Energy Savings from Moulton Niguel Water District Water Efficiency Programs

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Bren School of Environmental Science & Management

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The Group Project is required of all students in the Master of Environmental Science and Management (MESM) Program. The project is a year-long activity in which small groups of students conduct focused, interdisciplinary research on the scientific, management, and policy dimensions of a specific environmental issue. This Group Project Final Report is authored by MESM students and has been reviewed and approved by:

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[1] Formerly Moulton Niguel Water District
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Abbreviations

Abbreviation	Definition
AF	Acre-foot/feet
AMI	Advanced Metering Infrastructure
CCF	One Hundred Cubic Feet
CaDC	California Data Collaborative
CH_4	Methane
CO	Carbon Monoxide
CO_2	Carbon Dioxide
CPUC	California Public Utilities Commission
CRA	Colorado River Aqueduct
DID	Difference-in-Differences
EPA	Environmental Protection Agency
E.O.	Executive Order
ET	Evapotranspiration
GHG	Greenhouse Gas
GWh	Gigawatt-hour
HET	High-Efficiency Toilet
HECW	High-Efficiency Clothes Washer
ID	Identification
IQR	Interquartile Range
gCO_2e	Grams of Carbon Dioxide Equivalent
$kgCO_2e$	Kilograms of Carbon Dioxide Equivalent
kW	Kilowatt
kWh	Kilowatt-hour

LADWP	Los Angeles Department of Water and Power
LCA	Life Cycle Assessment
MG	Million Gallons
MNWD	Moulton Niguel Water District
MWD	Metropolitan Water District of Southern California
MWDOC	Municipal Water District of Orange County
MWh	Megawatt-hour
NO_x	Nitrogen Oxides
PM_{10}	Particulate Matter
RSN	Rotating Spray Nozzles
R1	Single-family Residential Household Rate Type
R2	Condos and Townhomes Rate Type
SB	Senate Bill
SCE	Southern California Edison
SDG&E	San Diego Gas & Electric
SO_x	Sulfur Oxides
SWP	State Water Project
SYN	Synthetic Turf
T	Turf Removal
UC	University of California
UCR	University of California, Riverside
UT	University of Texas
VOC	Volatile Organic Compound
WBIC	Weather Based Irrigation Controller
WBIC-DI	Weather Based Irrigation Control Direct Installation

Abstract

The movement, treatment and heating of water comprises 19% of California's overall electricity use and 10% of the state's greenhouse gas (GHG) emissions. The well-established link between water use, energy use, and greenhouse gas emissions can be used to identify potential savings and mitigation strategies from water efficiency rebate programs. The project executed in this report aims to quantify the co-benefits of water efficiency programs in a clear and straightforward manner. This will provide insight to utilities on where their future efforts should be focused on for further water and energy savings and GHG mitigation. Working with Moulton Niguel Water District, and referencing their previous study partnered with University of California, Riverside (UCR), analyses were conducted using a series of multivariable regression models along with a difference-in-differences approach. This project produced differing results from that of the UCR study for water savings; however, similar trends were found relating to indoor rebate programs (i.e., high-efficiency toilets, high-efficiency clothes washers). Embedded energy was found to be largely dependent on upstream energy use while embedded GHG emissions were found to have decreased significantly over time due to reductions in grid emissions factors. The results from this project demonstrate that energy savings resulting from water saved through efficiency programs can be quantified, and that these energy savings can then be translated into mitigated greenhouse gas emissions.

Executive Summary

California has implemented statewide goals through legislation to reduce and track the state's overall greenhouse gas emissions. The movement, treatment and heating of water comprises 19% of California's overall electricity use and 10% of the state's greenhouse gas (GHG) emissions. Despite this well-established link between water use, energy use, and GHG emissions, few studies have examined the energy savings and emissions mitigations that result from programs meant to reduce household water use. Moreover, legal and operational barriers make it difficult for electric utilities and water providers to work together on device efficiency programs designed to reduce water use, energy consumption, and GHG emissions simultaneously.

Moulton Niguel Water District (MNWD) partnered with the Bren School of Environmental Science & Management at the University of California, Santa Barbara for this Master's group project. MNWD serves over 170,000 customers across six cities in Orange County, CA. Approximately 85% of these customers are residential. All the water supplied to MNWD's residential customers comes from the State Water Project (SWP) and the Colorado River Aqueduct (CRA), purchased from the Metropolitan Water District of Southern California (MWD). MNWD has been collecting extensive water use data since 2010. In 2015, MNWD partnered with University of California, Riverside (UCR) to study the water savings associated with a switch to an allocation-based rate structure and implementation of their residential water efficiency rebate programs. This project builds off of MNWD's previous assessments of its rebate programs.

The goal of this project is to quantify the co-benefits of water efficiency programs in a clear and straightforward manner. This will provide insight to utilities on where their future efforts should be focused for further water and energy savings and GHG mitigation. It can also support decision-making in future policy from state agencies to potentially encourage more collaboration of water and energy utilities. To achieve the goal of the project, the following objectives were completed:

1) Quantify the energy saved, greenhouse gas (GHG) emissions mitigated, and energy costs avoided through water use reductions associated with MNWD's residential water efficiency rebate programs; and
2) Develop a framework that allows other municipal water districts and water utilities to estimate the energy saved and GHG emissions mitigated through their own water efficiency rebate programs, using the methods of Objective 1 as a starting point.

For the first objective, water savings per unit rebate were first quantified for five of MNWD's rebate programs: high-efficiency toilets, high-efficiency clothes washers, weather-based irrigation controllers, rotating sprinkler nozzles, and turf replacement. This was done using a multi-variable linear regression model fit to customer characteristics and water use data from the years 2010-2019, and through effect size estimation using the difference-in-differences method. The results from the two methods were then compared to the water savings calculated by UCR to determine accuracy. Then, embedded energy factors were developed for MNWD's potable water supply and wastewater effluent using facility energy use data from San Diego Gas and Electric (SDG&E) and Southern California Edison (SCE), and with source water embedded energy factors provided by MWD. Emissions factors were applied to the embedded energy factors to generate embedded emissions. For the final step, avoided water use, embedded energy, and embedded emissions results were translated into energy saved and emissions mitigated. Embedded energy and GHG emissions factors for MNWD's residential potable water supply wastewater effluent were successfully developed. Embedded energy remained relatively constant throughout the study period, and was largely composed of energy use during transport via the SWP and CRA. It is hypothesized that variations in embedded energy are due to variations in the relative proportions of water obtained from the SWP vs. the CRA; however, data was not available on these proportions to confirm this hypothesis. Embedded GHG emissions were found to have decreased significantly over the course of the study period, from a peak of 691 $kgCO_2e$/acre-foot (AF) in 2012 to a low of 425 $kgCO_2e$/AF in 2017. This was the result of the CA energy grid becoming cleaner as the supply of renewable energy increased, but may have also been influenced by changing SWP/CRA source water proportions.

Because embedded energy and GHG emissions factors had a high degree of confidence, the results of UCR's study were used for estimates of rebate water savings. Savings estimated using linear regression and difference-in-differences estimation did not align with UCR's results, suggesting that this study's methods applied insufficient correction for confounding factors. Using their estimates preserved both accuracy of this study's results and the validity of the proof-of-concept demonstration that this study represents.

Program-level savings were calculated using developed embedded energy and GHG emissions factors, per-device estimates of water savings from UCR's study, and rebate invoice data provided by MNWD. Past rebate participation most heavily influenced the rate of accumulation of total energy and GHG savings, whereas savings in a given year were more affected by that year's embedded energy and GHG factors. Ultimately, district-level water savings of 4,087 AF during the study period (2010-2019) translated into energy and GHG savings of 10,497 MWh and 2,678 metric tons CO_2e, respectively, across MNWD's entire water supply chain.

A framework for repeating this study's calculation of program-level energy savings and GHG mitigation was then created. Specific methods were not recommended for calculating water savings from rebate programs due to the complexity of this task; however, methods for calculating embedded energy and emissions factors are described. The framework largely consists of the Phase III equations rewritten in more general forms so that they can be applied to a broader range of rebate programs in service areas with different water supply portfolios. It also includes basic recommendations for data management and factors that must be considered when performing the analysis. The framework does not propose novel methods of analysis; rather, it distills existing methods into a set of fundamental equations that, when used, make performing this type of analysis more straightforward.

The first significant finding of this project was the variability of water savings. Rebate water savings appear to be rather program-specific, as a comparison of UCR's results to savings found by programs for the same devices in nearby service areas differed considerably. Rebate savings are also influenced by external factors such as behavioral messaging and widespread availability of water-efficient devices that must be corrected for, demonstrated by the misalignment of UCR's results and savings estimated by linear regression and difference-in-differences. Because of the high variability of rebate program water savings, forecasting using past analyses or studies may not give accurate results for future program savings. This is due to the number of factors that need to be accounted for, such as water savings for a given rebate type varying between utilities, using differing methods of installation, and water use behavior changes over time. One potential way to ease the analysis of water savings is the installation of new technologies that improve data resolution, such as advanced metering infrastructure (AMI). Because AMI generates an immense amount of data, storage and management become even more important.

This study's second significant finding, the importance of data management, became clear as the analysis was conducted. The first goal in good data management is accessibility. However, the end goal for utilities' data collection should be usability. Understanding how the data will be used, such as the programs and analytical methods, could reduce the time and the number of assumptions needed during preparation. Additionally, frequent curation of existing data could help avoid future data quality issues, reduce bias, and improve overall accuracy of results. Improving data management and overall accessibility can also foster data sharing and communication between water and energy utilities.

The results from this project demonstrate that energy savings from water saved through efficiency programs and the resultant greenhouse gas emissions can be quantified. Understanding which programs yield the highest amount of water savings, and therefore energy savings, allows water utilities to invest more on specific programs, such as outdoor versus indoor. Additionally, understanding where within a water utility's system boundary (e.g., service area versus imported water supply) water has the highest embedded energy can help a water utility target programs to maximize the efficiency of energy savings. Likewise, embedded emissions values can help utilities target efficiency programs to reduce their carbon footprint. The framework developed by this project provides a set of governing equations that other water utilities can use when creating these factors to understand their own operations.

Several opportunities exist for refining the approach taken in this study and defined in its proposed framework. Improving data management and sharing best practices will streamline the calculation of embedded energy and emissions factors. Additional data curation and verification will increase the accuracy of savings estimates, as will the standardization of ways to control for confounding factors during statistical analysis of water use. The ways in which spatial variability of water savings, embedded energy, and embedded GHG emissions can be captured should be further investigated. The sensitivity of analysis results to temporal resolution should also be investigated. Finally, repeating this type of analysis and refining it will help identify policy changes that may make it easier for water and energy providers to collaborate on joint device efficiency programs.

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Introduction

California has implemented statewide goals through legislation to reduce and track the state's overall greenhouse gas emissions. The movement, treatment and heating of water comprises 19% of California's overall electricity use and 10% of the state's greenhouse gas (GHG) emissions. Despite this well-established link between water use, energy use, and GHG emissions, few studies have examined the energy savings and emissions mitigations that result from programs meant to reduce household water use. Moreover, legal and operational barriers make it difficult for electric utilities and water providers to work together on device efficiency programs designed to reduce water use, energy consumption, and GHG emissions simultaneously (Atwater et al., 2020).

Moulton Niguel Water District (MNWD) partnered with the Bren School of Environmental Science & Management for this Master's group project. MNWD serves over 170,000 customers across six cities in Orange County, California, and approximately 85% of these customers are residential. All the water supplied to MNWD's residential customers comes from the State Water Project (SWP) and the Colorado River Aqueduct (CRA), purchased from the Metropolitan Water District of Southern California (MWD). MNWD has been collecting extensive water use data since 2010. In 2015, MNWD partnered with the University of California, Riverside to study the water savings associated with their switch to an allocation-based rate structure and implementation of their residential water efficiency rebate programs. This project builds off of MNWD's previous assessments of its rebate programs.

1. Project Significance

Energy is required to move, treat, and heat water. Water-related activities comprise approximately 20% of California's overall electricity use, which generates up to 10% of the state's greenhouse gas (GHG) emissions (Escriva-Bou et al., 2018). As a leader in energy efficiency, California's water industry sector gives the state an opportunity to progress towards the 2030 emissions targets established by California Senate Bill (SB) 32 (2016) (Atwater et al., 2020).

The water and energy sectors have traditionally been siloed, wherein minimal collaboration between the two sectors has taken place. As a result, legislation establishing conservation targets has historically addressed each sector separately. However, California has begun to make policy connections. Specifically, SB 1425 (2016) requires the California Environmental Protection Agency (EPA) to oversee a repository for voluntary reporting of GHG emissions from water-energy related activities. Despite the absence of legislative mandates, water and electric utilities have begun to focus their resource conservation programs on this connection.

Moulton Niguel Water District (MNWD) has actively participated in efforts that support SB 1425 (2016). The district has been collecting water and energy data since 2010 and 2015, respectively, and has been a member of the California Data Collaborative since 2016 in an effort to better inform decision making in the water industry. MNWD is currently participating in a case study with the University of California, Davis to address supply and demand imbalances on the California energy grid while reducing total energy use and GHG emissions by optimizing the timing of water pumping operations. In 2015, MNWD partnered with the University of

California, Riverside (UCR) to study the water savings associated with their switch to an allocation-based rate structure and their residential water efficiency rebate programs. This project builds off of MNWD's previous work, as it seeks to quantify the GHG emissions mitigated and the energy saved by the implementation of MNWD's rebate programs.

This project has important implications for potential cooperative resource efficiency programs between electric, gas, and water utilities. It quantifies how energy savings and emissions mitigation can be realized from residential water efficiency rebate programs. In this way, this project hopes to be a "proof of concept," as it will demonstrate the potential benefits of cooperative resource efficiency programs. In April 2020, MNWD co-authored a white paper with the Southern California Water Coalition on cooperative resource efficiency programs between electric, gas and water utilities, which detailed some of the barriers that remain for such programs. This project also aims to address some of those barriers through the development of a framework for estimating energy savings and emissions mitigation from water efficiency rebate programs.

The framework will be an easy-to-use guide that encourages partnerships by giving utilities a way to estimate potential benefits. While several key legal barriers currently limit such partnerships, this framework could also be used to aid decision-makers in addressing these barriers. Finally, there is potential for this project to lay the groundwork for addressing other barriers to cooperative residential efficiency programs, including insufficient data, inconsistent evaluation methodology, metering differences, and the challenge of targeting eligible customers.

2. Project Objectives

The objectives for the project are the following:

Objective 1: Quantify the energy saved, greenhouse gas (GHG) emissions mitigated, and energy costs avoided through water use reductions associated with MNWD's residential water efficiency rebate programs.

Objective 2: Develop a framework that allows other municipal water districts and utilities to estimate the energy saved and GHG emissions mitigated through water use reductions associated with their own water efficiency rebate programs using the results and process of Objective 1 as a reference point.

3. Background

3.1 Moulton Niguel Water District

Moulton Niguel Water District (MNWD)'s water portfolio is made up of imported and recycled water. Currently, MNWD uses recycled water for non-potable uses (e.g., landscape and golf course irrigation). Imported water is supplied from the Metropolitan Water District of Southern California (MWD) through its member agency, the Municipal Water District of Orange County (MWDOC) (Moulton Niguel Water District, 2015).

Figure 1. State Water Project and Colorado River Aqueduct routes to Southern California water districts. Data Source: California Department of Water Resources and USGS National Hydrography and Chino Basin Water Conservation District (2016)

MWD's water supply mix from the SWP and CRA for a given year will depend on the amount of precipitation and snowfall in the northern Sierra Nevada Region. During dry or drought years, MWD will receive most of their water from the CRA (Personal Communication with MWD, 2020). However, during an average year, MNWD reports that 45% is from the SWP and 55% is from the CRA (MNWD, 2015).

Due to jurisdictional boundaries, MNWD has two energy suppliers, Southern California Edison (SCE) and San Diego Gas & Electric (SDG&E). These suppliers meter MNWD's energy usage from their lift stations and pumps used to transport water to customers and wastewater treatment plants. Of the 128 electric meters utilized by MNWD from 2009-2020, 45 are supplied by SCE and 83 are supplied by SDG&E (SCE and SDG&E, 2020).

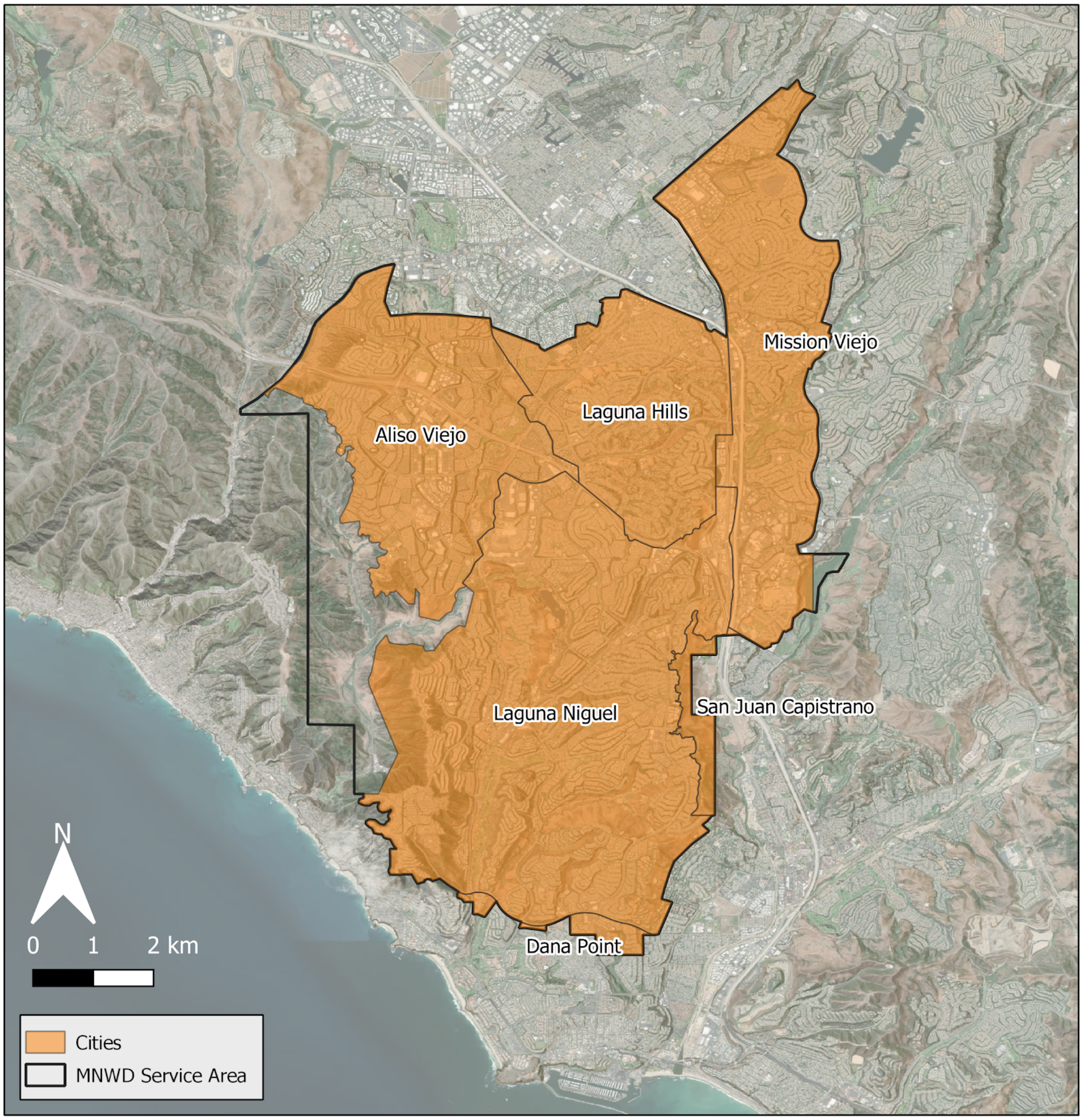


Figure 2. Service area of Moulton Niguel Water District, overlapping six cities in Orange County, California. Data Source: MNWD (2020)

MNWD currently serves just over 170,000 customers in the cities of Laguna Niguel, Aliso Viejo, Mission Viejo, Laguna Hills, Dana Point, and San Juan Capistrano (**Figure 2**). All six cities are located in Orange County, California. Eighty-five percent of their customers are single-family households. The majority of MNWD customers reside in Laguna Niguel where the median household income is $108,537[2], which is about 1.75 times higher than the national average and 1.5 times higher than the state average (US Census, 2019). MNWD offers a variety of indoor and

[2] The median household income range of all six cities is $91,600 to $188,477 (Census, 2019).

outdoor water efficiency device rebate programs for their residential customers. Rebate device programs are listed in **Table 1**. Rebate programs are administered by the MWDOC, with the exception of artificial turf installation, which was only administered by MWDOC when completed in conjunction with turf removal. MNWD stopped providing an incentive for artificial turf in December 2019 (Personal Communication with MNWD, 2020).

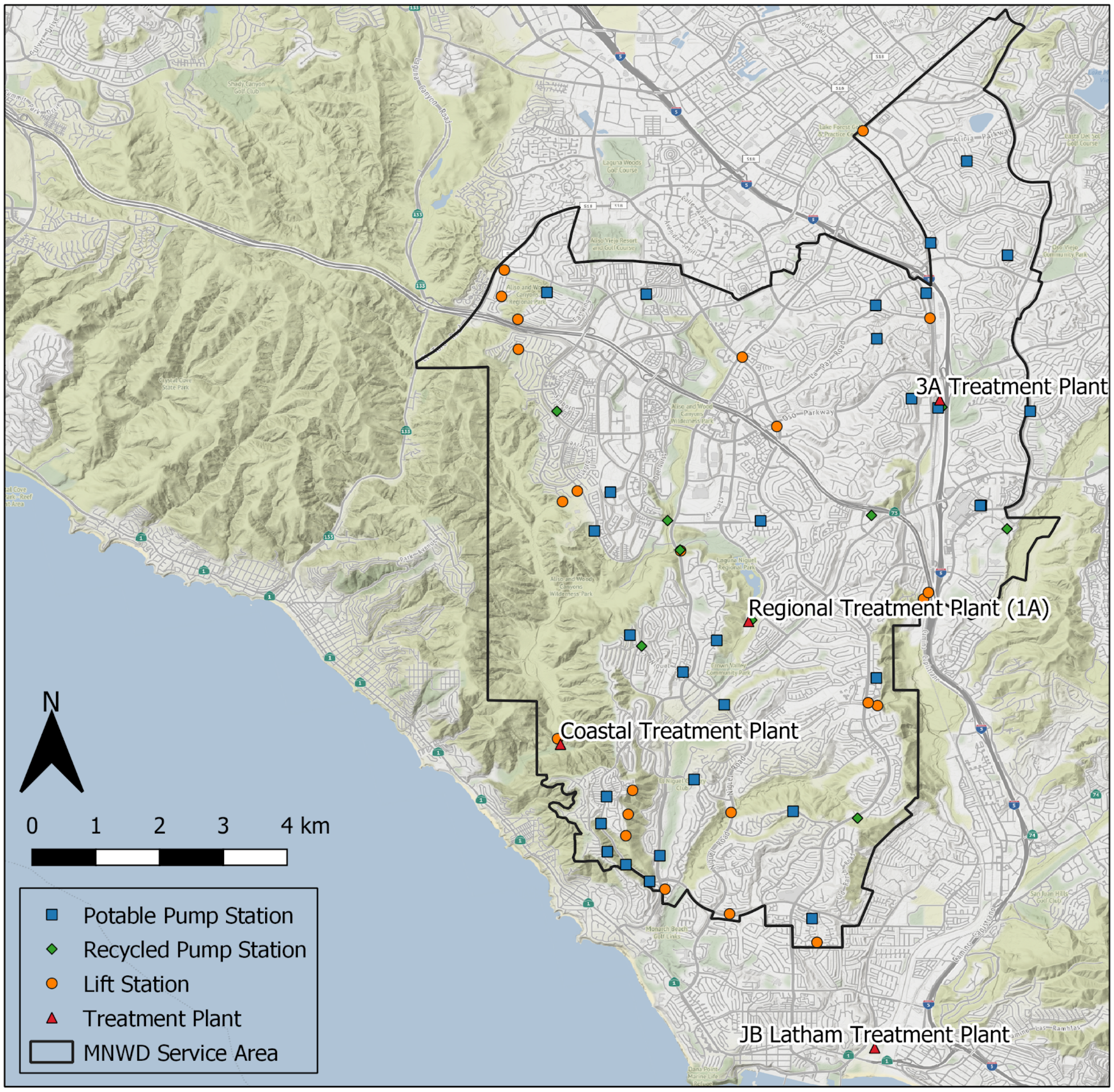


Figure 3. Wastewater treatment plants, pump stations and lift stations for Moulton Niguel Water District. Data Source: MNWD (2020)

Using 16 lift stations, MNWD transports its wastewater to three treatment plants. MNWD handles one of the treatment plants, Plant 3A. The other two treatment plants, the Regional and J.B. Latham Treatment Plants are handled by the South Orange County Wastewater Authority (Personal Communication with MNWD, 2020).

Table 1. Device rebate and turf removal programs offered to residential customers by Moulton Niguel Water District. Source: MNWD 2015 Urban Water Management Plan

Device Rebate and Turf Removal Programs
High Efficiency Clothes Washer
Premium High Efficiency Toilet
Rotating Sprinkler Nozzles
Turf Removal Program
Weather-Based Smart Sprinkler Timer
Naturescape Turf-to-Native Garden Program
Rain Barrels and Cisterns
Soil Moisture Sensor Controller

3.2 California Data Collaborative
Moulton Niguel Water District (MNWD) is one of ten members of the California Data Collaborative (CaDC), a nonprofit organization. The CaDC began as a pilot project in January 2016, in direct response to the drought and water conservation mandates of 2015. (Personal Communication with Christopher Tull, 2021). The CaDC eventually established itself as an organization which uses water consumption data from the 3.7 million people served by CaDC's member water utility agencies to "improve efficiencies, refine demand management strategies and promote long-term sustainable solutions across California's natural resources" (California Data Collaborative, 2020).

The CaDC creates industry-relevant applications and software for their member agencies and collaborates with universities to help conduct research by acting as a data-sharing hub and liaison. The CaDC's overall goal is to "make informed data-driven decisions responsive to tomorrow's water needs" (California Data Collaborative, 2020). This project aims to align with the CaDC's goals in its exploration of potential applications of collected data and the challenges of working with and effectively managing such data.

3.3 MNWD UC Studies
Moulton Niguel Water District (MNWD)'s prior and current collaboration with the University of California (UC) campuses, Davis and Riverside, has allowed the district to contribute to meeting California's statewide greenhouse gas (GHG) reduction goals and evaluate their water efficiency programs. MNWD has partnered with the UC Davis Center for Water and Energy Efficiency to develop an adaptable energy-management system (Kerlin, 2017). This is MNWD's second collaboration with UC Davis. Their first collaboration analyzed the energy grid imbalances from water utilities using the district's reclaimed water system offline hydraulic model as a case study (Good, 2018).

In 2015, MNWD contracted UC Riverside (UCR) to analyze residential water usage and incentives for customer participation in their water efficiency programs (Schwabe et al, 2017). This project was conducted in three phases. Phase I identified the main drivers of water usage and program participation using MNWD's current records, and then calculated the revenue effects of different programs. Phase II distributed a survey to residential customers to gauge their awareness and reported adoption rates of the available programs. Lastly, Phase III used the results of Phase II to produce new results for Phase I. These new results compared the outcomes from the different datasets to get a better understanding of residential customer behaviors.

Five[3] of eight water efficiency programs covering 16,277 residential customers were evaluated for Phase I. The timeline of the data used was 45 months prior to and after a rate change for residential customers. From this evaluation, it was discovered that MNWD outdoor programs saved more water per household than the indoor programs. However, when looking at overall participation rates, indoor programs had a higher rate than outdoor programs.

UCR also assessed if participation in certain programs was influenced by participation in other programs. If customers participated in two programs, it was likely that one of the programs was either the synthetic turf or turf replacement programs. However, there was a high number of customers who participated in both the high-efficiency toilets and high-efficiency clothes washers programs. Customers who only participated in one program were more likely to choose the program for high-efficiency clothes washers. Rebate rates did have an effect on participation rates within the observation period.

The results from Phase I determined the content of the survey distributed in Phase II. The survey was sent to 46,849 of MNWD's residential customers in physical and, when possible, digital form. The overall response rate was 8.4% (3,958/46,849). Results from the survey showed that most residential customers were aware of MNWD indoor programs, but also were investing in other water efficient technology, such as low-flow shower heads, which were not part of MNWD programs. Other than the turf removal program, most customers were not aware of MNWD outdoor programs.

Phase III results were slightly more detailed and informative than Phase I because the survey results included self-reported water efficiency technology adoption not supported by a MNWD program. The difference between the survey results and rebate participation records provided by MNWD were significant, even after biases were considered. Major findings in Phase III showed that water efficient behaviors or investments in technology are not 100% accounted for or driven by water efficiency programs. More specifically, there was a higher percentage of customers who voluntarily switched to water efficient technology without participating in the programs offered by MNWD. Phase III also evaluated enrollment timelines and factors that influenced them.

The study conducted by UCR informed MNWD on the water savings, costs, and customer motivation for program participation. It conducted a robust analysis that included ground truthing. While the energy saved and GHG emissions mitigated by these programs were not

[3] Turfgrass replacement, synthetic turf installation, weather-based irrigation controllers, high efficiency toilets, and high efficiency clothes washers

assessed, UCR's research provided MNWD with the foundation and guidance to determine the co-benefits of their water efficiency programs.

3.4 Water-Energy Efficiency Task Force Paper

In addition to collaborating with the UC campuses, MNWD helped author a policy paper by the Water-Energy Efficiency Task Force of the Southern California Water Coalition (2020) that further explored the limitations and barriers water and energy utilities face when attempting to form partnerships to achieve the greatest savings potential.

Four common barriers were identified and categorized into the following: legal matters, finding common customers, getting the word out, and program operations and management.

- **Legal issues**
  Water and energy rebate programs have different regulations regarding tax exemptions. More specifically, the formation of a partnership could put a customer over the income threshold for what is considered taxable. Other legal issues such as disclosure of customer data and contractual agreement between utilities are major barriers.
- **Finding common customers**
  The number of water utilities versus energy providers differs drastically, creating a misalignment of service areas. The effort needed to identify overlapping service areas and determine customer eligibility may result in high administrative costs.
- **Getting the word out**
  Due to service area misalignments and other factors, the study reported that customer awareness of programs and eligibility also became a problem.
- **Program operations and management**
  In addition to the difficulties in determining eligibility, metering also contributes to challenges, as water and energy utilities differ in metering schema amongst ratepayer classes.

Some of the solutions proposed to overcome barriers included using past inter-utility agreements to master and streamline partnerships, using spatial data to identify common customers between utilities, initiating early communication between the two utilities to identify preferences and approval processes, streamlining the program enrollment process, and creating a "one-stop shop" for available programs. The paper also noted future research was needed to help address barriers such as legal contracting pathways, data sharing, standardizing methodology to calculate embedded energy in water and water savings, and regulation misalignment for inter-resource efficiency programs.

The paper also found that water and energy utilities are unable to accurately calculate energy savings from water efficiency programs due to the lack of a standardized methodology. Some progress has been made by researchers at UC Davis to calculate embedded energy in water using a sophisticated approach, which uses operational zones to evaluate embedded energy by pressure zone. Additionally, the lack of incentives for calculating energy savings from avoided cold water production, transport, and use has not supported the need to create a standardized methodology. Energy utilities do not get significant credit from the California Public Utilities Commission (CPUC) for energy saved from cold water efficiencies. To address the lack of incentives, the authors recommend energy and water utilities align their goals and have the CPUC adopt a value for cold water.

3.5 Drought

From late 2011 to mid-2019, California experienced its longest period of drought in the state's recorded history (National Integrated Drought Information System, 2020). The year 2014 was one of the state's most intense drought years and was therefore a pivotal point in California's response to mitigating the effects of drought. Former Governor Jerry Brown declared a state of emergency due to drought and announced a voluntary 20% reduction in potable water use. Then, in 2015, Governor Jerry Brown signed Executive Order B-29-15, which required that the state reduce its potable water usage by 25%. MNWD was directed to achieve a 20% reduction from its 2013 water consumption baseline (Ordinance No. 15-01, 2015). During this time period, Metropolitan Water District (MWD) and MNWD invested in drought-related marketing, which greatly increased turf removal participation (Personal Communication with MNWD, 2020).

In 2016, Governor Jerry Brown implemented legislation for water conservation that would create a framework to " permanently ban wasteful water use practices" and a year later declared an end to the statewide drought emergency (Executive Order B-37-16, 2016). The state, as a whole, has continued to show low water usage levels compared to pre-severe drought years, however, water usage has slightly increased since the statewide drought emergency was announced (California State Water Resources Control Board, 2017). MNWD has seen increases in rebate participation since 2012. The increase in rebate participation can be attributed to a variety of factors, such as increased rebate incentive levels, increased marketing, water usage restrictions due to the implementation of water shortage emergencies, and change in rate structures.

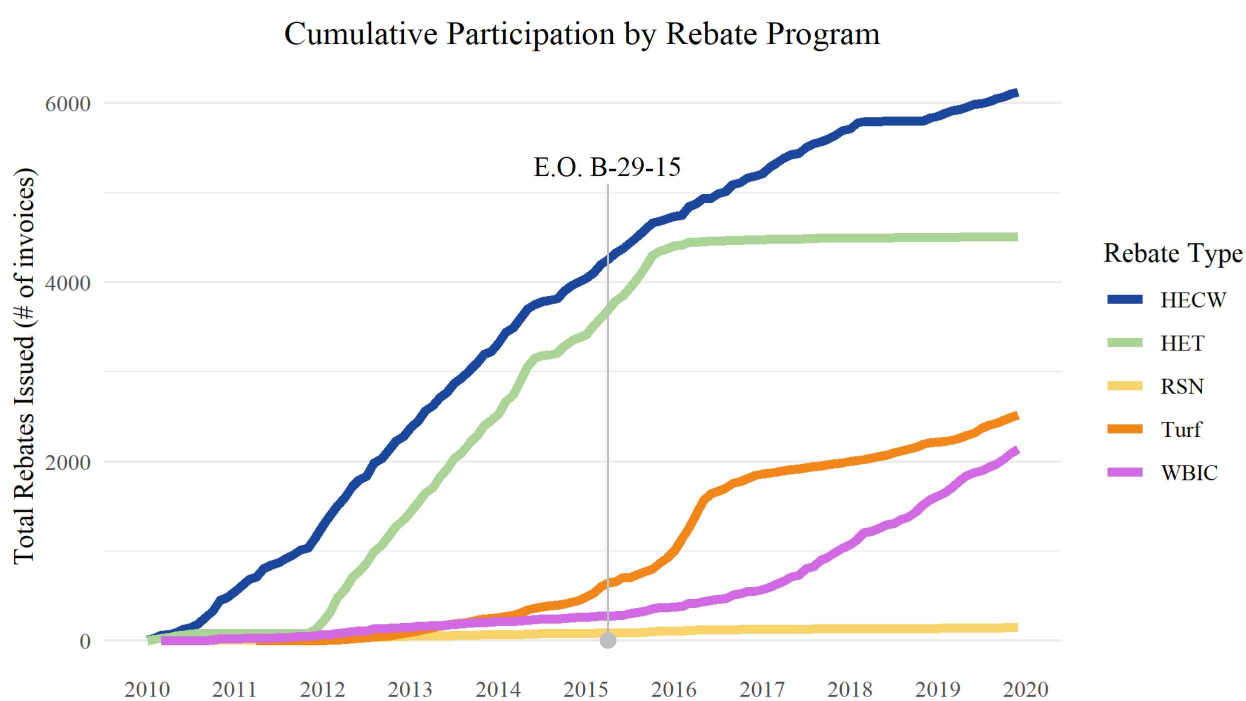


Figure 4. Cumulative rebate participation for five water efficiency programs for Moulton Niguel Water District from 2010-2020. Data Source: Moulton Niguel Water District

4. Literature Review

4.1 Water Efficiency Programs

The goal of water efficiency programs is to reduce the amount of water used in a variety of daily tasks. However, increased efficiency can sometimes lead to rebound effects: the increased use of a resource due to the decreased cost of the service, such as the increased efficiency of an appliance leading to more use (Bennear et al., 2011). A study conducted by The Nicholas School of the Environment at Duke University and North Carolina State University evaluated the rebound effects for water efficiency programs. The Town of Cary Public Works and Utilities Department's High Efficiency Toilet program was used as the case study. The potential effects of the current rebate process were also analyzed. The study evaluated if payment after replacement of appliances influences whether a household upgrades to more efficient appliances. For 683 households that participated in the rebate programs, it was found that no rebound effects occurred in the sample. Additionally, only 47% of the households considered the rebate as a serendipitous gain in income, signifying that almost half of households would upgrade to more efficient appliances without incentivization.

Some utilities explore methods on how to further increase water use efficiency without interfering with customer behavior. A case study in Austin, Texas at the University of Texas (UT) campus done by Stillwell (2011) sought to evaluate the effects of reclaimed water use on energy use, greenhouse gases (GHG), and UT's finances. More specifically, this study sought to increase water use efficiency by offsetting overall water use with reclaimed water in non-potable applications (e.g., toilets, outdoors). The campus supports 75,000 people, which results in total campus water usage of 7.9 million liters/day. Based on a study by Klotz Associates and Layton et. al (2009), the authors estimated that 6.2 million liters/day of the 7.9 million/day could be met with reclaimed water, and used that value for their analysis.

The analysis done by Stillwell (2011) employed EPANet modeling software in conjunction with historical datasets to compare the embedded energy, and carbon emissions by extension, of drinking water and reclaimed water. Due to inconsistencies in electricity pricing and water sources, the author's analysis found that the ultimate effect on energy use and GHG emissions could be a reduction or an increase. For example, using reclaimed water could save 44 kilowatt-hours (kWh) or use an additional 68 kWh of electricity per day. Despite variances, the authors argue that water reuse is still a preferred alternative to development of the marginal "next" water source, as it becomes an energy and/or cost saving strategy compared to groundwater or desalination. They also argue that reclaimed water offers a reliable local water supply that is resistant to droughts, has a lower levelized cost than potable water and reduces nutrient loading to surface waters.

The literature reviewed shows various methods exist to evaluate water efficiency programs. Some of the methods include calculating participation rates, performing a cost benefit analysis, evaluating customer behavior and demographics, analyzing the effectiveness of incentives, and measuring water savings. Studies typically use a combination of methods to evaluate programs. Variation further exists within the methods used. For example, as detailed in "Rewiring Water Conservation for Energy: How Southern California Utilities Make It Work" (Atwater et al, 2020), no standard methodology exists for water utilities to measure water savings from water efficiency programs. The large variety of methods employed are due to the differences in the questions utilities are trying to answer, the goals they are trying to achieve and the resources available to conduct evaluations. Therefore, given the large differences in methods and objectives, it is difficult to assess which approach is best. Additionally, selecting which water efficiency programs to implement is not always influenced or guided by past evaluations of water efficiency programs. Program selection can be constrained by the utility's use of wholesale suppliers and available government rebate programs (Atwater et al., 2020). This can limit the maximum potential savings from water efficiency programs.

4.2 Past Mutual Resource Conservation Programs

Few studies have explored partnerships between water and energy utilities to implement and collaborate on efficiency programs. In 2009, the California Public Utilities Commission (CPUC) conducted research in this field to find potential, future partnerships to "capture water-related embedded energy savings." This research was initiated due to a ruling in 2005. Nine pilot programs were implemented by Pacific Gas and Electric Company, Southern California Edison (SCE), and San Diego Gas and Electric (SDG&E) Company (ECONorthwest, 2011).

Results from the programs concluded that the leak detection program from SCE offered the most energy savings and did so at a low cost. Other programs that showed significant savings included a commercial toilet retrofit program and recycled water programs. Six out of the nine programs evaluated showed that the implementation and administrative costs of the programs exceeded the energy benefits. Concluded from the study, areas that needed further research included the energy intensity of tertiary recycled water treatment. Additionally, analyzing the effects of the end-user's energy consumption on overall energy savings is something to be explored or incorporated in other studies. The CPUC study listed budget constraints as a limitation, which was why only nine programs were implemented and evaluated. The policy paper by the Water-Energy Efficiency Task Force of the Southern California Water Coalition (2020) stated prior in this report further explored the limitations and barriers water and energy utilities face when attempting to form partnerships to achieve the greatest savings potential. The four common barriers identified were: legal matters, finding common customers, getting the word out, and program operations and management (See 3.4 Water-Energy Efficiency Task Force Paper).

Other studies, such as one from the American Council for an Energy-Efficient Economy and the Alliance for Water Efficiency, have found similar barriers for water and energy partnerships, such as quantifying embedded energy (Young and Mackres, 2013). However, this study recognized successful water and energy efficiency partnership programs. The programs recognized were similarly structured, cost-effective, involved partnerships between different sectors (i.e., nonprofits, government, etc.), set a broader goal for integrated resource management, streamlined the application process, required upfront investments, and were innovatively designed.

4.3 Mandates and Water Consumption

Water consumption behavior is impacted by a variety of factors, including media coverage, policy, and climate events. A study conducted in Costa Mesa, California analyzed how residential water users of the Mesa Water District reacted to policy and media coverage during the 2012-2016 drought. Of the cities served by the water district, the lowest median income is $28,500 and the highest is $156,500.

Using a consumption change detection method, the authors separated out consumption into four phases: pre, voluntary, mandatory, and post. Overall, 75% of customers reportedly saved water in at least one phase during 2013-2016. 80% of those customers voluntarily saved water during the period of increased media coverage prior to the implementation of conservation mandates. Although savings were found in the midst of the drought period, rebound effects of 16% were detected in 2015-2016 and mainly found in more affluent and educated households (Bolorinos et al, 2020).

A similar study was conducted in Los Angeles, California for the Los Angeles Department of Water and Power (Mini, C. et al, 2014). While the study was implemented in a different time period, 2008 - 2010, it still took place during a drought. The study consisted of three phases: voluntary, mandatory, and mandatory with a price increase and decrease in household allocation. The study used a linear mixed-effects regression model. Slightly different results were obtained, where a mandatory water use restriction and price increase showed the most savings, which was between 19-23%. Voluntary water use restriction did not contribute significant savings.

4.4 Embedded Energy and Greenhouse Gas Emissions

Embedded energy, also known as embodied energy or energy intensity, is the total energy expended in conveyance, distribution, treatment, end-use, and recycling for a unit of water (Wilkinson et al., 2006). According to research done by Griffiths-Sattenspiel (2009), California's total water-related energy consumption was 48 gigawatt-hours (GWh) of electricity, 4.3 billion therms of natural gas and 88 million gallons (MG) of diesel fuel in 2001. This consumption led to approximately 38.8 million metric tons of carbon dioxide (CO_2) emissions.
The energy intensity of water is affected by the location, type and character of both the water sources and users, while greenhouse gas (GHG) emissions are dependent upon the source of the energy. For example, if a water pump is actuated by electricity supplied from a coal-fired power plant, the GHG emissions will be significantly higher than if the electricity was supplied by renewable sources (Cooley et al., 2012). The following components of water systems all play significant roles in the water-energy nexus: water extraction, conveyance, pre-treatment and distribution, customer end-use, and wastewater collection and treatment (Wilkinson, 2000).

Wilkinson divided the energy use of a water utility system into four basic elements:

1) Water extraction, transportation and storage
A "raw" water source can be from underground aquifers, brackish water desalination, local surface water, other watersheds, and wastewater treatment plants. Energy intensity varies by water source. For example, groundwater is often located close to the point of use, so extraction occupies the major proportion of its energy consumption. In contrast, the extraction energy for surface water is near zero, but imported surface water has more significant consumption during transportation. Desalination of brackish water and seawater became popular as the process efficiency increased. As an example, the water from the Chino desalter (1,700 kilowatt-hours /acre-foot (kWh/AF)) has less energy intensity than any imported water (over 2,000 kWh/AF) (Wilkinson et al., 2006). Reclaimed water is similar to local surface water, except the water source is wastewater treatment plants. The treated water consumes negligible energy on

extraction and conveyance but may require distribution and secondary treatment depending on the locations and requirements of the end-uses (Cooley et al., 2012).

California, with its highly variable topography, has higher energy intensity for water compared to the national average due to pumping over long distances and mountains (Copeland & Carter, 2017). Imported water sources have additional effects on conveyance energy: The San Francisco and Los Angeles aqueducts generate more energy than they consume during conveyance. However, transmission from the State Water Project (SWP) and the Colorado River Aqueduct (CRA) requires significant energy expenditure (Wilkinson, 2000). Transporting one acre-foot (AF) of water to Southern California from the SWP requires approximately 3 megawatt-hours (MWh), and transporting it from the CRA requires approximately 2 MWh (Man, 1996). On average, imported water supplies (2,567 kWh/AF) are more energy intensive than local sources of groundwater (950 kWh/AF) and reclaimed water (400 kWh/AF) (Wilkinson et al., 2006).

2) Water pre-treatment and distribution among service areas
Energy consumption for water treatment is affected by the quality of the original water, the topography, and the output requirements. As water policies become more stringent, pre-treatment will require new, more energy intensive control technologies (Wilkinson, 2000). Traditional approaches use filtration to remove suspended solids and pump chlorine into water for disinfection. Water systems require adequate pressurization throughout the system to properly distribute water to end-users. A 2002 report by the Electric Power Research Institute estimated that moving and treating water and wastewater contributes to about 4% of the nation's electricity use and is estimated to increase by 63% by 2050 (Copeland & Carter, 2017).

3) Additional pumping, treatment and thermal inputs on site
Water is pumped and allocated to individual households or commercial sites. Once water arrives to the end-users, it may undergo further treatment to fulfill that user’s specific needs.The purification, cooling and heating processes all consume energy. A study conducted for SCE found that energy use related to water use is the third highest energy consumer in most of their customers’ households. Water heating is especially impactful, as it accounts for 40% of water-related energy use and 70% of water-related carbon emissions (Copeland & Carter, 2017). For commercial consumers, the embedded energy is zero for single-pass cooling and landscape irrigation and 207.8 MWh/MG for water-cooled chillers, though there are unanalyzed processes that are believed to be more energy intensive. Excluding thermal processes, residential water use can consume between 0 kWh/MG (e.g., toilet flushing) and 203.6 MWh/MG (e.g., dishwashers) (Griffiths-Sattenspiel, 2009).

4) Wastewater collection, treatment, and discharge
The collection of wastewater from users and the ensuing transportation to the treatment plants requires more energy than transporting raw water: pumps require additional power to move water mixed with solids in order to avoid blockages in the pipes. A lack of effective wastewater storage also impacts energy use; pumps need to continuously transport wastewater from end-users to treatment plants because the system cannot absorb peak load. This forces pump stations to install more stand-by generators to protect the system from overflow. The systems must be able to operate at peak flow at all times, which leads to higher energy intensity (Burton, 1996).

Wastewater treatment also requires a significant amount of energy. This treatment has four components: preliminary physical treatment, secondary biological treatment, advanced treatment, and disinfection before reuse or discharge. Combining these components with the model provided by Wilkinson (2000), the energy intensity of wastewater treatment plants can be calculated. On average, treating one million gallons requires 1 kWh/MG to 3 kWh/MG, with some utilities requiring more (Griffiths-Sattenspiel, 2009). During the biological process, engineered microbes utilize organic pollutants in wastewater as their nutrient sources. The microbes will emit large amounts of CO_2 through respiration. However, based on EPA's guidelines, those carbon emissions are bio-generated, and thus are excluded from GHG accounting. CH_4 and NO_x are generated due to incomplete digestion in wastewater treatment. Because of the significant warming potentials of CH_4 and NO_x, they are included in GHG inventories even though their quantities are significantly smaller than CO_2 (Gómez, D. R. et al., 2006). After treatment, the wastewater is either discharged to surface reservoirs or transported to end-users as reclaimed water (Cooley et al., 2012).

Having mixed energy sources for different pumping stations makes obtaining precise estimations of GHG emissions challenging (Cooley et al., 2012). For utilities, it is also difficult to accurately trace the exact water and energy consumption related to certain end-uses from water, electricity and gas meters within individual households (Clarke et al., 2009). Without precise measurement, the effects of changes in users' behaviors on water and energy savings will be harder to capture. Some wastewater treatment plants produce energy themselves with bio-gas generated during the process, which improves the energy efficiency and GHG emission mitigation of the overall treatment process. However, most water-energy guidelines and models do not account for this, due to the lack of data (Copeland & Carter, 2017).

4.5 Energy Savings from Water Efficiency Programs

The Department of Food Science & Technology, the Center for Water-Energy Efficiency, and the Department of Civil & Environmental Engineering at UC Davis conducted a study to determine the cost-effectiveness of water conservation programs compared to energy efficiency programs. The Los Angeles Department of Water and Power (LADWP) was used as the case study. In fiscal year 2018-2019, LADWP spent five times more of their budget on energy efficiency programs than on water conservation programs. To calculate cost-effectiveness, estimated water savings for "nine hardware based water conservation measures" in LADWP's service area and energy intensity values were used to calculate the levelized cost of the saved energy metric (Spang et al., 2020). The energy intensity values were dependent on boundaries selected by the authors of the study.

The first system boundary only contained the LADWP service area; the second boundary expanded upon the first to include the SWP, CRA, and the Los Angeles Aqueduct; and the third boundary used the hydrologic zone of LADWP. The second and third system boundaries were both found to contain similar areas. Additionally, the volume of water used within each system was separated into indoor and outdoor use.

The second boundary that included the service area and imported water sources had the highest energy intensity value, specifically for outdoor water. When comparing this expanded boundary with the third boundary that used the hydrologic zone, the hydrologic zone had a 14% higher energy intensity value. Overall, the study emphasized the importance of defining system boundaries to calculate energy intensity values.

Energy savings from water conservations programs were also analyzed. The second (service area plus imported sources) and third boundary (hydrologic zone) contained the highest amount of energy savings of about 25,000 MWh each. Compared to the water distribution energy savings, the wastewater energy savings did not change much between the different system boundaries.

The levelized cost of saved energy metric was used to determine cost-effectiveness. The water conservation mechanisms that were deemed the most cost-effective were outdoor programs. The study highlighted that even though outdoor programs for residential households do not include energy from wastewater treatment, the energy savings were more significant for outdoor than indoor water usage. This is due to the disparity between outdoor and indoor use. Out of nine water conservation programs, only one program—the high-efficiency washing machine program—did not show competitive energy or cost savings when compared to energy efficiency programs. A major takeaway from the study was the need for LADWP to reallocate their budget from energy efficiency programs to water conservation programs to help meet future water reduction targets imposed by the mayor of Los Angeles (Spang et al, 2020).

4.6 Existing Models and Frameworks

Academic studies and technical documents detailing analysis frameworks, computational models, and software tools were reviewed to guide the technical approach. This section overlaps others in this review: an explanation of methodology allowing others to verify results is a hallmark of scientific study. In this section, however, literature that described frameworks and models which can be applied to a broader class of analyses were the primary focus. Specifically examined were the scope of their analyses, their methods[4], their assumptions, and their inputs and outputs. The goal of this review was to explore similarities and differences among what the frameworks, models, and tools were designed to quantify, as well as their intended user(s).

The River Network's Water~Energy Toolkit (Griffiths-Sattenspiel, 2010) allows the user to estimate household-level water-energy savings and GHG emissions mitigation from water efficient devices. This toolkit is a set of spreadsheet-based calculators applicable anywhere within the U.S. and is available online. It provides a calculator for community-wide water-energy savings and for new water supply sources. The toolkit also provides instructions on how to calculate more precise numbers for the quantities its calculators estimate. This toolkit is an example of the level of detail and functionality necessary for an educational software tool, while providing an overview of the most influential aspects of water end-use.

Similar to the Water~Energy Toolkit, the Bureau of Reclamation's Greenhouse Gas Emissions Calculator for the Water Sector (Blickenstaff, 2012) is a spreadsheet-based model. It allows the user to estimate total GHG emissions from urban water use from 1990-2050 for a service area. However, unlike the Water~Energy Toolkit, it is specific to Southern California, and is not available online. It accounts for emissions during all phases of the urban water use cycle, with the notable exception of end-use associated emissions. The model inputs coarse-grained data applicable to an entire service area, data to which any water utility would reasonably expect to

[4] All employed the approach of Wilkinson (2000) to some degree.

have access. It can rely heavily on default data generally applicable to Southern California. The model requires only population data from 1990, 2000, 2010, and present, and the user is given the option to add further data to increase accuracy. This calculator is likely too technical to serve as an educational tool, yet also may not be accurate enough to provide useful numbers to decision-makers.

The Pacific Institute's Water to Air spreadsheet-based model (Wolff et al., 2004) provides an excellent contrast to the Bureau of Reclamation's model. Available online from the Pacific Institute, it requires more detailed inputs of data, data to which the public would not have access, and it produces a more accurate result. Created for use by Cohen et al. (2004), this model takes a facility-level approach to quantifying the total energy use and air emissions of a water supply system under two urban water management scenarios. The model uses emissions factors for VOCs, CO_2, CO, NO_x, SO_x, total particulates and PM_{10} for the generation portfolio from which each facility obtains its energy. However, the user cannot alter these emissions factors. These factors are based on the 2004 California Grid mix and there was no indication they have been updated. This outdated data could compromise the accuracy of this model's facility-level approach.

The Santa Clarita Valley Water District's Watts to Water model (Larabee et al., 2011) estimates the energy savings and air pollution emissions mitigation from their customers' water use efficiency programs. Watts to Water is a modified version of the Water to Air model, and is distinct from it in three key ways:

> (1) Watts to Water computes savings based on incremental changes over time as opposed to the difference between two specific points in time;
> (2) the model works backward from customer conservation and recycled water volumes to account for system losses when calculating the volume of avoided water use; and
> (3) the model computes customer conservation volumes based on known numbers for the specific conservation devices distributed.

Maas (2009) details work done by the POLIS Project on Ecological Governance estimating energy savings and air pollution emissions mitigation from their customer water use efficiency programs in Ontario. It also provides guidance on how their analysis may be adapted for use across Canada. While this study calculated quantities similar to those found by Larabee et al. (2011) it employed a top-down approach which contrasts well with Larabee et al.'s bottom-up approach. The two studies considered other useful details including water and energy losses during transmission, and aggregation of emissions into units of equivalent grams of CO_2 based on global warming potential (gCO_2e). While neither Larabee et al. (2011) nor Maas (2009) made their models available for download, both studies detailed analysis frameworks that make it easy to replicate their approaches.

Horvath & Stokes (2011) establish the most technical framework of any examined in this review. Their report takes a complete life cycle analysis (LCA) approach to calculating energy savings and emissions mitigation aspects of water management decisions. Its scope extends to the energy use and emissions during the full materials life cycle of the physical infrastructure used to convey, treat water, use water, and produce energy. Two software tools were produced for applying this framework, one for wastewater systems and another for water supply systems. The level of detail the authors employed in their LCA approach would be impractical to mimic in a framework designed for ease of use.

The Water-Energy GHG Metrics 2.0 (The Climate Registry, 2018) provides guidelines for tracking the energy and GHG emissions intensity of water management operations in Southern California. An example of these metrics is the coefficient by which imported source water volumes are multiplied to find total emissions; an example of a corresponding guideline is how scope of analysis should determine what sources of emissions are considered when calculating this coefficient. Because the guidelines are designed to be generalizable, this document functions well as a companion document to more site-specific analyses like this project. The guidelines mainly address the following topics: scope of analysis, definition of system boundaries, specification of spatial and temporal accuracy, and appropriate units. Pending further assessment of how widely these guidelines are used by water utilities across California, closely following them would increase the applicability of a framework for calculating energy saved and emissions mitigated by end-use efficiency programs.

The literature review in this area highlighted the Southern California Water Coalition's observation that no standardized methodology exists for estimating the water or energy savings from water efficiency programs. Most of the frameworks examined calculate energy and emissions intensity of water systems; few explicitly found avoided energy or mitigated emissions resulting from water efficiency programs. Overall, the accuracy of the frameworks was directly proportional to their complexity and indirectly proportional to their ease of use. Spatial variability had little importance in these analyses, and no study examined considered diurnal variability of water savings.

5. Methods

The methods used for this study were compartmentalized into three sections: water, energy and greenhouse gases (GHG), and the water-energy nexus. The first section calculated water savings from residential customers who participated in five selected rebate programs. These numbers were then compared to water savings calculated by the University of California, Riverside (UCR) to determine accuracy. The second section calculated embedded energy and GHG emissions for MNWD's potable water distribution system and wastewater treatment system. The third section calculated the energy saved and GHG emissions mitigated through the water savings achieved by MNWD's water efficiency programs. Due to the inaccuracy of the results of the first section, water savings calculated by UCR were used for the third section. After calculating results for the primary objectives, the framework was completed.

5.1 Water Savings

Water savings per unit rebate were calculated using two methods: linear regression and differences-in-differences (DID). The reasons for using two methods are discussed in detail in the following sections (See 5.1.2. Analytical Methods). Five of the eight rebate programs offered to MNWD's residential customers were evaluated using linear regression. Two of these programs were for indoor devices: high-efficiency clothes washers (HECW) and high-efficiency toilets (HET). The other three were for outdoor devices: weather-based irrigation controllers (WBIC), rotating sprinkler nozzles (RSN), and turf removal (T). Rebates for turf removal were combined with rebates for synthetic turf (SYN) installation, as MNWD grouped these two rebates into a single rebate type beginning in 2014 due to their similarity. The listed programs were chosen due to their high participation rate among residential customers and their water saving effectiveness according to past studies. Of these five, four were also evaluated using DID (HECW, HET, WBIC, and T). RSN was excluded due to the small sample size after filtering conditions were applied.

5.1.1 Data Sources

The data used for the linear regression and DID methods synthesized three datasets: water usage, rebate participation, and customer characteristics. Monthly water usage was available from 1986 to 2020. Rebate participation data was available from December 2009 to March 2020. The rebate participation data includes invoice dates and the number of units installed for each rebate program. Customer characteristic data included the irrigated area, number of people per household, rate schedule type (house or condo/townhouse), customer class type (single family or multi-family), and account opening and closing dates. In addition to those three datasets, the linear regression model also used evapotranspiration and precipitation data for MNWD service addresses. For data formatting and preparation, see Appendix 2.1.

5.1.2 Analytical Methods

Before applying methods, an examination of water use and characteristics of MNWD's residential customers was conducted. This was done to discern general patterns in the variables influencing water use, such as household size, irrigated area, precipitation depth, and rebate participation. Examining these variables, as well as the 12-month moving/rolling average of water use among rebate participants and non-participating accounts provided context to our analysis. Results are shown in Section 6.1.

Several factors were identified that could potentially obscure results, including the presence of a strong seasonal cycle, the impact of drought messaging on water use behavior, installation of rebate-eligible devices by non-participants, and rebound effects. Controlling for these factors would require considerable data on household characteristics, such as that obtained by the customer survey used in Phase II of UCR's study. In the absence of a survey, two methods were selected that were partially able to account for these factors: multi-variable linear regression and effect size estimation by difference-in-differences (DID). By using them both and comparing results to UCR's savings estimates, this study assessed both the degree to which the factors obscured results, and whether either was robust enough to confounding factors to be recommended in the developed framework. Further discussion of these factors and their potential impacts on savings estimates are found in the discussion section of this report, see Section 7.

5.1.2.1 Multi-variable Linear Regression

Water use, user characteristics, rebate participation, and weather data was synthesized so that each row of the dataset represented an account-month. A multi-variable linear regression model was fit to the synthesized dataset. To reduce statistical noise, the synthesized dataset only contained data from a stratified random sample of the accounts retained after applying data quality filtering conditions (see Appendix 2.1). To draw the sample, the retained accounts were stratified into two groups: those who participated in any of the five selected rebate programs, and those who did not. From each group, a random sample of 5,000 unique accounts was drawn. Each sample of 5,000 accounts was further stratified into five samples of 1,000 accounts based on each account's percentile of water use in 2009. The five within-rebate-group percentile classes were: 1 % to 20 %, 20 % to 40 %, 40% to 60%, 60% to 80%, and 80% to 99%. Samples were not drawn from below the 1st percentile or above the 99th percentile to exclude potential outliers.

Metered water use was then predicted based on the following variables:

- **Cumulative rebate quantity**
  For each account-month, the cumulative number of rebate units obtained by that account before and during that month was calculated during preparation of the dataset. By utilizing these quantities as predictor variables of water use, their coefficients in the resultant model gave an estimate of the magnitude of water savings per unit rebate (negative coefficient) or the magnitude of the rebound effect (positive coefficient).
- **Weather-based irrigation controller rebate participation**
  A binary participation variable was used instead of cumulative rebate quantity for the weather-based irrigation controller (WBIC) rebate program. This was done for two reasons. First, most accounts participating in the WBIC program received a rebate for a single controller: of the 1,242 rebate invoices examined, 1,182 received one controller, 59 received two, and only one account received three. Second, statistical accuracy of the WBIC coefficient increased when this change was made (p-value decreased from $p = 0.783$ to $p = 0.113$), though the coefficient remained statistically insignificant.
- **Eventual rebate participation**
  Each account was assigned a binary indicator designating whether the account holder participated in any rebate program at any point during the study period (2010-2019). This accounted for the fact that there may be some fundamental difference in water use behavior between rebate participants and non-participants. For example, if customers

who chose to participate in the rebate program did so because they were already concerned about sustainability this would be taken into account.

- **Evapotranspiration (ET)**
  This variable represents average monthly evapotranspiration across MNWD's service area as calculated by MNWD. For months with missing data, the average evapotranspiration (ET) for that month in other years was used. An approximately linear relationship between ET and mean use was observed, so the variable was not transformed.
- **Rainfall**
  This variable represents average precipitation in that month across MNWD's service area. As with ET, for months with missing data, the average rainfall depth for that month in other years was used. A nonlinear relationship between precipitation depth and average rainfall was observed (**Figure 20** in Appendix 5). To account for this, the square root of rainfall depth was used as the predictor, as this transformation produced a more approximately linear relationship (**Figure 21** in Appendix 5).
- **Number of residents**
  This variable indicated the recorded number of residents in that account's household. An approximately linear relationship between residents and mean monthly use was observed, eliminating the need for variable transformation (see **Figure 22** in Appendix 5).
- **Irrigated area**
  This variable allowed prediction of how household water use changed based on the recorded total irrigated area on that account's property. A nonlinear relationship between irrigated area and mean monthly water use was observed (**Figure 23** in Appendix 5). To account for this, a variable transformation was applied. The square root of the irrigated area was used as a predictor, as the relationship between the square root of irrigated area and mean monthly water use appeared to be more linear.
- **Rate schedule**
  This factor variable indicated whether an account had the rate type for single-family residential households (R1) or the rate type for condos and townhomes (R2).
- **Year**
  The year to which a given account-month of water use corresponded was represented as a factor variable. While water use behavior changes from year to year, it does not show a steady increase or decrease over time, making representation of year as a numeric variable inappropriate.

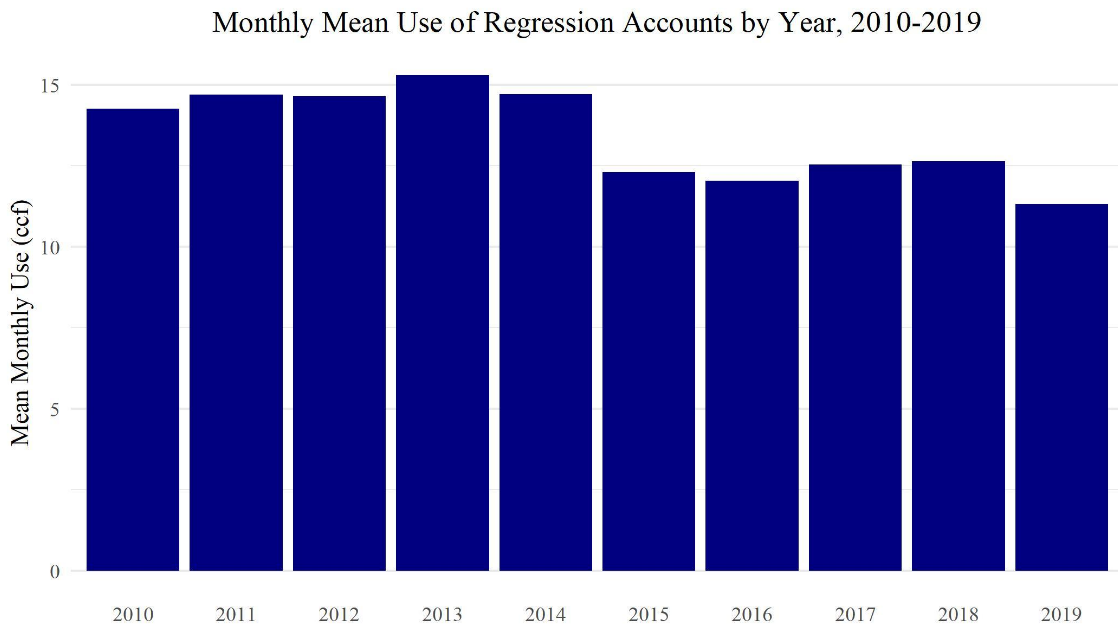


Figure 5. Monthly average water use from 2010 to 2019 for sampled accounts used in regression analysis. Data Source: Moulton Niguel Water District

- **Month**
  Month was also represented as a factor variable. The inclusion of month accounted for the presence of a strong seasonal cycle in water use, shown below in **Figure 6.**

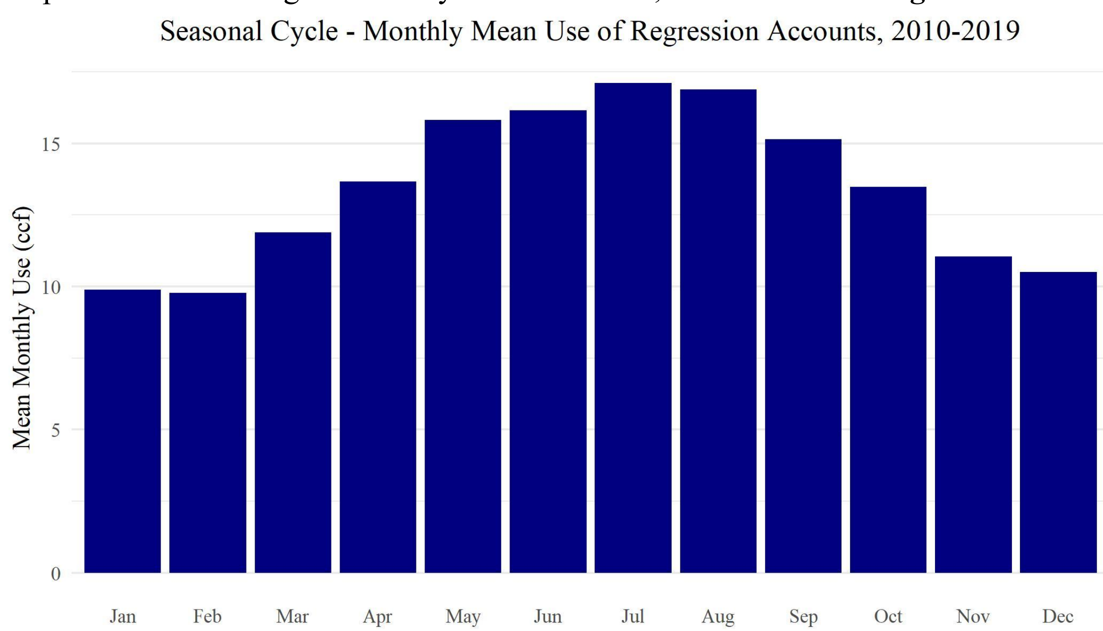


Figure 6. Seasonal cycle of monthly average water use from 2010 to 2019 for sampled accounts used in regression analysis. Data Source: Moulton Niguel Water District

- **Executive Order B-29-15**
  A binary indicator was assigned to each account-month indicating whether it was before or after former Governor Jerry Brown signed E.O. B-29-15 in May of 2015. This was to account for changes in water use behavior due to drought messaging, reflected in the drop in mean monthly use in 2015 and onwards (**Figure 6** above).
- **Prior use**
  Each account-month was also assigned that account's use in that same month in 2009.
- **Drought severity**
  Using data from the National Integrated Drought Information System, a single metric was calculated to represent the severity of drought in Orange County for each month in the study period. For each date for which data was available, this metric was calculated by adding the proportion of the county area with conditions that were "Abnormally Dry," "Moderate Drought," "Severe Drought," "Extreme Drought," "Exceptional Drought," or drier. The mean value of this metric was then calculated for each month in the study period. This variable was included to further account for potential drought messaging or shifts in water use behavior due to drought awareness.

Alternative approaches to regression analysis were explored in order to estimate rebate savings more accurately, specifically to account for the ways in which savings may vary through time and between customers. None produced satisfactory results, suffering from some combination of poor model fit or statistically insignificant cumulative rebate quantity coefficients. Brief descriptions of these approaches can be found in Appendix 6.

5.1.2.2 Difference-in-Differences

Difference-in-differences (DID) is a statistical method widely used in estimating the impact of interference or treatment (Schmitt et al., 2018; Schwabe, K., 2017). This method combines cross-sectional and time-series analysis and also mitigates the limitations of those two approaches. While cross-sectional studies compare variations across locations or groups of interest at the same points in time, time-series studies compare temporal variation for a single location or group. The DID method finds the difference between the changes in groups, mostly for treatment groups and control groups, before and after a certain intervention. Past studies have shown that DID can reduce the bias in treatment-and-control comparison (i.e., cross-sectional analysis) which stem from the permanent or intrinsic difference between the groups. DID can also mitigate the bias in before-and-after comparison (i.e., time-series analysis) due to other confounders that would influence the outcomes.

DID compares treatment and control groups, and time periods before and after the treatment. Customers were therefore separated into treatment groups and control groups for each rebate program. The customers in the control groups did not participate in any rebate program offered by MNWD during our study period between 2010 and 2019, while all customers in the treatment groups participated in one specific rebate program during this period.

For each rebate program, a treatment and control group was created. Each treatment group consisted of customers who only joined their rebate program after the first two years of their study time frames. In the control group customer selection process, each participating customer would be matched with a non-participating customer who had the same amount of residents in their household, same rate schedule (i.e., R1 or R2), and a similar irrigable area (less or above 200 ft^2 compared to the rebate customer). To avoid the impact of extreme water users and abnormal meter reading records due to errors or leakage, filtering regarding water usage behavior was applied: all chosen customers needed to have less than 100 centum cubic feet (ccf) water use, as well as non-zero and continual water meter readings, for any given month during the study period. The continuity of consumption records was important for this analysis because it indicated stable resident characteristics and water use habits in those households.

The selection of each time period was based on the participation rates for each program, dry and wet years for California, and the dates of the state executive orders. The time periods were divided into pre-rebate periods and post-rebate periods. The first two years of each period being the pre-rebate, and the last three the post-rebate. The pre-rebate period served as a baseline and observed the general difference in water use behaviors between the treatment and control groups. During the post-rebate period, rebate participants started to install their rebate-eligible equipment gradually at different times, while the control group remained non-participants. The post-rebate period demonstrated the increasing difference of water use between the two groups, caused by rebate devices gradually being installed.

Four rebate programs (high efficiency clothes washers (HECW), high efficiency toilets (HET), weather-based irrigation controllers (WBIC), and rotating spray nozzles (RSN)) had a pre-rebate period of January 2010 to December 2011 and a post-rebate period of January 2012 to December 2014. While the remaining program (turf removal) used January 2015 to December 2016 as the pre-rebate period and January 2017 to December 2019 as the post-rebate period. These timelines and their corresponding programs are presented in **Figure 7**. After filtering, a number of non-participants were selected for each of the rebate programs to act as a control against the participants of the corresponding program. This included HECW (18,747), HET (18,705), RSN (1,044), T (16,149), and WBIC (9,969) non-participant customers.

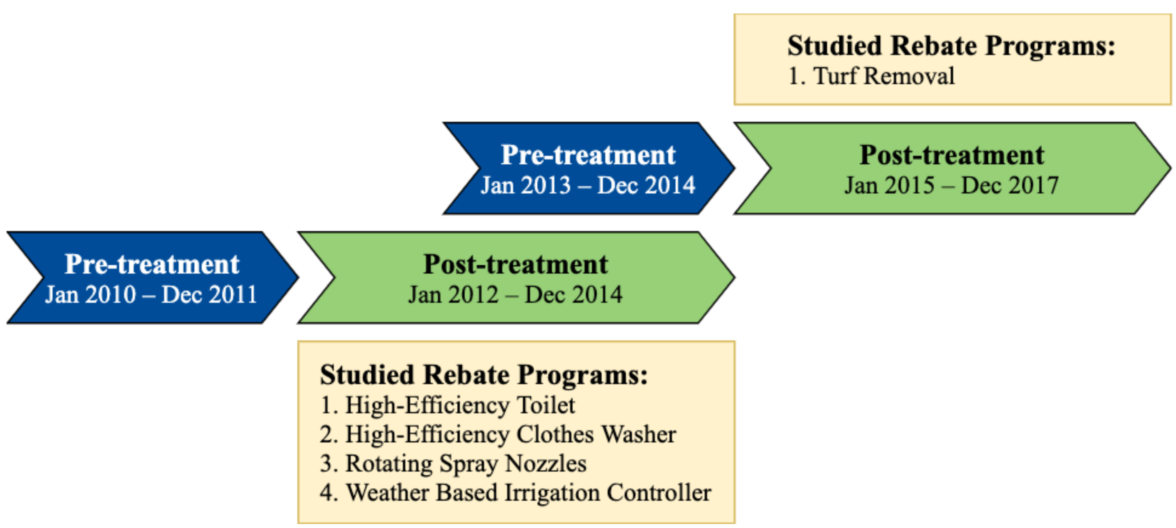


Figure 7. The study timeline for the five different rebate programs.

DID analysis is based on the assumption of parallel trends. The absence of parallel trends before the intervention often means that other confounders play important roles in impacting the outcome, leading to a biased estimation of the impact of the intervention itself. Given the lack of robust statistical methods in examining this assumption, a visual inspection helps judge whether the data meets the basic parallel trend assumption. In **Figure 8**, similar patterns and trends of water consumption in the pre-treatment period are demonstrated between the treatment and control groups for all rebate programs except for the rotating spray nozzles (RSN). Considering the small sample size and its failure to meet the key assumption, RSN was not considered in the DID analysis. Therefore, the DID model is believed to generate valid estimates for WBIC, HECW, HET, and T programs.

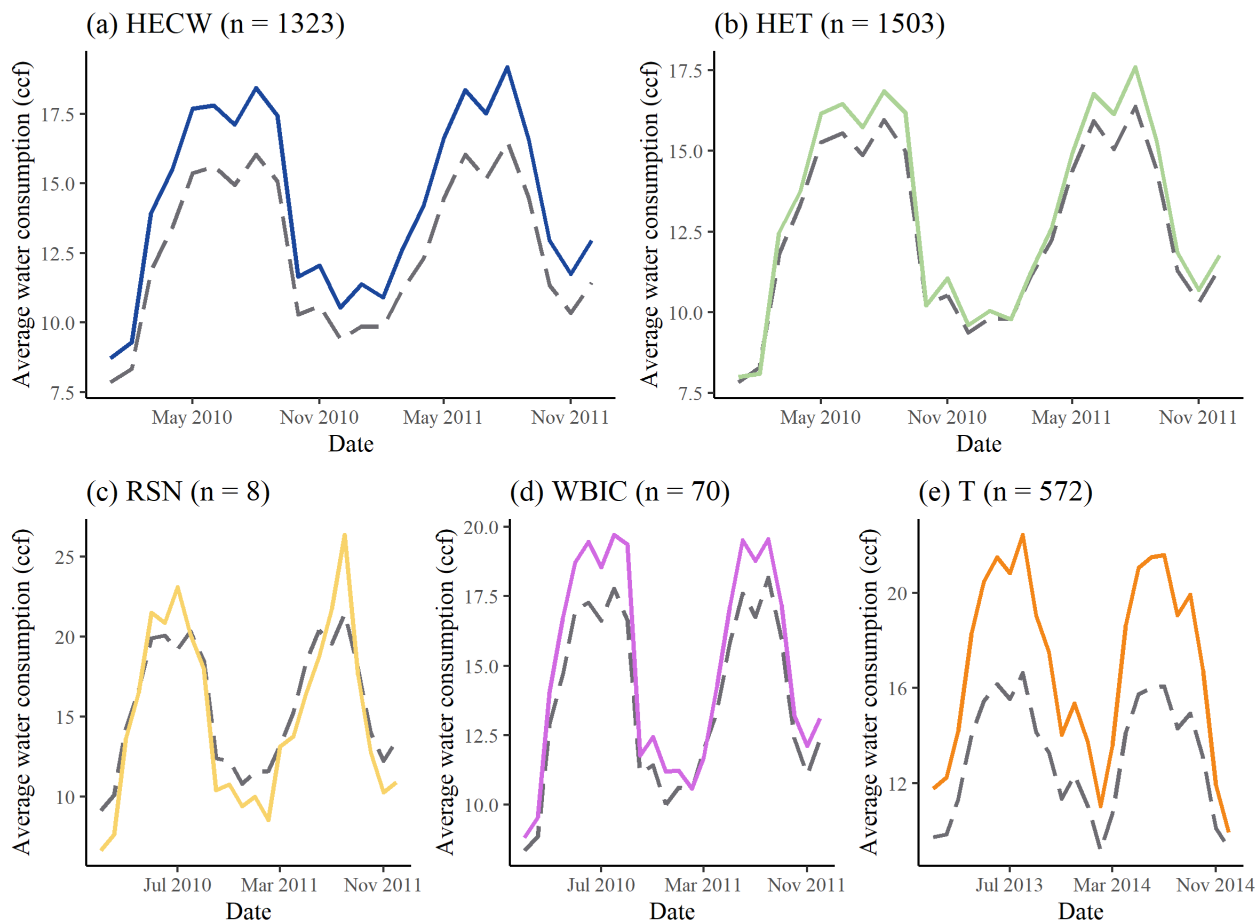


Figure 8. The monthly average water usage for each rebate group and their matched control groups during the pre-intervention period. The colored lines represent rebate groups and the dashed grey lines represent their matched control groups. This figure is used to visually examine whether the data met the parallel assumption required for the DID model. Note that the Date axis for (e) T is different from other programs due to its different pre-rebate period. The “n” in the titles are the sample sizes for rebate customers. Data Source: Moulton Niguel Water District.

To quantify the water savings related to one unit of rebate installation from the DID model, three steps are needed. First, a matching strategy was applied to find control customers for each treatment customer that would experience the same or similar fluctuations due to other drivers of water use. For each individual rebate participant, their matched control customers needed to share similar characteristics with them. Since participants were joining on different dates during the post-intervention period, each participant had their own pre- and post-rebate period which was divided based on their earliest rebate joining date.

Once the control group and study period was settled for each participant in a specific rebate program, the monthly average water use was calculated separately for each participant and their matched customers in their specific pre- and post-rebate periods. The first component estimated was the time-series difference, which is the difference before and after the treatment for individual rebate participants and for their matched control as a whole. The result for difference-in-differences was obtained by taking the time-series difference for rebate customers minus the difference for their matched control. Repeating the steps above for each individual rebate customer, the distribution of DID results were examined with histograms. Some outliers were found and trimmed to avoid their distorting impact on average water savings. Specifically, any DID results that were less than -15 or over 15 ccf (billing unit) were excluded from future steps and considered as dramatic changes. The number of outliers for all rebate programs account for less than 0.1% of their rebate sample sizes. The monthly average water savings per invoice of one rebate was the trimmed average difference-in-differences results for that type of rebate.

Some customers might join the turf removal program more than once or install multiple devices at one time (common for toilets and irrigation controllers). Therefore, the number of rebate invoices is not always equal to the number of rebate services or devices. To calculate the water savings per unit of rebate installation, the average DID results were normalized by dividing by the mean rebate quantity per instance.

5.2 Energy Usage and GHG Emissions
Embedded energy and greenhouse gases (GHG) were calculated for three functional domains (potable distribution, recycled distribution, and wastewater) for each year in the study period (2010-2019). MNWD's electricity usage was calculated using data from its two electric suppliers, the utilities Southern California Edison (SCE) and San Diego Gas and Electric (SDG&E). MNWD's electricity usage, Metropolitan Water District's (MWD) supplied water embedded energy values, and emissions factors were then used to derive values for energy and GHG emissions per acre-foot of water.

5.2.1 Data Sources
Data for MNWD's operational energy consumption was collected by the two electric utilities, SCE and SDG&E, and provided by MNWD. This included energy consumption for all MNWD service accounts from 2009 to 2020 as well as energy cost data from 2009 to mid 2014 and from 2017 to 2020. The majority of this portion of the analysis was conducted using the provided energy consumption files, which reported consumption in 15-minute increments for all days mid 2014 to mid 2020 and in monthly increments for all months 2009 to mid 2014. MNWD also provided pressure zone and billing data. Wastewater data for this project included values from

two of the three wastewater treatment plants that receive effluent from MNWD's service area: Plant 3A and Joint Regional Treatment Plant. Values for the third treatment plant, J.B. Latham, were not available prior to the completion of this report. For data formatting and preparation, see Appendix 2.2.

5.2.2 Analytical Methods

Two analytical methods were used during this portion of the project. A regression model employing predictor variables such as functional domain, seasonality, and meter rate type was established to aid in forecasting energy consumption. This forecasting model was created to aid development of the Objective 2 framework. Separate, simple regression models were used in conjunction with averaging methods to fill in data gaps. Filling in these gaps was necessary for the completion of the embedded energy and GHG calculations.

5.2.2.1 Regression

Using the comprehensive 2009 - 2019 energy consumption dataset (Appendix 2.2), a multi-variable regression model was developed. The goal of this regression model was to forecast energy consumption for each meter. The variables used in the model included month, functional domain, elevation, and rate type. Month was used in order to account for seasonal trends. The energy use for potable, recycled, and wastewater distribution differ significantly from one another. Thus, including functional domain as a predictor was necessary. Between the two electric utilities, there are over 20 unique rate types assigned to the various meters. These rate types are assigned based on the average consumption of the meter. Rate types tend not to change, and for meters which did exhibit a change in assigned rate type, the characteristics of the rate type would often be similar to the characteristics of the previous rate type. Geolocating was performed for each electric meter using the addresses provided by SCE and SDG&E. The provided addresses were entered into an online geolocating tool in order to determine the latitude/longitude coordinates and elevation of each meter. The elevation is relevant as it affects the energy required to pump water.

Initially, year and pressure zone were also included in the model. Geolocation was used to find and include pressure zones in the model in order to account for the energy required to move water from one level of pressure to another. Data detailing pressure at a given meter was inaccessible. Consequently, this variable proved to be inaccurate in the model calculations and had no real effect on the resulting R^2 value of the model. Other sensitivity analyses proved that year did not have a significant impact on the resulting R^2 value either.

5.2.2.2 Embedded Energy and Greenhouse Gases

Water volumes were separated into three functional domains: potable distribution, recycled distribution, and wastewater. These volumes were summed for each year. Published utility-specific emission factors were obtained and used whenever possible. For years when an emissions factor was unavailable, a regression analysis was used to estimate a value. To obtain emissions for an electric meter in a given year, electricity usage was multiplied by an emissions factor based upon its managing utility and the year.

For each year, the following steps were completed: Electricity usage and emissions were summed for each meter. The values for the meters were then grouped by their functional domains and summed. In order to account for upstream energy consumption in the potable distribution domain, the embedded energy values provided by Metropolitan Water District of Southern California (MWD) were multiplied by the imported water volume. The resulting energy usage was added to MNWD's potable distribution electricity usage. When a derived number was unavailable for MWD's embedded energy, the average of the derived values was used. For embedded energy, the total electricity usage was divided by the relevant water volume for a domain. For embedded GHG, the calculated emissions values were divided by the relevant water volume for a domain. In order to account for upstream GHG emissions, the regional emissions factor was multiplied by the upstream electricity usage calculated earlier. The resulting emissions value was added to MNWD's potable distribution emissions.

5.3 Water and Energy Nexus

After savings per unit rebate were estimated and embedded energy and emissions factors were found, total savings were calculated. For each rebate invoice, water savings were estimated in each month of the study period between the issuance of the invoice and the end of the study period (31 December 2019). Then, energy savings and emissions mitigation were calculated by multiplying the water savings in each month by the embedded energy and emissions factor, respectively, appropriate to that month. Finally, savings were summed over all rebate invoices to arrive at total district-level savings over the years 2010 – 2019.

5.3.1 Data Sources

The primary data used in this section were the results from the water, energy, and GHG sections above:

- Estimates of water savings per month per unit rebate participation for each of the five rebate programs (ccf/unit-month)
- Annual embedded energy for potable water distribution, and wastewater collection and treatment (kWh/AF)
- Annual embedded GHG emissions for potable water distribution and wastewater collection and treatment (kgCO_2e/AF)

Due to system losses, avoided imported water volume is greater than the water volume saved by rebate participants. This difference is significant, as embedded energy during conveyance comprises a significant portion of total embedded energy. To account for this, system loss factors were developed that, when multiplied by a quantity of end-use savings, produced the volume of avoided water imports from those savings. To calculate these factors, reported annual real losses and authorized consumption were drawn from MNWD's water audit reports from fiscal years 2015-2019. Per MNWD's water audit reports, real losses are the annual volume of physical water lost through all types of leaks, breaks, and overflows. Authorized consumption is defined as the annual volume of metered and/or unmetered water taken by registered customers, the utility's own uses, and uses of others who are implicitly or explicitly authorized to do so by the water utility. These reports were in the form of spreadsheets produced using the American Water Works Association's Free Water Audit Software v5.0.

Table 2. Real losses, authorized consumption, and calculated loss factors, 2015-2019. Methods for calculating loss factors described in 5.3.2.

Year	Real Losses (AF)	Authorized Consumption (AF)	Loss Factor
2015	1700	24936	1.068
2016	1846	21467	1.086
2017	1721	21511	1.080
2018	1762	23228	1.076
2019	1472	21232	1.069

The normalized results of Phase III of the UC Riverside (UCR) study were used for the estimated monthly water savings resulting from rebate participation due to concerns about the accuracy of the water saving results of this analysis (see Section 6.1.4). Because UCR's study found savings from rebate program participation regardless of rebate quantity, the savings were normalized by the mean rebate quantity displayed below in **Table 3**. The original and normalized water saving values are displayed below in **Table 4**.

Table 3. Number of rebate invoices used in the final analysis. Data Source: Moulton Niguel Water District

Rebate Program	Number of Rebates	Mean Quantity
High-efficiency toilets	5162	1.66 toilets
High-efficiency clothes washers	6945	1.00 washers
Rotating spray nozzles	155	45.77 nozzles
Turf Removal	2155	831.1 ft^2 removed
Weather-based irrigation controllers	1242	1.05 controllers

Table 4. Water savings for five water efficiency rebate programs per program participation calculated by the University of California, Riverside and normalized to savings per unit rebate. Data Source: Schwabe, K. et al. (2017)

Rebate Program Type	Savings from Program Participation (ccf/month)	Normalized Savings per Unit Rebate (ccf/month)
High-efficiency toilets	1.53	0.92 per toilet
High-efficiency clothes washers	1.87	1.87 per washer
Rotating spray nozzles	0.98	0.021 per nozzle
Turf removal	0.85	0.00102 per ft^2
Weather-based irrigation controllers	0.99	0.94 per controller

5.3.2 Analytical Methods

For the synthesis portion of our analysis, two critical simplifying assumptions were made. First, it was assumed that monthly water savings per unit rebate remained constant over time. It was also assumed that water savings increased linearly with rebate quantity. The limitations and implications of these assumptions are explored in the discussion section of this report, see Section 7.2.

These annual system water loss factors L were calculated by the following formula:

$$L = 1 + \frac{real\ losses}{authorized\ consumption} \quad (1)$$

Because MNWD lacked audits for the years 2010-2014, the loss factors for those years were assumed to be the average of the years 2015-2019 (1.076).

The water savings in each month t after accounting for system losses (s_t) for a given instance of rebate participation i were calculated according to the following formula:

$$s_t = s_r * q_i * L \quad (2)$$

where s_r = estimated savings per unit of rebate r,
q_i = quantity of rebate units for the instance i, and
L = annual loss factor appropriate for that month

To calculate the total savings within the study period from a given instance of rebate participation (S_i), s_t was calculated for each month of participation and then summed across all months of rebate participation:

$$S_i = \sum_t s_t = \sum_t s_r * q_i * L \quad (3)$$

To calculate savings across all rebate instances (S_{total}), S_i was summed across all rebate instances i according to the mathematical expression:

$$S_{total} = \sum_i S_i = \sum_i \sum_t s_r * q_i * L \qquad (4)$$

To calculate energy use avoided during potable distribution, water savings in each month were multiplied by the appropriate potable distribution embedded energy factor calculated for each year. Likewise, to calculate GHG emission mitigated during potable distribution, water savings in each month were multiplied by the appropriate potable distribution embedded emissions factor calculated for each year. As with water savings, the calculation of total energy use avoided during potable distribution by each rebate instance (E_i) and total GHG emissions mitigated during potable distribution by each rebate instance (G_i) can be represented mathematically:

$$E_i = \sum_t s_r * q_i * L * f_t \qquad (5)$$

where f_t = the potable distribution embedded energy of month t, and

$$G_i = \sum_t s_r * q_i * L * g_t \qquad (6)$$

where g_t = the potable distribution embedded GHG of month t.

As with water savings, energy and GHG savings during potable distribution for each rebate instance i were summed across all rebate instances to arrive at the total energy savings and GHG emissions mitigation during potable distribution. Stated mathematically:

$$E_{potable} = \sum_i E_i \text{ and } G_{potable} = \sum_i G_i \qquad (7)$$

To find total energy saved and GHG emissions mitigated, we calculated the impacts of rebate unit water savings on wastewater energy use and GHG emissions through reduced wastewater inflows. This involved consideration only of savings from high-efficiency clothes washers and high-efficiency toilets, as the other three rebate programs studied do not produce any wastewater effluent.

Wastewater inflow reductions were calculated using the product of unit savings and rebate quantity in each month of participation. Transmission losses in this portion of the residential water use cycle were ignored due to the lack of data on losses during wastewater conveyance. Avoided energy use was calculated by multiplying these inflow reductions by the year-appropriate calculated wastewater embedded energy; likewise, GHG emissions mitigated were calculated by multiplying the reductions by the year-appropriate wastewater embedded emissions. Stated mathematically:

$$E_{i-ww} = \sum_t s_r * q_i * f_{t-ww} \text{ and } G_{i-ww} = \sum_t s_r * q_i * g_{t-ww} \qquad (8)$$

where f_{t-ww} = the wastewater treatment embedded energy of month t, and
g_{t-ww} = the wastewater treatment embedded GHG emissions of month t.

Total avoided wastewater energy use and GHG emissions were then calculated by summing across all instances, *i,* of participation in the high-efficiency toilet and high-efficiency clothes washer rebate programs.

$$E_{wastewater} = \sum_i E_{i-ww} \text{ and } G_{wastewater} = \sum_i G_{i-ww} \quad (9)$$

Then, total energy use in the water supply chain avoided through these residential water efficiency rebate programs was estimated by adding together avoided use during potable distribution and avoided use during wastewater treatment. Likewise, total GHG emissions in the supply chain mitigated through these programs was estimated by adding together emissions mitigated during potable distribution and emissions mitigated during wastewater treatment.

$$E_{total} = E_{potable} + E_{wastewater} \quad (10)$$

$$G_{total} = G_{potable} + G_{wastewater} \quad (11)$$

In this phase of the analysis, energy use and GHG emissions (and therefore potential savings) were not considered during two components of the water use cycle: 1) production, distribution, and post-use treatment of recycled water and 2) and customer end-use energy inputs. For recycled water, the approach of Spang et al. (2020) was followed, which ignored recycled water because none of the residential rebate devices considered used recycled water. For customer end-use, there was a lack of data necessary for an accurate estimate, including water temperature at the service point, relative distribution of electric vs. gas water heaters, average stock efficiency of said heaters, the temperature to which water was heated, and the proportion of water consumption that is hot water by high-efficiency clothes washers (the only device of the five that uses hot water). As a result, customer end-use was not considered in this analysis.

6. Results
This section discusses the results of the analysis using the methods presented in the previous section. These include the household characteristics among Moulton Niguel Water District (MNWD)'s residential customers, and results of the regression and difference-in-differences (DID) models used to estimate rebate savings from these customers. Estimated savings are also compared to those savings estimated by the previous UC Riverside (UCR) study. This section also presents the calculated embedded energy and greenhouse gas (GHG) emissions for water within the district. Finally, it explores the district-level savings of water, energy, and emissions from 2010-2019 for the five programs examined.

6.1 Water Consumption Savings

6.1.1 Customer Characteristics Exploration
Household size was found to vary between 1 and 15 residents among MNWD's residential customers, with the majority of households having 4 residents or less. The large number of households with 4 residents is largely due to a procedural factor. When considering household size in establishing each account's water budget, MNWD uses a default value of 4 for those accounts for which it lacks data. Personal communication with MNWD indicated that customers can clarify and update their household numbers, and the District has implemented procedural processes to capture household population at the date that service begins. While inaccurate household size data may distort regression model results, it was not corrected for due to the use of UCR's savings results in Phases III and IV.

Table 5. Distribution of household size among Moulton Niguel Water District's residential customers. Data Source: Moulton Niguel Water District

Number of Residents	Total Accounts	Number of Residents	Total Accounts
1	3242	9	70
2	4556	10	41
3	8700	11	13
4	26478	12	1
5	3320	13	2
6	1663	14	1
7	354	15	1
8	178	-	-

Irrigated areas of households were skewed to the right and mainly under 5,000 ft^2 (See **Figure 10**). Some outliers did exist that were greater than 5,000 ft^2. MNWD uses satellite imagery to obtain irrigated area values for their customers. When MNWD converted to water-budget-based rates, many townhouses/condos (R2) were assigned a default value of 300 ft^2 (Personal communication with MNWD, 2021).

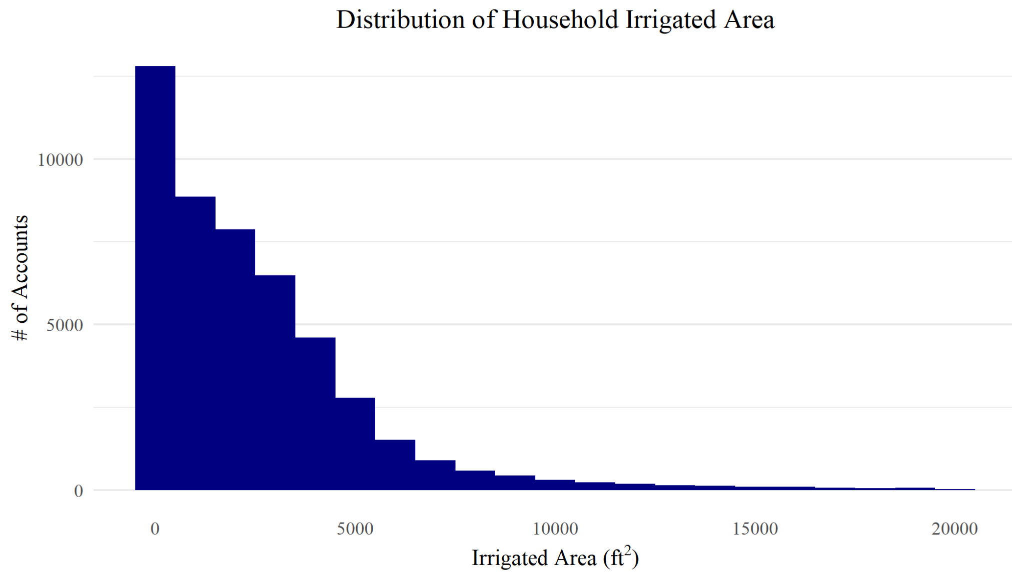


Figure 9. The distribution of irrigable area in square feet for residential customers. Data Source: Moulton Niguel Water District

The rolling/moving average for residential water use showed two findings. First, after Executive Order B-29-15, water usage for both rebate and non-rebate participants displayed a decreasing trend with an increase in late 2017/early 2018 in the months following Governor Jerry Brown's lifting of the drought state of emergency. Second, the difference in water use between rebate and non-rebate participants eventually narrowed.

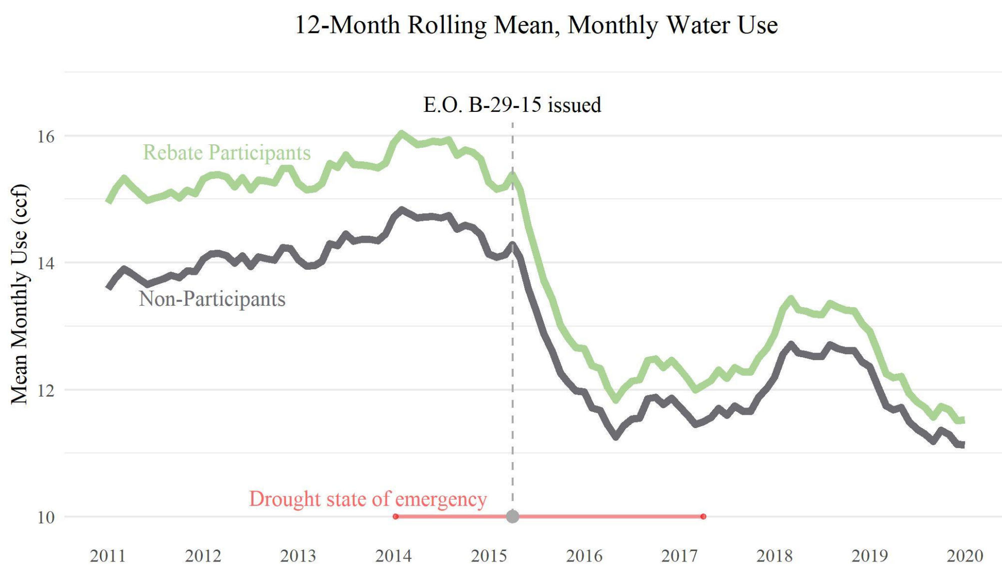


Figure 10. The rolling/moving average water use for customers who eventually joined a rebate program and who never joined a rebate program from 2011 to 2020. Data Source: Moulton Niguel Water District

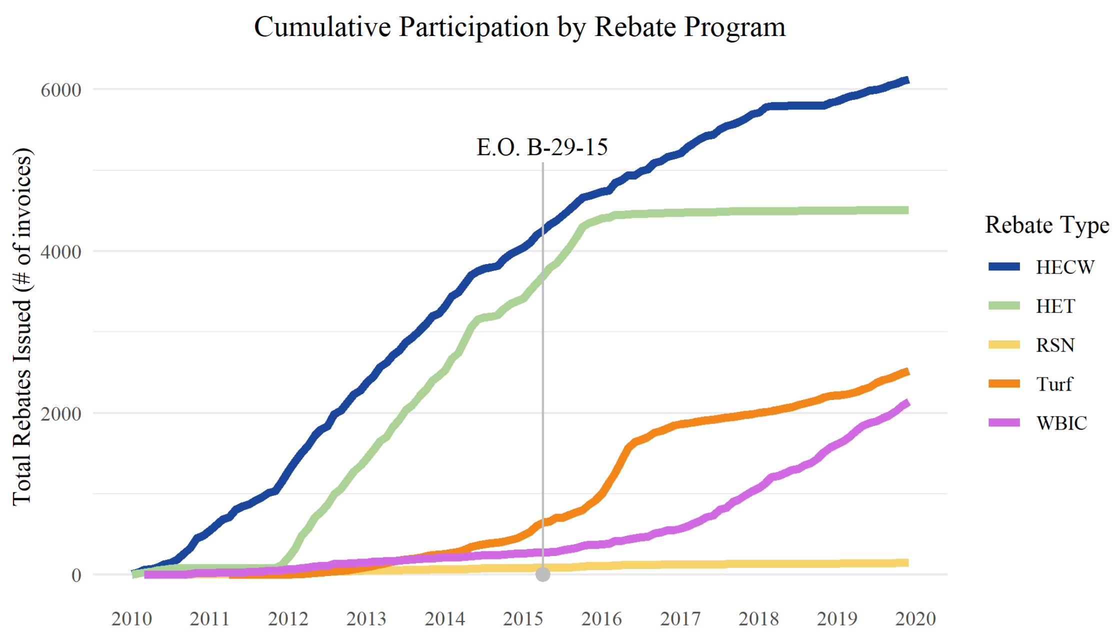


Figure 11. Cumulative rebate participation for five regional water efficiency programs for Moulton Niguel Water District from 2010-2020. Data Source: Moulton Niguel Water District

6.1.2 Regression Model Coefficient Results and Implications

Coefficients for the cumulative quantities of participation in the HECW, HET, RSN, and Turf rebate programs examined are shown below in **Table 6**, as is the coefficient for participation in the WBIC program.

Table 6. Selected regression model coefficients. Because quantities predicted monthly water use, negative coefficients indicate a predicted decrease in water use. The adjusted R^2 is 0.5321. Data Source: Moulton Niguel Water District

Variable Type	Model Coefficient	Standard Deviation	Water Savings (gallons/month)
High-efficiency toilets installed	-0.258	0.98	193.0 per toilet
High-efficiency clothes washers installed	-0.380	1.64	284.3 per washer
Rotating spray nozzles installed	0.0098	0.12	-7.4 per nozzle
Area of turf removed	-0.0017	0.003	1.28 per ft^2
Participation in the weather-based irrigation controller rebate program (binary)	0.0693	4.38	-51.8 per rebate issued
Number of household residents	1.152	0.65	-862 per person
Post Executive Order B-29-15	-3.400	4.85	2543

Based on the coefficients in the regression model, both indoor rebate programs (HET, HECW) were found to result in per-device savings. Each efficient toilet installed was estimated to reduce water use by 193.0 gallons per month, and each efficient clothes washer installed reduced consumption by 284.3 gallons per month. Attempts to capture intra-annual variability of savings showed little seasonality in the savings for these two programs (not displayed).

The regression model found mixed results for the outdoor rebate programs. Each ft^2 of turf removed was estimated to have resulted in monthly water savings of 1.28 gallons. However, each rotating spray nozzle installed was estimated to increase monthly water use by 7.35 gallons. Participation in the weather-based irrigation controller program (not considering the number of controllers installed) predicted an increase in water use of 51.8 gallons per month. The coefficient for the binary WBIC participation variable was the only model coefficient that was not statistically significant at the 95% confidence level, with a p-value of 0.113. Possible explanations for this lack of significance, as well as for the increase in water use found by the regression model generally, are explored further in the discussion section of this report.

Several variables were found to be highly influential on household water use. Seasonality had a large effect on water relative to rebate participation: the magnitude of the coefficient for each month of the year was found to be greater than the largest rebate quantity coefficient for all months but one (February). Number of residents also increased water use, predicting a monthly use increase of 862 gallons for each additional resident; however, this was also likely a factor of each household's water budget-based rate being determined in part by the number of household residents. Finally, monthly water use was predicted to be 2543 gallons lower in months following the issuance of E.O. B-29-15, all else being equal - one of the largest-magnitude coefficients in the model. A full table of all model coefficients can be found in Appendix 5.

6.1.3 DID Model Results

As mentioned in the method section (5.1.2.2), RSN was excluded from the difference-in-differences (DID) analysis due to the small sample size and violation of the key assumption of parallel trends. Therefore, this results section will only discuss the water savings for HECW, HET, T, and WBIC.

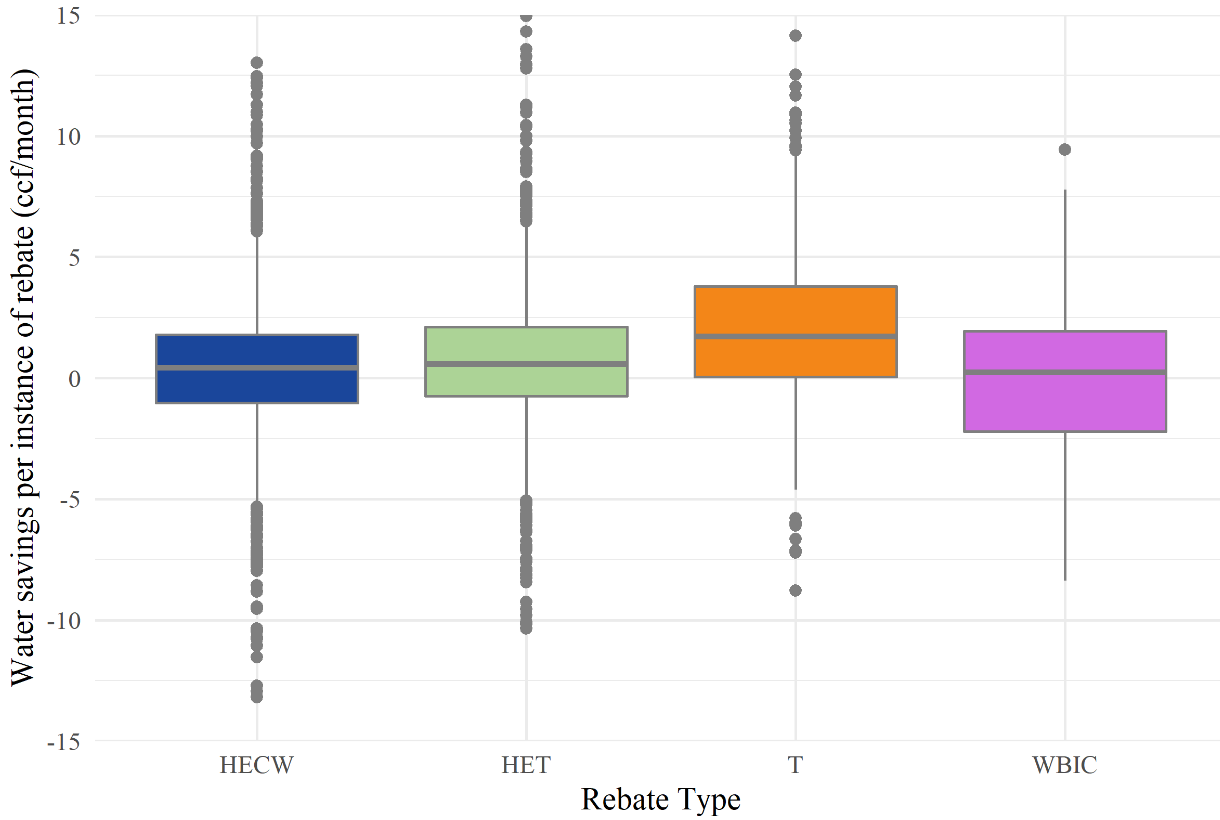


Figure 12. The boxplot for the water savings per instance of rebate calculated with the DID method, showing the distribution of individual customer's water saving results. The middle grey horizontal lines represent medians, the boxes present interquartile ranges (IQR, i.e., 25th to the 75th percentile or Q1 to Q3), the grey vertical lines (whiskers) extend from (Q1 – 1.5 IQR) to (Q3 + 1.5 IQR), and the grey points are counted as outliers. The unit of water savings is ccf per month. Data Source: Moulton Niguel Water District.

Notably, in **Figure 12**, all water saving medians for those four rebate programs are positive, which means at least half of the customers did save water through installing those devices. Among the four programs, turf removal (T) had the highest median savings per instance of rebate. This result shows the significant positive impact from outdoor water efficiency programs. The range of the box (the 25th to the 75th percentile) varies among the programs: the range of WBIC is the largest, followed by T and then HET, with HECW approximately equal to HET. The number of outliers is also different: HECW and HET have the largest number, and are approximately the same, followed by T and then WBIC. These two phenomena might be due to sample size difference. As shown in **Table 7**, the sample size pattern is HET > HECW > T > WBIC. The magnitude of HET and HECW are close but much higher than the other two programs. Therefore, the larger the sample sizes are, the less influence the outliers would have, and the more accurate and significant water saving results this study is likely to obtain.

Table 7. Monthly water savings for installing one unit of rebate with DID method. Negative numbers mean that a rebate program contributes to more water use. The first value in the 'Water Savings' column is the average savings, the second value after the "±" sign is the standard deviation. Data Source: Moulton Niguel Water District.

Rebate Program Type	Sample Size	Water Savings (ccf per Unit of Rebate Installation per Month)	Water Savings (Gallons per Unit of Rebate Installation per Month)
High-efficiency toilets	1503	0.41 ± 1.68	310.28 ± 1253.24
High-efficiency clothes washers	1323	0.38 ± 2.68	287.22 ± 2006.60
Area of turf removed (ft^2)	572	0.0023 ± 0.0037	1.70 ± 2.75
Weather-based irrigation controller	70	-0.017 ± 3.00	-12.55 ± 2245.83

As seen in **Table 7**, efficient toilets were predicted to save more water on average than other programs per unit. Although the magnitude of water savings from turf removal is far lower than other programs per unit, households typically replace hundreds of square feet of turf at one time (in contrast to toilets and washing machines). It is worth noting that weather-based irrigation controllers (WBIC) appeared to slightly increase water consumption. However, WBIC had a positive median, suggesting overall water use decreased (see **Figure 12**). Additionally, the standard deviation for WBIC is the highest (3.00 ccf/month) among the programs. It also has the smallest sample size (70). Those factors may undermine the reliability of the water saving results. It is probable that WBIC devices can save water. Due to data limitations, this study was unable to obtain a more accurate and significant estimate for the WBIC program.

6.1.4 Comparison of Water Savings Results

Table 8 displays monthly savings realized through participation in each of the rebate programs examined, as estimated by Phase III of UCR's study (Schwabe, K., 2017). It also displays the mean quantity of rebate devices (or area of turf removed) issued for the rebate invoices that this study examined, and the total number of invoices examined for each rebate type.

Table 8. UCR estimated water savings (ccf/month), average rebate quantity, and total invoices examined for five rebate programs. Data Source: Schwabe, K. et al. (2017)

Rebate Program Type	UCR-Estimated Savings (ccf/month)	Mean Rebate Quantity	Total Invoices Examined
High-efficiency toilets	1.53	1.663 toilets	5162
High-efficiency clothes washers	1.87	1.000 washers	6945
Rotating spray nozzles	0.98	45.768 nozzles	155

Turf removal	0.85	831.146 ft^2 replaced	2155
Weather-based irrigation controllers	0.99	1.049 controllers installed	1242

Table 9 displays the monthly water savings per unit rebate issued as estimated by the multi-variable linear regression model and the DID method. It also displays the monthly water savings as estimated by Phase III of the UCR study, normalized (divided) by the mean rebate quantity for the rebate invoices examined in this study. This normalization was done to put the monthly savings estimates in a set of consistent units (monthly savings per unit of rebate issued).

Table 9. Comparison of UCR's water savings and calculated water savings using a regression model and the DID method used in this study. Data Source: Schwabe, K. et al. (2017) and Moulton Niguel Water District

Rebate Program Type	Water Savings (ccf/month) by Source		
	UCR (Normalized)	Regression Model	DID Method
High-efficiency toilets	0.92 per toilet	0.26 per toilet	0.41 per toilet
High-efficiency clothes washers	1.87 per washer	0.38 per washer	0.38 per washer
Rotating spray nozzles	0.021 per nozzle	-0.01 per nozzle	Not examined
Turf removal	0.102 per 100 ft^2	0.107 per 100 ft^2	0.230 per 100 ft^2
Weather-based irrigation controllers	0.94 per controller	-0.066 per controller*	-0.017 per controller

* The regression model coefficient for WBIC was also normalized by the mean number of controllers installed

As can be seen in **Table 9**, estimated monthly savings varied between the two methods used in this study. Moreover, the estimates obtained in this study diverged considerably from those in Phase III of UCR's study, especially when one considers the magnitude of the standard deviation of estimates. With the exception of regression-estimated turf removal savings, the two methods used in this study consistently found lower and even negative savings (suggesting increased water use).

The difference between savings estimated in this study vs. those estimated in Phase III of UCR's study mirrors the difference in savings estimated in Phase I vs in Phase III of UCR's study. The implications of this finding are discussed further in the Discussion section; however, it suggests that the methods employed did not sufficiently correct for external factors as was done in UCR Phase III. For this reason, it is probable that the monthly water savings estimated via regression and DID in this study are less accurate estimates of monthly water savings than those estimated by the UCR study. As a result, only the UCR normalized monthly water savings estimates were used in Phases III and IV of this study.

6.2 Energy Intensity and Embedded Greenhouse Gases

Embedded energy and embedded GHG values were found for all years 2010 - 2019 and calculated by functional domain. All embedded energy values are reported in kWh/AF and embedded GHG values are reported in kgCO_2e/AF. A large portion of embedded energy and emissions came from potable water distribution; however, the majority of the embedded energy and resultant emissions from the potable water functional domain is attributed to upstream usage by MWD. When observing MWD supply and MNWD potable water as separate entities, it becomes apparent how small the embedded energy of MNWD's potable water distribution system is compared to MWD's supply.

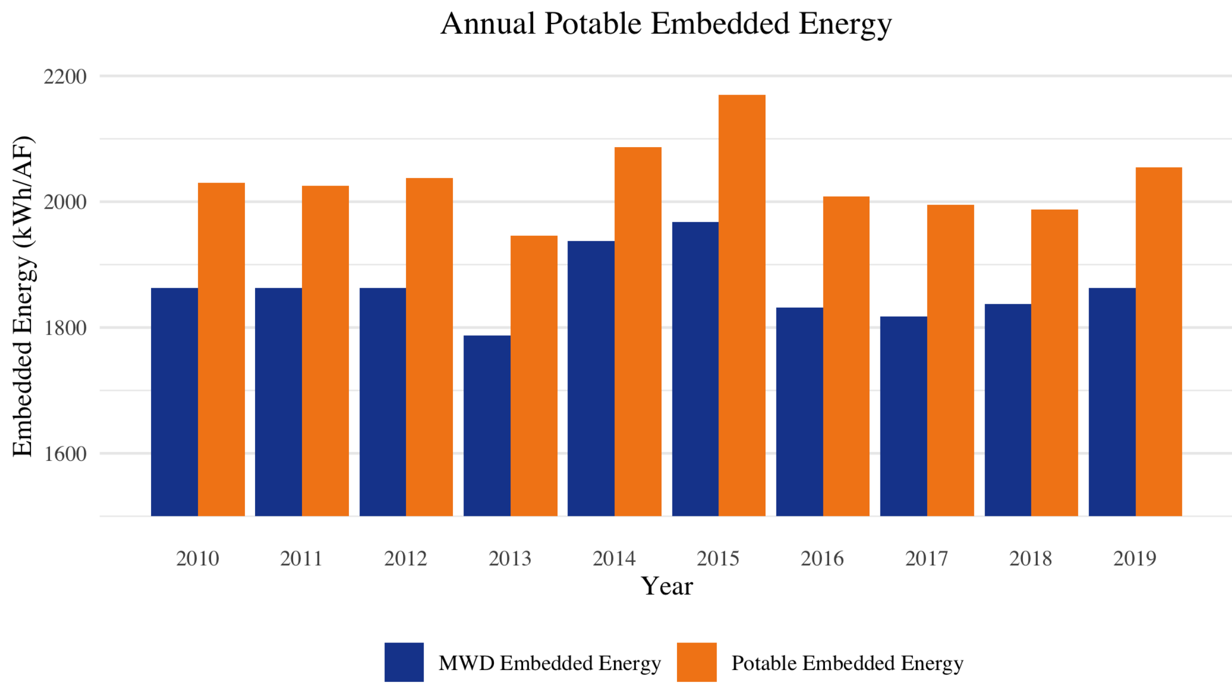


Figure 13. Total embedded energy in MNWD's potable water, as well as MWD's contribution to that value. MNWD's distribution system contributes very little to the total potable embedded energy. Note the general increase in 2014 and 2015; this change is a result of the imported water volume decreasing while the energy use remained similar.

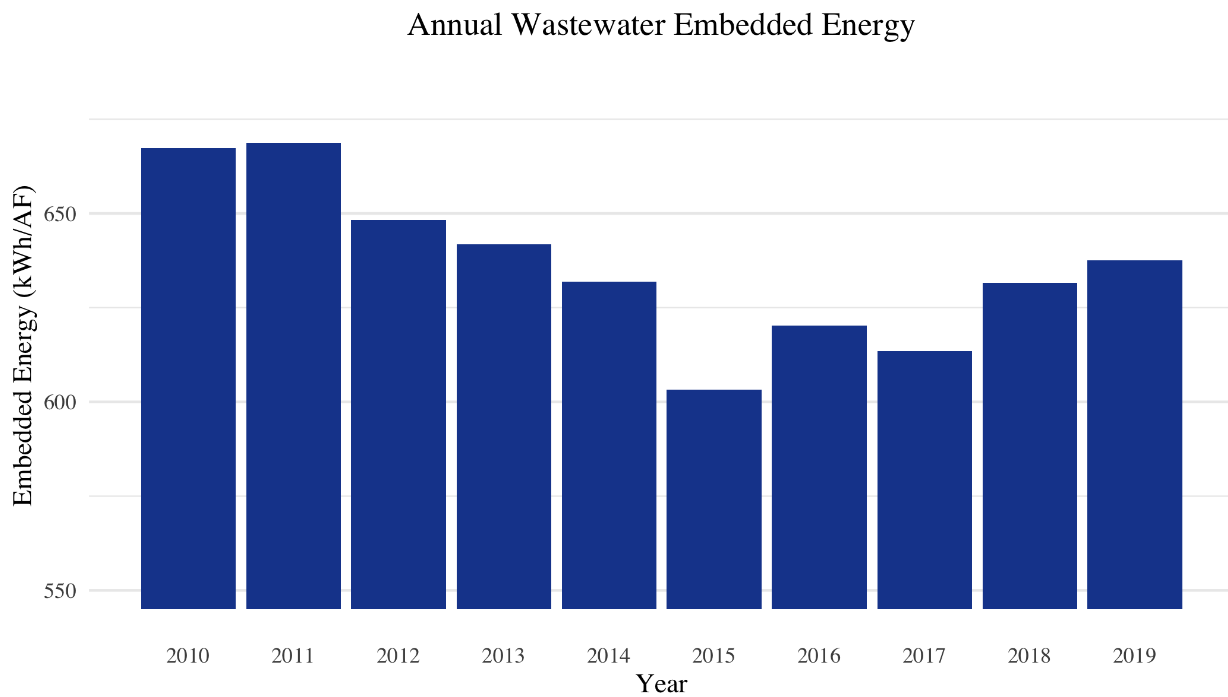


Figure 14. Embedded energy in wastewater for MNWD from 2010-2019. The decrease in 2015 is a result of the wastewater volume being at its peak, while the wastewater energy use also fell.

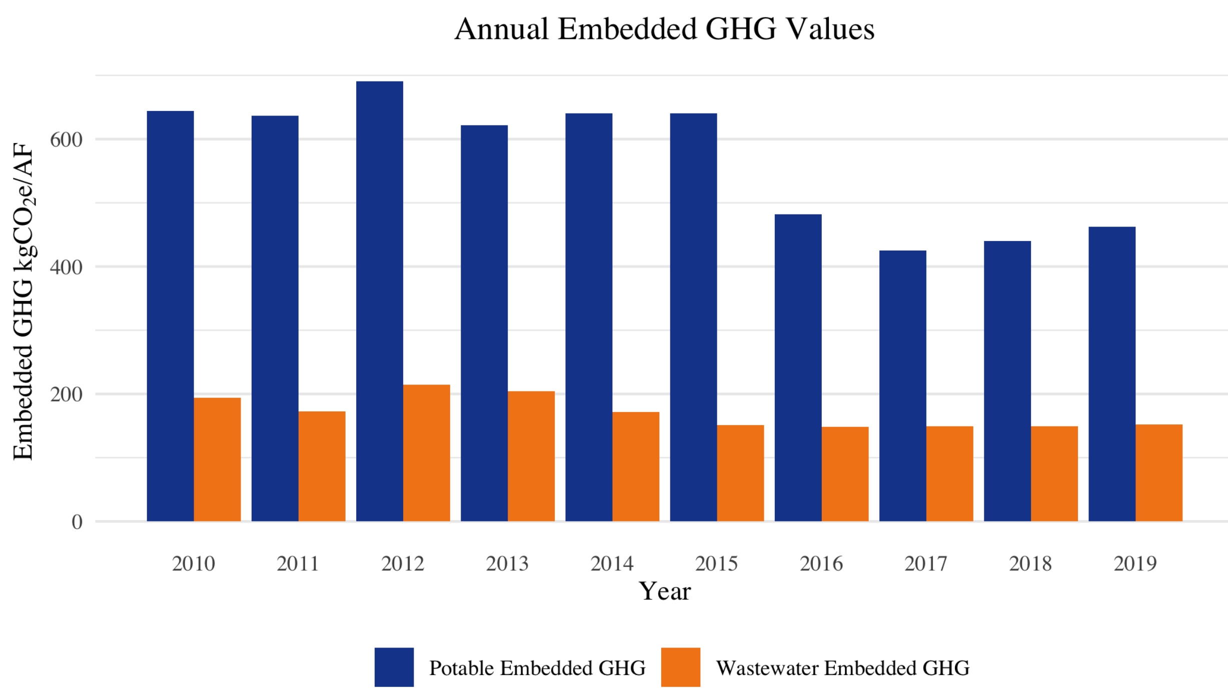


Figure 15. Embedded GHG values for the potable water distribution and wastewater functional domains of the MNWD water distribution system for 2010-2019. Unlike embedded energy, embedded emissions decrease over the study period, due to reductions in grid emissions factors.

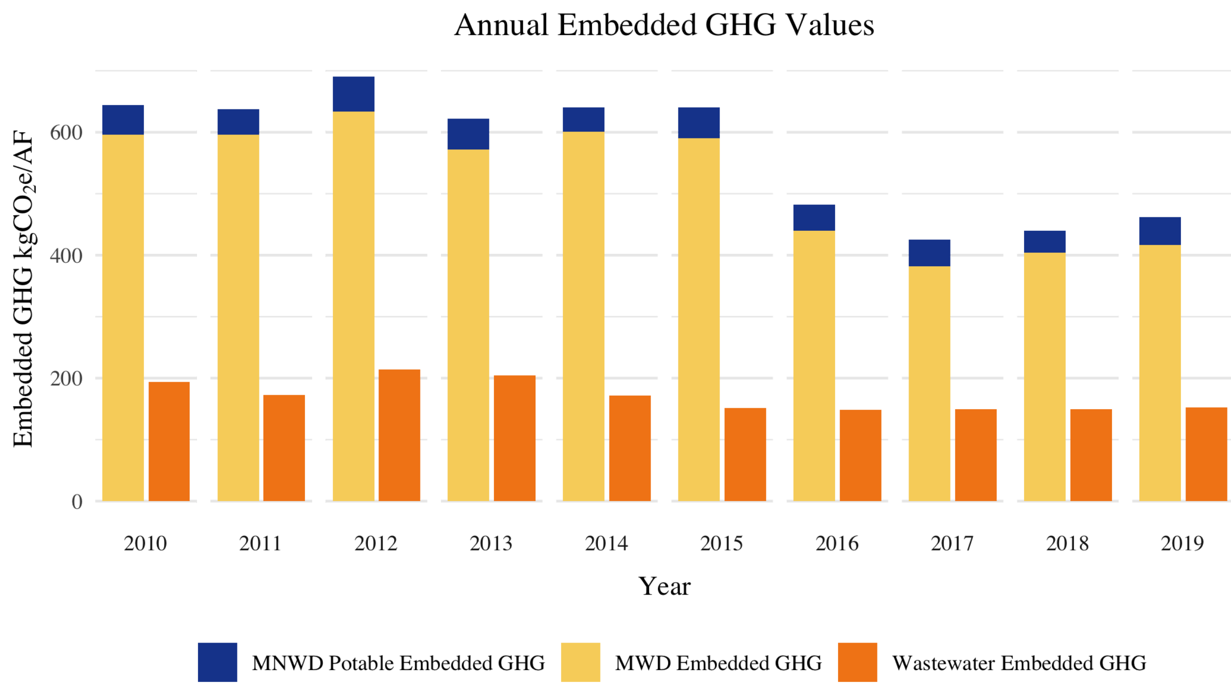


Figure 16. Similar to **Figure 15**, but potable embedded emissions are separated by relative contribution by MWD and MNWD. While potable embedded GHG are significantly greater than the values for the wastewater domain, it is important to note that most of the emissions are occurring outside of MNWD's district boundary. Within MNWD's boundary, wastewater accounts for significantly more GHG than potable distribution.

6.3 Water Saved, Energy Saved, and Emissions Mitigated from Rebate Programs

As mentioned in Section 6.1.4, the final analysis of this study was conducted using the estimates of monthly water savings obtained in Phase III of UCR's study to preserve accuracy. The results of the final analysis are tabulated below in **Table 10**. **Figures 17-19** below display how these savings accrued through time, how the rate of savings changed over time, and the relative contribution of each rebate program to total savings.

Table 10. Estimates of total water saved, energy saved, and greenhouse gas emissions mitigated by MNWD's examined rebate programs, 2010-2019.

Rebate Program Type (# of rebates examined)	Total Water Saved (AF)	Total Energy Saved (MWh)	Total Emissions Mitigated (metric tons CO_2e)
High-efficiency toilets (n = 5162)	1438	3767	957
High-efficiency clothes washers (n = 6945)	2302	6027	1554
Rotating spray nozzles (n = 155)	24	50	13

Turf removal (n = 2155)	201	406	94
Weather-based irrigation controllers (n = 1242)	122	247	60
Total	**4087**	**10497**	**2678**

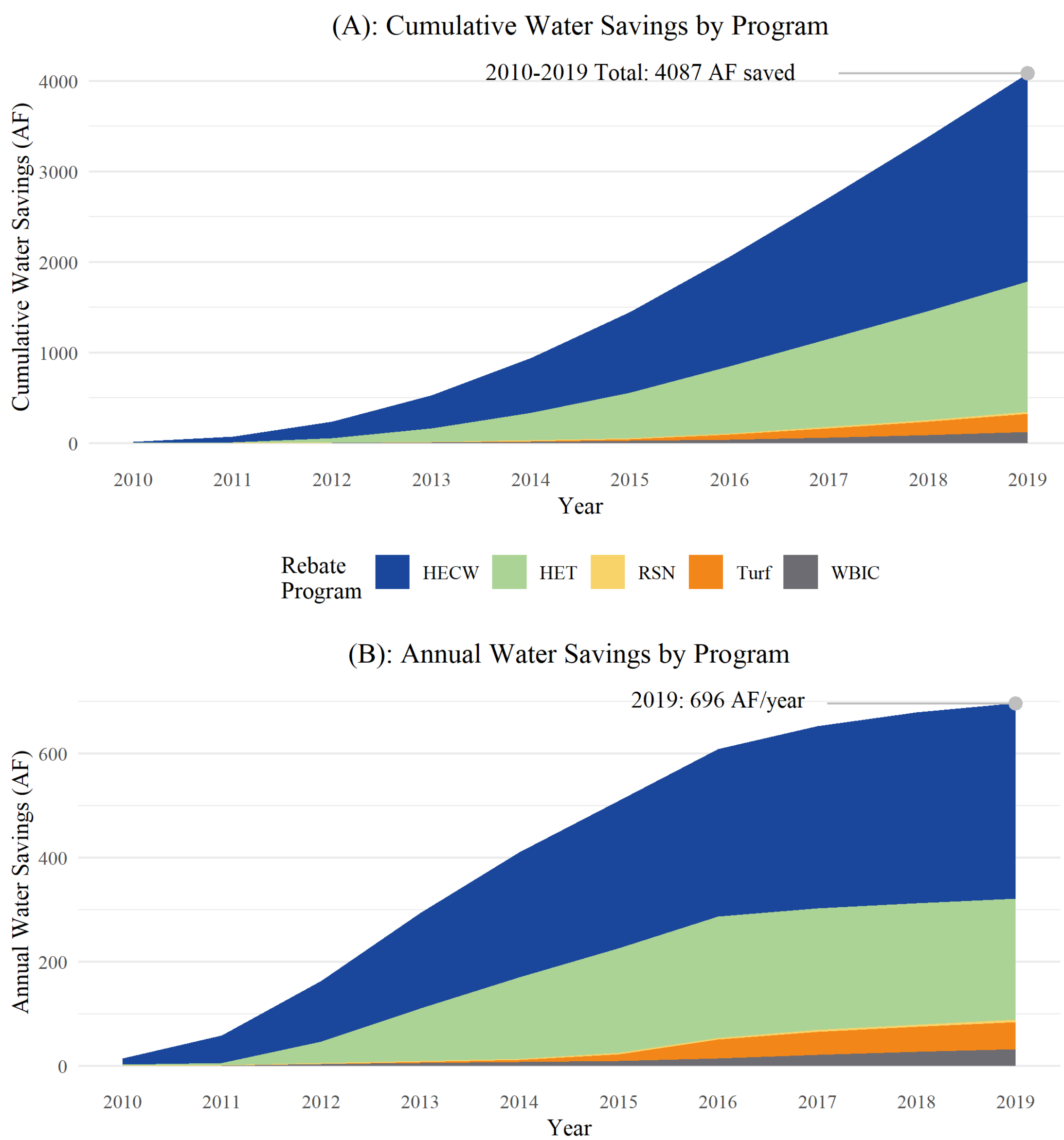
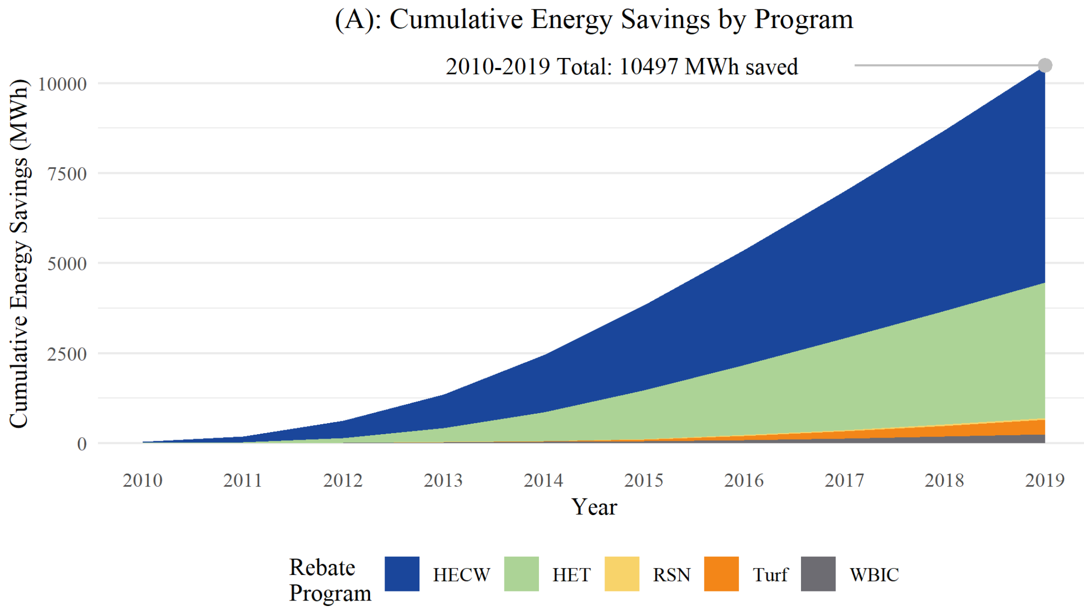


Figure 17. (A) above shows cumulative water savings over time delineated by rebate program. **(B)** above shows water savings in each year of the study period, also delineated.

As is visible in **Figure 17**, the HECW and HET programs make up the bulk of total savings. This is to be expected, as the majority of rebates examined were issued through those two programs

(12,107 out of 15,659). **Figure 17 (B)** shows how the Turf and WBIC programs comprise a larger proportion of annual savings in 2019 than they do of cumulative savings during the study period. This is because participation in those two programs was greater after 2015, whereas many of the accounts that participated in the HECW and HET programs did so before 2015 (see **Figure 11**).



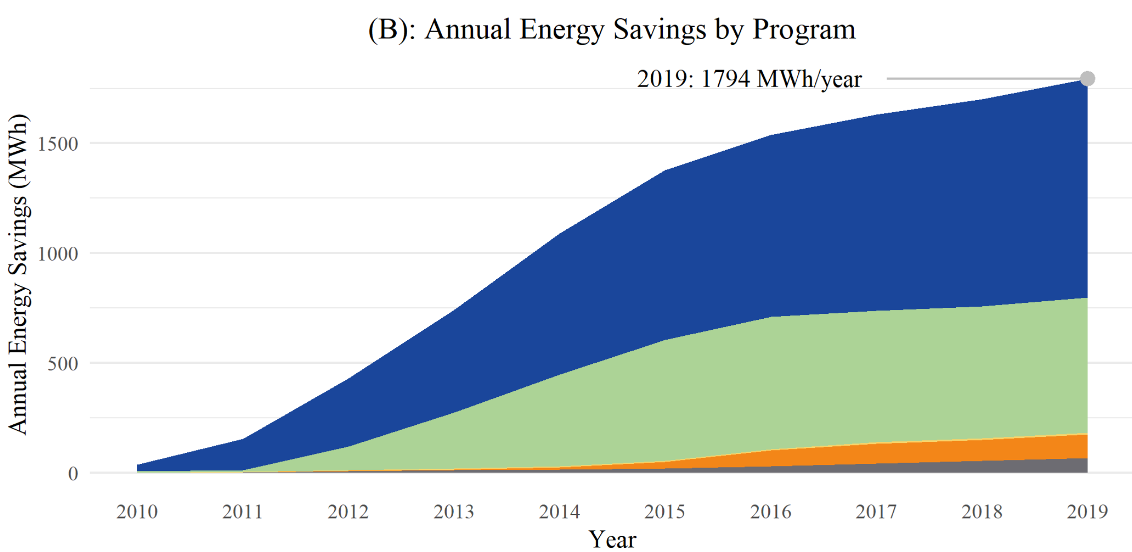


Figure 18. (A) above shows cumulative energy savings over time delineated by rebate program. **(B)** shows energy savings in each year of the study period, also delineated. Both graphs include savings from both potable distribution and wastewater.

Energy savings shown in **Figure 18** have patterns similar to those in the water savings in **Figure 17**. However, the HECW and HET programs make up a slightly larger proportion of total and annual energy savings because these programs also accrue savings from avoided wastewater treatment. Annual savings show a slightly steeper increase from 2018 to 2019 than water savings because embedded energy rose in 2019 after remaining relatively constant from 2016 to 2018.

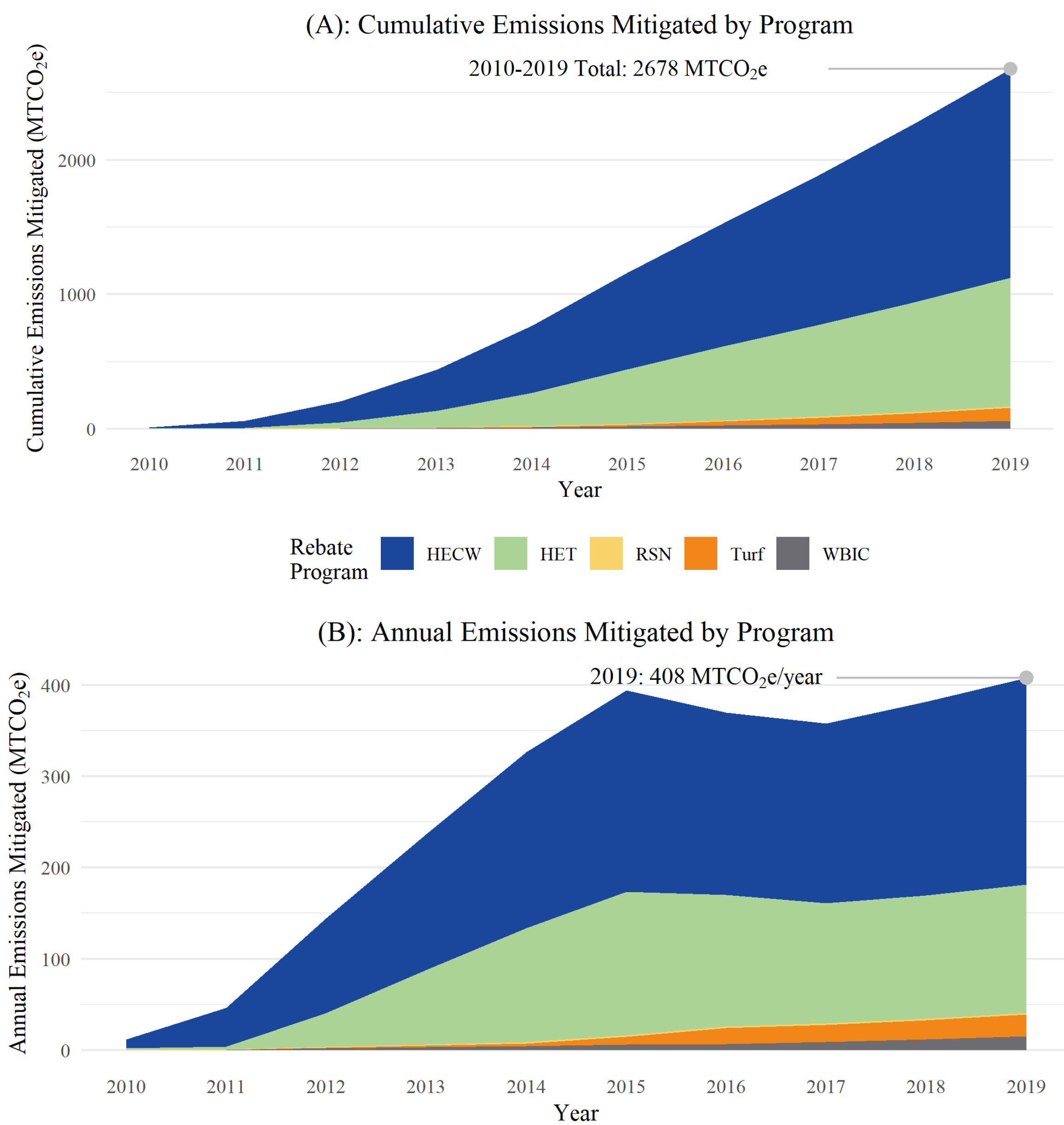


Figure 19. (A) above shows cumulative emissions mitigated over time delineated by rebate program. **(B)** shows emissions mitigated in each year of the study period, also delineated. Both graphs include mitigation from both potable distribution and wastewater.

In contrast to **Figures 17 and 18**, **Figure 19** above shows slightly different patterns. Annual emissions mitigated declined from 2015-2017 due to reductions in embedded emissions resulting from a cleaner energy grid mix (see **Figure 16**). This caused the rate of accumulation of emissions mitigation to decelerate slightly during those years, whereas accumulation of water and energy savings continued to accelerate; however, this deceleration was fairly minor.

7. Discussion

This section contains additional discussion related to project methods and results presented in the previous sections, beginning with project-level results and framework development. It explores potential explanations for the magnitudes of water savings found, including the influence of certain customer characteristics, assumptions, and method choices. The section also discusses causes of the interannual variability seen in the embedded energy and greenhouse gas (GHG) emissions as well as addressing limitations of the data used.

7.1 Program-level Energy and Greenhouse Gas Savings and Framework Development

Based on the results shown in Section 6.3, total savings across all three categories were most influenced by rebate participation. The rate of accumulation of savings was driven more by the rate of rebate participation than by the magnitude of per-device savings. Though somewhat obvious, it then follows that the key to achieving the greatest savings is to increase overall rebate participation as opposed to solely participation in the highest per-participant savings programs. Related, total savings are sensitive to those rebate programs that have high participation rates. Total energy and GHG savings are therefore particularly sensitive to programs which, in addition to having high participation, accrue energy savings in many stages of the water use cycle (i.e., customer end-use and wastewater treatment in addition to potable distribution).

The rate of savings accumulation, or savings in a given year, appeared to be more influenced by variability of embedded energy and GHGs. The charts of cumulative savings each had similar trajectories, with smooth accelerating increases and approximately the same partitioning between rebate programs. However, annual energy savings showed a slight influence of variation in embedded energy. For annual emissions mitigation, the decrease in embedded GHGs due to grid updates had an obvious influence on savings in a given year.

Energy savings and GHG emissions calculated here are total water use supply chain savings. This has several implications. First, energy cost savings cannot be estimated without further partitioning because these savings are not directly attributable to Moulton Niguel Water District (MNWD). Additional methods would need to be employed to allow for estimation for direct energy cost savings. Second, GHG emissions mitigated are also not directly attributable to MNWD. While this does not lessen their impact in terms of overall climate action - GHGs are, after all, stock pollutants - it is a carbon accounting issue. Both MNWD and its water suppliers have emissions reductions goals, and it is not immediately obvious as to which entity's target reduction these emissions mitigated should be counted.

The methods used to calculate program-level savings strongly influenced framework development. Once all the requisite inputs had been obtained (rebate invoice data, water savings, and embedded factors), calculating program-level savings was simple and straightforward. The approach taken, based on established methods for calculating savings using embedded energy and GHG factors, could be summarized using the set of basic mathematical equations described in section 5.3.2. To create the framework, these equations were rewritten in more general forms so as to be applicable to the water use supply chains generally, rather than MNWD's supply chain specifically. Basic data requirements and management best practices were also listed to guide future analyses based on lessons learned during the completion of this project. The framework can be found in Appendix 7.

7.2 Water Savings and Rebates

7.2.1 Factors Influencing Household Water Consumption

The decision to use two separate methods for estimating water savings per unit rebate was driven by the presence of several confounding factors that had high potential to obscure results. These factors include sustainability messaging related to the drought and water use, installation of rebate-eligible devices among accounts that did not participate in rebate programs, and "rebound effects" or diminished water savings over time. Potential impacts of these factors are discussed in the following paragraphs.

Moulton Niguel Water District (MNWD)'s residential customers appear to have adjusted behavior in response to messaging about the severity of California's drought in the years from 2014 to 2016. This is evidenced by the magnitude of the "Post E.O. B-29-15"[5] indicator regression variable and visual inspection of district-level 12-month rolling average of water use. For some rebate participants, this may have driven their participation in a rebate program. Conversely, customers who installed eligible devices without rebate participation may have been motivated to do so by the same messaging. However, some customers may have only altered behavior, foregoing installation of a specific water-saving device, and they may or may not have continued with such water-conscious habits as drought messaging became less salient. They may have even adjusted behavior not in response to messaging or media coverage, but because of changes the MNWD made to per capita water budget allocations in order to encourage conservation.

Because the estimated magnitude of the response to drought conditions is large compared to estimated savings per unit of rebate participation, further research may obtain a more accurate estimate of rebate-driven savings over this time period. Evaluating the response to drought messaging, how that response manifested itself in water-efficient device installation, and how that installation was captured by records of rebate participation represents a potential approach for this research.

Beyond responses to drought messaging, installation of rebate-eligible devices without participation in rebate programs biases estimates of per-device savings downwards. This is because non-participants are implicitly assumed to have not installed such devices. When the water use of rebate participants is then compared to the use of non-participants, the estimate of water savings is decreased because the benchmark against which savings are measured is lower. To account for this, Phase II of UC Riverside (UCR)'s study used a survey that assessed device installation, and used its results to control for this behavior among non-participants. The current analysis lacked such a survey, and as a result had no way to control for this behavior. Moving forward, it may be wise for water providers to make the distribution of such surveys customary when attempting to measure the effectiveness of rebate programs, especially when measuring effectiveness during a period of drought or another time when installation by non-participants is expected. Further research into the drivers of such behavior may reveal ways to predict and account for it in these kinds of analyses based on demographic factors without the need for surveys.

[5] Gov. Jerry Brown's Executive Order B-29-15 required the state to reduce potable water usage by 25%

Estimates of savings from rebate participation may also be influenced by rebound effects, or the return to prior, less-efficient water use behaviors as time progresses. Rebound effects are expected to have a larger influence on savings estimates when longer time periods are studied. To properly account for this, savings must be studied in relation to the initial date of rebate participation to determine if some dynamic element is present. As with device installation by non-participants, further research into the magnitude of rebound effects and their drivers may reveal ways to account for rebound effects without complex methods based on household demographics.

In the case of UCR's study, responses to the survey issued in Phase II provided researchers with additional data on customer characteristics and behavior. That data was used in Phase III to correct for factors obscuring savings results, particularly sampling bias and implementation of water-conserving technologies, thereby improving accuracy of results. This correction resulted in savings estimates increasing relative to those found in Phase I.

7.2.2 Regression Model Findings of Water Use Increases

The multi-variable linear regression model described in 5.1.2.1 predicted savings for each unit of rebate participation in the high-efficiency toilet and clothes washer programs, as well as for the turf removal program. However, the model predicted that each nozzle installed through the rotating spray nozzle (RSN) program tended to increase monthly water use by approximately 1 ft^3. It also predicted that customers who participated in the weather-based irrigation controller (WBIC) program tended to use approximately 7 ft^3 per month more than those that did not, all else being equal.

One potential explanation for this could be the fact that the regression model predicted monthly water use. Customers who participated in these two programs could be those that irrigate significant areas, and have higher water usage as a result. When monthly water use is predicted, customers who are participating in the RSN or WBIC programs may be saving water relative to their past behavior, or relative to what they could have used if they had not installed a high efficiency device. Because their use is so high compared to other users the model may not capture this fact. This could also be the reason for the lack of statistical significance for the WBIC participation coefficient. Another potential explanation for the WBIC coefficient is that customers may have previously practiced debt irrigation (watering under plant requirements) while WBIC devices are designed to meet plant water based on weather conditions. The RSN devices may also be driving a behavioral shift. For example, users may think that they need to irrigate more because their newly installed nozzles are supplying each plant with less water than before.

7.2.3 DID Model Discussion

One of the steps in the DID model was comparing the average monthly water use in the pre-rebate period and the average use in the post-rebate period, assuming that rebate programs would save the same amount of water each month. Although it is easy to understand and quantify, some key information would inevitably be neglected, such as seasonality. The parallel trend inspection (shown in **Figure 8**) demonstrates the seasonality in customers' water consumption behaviors. It is also reasonable to anticipate that outdoor programs, especially the turf removal, tend to save more water in summer than in winter. This phenomenon is intuitive, given people are likely to water their garden more frequently in the warmer months due to higher evapotranspiration and higher water demand of vegetation. As the baseline water uses in colder months are already relatively low, the possibility for water savings are limited. The seasonality might influence the results of DID since each rebate participant had their own timeline based on their earliest joining date. If one customer joined in the summer of the earlier post-rebate period, they would more likely be observed to have higher water savings. In contrast, if they joined in the fall or winter during the last year of the post-rebate period, they might demonstrate lower water savings. One possible way to address the seasonality issue is to create the pre- and post-treatment periods in increments of 12 months around the rebate invoice dates. That would remove partial years from the assessment and the seasonal bias would be alleviated. However, due to time constraints, this study was not able to further improve the DID method.

Three interesting findings in the DID results are also worth discussing. First is the possible water use increase for the weather-based irrigation controller (WBIC). The mechanism of WBIC needs to be understood before properly interpreting the result. WBIC is a type of smart controller that can calculate evapotranspiration (i.e., the amount of water lost from soil and plants) using weather data, and therefore can automatically determine the appropriate irrigation schedule (Smart Water, 2015). It is possible that the controllers would increase irrigating time in response to warm and dry weather, leading to an increase in water usage. Another way to analyze the response to weather is to factor in the customer's water use efficiency; that is, the ratio of their water use to their overall water budget. The water budget captures various factors (such as water rate, customer characteristics and policy changes) and can be adjusted to address any changes.

The second finding is the magnitude of turf removal per unit. It might look concerning at the first glance since it is far smaller than other programs. In fact, the potential of water savings in this program is reasonably high because the unit of measurement was one square-foot of turf removed, rather than one device installed. The average irrigation area removed via the turf program from MNWD customers is 831.1 ft^2 (see Section 5.3.1). Consequently, the turf removal program could save about 1,415 gallons of water for one average household per month.

Lastly, it is worth noting that the estimated water savings for HET and HECW are not as high as advertised. For example, some companies claim that their water efficient toilets can save at least three gallons per flush (Constellation, 2017). Based on their statement, on average, one toilet can save over 450 gallons per month per person, which is higher than the findings of this study (about 310 gallons/month). One possible explanation is that device efficiency standards have been stringent in California for decades. In 1994, the national maximum flow standard for both commercial and residential toilets was 1.6 gallons per flush as the Energy Policy Act went into effect (Alliance for Water Efficiency, 2014). California went further and set the upper limit at 1.28 gallons per flush in 2016 (Peterson, 2015). As a result, customers may have already installed some low-flow toilets before the study started which would lower the baseline use in general. Additionally, the control group customers might have also purchased and used water efficient toilets on their own without reporting the device change to MNWD. The presence of unreported high-efficiency toilets in the control group would cause an underestimation in the water savings for rebate programs. Another potential reason the derived water savings for these two rebate programs is lower is that the water use difference in the pre-intervention period between HET or HECW participants and non-participants was not significant compared to other programs' participants (see **Figure 8**). Toilets are not unique; many other efficiency programs also face similar challenges. As the standard becomes tighter and decades of promotion compound, the market will be saturated by high water efficiency devices. The amount of water savings that can be captured from upgrading those devices will continue to decrease.

7.3 Water and Rebate Data Limitations

As noted in the UCR study, usage of water efficient devices without rebate participation was higher than usage with rebate participation. Specifically for MNWD, its residential customers' relatively low awareness of rebate programs, particularly of outdoor programs, naturally leads to low participation in rebate programs. Additionally, in the present day, more companies are setting corporate sustainability goals. This is due to compliance with current, new, or possibly future legislation and the implementation of federal programs, such as EPA WaterSense, that aid companies in establishing or improving their credibility by certifying their water efficiency products. For example, 100% of bathroom appliances sold at The Home Depot are now under the EPA WaterSense program—which certifies water efficiency products. This gives residential customers more access to water efficient devices.

Because many factors contribute to water savings, limitations existed in their calculation, such as the inability to decouple water savings from rebate program participation. Any sort of water savings calculation could be over- or underestimating the effect rebate programs has on the consumer. This is due to the limitations stated prior, policy implementations, and water shortage contingency stages implemented by MNWD. These stages range from voluntary to mandatory water reductions.

Limitations that existed with choosing which method to use to calculate water savings are mainly associated with the assumptions from the data provided and that rebate participation was voluntary and not randomized. Residential customers self-select themselves into participating in a rebate program which can create bias in the results. Biases include residential customers being more likely to be more environmentally conscious or willing to change behaviors to reduce water consumption.

Data collection by MNWD for customer characteristics could have also influenced the amount of water savings per person in each household. Default values for two customer characteristics are given to residential customers. The first being the number of people per household, which is based on the type of household or rate schedule a customer is given (single family household, R1, and condo/townhouse, R2). When water budget-based rates were first introduced, MNWD automatically assigned residential accounts a household size. Single family household (R1) customers were defaulted to 4 people and condos or townhouses (R2) to 3 people. Currently, when an account is opened with MNWD, the district determines the actual household population size. As noted prior, customers who were initially assigned a default value are given the opportunity to update their household size, but typically do not. Additionally, irrigated areas of households could also be given a default value. MNWD does calculate irrigable areas for each household using satellite imagery. However, a default value of 300 ft^2 is assigned for condos/townhouses with known patio/irrigable areas— unless a more accurate number can be obtained. The default value is based on the average of known condos/townhouses patio/irrigable areas.

Finally, choices made during data manipulation may bias savings results. Only studying accounts with continual, non-zero use for extended periods of time may mean that long-term homeowners are over-represented as compared to renters or those that recently purchased a home. While exploring the relationship between duration of home-ownership and water use patterns was beyond the scope of this analysis, long-term homeowners may have financial stability that makes them more able to afford water-efficient devices without rebate participation. Moreover, personal communication with MNWD indicates that new homeowners often participate in rebate programs during the first two years of moving into a new home. Filtering conditions for accounts with continual use over an extended period of time exclude these rebate participants, biasing savings estimates downwards. Overall, further research into effective methods to account for data gaps and heterogeneous timelines of water use is required. These methods could be employed when estimating rebate savings so as to capture the full spectrum of water use behavior.

7.4 Embedded Energy and Greenhouse Gas Emissions

The derived values for embedded energy did not vary significantly. This is especially true for potable embedded energy, for which energy expenditure during conveyance was the primary factor.

Embedded greenhouse gas values did vary, especially for potable distribution, for which they decreased significantly over the study period. As energy use and embedded energy did not significantly decrease, the primary cause of this decrease is changes in emissions factors. The overall emissions factor for California decreased greatly over the study period, driven by a variety of market forces and governmental policy. As seen in **Figure 20** below, the emissions factors for SCE and SDG&E also decreased following an initial spike.

7.5 Energy Data Limitations

The major limitation for the energy and GHG analysis was data availability. Because MNWD is first and foremost a water district, it is by nature rich in water-related data and less so in energy-related data. The energy data provided to MNWD by SCE and SDG&E was organized in the manner used by the relevant utility. There were differences between how data was collected and presented for meters falling under one utility's jurisdiction versus the other.

Furthermore, after receiving the energy data from SCE and SDG&E, data would often be combined and organized in a format more suitable for MNWD. This means that there were at least three different ways in which energy data was presented for the electric meters, which resulted in data gaps for energy consumption. A primary barrier was that both electric utilities discard energy data dating back more than three years, so data prior to 2017 is now inaccessible on their systems.

Many of MNWD's electric meters became inactive during the study period. These meters were therefore omitted in later comprehensive datasets, even if there was a record of their energy consumption for some portion of the study period. There is some discontinuity about certain meters' functional domains, while other meters may be unnamed and have little documentation about their functionality. MNWD requested that the electric utilities provide their most detailed electric meter data containing the original functional domain codes to help identify the true functional group for meters in dispute.

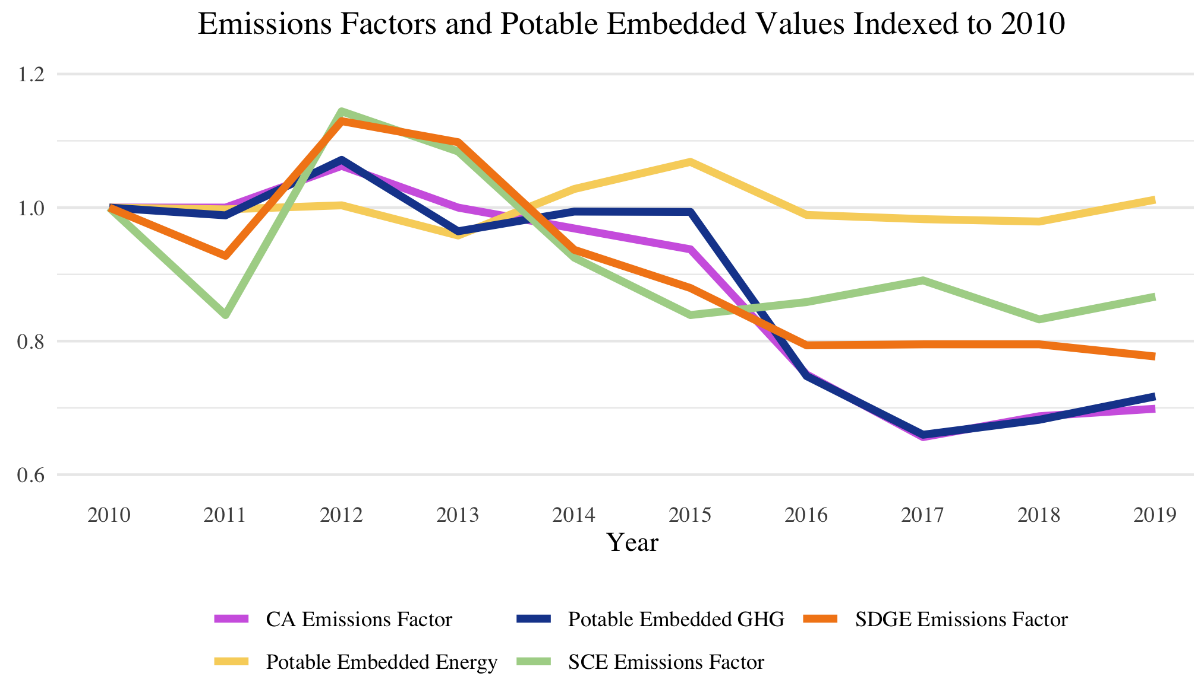


Figure 20. 2010-indexed plot of emissions factors, potable embedded energy and potable embedded greenhouse gases. Note the parallel trend between the decrease in the California regional emissions factor and the decrease in the embedded greenhouse gas values.

The energy regression model was originally meant to contain the following predictor variables: year and month to account for annual trends and seasonality, functional domain, the rate assigned to the meter by the electric utility, water use, rebate participation by residents using water associated with a given electric meter, the pressure zone the meter fell in, and the elevation above sea level of the meter. While there are addresses for each electric meter, the electric utilities do not store latitude/longitude coordinate data for those meters. These addresses were used in conjunction with a publicly available online geolocating tool to generate latitude/longitude coordinates. Because there was no data to define the pressure zone layout of the district, a GIS layer for lines of pressure was used in conjunction with proximal zoning in order to derive an estimate of pressure zone for each meter. Both of MNWD's electric utilities have an interconnected network system allowing multiple sources of supply to run together, making it difficult to tie electric meter use to water meter use. There may be multiple electric meters servicing a single water meter, as well as a single electric meter servicing multiple water meters, so there is no clear way to tie water use at a given water meter to energy use at a given electric meter.

These limitations may render the development of a repeatable framework difficult to achieve. The framework for this project is geared towards larger water districts, as smaller districts are more likely to lack the resources necessary to store data in workable formats. After being revealed in this project, these potential limitations can be relayed to MNWD and other water districts to help them better understand what data should be collected to aid in quantifying their energy and water savings. For MNWD, it may be beneficial to obtain coordinates for electric meters and pressure zone rasters as well as digitizing invoices and other files stored in scanned PDF formats to better analyze energy and water cost savings. Ultimately, the limitations revealed by this project were seen as an opportunity for future water-energy nexus projects to arise.

Conclusion

Based on the results from this project, we conclude that energy savings can be achieved from water saved through efficiency programs. These energy savings then translate to mitigated greenhouse gas emissions. Embedded energy was found to have remained relatively constant throughout the study period, and was largely dependent on energy use during transport via the State Water Project (SWP) and Colorado River Aqueduct (CRA) rather than MNWD's operations. Variations in embedded energy are thought to be due to change in the relative proportions of water obtained from the SWP and CRA, as each source has significantly different energy consumption; however, a lack of data on these proportions makes this hypothesis difficult to confirm. Embedded GHG emissions were found to have decreased significantly over the course of the study period. This is the result of the reduced emissions of the California energy grid as the supply of renewable energy sources increased.

Understanding which programs yield the highest water savings per dollar, and therefore energy savings, allows water utilities to invest more on specific programs, such as outdoor versus indoor. Additionally, understanding the locations (e.g. service area, imported or local water supply sources) with the highest embedded energy values can help a water utility identify where to target future energy savings initiatives. The amount of greenhouse gases mitigated is not only dependent on the energy used by a utility, but also the nature of the energy sources used (e.g. renewable or nonrenewable).

Further studies need to be conducted to streamline the process of calculating energy savings from efficiency programs, more specifically on how to calculate water savings in a streamlined, accurate manner. Once these processes are solidified, more utilities will be able to conduct their own analysis. This can aid decision-makers in changing existing policies that currently disincentivize water and energy utilities from collaborating on efficiency programs.

Appendices

Appendix 1: Software Programs

The majority of data provided by MNWD was in the forms of .xlsx and .csv file types and were formatted and analyzed using R programming language in the RStudio user interface. For reproducibility, all R projects were made with version control in a shared GitHub group.

1.1 Water

The dataset used in the multi-variable linear regression model was prepared in a JupyterLab kernel using the R programming language. The linear regression model was created using R in the RStudio user interface. In both instances, the tidyverse collection of R packages was used for basic data manipulation, and the lubridate and zoo packages were used for manipulation of dates.

1.2 Energy

The multi-variable energy regression forecast model was developed in RStudio while the regression used for filling data gaps was developed in Microsoft Excel. QGIS was used in order to geolocate the various SCE and SDG&E electric meters and pump stations operated under MNWD. For the large amount of scanned PDF files, Wondershare PDFelement was used in conjunction with the Tesseract OCR package in R to translate the documents into readable text files which were then compiled in Excel.

1.3 Water and Energy Nexus

All computational work for this portion of our analysis was performed with an original script written in JupyterLab in a kernel using the R programming language. Packages used in this script include Tidyverse, lubridate, zoo, and doParallel.

Appendix 2: Data Preparation

2.1 Water

MNWD provided two levels—raw hourly and monthly billing—of information for residential water consumption. The monthly data provided the most complete monthly water consumption usage for residential customer accounts. The billing water usage data frequently contained double or different or missing monthly meter readings for some accounts. MNWD recently installed advanced metering infrastructure (AMI) for 20% of their residential accounts, but the hourly water usage data was not used for this analysis. MNWD plans to install AMI for 100% of their customers by early 2022.

MNWD's data contains customer characteristic data for residential users. Information includes service address, account number, irrigable square feet, type of account, number of residents, and the effective opening and end date of the account. MNWD uses eight different accounts to distinguish types of residential customers. For this analysis, only R1 and R2 customers were used. R1 customers are single family households and R2 customers are condos or townhouses that are individually metered. MNWD does serve water-only customers, but these were excluded from the analysis due to the small number of accounts. Customer characteristics for all accounts were merged with their water consumption.

Rebate data which contained the number of units installed and the date the invoice was received by the account was merged with water usage and customer characteristics information. To ensure the accuracy of each household's water use, account numbers, rather than service addresses, were used to match rebate and customer characteristic information. Service addresses were not used because a household service address could change if a customer were to move but stay within the service boundaries of MNWD, while the account number would not change.

From the rebate data provided by MNWD, some rebates, such as rain barrels, were not included in the analysis due to low participation and the assumption that the energy savings from capturing rain water were not significant due to the low precipitation Southern California receives. Four classifications used for rebate programs were merged into two rebate programs. WBIC and WBIC-DI were merged into WBIC for the regression and difference-in-differences analysis, while SYN and T were merged into T for only the regression analysis. MNWD classifies WBIC and WBIC-DI separately because participants of the WBIC program were given the option by MNWD to install the controllers themselves or to have them professionally installed. SYN and T are classified as two different programs due to one being run by MWD and the other by MNWD. However, both programs essentially served the same purpose, so were grouped together. Rebate invoices that did not have dates were excluded from the analysis.

Once rebate, water usage, and customer characteristics data were merged, accounts were filtered. Any accounts that appeared as "0" or "9999999" or "NA" were excluded because customer characteristics and rebate information were not identifiable for that account. Additionally, any accounts with zero monthly water consumption were excluded. Extremely high water users (>100 ccfs per month) were also excluded as they only made up 1.5% of residential accounts.

For the regression analysis, further data preparation was conducted. The rebate and water usage data join dates were set to the first of the month for simplicity. The regression analysis used one additional rebate program, RSN. Accounts were then sampled according to the details stated in 5.1.2.1. Water usage and rebate data were filtered to only include data from these sampled accounts, which resulted in 10,000 accounts, each with 120 months of water usage data. For each sampled account and water usage observation, rebate participation quantities were cumulatively summed through time to create a column of the cumulative quantity of each rebate received. Two columns were additionally created, one for water use by each account for the same month in 2009 and the second, using a binary variable, to indicate whether that account ever joined a rebate program. To run the regression, the data was transformed—using the pivot_wider() function in R—to create five new columns, each representing the quantity of a given rebate received on a given date.

2.2 Energy and Greenhouse Gas Emissions
Both utilities reported energy usage in daily 15-minute intervals with kWh to kW conversions. The SDG&E data was provided in Excel files containing up to 65 sheets separated by customer account number. Selecting only kWh, these sheets were compiled into one comprehensive sheet in Excel and read into an R project for further wrangling along with the two single-sheet SCE kWh files. SDG&E expresses customer account numbers with unique 10-digit numbers. While SCE numbers are typically much shorter, 3000000000 is added to the account number by MNWD to match the number of digits in the SDG&E account numbers (e.g. 202717 = 3000202717).

Column names were formatted and renamed in such a way that SCE and SDG&E columns could match up with one another. Several columns from each utility-specific table were removed, as they were not necessary to carry out this project and/or were unique to one utility's dataset. Prior to removing the column "chnl_id" from the SDG&E table, all rows containing a channel ID of "102" were filtered out as they represented any excess energy that was sent back to the grid as opposed to the "101" and "103" channel IDs which indicated consumption for the given meter. A column labeled "utility" (contains "SCE" for SCE table and "SDGE" for SDG&E table) was added to each of the two tables before merging. Originally, the 2014 – 2019 SCE data was combined with the 2015 – 2019 SDG&E data. Following a data request, the group was provided with SCE/SDG&E energy consumption for 2009 – 2019 and, following a second request, SDG&E consumption for 2014 and 2017 gaps. The daily values were grouped by account number, meter number, year, and horizontally summed to find total monthly energy consumption by meter.

Outside of monthly kWh data, other electric meter files were used to create an electric meter detail file, which included:

- Date in which a given meter was introduced to the district and date of termination (if not current)
    - Provided by the respective utility
- Utility administered rate type
    - Provided by the respective utility
- Address
    - Pump station data
    - Energy and cost data
    - SCE/SDG&E energy invoices

- Latitude/longitude coordinates
    - Found by plugging the provided address into an online geolocator
- Pressure zone
    - QGIS was used with a layer of the district and a meter point layer developed with lat/long coordinates
    - Zone determined by the line of pressure the meter fell in or was closest to
- Elevation
    - Using meter point layer in QGIS and a topographic map
- Functional domains
    - provided by Ronin Goodall (MNWD)
    - any meter with "Administration Building" was removed from the dataset

All files listed above were wrangled and compiled in R. The electric meter detail was then merged to the monthly kWh table and a file with utility emissions factors to create one comprehensive 2009 – 2019 energy consumption file exhibiting all necessary variables for the Objective 1: Phase I analysis.

Using the comprehensive 2009 – 2019 energy consumption file developed in Appendix 2.2, electric meters were assigned a functional domain depending on their functionality: potable water distribution, recycled water distribution, or wastewater. The goal of this division was to observe embedded energy and emissions relative to the components of MNWD's distribution system. Emissions factors were assigned to each meter depending upon the year and the utility serving said meter. SCE emissions factors were reported by Edison International in their Corporate Social Responsibility reports for 2011-2019. SDG&E emissions factors were calculated by the Energy Policy Initiatives Center at the University of San Diego School of Law for 2010-2018. For upstream electricity usage, energy intensity values were provided by MWD for 2013-2018. The California regional emissions factor reported by the California Air Resources Board for 2010-2018 was used for upstream use. Water consumption data was also separated by functional domain. The following equations were then employed to calculate embedded values:

Potable:

$$E_{embedded} = (\left(m_e * i\right) + mn_e) / i \quad (11)$$

$$GHG_{embedded} = \left(\left(m_e * i * ca_{ef}\right) + \left(ua_e * ua_{ef}\right) + \left(ub_e * ub_{ef}\right)\right) / i \quad (12)$$

Recycled:

$$E_{embedded} = mn_e / r \quad (13)$$

$$GHG_{embedded} = \left(\left(ua_e * ua_{ef}\right) + \left(ub_e * ub_{ef}\right)\right) / r \quad (14)$$

Wastewater:

$$E_{embedded} = \left(mn_e + \left(t_e * t_{sf}\right)\right) / w \quad (15)$$

$$GHG_{embedded} = \left(\left(\left(ua_e + pa_e\right) * ua_{ef}\right) + \left(\left(ub_e + pb_e\right) * ub_{ef}\right)\right) / w \quad (16)$$

where:
$E_{embedded}$ = total embedded energy
$GHG_{embedded}$= total embedded GHG emissions
m_e = MWD energy intensity value
mn_e = MNWD total energy consumption (SCE + SDG&E)
i = total imported water volume
c_{ef} = California regional emissions factor
ua_e = SCE metered total energy consumption
ua_{ef} = SCE utilities emissions factor
ub_e = SDG&E metered total energy consumption
ub_{ef} = SDG&E utilities emissions factor
r = recycled water volume
t_e = total energy consumption from treatment plants
t_{sf} = treatment plant scaling factor
w = *t*otal wastewater volume
pa_e = 3A treatment plant total energy consumption
pb_e = Regional Treatment Plant (RTP) total energy consumption

Appendix 3: Assumptions

3.1 Water

Assumptions for customer characteristics and rebates resulted from MNWD and MWD data collection. When water budget-based rates were first introduced, MNWD automatically assigned residential accounts a household size. Single family household (R1) customers were defaulted to 4 people and condos or townhouses (R2) to 3 people. Currently, when an account is opened with MNWD, the district determines the actual household population size. Customers who were assigned a default value initially do have the ability to report the actual number of people in their household.

Customer rebate invoice dates from MWD were the only dates provided by MNWD for rebate installation timelines. These dates represented when customers received compensation for installing and joining a rebate program, but not when the installation occurred. MNWD states that the time lag between the customers joining or installing a device and reception of the invoice was initially six months, but now ranges from two to three months. For this study, we did not take lag into account because of the uncertainty of when accounts actually joined or installed devices for different rebate programs. The rebate application date would have served as the best proxy for the actual installation date. This is due to the process of requesting a rebate, which typically requires that the customer install the device before submitting the request. However, rebate application dates were not provided by MNWD for this analysis.

For the regression analysis, the average evapotranspiration across MNWD's service area was used instead of microzone evapotranspiration values. For years with no data, averages were taken from years with similar weather patterns. Additionally, a similar process was taken for missing precipitation values within the district's service area.

3.2 Energy and Greenhouse Gas Emissions

There were various assumptions in the energy and GHG analysis associated with all levels of the distribution process. MNWD receives its water from MWD, whose water supply originates from both the Colorado River Aqueduct (CRA) and the California State Water Project (SWP). Because MWD mixes two water sources together to achieve its annual water supply, there is inevitable variation in water mix ratios from year to year. As a result, it was assumed that MWD's estimated energy intensity values approximated the actual values without granular analysis of changes in the mix ratio. MWD was only able to supply embedded energy values for 2013 – 2018, so values for other years required utilization of regression and averaging. This assumes that MWD's average energy intensity provided a good estimate for years in which MWD did not have a reported value. It was also assumed that using annual numbers rather than monthly values allows for a smoothing of variation due to season or source water changes.

Being able to separate out water, energy, and GHG consumption by functional domains played a significant role in how findings could be reported and in the removal of recycled distribution. This allowed the analysis to focus on residential water use. This requires the assumption that assigning functional domains to the electric meters resulted in electricity use values emblematic of each group, and that excluding unidentifiable meters (e.g., meters not explicitly assigned a functionality by MNWD, SCE, or SDG&E) had no impact on the final embedded calculations. With the data coming from MNWD, SCE, and SDG&E sometimes in different file formats containing different time periods, there was also the assumption that there was no overlap in energy consumption data.

There were a few other assumptions relating to the energy-carbon component of the water-energy-carbon nexus. With GHG calculations, the assumption was that the observed trends in known emissions factors were sufficient justification for using regression to estimate unknown emissions factors for some years. Unavailable wastewater treatment data was calculated by taking the available 2019 treatment energy use and scaling it by wastewater volume for a given year. This required the assumption that wastewater energy use was directly proportional to wastewater volume. Finally, due to data and time constraints, as well as it lying outside of MNWD's system boundary, energy end-use was not addressed.

3.3 Water-Energy Nexus

The first assumption of the final analysis was that monthly water savings were constant over the entire study period. This meant that rebound effects were ignored, and savings were assumed to be permanent. It was determined that accounting for these rebound effects was beyond the scope of this analysis. This also required the assumption that water savings from a given rebate were constant in each month of the year. However, preliminary analysis of the seasonality of rebate savings suggested that, for outdoor rebate programs (weather-based irrigation controllers, turf removal, and rotating spray nozzles), savings per unit of rebate did show some variation throughout the year. Unfortunately, confirming the presence of seasonality and accurately estimating its magnitude proved to be beyond the scope of this analysis. Future research into this seasonality is required, as capturing it accurately will in turn allow for more accurate evaluations of the impact of water efficiency rebate programs.

For the second assumption, water savings were also assumed to increase linearly with rebate quantity. This assumption might be flawed in some cases due to the presence of "floor effects"; if a household is already using water very efficiently, the installation of a device through rebate participation may do little to affect overall household consumption. Furthermore, customers are likely to replace the most inefficient devices first. Savings are then reduced for subsequent devices as progressively more-efficient devices are replaced. Successive device installations may also lead to behavioral changes; for instance, customers may become less diligent about maintaining water-conserving habits when they know that they have highly efficient devices. Ultimately, while the response of water use to device installation may in fact be nonlinear, incorporating this aspect into savings estimates was beyond the scope of this analysis.

Appendix 4: Recycled Water Embedded Analysis

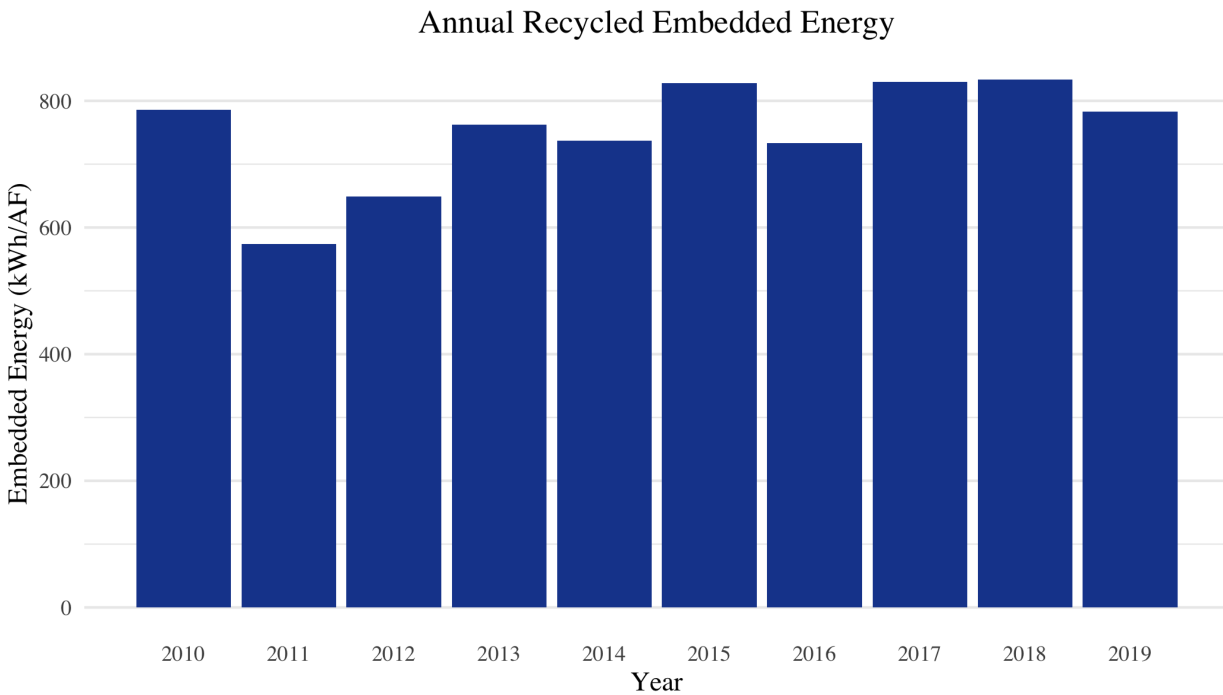


Figure 21. Recycled embedded energy for MNWD in all years 2010 to 2019. Recycled embedded energy is presented apart from potable and wastewater embedded values because recycled water is only used for commercial irrigation accounts. Annual embedded energy is somewhat variable between 2010 and 2019, with a low in 2011 due to significantly lower energy use.

Appendix 5: Embedded Energy and GHG Emissions for Potable Water and Wastewater

Table 11. Embedded energy and GHG values for MWD and MNWD potable water and wastewater. Numbers calculated for wastewater include data for two of the three wastewater treatment plants that receive MNWD's effluent. Primary Data Sources: Metropolitan Water District and Moulton Niguel Water District.

Year	MWD Embedded Energy	Potable Distribution Embedded Energy	Potable Distribution Embedded GHG	Wastewater Embedded Energy	Wastewater Embedded GHG
2010	1863	2030	645	667	194
2011	1863	2025	637	669	173
2012	1863	2037	691	648	214
2013	1787.2	1946	622	642	204
2014	1937.5	2087	641	632	172
2015	1967.4	2169	640	603	151
2016	1831.5	2008	482	620	149
2017	1817.5	1995	425	613	150
2018	1837	1988	440	632	149
2019	1863	2055	462	638	152

Table 12. Embedded energy and GHG values for MNWD recycled water distribution. Primary Data Sources: Metropolitan Water District and Moulton Niguel Water District.

Year	Recycled Distribution Embedded Energy	Recycled Distribution Embedded GHG
2010	786	224
2011	574	144
2012	649	211
2013	762	236
2014	737	194
2015	828	200

2016	734	176
2017	830	205
2018	834	195
2019	783	189

Appendix 6: Water Regression Model Supplemental Information

Table 13. Coefficients generated from the multivariable linear regression model used to estimate water savings among rebate participants. Data sources: Moulton Niguel Water District (MNWD) and the National Integrated Drought Information System (used for "Drought Severity").

	Variable	Coefficient
	Intercept	-5.131
	Prior use	0.42
Year	2011	0.387
	2012	0.699
	2013	1.613
	2014	1.79
	2015	2.363
	2016	3.42
	2017	2.706
	2018	3.28
	2019	1.682
Month	2	-0.352
	3	-1.421
	4	-1.569
	5	2.157
	6	0.693
	7	0.648
	8	1.008
	9	0.942
	10	0.454
	11	0.326
	12	0.526
	Everjoin - Yes	0.21
	Post E.O. - Yes	-3.4
	sqrt(Irrigated Area)	0.104
	# of residents	1.152
	Rate Type - R2	0.867
	ET	0.818
	sqrt(Precipitation)	-0.706

Rebate Quantity	HECW	-0.258
	HET	-0.38
	Turf	-0.00171
	RSN	0.00982
	WBIC participation	0.0693
	Drought Severity	-0.43

Interpretation of model coefficients

For the "year" variable, 2010 was used as a dummy variable. As a result, the coefficient for each year signifies how much predicted use increased on average relative to 2010, all other factors being equal. Likewise with "month", because January was the dummy variable, each month coefficient signifies the predicted increase in water use relative to water use in January, all else being equal. The coefficient of "Post E.O. - Yes" predicted a decrease in monthly water use of 3.4 ccf relative to months before the issuance of E.O. B-29-15, all other factors being equal.

The "irrigated area" variable was transformed with a square root. As a result, its coefficient indicates that, for two accounts whose only difference between them is total irrigated area, the predicted difference in water use between the two is the coefficient (0.104) multiplied by the square root of the difference in their irrigated areas. Likewise for precipitation, the difference in water use between two identical account-months will be the coefficient (-0.706) multiplied by the square root of precipitation depth. In this case, the negative coefficient signifies a predictable inverse relationship - higher precipitation months have a predicted lower water use. Evapotranspiration (ET) was not transformed; its direct relationship coefficient predicted an increase in monthly water use of 0.818 ccf/in, all else being equal. Finally, each point of increase in the constructed "drought severity" metric predicted a decrease in water use of 0.43 ccf/month, all other factors being equal.

The "rate type" variable coefficient indicates that water use was predicted to be 0.867 ccf/month higher among accounts with rate type R2 relative to R1 accounts. The "everjoin" variable (signifying whether or not an account ever joined a rebate program) coefficient indicates that water use was estimated to be 0.21 ccf/month higher among rebate participants relative to non-participants. Based on the "# of residents" variable, each additional household resident leads to a predicted increase of monthly water use of 1.152 ccf between two otherwise identical households. However, there may be a confounding effect here because household size factors into the water budget calculation for MNWD's budget-based rates.

For the rebate quantity variables, as explained in 6.1.2, the coefficient signifies the predicted change in monthly water use with each unit of rebate participation, all other factors being equal. The exception to this is the binary WBIC participation variable, which signifies the model-predicted change in water use from participation in the WBIC program regardless of controller quantity installed; however, as explained in 6.1.4 and 7.2.2, this predicted change is almost certainly erroneous.

Graphical exploration of selected model variables

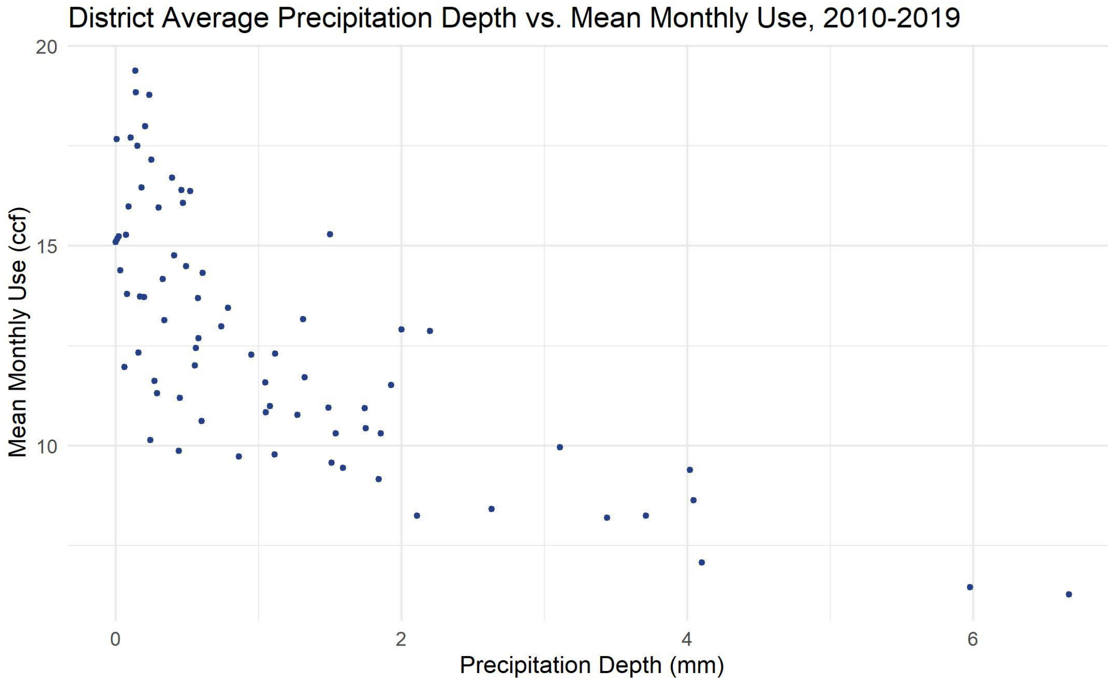


Figure 22. Moulton Niguel Water District average precipitation in millimeters against average account-monthly water use in ccf from 2010-2019. Data Source: MNWD

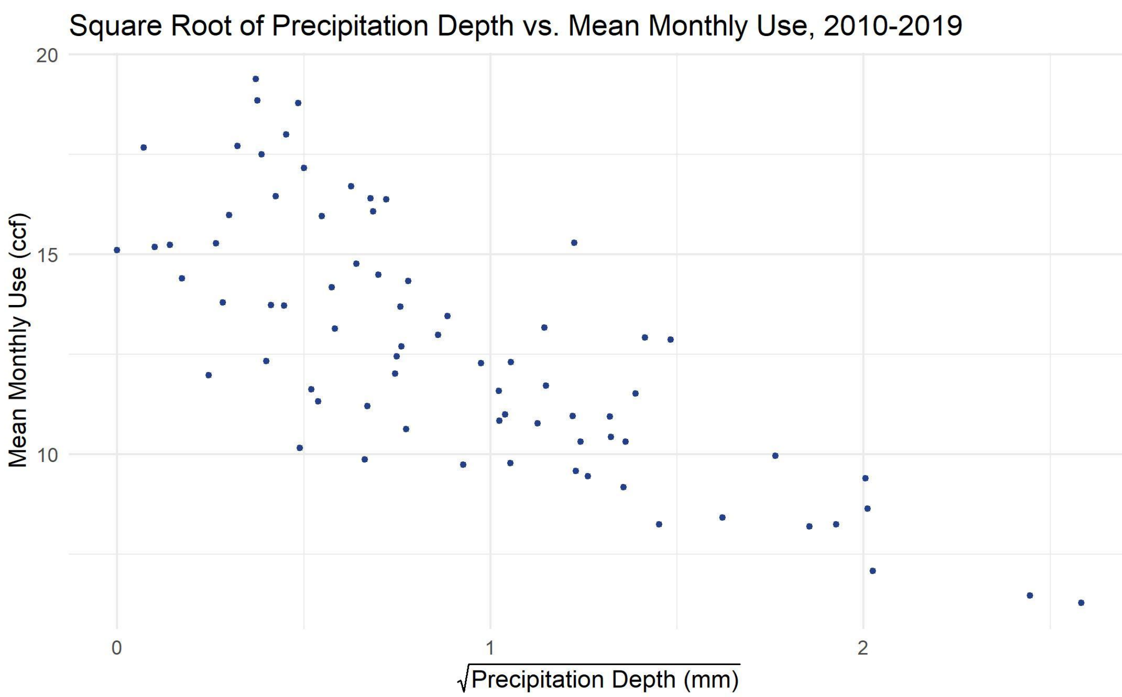


Figure 23. The square root of precipitation depth in millimeters for Moulton Water District against residential mean monthly use from 2010 to 2019. Data Source: MNWD

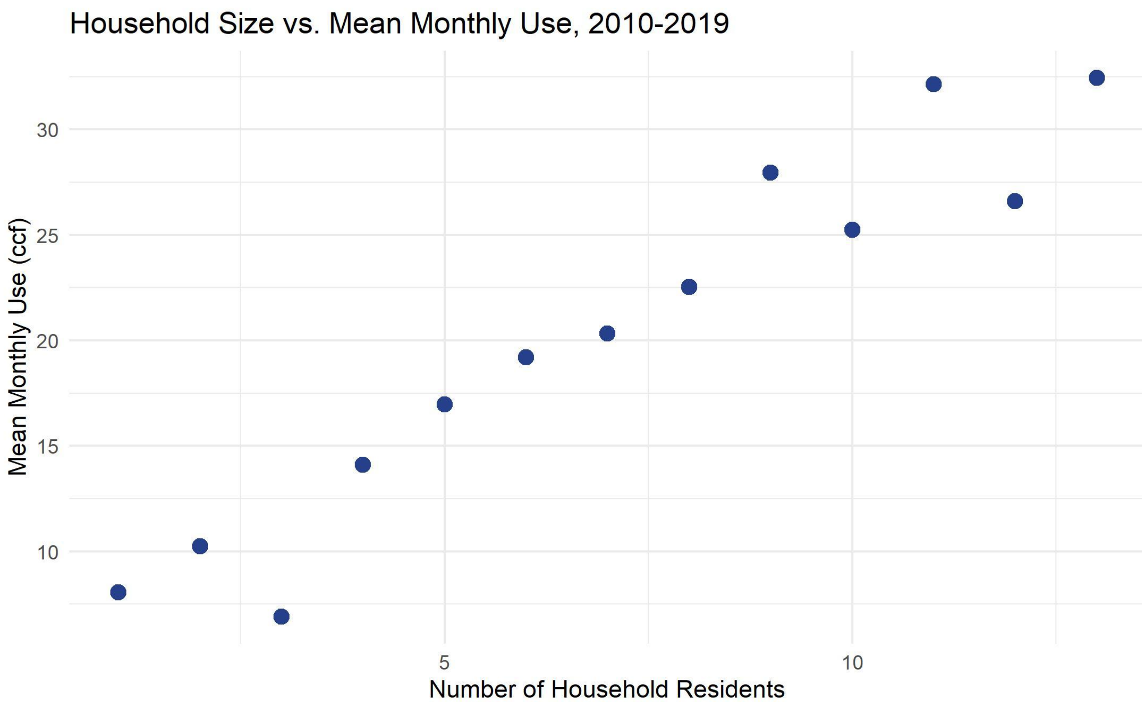


Figure 24. Residential household size against the mean monthly water use in ccf from 2010-2019. Data Source: Moulton Niguel Water District

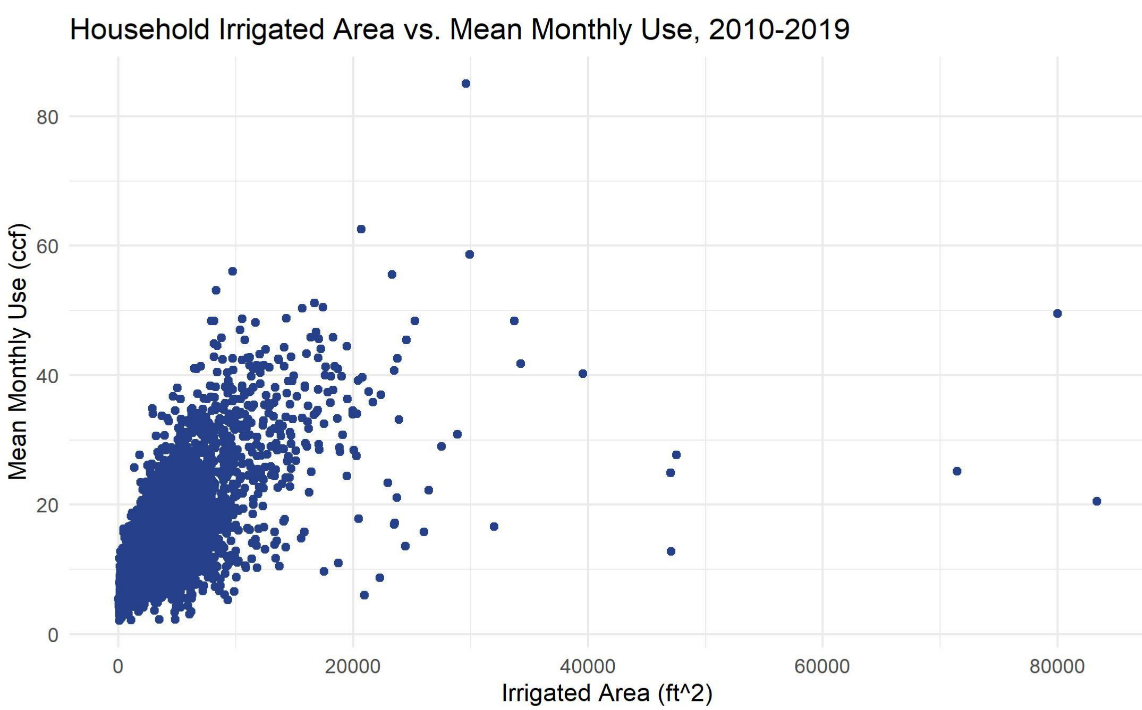


Figure 25. Residential household irrigated area against mean monthly use from 2010-2019. Data Source: Moulton Niguel Water District

Alternative regression model approaches

To more accurately quantify water savings from rebate participation, various approaches to modeling using the multi-variable linear regression model were attempted. The aim was to capture additional variability in rebate savings through time and between rebate participants; ultimately, however, none produced results of satisfactory accuracy. These alternative approaches to multi-variable linear regression included:

- Predicting reduction in water use relative to use in that same month in 2009 instead of predicting water use
- Spatial aggregation to the district level by summing water use and cumulative rebate quantities across all accounts in each month
- Temporal aggregation on an annual and quarterly basis for each account
- Fitting 12 separate linear regressions to data from each month across all years of the study period. This was done to estimate savings for each rebate program specific to each month of the year.
- Fitting 10 separate linear regressions to data from each year in the study period. This was done to estimate savings for each rebate program specific to each year in the study period, and potentially capture rebound effects.

Appendix 7: Framework

Introduction

Water's high density and specific heat make its movement and heating energy intensive. Because of this fact, conservation of water through the adoption of water-efficient devices and technologies also saves energy and thereby mitigates greenhouse gas emissions. However, despite this established theoretical link, no standardized methodology exists to calculate these co-benefits. This document proposes a methodological framework for quantifying the energy and greenhouse gas (GHG) co-benefits of customer water efficiency programs in an attempt to meet this need.

This method quantifies the energy saved and GHG emissions mitigated throughout the entire water supply chain when water is saved, specifically through the implementation of water-conserving technologies through utility-scale rebate programs. It does this by first calculating the water's embedded energy; that is, the energy expended during conveyance, distribution, end-use, and treatment of each unit of water. The embedded energy is then used to calculate embedded emissions; that is, the GHG emissions that resulted from the generation of the embedded energy. Finally, avoided energy use and GHG emissions are found by multiplying water savings volumes in each month of rebate participation by the calculated embedded energy and emissions factors, respectively. By repeating this process for all rebate invoices, program-level savings are calculated.

The framework requires the availability of various datasets in a digitized and curated/workable format. This may oftentimes be a limitation for smaller water systems; while they may have access to the types of data necessary to construct the requisite datasets, consolidation into workable files and curation for accuracy may strain organizational resources. Therefore, this framework may be understood to be designed for use by large water utilities.

Data requirements

Types of data needed to perform this analysis include:

- Invoices from rebate participation that indicate:
  - Type of device installed or technology implemented
  - Number of units installed/implemented (# of toilets, area of turf replaced, etc.)
  - Date of rebate issuance
- Estimates of monthly water saved per unit of rebate issued for each rebate program. If not already calculated, the following data are needed:
  - Customer water use data
  - Customer characteristics data, including but not limited to:
    - Household size
    - Household irrigated area
    - Water billing rate type
    - Demographic data such as median household income and education
  - Climatic data, including precipitation, evapotranspiration, and drought status
- Data necessary to calculate distribution system losses, specifically:
  - Volume of "real losses": the volume of physical water lost through all types of leaks, breaks, and overflows

    - Volume of "authorized consumption": the volume of metered and/or unmetered water taken by registered customers, the utility's own uses, and uses of others who are implicitly or explicitly authorized to do so by the water utility.
- Energy usage data for all water system accounts, including pump stations, sewage collection/lift stations, and wastewater treatment plants
- Emissions factors of delivered electricity for all electricity providers
- If available, embedded energy factors for each source in the water supply portfolio
- If rebates for technologies which use hot water are to be assessed, data on hot water heating in the service area including:
    - Water heater energy consumption per unit water heated (may require sub-metering)
    - Relative distribution of electric vs. natural gas hot water heaters in service area
    - For natural gas heaters, GHG emissions per unit water heated
    - For each rebate device assessed, the proportion of water use that is hot water
- If rebates for technologies which use water that is pressurized on-site are to be assessed, the following data are needed:
    - Energy consumption of on-site pressurization equipment (may require sub-metering)
    - Volume of total water pressurized (may require sub-metering)

Data considerations

Water savings estimates

Water saved for each unit of rebate issued should be estimated using a retrospective analysis of water use among those customers that participated in the rebate programs. This analysis should use an established statistical method for evaluating treatment effect size or another similar quantity. It is not appropriate to divide the difference in water use before and after rebate participation by the number of rebate units issued; changes in water use behavior due to other factors may obscure true savings.

The magnitude of calculated water savings can be influenced by a number of factors. These factors include the ability of the method used to account for variations in water use due to external factors, the number of external factors present, the efficiency of the device being replaced, and the presence of rebound effects. Calculated water savings may therefore be specific to a given utility or period of time. As such, estimates of savings from similar rebate programs (same device, nearby service area, etc.) may not reflect real savings from the program being examined. Estimates from other rebate programs are therefore not a responsible substitute for statistical analysis of water use among participants in the program. The exception to this is when data quality and/or quantity prohibit statistical accuracy.

Program-level results are sensitive to the volume of water saved per unit rebate because this method calculates energy and GHG savings based on embedded energy and emissions. Sensitivity is greater when the number of invoices/instances of rebate participation examined is large. As a result, calculating water savings with the maximum feasible degree of accuracy and precision is important in order to preserve the accuracy of program-level savings estimates

Temporal resolution

Water savings should be calculated with the maximum temporal resolution possible - likely savings per month. Other calculated data do not need to have a greater temporal resolution than water savings, as this will not increase accuracy. When a factor is calculated using two types of data that have differing degrees of temporal resolution, the factor should be calculated with the coarser of the two resolutions. For example, when calculating embedded energy, if 15-minute energy use is available but only annual water use is available, energy use should be aggregated to annual use and an annual embedded energy factor should be calculated.

Missing data

When appropriate, gaps in data should be filled using assumed values calculated based on the present data. For example, if real losses are available for some years in the period of analysis but not others, the average of the available years should be used for the missing years. Alternatively, if values are known for some quantity to which the missing data can be reasonably assumed to be directly proportional, the missing values can be estimated using this relationship. For example, if wastewater inflows to a plant are known for all years but treatment facility energy consumption is only known for some years. To estimate energy consumption for the missing years, average consumption is first divided by average inflows for the known years. The resulting ratio is then multiplied by the known inflows for the years with missing consumption to estimate those missing values. Assuming values based on professional judgement with no basis in the existing data is not a responsible strategy for filling data gaps.

End-use embedded energy and GHGs

Estimating energy consumption and GHG emissions during customer end-use requires data which water and electric utilities normally do not possess without submetering. Obtaining it may be possible using customer surveys. However, it is also possible that obtaining it may be outside the scope of the analysis or even beyond the technical capacity of the analyzing organization to do so. In these cases, an attempt should be made to estimate the energy and emissions embedded during end-use as opposed to disregarding the stage entirely, as prior analyses have found that these quantities can be quite significant.

Emissions factors of delivered electricity

Factors for the GHG emissions per unit of energy delivered should be obtained from the energy provider themselves or published literature. Methods for developing these factors are outside the scope of this framework.

Methodology
When calculating embedded energy and emissions factors, this method directs the user to calculate "total" quantities, such as total energy consumption. This "total" refers to a total within each unit of temporal resolution: for example, calculating annual embedded energy factors requires total annual energy use and total annual water use.

Embedded Energy Factors
Extraction and conveyance embedded energy for each source of water in a utility's supply portfolio (E_{source}) is found by first calculating the total energy consumption at all facilities involved in extracting raw water and transporting it to pre-use treatment facilities. This total is then divided by the total water volume obtained from that source. Next, for each source, its proportional contribution to total water supply (p_{source}) is calculated by dividing the total water volume obtained from that source by the total volume obtained from all sources. Finally, net extraction and conveyance embedded energy (E_{ext}) is found by adding together each source's embedded energy multiplied by its proportional contribution.

$$E_{ext} = \sum_{sources} p_{source} * E_{source}$$

Where: p_{source} = *[Source volume] / [Total supply volume]*
E_{source} = *[Source facilities consumption] / [Source volume]*

Energy embedded during treatment prior to distribution (E_{pt}) is found by dividing total energy consumption at all pre-distribution treatment facilities by the total water treated at those facilities.

E_{pt} = *[Treatment facilities energy consumption] / [Treated volume]*

Note: The supply portfolio of some water utilities is composed entirely of imported water purchased from a regional water wholesaler (i.e., Metropolitan Water District of Southern California). Such organizations may have already calculated embedded energy factors for the imported water they deliver, and approximate values for different hydrologic regions in California have been calculated during prior studies[6]. When a utility's portfolio is 100% imported water and these factors are available, they may be used in place of E_{ext} and E_{pt}. These factors may also be used in place of E_{source} where appropriate.

Energy embedded during system distribution (E_{dist}), is found by first calculating total direct energy consumption at all facilities involved in potable water distribution. This total is then divided by the volume of total water throughput.

E_{dist} = *[Distribution facilities energy consumption] / [Throughput volume]*

Service area topography can cause distribution embedded energy to vary across the service area. For utilities that service accounts across a wide range of elevations, multiple spatially-specific

[6] See Navigant 2015 (San Francisco, CA: California Public Utilities Commission) *Water/Energy Cost-Effectiveness Analysis: Revised Final Report*

E_{dist} factors should be calculated in order to capture this variability when data availability permits.

Energy embedded during customer end-use (E_{end}) is calculated for rebate devices that use water with some on-site energy input after distribution but before the physical use of water. This is most commonly water heating, but may involve on-site pressurization for some types of commercial or industrial devices. E_{end} may be ignored for devices that do not require on-site energy inputs.

For devices that use hot water, E_{end} is calculated with the product of water heater energy consumption per unit water heated (e_{heat}), the proportion of water heaters in the service area that are electric ($p_{electric}$), and the proportion of device water use that is hot water (p_{hot}).

$$E_{end} = e_{heat} * p_{electric} * p_{hot}$$

If e_{heat} cannot be calculated using submetering, it may be estimated by multiplying together the specific heat of water (c_{water}), the temperature change of water when it is heated (ΔT), and the average efficiency of the water heaters used (η).

$$e_{heat} \approx c_{water} * \Delta T * \eta$$

For devices that use water pressurized on-site, E_{end} is calculated by dividing the total energy consumption of on-site pressurization equipment by the total volume of water pressurized.

$$E_{end} = [\textit{Pressurization equipment energy consumption}] / [\textit{Pressurized volume}]$$

For devices which use hot water that is also pressurized on-site, E_{end} should be calculated for both heating and pressurization and then added together to obtain a composite E_{end} factor.

Energy embedded during wastewater treatment (E_{ww}) is obtained by first calculating total energy consumption at all facilities involved with sewage collection, and total energy consumption at all wastewater treatment plants. These two totals are added together, and then divided by the total wastewater volume treated. For rebate devices that do not produce wastewater effluent, E_{ww} can be ignored.

$$E_{ww} = \frac{[\textit{Collection facilities energy consumption}] + [\textit{Treatment facilities energy consumption}]}{[\textit{Wastewater volume treated}]}$$

Variations in facilities' technology, age, and operations may cause E_{ww} to vary between treatment facilities. When variation between facilities is significant and data availability permits, spatially-specific E_{ww} factors should be developed based on the treatment facility to which wastewater effluent from a given area flows. If variation is significant but spatial data is limited, a composite E_{ww} should be calculated using a weighted average, where each facility's proportion of total wastewater volume treated is used as a weighting factor.

Embedded Greenhouse Gas Emissions Factors

Greenhouse gas (GHG) emissions embedded during extraction and conveyance (G_{ext}), similar to embedded energy are first calculated for each source separately (G_{source}). For each source in a utility's supply portfolio, E_{source} is multiplied by an emissions factor of delivered electricity ($g_{deliver}$) specific to the supplying electric utility, the location of that source's extraction and conveyance facilities, and the time period in question. Then, net extraction and conveyance embedded emissions (G_{ext}) is found by adding together each source's embedded emissions multiplied by its proportional contribution to total water supplied (p_{source}).

$$G_{ext} = \sum_{sources} p_{source} * G_{source}$$

Where: p_{source} = *[Source volume] / [Total supply volume]*

$G_{source} = G_{source} * g_{deliver}$

Note: Facilities may receive electricity from multiple electricity providers during a given period of time. When these providers have differing $g_{deliver}$ factors, a composite $g_{deliver}$ should be calculated. This should be done using a weighted average where each provider's contribution to total electricity supplied is used as a weighting factor.

GHG emissions embedded during treatment prior to distribution (G_{pt}) are calculated by multiplying E_{pt} by the appropriate emissions factor of delivered electricity $g_{deliver}$, based on the supplying electric utility, facility location, and time period.

$$G_{pt} = E_{pt} * g_{deliver}$$

Note: Some utilities may obtain imported water via purchase from a regional wholesaler that has already calculated emissions embedded during extraction, conveyance, and pre-treatment. As with embedded energy, such factors for embedded emissions are appropriate to use in place of G_{source}, or G_{ext} and G_{pt} when the utility's supply portfolio is composed entirely of imported water.

GHG emissions embedded during system distribution (G_{dist}) are calculated by multiplying E_{dist} by the appropriate $g_{deliver}$ factor. If spatially-specific E_{dist} factors have been calculated, spatially-specific G_{dist} factors should also be calculated.

$$G_{dist} = E_{dist} * g_{deliver}$$

GHG emissions embedded during customer end-use (G_{end}), similar to E_{end}, can be neglected for those devices which require no onsite energy inputs. For devices which use hot water, two quantities are calculated and added. First, E_{end} is multiplied by the appropriate $g_{deliver}$ factor. This quantity is added to one minus the proportion of water heaters which are electric ($1 - p_{electric}$) multiplied by the average GHG emissions per unit water heated via gas-powered water heaters (g_{heater}).

$$G_{end} = (E_{end} * g_{deliver}) + ((1 - p_{electric}) * g_{heater})$$

For devices which use water pressurized on-site, E_{end} is multiplied by the appropriate $g_{deliver}$ factor.

$$G_{end} = E_{end} * g_{deliver}$$

For devices which use hot water that is pressurized on-site, G_{end} should be calculated separately for each process and then added together to obtain a composite G_{end} factor.

GHG emissions embedded during sewage collection and wastewater treatment (G_{ww}), as with E_{ww}, can be neglected if the rebate devices being examined do not produce wastewater. If spatially-specific E_{ww} factors have been developed, spatially-specific G_{ww} factors should be developed as well.

If all sewage collection facilities and wastewater treatment facilities receive electricity from the same electricity provider, G_{ww} can be calculated by multiplying E_{ww} by the appropriate $g_{deliver}$ factor.

$$G_{ww} = E_{ww} * g_{deliver}$$

If collection facilities and treatment facilities receive electricity from multiple electricity providers, total energy use at each facility should be multiplied by the emissions factor of delivered electricity appropriate to that facility ($g_{facility}$). Then, these products should be summed and divided by the total volume of wastewater treated.

$$G_{ww} = \frac{\sum_{facilities} [Facility\ energy\ use] * g_{facility}}{[Wastewater\ volume\ treated]}$$

Calculating program-level energy savings and emissions mitigation

Once all the necessary embedded energy and GHG emissions factors have been calculated, obtaining program-level savings is fairly straightforward, though it may be computationally intensive due to the number of operations required. The first step is to calculate annual (or sub-annual, if data availability permits) system loss factors (L) . These factors, when multiplied by rebate water savings (s_{rebate}), represent the volume of water that was not extracted/produced as a result of said savings. L is calculated by dividing real losses by authorized consumption, and then adding one to that quantity.

$$L = 1 + ([Real\ losses] / [Authorized\ consumption])$$

By multiplying L with s_{rebate}, the volume of water that was not extracted, conveyed, pre-treated, or distributed as a result of rebate water savings is calculated. Water use cycle energy savings (S_{energy}) in each time unit following a particular instance of rebate participation can then be calculated according to the following equation:

$$S_{energy} = ((E_{ext} + E_{pt} + E_{dist}) * s_{rebate} * L) + ((E_{end} + E_{ww}) * s_{rebate})$$

Where s_{rebate} is the calculated water savings per unit time of the rebate program being examined. Here, L is multiplied by E_{ext}, E_{pt}, and E_{dist} because the quantity of avoided water transported and treated is larger than s_{rebate} once system losses during distribution are taken into account. However, the quantity of water that does not have end-use energy inputs and/or is not treated is simply equal to s_{rebate}.

Similar to S_{energy}, water use cycle GHG emissions mitigated ($M_{emissions}$) is calculated by replacing each embedded energy factor in the previous equation with an embedded emissions factor.

$$M_{emissions} = ((G_{ext} + G_{pt} + G_{dist}) * s_{rebate} * L) + ((G_{end} + G_{ww}) * s_{rebate})$$

Calculating S_{energy} and $M_{emissions}$ for every unit of time in the study period after the issuance of a particular rebate and then adding them all together results in the total energy savings and GHG emissions mitigated, respectively, from that particular instance of rebate participation. Repeating this process for every rebate examined results in total program-level water use cycle energy savings and GHG emissions mitigation over the entire study period.

Incorporation of recycled water

If the devices in the rebate programs examined do not use recycled water, this section can be disregarded. For rebate devices which use recycled water, a process nearly identical to the one laid out above is followed. The difference is that a factor for the energy embedded during the recycling process ($E_{recycle}$) should be used in place of E_{ext} and E_{pt}. Similar to E_{ww}, this quantity is calculated by dividing total recycling facility energy consumption by total recycled water volume produced.

$$E_{recycle} = [\text{Total facility energy consumption}] / [\text{Total volume of recycled water produced}]$$

Similarly, a factor for the emissions embedded during the recycling process ($G_{recycle}$) should be used in place of G_{ext} and G_{pt}. Much like G_{ww}, $G_{recycle}$ is calculated by multiplying $E_{recycle}$ by the appropriate $g_{deliver}$.

$$G_{recycle} = E_{recycle} * g_{deliver}$$

If a device uses both recycled water and potable water, composite factors for the energy and emissions embedded in water during production (E_{prod} and G_{prod}, respectively) should be used. These composite factors are calculated by taking a weighted average of the embedded energy and emissions factors where the weighting term is the relative proportion of recycled water used by the device in question ($p_{recycle}$).

$$E_{prod} = E_{recycle} * p_{recycle} + (1 - p_{recycle}) * (E_{ext} + E_{pt})$$

$$G_{prod} = G_{recycle} * p_{recycle} + (1 - p_{recycle}) * (G_{ext} + G_{pt})$$

E_{prod} and G_{prod} are then used in place of the quantities ($E_{ext} + E_{pt}$) and ($G_{ext} + G_{pt}$), respectively, when calculating program-level savings.

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