2021

MULTI-DIMENSIONAL MODELING FOR ENVIRONMENTAL IMPACT ASSESSMENT AT INTERSECTIONS OF THE FOOD-ENERGY-WATER NEXUS

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MULTI-DIMENSIONAL MODELING FOR ENVIRONMENTAL IMPACT ASSESSMENT AT INTERSECTIONS OF THE FOOD-ENERGY-WATER NEXUS

By

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A DISSERTATION

Submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

In Civil Engineering

MICHIGAN TECHNOLOGICAL UNIVERSITY

2021

This dissertation has been approved in partial fulfillment of the requirements for the Degree of DOCTOR OF PHILOSOPHY in Civil Engineering.

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This dissertation is dedicated to the original Dr. Daignault. Thank you, Grandpa Frank, for your unconditional love, support, and belief that I could do anything.

Table of Contents

List of Figures

List of Tables

Author Contribution Statement

Chapter 2 is a republication of a journal article under review in *Resources, Conservation, and Recycling* (Daignault et al., 2021a). This work was a collaborative effort and has contributions from the following authors: Dr. Charles Wallace of the Computer Science Department at Michigan Technological University, Dr. David Watkins, Dr. Robert Handler, Dr. Sonya Ahamed of the Department of Civil, Environmental, and Geospatial Engineering at Michigan Technological University, and Dr. Yi Yang of the Ministry of Education, China, at the Key Laboratory of the Three Gorges Reservoir Region's Eco-Environment.

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David Watkins	Conceptualization, Funding Acquisition, Methodology, Supervision, Administration, Writing – Review and Edits
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Chapter 3 has been modified into a journal article under review in *Environmental Science and Technology* (Daignault et al., 2021b). This work was a collaborative effort and has contributions from the following authors: Dr. David Watkins of the Civil, Environmental, and Geospatial Engineering Department at Michigan Technological University, Dr. Timothy Smith of the Department of Byproducts and Biosystems Engineering at University of Minnesota, Dr. Mo Li of GDIT Inc., and Dr. Yi Yang of the

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Chapter 4 is in preparation to be submitted to a journal to be determined based on finished work. This work was a collaborative effort and has contributions from Dr. David Watkins of the Civil, Environmental, and Geospatial Engineering Department at Michigan Technological University and Dr. Ana Dyreson of the Mechanical Engineering Department at Michigan Technological University.

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Ana Dyreson	Conceptualization, Data Curation, Methodology, Modeling, Supervision, Writing – Review and Edits

Acknowledgements

This work was supported by NSF Grant CBET-1639342, "INFEWS/T3: Climate Change Mitigation via Reducing Household Food, Energy and Water Consumption: A Quantitative Analysis of Interventions and Impacts of Conservation."

Thank you to my committee for their feedback and guidance through this program. I could not have succeeded on my qualifying exam, proposal defense, and finally my dissertation defense without your help and mentorship. A very special thank you goes to my advisor, Dr. David Watkins, for his continuous support and guidance over the past four and a half years.

I would like to thank members of our collaborative FEWCON project team at Rutgers University, Arizona State University, University of Minnesota, Dartmouth College, Penn State University, and the U.S. Forest Service for their valuable contributions to the success of our study.

I'd like to acknowledge and thank Clayton Yochum, a friend and fellow MTU alum, who provided invaluable mentorship and assistance in my modeling endeavors using R software.

Finally, I would like to thank my family and friends. I would not have been able to persevere through this program without your love and support. Thank you especially to my parents, Paul and Sue Daignault. You are the best!

Preface

The FEWCON project provided the opportunity to work as part of a multidisciplinary team of scientists and engineers including social scientists, climate scientists, computer scientists, civil engineers and environmental engineers. While I've worked as a team member on big projects before, they have never been this multidisciplinary in nature. This experience has broadened my awareness of how approaches to problem solving can look very different from different disciplines' perspectives, how communication styles can vary between disciplines, and how powerful it is to work through problems together as a multidisciplinary team to come up with ideas, and ultimately, solutions.

One of the most valuable things I learned through my PhD research experience is how to consider social science concepts as they relate to my work as an engineer and educator of future engineers. Civil engineering is required to design infrastructure to serve populations in communities around the world. Municipalities are responsible for funding, designing, constructing, and maintaining infrastructure such as roads, bridges, water and wastewater treatment facilities, water and wastewater distribution and collection systems, and more. These projects are expected to be completed in an economic and efficient manner, with strict design standards met. Through an engineering lens, these projects are completed as efficiently as possible to meet the demand or need for the service. However, thought must be given to how a given design or system will shape the lives of community members and users of the system. A social science perspective on the systemic paradigm, paired with sound engineering judgement and design, would result in innovative execution of projects.

Social science concepts can be considered in all steps of the engineering design project, from scope through project completion. Systems and infrastructure create an invisible "lock-in" for humans using the system, and engineers and planners need to be aware of the implications of their designs. Social science concepts are critical to consider to ensure that the end user of the engineering decision benefits from the project, but also to ensure that environment benefits from the project. Engineers work closely with government agencies and play a key role in development of policy and infrastructure. There is opportunity for engineers to embrace concepts outside of their traditional realm of knowledge to influence socially responsible and sustainable decision making.

I will continue on from this doctoral experience working as an engineering educator. I look forward to incorporating social science, sustainability, and resilience concepts into my courses and encouraging students to consider the attitudes, beliefs, and values of the people they will serve in the future as well as how their designs will impact the economy and environment for current and future generations. It's an exciting time to educate the next generation of engineers, and I am grateful to get to play a role in that. Thank you to the FEWCON team for sharing your expertise and talents with me over the past nearly five years and helping me grow as an engineer.

Abstract

This dissertation uses multi-dimensional modeling for environmental impact assessment at intersections of the Food-Energy-Water (FEW) Nexus, including life cycle assessment (LCA) modeling for quantification of environmental impacts due to household FEW consumption, a linear regression framework for quantification of water-use impacts of marginal electricity generation, and a multi-objective optimization model to assess monetization of water withdrawals for electricity generation and impacts to water stress due to electricity dispatch schemes. Chapter 2 of this dissertation summarizes the development of an LCA model that quantifies the direct and indirect environmental impacts of household FEW consumption. The model is executed through a novel household consumption tracker called the HomeTracker. The result of this work is an open-source software application that has been used to support experimental research taking place in suburban households in the midwestern United States for identification of effective interventions to inform household consumption behavior change. Chapter 3 addresses the need to quantify the water-use impacts of marginal electricity generation. A linear regression methodology is used to quantify water withdrawal and consumption impacts due to marginal generation, and a case study is presented to demonstrate how the framework can be applied to generate marginal water factors (MWFs) at multiple temporal resolutions. Results illustrate that MWFs vary in space and time and are lower when renewables are deployed on the margin. Chapter 4 investigates the effect of implementing a dispatch cost per unit water withdrawals for electricity generation on water stress at the watershed scale. Impacts to water stress are assessed using a

freshwater withdrawal to availability ratio, which quantifies water stress at the watershed level. Adding a dispatch cost per unit water withdrawal decreases water withdrawals up to 92% with a 45% increase in generation cost. The key contribution of this work is an advancement of knowledge of FEW Nexus systems at multiple spatial and temporal scales through life cycle assessment modeling, statistical modeling, and optimization modeling. Future work will include spatial and temporal improvements to models including expansion of geographic coverage and increased temporal resolution as data becomes available.

1 Introduction and Chapter Summaries

1.1 Introduction

Food, energy, and water (FEW) are three essential sources of life for all humanity, and FEW security contributes to the function of society. This security can be described as having reliable access to food, energy, and water in sufficiently available quantities to meet demand. In the face of a growing population, changes to demographics and economics, and a changing climate, pressure on FEW and competition between sectors is increasing (Endo et al. 2017; Miralles-Wilhelm 2016; Flammini et al. 2014). These changes can increase risk of FEW scarcity (Al-Saidi and Elagib 2017). Demand for food, energy and water are projected to increase: there is a projected increase in food consumption of 60 percent by 2050, an increase in energy consumption of 80 percent by 2050, and an increase in water withdrawals of 18 and 50 percent in developed and developing countries, respectively (Flammini et al. 2014). Joint management of food, energy, and water may help to reduce conflicts and ensure reliability and sustainability in FEW systems (Scanlon et al. 2017).

The food-energy-water nexus (FEW Nexus) refers to the interdependency of food, energy, and water (Newell, Goldstein, and Foster 2019; Proctor, Tabatabaie, and Murthy 2020; Zhang et al. 2019). For example, water is required to grow food and is used to both generate energy and for the generation of energy from other sources, energy is required to pump water through distribution systems and process food products, and some foods may be used as a fuel source for bioenergy generation. Growing crops for food and fuel may also increase competition for land and water. Interdependencies between food, energy, and water within the nexus include the “food-energy nexus”, “food-water nexus” and the “energy-water nexus”. These interdependencies are shown graphically in **Figure 1-1** and described in more detail in **Table 1-1**.

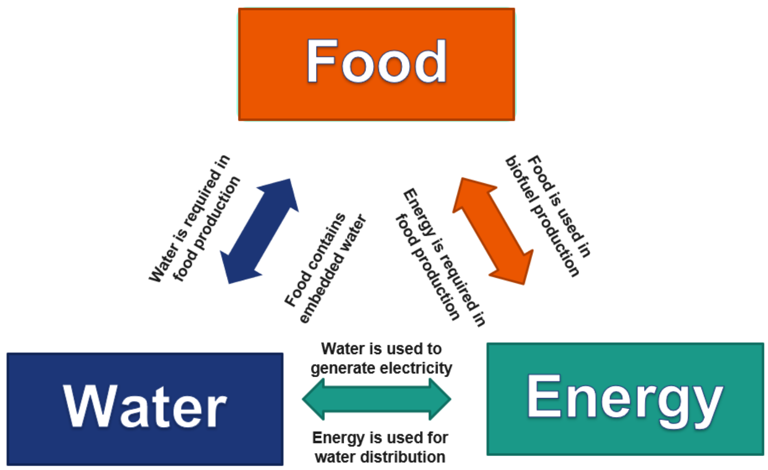

Figure 1-1 Graphical representation of the interdependencies between Food-Energy-Water (FEW)

The concept of the FEW Nexus gained traction among the research community after the 2011 conference, “The Water, Energy, and Food Security Nexus – Solutions for the Green Economy” that took place in Bonn, Germany (Zhang et al. 2019; Endo et al. 2017). The background paper for the conference describes the FEW Nexus as including natural resources and associated systems, physical infrastructure, institutions, socio-economic systems that may either benefit from, or impact in some way the food, energy, and water resources (Hoff 2011). These three sectors have been historically managed and regulated independent of one another, and consequences on one sector due to another were largely unknown (Miralles-Wilhelm 2016). The FEW Nexus management strategy shifts focus from management of one sector to linking the three sectors in management decisions and exploring tradeoffs and co-benefits of joint FEW management.

Table 1-1 Summary of the interdependencies within the Food-Energy-Water Nexus, description of the relationships between the sectors, and examples from the literature.

Interdependency	Relationship	Description	References
Food-Energy Nexus	Food for Energy	Feedstock for biofuel	(D'Odorico et al. 2018; Rodionova et al. 2017; Groom, Gray, and Townsend 2008)
	Energy for Food	Operating machinery Food processing and packing Food transportation Food heating and refrigeration	(D'Odorico et al. 2018; Weber and Matthews 2008; Canning 2011; Clark and Tilman 2017)
Food-Water Nexus	Water for Food	Crop irrigation Food processing	(D'Odorico et al. 2018; FAO and WWC 2015; Steduto et al. 2017; Turral, Burke, and Faurès 2011; Maupin et al. 2017)
Water-Energy Nexus	Energy for Water	Water supply and distribution Water and wastewater treatment Groundwater pumping	(D'Odorico et al. 2018; Mo et al. 2010; Madani and Khatami 2015; Healy et al. 2015; Scott et al. 2011)
	Water for Energy	Crude oil production Natural gas production Coal mining Power generation Thermoelectric cooling Hydropower	(D'Odorico et al. 2018; Hightower, Reible, and Webber 2013; Sanders 2015; Grubert and Sanders 2018; Healy et al. 2015; Maupin et al. 2017)

Viewing FEW management decisions through a water-specific lens requires integrating water research with food and energy research to successfully perform integrated work that will inform infrastructure development, technology, and policy decisions (Cai et al. 2018). Other scholars argue that water is the key piece of the FEW Nexus, noting that food cannot be grown without water and that meeting electricity demand depends on available water supplies (Schull et al. 2020). As a result, current FEW Nexus literature is often water-centric, and it is recommended to take a balanced approach in FEW Nexus analyses (Smajgl, Ward, and Pluschke 2016).

The concept of strong sustainability stresses that our social and economic systems operate within the limits of the natural environment (Ott 2003). Ensuring sustainability in FEW systems requires an acknowledgement that there are constraints on available food, energy, and water to support development, and that development can only occur sustainably if it works within these constraints (Weitz, Nilsson, and Davis 2014). Kurian et al. (2017) recommends taking interdisciplinary and transdisciplinary approaches to FEW Nexus research (Kurian 2017). FEW Nexus research lacks consideration for social, economic and policy issues, and that social objectives have been less prioritized than environmental or economic objectives (Portney et al. 2018; Chapman, McLellan, and Tezuka 2016). Social scientists, engineers, climate scientists, policy makers, and others must work together to understand FEW Nexus issues, focusing not only on the physical aspects of the systems but also the social and economic issues (Scanlon et al. 2017; Proctor, Tabatabaie, and Murthy 2020).

There have been multiple publications that summarize the state of the FEW Nexus literature, identify existing tools, and make the case for future FEW Nexus research needs (Albrecht, Crootof, and Scott 2018; Endo et al. 2017; Newell, Goldstein, and Foster 2019; Zhang et al. 2019). The body of research has grown since the Bonn 2011 Conference, with hundreds of organizations launching FEW Nexus-related initiatives and a body of literature that, as of 2019, has exceeded 450 papers (Zhang et al. 2019). This work is being completed as part of a national research program initiated by the National Science Foundation, titled "Innovations at the Nexus of Food, Energy, and Water Systems" (INFEWS) (NSF 2018). The objective of this research program is to develop understanding of the FEW Nexus as an integration of social, engineering, physical and natural systems. The INFEWS program has four key goals as identified in the program summary: 1. Significantly advance our understanding of the food-energy-water system of systems through quantitative, predictive and computational modeling, including support for relevant cyberinfrastructure; 2. Develop real-time, cyber-enabled interfaces that improve understanding of the behavior of FEW systems and increase decision support capability; 3. Enable research that will lead to innovative and integrated social, engineering, physical, and natural systems solutions to critical FEW systems problems; and 4. Grow the scientific workforce capable of studying and managing the FEW system of systems, through education and other professional development opportunities.

Al-Saidi et al. (2017) proposes three methods of integration for FEW Nexus work including integration through incorporation, integration through cross-linking, and integration through assimilation with an emphasis on a need for tools that increase understanding of incorporation and cross-linking of nexus issues. Integration as incorporation holds food, energy, and water as important to management decisions, and is used to inform policy, make investment decisions, or assist with resource planning, while integration as cross-linking is beneficial for establishing environmental regulations and can include linkage of the nexus at multiple scales and with various sector combinations, as summarized in Table 1 (Al-Saidi and Elagib 2017). The research summarized in this dissertation contributes to understanding of incorporation and cross-linking of nexus issues and advance knowledge of FEW Nexus systems through three primary research objectives. Objective 1 is to develop a life cycle assessment model that supports household consumption research through an open-source tool that provides meaningful feedback to users by quantifying direct and indirect environmental impacts of FEW consumption at the household level. Objective 2 is to expand upon existing water-use intensity estimates due to electricity generation by proposing a framework for development of marginal water-use factors that could be used to quantify the water withdrawal and consumption impacts of marginal electricity generation. Objective 3 is to develop a framework that identifies water withdrawal reduction opportunities through monetization of water for electricity generation to reduce water stress at the watershed scale.

1.2 Chapter 2 Summary

Households require direct consumption of food, energy, and water to power homes, meet nutritional requirements, and maintain cleanliness. While consumers can often visually comprehend the direct consumption of FEW, such as water coming out of a tap or eating a meal, the indirect impacts of this consumption remain unseen. Changes in household consumption behavior have the opportunity to reduce environmental impact on greenhouse gas emissions and water use, and this work develops a tool to identify what those opportunities are. This work uses life cycle assessment (LCA) to quantify direct and indirect environmental impacts of household consumption. The result of this work is an open-source tool that provides meaningful feedback to users by informing them of their direct and indirect household FEW consumption. The development of this life cycle assessment-based tool allows for examination of what users purchase and consume over an extended period of time and is currently being used to provide messaging to users that can inform meaningful behavior change.

1.3 Chapter 3 Summary

The interdependency between water and energy is known as the water-energy nexus. Significant volumes of water are used for electricity generation, and water use rates can vary substantially as generating facilities on the grid are operated to respond to changes in demand. Generation that responds to a change in demand is called marginal generation, and energy policy evaluation requires an understanding of water use requirements of marginal generation, particularly as electric utilities increase deployment of renewables on the margin. This work develops a novel framework for calculation of marginal water-use factors (MWFs), which represent both the water withdrawal and water consumption intensity of marginal electricity generation. The Midcontinent Independent System Operator (MISO) region is used as a case study to demonstrate how the framework can be applied to generate MWFs at different spatial and temporal resolutions. Results illustrate that MWFs vary significantly in space and time and are lower when renewables are deployed on the margin.

1.4 Chapter 4 Summary

The electricity grid is typically operated by using economic dispatch, a scenario in which generators are fired in order to meet demand and provide the least-cost electricity to the consumer. However, using the least-cost generators can result in large water withdrawal volumes that can contribute to water stress. This work develops a framework to assess the changes in dispatch order and associated impacts to water stress due to implementation of water withdrawal fees for electricity generation. Four cost scenarios are evaluated, and results show that water withdrawals can be reduced by up to 92%, but that the reduction comes with a tradeoff as generation costs increase by up to 45%. Results also show that while total volumes of water withdrawn can be reduced by implementing water withdrawal fees, water stress at the watershed level remains relatively unchanged due to low-runoff conditions and large volumes of withdrawal within the watershed by other users such as municipal, industrial, agriculture and more.

These research objectives contribute to understanding of nexus issues by using life cycle assessment modeling to understand FEW consumption impacts at the household level, by modeling aspects of the water-energy nexus using existing and novel tools, and finally by assessing the water-energy nexus at multiple spatial and temporal scales. These objectives also work toward sustainable approaches to FEW Nexus issues by accounting for social, economic, and environmental considerations related to FEW decision-making.

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2 Development of a Life Cycle Assessment Model for Understanding the Food-Energy-Water Nexus at the Household Scale

2.1 Introduction

The food-energy-water (FEW) nexus refers to the interdependency of food, energy, and water. Pressure on FEW increases due to global population growth, increase in per capita consumption, changes in dietary preferences to include more animal products, and a changing climate (Scanlon et al. 2017; Flammini et al. 2014). Globally, household consumption accounted for 65% of total greenhouse gas emissions and 81 percent of indirect total freshwater use in 2007 (Ivanova et al. 2016). In the United States, over 80 percent of greenhouse gas emissions have been attributed to consumption at the household level (Jones and Kammen 2011). Thus, there is an opportunity to reduce water use and greenhouse gases emissions impacts globally and domestically through changes in household consumption behavior, and an understanding of current behavior trends can help identify effective interventions.

Households consume food, energy, and water for everyday tasks such nourishment, powering homes, hygiene and more which results in direct and indirect environmental impact. The average water footprint of an individual person's diet varies between approximately 158,500 and 264,000 gallons per year per person depending on dietary preferences (D'Odorico et al. 2018). The average greenhouse gas emissions from a person's diet is estimated at 4.7 kg CO_2 eq. per day (Heller et al. 2018). Electricity generation requires significant volumes of freshwater use and emits greenhouse gases into the atmosphere. Over 40 percent of United States energy is consumed for household and commercial purposes (Chini et al. 2016). While the industry average water use for electricity generation has been cited as 25 gallons per kWh, the water use intensity of electricity generation varies by orders of magnitude depending on fuel mix, generation prime mover, and cooling technology (Grubert and Sanders 2018; Sovacool and Sovacool 2009). Greenhouse gas emissions intensity of electricity generation also depends on fuel mix, generation prime mover, as well as emissions controls.

Multiple studies have investigated the environmental impacts, including greenhouse gas emissions and water use, of dietary choices and maintaining a healthy diet (Hallström et al. 2017; Heller and Keoleian 2015; Tom, Fischbeck, and Hendrickson 2016). Agricultural activities have negative impacts on the environment through emission of greenhouse gases, intensive use of fertilizers and pesticides, withdrawal and consumption of freshwater, land use change, and degradation of biodiversity (Yang et al. 2018). The agricultural sector accounts for approximately 70 percent of global water withdrawals (Marston et al. 2018). In addition, the environmental impact of food consumption at the household level has been quantified and related to sociodemographic characteristics such as race, income, and education level (Boehm et al. 2018). Other studies attempt to quantify the environmental impact of water and energy at the household level, both within the United States and globally (Ivanova et al. 2016; Chini et al. 2016). Work by Jones and Kammen (2011) quantifies environmental impact, specifically greenhouse gas emissions, at the household level through an open-access online tool titled “Cool

California" that can be used to calculate household carbon footprint and inform behavior change.

The Food-Energy-Water Conscious (FEWCON) project aims to identify potential interventions for reducing the environmental impacts of household food, energy, and water consumption. The project collects data to identify household consumption behavior and cost-effective interventions using mixed-methods approaches, including interactive role-playing activities, qualitative interviews with homeowners, household surveys to examine existing attitudes and behaviors related to food, energy, and water consumption and experimental research in residential households selected to be representative of suburban populations in the United States. The experimental research takes place in Lake County, Illinois with 174 household study participants. A specific task to support the household experimental research is to develop a user interface with supporting information grounded in life cycle assessment (LCA) methods in order to provide households information related to their consumption and associated environmental impacts. This FEW consumption-based life cycle assessment framework has been developed in conjunction with a novel Household Metabolism Tracker application, called HomeTracker, to support data collection that allows researchers to answer questions about household consumption behavior, and identify interventions that can be effective in reducing the environmental impacts of household consumption. Through HomeTracker, study participants enter their grocery and restaurant receipt purchases, monthly water bills, monthly natural gas bills, and monthly electricity bills. Environmental impacts, including greenhouse gas emissions and water use, are calculated from this consumption, and feedback is provided to participants in a visual interface highlighting the environmental impact of their household consumption.

While existing literature assess the environmental impact of various aspects of household consumption, they generally do not address the direct and indirect water use and greenhouse gas emissions impacts of food, water, and energy holistically. Additionally, many of the existing studies use datasets that represent an average level of consumption or a snapshot in time of consumption behavior rather than an extended period of time such as a month or year that would allow for temporal trends to be assessed. This research fills a gap in sustainability science by creating an open-source tool that provides timely feedback on environmental impacts of FEW consumption at the household level. The development of a life cycle assessment model for use with the HomeTracker allows for examination of what consumers actually purchase and consume over an extended period of time at multiple temporal scales. Software development for the HomeTracker application, participant FEW data collection procedures, and environmental impact factors used to calculate indirect and total water use and greenhouse gas emissions in the model are summarized in the methods section. Sample data is then presented to demonstrate how the HomeTracker application and life cycle assessment model are applied in the FEWCON study. Finally, limitations of the tool and future work are discussed.

2.2 Methods

2.2.1 Software Development

As the central communication medium for participants in the FEWCON consumption study, the HomeTracker system has a number of key system requirements, including continuous collection of consumption data, minimization of participant burden, maintenance of privacy, and clarity and accuracy of feedback. These requirements are detailed below.

Collection of data. These data include electricity, natural gas, water, and food consumption. Households in the study area have a single common electrical utility, which simplifies the data collection process, but natural gas and water providers vary between households. Food data collection duration is adjustable in HomeTracker. For our study purposes, multiple 2-week collection intervals were selected, but this does not have to be a fixed setting within the modeling framework. In addition to these quantitative data, households are asked to respond to a series of surveys and invited to provide reflective statements on their consumption behavior through open-ended survey questions and a journaling feature in HomeTracker.

Minimization of participant burden. HomeTracker is designed to minimize the data collection burden for two primary reasons. First, excessive requirements on entering data may diminish participation in the project and erode retention of household participants. Second, relying on household data entry introduces risk of error, as study participants may vary widely in their comfort with digital technology and their understanding of the data requirements of the study.

Maintenance of privacy. Quantitative and qualitative data must be maintained on a per-household basis, but identifying information is removed before sharing the data set widely among project personnel. The HomeTracker project manager monitors individual household behavior and communicates with participants as needed, such as when a household fails to provide requested food consumption data.

Clarity and accuracy of feedback. Households receive periodic feedback on their consumption during one component of the study period. The feedback takes the form of a series of messages in graphical and textual form, quantifying the environmental impact of household consumption in terms of greenhouse gas emissions and water use and comparing them to established average household consumption values. Participating households view these messages and complete a brief survey on their reactions to them. Inaccuracies are noted by participants and communicated to the project manager.

The HomeTracker system involves a number of user roles and data sources that are connected through an interactive web application as shown in **Figure 2-1**. The foundation for the HomeTracker application is Grails, an open-source Java-based framework that uses the Apache Groovy programming language. An Apache Tomcat server hosted at Michigan Technological University provides Java Database Connectivity (JDBC) between the application and the MariaDB relational database management system.

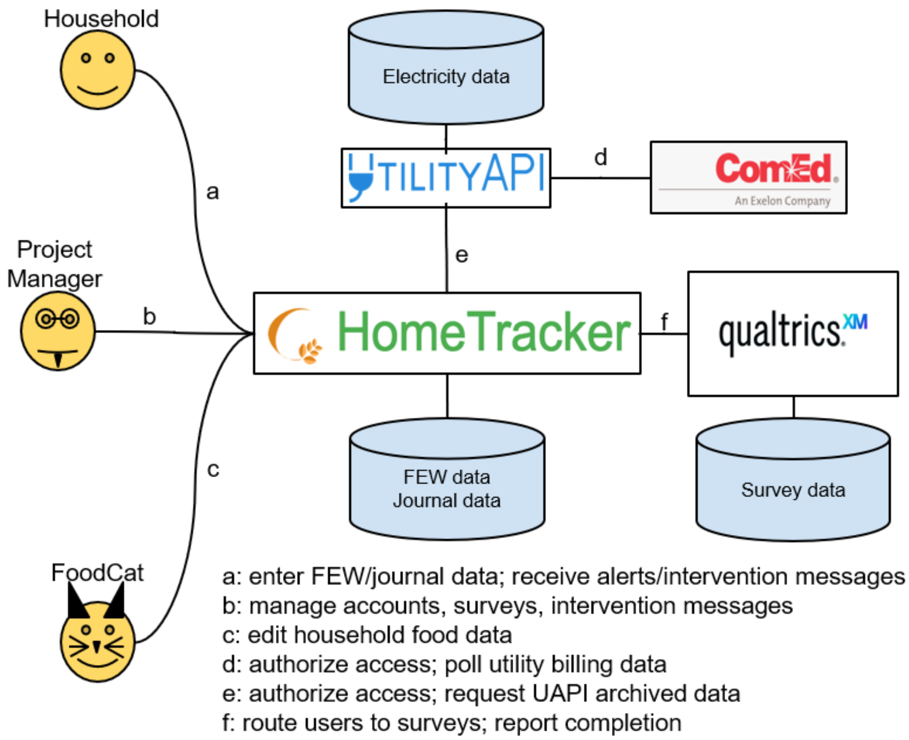

Figure 2-1 HomeTracker architecture

Implementing HomeTracker as a web application allows household participants to access the service through any device that supports a standard web browser. Since Grails is the application framework used in Michigan Technological University's User Interface Design and Implementation course, students can easily transition from that course into a HomeTracker development role.

HomeTracker provides access for a number of user roles. Each *household* in the study is assigned a password-protected account, which members are expected to log into regularly to enter data or read messages. The *project manager*, who serves as the liaison with participating households, can log in as an administrator to view household activity on HomeTracker, to add or modify household accounts, to add or modify surveys and intervention messages, to open or close food collection periods, or to download all or part of the study data. Project staff who are charged with food categorization (informally referred to as *food cats*) can log in to access uploaded purchases and fill in category and price information for purchase line items.

In designing the data acquisition processes, automation is favored for easing the burden on household participants, but only if the underlying technology is robust and comes at minimal risk to accuracy of the data. Unfortunately, our investigations into state-of-the-art technologies for automated data collection indicated significant risks in using automation; consequently, most of our data entry functions are manual in nature. We initially explored the use of in-house sensor devices (*e.g.* Smappee, Sense) that household owners can install on the metering equipment in their houses. Many of these devices offer APIs that allow third parties to access data collected by the devices. After some experience installing a few such devices in local houses, it became clear that the risk of faulty installation made this option infeasible.

Fortunately, an alternative automated means of collecting electricity consumption data that avoids the costs and inaccuracies of in-house installation was identified. The study area's local service provider, Commonwealth Edison (ComEd), partners with a company called UtilityAPI to provide electricity billing data, for consumers who authorize it, to third-party applications. UtilityAPI stores up-to-date versions of these data on its own secure servers so that apps like HomeTracker can access them as needed. In addition, subscribing to the UtilityAPI service provides access to a rich set of additional historical billing data for authorizing consumers. Household participants must authorize UtilityAPI to access their ComEd billing data. Completing the authorization form creates secure credentials that HomeTracker then uses to access data through UtilityAPI.

Unlike electricity, the utilities supplying natural gas and water vary within the study area. The smaller-scope authorities providing these utilities, particularly the local municipalities in charge of water supply, do not have the resources to provide third-party data access. While there are home-installed sensors (e.g., Sense, PecanStreet) that provide monitoring, most of these products were not available during the development of HomeTracker, and risk and cost concerns over installation and maintenance made this option infeasible. Participants instead enter their gas and water billing data manually in HomeTracker using the standard billing statements they receive at regular intervals.

Food data collection occurs during several specified two-week periods in the study. During these periods, household participants are asked to upload all purchases, both *food at home* (i.e., food purchased with the intent of preparing it at home) and *food away from home* (i.e., food prepared and purchased outside the home). Participants distinguish between full service restaurants, defined as food establishments that provide not only preparation but also service of the food and limited service restaurants, defined as establishments like delicatessens or cafeterias that prepare but do not serve the food. For food at home, the itemized breakdown of the purchases allows for greater detail and more nuanced analysis. In entering these purchases into HomeTracker, participants are asked to provide per-item details of such purchases. If the purchase includes a receipt, the household participant uploads images of the receipt and provides an item-by-item description of the purchase. Later, food categorizer staff consult the receipt images and participant descriptions of the line items and supply category and price information. For a purchase without receipt images (*e.g.*, farmer's market, forgotten or lost receipt), household participants provide item-by-item descriptions and prices of the line items.

Development of HomeTracker began in summer 2018. HomeTracker developers worked iteratively with members of the project team in designing and implementing the app, according to the needs and expectations of the project scientists. In spring 2019, students at Michigan Technological University and Rutgers University provided initial user testing, followed by a pilot test with household volunteers from the Rutgers community (Heaney 2019). User feedback from this testing drove changes to the interface design, along with development of the HomeTracker User Guide, in summer 2019. A second round of user testing was conducted among FEWCON project staff and a small group of volunteers in Lake County, evaluating the revised interface and checking that the HomeTracker app and the User Guide were compatible. HomeTracker was deployed and made available to study participants in February 2020.

2.2.2 Participant Interface

The HomeTracker home screen provides access to the functions of the application. **Figure 2-2** shows alerts, colored orange, that indicate conditions that may require action by the household participant. Options to read intervention messages, provide open-ended journal entries on their consumption behavior, or take surveys are all shown in blue. Data entry options, colored green, include modifying the household membership and entering food, natural gas, and water consumption, as shown in **Figure 2-3**. Manual electricity entry can also be included, though electricity consumption is typically accessed automatically via UtilityAPI. Icons showing question marks are included in the user interface to provide users with additional information and educational resources to better understand the HomeTracker.

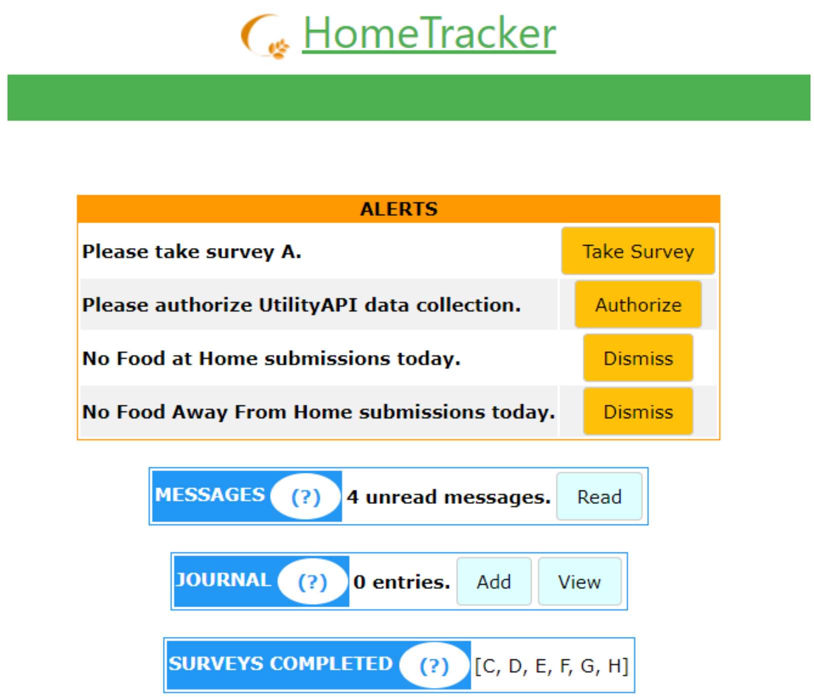

Figure 2-2 HomeTracker home screen: alerts, messages, journal entry, and surveys

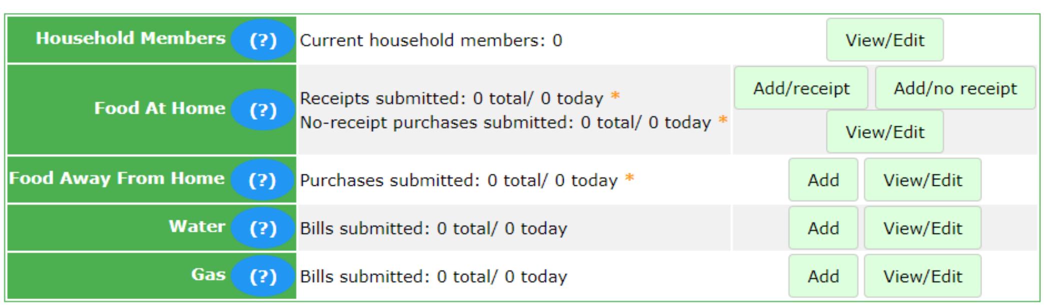

Figure 2-3 HomeTracker home screen: data entry for members, food, water, and natural gas

Participants enter information for all food purchases during the specified collection periods, including food that is consumed outside of the home. Household food can include food and beverages that are purchased by household members from multiple sources (French et al. 2008). The HomeTracker interface allows participants to enter food data in the two broad categories of food at home and food away from home.

Receipts for Food at Home purchases are annotated, photographed and uploaded to the HomeTracker. To aid with the food categorization process, participants are asked to provide a common name for the receipt line items.

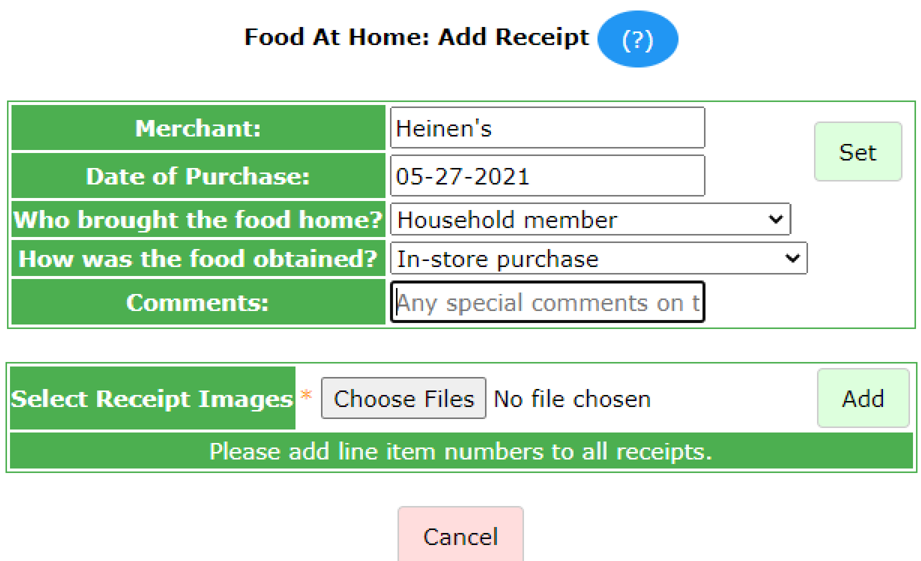

Figure 2-4 HomeTracker interface: Food At Home receipt entry screen with option to upload receipt image

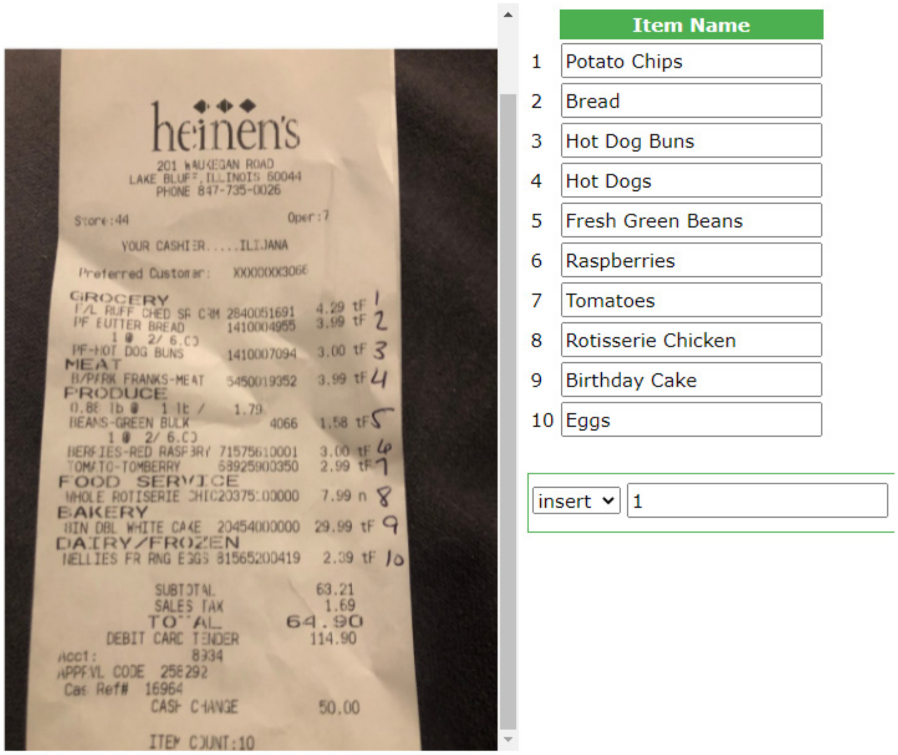

Figure 2-5 Screenshot of receipt upload and annotation for categorization

Once participants upload their annotated receipts and submit them with common name descriptors, a team of categorizers assigns each item to a category (categories are described in Section 2.2.3.5) and enters the price of the item. If a receipt is missing for a particular food purchase, the participant can manually enter the items purchased and associated price without uploading a receipt.

Food Away From Home purchases are entered as a lump sum dollar amount and categorized as Limited-Service or Full-Service Restaurant purchases, following the definitions by Heaney (Heaney 2019).

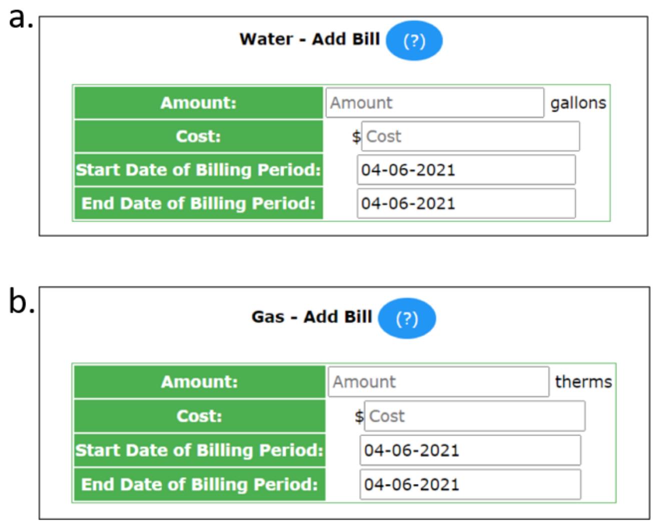

Figure 2-6 (a) Screenshot of HomeTracker user interface for entering water bills and (b) Screenshot of HomeTracker user interface for entering natural gas bills

Natural gas and water consumption are manually entered from user utility bills. Users enter the amount of natural gas billed in therms and U.S. Dollars, as well as the billing period. Users enter the amount of water billed in gallons and U.S. Dollars, as well as the billing period. The user guide provides specific instructions for locating the correct information from utility water bills. If users do not have a water provider, they are supplied with a water estimator guide asked to estimate their water use in gallons. The HomeTracker user guide is included in the Supplementary Material. Participants need to authorize electricity data collection through UtilityAPI Green Button Connect, but do not need to manually enter any additional information.

Throughout the study, participants fill out multiple surveys which are administered to participants approximately once per month to provide the research team with additional demographic and residential energy consumption data. Surveys are assigned periodically through the study duration to collect additional information about attitudes and beliefs that may impact their consumption habits. HomeTracker is linked with Qualitrics to administer surveys through the software interface. When participants log in to HomeTracker, they receive an alert of any new survey to complete; the alert includes a link to the survey hosted on the Qualtrics website. Upon completion, participants follow a link back to HomeTracker, which then marks the survey as completed.

2.2.3 Environmental Impact Factors

This work uses a life cycle assessment (LCA) approach to quantify direct and indirect environmental impacts of household consumption of food, energy, and water. Life cycle assessment is used to assess the potential environmental impact of a product, process or service using four key steps: i) Goal definition and scoping, ii) Inventory analysis, iii) Impact assessment, and iv) Interpretation of results (Curran 2006). The framework for this LCA-based environmental impact model starts with input of direct household FEW consumption values. These include water in gallons (gal), electricity in kilowatt hours (kWh), natural gas in therms (therm), and food purchases in U.S. dollars (USD). Environmental impact factors are applied to determine the direct and indirect environmental impact due to the consumption. The direct and indirect environmental impacts are summed to output total water withdrawal in gallons and total greenhouse gas emissions in kilograms of carbon dioxide equivalents or kg CO_2 eq. Carbon dioxide equivalent is a measure that is used to compare the emissions from greenhouse gas emissions based on global warming potential. Direct and indirect environmental impacts are accounted for as shown in **Figure 2-7**.

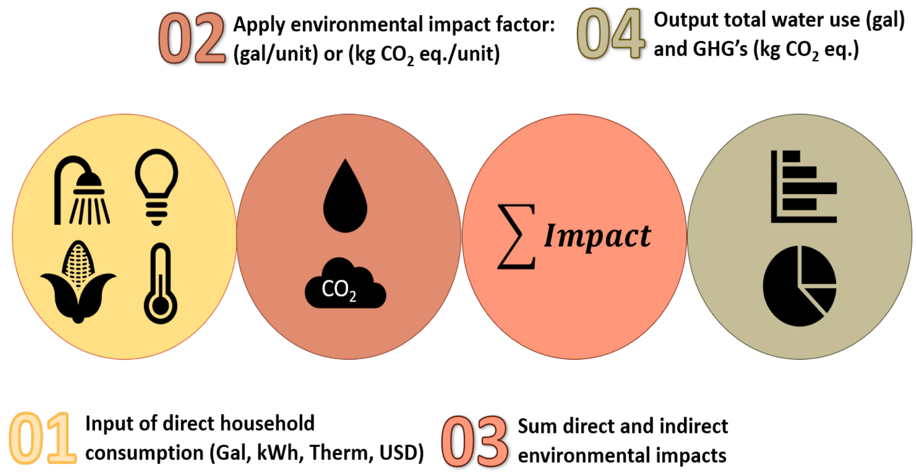

Figure 2-7 Schematic representing direct and indirect inputs for consumption-based environmental impact assessment of water use in gallons and greenhouse gas emissions in kg CO_2 eq

The environmental impact factors used to calculate the environmental impact of indirect resource consumption are summarized in **Table 2-1**.

Table 2-1 Summary of environmental impact factors for indirect resource consumption

Environmental Impact	Indirect Contributor	Factor	Units	Scale
Water Use	Water	3.01	Gal/Gal	National
	Electricity	See Table 2-3	Gal/kWh	Regional
	Natural Gas	0.46	Gal/Therm	National
	Food	See Figure 2-8	Gal/USD	National
Greenhouse Gas Emissions	Water	0.329	kg CO_2 eq./Gal	National
	Electricity	0.643	kg CO_2 eq./kWh	Midwest
	Natural Gas	8.05	kg CO_2 eq./Therm	Midwest
	Food	See Figure 2-8	kg CO_2 eq./Therm	National

2.2.3.1 Water Use Factors

Water use in this study refers to water withdrawn from its original source. Water use per therm of natural gas was estimated from a study that developed life cycle water use factors for different stages of conventional and shale gas life cycles, combined with

Energy Information Administration data on the current proportion of each gas source currently in use in the U.S. (Ali and Kumar 2016; EIA 2019c). Water use per gallon of water used at the household is a cumulative estimate that includes both direct water use and indirect water use embedded in all of the materials and energy required to treat and deliver water to the home, as well as all of the unit operations involved in treating water after it leaves the household in a standard municipal wastewater treatment system. Life cycle inventory data for upstream water treatment and delivery as well as downstream wastewater treatment, comes from the Ecoinvent database. This database provides life cycle inventory data for use in Life Cycle Assessment, and is known for its transparency and comprehensiveness (Wernet et al. 2016).

2.2.3.2 Greenhouse Gas Emissions Factors

Greenhouse gas emissions per gallon of water used in the household are also estimated from Ecoinvent, analyzed with the Intergovernmental Panel on Climate Change 2013 GWP 100a method, which is an impact assessment method that expresses emissions impacts of climate-active greenhouse gas emissions in kilograms of carbon dioxide equivalents. Greenhouse gas emissions per kilowatt hour (kWh) of electricity generated were estimated by combining U.S. EPA eGRID data on average emissions per kWh for power plant emissions in the RFC West subregion, combined with the average grid composition in the region and the upstream emissions impacts for fuel production for each relevant fuel type from Ecoinvent (EPA 2018). Greenhouse gas emissions per therm of natural gas were estimated by combining combustion emissions per therm of natural gas with Ecoinvent data on upstream natural gas processing and transmission.

2.2.3.3 Norming Factors

Table 2-2 shows the average environmental impact values that are displayed as norming feedback to households participating in the FEWCON study (Steg and Vlek 2009). These values were selected to be as representative as possible of Lake County, IL. The average volume of water for domestic water use is 6254 gallons per household per month. This data comes from the United States Geological Survey (USGS) Water Resources National Water Information System (USGS 2018). The average household electricity use is 796 kWh per month. This data comes from the 2018 Residential Energy Consumption Survey (RECS) Report and is based on an annual average that was divided by twelve to represent a monthly average (EIA 2015). This data is representative of the year 2015. The average household natural gas use is 64 therms per month, and this value was obtained consistent with electricity use average data. The average dollar amount spent on food at home and food away from home is 658 U.S. Dollars and comes from the U.S. Bureau of Labor Statistics 2018 Consumer Expenditure Survey: Table 1400 (BLS 2018). The average water footprint and greenhouse gas emissions footprint for food is calculated based on the average dollar amount spent using the United States Environmentally Extended Input Output model (Yang et al. 2017b).

Table 2-2 Summary of average impact values for household norming feedback

Consumption Category	Monthly Average	Units	Scale	Reference
Water	6254	Gal	Lake County	USGS
Electricity	796	kWh	Midwest	RECS Survey
Natural Gas	64	Therm	Midwest	RECS Survey
Food	658	USD	National	CES Survey

2.2.3.4 Water Use Intensity for Electricity Generation in PJM

The Pennsylvania-New Jersey-Maryland Interconnection (PJM) is a Regional Transmission Organization (RTO) that administers the grid for 13 states including: Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia, as well as the District of Columbia. The water use intensity of electricity generation for the entire fuel mix in PJM was calculated at a monthly resolution for 2019 to best represent the FEWCON study-area. The United States Energy Information Administration reports monthly thermoelectric cooling water data at the generator level for power plants in the United States in Form EIA-923 (EIA 2019a). This form was cross-indexed with Form EIA-860(EIA 2019b) to identify plants that are connected to the PJM grid. Since Form EIA-923 only reports on thermoelectric generators, electricity generation data from PJM was used to determine how much electricity generation was attributed to hydroelectric, solar, and wind generation (PJM 2019). Total water withdrawal and total generation were aggregated by month. Average monthly water withdrawal intensities (gallons/MWh) for month i were calculated for PJM using Equation 2-1.

$$AWF_i = \frac{W_i}{G_i} \tag{2-1}$$

where W_i represents the total water withdrawal (gallons) for month i, and G_i represents total electricity generation (MWh) for month i. Monthly water withdrawal intensity values for PJM are shown in **Table 2-3**.

Table 2-3 Monthly water withdrawal intensities for PJM

Month	Water Withdrawal Intensity (Gal/MWh)
January	10569
February	9621
March	9850
April	11910
May	12505
June	12312
July	11972
August	11926
September	11894
October	12219
November	11218
December	11288

Withdrawal intensities are relatively low during all months of the year in PJM with a low value of 9621 Gal/MWh in March and a high value of 12505 Gal/MWh in May. The largest contributors to the PJM annual fuel mix are coal at 24%, gas at 36%, and nuclear at 34%. There are very limited renewables in the fuel mix, with 2% hydro, 3% wind, and 1% other renewables. Nuclear is a low withdrawal intensity baseload generation source, likely contributing to the overall low intensities observed in **Table 2-3**. Lower intensities observed January-March can likely be attributed to cooler temperatures, as well as higher deployment of wind energy.

2.2.3.5 United States Environmentally Extended Input-Output Model (USEEIO)

The United States Environmentally Extended Input-Output Model (USEEIO) is a United States-specific environmentally extended input-output model that can be used to quantify environmental impacts of production and consumption of 389 industry sectors. Environmental data allows for quantification of impacts related to land cover, water, energy use, mineral use, greenhouse gas emissions, air pollutants, nutrients, and toxics.

This model was selected for use in this research task as it is useful in performing streamlined life cycle assessment. Environmental impact is quantified per U.S. Dollar spent, allowing for simple calculation of environmental impact based on purchase data submitted by participants through the HomeTracker interface. The environmental impacts, specifically water use and greenhouse gas emissions, can be calculated for 29 detailed categories of food-related spending. Greenhouse gas emissions are estimated using the 2013 greenhouse gas inventory as compiled by the U.S. Environmental Protection Agency while water withdrawals were determined for irrigation of crops, watering of livestock, cooling water in thermoelectric power generation, mining operations, and other commercial and industrial purposes using multiple data sources as outlined in the USEEIO Model Details (Yang et al. 2017a).

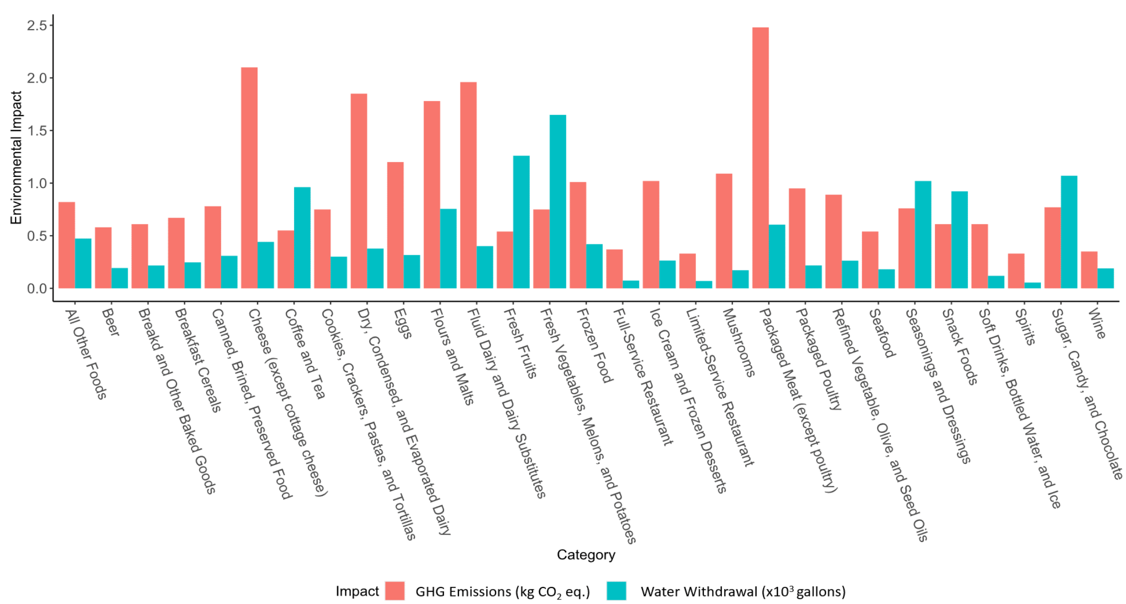

Figure 2-8 Environmental impact factors for calculation of greenhouse gas emissions (kg CO_2 eq.) and water withdrawal (gallons) resulting from food consumption

Figure 2-8 represents the environmental impact factors for calculation of greenhouse gas emissions and water withdrawal resultant from food consumption. Packaged meat and dairy have the highest greenhouse gas emissions per dollar spent, while fresh fruits, breakfast cereals, and seafood have notably lower greenhouse gas emissions per dollar spent. Fresh vegetables, melons, and potatoes require the most water per dollar spent. Other water-intense categories include fresh fruits; sugar candy and chocolate; snack foods; coffee & tea; and seasonings and dressings. Less water intense categories include mushrooms, breakfast cereal, and seafood. Full-service and limited-service restaurant impacts are relatively low for both greenhouse gas emissions and water withdrawal per dollar spent compared to other food categories, due to the increase in price of goods purchased at a restaurant rather than at a market, effectively increasing the denominator on the "impact per dollar" spent factor.

2.3 Results and Discussion

The HomeTracker software model has been applied as part of the FEWCON study, which includes 174 households from Lake County IL. To illustrate how HomeTracker was applied, sample output for one month of consumption data from two contrasting households is summarized in **Table 2-4**.

Table 2-4 Sample household output data for June 2020

Household	Resource	Amount	Units	GHGs (Kg CO2 Eq.)	Water Use (Gal)
1	Food	260	$	219	14901
	Water	1500	gal	6	4500
	Natural Gas	10.5	therm	85	5
	Electricity	464	kwh	298	5707
	Total			**608**	**25113**
2	Food	1060	$	1168	68395
	Water	5250	gal	21	15750
	Natural Gas	38	therm	304	17
	Electricity	1399	kwh	900	17207
	Total			**2393**	**101369**

Household 1 consumed notably less than household 2 in all categories, resulting in 74 percent less water use and 75 percent less greenhouse gas emission. Survey data that is collected through HomeTracker can be used to elaborate on household characteristics that support these trends. In this example, household 1 is a one-person household with a home size of 1,238 square feet, while household 2 is a three-person household with a home size of 1,938 square feet.

Households receive feedback about their consumption and environmental impact in the form of a bar chart that compares them with average household consumption values for Lake County. As shown in **Figure 2-9** and **Figure 2-10**, household 1 contributes less environmental impact in terms of both greenhouse gas emissions and water use than the average Lake County household, while household 2 has greater environmental impacts than the average household. Average household consumption values are based on a household size of 2.5 people.

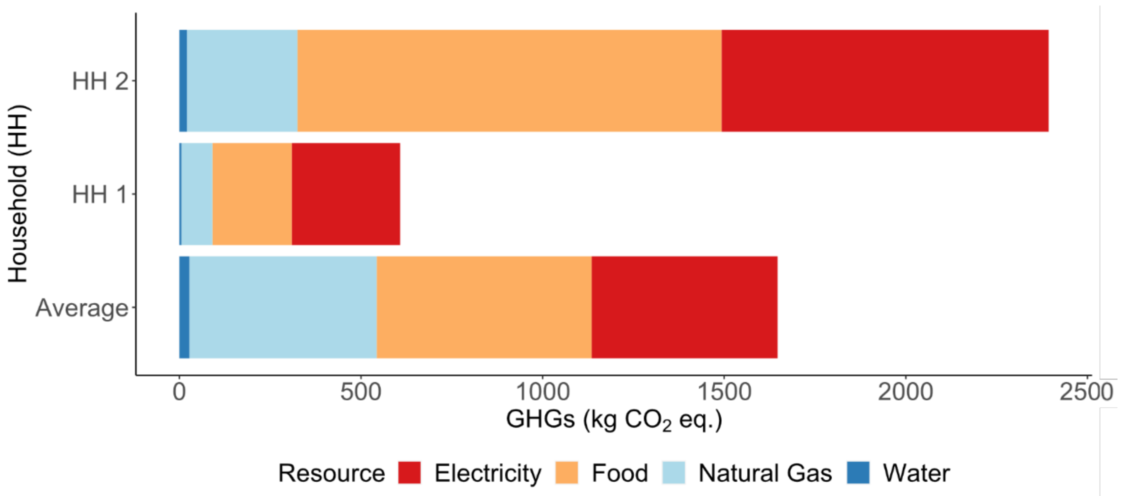

Figure 2-9 Comparison of household greenhouse gas emissions with average emissions in Lake County

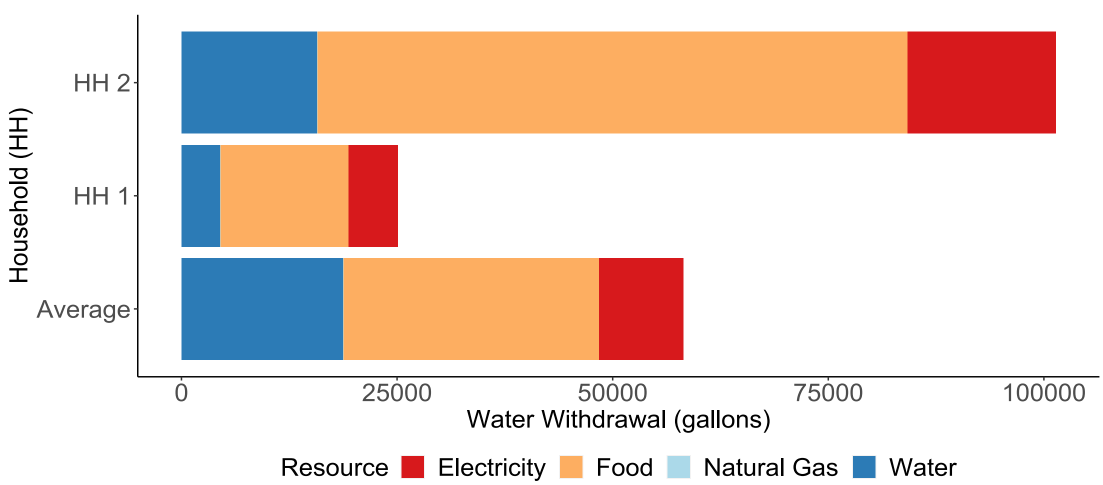

Figure 2-10 Comparison of household water use with average water use in Lake County

Despite large differences in consumption amounts between the two households, a look at the percent contributions to environmental impact from each resource category shows that the households' relative contributions to environmental impact are actually quite similar. **Figure 2-11** shows that water use impacts from natural gas consumption in both households are nearly negligible, and the largest fraction of water use stemmed from food consumption in both households. Greenhouse gas emissions from food consumption are higher in household 2, indicating that they may have consumed a larger amount of animal products compared with household 1. By contrast, household 2 had a smaller contribution to greenhouse gas emissions from electricity consumption than household 1, indicating that household 2 may be more energy efficient.

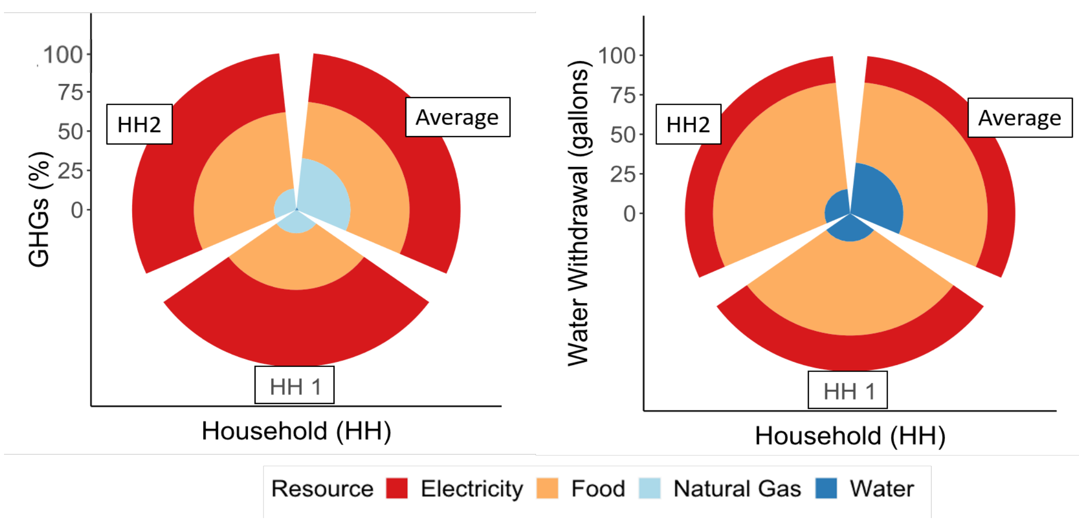

Figure 2-11 Percent contribution to environmental impact from resource consumption categories. Greenhouse gas emissions are shown on the left pane in units of kg CO_2 eq. and water use on the right in units of gallons.

In addition to this output, households will receive messages to educate them on the consequences of consumption habits and can inform behavior change. Example messages are summarized in **Table 2-5**.

Table 2-5 Sample Intervention Message Feedback to Participants

Message 1	Changing your old incandescent light bulbs to newer light emitting diodes (LEDs) can reduce your household GHG emissions from electricity use by 1000 lb per year (5%) and reduce your household water footprint by over 16,000 gallons per year (2%).
Message 2	Switching your household to a renewable energy option at your electric utility could reduce your household GHG emissions by over 10,500 lb per year (43%) and reduce your household water footprint by over 230,000 gallons (27%).
Message 3	Lowering your thermostat by 5 degrees in the winter can reduce your household GHG emissions by 740 lb per year (4%); and for homes with A/C, raising your thermostat by 5 degrees in the summer can reduce your household GHG emissions by an additional 630 lb per year (3%).

Figure **2-12** shows example timeseries output for a sample household showing electricity use in kilowatt hours (kWh) and natural gas use in therms (therm). While users do not receive feedback based on timeseries data, it allows researchers to assess temporal trends in household resource consumption. This particular household consumed higher amounts of electricity during the winter months and a spike in electricity use during the month of July. This household also used higher amounts of natural gas during the winter months, which is likely due to household heating.

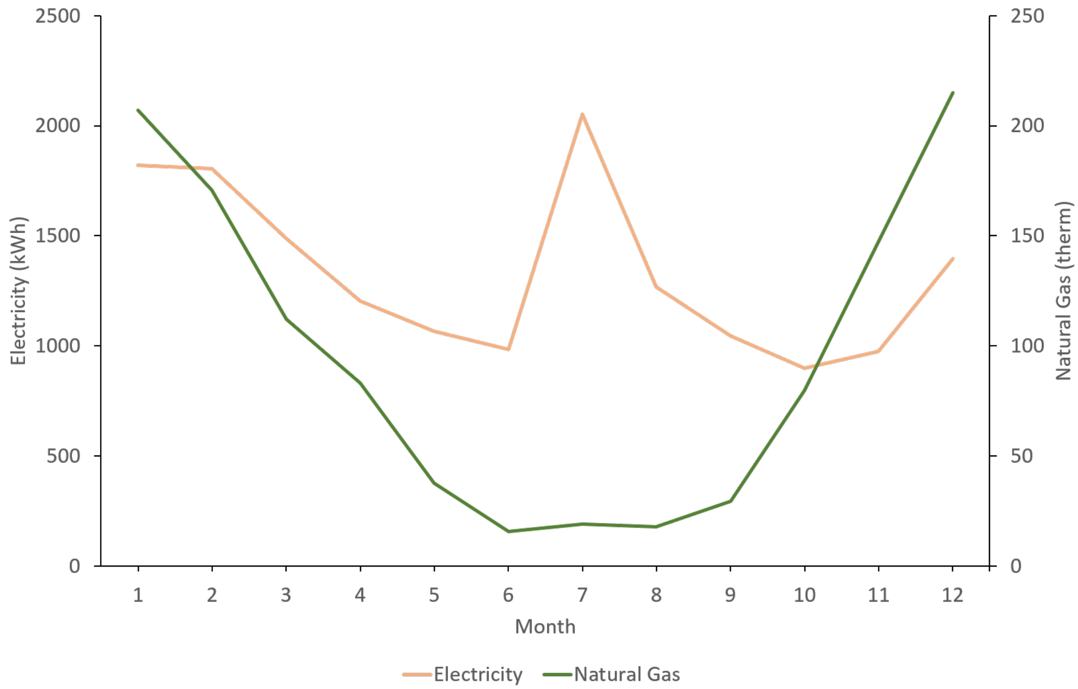

Figure 2-12 Example timeseries output for sample household showing electricity (kWh) and natural gas (therm) consumption for a one-year duration

This work supports quantification of the environmental impact values for household consumption in a typical U.S. Suburban area, and allows for examination of what consumers actually purchase and consume over an extended period of time. The HomeTracker has been implemented in an intervention study with a data collection period running from March 2021 through August 2021. The study included two two-week food collection periods, continuous electricity monitoring, bi-monthly water data input, and monthly natural gas input. Households also received messaging and took surveys throughout the study. Once processed and cleaned, the resulting dataset will be useful in analyzing trends in household consumption and the subsequent impact to water resources and greenhouse gas emissions.

The HomeTracker application is available on GitHub as an open-source tool, via a Creative Commons license, and can be continuously updated or modified for use in any geographic location in the United States. Limitations of the model in its current version include the fact that the model results are only applicable to residents of Lake County at this time; however, the application can be tailored for use in future studies to support household consumption research projects to generate additional results and contribute to a larger household FEW consumption dataset. Limitations also include limited data availability at appropriate spatial and temporal resolutions, resulting in a model that depends on data at multiple spatial and temporal scales.

Future work may include updates to the environmental impact factors to improve spatial and temporal resolution, in areas where data availability allows for this change. It may also include expansion of the geographic coverage of environmental impact factors to allow users across the United States to benefit from use of the HomeTracker without modifying the source code. In addition, as sensor and automation technology become more robust and affordable, HomeTracker can be modified to reduce the burden of data entry on users. Water, energy, and greenhouse gas emissions are the environmental impacts that have been assessed in this work. However, USEEIO is capable of outputting other environmental impact parameters such as acid rain, eutrophication, freshwater aquatic ecotoxicity, human health, pesticides, smog formation, and hazardous air pollutants (Yang et al. 2017b). Future work can include an expansion of HomeTracker to support investigation of not just the FEW Nexus, but also the Water-Energy-Food-Ecosystems Nexus or impacts of consumption on human health (GWP 2020).

2.4 References

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3 Framework for Assessing the Water Use Impacts of Marginal Electricity Generation

3.1 Introduction

Water and energy are intricately linked in numerous ways in a relationship known as the water-energy nexus (Scott et al. 2011; Ackerman and Fisher 2013; Van Vliet et al. 2016; Yang and Chen 2016). For example, energy is required to withdraw, treat, and transport water for use in homes, business and industry; and water is consumed and its quality transformed by energy production. Water use for electricity generation can vary significantly based on location, fuel source, and plant technology. Water use in this study refers to both water withdrawal and consumption of freshwater for electricity generation. Approximately 89% of all electricity in the United States is generated at thermoelectric power plants, where water is required for steam creation as well as cooling water for steam condensation; and over 90% of water used in thermoelectric power generation is for cooling (Healy et al. 2015). In 2010 it was reported that 45% of total water withdrawals for all uses were for thermoelectric power generation (Maupin et al. 2017).

Several previous studies have assessed the impacts of water withdrawal and consumption by the energy sector. These include a global meta-analysis of water use of electricity technologies and summaries of existing literature quantifying the impacts of water withdrawals and consumption by electricity generating technologies in the United States (Macknick, Newmark, et al. 2012; Meldrum et al. 2013; Jin et al. 2019). Macknick et al. (2012) report a wide range of operational withdrawal and consumption factors for electricity generation, with variation across fuel types and technology types used for generation, and find that, depending on technology type there could be either an increase or decrease in water use corresponding with reduced greenhouse gas emissions. Meldrum et al. (2013) determine water use impact factors across the entire life cycle of electricity generating technologies. They find that electricity generated by photovoltaics and wind has the lowest water use, and electricity generated by thermoelectric generation facilities has the highest water use. They also note that within life cycle stages, water use for thermoelectric cooling makes up the largest fraction of the total water use, with up to 60,000 gallons/MWh being required using once-through steam technologies (Meldrum et al. 2013). Peer et al. quantify regional consumption intensities for the United States electricity grid that includes water consumed both upstream of the point of generation and at the point of generation (Peer, Grubert, and Sanders 2019). Grubert and Sanders quantify water withdrawal and consumption in detail across fuel types, life cycle stages, and water sources for the U.S. energy system, increasing the level of detail in available water use intensity estimates (Grubert and Sanders 2018). Other research that calculates average water withdrawal and consumption intensity factors (i.e., in gallons/MWh) includes a study by Peer and Sanders in which factors are calculated based on Energy Information Administration data, and a study by Diehl and Harris that uses linked heat-and water-budget models to estimate thermoelectric water consumption (Diehl and Harris 2014; Peer and Sanders 2016).

Electric utilities continuously monitor and forecast electricity demand, with different plants satisfying the demand requirements throughout the day. A change in power generation that responds to an increase in demand is referred to as marginal generation (Farhat and Ugursal

2010). Environmental impact assessment of marginal generation is useful in predicting the impacts of policy interventions such as improving energy efficiency and demand shifting, since different generating units are brought on line or ramped up or down to respond to changes in demand. Marginal emissions factors (MEFs), which estimate the emission intensity of marginal power generation, have been calculated for greenhouse gases and other air pollutants including carbon dioxide, sulfur dioxide, and nitrous oxide (Siler-Evans, Azevedo, and Morgan 2012). While MEFs have traditionally been calculated for emitting energy sources such as coal, natural gas, and nuclear, more recent work by Li et al. expands the scope of MEFs and uses a linear regression approach to account for renewable, non-emitting sources, such as wind energy (Li et al. 2017). As electric utilities explore renewable energy futures and increase deployment of renewable energy sources on the margin, it is also useful to understand how changes in marginal electricity generation will impact freshwater resources. Quantifying environmental impacts of marginal generation is used for estimating avoided emissions and water use from bulk energy storage technologies and demand side management programs. It is also useful for understanding the impact of marginal electricity generation has on emissions and water use as the penetration of renewable energy sources increases.

The water withdrawal and consumption intensities of electricity generation have been quantified by fuel and technology type, and multiple studies have quantified and discussed the greenhouse gas emissions and other air pollutant impacts of marginal electricity generation (Hawkes 2010; Thind et al. 2017). However, the water use impacts of marginal electricity generation have not been assessed. This work fills a gap in the literature by proposing a framework to develop novel marginal water-use factors (MWFs) that can be used to quantify the water withdrawal and consumption impacts of marginal electricity generation. A linear regression approach is applied to generate MWFs at annual, monthly, and month-hour scales, using the Midcontinent Independent System Operator (MISO) region as a case study. MISO is a non-profit regional transmission organization (RTO) that administers the market for electricity producers in the midcontinent United States (US) and Canada. Spatial and temporal variation in MWFs for MISO and its three subregions (North, Central, and South) are assessed, and analysis limitations, policy implications, and recommendations for future work are discussed.

3.2 Materials and Methods

3.2.1 Water Use Definitions

Water use in this study refers to both the withdrawal and consumption of freshwater for electricity generation. According to the United States Geological Survey, water withdrawal is defined as water that is removed from its original source, some of which may be consumed or transformed, and a portion of which is returned to a water source and becomes available for future use; water consumption is defined as water that is withdrawn from its original source and is no longer available for near-term future use due to processes such as evaporation and transpiration, uptake by crops, or consumption by animals or humans (Healy et al. 2015). A recent study by Grubert et al. highlights the importance of avoiding ambiguity in defining water withdrawal and water consumption, noting that word choice can result in changes to reported water use without changing underlying data (Grubert, Rogers, and Sanders 2020). In this study, withdrawal and consumption are defined consistent with the definitions established by the Energy Information Administration (EIA) Instructions for water use reporting (EIA 2021). **Table 3-1** provides a summary of the definitions used by the EIA to define water withdrawal and consumption used for thermoelectric cooling at United States powerplants for respective cooling technology types (EIA 2021).

Table 3-1 EIA Reporting Instructions Water Withdrawal and Water Consumption Definitions by Cooling Technology Type

Technology Type	Withdrawal Definition	Consumption Definition
Once-Through System without Cooling Ponds or Canals	Water that is removed from a water body for cooling	Evaporative losses are not expected
Once-Through System with Cooling Pond or Canal	Water that is removed from a water body for cooling	Evaporative losses are not expected
Recirculating System with Pond and No Tower	Water flow to the condenser from the cooling pond	Evaporative losses that occur within the cooling pond
Recirculating System with Tower and No Pond	Cooling tower makeup water that is removed from a water body	Evaporative losses from cooling tower(s)
Recirculating Cooling Circuit with both Towers and Ponds	Water flow to the condenser	Evaporative losses from cooling pond and tower(s)
Dry Cooling Hybrid Systems	Cooling tower makeup water that is removed from a water body	Evaporative losses from cooling tower(s)

3.2.2 System Boundary

Providing electricity that is generated using thermoelectric cooling to the end user requires water consumption and/or withdrawal in life cycle stages including fuel extraction, fuel processing, transportation, electricity generation, and distribution (Healy et al. 2015). Electricity generated using solar and wind technologies require water withdrawal during the raw materials extraction, infrastructure manufacturing, and distribution phases, but are assumed to require no water during the generation phase (Ackerman and Fisher 2013). In order to capture the withdrawal and consumption impacts of the marginal fuel mix, this work considers only the volume of water withdrawn and/or consumed for use in the electricity generation stage, as illustrated in **Figure 3-1**.

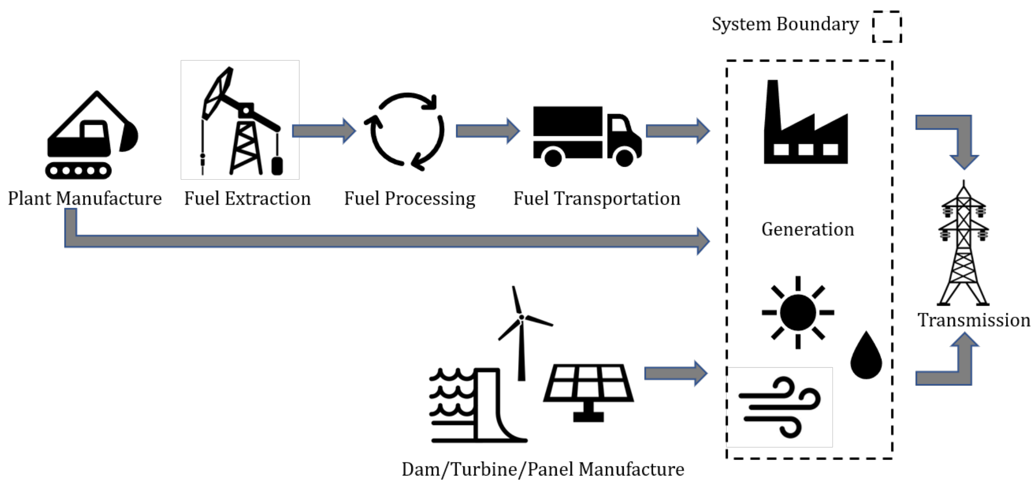

Figure 3-1 Life Cycle Stages and Study System Boundary for Fuel Types in MISO Average and Marginal Fuel Mixes 2019

3.2.3 Study Area

Midcontinent Independent System Operator (MISO) is a non-profit regional transmission organization (RTO) that administers the market for electricity producers in the central United States (US) and Canada. MISO is responsible for power transmission in 15 US states as well as the Canadian province of Manitoba, and is divided into three subregions: MISO North, MISO Central, and MISO South. A map of MISO is included in the Appendix A, **Figure A1**. As shown in **Figure 3-2**, MISO and its three subregions vary in their average and marginal fuel mixes. The fuel type "other" is defined by MISO Energy as the combination of solar, pumped storage hydro, diesel, demand response resources, external asynchronous resources, and a varied assortment of solid waste, garbage, and wood pulp burners (MISO 2020).

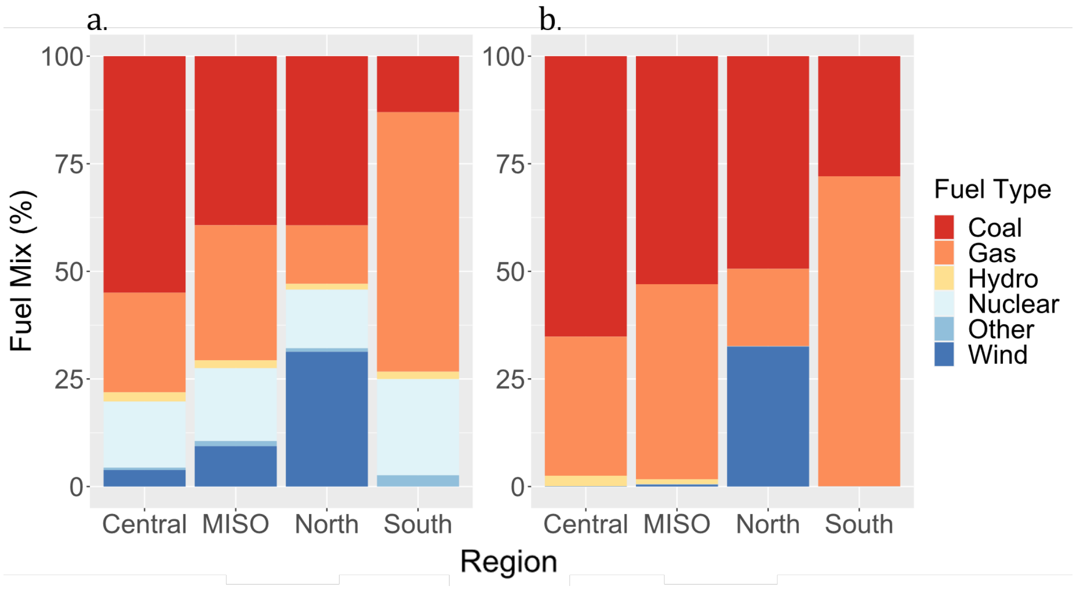

Figure 3-2 (a) Regional and Subregional Average and (b) Regional and Subregional Marginal Fuel Mix for MISO in 2019.

In MISO North and MISO Central, coal made up the largest fraction of the average fuel mix in 2019, comprising 55% and 39%, respectively. However, in MISO South, natural gas was the primary source, comprising 60% of the average fuel mix. The North region is unique in that 31% of the average fuel mix was comprised of wind. Coal and natural gas dominated the marginal fuel mix, with the exception of MISO North where wind comprised nearly 33% of the marginal fuel mix. Fuel mixes were calculated using data sources summarized in Section 3.2.4.

3.2.4 Data Sources

The data sources used for this analysis include the Environmental Protection Agency Air Market Program Data (AMPD)(EPA 2019), the United States Energy Information Administration (EIA) Form-923, and Form EIA-860 (EIA 2019b), historical fuel mix data from MISO (MISO 2019b), and finally marginal generation data from MISO (MISO 2019a). The United States Energy Information Administration collects monthly thermoelectric cooling water data at the generator level for power plants in the United States using Form EIA-923 (EIA 2019a). For this study, Form EIA-923 was cross-indexed with Form EIA-860, which includes the balancing authority name for each plant, to determine which plants are connected to the MISO grid. The data was then categorized by MISO subregion: North, Central, or South. Data sources are summarized in **Table A1** of Appendix A.

3.2.5 Hourly Water Use Estimates

The most significant limitation of this study is the lack of reported hourly water use data. To demonstrate the framework developed herein to calculate MWFs, it was necessary to estimate hourly water use based on monthly reported water use for thermoelectric cooling by fuel type, both for consumption and withdrawal as described in this section. This temporal resolution is the finest resolution of reported water use data available, based on reported cooling summary data in form EIA-923 for 2019. Further, it is acknowledged that water withdrawal and consumption intensities vary significantly by cooling technology in addition to fuel type. However, marginal generation data is recorded only by fuel-on-the-margin rather than at the individual generator level, necessitating water use estimates based on fuel type. Details on how the data was cleaned before developing the water use intensity factors, as well as a summary of cooling technologies used at thermoelectric cooling plants in MISO and its subregions, can be found in Appendix A.

Water withdrawal, water consumption, and total generation data were aggregated by month, fuel type, and subregion. Average monthly water withdrawal and consumption intensities (gallons/MWh) for month i and fuel type j were then calculated for MISO and each subregion using Equation 3-1.

$$AWF_{i,j} = \frac{W_{i,j}}{G_{i,j}} \tag{3-1}$$

where $W_{i,j}$ represents the water withdrawal/consumption (gallons) for month i and fuel type j, and $G_{i,j}$ represents electricity generation (MWh) for month i and fuel type j. Water use intensity values for withdrawal and consumption by fuel type in MISO and each subregion for 2019 are shown in **Figure 3-3** through **Figure 3-5**.

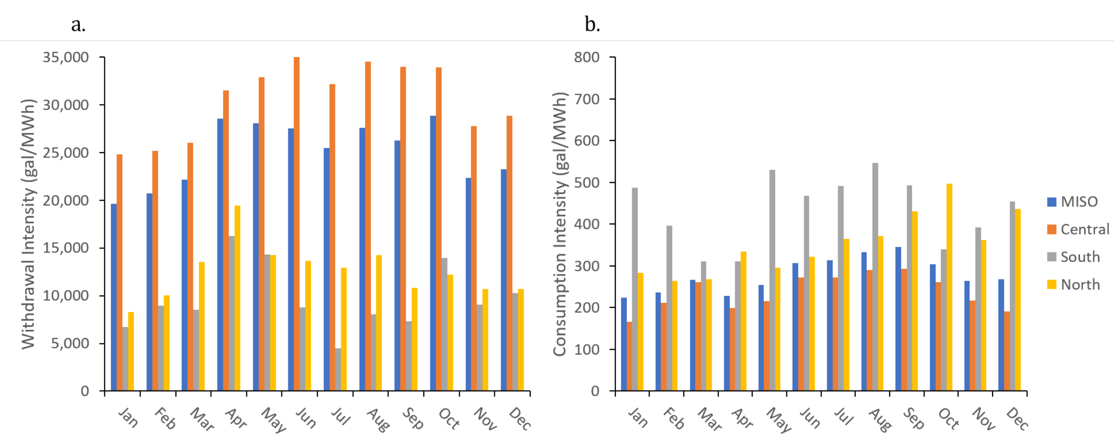

Figure 3-3 (a) Regional and Subregional Withdrawal Intensities and (b) Regional and Subregional Consumption Intensities for Coal Generation in MISO for 2019.

As shown in **Figure 3-3**(a), water withdrawal intensity is highest in the Central region where coal makes up 55% of the fuel mix, generated with conventional steam. Of this coal generation, nearly 60% is generated using once-through cooling technology which contributes to large volumes of water withdrawal. This also contributes to the lower consumption intensities shown for the Central region in **Figure 3-3**(b). Withdrawal intensities in the South and North regions are notably lower. Coal only makes up 13% of the fuel mix in the South Region, and 53% of the generation from conventional steam coal uses recirculating cooling technology, resulting in lower withdrawal intensity. Coal contributes to 39% of the fuel mix in MISO North, and 64% of generation using conventional steam coal in the North Region uses recirculating cooling technology. Recirculating cooling technology also contributes to the higher consumption intensities in the North and South regions due to increased evaporation from cooling ponds and cooling towers.

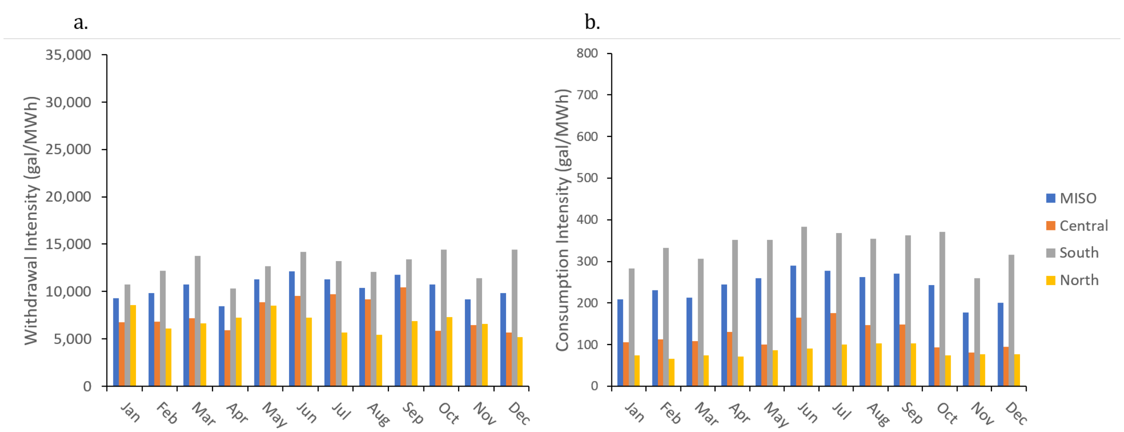

Figure 3-4 (a) Regional and Subregional Withdrawal Intensities and (b) Regional and Subregional Consumption Intensities for Natural Gas Generation in MISO for 2019.

Natural gas generation in all three subregions uses natural gas combined cycle and natural gas steam turbine technologies. Natural gas makes up 13% of the North average fuel mix, 23% of the Central average fuel mix, and 60% of the South average fuel mix. **Figure 3-4** shows withdrawal and consumption intensities in the North region are lowest which reflect that 91% of generation from natural gas steam turbines uses recirculating induced draft cooling. Withdrawal intensities are higher in the South and Central regions as generation by natural gas steam turbines uses 70% and 24% once-through cooling technology with no pond, respectively.

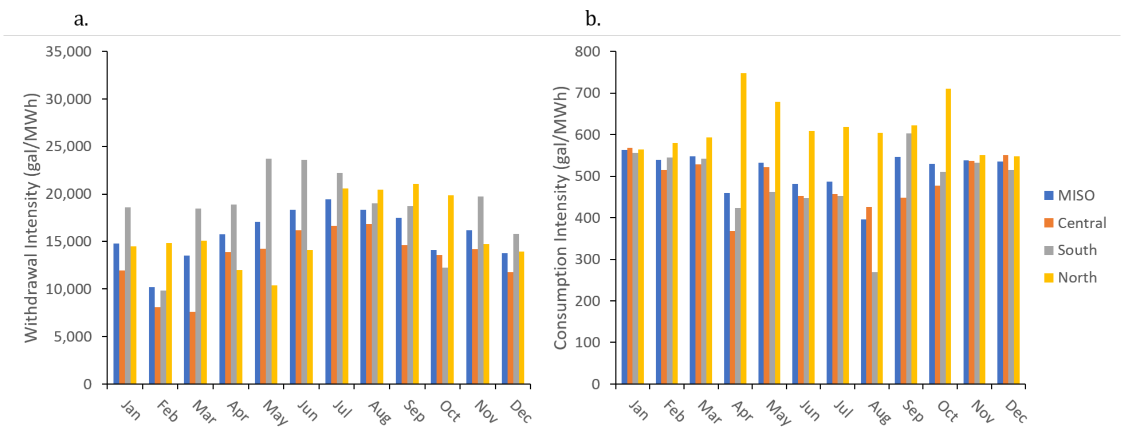

Figure 3-5 (a) Regional and Subregional Withdrawal Intensities and (b) Regional and Subregional Consumption Intensities for Nuclear Generation in MISO for 2019.

Nuclear makes up 13% of the average fuel mix in the North Region, 15% of the average fuel mix in the Central region, and 22% of the average fuel mix in the South region. **Figure 3-5** shows withdrawal intensities are fairly consistent across regions, with notable increases in withdrawal intensity during the spring and early summer months in the South region. Consumption intensities for nuclear generation are high in all regions, particularly in the North region from April through October 2019.

Hourly generation data by fuel type and subregion from the AMPD dataset and MISO historical hourly generation data for 2019, and water use intensities presented in **Figure 3-3** through **Figure 3-5**, were used to estimate hourly water use as shown in Equations 3-2 and 3-3.

$$CV_{h,m,r} = \sum(G_{f,h,m,r} \times I_{f,m,r}) \tag{3-2}$$

where $CV_{h,m,r}$ represents the volume of water consumed (gal) during hour h of month m in region or subregion r, $G_{f,h,m,r}$ represents the gross generation (MWh) for fuel type f during hour h of month m in region or subregion r, and $I_{f,m,r}$ represents the consumption intensity (Gal/MWh) for fuel type f in month m in region or subregion r.

$$WV_{h,m,r} = \sum(G_{f,h,m,r} \times I_{f,m,r}) \tag{3-3}$$

where $CV_{h,m,r}$ represents the volume of water withdrawn (gal) during hour h of month m in region or subregion r, $G_{f,h,m,r}$ represents the gross generation (MWh) for fuel type f during hour h of month m in region or subregion r, and $I_{f,m,r}$ represents the withdrawal intensity (Gal/MWh) for fuel type f in month m in region or subregion r. This procedure was used to estimate hourly water withdrawal and consumption in MISO and each of the three subregions for 2019.

3.2.6 MWF of Electricity Generation Using Linear Regression

Marginal generation was determined following the methodology developed by Li et al. in which the 5-minute real-time fuel-on-the-margin data from MISO is used to identify which fuel types are on the margin in a given hour (Li et al. 2017). It should be noted that more than one fuel type can be on the margin during the same hour. Estimated hourly water withdrawal and consumption data and reported marginal generation data for 2019 were used in a linear regression model to estimate MWFs at multiple temporal resolutions including annual, monthly, and month-hour. The framework to calculate marginal water factors is presented in **Figure 3-6**.

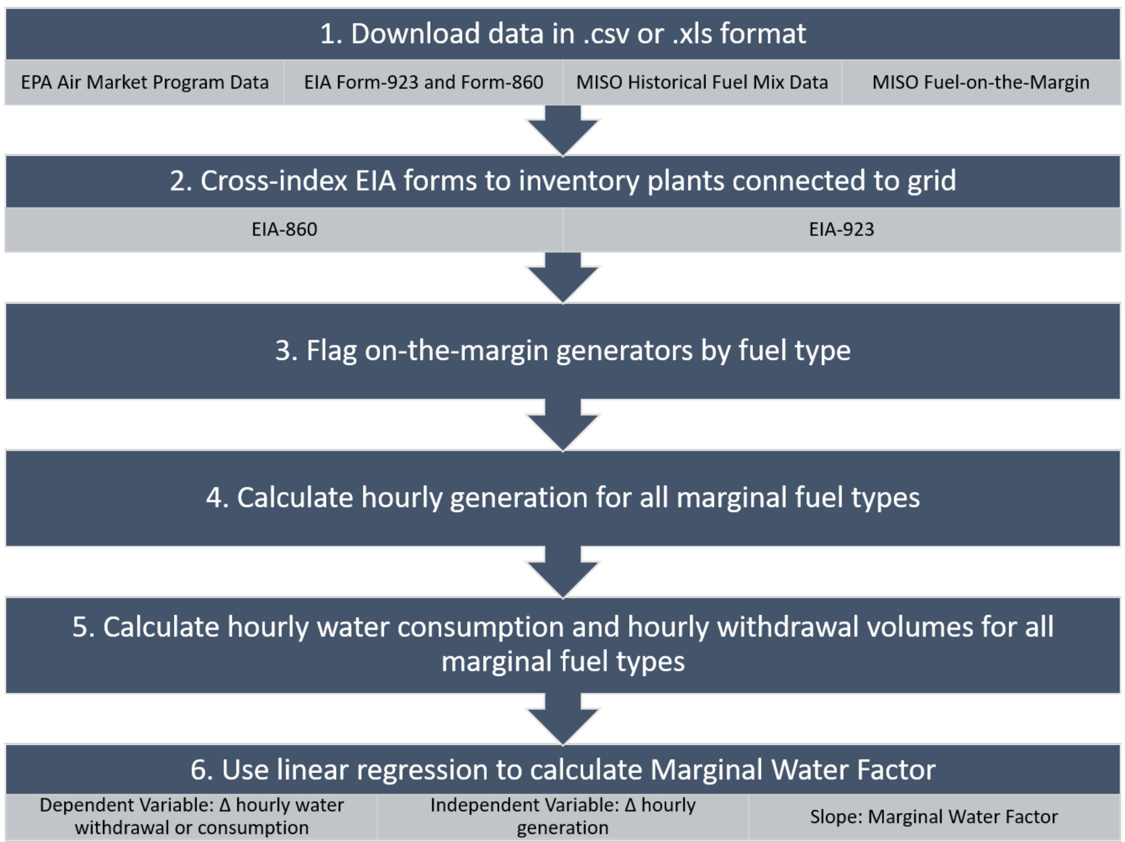

Figure 3-6 Framework for calculation of marginal water factors at annual, monthly, or month-hour temporal scales.

This method is shown in Equations 3-4 through 3-6:

$$\Delta W_h = \beta \Delta G_h + \varepsilon \tag{3-4}$$

where

$$\Delta W_h = W_h - W_{h-1} \tag{3-5}$$

and

$$\Delta G_h = G_h - G_{h-1} \tag{3-6}$$

where ΔW_h represents the change in water use within an hour (gallons), ΔG_h represents the change in generation within an hour (MWh), and the slope of the linear regression β represents the estimated MWF (gallons/MWh). Data from 2019 was used to estimate MWFs at annual, monthly, and month-hour scales, as discussed in Section 3.3.

3.3 Results and Discussion

3.3.1 MWFs at Annual Timescale

Annual MWFs calculated for MISO and the three subregions are summarized along with R^2 and $\boldsymbol{\sigma}$ values from the regression model in **Table 3-2**. The R^2 values represent the fraction of the variability in the dependent variable, change in water withdrawal or consumption, explained by the independent variable, change in marginal generation. The $\boldsymbol{\sigma}$ values represent the standard deviation of the slope of the regression. The annual MWFs are compared with annual average water use intensities, which reflect the water withdrawal and consumption intensities of the average fuel mix, referred to here as Average Water-Use Factors (AWFs).

Table 3-2 Annual Marginal Water-Use factors (MWFs) and Annual Average Water-Use Factors (AWFs) for Regional (MISO) and Subregional (North, Central, and South) Electricity Generation in 2019

Region	Consumption (gal/MWh)				Withdrawal (gal/MWh)			
	MWF±2σ	R^2	AWF	%*	MWF±2σ	R^2	AWF	%*
Central	518±6	0.33	465	11	24073±70	0.90	21124	14
MISO	456±4	0.56	408	12	18809±38	0.95	15843	19
North	254±3	0.35	295	14	7851±82	0.41	7800	1
South	203±2	0.58	405	50	12281±32	0.92	13383	8

*Percent Difference |(Marginal Water Factor - Average Water Factor)|/Average Water Factor*100

Table 3-2 shows that annual MWFs for withdrawal have high R^2 values in MISO, Central, and South. However, R^2 values for withdrawal MWFs in MISO North are notably lower. Wind is on the margin approximately 33% of the time in MISO North in 2019, and due to the fact that wind does not require water withdrawal or consumption to generate electricity, the correlation between power generation and water withdrawal or consumption is weaker in MISO North. Annual MWFs highlight the importance of sub-regional analysis, given that MWFs for withdrawal range from 7,851 gal/MWh in the North region to 24,073 in the Central region, and MWFs for consumption range from 203 gal/MWh in the South region to 518 gal/MWh in the North region. Applying the MISO annual MWF for withdrawal or consumption to any of the three subregions could significantly overestimate or underestimate the water use impacts of marginal generation.

The comparison of annual AWFs with annual MWFs shows that the use of MWFs for assessment of water use impacts due to marginal electricity generation are meaningful to consider when making dispatch decisions. For example, using the AWF to estimate marginal electricity generation values in the South Region could overestimate water consumption impacts by approximately 50%, and in the Central region it could underestimate water withdrawal impacts by approximately 14%.

3.3.2 MWFs at Monthly Timescale

Monthly MWFs for withdrawal are summarized in **Table 3-3**. There are seasonal trends in all regions, with an increase in MWFs primarily during the spring and low-flow summer months. While cooling water use during the wet season does not significantly impact streamflow, increased water use and decreased water availability in dry seasons can increase the risk of ecosystem impacts (Mu et al. 2020). An increase in marginal withdrawal intensity was especially notable in the North Region during the summer months (June-August) when wind energy is not as prevalent and water withdrawals increase. Climate projections for the Midwest Region show a decrease in mean annual monthly precipitation during the summer and autumn months, with an increased risk of seasonal and multiyear droughts through the remainder of 21st century (Mishra, Cherkauer, and Shukla 2010; Austin, Wolock, and Nelms 2018). This has implications for the future reliability of thermoelectric generators in this region, such as increased risk of curtailment during peak demand hours, highlighting the importance of quantifying the marginal water use impacts of dispatch.

Table 3-3 Monthly Withdrawal Marginal Water-Use factors (MWF) for Regional (MISO) and Subregional (North, Central, and South) Electricity Generation

Region	Central		MISO		North		South	
Intensity (gal/MWh)	MWF±2σ	AWF	MWF±2σ	AWF	MWF±2σ	AWF	MWF±2σ	AWF
January	19060±178	20817	14919±99	14862	6476±190	5997	10071±88	11984
February	20193±182	20142	16212±116	14527	6718±267	6941	12196±96	10892
March	18835±185	19948	16113±143	15220	5877±314	7444	13337±143	13837
April	22090±254	21795	18385±187	15714	4977±402	7198	12396±114	12543
May	27529±236	25840	20999±138	17906	7596±383	7012	14022±131	14256
June	28288±256	26073	20886±116	18596	10539±287	8488	13449±110	14831
July	23840±211	25397	19014±98	18275	11061±197	9274	11137±131	13264
August	25848±218	26849	19656±85	18720	10981±248	9927	11413±112	12710
September	26478±263	26316	19223±105	17722	7376±287	7465	11905±72	13079
October	25395±220	24745	19880±127	16556	6063±297	6315	14753±92	12215
November	21311±244	21729	16274±163	15042	5808±240	6341	10969±85	11922
December	20909±201	20974	16863±138	14679	4968±233	6165	13006±121	12085

Monthly MWFs for consumption are summarized in **Table 3-4**. Consumption intensities of marginal generation were highest during the winter months in the Central region in 2019, while consumption intensities of marginal generation were highest during the summer months in the North and South regions.

Table 3-4 Monthly Consumption Marginal Water-Use Factors (MWF) for Regional (MISO) and Subregional (North, Central, and South) Electricity Generation

Region	Central		MISO		North		South	
Intensity (gal/MWh)	MWF±2$\boldsymbol{\sigma}$	AWF	MWF±2$\boldsymbol{\sigma}$	AWF	MWF±2$\boldsymbol{\sigma}$	AWF	MWF±2$\boldsymbol{\sigma}$	AWF
January	589±26	331	502±15	316	307±12	205	185±5	395
February	576±31	259	494±19	276	259±15	203	136±8	383
March	686±29	391	548±17	335	166±12	193	163±6	368
April	651±34	340	516±20	311	80±7	206	178±12	353
May	364±22	368	366±11	335	140±7	224	152±8	371
June	402±17	401	407±9	365	273±8	244	233±5	399
July	500±17	393	468±10	364	345±8	266	261±4	392
August	514±19	393	473±10	353	328±9	269	238±5	350
September	562±21	411	478±10	379	285±12	255	223±4	423
October	418±14	405	384±8	356	198±9	234	157±4	381
November	529±22	378	423±11	324	218±11	218	148±4	335
December	588±27	368	470±14	331	269±13	241	161±4	356

3.3.3 MWFs at Month-Hour Timescale

Month-hour MWFs have the potential to offer insight into the water withdrawal and consumption impacts due to marginal electricity generation at the hourly level. Month-hour MWFs represent the average water withdrawal or consumption intensity during a given hour of each day in the month resulting from the marginal fuel mix during those periods. **Figure 3-7** shows seasonal and hourly trends of month-hour MWFs for withdrawals, while

Figure 3-8 shows seasonal and hourly trends of month-hour MWFs for consumption in MISO and each of the three subregions for the year 2019.

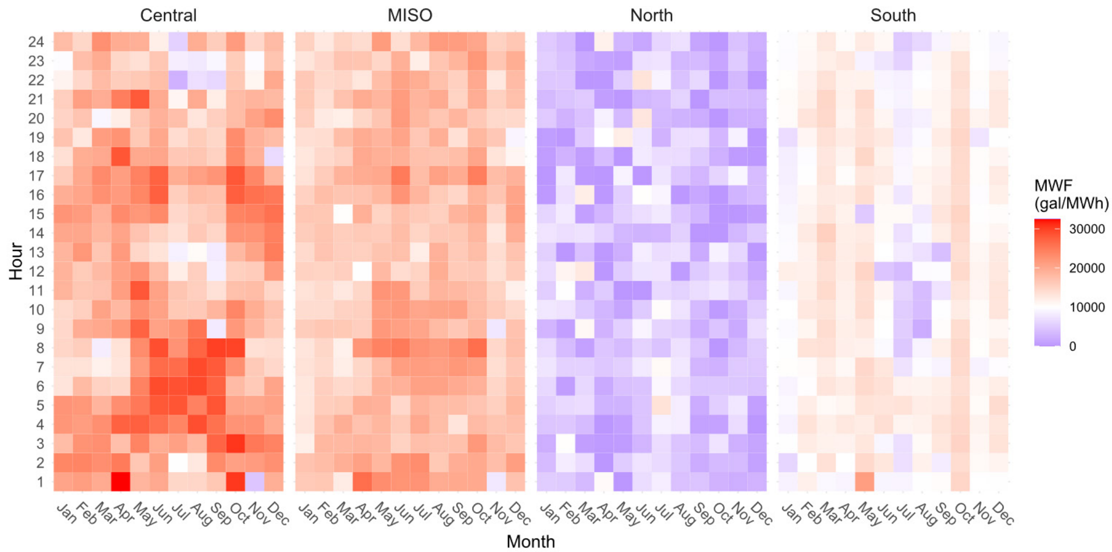

Figure 3-7 Month-hour marginal water-use factors for withdrawal in MISO and its subregions in 2019.

Figure 3-7 shows the relatively low marginal water withdrawal intensities at all hours of the day in MISO North compared to the other regions, which reflects the unique presence of wind on the margin in this region. An increase in marginal withdrawal intensity is observed in the morning hours during the summer months in the Central region, indicating a larger fraction of coal used to meet peak morning demands. Similarly, intensities are higher during the late afternoon hours in the Central Region. Month-hour MWFs in the South Region are fairly consistent across all hours of the day in any given month, with a decrease in withdrawal intensity during the summer months, particularly during mid-morning hours.

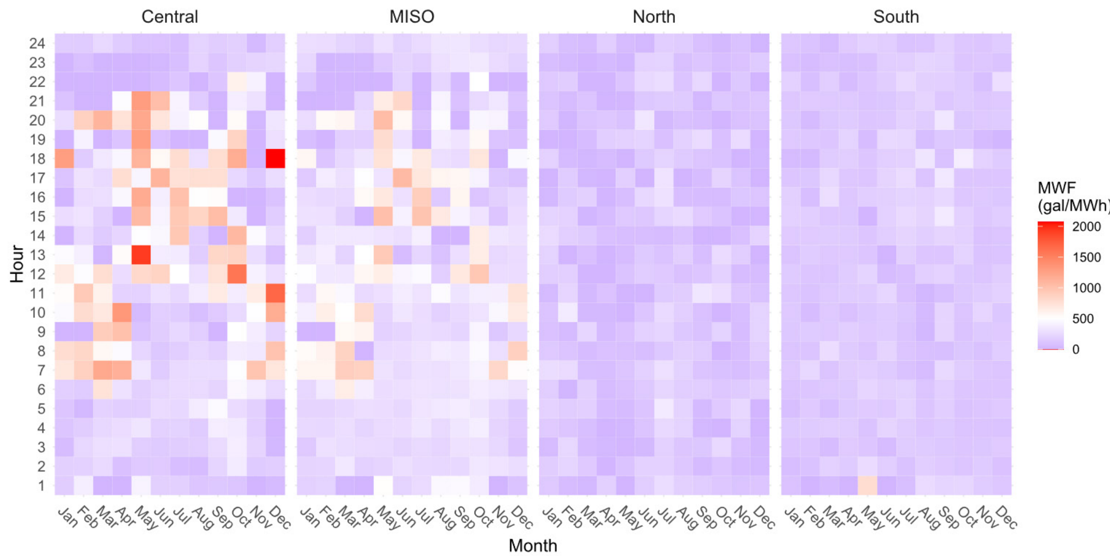

Figure 3-8 Month-hour marginal water-use factors for consumption in MISO and its subregions in 2019.

Figure 3-8 shows relative homogeneity in water consumption intensities due to marginal generation during all hours of the day and across months in the North and South regions. The Central region shows increased consumption intensities during the peak demand morning hours during the winter months, and increased consumption intensities during the afternoon and early evening hours during the summer months.

The development of month-hour MWFs offers an opportunity to investigate potential water use savings impacts from behavior changes such as load shifting. Household activities such as appliance use, heating and air conditioning contribute to variable demand for electricity and marginal generation. Many of these activities can be performed at flexible times of day, and their impact on water use will vary depending on what type of generator is used to meet the additional demand.

Due to data limitations, month-hour MWFs have been developed using estimated hourly water use data. The availability of hourly water use data, for both withdrawal and consumption, would allow for the development of more accurate estimates that could be used in decision making. Additionally, estimates would be more accurate if marginal generation data was available at the plant level with specific technology types rather than only by fuel type. This paper echoes others in calling for improved reporting of cooling water use data, specifically at the hourly timescale, for enhanced understanding of water use for electricity generation (Averyt et al. 2013; GAO 2009; Grubert and Sanders 2018). For example, hourly data could be useful in multipurpose reservoir operations where releases fluctuate throughout the day, and in the management of water temperatures for sensitive ecosystems where withdrawals and discharges could have significant impacts (Khangaonkar and Yang 2008; Logan and Stillwell 2018; Lindquist, McGee, and Cole 1996).

3.3.4 Fuel Mix with Increased Renewables

Climate change is expected to increase the risk of water scarcity and adverse ecosystem impacts, creating new challenges in the management of water and energy. Both reduction of greenhouse gas emissions and water withdrawals must be pursued to ensure nexus sustainability. A switch to a low-carbon energy future will have varying impacts on water use depending on fuel source, technology used, and location of plant retirements or new installations. According to Kyle et al., there could be geographic shifts in electricity generation that result in changes in water availability at the basin or regional scale (Kyle et al. 2013). Low-carbon technologies include solar photovoltaic, geothermal, wind energy, biomass, hydropower, nuclear, and concentrated solar power, and water use intensities for these technologies vary significantly (Healy et al. 2015). For example, nuclear power generation requires significant amounts of water consumption for cooling processes, while wind energy does not require any water in the electricity generation process. In the generation stage, solar panels only require water for cleaning, while concentrated solar power uses water volumes similar to that of thermoelectric power generation due to its use of steam turbines (D'Odorico et al. 2018). A modeling study by Arent et al. shows that with 80% renewable energy, water withdrawals and consumption could be reduced by up to 51% by 2050 (Arent et al. 2014). Studies by Johst and Rosthein as well as Macknick et al. predict even larger reductions with 80% renewable energy by 2050 -- up to 70% and 85% reduction in water consumption, respectively (Johst and Rothstein 2014; Macknick, Sattler, et al. 2012). In comparison, this study finds that with approximately 30% renewable energy in the average and marginal fuel mixes in MISO North, water withdrawal and consumption amounts are reduced approximately 76% and 62% respectively on an annual basis relative to MISO Central, which has just 4% and 0.1% renewable energy in the average and marginal fuel mixes, respectively. Of course, many other factors contribute to this difference, including demand peaking factors, cooling technologies, plant age, and regional climate.

Figure 3-8 shows the change in average and marginal fuel mixes in MISO North from 2014 to 2019. Coal remains the primary fuel type, but the percentage of coal has decreased over time in both fuel mixes. Natural gas use has increased in the average fuel mix, and plateaued in the marginal fuel mix until a slight decrease in 2019. Although a decrease of wind penetration in 2018 was compensated with the use of coal, the presence of renewables has increased in both the average and marginal fuel mixes in MISO North during this recent period. With decreasing costs for renewables and the advancement of storage technologies, it is likely that the percentage of renewables in the fuel mixes will continue to increase (Stehly, Beiter, and Duffy 2020).

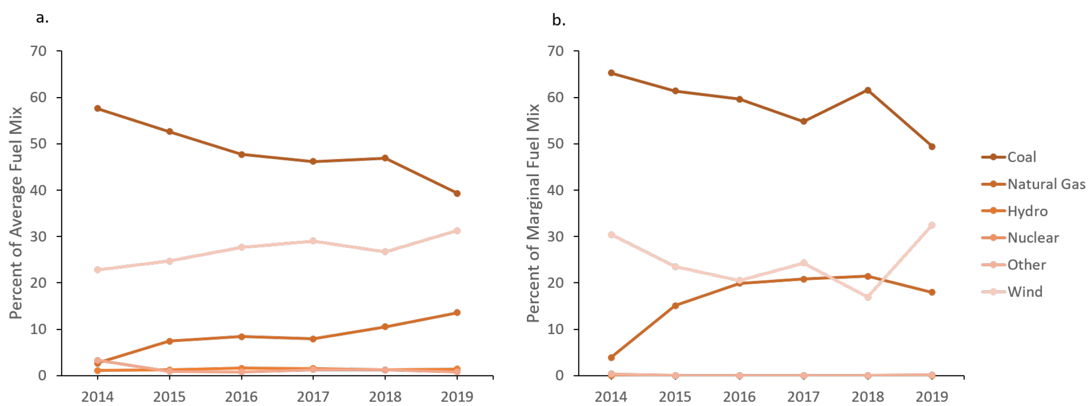

Figure 3-9 a) Average and b) marginal fuel mixes in MISO North from 2014-2019.

The MWFs developed using linear regression methodology are short-term, and they reflect factors such as fuel type, technology type, dispatchability, and timing for an essentially fixed portfolio of generating facilities, rather than structural changes in the electricity system that occur on multi-year or decadal time scales. This methodology could be used for development of short-term MWFs in any regional grid system in the United States, assuming data were available at the appropriate timescale. MWFs could be analyzed in conjunction with marginal emissions factors to assess tradeoffs between greenhouse gas emissions and water use impacts of marginal electricity generation and interventions such as energy storage, demand-side management, increased renewable energy in the fuel mix, and other shifts in technology used for electricity generation.

For greater insight into water use impacts at multiple spatial and temporal scales, future work should focus on improved data collection, availability, and transparency for the calculation of marginal water factors. The development of a methodology to generate MWFs creates an opportunity to assess tradeoffs between the water use impacts and emissions impacts of marginal electricity generation at a finer temporal resolution, using marginal emissions factors as developed by Li et al. and marginal water-use factors illustrated herein. In addition, economic and environmental tradeoffs of electricity dispatch can be assessed with respect to impacts such as water stress and human health risk. While traditional economic dispatch seeks to provide consumers with the lowest-cost electricity, a balanced strategy of economic and environmental dispatch may be effective in reducing environmental impacts while also keeping electricity costs at acceptable levels (Razeghi, Brouwer, and Samuelsen 2016).

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4 Production cost modeling for water stress mitigation: assessing the impacts of monetizing water withdrawals for electricity generation

4.1 Introduction

The water-energy nexus is manifest at a range of scales, including municipal, watershed, and regional electrical grid scales. Freshwater is required to generate electricity, and electricity is required to treat and distribute water. Pressure on freshwater resources is increasing with a growing population, changing climate, and competition between other sectors such as agriculture (Madani and Khatami 2015; Sovacool and Sovacool 2009). Joint management of water and energy for conservation is a critical challenge facing today's policy makers and managers to ensure a sustainable and reliable supply (Dai et al. 2018; Sanders 2015). Finding solutions to water-energy nexus management problems requires a holistic view and trade-off analysis (Webster, Donohoo, and Palmintier 2013).

The NSF Energy-Water Nexus Workshop in December 2013 identified nine high-priority research areas related to water and energy management. These high-priority research areas include: Development of decision support tools, cross-sectoral systems integration, and source switching (Hightower, Reible, and Webber 2013). Tools that can be used by policy makers to evaluate cross-sectoral impacts of water and energy decisions need to be developed. Cross-sectoral systems integration echoes the fundamental concept of water-energy nexus in that both the water sector and the energy sector have the potential to help mitigate issues within the other sector. Finally, source switching refers to switching the source of water use or electricity generation to mitigate problems within the water-energy nexus.

Electricity dispatch refers to the order in which generator units are fired to provide electricity. To provide consumers with the lowest-cost electricity possible, economic dispatch is used to dispatch the lowest-cost electricity first (DOE 2012). A similar dispatch strategy can be used but with an environmental objective, and this is known as environmental dispatch. Under this dispatch scenario, generators with the lowest environmental impact are dispatched first to meet demand. A spatially and temporally resolved model, for example, a Unit Commitment and Dispatch Model (UC&D) or Security Constraint Unit Commitment (SCUS), should be used to capture the impacts of dispatch; a mix of economic and environmental dispatch can be effective in reducing environmental impacts such as emissions while also keeping the cost of electricity generation at acceptable levels (Razeghi, Brouwer, and Samuelsen 2016).

Researchers aim to quantify environmental trade-offs at decision-relevant scales. Unit commitment and dispatch modeling has been used to quantify hourly water consumption, emissions, and marginal heat rates, noting that environmental priorities are not always aligned in that some emissions-saving technologies require significant water use, for example nuclear power generation (Peer et al. 2016). Optimization modeling is also used to assess the emissions impacts and trade-offs of electricity generation. Multi-objective optimization can be used to minimize or limit negative consequences to one sector due to optimization in another (Parkinson et al. 2018). Optimization has been used to assess emissions impacts of generation specifically by using market-oriented price signals for nitrous oxide (NOx) emissions to reduce emissions (Alhajeri et al. 2011). This method prioritizes dispatch of plants with lower NOx emissions due to the least-cost dispatch priority, thereby allowing NOx emissions to be rapidly reduced. This offers an alternative to NOx reduction policies that focus on long-term investments such as pollution controls or change in fuel mix. Another study that uses mixed-integer linear programming in a generation capacity expansion model finds that reductions in emissions can lead to increases in water withdrawals, unless water use restrictions are implemented. This study also finds that if emissions and water withdrawals are both restricted, the cost of electricity will increase due to necessary changes in the generation mix (Webster, Donohoo, and Palmintier 2013). The Regional Energy Development System (ReEDS) model by the National Renewable Energy Laboratory was used to explore future scenarios for low-carbon electricity generation and the associated impacts on water use, finding that scenarios resulting in the lowest electricity prices also result in the highest water consumption and high carbon emissions due to low diversity in the fuel mix (Clemmer et al. 2013).

Monetization of resources is one approach to controlling emissions and water use in electricity generation. A 2016 assessment of valuation of water withdrawals notes that existing water rates can be ineffective in inciting change, and that prices would need to be increased by a factor of 217 to achieve a compromise between economic, water withdrawals, and greenhouse gas emissions (Fuentes-Cortés et al. 2018). Another study investigates the potential reductions in water consumption and withdrawals within the power sector that would result from an increase in the cost of water paid by power producers in the Electric Reliability Council of Texas (ERCOT) grid. The study found that while withdrawals could be reduced by as much as 75% by implementing water fees, generation costs would increase by up to 120% (Sanders et al. 2014).

Another Texas-based study investigates the potential for environmental dispatching based on water availability to reduce water competition. In this scenario, the spatial location of electricity generation would be adjusted to increase water availability in drought-vulnerable areas. The study finds that shifting electricity production from plants in areas experiencing drought would be feasible given existing transmission and distribution constraints, and demonstrates that it is possible to operate the grid such that water can be "delivered" virtually to drought-stricken regions by making shifts in location of power generation (Pacsi et al. 2013). Water stress indicates the measurement of water use relative to water availability (Lee et al. 2019). A study by Averyt et al. (2013) assesses stress in the freshwater system by sector, defining water stress as a ratio of water use to water supplies within a given watershed or river basin. The study finds that a single powerplant within a watershed can cause water stress, and that while impacts due to thermoelectric generation may be minimal on a national level, the impacts can be severe at the watershed level (Averyt et al. 2013).

Water stress is a concept that has been widely studied e.g. (Alian 2017; Vorosmarty et al. 2018), but there are very few studies in the literature that account for water stress in environmental tradeoff analyses of electricity generation using unit commitment and dispatch modeling. This work contributes to the existing water-energy nexus literature by creating a framework to rank water stress at the watershed scale due to water withdrawals in dispatch modeling, allowing for an assessment of the price elasticity of water withdrawals for energy generation, what generation is displaced as a result of the switch to less water-intensive generators to minimize cost, and tradeoffs between water withdrawals and cost.

4.2 Methods

4.2.1 Software

Multiple software programs are available to perform unit commitment and dispatch modeling. The software programs considered for this work are described and summarized in **Table 4-1**.

Table 4-1 Summary of software and optimization models considered for assessment of grid-level environmental tradeoffs

Software	Resources	References
PLEXOS Integrated Energy Model	https://energyexemplar.com/solutions/plexos/	(Sanders et al. 2014) (Peer et al. 2016)
PowerWorld	https://www.powerworld.com/solutions/faculty	(Pacsi et al. 2013)
ReEDS (Regional Energy Deployment System)	https://www.nrel.gov/analysis/reeds/about-reeds.html	(Clemmer et al. 2013)
SAInt (Scenario Analysis Interface for Energy Systems)	https://www.encoord.com/SAInt.html#top	(Guerra et al. 2021; Craig et al. 2020)
Scalable Integrated Infrastructure Planning Model (SIIP)	https://www.nrel.gov/analysis/siip.html	(Henriquez-Auba et al. 2021)

The PowerWorld simulator can be used in transmission planning, power markets, renewable energy, and real-time operations. The Regional Energy Deployment System Model (ReEDS) is used to simulate the integration of renewable energy technologies to the electricity sector. It has been used to link with water and climate models and is publicly available on the National Renewable Energy Laboratory (NREL) GitHub. The Scenario Analysis Interface for Energy Systems (SAInt) allows users to model energy networks and markets. The software allows for simulation-based and optimization-based models to be run for assessment of trade-offs. The Scalable Integrated Infrastructure Planning Model (SIIP) is an open-source software suite developed by NREL and is a modeling framework to solve scheduling problems and model infrastructure systems at multiple spatial and temporal scales. In addition to these models, it is possible to develop a model from scratch using optimization software such as AMPL. This software, developed by AMPL Optimization, Inc., is an algebraic modeling language that is used to solve high-complexity problems. PLEXOS offers a suite of software applications that can be used to model electricity and water markets including transmission modeling, reliability analysis, hydropower optimization, dispatch optimization, and electricity-water co-optimization. Due to these capabilities and availability of an academic license, PLEXOS Version 8.300 R02 x64 Edition was used to perform the modeling simulations for this work.

4.2.2 Electricity System, Water Withdrawal, and Hydrology Data

Change in technologies, regulations, costs, and social expectations have resulted in a shift in the power generation sector (Peer and Sanders 2018). Shifts include an increase in gas-fired generation as a result of a decrease in natural gas prices, as well as an increase in variable deployment of renewable energy generators. (Guerra et al. 2021). Due to these recent shifts in the electricity generation sector, it was necessary to choose a dataset that is representative of modern power systems. The primary dataset used in this work is the Institute of Electrical and Electronics Engineers (IEEE) Reliability Test System (RTS) 2019 update (Barrows et al. 2019). While the dataset is not based on any specific power system, the dataset is representative of a modern power system that includes increased renewables such as wind, solar photovoltaic, concentrating solar power, and storage. The goal of the dataset is to provide researchers with a model that allows for examination of current and future challenges in power systems.

The test system includes 158 individual generating units including: concentrating solar power, coal, combined cycle gas, combustion turbine gas, hydroelectric, nuclear, oil combustion turbine, oil steam turbine, solar photo-voltaic, wind, and storage generators. There are 73 demand nodes covering an area of approximately 250 miles by 250 miles. Summary tables and data access details for the RTS-GMLC test system can be found on the RTS-GMLC GitHub repository at https://github.com/GridMod/RTS-GMLC as well as in the Supporting Information in Appendix B.

Table 4-2 Summary of data sources for production cost modeling and water stress calculations

Data	Source	Temporal Resolution	Spatial Resolution	Year	Link
			Production Cost Modeling Data		
Grid Test System	IEEE	Hourly	NA	2020	https://github.com/GridMod/RTS-GMLC
Thermoelectric Cooling	EIA	Monthly	Generator	2019	https://www.eia.gov/electricity/data/water/
Fuel Price	EIA	Annual	NA	2020	https://www.eia.gov/outlooks/steo/tables/pdf/2tab.pdf
			Water Stress Data		
Withdrawals by Sector	USGS	Annual	County	2015	https://www.sciencebase.gov/catalog/item/get/5af3311be4b0da30c1b245d8
County Boundary	TIGER	NA	County	2019	https://catalog.data.gov/dataset/tiger-line-shapefile-2019-nation-u-s-current-county-and-equivalent-national-shapefile
HUC8 Watershed Boundary	USGS	NA	Watershed	2016	https://www.usgs.gov/core-science-systems/ngp/national-hydrography/access-national-hydrography-products
Runoff	USGS	Monthly	Watershed	2019	https://waterwatch.usgs.gov/index.php?id=wwds

The IEEE RTS-GMLC dataset does not include specific cooling technologies for each generator, and therefore cooling technologies and water withdrawal intensities were assumed and assigned to each generator. Data from the Energy Information Administration (EIA) Form-923 was used to assign cooling technologies and withdrawal intensities that are representative of the test system geographic location in the American

Southwest for August 2019. Water withdrawals reported by the EIA were assigned according to **Table B3** in Appendix B, Supporting Information. It must be acknowledged that definitions of water use, water consumption, or water withdrawal can be inconsistent across the literature (Grubert, Rogers, and Sanders 2020). The IEEE RTS-GMLC dataset and EIA fuel prices are updated to the year 2020 as summarized in **Table 4-2**. Simulations were run for August 2020, and it is assumed that significant changes have not occurred between the publish date and 2020 for the other datasets.

4.2.3 Production Cost Modeling

Production cost modeling is performed using unit commitment and dispatch to model generation and transmission systems by finding the least-cost solution to meet demand in a given time interval (Barrows et al. 2014). The generic unit commitment and dispatch optimization model uses an objective function and constraints to minimize total system cost, as shown in Equation 4-1. Total system cost includes operational cost, which is a function of variable fuel cost and generation output, as well as a fixed start-up cost per generating unit.

$$Minimize\ F = \sum_{t=1}^{T} \sum_{i=1}^{N} [C_i \times P_{Gi}(t) + S_i \times u_i^S(t)] \tag{4-1}$$

where *F* is the total cost ($), C_i is the fuel cost ($) of gen unit *i*, P_{Gi} is the generation output (MWh) of generator unit i, S_i is the start-up cost ($) of generator unit i, and u_i^S is the integer start up indicator of generator unit *i*. This objective function is subject to constraints shown in Equations 4-2 through 4-4. These constraints include the energy balance and the generator operating range.

$$\sum_{i=1}^{N} P_{Gi}(t) = P_d(t) \tag{4-2}$$

where P_{Gi} represents the generation output (MWh) of generator unit i and P_d represents the total demand plus losses at time t. This constraint ensures that production meets demand.

$$P_{G_i}^{min} \times u_i(t) \leq P_{G_i} \leq P_{G_i}^{max} \times u_i(t) \tag{4-3}$$

where $u_i(t)$ represents the unit commitment of generator i at time t. This constraint limits the generator operating range.

$$u_i, u_i^s \in [0,1] \tag{4-4}$$

Modeling the impacts of monetizing water withdrawals requires adding water withdrawal impacts to the model. This was done by adding withdrawal intensity values to each individual generator, in unit of gal/MWh, as summarized in Table 2. Additionally, a fee was added per unit of water withdrawn, and the objective function is adjusted to reflect the change in total cost as shown in Equation 4-5. In the context of this analysis, water withdrawals are being equated to emissions. Two types of prices can be included; the emission accounting price and the emission dispatch price. The emission accounting price is used in the emission production cost calculation after the simulation has been completed, and represents the cost assigned to generators for their emissions. This analysis uses the emission dispatch price, also known as emission shadow price or marginal cost, to adjust generator offer prices to account for emissions.

$$Minimize\ F = \sum_{t=1}^{T} \sum_{i=1}^{N} [C_i \times P_{Gi}(t) + C_w \times V_{wi}(t) + S_i \times u_i^S(t)] \quad (4\text{-}5)$$

Equation 4-5 represents the objective function, accounting for emission dispatch price, in which total cost ($) is minimized; here, where C_i is the fuel cost ($) of generator unit *i*, P_{Gi} is the generation output (MWh) of generator unit i, C_w is the cost ($/gal) per unit of water withdrawn, V_{wi} is the volume of water withdrawn (gal) by generator unit i, S_i is the start-up cost ($) of generator unit *i*, and u_i^S is the integer start up indicator of generator unit *i*. This objective function is also subject to constraints shown in Equations 4-2 through 4-4.

To illustrate the potential impacts of monetization on system water withdrawals and generation cost, four scenarios were evaluated for the month of August 2020, as summarized in **Table 4-3**.

Table 4-3 Water withdrawal monetization scenario summary

Scenario	Emission Dispatch Price ($/Gal)
1	0
2	3×10^{-5}
3	3×10^{-4}
4	3×10^{-3}

All scenarios were evaluated using a day-ahead model with a planning horizon of one month and an interval length of one hour. Scenario 1 is the base case, in which no fees were applied. Scenario 2 applied an emission dispatch price of 3×10^{-5} dollars per gallon, Scenario 3 applied an emission dispatch prices of 3×10^{-4} dollars per gallon, and Scenario 4 applied an emissions dispatch price of 3×10^{-3} dollars per gallon.

4.2.4 Water Stress Accounting

Water stress was quantified using the freshwater withdrawal to availability ratio (WTA), following the procedure presented by Wang et al. (2017) with some modifications. The WTA ratio is calculated using Equation 4-7, where $WTA_{i,j}$ is the freshwater withdrawal to availability ratio for watershed *i* in month j, $W_{i,j}$ is the total water withdrawal in watershed *i* for month j, and $A_{i,j}$ is the freshwater availability in watershed *i* for month j.

$$WTA_{i,j} = \frac{W_{i,j}}{A_{i,j}} \tag{4-7}$$

Withdrawal to availability ratios were calculated at the HUC8 watershed scale which required harmonizing all data used in the calculations to the watershed scale.

Freshwater availability, defined as the monthly runoff, was determined using HUC8 watershed runoff values published through United States Geological Survey (USGS) Waterwatch. Runoff is calculated using USGS historical streamgage flow data, drainage basin boundaries to each streamgage, and the boundaries of the HUC8 watersheds. Runoff is computed in flow per unit area for each streamgage basin, and then the basin boundaries are overlain with HUC8 boundaries to create a weighting factor for each basin. The result is a single weighted-average runoff value for the HUC8 watershed. More details on this procedure can be found in the “Calculation of Hydrologic Unit Code (HUC) runoff” document from USGS (USGS 2011).

Water withdrawals in each watershed were determined using the USGS 2015 dataset, *Estimated Use of Water in the United States County-Level Data for 2015* (Dieter 2018).

This dataset reports annual withdrawals at the county level for specific use categories including public supply, domestic, industrial, irrigation, livestock, aquaculture, mining, and thermoelectric. Thermoelectric withdrawals from the USGS dataset were excluded from this analysis, and withdrawal volumes from the simulations using PLEXOS were included so that impacts of dispatch order could be accounted for. The reported county withdrawals were allocated to respective HUC8 watersheds using factors presented in **Table B4** in Appendix B Supporting Information. Withdrawals were allocated based on the area of each county within the HUC8 watershed boundary, assuming an even distribution of water use per area. County boundaries were overlaid with watershed boundaries and intersected to calculate the ratio, or factor, to apply to the total withdrawals to assign a withdrawal volume to the watershed.

Since the RTS-GMLC dataset does not represent actual existing infrastructure, it was necessary to assign the buses in the test system to watersheds based on test system coordinates. Coordinates provided in the dataset were intersected with the National Hydrography Dataset HUC8 watershed shapefiles as shown in **Figure 4-1** (USGS 2013).

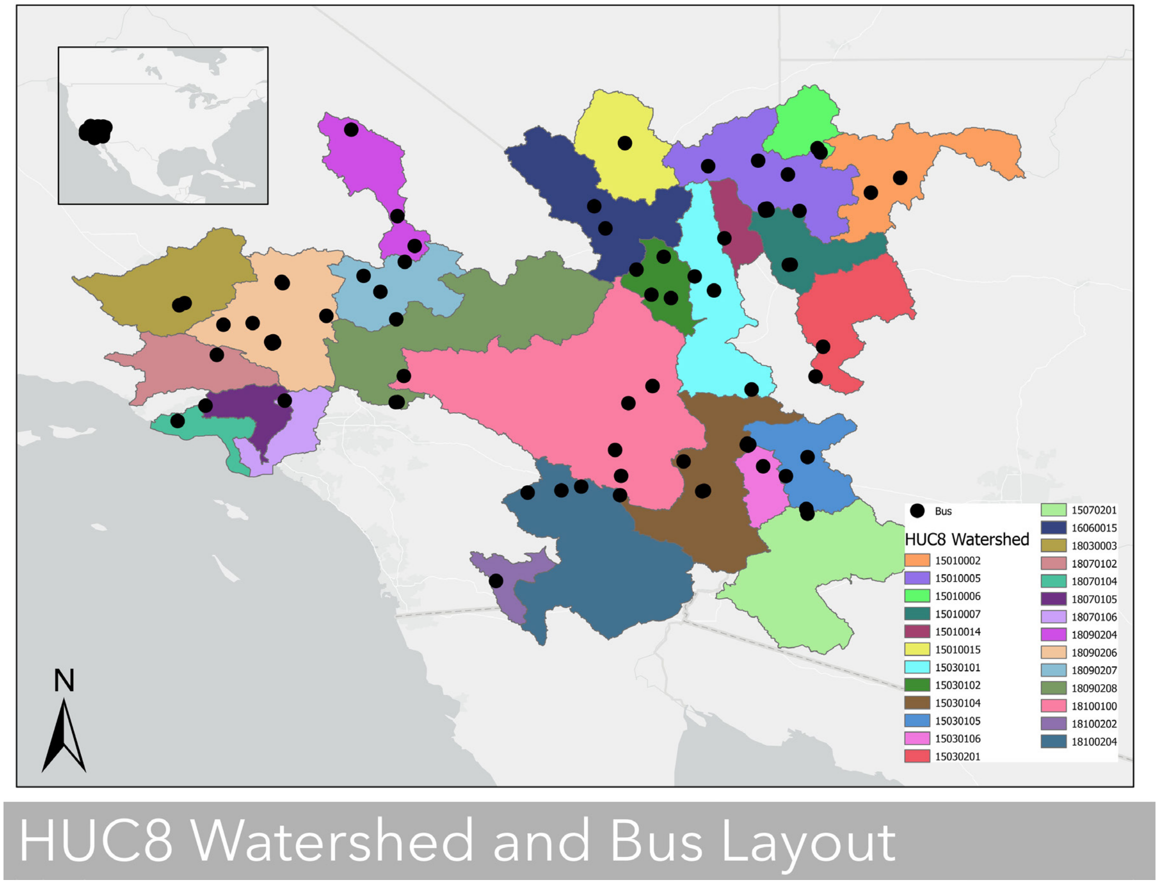

Figure 4-1 Bus layout for RTS-GMLC with National Hydrography Dataset HUC8 watershed shapefiles.

Bus nodes were assigned to watersheds based on the intersection of the two shapefiles. Watershed names, HUC8 codes, and Bus IDs are summarized in in **Table 4-4**. Individual generator ID's, fuel types, technology types, cooling technologies, and withdrawal intensities are summarized in **Table B3** Appendix B Supporting Information.

Table 4-4 Network Bus Inventory Watershed Assignments and Associated HUC8 Code.

Watershed	Bus ID	HUC8
Antelope-Fremont Valleys	303, 305, 306, 309, 310, 311, 312, 314, 324	18090206
Big Sandy	107, 108	15030201
Bouse Wash	104, 105	15030105
Carrizo Creek	122	18100202
Coyote-Cuddeback Lakes	315, 316, 317, 319	18090207
Detrital Wash	214	15010014
Grand Canyon	207, 208	15010002
Grand Wash	201, 202	15010006
Havasu-Mohave Lakes	113, 215, 216	15030101
Imperial Reservoir	103, 109, 110, 111, 112, 114, 124	15030104
Ivanpah-Pahrump Valleys	220, 223	16060015
Lake Mead	204, 205, 206, 209, 210, 211, 212, 213	15010005
Las Vegas Wash	222	15010015
Los Angeles	308	18070105
Lower Gila	101, 102	15070201
Middle Kern-Upper Tehachapi-Grapevine	301, 302	18030003
Mojave	323, 325	18090208
Panamint Valley	318, 321, 322	18090204
Piute Wash	217, 218, 219, 221	15030102
Red Lake	203, 224	15010007
Salton Sea	115, 117, 118, 121	18100204
San Gabriel	313	18070106
Santa Clara	304	18070102
Santa Monica Bay	307	18070104
Southern Mojave	116, 119, 120, 123, 320	18100100
Tyson Wash	106	15030106

The WTA ratio was calculated at a monthly resolution for each of the watersheds for Scenarios 1-4 summarized in **Table 4-3**. Water stress thresholds for the WTA ratios were evaluated for each watershed to determine which watersheds are the most severely stressed and which experience little or no stress. Thresholds are summarized in **Table 4-5** (Brown and Matlock 2011; Wang et al. 2017).

Table 4-5 Water Stress thresholds based on Freshwater Withdrawal to Availability Ratio

Stress Level	w.t.a	Rank
No Stress	<0.1	1
Low Stress	0.1 ≤ w.t.a <0.2	2
Moderate Stress	0.2 ≤ w.t.a <0.4	3
Severe Stress	0.4 ≤ w.t.a <1	4
Extreme Stress	>1	5

4.3 Results and Discussion

The month of August was selected to evaluate water stress as it is a low-flow month. **Figure 4-2** shows runoff values for the test system watersheds in the year 2019, illustrating the low-flows observed during late summer and autumn months.

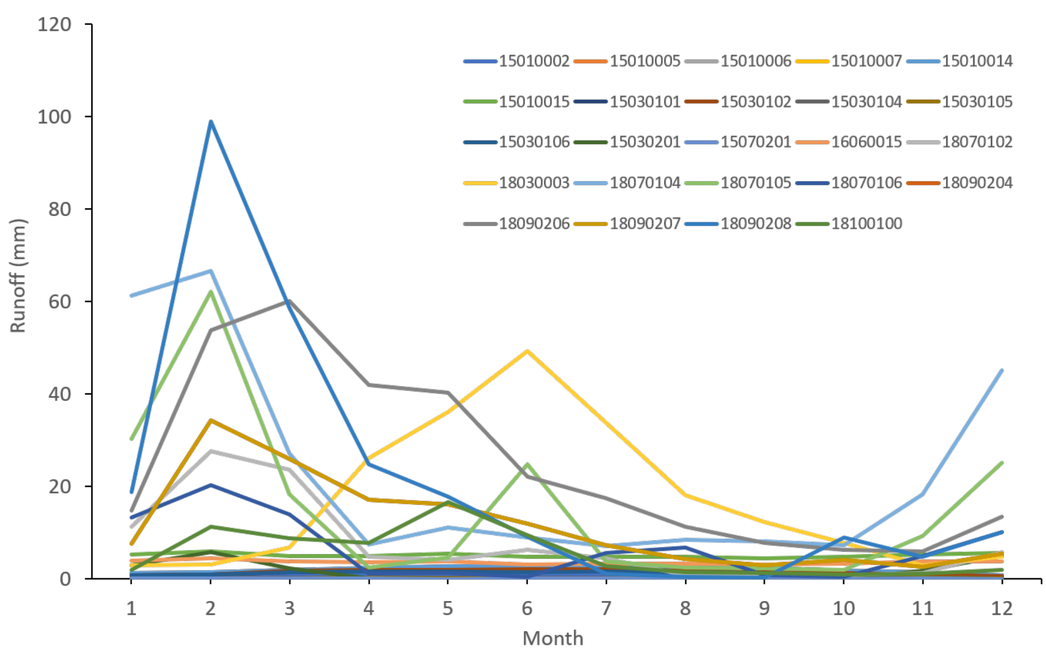

Figure 4-2 Annual runoff timeseries at monthly interval for test system watersheds in 2019 (USGS Waterwatch).

A unit commitment and dispatch model was run at an hourly timestep for August 2020 using PLEXOS for Scenarios 1-4. The results of these simulations provided the water withdrawal volumes required for electricity generation in the RTS-GMLC test system used to determine water stress at the watershed level. Total withdrawals and total generation cost for the test system for August 2020 are summarized in **Table 4-6**.

Table 4-6 Total withdrawals in million gallons (MGal) and total generation cost in dollars ($) for scenarios 1-4.

Scenario	Emission Dispatch Price ($/Gal)	Total August Withdrawals (MGal)	Total August Generation Cost ($)
1	0	56265	51,854,110
2	3×10^{-5}	50260	53,359,140
3	3×10^{-4}	20710	61,817,740
4	3×10^{-3}	4490	75,478,040

Results presented in **Table 4-6** show that monetization of withdrawals is an effective way to reduce overall water withdrawals within the electricity system. Withdrawals decreased by approximately 11% under scenario 2, 63% under scenario 3, and 92% under scenario four. While the reductions in withdrawals are notable, they come at a cost tradeoff. To achieve 92% reduction in system withdrawals for electricity generation, an additional cost of $23.6 million would have to be paid by generators. This 45% increase in generation cost would have impacts on end users as cost of electricity would increase.

Reductions in withdrawals can be explained by shifts in generators used to meet demand. Generation technology, fuel type, and cooling technology all have an impact on how much water is withdrawn for electricity generation. Additionally, each fuel type varies in cost ($/MMBtu) as summarized in **Table 4-7** (EIA 2021b). To meet demand at the lowest cost possible, the cost of fuel and monetized water withdrawals must be considered.

Table 4-7 Generation fuel costs in dollars per metric million British thermal unit ($/MMBtu) for 2020

Fuel	Price ($/MMBtu)
Coal	1.93
Hydro	0.00
Natural Gas	2.39
Nuclear	0.73
Oil	13.27
Solar	0.00
Wind	0.00

Generation using renewable energy such as hydroelectric, solar, and wind technologies does not require fuels, and therefore does not have an associated fuel cost. Oil is the most expensive fuel at $13.27 per MMBtu while nuclear is the least expensive fuel at $0.73 per MMBtu. There is not a large difference in fuel cost between coal and natural gas as natural gas prices have decreased in recent years due to an increase in supply of the fuel (EIA 2021a).

Figure 4-3 shows contributions to generation from generator types in the test system under Scenarios 1-4. Despite being a large user of water for thermoelectric cooling, nuclear generation remains consistent under scenarios 1-3, likely due to the low cost of fuel per MMBtu. However, under scenario 4, contributions from nuclear are nearly negligible, indicating that the monetization of withdrawals shifted the dispatch to combustion turbine natural gas generators. Generation from combined cycle natural gas is dominant under all four scenarios, but decreases slightly as monetization of withdrawals increases. Generation from coal increases under scenario 4. Contributions from oil, solar, and wind remain fairly consistent in all four scenarios.

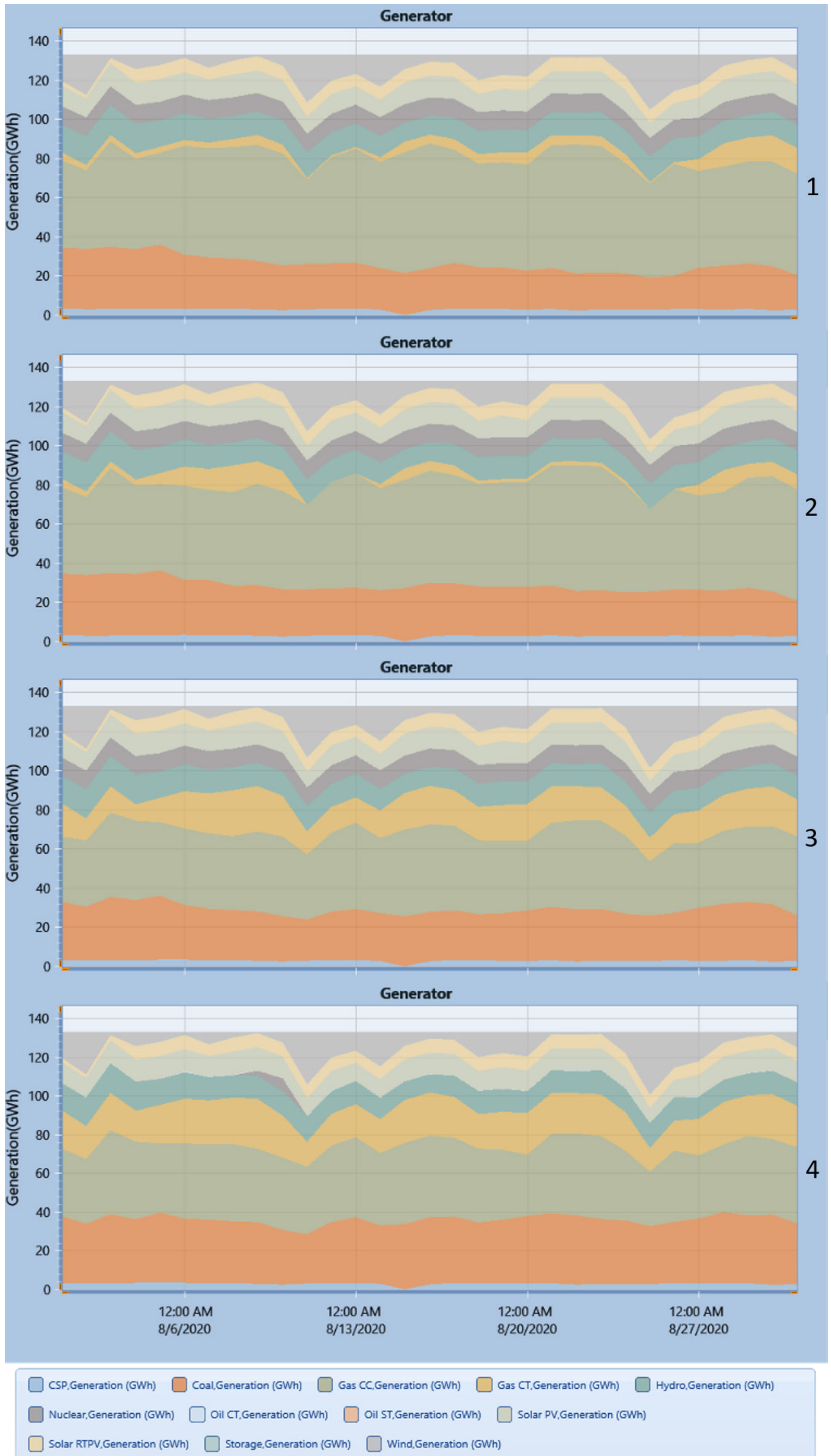

Figure 4-3 Generation in Gigawatt-Hours (GWh) by generator technology type for the test system under Scenarios 1-4 in August 2020

Despite the notable decrease in overall water withdrawals for electricity generation in the test system, the reductions in withdrawals at the watershed scale were not large enough to mitigate water stress in many of the test system watersheds. Under Scenario 1 with no monetization of withdrawals, 13 of the watersheds were ranked as extremely stressed, 7 were ranked as severely stressed, 2 were ranked as moderately stressed, and 4 were ranked as having no stress. Water stress rankings by watershed for Scenarios 1-4 are shown in **Figure 4-4**.

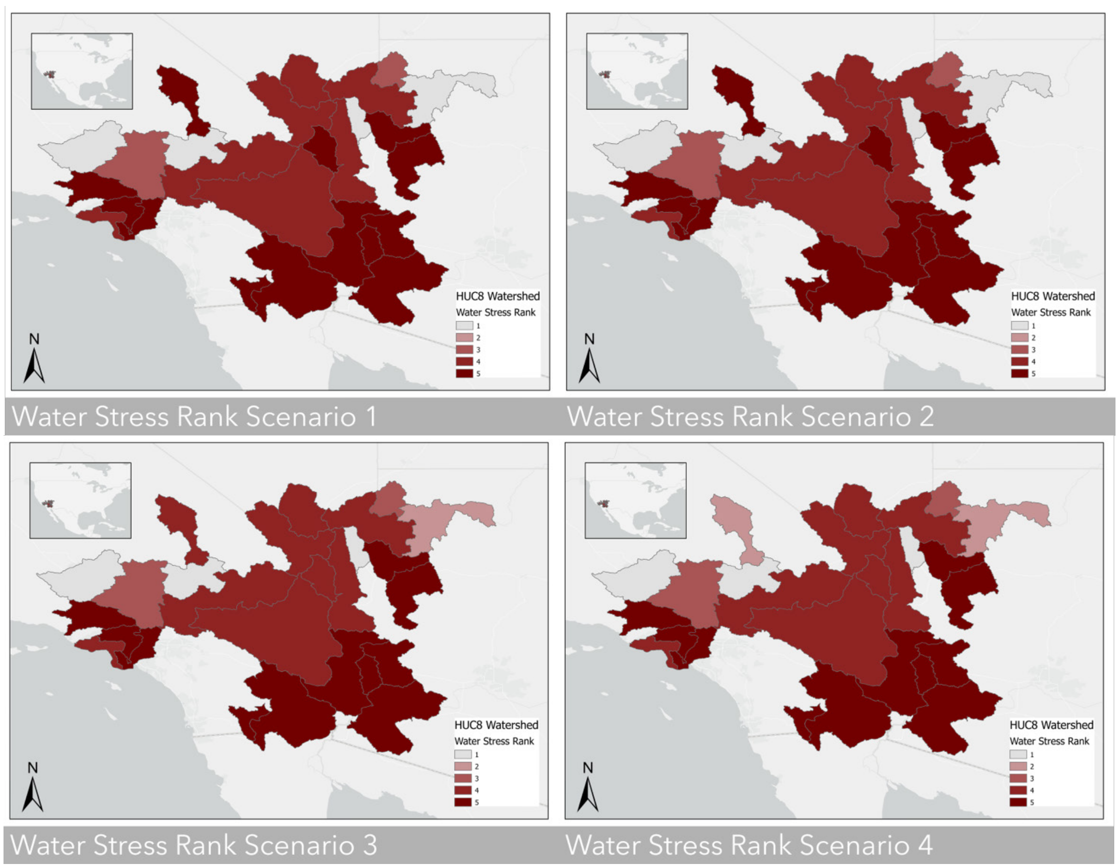

Figure 4-4 Water stress rank for test system watersheds under Scenarios 1-4.

Under scenario 2, slight reductions in withdrawals for electricity generation were observed, but the reductions were not significant enough to change the water stress rank determined by the WTA. Under scenario 3, the rank increased from no stress to low stress in watershed 15010002 due to a shift in generator dispatch in the system. This watershed did not have any units contributing to system generation under Scenarios 1 and 2, but under scenarios 3 and 4 natural gas combustion turbine generators with recirculating cooling towers contributed to system generation. Watersheds 18090204 and 15030102 decreased from extremely stressed to severely stressed under scenario 3, and 18090204 decreased even further to low stress under scenario 4. Dispatch shifted away from the combined cycle natural gas generator with a once-through cooling system in 18090204 due to the large fees on withdrawal volumes for generation under Scenario 4.

The contributions of withdrawals for electricity generation to total watershed withdrawals are summarized along with water stress rank for each test system watershed in **Table 4-8**. These values help illustrate how other factors may be inhibiting decreases in water stress rank despite the large decrease in total withdrawals in the test system. For example, in watershed 15030102, water withdrawals for electricity generation made up 99% of total withdrawals in the watershed under Scenario 1 with no monetization of withdrawals. Under Scenario 4, dispatch shifted such that withdrawals for electricity generation were negligible, making up 0% of total withdrawals in the watershed. Despite this, the water stress rank only dropped from extreme to severe. This indicates that runoff in the watershed was so low during August 2019 that even drastic reductions in withdrawal volumes were not enough to mitigate water stress.

Table 4-8 Water stress rank and percent of total withdrawals that are for electricity generation for test system watersheds under Scenarios 1-4.

	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
HUC8	% Total Withd.	Water Stress Rank	% Total Withd.	Water Stress Rank	% Total Withd.	Water Stress Rank	% Total Withd.	Water Stress Rank
18090206	0%	3	0%	3	0%	3	0%	3
15030201	58%	5	58%	5	60%	5	56%	5
15030105	0%	5	0%	5	0%	5	0%	5
18100202	20%	5	20%	5	20%	5	20%	5
18090207	9%	1	9%	1	13%	1	15%	1
15010014	0%	1	0%	1	0%	1	0%	1
15010002	0%	1	0%	1	20%	2	23%	2
15010006	34%	3	34%	3	35%	3	38%	3
15030101	18%	4	18%	4	20%	4	21%	4
15030104	0%	5	0%	5	0%	5	0%	5
16060015	1%	4	2%	4	2%	4	5%	4
15010005	11%	4	9%	4	16%	4	12%	4
15010015	14%	4	14%	4	14%	4	14%	4
18070105	0%	5	0%	5	0%	5	0%	5
15070201	14%	5	13%	5	0%	5	1%	5
18030003	0%	1	0%	1	2%	1	3%	1
18090208	25%	4	25%	4	27%	4	29%	4
18090204	99%	5	99%	5	97%	4	88%	2
15030102	97%	5	95%	5	12%	4	0%	4
15010007	0%	5	0%	5	0%	5	0%	5
18100204	51%	5	51%	5	50%	5	4%	5
18070106	67%	5	65%	5	0%	5	0%	5
18070102	0%	5	0%	5	0%	5	0%	5
18070104	0%	4	0%	4	1%	4	2%	4
18100100	3%	4	4%	4	6%	4	7%	4
15030106	0%	5	0%	5	0%	5	0%	5

Trends in runoff published by USGS for 2019 show that for many of these watersheds, water availability was extremely limited. Despite overall trends for the United States showing that runoff streamflow in 2019 was above average, seasonal trends show that the test system region experienced runoff streamflow that was either below normal or extremely below normal for the late summer and early autumn months (USGS 2019).

Water users in this region are competing for limited volumes of water, and results of this analysis show that decreasing the volume of water withdrawn for electricity generation alone is not enough to mitigate water stress at the watershed level. Applying a dispatch price to water withdrawals is an effective method to reduce the total monthly volume of water required to meet electricity demand within the test system, but comes with an increased cost of electricity generation. While monetizing water withdrawals alone is not effective in reducing water stress at the watershed level, joint interventions with other withdrawal sectors may help reduce water stress during low flow seasons. Additionally, more targeted interventions at the plant level can be implemented to consistently reduce water stress at the point of withdrawal. Assessment of water stress at the point of withdrawal will be considered as future work and is described in more detail in the next section.

4.3.1 Future Work

The WTA ratio is only one indicator of water stress. Other indicators, as summarized in **Table 4-9** could also be investigated (Alian 2017). Ecological water stress is described as catchment-scale water stress that causes ecologically harmful stream flow disturbances (Alian 2017). Some states regulate large withdrawals to avoid these harmful stream flow disturbances. For example, the State of Michigan uses the Michigan Water Withdrawal Assessment Process to regulate new or increased large withdrawals of over 100,000 gallons per day to mitigate or avoid adverse resource impacts to aquatic ecosystems and streamflow (Hamilton and Seelbach 2011). To the author’s knowledge, existing UC&D

models do not account for limits on water withdrawals for thermoelectric generation to prevent adverse ecosystem impacts.

Table 4-9 Summary of water stress indicators from the literature Alian (2017).

Indicator	Description	Mathematical Formulation	Reference
Falkenmark Water Scarcity Indicator (WSI)	Proportion of annual runoff available for human use	$\frac{Water\ Availability}{Population}$	(Falkenmark 1989)
Water Resources Vulnerability Index	Total annual withdrawals as a percentage of the available water resources	$\frac{Total\ Annual\ Withdrawal}{Annual\ Water\ Resources}$	(Raskin et al. 1997)
Physical Scarcity Indicators	Water scarcity due to not having enough renewable water resources even after considering future adaptive capacity	$\frac{Outflow}{Developed\ Water\ Resources}$	(Seckler 1998)
Social Water Stress Index	Capacity to adapt to human stress through UNDP's Human Development Index	$\frac{Falkenmark\ WSI}{Human\ Development\ Index}$	(OhIsson 2000)
Modified Water Exploitation Index	Percentage of total annual freshwater demand relative to long-term mean annual freshwater availability	$\frac{(Abstraction - Return)}{(Flow + Abstraction - Return)}$	(EEA 2013)

Additional future work may include applying the framework developed in this chapter to determine if electricity generation in the water-rich Great Lakes Basin contributes to water stress, specifically focusing on potential ecological water stress in vulnerable rivers and streams (Alian et al. 2019). However, the necessary data for the Eastern Interconnection, the corresponding regional electricity grid is not publicly available at this time. If this data becomes available, an ecological water stress mitigation assessment can be completed by assessing water stress at the point of withdrawal. Severely stressed streams will be identified and withdrawal limits will be applied in PLEXOS. The limits will shift the dispatch order to less water intensive generators, and updated withdrawal values from PLEXOS can be used to reassess water stress at the point of withdrawal and determine if the limit was effective in mitigating ecological water stress. A combination of monetization of withdrawals as well as withdrawal limits can also be used to reduce withdrawals while also working to keep electricity prices reasonable for the end user.

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5 Conclusion and Future Work

5.1 Conclusion

This dissertation presented multi-dimensional modeling for environmental impact assessment at intersections of the Food-Energy-Water (FEW) Nexus to help inform joint-resource management decisions by assessing tradeoffs and optimizing co-benefits. This work took a sustainability-based approach to FEW Nexus research by considering the social, economic, and environmental aspects of joint-resource management issues. The key contribution of this work is an advancement of knowledge of FEW Nexus systems at multiple spatial and temporal scales through life cycle assessment modeling, statistical modeling, and optimization modeling.

Chapter 2 summarized the development of a life cycle assessment model and associated novel software application, HomeTracker, to quantify direct and indirect environmental impacts due to household consumption in a typical United States suburban area. This tool provides meaningful feedback to users that can help inform behavior change to mitigate environmental impacts of household FEW consumption. The result of this work is an open-source software application that can be applied in future research projects, and a large household FEW consumption database that allows researchers to assess what households purchase and consume over an extended period of time, along with the environmental impacts of that consumption.

Chapter 3 investigated the water use impacts of electricity generation through development of a novel framework to quantify water withdrawals and consumption impacts from marginal electricity generation at the annual, monthly, and month-hour scale. Impact factors called Marginal Water Factors (MWFs) were developed for a case study of a regional transmission operator (RTO), the Midcontinent Independent System Operator, showing that water use impacts were lower when renewable energy sources were deployed on the margin. This framework can be applied to calculate MWFs for any RTO in the United States. These factors can be used to investigate water use savings from load shifting and evaluate impacts of interventions such as energy storage, demand-side management, and shifts in generator technology.

Chapter 4 presented a framework to assess the trade-offs between minimum-cost electricity generation and dispatch and water stress at the watershed level. A thermoelectric cooling dataset was developed to complement the IEEE RTS-GMLC test system for analysis of hydrologic and water resources-related interventions associated with generator dispatch order. Production cost modeling was used to determine water stress in the RTS-GMLC test system under four monetization scenarios, and results showed that while water withdrawals can be reduced with monetization of withdrawals, there is a cost tradeoff with an increase in generation cost even with shift in dispatch to lower withdrawal intensity generators.

5.2 Future Work

This dissertation contributes to the FEW Nexus bodies of research by using life cycle assessment modeling to understand resource consumption impacts at the household level, by modeling aspects of the water-energy nexus using existing and novel tools, and finally by assessing the water-energy nexus at multiple spatial and temporal scales. Despite the contribution, several key knowledge gaps remain. Future work primarily includes updates to the models as data improves spatially and temporally. Improvements to the HomeTracker may include expansion of geographic coverage of environmental impact factors to allow for broader application of the software without modification of the source code. Additionally, as the data collected through use of the HomeTracker is made available, further analysis on household consumption will be completed to better understand consumption behavior at multiple timescales. For electricity generation and dispatch modeling, there is a need for improved reporting of cooling water use, particularly at the hourly timescale to improve understanding of water use requirements for marginal electricity generation. Results of the linear regression model presented in Chapter 3 would be more useful for policy development and decision making with the availability of hourly thermoelectric cooling data. Future work may also include expanding the water stress mitigation assessment to other regions in order to compare the impacts to ecological water stress in different hydroclimatic settings. The assessment may also be applied under different climate change scenarios

A Chapter 3 Supporting Information

A.1 Study Area

Figure A1 shows the Midcontinent Independent System Operator (MISO) Region and its subregions: MISO North, MISO Central, and MISO South. MISO North includes the states Iowa, Montana, Minnesota, North Dakota, and the province of Manitoba. MISO Central includes the states Michigan, Missouri, Illinois, Indiana, Wisconsin, and Kentucky. MISO South includes the states Arkansas, Louisiana, Mississippi, and Texas. The province of Manitoba has been excluded from this study, as the data used is specific to the United States.

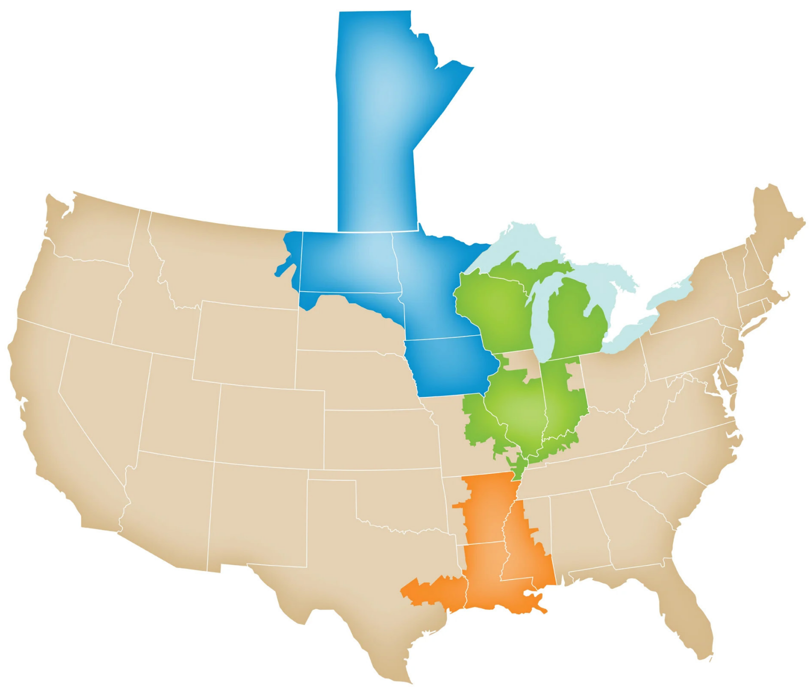

Figure A1 Midcontinent Independent System Operator by subregion with the North Region shown in blue, the Central Region shown in green, and the South region shown in orange (MISO 2020).

A.2 Data Sources and Processing

Table A1 summarizes datasets, sources, temporal resolution, geographic coverage and access URLs for 2019 datasets that were used for the analysis summarized in the main article.

Table A1 Sources and Details for 2019 Data Used for Marginal Water-Use Factor Analysis

Dataset	Agency	Temporal Resolution	Geographic Coverage	Access URL
Air Market Program Data	U.S. Environmental Protection Agency	Hourly	United States	https://ampd.epa.gov/ampd/
EIA Form-923	U.S. Energy Information Administration	Monthly	United States	https://www.eia.gov/electricity/data/water/
EIA Form-860	U.S. Energy Information Administration	N/A	United States	https://www.eia.gov/electricity/data/eia860/
MISO Historical Generation Fuel Mix	Midcontinent Independent System Operator	Hourly	United States & Canada	https://www.misoenergy.org/markets-and-operations/real-time--market-data/market-reports
MISO Historical Real-Time Fuel on the Margin	Midcontinent Independent System Operator	5-Minute	United States & Canada	https://www.misoenergy.org/markets-and-operations/real-time--market-data/market-reports

Cooling water data from the EIA Form-923 was cleaned before inclusion in the analysis to ensure that water use intensities were reflective of the fuel mix in each region. Following Peer and Sanders 2016, power plants with multiple fuels, defined as the primary fuel representing less than 95% of total generation, were removed from the dataset (Peer and Sanders 2016). Additionally, plants with “Generator Primary

Technology” listed as “Multiple” were removed from the dataset. Generation from “Generator Primary Technology” types including “Municipal Solid Waste” and “Wood/Wood Waste Biomass” have been assumed in the category of “Other” per the definition by the Midcontinent Independent System Operator.

Water use intensities for withdrawal and consumption were compared with literature estimates for water withdrawal and consumption intensities from the literature review by Macknick et al. 2012 to verify that they fell within reasonable and expected range based on prime mover and cooling technology types (Macknick et al. 2012). All water use intensities calculated in Section 3.2.5 of the main article fell within the expected range of reported literature values.

A.3 Regional and Subregional Cooling Technology

Figures A2-A5 show the breakdown of cooling technology type by prime mover in MISO and each of the subregions. The percentages represent percent of total generation using each cooling technology type by prime mover, and were determined from the cleaned dataset described in Section A.2 Data Sources and Processing. Water withdrawal and consumption intensities vary significantly by cooling technology in addition to fuel type. Understanding the contributions to generation from each cooling technology types allows for a better understanding of the water use intensities that are calculated based on fuel type.

Four prime movers contributed to generation in MISO and the three subregions: Conventional Steam Coal, Natural Gas Steam Turbine, Natural Gas Fired Combined

Cycle, and Nuclear. Cooling technologies in MISO and the three subregions include: Once-through with Cooling Pond, Once-through no Cooling Pond, Recirculating with Cooling pond, Recirculating with Induced Draft, Recirculating with Natural Draft, and a Mixture of Cooling Types. Once-through cooling systems, sometimes referred to as open-loop cooling systems, result in large volumes of water withdrawal. On the other hand, recirculating systems, sometimes referred to as closed-loop cooling systems, withdraw less water as the water is recirculated through the system multiple times before being discharged to its original source. Recirculating systems can result in larger volumes of water consumption due to increased evaporation.(Healy et al. 2015) These cooling technologies may or may not include a cooling pond, which also impacts evaporation rates. Definitions for withdrawal and consumption vary depending on cooling type and are summarized in the Appendix for Schedule 8D Instructions by the Energy Information Administration(EIA 2021) as well as in Table 1 of the main article.

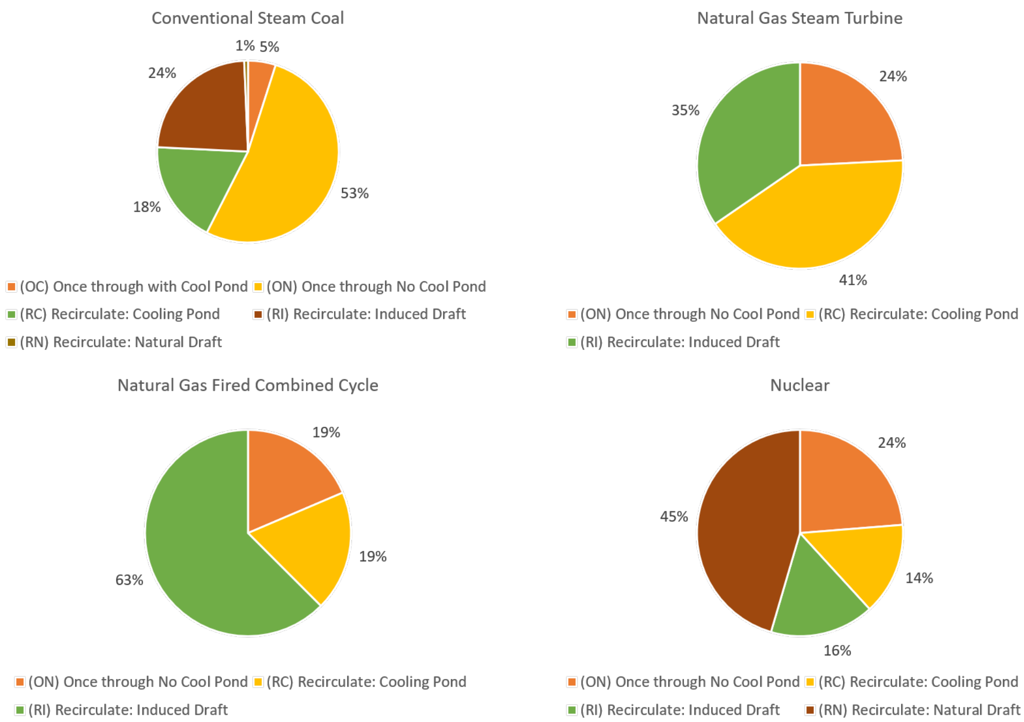

Figure A2 Percent contribution to total generation from each cooling technology type by Prime Mover for MISO Central 2019 (EIA 2019).

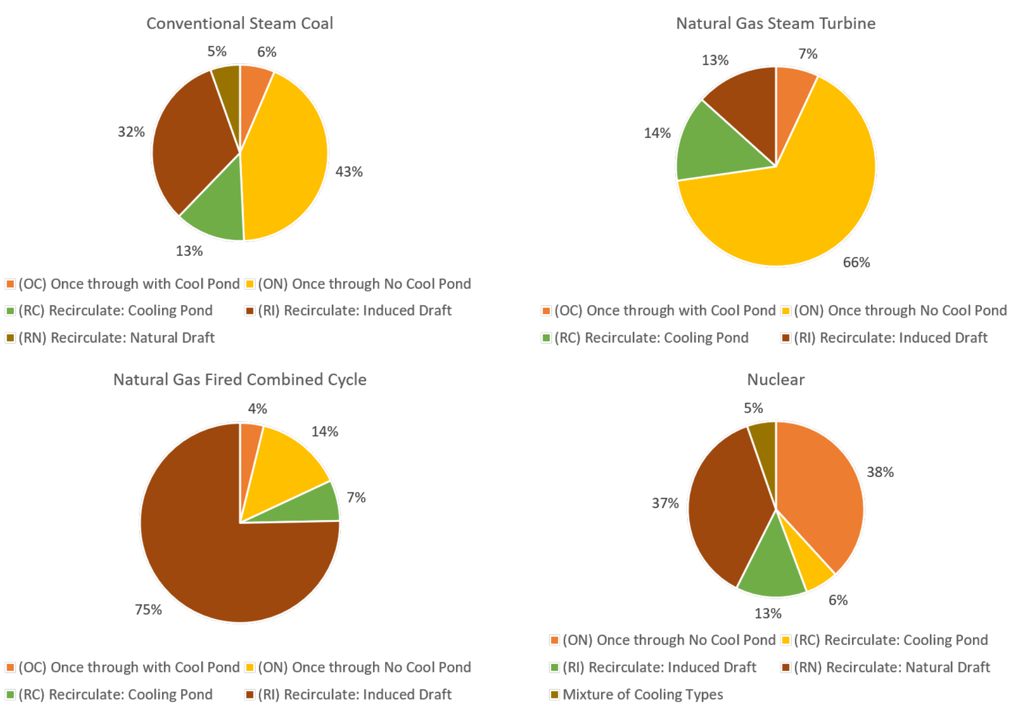

Figure A3 Percent contribution to total generation from each cooling technology type by Prime Mover for MISO 2019 (EIA 2019).

Figure A4 Percent contribution to total generation from each cooling technology type by Prime Mover for MISO North 2019 (EIA 2019).

Figure A5 Percent contribution to total generation from each cooling technology type by Prime Mover for MISO South 2019 (EIA 2019).

A.4 References

EIA. 2019. "Annual Cooling Summary Data - EIA-923 data file." In.

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Healy, Richard W, William M Alley, Mark A Engle, Peter B McMahon, and Jerad D Bales. 2015. "The water-energy nexus: an earth science perspective." In.: US Geological Survey.

Macknick, Jordan, Robin Newmark, Garvin Heath, and Kathleen C Hallett. 2012. 'Operational water consumption and withdrawal factors for electricity generating technologies: a review of existing literature', *Environmental Research Letters*, 7: 045802.

MISO. 2020. 'MISO Energy Home', Accessed April 16, 2020. https://www.misoenergy.org/.

Peer, Rebecca AM, and Kelly T Sanders. 2016. 'Characterizing cooling water source and usage patterns across US thermoelectric power plants: a comprehensive assessment of self-reported cooling water data', *Environmental Research Letters*, 11: 124030.

B Chapter 4 Supporting Information

Table B1 EIA Reporting Instructions Water Withdrawal and Water Consumption Definitions by Cooling Technology Type

Technology Type	Withdrawal Definition	Consumption Definition
Once-Through System without Cooling Ponds or Canals	Water that is removed from a water body for cooling	Evaporative losses are not expected
Once-Through System with Cooling Pond or Canal	Water that is removed from a water body for cooling	Evaporative losses are not expected
Recirculating System with Pond and No Tower	Water flow to the condenser from the cooling pond	Evaporative losses that occur within the cooling pond
Recirculating System with Tower and No Pond	Cooling tower makeup water that is removed from a water body	Evaporative losses from cooling tower(s)
Recirculating Cooling Circuit with both Towers and Ponds	Water flow to the condenser	Evaporative losses from cooling pond and tower(s)
Dry Cooling Hybrid Systems	Cooling tower makeup water that is removed from a water body	Evaporative losses from cooling tower(s)

Table B2 Summary of generating unit quantities, fuel type, technology type, assigned cooling technology, and mean water withdrawal estimates from the literature

Fuel Type	Technology	Cooling Technology	N	Mean Withdrawal Intensity (Gal/MWh)	Source
CSP	Trough	Hybrid	1	338	Macknick 2011
Coal	Generic	Tower	8	1005	Macknick 2011
		Once-Through	8	36350	Macknick 2011
Gas	Combined Cycle	Cooling Tower	6	250	Meldrum 2013
		Dry Cooling	4	4	Meldrum 2013
	Combustion Turbine	NA	27	50	Meldrum 2013
Hydro	In-Stream/Reservoir	NA	20	4491	Macknick 2011
Nuclear	Nuclear	Cooling Tower	1	1100	Meldrum 2013
Oil	Combustion Turbine	NA	12	50	*
	Steam Turbine	Once-Through	7	36350	**
Solar PV	Flat Paneled	NA	12	6	Meldrum 2013
	Concentrated PV	NA	13	30	Meldrum 2013
Solar RTPV	Roof Top Flat Paneled	NA	31	6	Meldrum 2013
Wind	Onshore	NA	4	1	Meldrum 2013

*Assumed to operate consistent with natural gas combustion turbine
**Assumed to operate consistent with a coal fired steam turbine

Table B3 Summary of system buses, generators, fuel type, cooling technology, and withdrawal intensities (gal/MWh) for RTS-GMLC test system

Bus ID	GEN UID	Category	Fuel	Cooling Technology	Withdrawal Intensity (gal/MWh)
101	101_CT_1	Oil CT	Oil	Recirculate	958
	101_CT_2	Oil CT	Oil	Recirculate	985
	101_PV_1	Solar PV	Solar	NA	6
	101_PV_2	Solar PV	Solar	NA	6
	101_PV_3	Solar PV	Solar	NA	6
	101_PV_4	Solar PV	Solar	NA	6
	101_STEAM_3	Coal	Coal	Once Through	46131
	101_STEAM_4	Coal	Coal	Once Through	46131
102	102_CT_1	Oil CT	Oil	Recirculate	958
	102_CT_2	Oil CT	Oil	Recirculate	985
	102_PV_1	Solar PV	Solar	NA	6
	102_PV_2	Solar PV	Solar	NA	6
	102_STEAM_3	Coal	Coal	Recirculate	928
	102_STEAM_4	Coal	Coal	Recirculate	929
103	103_PV_1	Solar PV	Solar	NA	6
104	104_PV_1	Solar PV	Solar	NA	6
107	107_CC_1	Gas CC	NG	Recirculate	1486
113	113_CT_1	Gas CT	NG	Recirculate	343
	113_CT_2	Gas CT	NG	Recirculate	343
	113_CT_3	Gas CT	NG	Recirculate	343
	113_CT_4	Gas CT	NG	Recirculate	343
	113_PV_1	Solar PV	Solar	NA	6
114	114_SYNC_COND_1	Sync_Cond	Sync_Cond		0
115	115_STEAM_1	Oil ST	Oil	Recirculate	958
	115_STEAM_2	Oil ST	Oil	Recirculate	985
	115_STEAM_3	Coal	Coal	Recirculate	928
116	116_STEAM_1	Coal	Coal	Recirculate	929
118	118_CC_1	Gas CC	NG	Recirculate	425
	118_RTPV_1	Solar RTPV	Solar	NA	6
	118_RTPV_10	Solar RTPV	Solar	NA	6
	118_RTPV_2	Solar RTPV	Solar	NA	6

	118_RTPV_3	Solar RTPV	Solar	NA	6
	118_RTPV_4	Solar RTPV	Solar	NA	6
	118_RTPV_5	Solar RTPV	Solar	NA	6
	118_RTPV_6	Solar RTPV	Solar	NA	6
	118_RTPV_7	Solar RTPV	Solar	NA	6
	118_RTPV_8	Solar RTPV	Solar	NA	6
	118_RTPV_9	Solar RTPV	Solar	NA	6
119	119_PV_1	Solar PV	Solar	NA	6
121	121_NUCLEAR_1	Nuclear	Nuclear	Once Through	45929
122	122_HYDRO_1	Hydro	Hydro	NA	4491
	122_HYDRO_2	Hydro	Hydro	NA	4491
	122_HYDRO_3	Hydro	Hydro	NA	4491
	122_HYDRO_4	Hydro	Hydro	NA	4491
	122_HYDRO_5	Hydro	Hydro	NA	4491
	122_HYDRO_6	Hydro	Hydro	NA	4491
	122_WIND_1	Wind	Wind	NA	1
	123_CT_1	Gas CT	NG	Recirculate	1395
	123_CT_4	Gas CT	NG	Recirculate	1395
	123_CT_5	Gas CT	NG	Recirculate	1396
123	123_STEAM_2	Coal	Coal	Recirculate	928
	123_STEAM_3	Coal	Coal	Recirculate	929
201	201_CT_1	Oil CT	Oil	Recirculate	440
	201_CT_2	Oil CT	Oil	Recirculate	292
	201_HYDRO_4	Hydro	Hydro	NA	4491
	201_STEAM_3	Coal	Coal	Recirculate	754
202	202_CT_1	Oil CT	Oil	Recirculate	618
	202_CT_2	Oil CT	Oil	Recirculate	619
	202_STEAM_3	Coal	Coal	Recirculate	754
	202_STEAM_4	Coal	Coal	Recirculate	754
207	207_CT_1	Gas CT	NG	Recirculate	1395
	207_CT_2	Gas CT	NG	Recirculate	1395
212	212_CSP_1	CSP	Solar	NA	338
213	213_CC_3	Gas CC	NG	Recirculate	775
	213_CT_1	Gas CT	NG	Recirculate	10911
	213_CT_2	Gas CT	NG	Recirculate	10912

	213_RTPV_1	Solar RTPV	Solar	NA	6
214	214_SYNC_COND_1	Sync_Cond	Sync_Cond		0
215	215_CT_4	Gas CT	NG	Recirculate	343
	215_CT_5	Gas CT	NG	Recirculate	343
	215_HYDRO_1	Hydro	Hydro	NA	4491
	215_HYDRO_2	Hydro	Hydro	NA	4491
	215_HYDRO_3	Hydro	Hydro	NA	4491
	215_PV_1	Solar PV	Solar	NA	4491
216	216_STEAM_1	Coal	Coal	Recirculate	174
218	218_CC_1	Gas CC	NG	Once Through	57677
221	221_CC_1	Gas CC	NG	Once Through	57677
222	222_HYDRO_1	Hydro	Hydro	NA	4491
	222_HYDRO_2	Hydro	Hydro	NA	4491
	222_HYDRO_3	Hydro	Hydro	NA	4491
	222_HYDRO_4	Hydro	Hydro	NA	4491
	222_HYDRO_5	Hydro	Hydro	NA	4491
	222_HYDRO_6	Hydro	Hydro	NA	4491
223	223_CT_4	Gas CT	NG	Recirculate	10911
	223_CT_5	Gas CT	NG	Recirculate	10911
	223_CT_6	Gas CT	NG	Recirculate	10911
	223_STEAM_1	Coal	Coal	Recirculate	174
	223_STEAM_2	Coal	Coal	Recirculate	175
	223_STEAM_3	Coal	Coal	Recirculate	176
301	301_CT_1	Oil CT	Oil	Recirculate	958
	301_CT_2	Oil CT	Oil	Recirculate	985
	301_CT_3	Gas CT	NG	Recirculate	724
	301_CT_4	Gas CT	NG	Recirculate	725
302	302_CT_1	Oil CT	Oil	Recirculate	958
	302_CT_2	Oil CT	Oil	Recirculate	985
	302_CT_3	Gas CT	NG	Recirculate	724
	302_CT_4	Gas CT	NG	Recirculate	725
303	303_WIND_1	Wind	Wind	NA	1
307	307_CT_1	Gas CT	NG	Recirculate	724
	307_CT_2	Gas CT	NG	Recirculate	725
308	308_RTPV_1	Solar RTPV	Solar	NA	6
309	309_WIND_1	Wind	Wind	NA	1
310	310_PV_1	Solar PV	Solar	NA	6
	310_PV_2	Solar PV	Solar	NA	30

312	312_PV_1	Solar PV	Solar	NA	30
313	313_CC_1	Gas CC	NG	Once Through	57677
	313_PV_1	Solar PV	Solar	NA	30
	313_PV_2	Solar PV	Solar	NA	30
	313_RTPV_1	Solar RTPV	Solar	NA	6
	313_RTPV_10	Solar RTPV	Solar	NA	6
	313_RTPV_11	Solar RTPV	Solar	NA	6
	313_RTPV_12	Solar RTPV	Solar	NA	6
	313_RTPV_13	Solar RTPV	Solar	NA	6
	313_RTPV_2	Solar RTPV	Solar	NA	6
	313_RTPV_3	Solar RTPV	Solar	NA	6
	313_RTPV_4	Solar RTPV	Solar	NA	6
	313_RTPV_5	Solar RTPV	Solar	NA	6
	313_RTPV_6	Solar RTPV	Solar	NA	6
	313_RTPV_7	Solar RTPV	Solar	NA	6
	313_RTPV_8	Solar RTPV	Solar	NA	6
	313_RTPV_9	Solar RTPV	Solar	NA	6
	313_STORAGE_1	Storage	Storage	NA	0
314	314_PV_1	Solar PV	Solar	NA	30
	314_PV_2	Solar PV	Solar	NA	30
	314_PV_3	Solar PV	Solar	NA	30
	314_PV_4	Solar PV	Solar	NA	30
	314_SYNC_COND_1	Sync_Cond	Sync_Cond	NA	0
315	315_CT_6	Gas CT	NG	Recirculate	343
	315_CT_7	Gas CT	NG	Recirculate	343
	315_CT_8	Gas CT	NG	Recirculate	343
	315_STEAM_1	Oil ST	Oil	Recirculate	958
	315_STEAM_2	Oil ST	Oil	Recirculate	958
	315_STEAM_3	Oil ST	Oil	Recirculate	958
	315_STEAM_4	Oil ST	Oil	Recirculate	958
	315_STEAM_5	Oil ST	Oil	Recirculate	958

316	316_STEAM_1	Coal	Coal	Recirculate	176
317	317_WIND_1	Wind	Wind	NA	1
318	318_CC_1	Gas CC	NG	Recirculate	744
319	319_PV_1	Solar PV	Solar	NA	30
320	320_PV_1	Solar PV	Solar	NA	30
	320_RTPV_1	Solar RTPV	Solar	NA	6
	320_RTPV_2	Solar RTPV	Solar	NA	6
	320_RTPV_3	Solar RTPV	Solar	NA	6
	320_RTPV_4	Solar RTPV	Solar	NA	6
	320_RTPV_5	Solar RTPV	Solar	NA	6
	320_RTPV_6	Solar RTPV	Solar	NA	6
321	321_CC_1	Gas CC	NG	Once Through	45853
322	322_CT_5	Gas CT	NG	Recirculate	724
	322_CT_6	Gas CT	NG	Recirculate	725
	322_HYDRO_1	Hydro	Hydro	NA	4491
	322_HYDRO_2	Hydro	Hydro	NA	4491
	322_HYDRO_3	Hydro	Hydro	NA	4491
	322_HYDRO_4	Hydro	Hydro	NA	4491
323	323_CC_1	Gas CC	NG	Recirculate	686
	323_CC_2	Gas CC	NG	Recirculate	687
324	324_PV_1	Solar PV	Solar	NA	30
	324_PV_2	Solar PV	Solar	NA	30
	324_PV_3	Solar PV	Solar	NA	30

Table B4 Factors used to determine volume of total county withdrawals allocated to each watershed based on ratio of watershed area within county boundary to total county area

County	Watershed	Factor
Clark	Grand Wash	0.012
	Havasu-Mohave Lakes	0.076
	Ivanpah-Pahrump Valleys	0.200
	Lake Mead	0.149
	Las Vegas Wash	0.242
	Piute Wash	0.041
Coconino	Grand Canyon	0.030
	Grand Canyon	0.038
	Red Lake	0.003
Imperial	Carrizo Creek	0.036
	Imperial Reservoir	0.163
	Salton Sea	0.680
	Southern Mojave	0.009
Inyo	Ivanpah-Pahrump Valleys	0.024
	Panamint Valley	0.123
Kern	Antelope Fremont Valleys	0.245
	Middle Kern Upper Tehachapi-Grapevine	0.314
La Paz	Bouse	0.359
	Imperial Reservoir	0.304
	Lower Gila	0.013
	Tyson Wash	0.119
Los Angeles	Antelope Freemont Valleys	0.285
	Los Angeles	0.196
	San Gabriel	0.177
	Santa Clara	0.182
	Santa Monica Bay	0.079
Maricopa	Lower Gila	0.066
Mohave	Big Sandy	0.089
	Detrital Wash	0.038
	Grand Canyon	0.069
	Grand Wash	0.048
	Havasu-Mohave Lakes	0.069
	Lake Mead	0.095
	Red Lake	0.072
Nye	Ivanpah-Pahrump Valleys	0.019
Orange	San Gabriel	0.127

Riverside	Imperial Reservoir	0.094
	Salton Sea	0.101
	Southern Mojave	0.341
San Bernadino	Antelope-Fremont Valleys	0.001
	Antelope-Fremont Valleys	0.002
	Antelope-Fremont Valleys	0.001
	Antelope-Fremont Valleys	0.002
	Coyote-Cuddleback Lakes	0.090
	Havasu-Mohave Lakes	0.046
	Havasu-Mohave Lakes	0.004
	Imperial Reservoir	0.023
	Ivanpah-Pahrump Valleys	0.030
	Mojave	0.225
	Panamint Valley	0.019
	Piute Wash	0.035
	Southern Mojave	0.317
San Diego	Carrizo Creek	0.091
	Salton Sea	0.015
	Salton Sea	0.008
San Luis Obispo	Middle Kern Upper Tehachapi-Grapevine	0.024
Santa Barbara	Santa Clara	0.001
Ventura	Los Angeles	0.000
	Los Angeles	0.005
	Middle Kern Upper Tehachapi-Grapevine	0.001
	Middle Kern Upper Tehachapi-Grapevine	0.006
	Santa Clara	0.426
	Santa Monica Bay	0.042
Yavapai	Big Sandy	0.072
	Red Lake	0.007
Yuma	Imperial Reservoir	0.012
	Imperial Reservoir	0.018
	Lower Gila	0.647
	Tyson Wash	0.034