

For each of 50 load zones in SWITCH, we model an urban (non-agricultural) indoor and an urban outdoor water demand node in WEAP. For each urban indoor demand node, total water demand is modeled as the product of a water use rate per-capita by sector * regional population. We include water use by the Domestic and Commercial and Industrial (C&I) sectors in each urban indoor node, and use the historical (2005, 2010, and 2015) average annual water use per-capita for all future simulation years.[59] These per-capita rates are calculated based on historical USGS data by sector and county, divided by annual population by county [358]. Finally, these county level water use and population data are aggregated and assigned to the appropriate WEAP indoor urban demand nodes based on a spatial analysis that weights the data by the overlapping population density of each county with the area of each corresponding SWITCH zone.

Because Domestic water data from USGS includes both indoor and outdoor water use, we parse out the indoor portion based on per-capita indoor water use data collected for specific cities in our study area (Table 52). For cities for which we cannot find per-capita indoor use, we assign the indoor per-capita value from the nearest city with data. Finally, we subtract this indoor per-capita value from the total USGS indoor + outdoor per-capita value to derive the Outdoor Share. The (1 - Outdoor Share) fraction is used to adjust the Urban land area for each catchment to only include the indoor portion for the demand nodes. For C&I water, we make a simplifying assumption that the demand is only for indoor use from the commercial, industrial, mining, livestock, aquaculture, and thermoelectric sectors as categorized by USGS [358]. We calculate a per-capita C&I water demand as the total water use from these sectors divided by population. In reality, these C&I water uses are likely to change by other rates, i.e. production, square footage, electricity use, but because we do not have such sectoral data, we make a simplifying assumption that it also changes along with population growth. This is an area for future research.

To capture the climate sensitivity of urban outdoor watering, for each urban indoor water demand object, there is also a separate outdoor urban water demand catchment object, that is the same Urban land area multiplied by Outdoor Share for each catchment. The land area of these outdoor urban catchment objects is the sum of the urban areas for all elevation bands of the main catchment object.

Table 52. Residential indoor per capita water use for selected cities in study area.

Location	Residential indoor per capita water use per day (gpcd)	Source
Denver	50	[407]
Utah average (Salt Lake City)	60	[408]
CA average	54	[409]
San Diego	51 (assuming average household size of 3)	[410]

[59] Future research will simulate changes in per-capita water use rates as part of conservation programs.

Los Angeles	60 (assuming average household size of 2.8)	[410]
San Francisco	41 (Residential gpcd, assumed all indoor)	[411]
Sacramento	68 (average of single-family and multi-family gpcd)	[412]
Seattle	51.9	[413]
Phoenix	55	[414]
Portland	50	[415]
US average	58.6	[416]

ii. Agricultural demand

Irrigation water demand is determined based on the irrigated land area, which is calculated for each catchment as the "Agriculture" land area multiplied by the fraction of agricultural area that is irrigated for each catchment area (IrrigFrac). IrrigFrac is calculated as the irrigated land area from the 2017 (MODIS) Irrigated Agriculture Datasets for the Conterminous United States [359], divided by the total agricultural area from the 2016 National Land Cover Database [360]. For the irrigated land area, the water use is calculated as part of the mass-balance equation using a Penman-Monteith formulation of evapotranspiration (ET), an average representative crop coefficient, and soil moisture thresholds. The remaining non-irrigated Agriculture land area is added into the Grass and Shrub land use category: Agriculture[ha] * (1-IrrigFrac) because it is assumed that non-irrigated agricultural land has similar attributes to Grass and Shrub lands.

d. Demand priorities and supply preferences

Two user-defined priority systems are used to determine monthly allocations from supplies to demand sites, and for instream environmental flow requirements, reservoir storage, and hydropower generation [355]. Competing demand sites and flow requirements are allocated water according to their demand priorities. Sites can share the same priority. These are useful in representing water rights, and are also important during a water shortage, in which case higher priorities are satisfied as fully as possible before lower priorities are considered. If priorities are the same, shortages will be equally shared. Typically, highest priorities are for critical demands that must be satisfied during a shortfall, such as a municipal water supply. When demand sites are connected to more than one supply source, their supply preferences may also be ranked. These are attached to transmission links. Using the supply preferences and demand priorities, WEAP determines the allocation order to follow when allocating the water. The allocation order represents the actual calculation order used by WEAP for allocating water.

In this analysis, with 1 being the highest priority, we have assigned demand priorities as follows: 1) environmental flows, 2) urban indoor, 3) urban outdoor, 3) agriculture, 4) reservoir storage, and 5) hydropower. We have assigned supply preferences as follows: 1) reuse (when available), 2) surface water, 3) groundwater.

e. Reservoirs, Diversions, Desalination, and Reuse

We include 132 major reservoirs in the WEAP model of the WUS, which together provide 260 Billion m^3 of available storage capacity. Reservoir storage is divided into four zones, or pools. These include, from top to bottom, the flood-control zone, conservation zone, buffer zone and inactive zone [355]. The conservation and buffer pools, together, constitute the reservoir's active storage. WEAP will ensure that the flood-control zone is always kept vacant, i.e., the volume of water in the reservoir cannot exceed the top of the conservation pool. WEAP allows the reservoir to freely release water from the conservation pool to fully meet withdrawal and other downstream requirements. Once the storage level drops into the buffer pool, the release will be restricted according to the buffer coefficient, to conserve the reservoir's dwindling supplies. Water in the inactive pool is not available for allocation, although under extreme conditions evaporation may draw the reservoir into the inactive pool. Parameters to characterize reservoir storage capacity and volume-area relationship are from National Inventory of Dams data [361]. We also account for evaporation from the surface of the reservoirs for each climate scenario, based on the temperature data of the catchment where the reservoir is located.

Major conveyance projects or diversions are included in WEAP: the State Water Project (California Aqueduct and Coastal, East, and West Branches), Central Valley Project, Friant Kern Canal, Los Angeles Aqueduct, Colorado River Aqueduct, Central Arizona Project, All American Canal, Central Utah Project, Roberts Tunnel, Moffat Tunnel, and Boustead Tunnel. For the State Water Project and Central Valley Project diversions, releases are constrained based on available volumes determined by a water year categorization, calculated based on a River index of the Pit and Feather Rivers' streamflow. A monthly pattern of maximum releases is also imposed based on historical allocations.

We include one desalination plant in Carlsbad, California [362] which provides water to San Diego, and also model non-potable reuse to the urban outdoor demand use up to 5% of return flows of urban indoor demand nodes in the drier Southwest states (California, Arizona, and Nevada).

f. Hydropower generators

We include 194 individual hydropower generators in the WEAP model, which together provide 48 GW of capacity. These are all the generators greater than 30 MW in the United States portion of the WECC region, the threshold used by California for its Renewable Portfolio standard to denote "large hydro." Only one generator is included in Canada, because of limited data available for calibration.

Hydropower generators are either included as run-of-river or as reservoir hydropower. Power is generated as the WEAP model releases water from the reservoir, or as water flows through the run-of-river turbines, based on the supply and demand priorities discussed above. The generators are characterized based on head, tailwater elevation, and max turbine flow. In order to match the SWITCH baseline hydropower generation as closely as possible, the WEAP hydropower is further calibrated to adjust generation to meet the historical average monthly pattern, the annual average generation levels, and the annual average capacity factors, per the equations and

Table 53. Data is based on EIA net generation, NID dam data, and USBR dam and powerhouse data, and filled in as much as possible from other documentation from FERC filings, utility websites [361], [363]–[365].

The monthly generation is calculated based on the head and volumetric flow rates through the turbine. Because of limited publicly available Max Turbine Flow data, we derive it using other available data on the installed capacity (max capacity) and the head, based on the following equations. The Max Turbine Flow parameter is also adjusted for each month based on historical monthly and annual generation data to best match the SWITCH baseline data that uses the same historical monthly data from EIA.

$$\mathrm{MonthlyGen} = 1000[\mathrm{kg/m^3}] * \mathrm{Head} * 9.806 * \mathrm{VolumeThroughTurbine_m}$$

$$\text{VolumeThroughTurbine}_{\text{m}} = \text{Min}(\text{Release}_{\text{m}}, \text{MaxTurbineFlow}_{\text{m}})$$

$$MaxTurbineFlow_m = InstalledCapacity[MW] * 10^6/(9.81 * 1000 * Head) * MonthlyEnergyFrac * 12 * CapacityFactor * AverageMonthlyStorageFrac$$

Table 53. Hydropower parameters and formulation for reservoir and run-of-river hydropower.

WEAP Variable	Reservoir based hydro	Run-of-river hydro	Sources
Max turbine flow	(Installed Capacity[MW] * 10^6) /(9.81 * 1000 * Hydraulic Head[m]) * Monthly Energy Pattern * 12 * Capacity Factor * (PrevTSValue(Storage Volume[Million m^3],1,12, Average)/Storage Capacity[Million m^3])	(Installed Capacity[MW] * 10^6) /(9.81 * 1000 * Fixed Head[m]) * Monthly Energy Pattern * 12 * Capacity Factor	
Tailwater elevation	0 unless specified for certain reservoirs (Hoover, Glen Canyon, Grand Coulee, Big Creek 4, Mayfield, San Luis)	NA	
Capacity Factor	Historical capacity factor (averaged 2004 - 2018) [%]	Historical capacity factor (averaged 2004 - 2018) * calibration factor (0.75) [%]	
Annual Energy Target	Historical annual generation (averaged 2004 - 2018) * calibration factor (1.33) [GWh]	Historical annual generation (averaged 2004 - 2018) [GWh]	EIA form 923
Monthly Energy Pattern	Monthly fraction of annual generation (averaged 2004 - 2018) [%]	Monthly fraction of annual generation (averaged 2004 - 2018) [%]	EIA form 923
Installed Capacity	Nameplate capacity installed [MW]	Nameplate capacity installed [MW]	EIA form 860
Hydraulic Head	Head aka Rated Head [m]	NA	USBR, NID, other sources
Fixed Head	NA	Head aka Rated Head [m]	USBR, NID, other sources

g. Energy demand for water

Electricity powers all stages of the managed water cycle, including groundwater pumping, long-distance conveyance, treatment, use, wastewater treatment, reuse, and desalination. In the WEAP model, we track this embedded energy by applying energy intensity values (energy use per unit of water, kWh/m^3) associated with the water volumes calculated in WEAP throughout the stages of the managed water cycle (Figure 28). Energy intensity values are either derived from endogenous model data (i.e. groundwater pumping based on water depth), calculated from input data (distribution energy, water heating energy, agricultural energy), or based on averages from the literature (desalination, treatment, wastewater treatment, reuse) as described below and in Table 54.

Groundwater pumping energy is calculated based on the lift, pump efficiency, and volumetric flow rate. For each groundwater object, the lift in meters is the aquifer water depth resulting from the WEAP model for each month. For all groundwater pumping, we assume an average pump efficiency of 49% based on [199], [366].

$$\text{Energy} = \text{Flow}[\text{m}^3] * \text{Lift}[\text{m}] * \text{GroundwaterPumpEI}[\text{kWh}/\text{m}^3]$$

Energy for water conveyance, typically for inter-basin water transfers, is calculated based on the lift, pump efficiency, and volumetric flow rate. For each conveyance object, the lift in meters is the height that water needs to be raised for the specific project (Table 54). We assume a pump efficiency of 57% (the highest pump efficiency in [199]). Gravity- fed conveyance projects, such as the Los Angeles Aqueduct, are assumed to consume no energy.

$$\text{Energy} = \text{Flow}[\text{m}^3] * \text{Lift}[\text{m}] * \text{ConveyanceEI}[\text{kWh}/\text{m}^3]$$

Water treatment energy, which we assume is with conventional drinking water treatment, is applied for all urban demands (domestic indoor and outdoor, and CII). We use an average value from the literature [55], [58], [61], [64, p. 1], [65, p. 2], [73], [76], [207]. Water distribution energy is the energy required to pump and distribute water from the treatment plant to the end-user, and is also applied for all urban demands. Distribution energy increases with steeper terrain, and we therefore calculate the average slope-length of each urban demand node area/SWITCH load zone in QGIS based on the topography overlaying the urban land areas [357], [360]. We rank and categorize the demand nodes based on their slope-length values with the top third assigned hilly, middle third assigned moderate, and bottom third assigned flat distribution energy intensity values (0.79, 0.41, 0.04 kWh/m^3 respectively) [203].

Energy for agricultural water use includes the energy intensity for local surface water deliveries (averaged from [55], [58], [61], [64, p. 1], [65, p. 2], [73], [76], [207]) and for irrigation (pumping and pressurization). The energy intensity for irrigation is calculated as a weighted average based on California data for the historical average applied water by crop [216], typical irrigation technology currently installed by crop [215], and the energy intensity for each irrigation technology [199] (0.01 kWh/m^3, 0.23 kWh/m^3 for standard sprinklers, and 0.17 kWh/m^3 for micro/drip irrigation) .

Energy for Domestic[60] water heating is tracked and is calculated as the product of the average electric water heater saturation by state [367, p. 8], the average hot water share in typical residential homes (33.2%) [206], and the specific heat of water ($Q = mc\Delta T/\eta$) based on typical water heater characteristics (90% efficiency, about 44 degrees C of warming based on average 10 C inlet and 54 C outlet temperatures).

Energy for desalination is assumed to be from seawater, averaged from literature [55], [58], [61], [64, p. 1], [65, p. 2], [73], [76], [207]. Energy for wastewater treatment applied to return flows from all urban indoor water, is assumed to be for secondary treatment, and is averaged from literature [55], [58], [61], [64, p. 1], [65, p. 2], [73], [76], [207]. For water non-potable reuse, we apply an energy intensity for incremental treatment above secondary wastewater treatment.

Table 54. Energy Intensity values related to water.

Energy use category	Energy Intensity	Units	Notes
Groundwater	0.0056	kwh/(meter lift *	kwh/(meter lift * monthly volume) = g (9.8) * joule to watt hour

[60] We do not track energy use for commercial and industrial water heating because of lack of available data on hot water shares of such a diverse set of water end-uses.

Pumping		monthly volume)	conv (0.0002778) / average pump efficiency (0.49)
Conveyance	0.0048	kwh/(meter lift * monthly volume)	kwh/(meter lift * monthly volume) = g (9.8) * joule to watt hour conv (0.0002778) / max pump efficiency (0.57) Central Arizona Project: 720 m Central Utah Project: 30 m Colorado River Aqueduct: 400 m Central Valley Project: 50 m Otero Pump: 105 m Rio Chama: 30 m State Water Project (SWP): 100 m SWP Coastal Branch: 200 m SWP East Branch: 748 m SWP West Branch: 70 m
Desalination	3.76	kWh/m^3	for seawater desal
Municipal Drinking Water Treatment	0.25	kWh/m^3	for conventional drinking water treatment
Municipal water distribution			distribution energy values applied to urban demand nodes depending on higher slope-length values (hilly terrain has higher distribution energy requirements)
Agricultural water use	0.17	kWh/m^3	local surface water deliveries + average irrigation (pumping and pressurization)
Water heating			for heating water from x to x C, assuming electric water heater saturation from EIA, and hot water share of indoor water use ElectricHeaterSaturation * hot water share * (4.2/3600 * monthly volume * 44 degrees C of heating/ water heater efficiency)
Wastewater Treatment	0.65	kWh/m^3	for secondary wastewater treatment
Non-Potable Reuse Treatment	0.4	kWh/m^3	for non potable reuse, marginal treatment above secondary wastewater treatment

h. Calibration

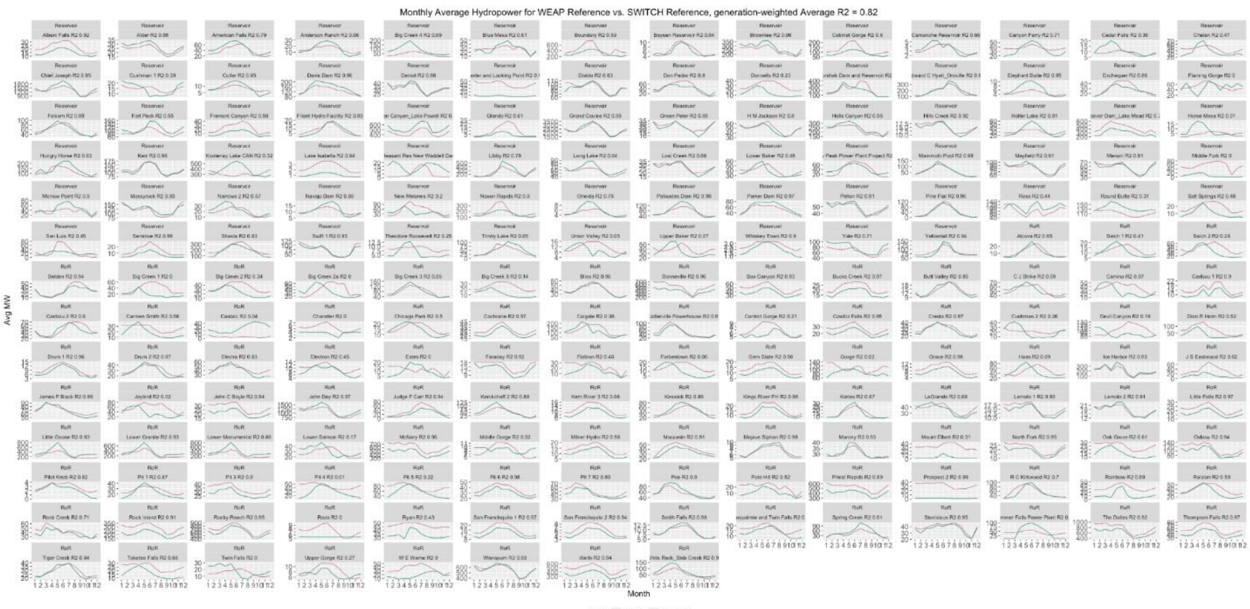
i. Streamflow

The catchment parameters in WEAP are adjusted based on a calibration of modeled streamflows compared to observed gauge data for USGS gauging locations on rivers and diversions. Typically, managed flow is calibrated, including on the Columbia River below Grand Coulee Dam, Snake River below Hells Canyon Dam, Missouri River below Fort Peck Dam, inflows to Lake Powell, and Sacramento Delta outflow. Figure 29 in the main text of Chapter 4 is a summary of goodness-of-fit statistics including correlation and bias across key hydrologic points that are simulated in the WEAP model across the WUS, while Figure 30 in Chapter 4 shows the time series of observed compared to modeled streamflows and goodness-of-fit statistics for three important locations: Sacramento Delta outflow, inflows to Lake Powell, and Columbia River below Grand Coulee Dam.

ii. Hydropower

We match WEAP hydropower generation results from the Reference scenario (no climate change) as closely as possible to the SWITCH baseline scenario (no climate change) before applying the climate change factors when integrating the models. We manually calibrate the average monthly WEAP hydropower generation by generator to match the historical observed average generation from the EIA 2004 - 2018 [364], which is used for the SWITCH baseline scenario, based on the R^2 values of each generator and the average generation-weighted R^2 across all generators. Initial WEAP results showed run-of-river generators under-generating overall compared to the SWITCH baseline, and reservoir generators over-generating especially in spring months. Therefore in the calibration we apply a calibration factor of 1.33 to scale up the run-of-river generators, and a factor of 0.75 to scale down the reservoir generators. Figure 47 shows the monthly average WEAP reference generation compared to the SWITCH monthly average generation based on historical EIA data. After this calibration, the final generation-weighted R^2 across all generators is 0.82.

Figure 47. Monthly average hydropower generation in WEAP compared to SWITCH baseline scenario for calibration.



iii. Statewide water use

Given the large study area and resolution of the WEAP model, we compare water supply deliveries from the reference case to historical observed water use at the state level. We compare with 2 sources: USGS data [358] and data collected from individual state water resources websites [368]–[376], which were available for some but not all of the same years as the USGS data (Table 34).

iv. Calibrated catchment parameters

All the catchment objects hydrological parameters include crop coefficient (Kc), Soil Water Capacity (SWC), Runoff Resistance Factor (RRF), Root Zone Conductivity (RZC), Preferred Flow Direction (PFD), Deep Water Capacity (DeepCap), and Deep Conductivity (DeepCond). These are defined by the Land Use category of each catchment. Based on the calibration process described above, a set of these hydrological parameters (Table 55) are used for catchments classified as “Arid”, “Humid”, and “West.” Arid catchments include areas in the Southwest, Humid catchments include areas in the Pacific Northwest and Northern California, and West catchments include the Intermountain West region.

Table 55. Calibrated hydrological parameters for catchment objects.

Parameter	Arid	Humid	West
Deep Capacity (Effective water holding capacity of deep soil layer)	501	2000	800
Deep Conductivity (Conductivity rate [length/time] of deep soil layer)	50	500	200

Crop coefficient (Kc)	1.05	1.05	1.05
Kcint	Monthly Values: Jan - April: 1 May - June: 1.1 Jul: 1.3 Aug - Sep: 1.5 Oct - Nov: 1.3 Dec: 1		Monthly Values: Jan - April: 1 May - June: 1.1 Jul: 1.3 Aug - Sep: 1.5 Oct - Nov: 1.3 Dec: 1
Preferred flow direction (PFD) - Mild	0.6	0.2	0.4
Preferred flow direction (PFD) - Steep	0.9	0.6	0.75
Runoff resistance factor (RRF)	Agriculture: 5 Forest: 5 Grass and Shrub: 4 Other (barren/rocks): 4 Urban: 1 Urban outdoor: 3	Agriculture: 5 Forest: 5 Grass and Shrub: 4 Other (barren/rocks): 3 Urban: 2 Urban outdoor: 4	Agriculture: 6 Forest: 5 Grass and Shrub: 4 Other (barren/rocks): 2 Urban: 1 Urban outdoor: 4
Root zone conductivity (RZC)	Agriculture: 100 * 0.45 Forest: 125 * 0.45 Grass and Shrub: 80 * 0.45 Other (barren/rocks): 50 * 0.45 Urban: 90 * 0.45 Urban outdoor: 125 * 0.45	Agriculture: 350 * 0.75 Forest: 500 * 0.75 Grass and Shrub: 400 * 0.75 Other (barren/rocks): 400 * 0.75 Urban: 250 * 0.75 Urban outdoor: 350 * 0.75	Agriculture: 300 * 0.66 Forest: 450 * 0.66 Grass and Shrub: 275 * 0.66 Other (barren/rocks): 200 * 0.66 Urban: 100 * 0.66 Urban outdoor: 250 * 0.66
Soil Water Capacity (SWC)	Deep (Agriculture, Forest, Urban): 800 Shallow (Grass and Shrub, Other): 550	Deep (Agriculture, Forest, Urban): 1200 Shallow (Grass and Shrub, Other): 800	Deep (Agriculture, Forest, Urban): 1200 Shallow (Grass and Shrub, Other): 800
Freezing point temperature (Tf)	-5 C	-5 C	-3 C
Melting point temperature (Tl)	10 C	5 C	10 C
Z2 (Initial value at start of simulation)	15	20	15

i. Model Handshake

Table 56 shows the mapping of the hourly weights used to convert monthly WEAP results on energy use related to water, by energy use category and associated WEAP object.

Table 56. Matching of Hourly Weights with Energy Use Categories.

Hour weighting category	**Sector**	**Energy uses included**	**Related WEAP object**
Domestic hour weight	Domestic	Municipal Treatment + Distribution Energy + Water Heating	Demand Site Electricity Use Monthly
Commercial Industrial hour weight	Commercial and Industrial	Municipal Treatment + Distribution Energy	Demand Site Electricity Use Monthly
Groundwater pump hour weight	Urban Indoor	Groundwater pumping	Transmission Link Electricity Use Monthly
Domestic hour weight	Urban Indoor	Desalination	Transmission Link Electricity Use Monthly
Urban outdoor hour weight	Urban Outdoor	Municipal Treatment + Distribution Energy	Transmission Link Electricity Use Monthly
Urban outdoor hour weight	Urban Outdoor	Desalination	Transmission Link Electricity Use Monthly
Urban outdoor hour weight	Urban Outdoor	Non-potable reuse + Distribution Energy	Transmission Link Electricity Use Monthly
Groundwater pump hour weight	Urban Outdoor	Groundwater pumping + Municipal Treatment + Distribution Energy	Transmission Link Electricity Use Monthly

Agricultural Use hour weight	Agricultural	Agricultural Use	Transmission Link Electricity Use Monthly
Groundwater pump hour weight	Agricultural	Groundwater pumping + Agricultural Use	Transmission Link Electricity Use Monthly
Diversion hour weight	Conveyance	Conveyance pumping	Diversion Electricity Use Monthly
Wastewater treatment hour weight	Urban Indoor	Wastewater Treatment	Electricity Use Return Flows Monthly

Chapter 5 Appendix

Focus Group Interview Guide

1. Introduction to the meeting
2. Goals - 3 main ones:
    - Gather feedback on preliminary research results and identify a way forward
    - Hear from resource managers about any examples of significant energy water interactions in the region (or absence of them) and why they were important for planning
    - Hear from managers & scientists on what scientific information about these interactions (metrics, drivers) can potentially help inform the management context under future climates
3. Presentation on context of the Water-Energy modeling effort
4. Presentation about WEAP model of Western US (12 mins)
5. Feedback/Discussion on WEAP preliminary results and steps forward (~ 30 mins)
    - Can this regional scale WEAP model be useful for you? If so, how, and which of these results stand out to you as useful for your management context?
    - In the context of climate change, what are the most critical conditions that concern you in your management context? (droughts, groundwater levels, floods, water demand, reservoir storage)
    - What other water management metrics would be useful to you from this region-scale model?
    - Future water supply deliveries by sector and by source?
    - Inter-basin water transfer deliveries?
    - Groundwater use?
6. 2 minute stretch break if needed
7. Managers share examples of energy-water interactions and their relevance (~5-7 mins)
8. Presentation on motivation and framework, method of linking WEAP and SWITCH, and preliminary results (12 mins)
9. Feedback/Discussion on SWITCH preliminary results and steps forward (~30 mins)
    - Which of these results on energy impacts stand out to you?
        - Are you more interested in annual, seasonal, decadal trends?
        - Specific regional trends?
        - Range of results across climate scenarios?
    - Does the energy intensity of the water system factor into your decisions (as cost, energy, or carbon implications)?
    - Are there ways you quantify or consider energy as a water provider that we have not included here?
    - [Poll about adaptation options] Which of these climate adaptation measures are you considering or would you consider (to augment future supplies or increase conservation)? [present menu of options]
        - Water conservation
        - Water recycling
        - Groundwater recharge
        - Changing reservoir operations
        - Desalination

- Import restrictions

10. Managers share examples of energy-water interactions and their relevance (~5-7 mins)
11. For Guided Discussion:
    - Can you remember any significant energy-water interactions from the past (or lack thereof) that were particularly impactful in your agency and/or region? When was this? What made these interactions significant? How did the interactions affect your operations or decisions?
    - How do you quantify energy use as a water provider, and have you considered energy as part of prior decisions?
    - Has the electricity generation portfolio factored into prior water management decisions by your agency?
    - What statistical properties or understanding of drivers should we focus on for our research so that it is most useful to the management context ? Please wherever possible refer back to prelim results and how they can be expanded or advanced in a useful manner?
    - Are there ways you quantify or consider energy as a water provider that we have not included here?
    - Has the electricity generation portfolio, cost, or carbon intensity factored into prior water management decisions by your agency?
    - Do any of these results change your mind about energy implications of water management decisions?

Survey questions

1. Can you summarize 3 (or more) key takeaways from the interactions you had with the scientists in the focus group discussions for the Multi-Sector Interactions working group, particularly as they relate to your regional decision context?

2. What was most valuable about this process?

3. Did you learn something new from the scientists that could directly inform your work?

4. Can you briefly describe 2-3 important water-energy interactions that are/could be particularly impactful to your agency or region? (short descriptions would suffice)

5. Does the energy intensity of the water system factor into your agency's decisions (as cost, energy, or carbon implications)? Why or why not?

6. Can you identify 2-4 specific management decisions in your agency that could potentially change (or be improved) based on the research that is being conducted in this working group?

7. What specific outputs or results would you like to see from this working group that could be of most use to your region or agency?

8. What questions (related to this research working group) might remain unanswered?

9. Do you have any other comments or suggestions on the engagement process for the working group discussions?