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Forecasting Urban Water Demand and Effects on Wastewater Management: An Integrated Systems Approach with Uncertainty

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Abstract

Water demand forecasting is an important tool for integrated water management. Long-term demand predictions include inherent uncertainty, but few studies have investigated empirical methods to forecast water demand that include uncertainty from many driving factors or evaluate how changes in demand affect linked systems such as wastewater conveyance and treatment. This study presents a novel approach for long-term urban water demand forecasting that: 1) integrates uncertainty in technology, behavior, and climate, and 2) estimates effects of demand changes on wastewater management systems. We demonstrate this using a case study of 350 urban water supply agencies and more than 300 wastewater treatment systems in California serving 31 million people. For the period from 2020-2030, we used modeling with Monte Carlo simulations to estimate future scenarios of urban water demand given changes in efficiency, climate, water rates, and population. Effects of demand changes on wastewater management were estimated using network modeling and novel evaluation metrics. In modeled scenarios, future per capita water demand in California cities decreases by 8 to 12% depending on the included factors, while total volumetric demand declines by up to 11%. Efficiency changes had the largest impact. Wastewater agencies experience up to a 10% reduction in wastewater influent flow, but differences exist across regions and facilities. Aligning future water supply investments with integrated demand forecasts could forgo as much as \$860 million in investments for new water supply capacity, but tradeoffs exist if such new capacity is important for future supply reliability with severe drought. Results demonstrate the value of incorporating social, technological, and climate factors in demand forecasting through stochastic approaches.

Introduction

Water demand forecasting is an important tool for integrated water management. Demand forecasting uses empirical methods to predict water demand over short, medium, and long timeframes (Bougadis et al. 2005; Rinaudo 2015; Richter et al. 2020). Steady declines in per capita urban water use in the U.S. during recent decades have emphasized the importance of demand forecasting to ensure reliable and cost-effective future operations (Dieter et al. 2018; Diringer et al. 2018; Richter et al. 2020). Demand forecasting can consider many possible social, environmental, and technological factors that influence water demand (House-Peters and Chang 2011; Worland et al. 2018; Alzraiee et al. 2024). Water agencies use forecasting at multiple timescales. Short-term forecasting informs daily and weekly operations where peak demand is important for reliability (Wong 1972; Zhou et al. 2002; Day and Howe 2003; Adamowski 2008), while medium- and long-term demand estimates inform investments in programs and policies that can take years to plan and capitalize (AWWA 2006; Gober et al. 2016; Richter et al. 2020).

In regions that experience drought and water scarcity, such as western North America, demand forecasting can help balance investments and policies for demand management with new and expensive sources of supply (Olmstead and Stavins 2009). Significant reductions in per capita water use in these arid and semi-arid regions have resulted from: federal and state regulations that increase efficiency (DeOreo et al. 2016); adopting rate structures that promote conservation (Wichman et al. 2016); muted rebound effects after drought where water demand does not return to pre-drought levels (Lee et al. 2021); media attention and public messaging that promote water-wise habits (Quesnel and Ajami 2017); behavioral changes (Bijoor 2021); and investments in water-saving strategies (DeOreo et al. 2016; AWE 2019; Pincetl et al. 2019a; Chesnutt 2020; Green et al. 2024). Recent droughts in California instigated thousands of turf landscapes being replaced with water-wise options (Pincetl et al. 2019a; Green et al. 2024), which can continue to reduce water demand over time (AWE 2019; Bijoor 2021). Water demand can also be affected by unpredictable disruptions, such as economic recessions or global health events like the response to the novel Corona Virus (COVID-19) pandemic in 2020 (Kiefer et al. 2016; Li et al. 2021). Finally, large-scale economic shifts such as the growth of data centers can have significant impacts on

overall water withdrawals, which could occur in cities (Debaere and Kurzendoerfer 2017; Siddik et al. 2021).

Changes in urban water demand also impact other urban systems (Daigger 2011). For instance, studies have evaluated the effects of water use efficiency and conservation change on the quantity and quality of wastewater effluent that is conveyed to wastewater treatment facilities (DeZellar and Maier 1980; Maier et al. 1981; Tran et al. 2017). This has been a challenging issue in California, where the state faced widespread drought that instigated policy targets for mandatory conservation from 2014-2015 (Lund et al. 2018). Rapid changes in demand added to long-term declines in per capita use that resulted in operational challenges for wastewater systems, many of which are aging and designed to operate with higher flows and lower concentrations of key constituents such as Total Suspended Solids and Biochemical Oxygen Demand (Schwabe et al. 2020; Porse et al. 2023). Adapting current water and wastewater systems to future drought and on-going efficiency requires integrated planning across urban water sectors to meet operational, financial, and other goals (Porse et al. 2017; Pincetl et al. 2019b).

Inherent uncertainties exist in demand forecasting (see Section 1 in the Supplemental Data). Stochastic methods for demand forecasting are more common in short-term forecasting models where influencing factors can be estimated with increased precision (Bougadis et al. 2005; Tiwari and Adamowski 2013; Gagliardi et al. 2017; Anele et al. 2018). Long-term planning must consider additional known and emerging factors including predicted changes in climate, sociodemographic trends, water availability, water rates, and more (Balling and Gober 2007; Rinaudo 2015; Gober et al. 2016). Scenario planning methods have also been used in water management that include demand forecasting (Westcott 2004). For instance, studies have evaluated future water supply reliability investments given trajectories of demand that depend on drought, climate change, land use changes, population, and disasters (Means et al. 2005; Scott et al. 2012; Kang and Lansey 2014). Yet, such methods are still not common practice in the water sector and there is a continued need for demonstration of empirical and replicable methods that use systems analysis and incorporate uncertainty in demand forecasting by considering multiple technological, sociodemographic, and climate factors (Donkor et al. 2014).

In this paper, we present a systems-based approach for long-term water demand forecasting with uncertainty to evaluate effects of demand changes on water and wastewater management systems. For a case study of 350 urban water supply agencies (defined as agencies that support over 3,000 retail customers or 3,000 acre-feet of retail water annually) and 329 associated wastewater management systems in California that together serve 31 million people (79% of the state's population), Monte Carlo simulations are used to develop scenarios of changes in urban water demand from 2020-2030, which incorporate uncertainty of input parameters including population, indoor and outdoor water use efficiency, drought effects, and retail water rates (price). The procedure integrates statistical modeling (linear regression) and mechanistic modeling within a Monte Carlo framework to estimate changes in urban water demand through 2030 through a stochastic approach with random sampling. Next, we use network modeling of connectivity between water supply and wastewater management systems to evaluate effects on wastewater influent production that flows to collection and treatment systems. A novel index, the Demand Change Factor, quantifies the impact of forecasted changes in demand with conservation. The approach demonstrates how to incorporate uncertainty in demand forecasting and the importance of including an uncertainty-based approach with scenarios that incorporate a range of potential influences on future urban water planning.

Methods

We modeled total and per capita future water demand for each of 350 water supply agencies, accounting for seasonal and annual changes in demand, increased efficiency of indoor and outdoor water fixtures and appliances, effects of drought on water demand, climate factors, land use density, retail water rates (price), and population change (Figure S4). Social preferences, media coverage, and economic trends such as recession have all been shown to influence water demand, and though important, these factors were not included here due to a lack of agency-specific data (Wentz and Gober 2007; Ouyang et al. 2014; Wentz et al. 2014; Kiefer et al. 2016; Quesnel and Ajami 2017, 2019; Pincetl et al. 2019a; Marx 2021; Green et al. 2024).

For each water supply agency, D_{cur_g} is current per capita demand in an agency (g) and D_{fut_g} is future per capita demand in the agency (g) at the end of the forecasting period. Each Monte Carlo simulation (n) includes a randomly sampled value from an empirical probability distribution for each input parameter used to model indoor and outdoor demands. Sampled input parameters included lifetimes of fixtures and appliances based on industry data, outdoor irrigation efficiency rates resulting from changes in building codes and incentivized turf replacement, evapotranspiration, landscape area, population change, retail water rates based on price elasticity values, and effects of net drought based on statistical modeling of agency-specific water demand during the 2012-2016 drought in California. Data sources, which are described below, are noted in more detail in Tables S17 and S18 of the Supplemental Data.

The average future per capita demand ($\bar{D}_{fut_g}$) for an agency across simulations is:

$$\bar{D}_{fut_g} = \frac{\sum_{n=1}^N \left[\left(D_{cur_{g,i}} - (e_{g,i,n} D_{cur_{g,i}}) \right) + \left(D_{cur_{g,o}} - (e_{g,o,n} D_{fut_{g,o}}) \right) \right]}{N} \quad (1)$$

where $D_{cur_{g,i}}$ is current indoor per capita demand across all sectors (residential, commercial, industrial, and institutional), $D_{cur_{g,o}}$ is outdoor per capita demand across all sectors, $e_{g,i,n}$ is the cumulative rate of efficiency for indoor fixtures and appliances in an agency derived from end-use modeling in simulation n during the modeled period, $e_{g,o,n}$ is the cumulative rate of efficiency for outdoor fixtures in an agency-based on building code changes for landscaping and on-going incentivized turf replacement, $D_{fut_{g,o}}$ is future outdoor demand, and N is the total number of simulations. While the efficiency factor for indoor demand was applied directly to current per capita use, the efficiency factor for outdoor demand was applied to a future baseline demand that considered annual variations in factors of evapotranspiration, precipitation, and landscape area, as described below. The indoor and outdoor efficiency factors (Equations 2 and 3) are composite coefficients (0 to 1) of underlying agency-specific drivers of efficiency from technological improvements ($e_{g,t,n}$), changes in codes and standards ($e_{g,c,n}$), impacts of retail water rate changes to reduce demand ($e_{g,e,n}$), and drought effects ($e_{g,d,n}$):

$$e_{g,i,n} = f(e_{g,t,n}, e_{g,c,n}, e_{g,e,n}) \quad (2)$$

$$e_{g,o,n} = f(e_{g,c,n}, e_{g,e,n}, e_{g,d,n}) \quad (3)$$

Methods, assumptions, and equations used to estimate indoor efficiency changes for both indoor and outdoor efficiency are described further below in the section *Estimating Future Water Demand with Uncertainty*. Efficiency changes from technological improvements and codes and standards ($e_{t,c,n}$, $e_{g,c,n}$) were estimated using end-use modeling, which is summarized below and detailed in Section 4 of the *Supplemental Data*. Equations and data used to estimate the efficiency changes from retail water rates ($e_{t,e,n}$) is described further below under the heading *Changes from Retail Water Rates*.

Each water agency has a distinct indoor and outdoor efficiency rate in each simulation. A rate value of 1.0 would indicate no efficiency improvements and values less than one would indicate some level of efficiency. The methods used to estimate the efficiency impact of each of the drivers are described below. Average total future demand for an agency across all simulations ($\bar{T}_{fut_g}$) is the product of future per capita demand of an agency in a simulation ($D_{fut_{g,n}}$) and the randomly sampled future population value in the simulation ($p_{fut_{g,n}}$), averaged over all simulations:

$$\bar{T}_{fut_g} = \frac{\sum_{n=1}^N p_{fut_{g,n}} D_{fut_{g,n}}}{N} \quad (4)$$

The impact of cumulative changes in efficiency and population was estimated using a novel metric, the *Demand Change Factor (DCF)*. DCF values are the ratio of future to current demand, which captures the magnitude and direction of future water demand in relation to current demand (Equation 5). Values less than 1 indicate agencies with a net decrease in future demand, while values greater than or equal to 1 indicate agencies with a net increase in future demand. The DCF for an agency (DCF_g) is defined as:

$$DCF_g = \frac{\bar{T}_{fut_g}}{T_{cur_g}} \quad (5)$$

Scenarios of Future Water Demand

Five scenarios of future water demand were modeled. Each scenario included different combinations of sources of uncertainty as input factors (population change, indoor and outdoor efficiency, retail water rates (prices), and drought effects) to understand the influence of each factor in comparison to a baseline with only population changes.

The modeled scenarios were: 1) baseline future demand with projected population changes; 2) baseline plus efficiency improvements from new fixtures and appliances (indoor and outdoor) as well as changes in retail water rates; 3) baseline plus estimated effects of a severe drought, as well as changes in retail water rates; 4) baseline future demand plus efficiency improvements from new fixtures and appliances (indoor and outdoor), as well as estimated effects of a severe drought; and 5) baseline future demand plus efficiency from all factors (see Table 1). For each scenario, 1,000 simulations of future demand were developed by randomly selecting from parameter distributions of sources of uncertainty.

Current Baseline Water Demand

Water demand (2013-2019) was evaluated for each water supply agency based on self-reported data collected by state water agencies in California. First, the California State Water Resource Control Board (Water Board) annually collects Electronic Annual Reports (eAR) that report monthly total water demand for residential, commercial, industrial, institutional, and landscape irrigation sectors. Second, the California Department of Water Resources (DWR) collects and publishes Urban Water Management Plans (UWMPs) submitted every 5 years by water supply agencies (DWR 2023). Values for water deliveries were used that do not include leaks that may occur in the water distribution systems but would include leaks that can occur at properties. Data were cleaned and formatted to correct errors through several methods. First, we visually inspected time series graphs of total and residential demand for individual water supply agencies and identified visual outliers of missing data. Second, we estimated residential and total per capita demand for each month in reported data and flagged unrealistic values that were three or more times greater than the previous month. Identified records of erroneous data were

examined and analysis created a typology of errors, including misreported units (i.e. millions of gallons reported as acre-feet), missing data, and erroneous entries. The time series was corrected by correcting the units in instances when the resulting value matched closely with the preceding and following years, or by interpolating a value for the erroneous or missing entry from values in the same month of the previous and following years. Corrected data files were compiled for each water supply agency and are available through the online software platform and repository *Hydroshare* (sponsored by the Consortium of Universities for the Advancement of Hydrologic Science, Inc.) or by request to the authors.

For residential water demand, the split between indoor and outdoor demand is not reported in statewide sources and required estimation. Two methods were used to disaggregate indoor and outdoor demand (Table S1). First, values of residential indoor water demand for 154 (44%) water supply agencies were adopted from published work that used seasonal decomposition methods to evaluate the approximate percentage of landscape irrigation by season in water supply agencies that provided data (DWR 2021). The average value of indoor demand for this group was 51 gallons per person per day (gpcd), and the median value was 48 gpcd (Method 1). Second, for water supply agencies without data to use Method 1, a linear transfer function (Method 2) was developed to estimate indoor demand based on relating indoor demand and minimum month demand for the 154 water supply agencies with seasonally adjusted indoor water demand data (Method 2). Total outdoor demand was then estimated by subtracting total indoor demand from total reported demand. For commercial, industrial, and institutional water demand, the split of indoor and outdoor demand can vary widely between water supply agencies based on industries and commercial property characteristics. Within agency-specific methods to accurately disaggregate indoor and outdoor uses, we assumed that 70% of demand was for indoor uses.

Estimating Future Water Demand with Uncertainty

Future water demand was estimated by applying efficiency rates to current water demand with parameter sampling (Equation 1). The rates of efficiency in a scenario are the cumulative percent reduction in demand from parameters noted in Table 1. Uncertainty was introduced through sampling from a

distribution of values for the factors of population change, retail water rate changes, indoor fixtures efficiency (end-use modeling), and outdoor irrigation efficiency improvements, and drought.

Population Change: Population projections for agency service areas in California were evaluated from two sources: self-reported estimates through 2045 within required Urban Water Management Plans (UWMPs) and county-level estimates from the Department of Finance (DoF) through 2030. Comparing the projected populations from both sources, self-reported estimates were approximately 4.5% larger than estimates from DoF data (Table S2). The range of uncertainty considered in the analysis incorporated the discrepancies in future estimates from these two sources as upper and lower values for the percent change in demand for an agency. For each scenario, the value used for 2030 population was sampled from a distribution assumed to be normal with mean equal to the reported values in UWMPs and standard deviation equal to 4.5% of the mean.

Changes in Retail Water Rates ($e_{p,e,n}$): Changes in retail water rates affect the amount of water that customers use, but the exact relationship depends on many factors including rate structures, water bill formats, temperature, precipitation, irrigation needs, and other factors. It was prohibitive to collect data for all water supply agencies represented in the study and develop individualized forecasting scenarios of water rate changes. Alternatively, a simple representation of price changes on demand is captured as the own-price elasticity of demand, which is the ratio of the percent change in the quantity demanded of water and the percentage change in the water unit price:

$$e_p = \frac{dQ/Q}{dP/P} \quad (5)$$

Price elasticity data for all major water supply agencies in California are not readily available, but studies have estimated price elasticity values for residential water demand in major metropolitan water agencies (Buck et al. 2016). A parameter distribution for price elasticity values was developed assuming normally distributed values with a mean of -0.16 and standard deviation of 0.03 derived from literature

(Buck et al. 2016) and lower and upper boundary estimates of 1% and 3% increases in annual retail water rates for an agency through the modeled period. A distribution of percent changes in volumetric demand at the end of the modeled period (10 years) was generated as the product of a set of randomly selected values for price elasticity and percent change in water rates, yielding a right-tailed distribution ($mean = 0.03$, $st.dev. = 0.01$), which infers that the average decrease in assumed water demand due to price changes over the course of ten years is 3% in real dollars. This reflects the uncertain increases in prices due to the ever-increasing real cost of supplying urban water controlling for inflation.

Changes from End-Use Modeling of Household Indoor Water Use Efficiency ($e_{t,c,n}$, $e_{g,c,n}$): When fixtures and appliances are replaced, they are typically replaced by more efficient devices required by state and federal laws, whereby new fixtures sold in the marketplace must meet certain efficiency standards that exceed past requirements. Fixture efficiency in households was incorporated into the modeled scenarios through a deterministic approach with end-use modeling, which integrated land use and building ages to estimate current and future efficiency within a household from 2020 through 2030.

Fixture efficiency improvements included both code-based (natural) and incentivized (enhanced) replacement. The code-based replacement rate is the rate at which existing devices are replaced with newer ones after failure or end-of-life. Code-based replacement is driven by the lifetime of devices, the frequency of use that can limit or extend the typical device lifetime, as well as land use factors such as the rate of home construction or remodeling. The incentivized replacement rate is the rate at which devices are replaced before their end-of-life. Residents can choose to replace devices before end-of-life to take advantage of utility incentives or for personal preferences. Parcel information for all properties in the state of California was derived from a commercial product (Digital Map Products 2021). For each water agency, a data file was created with a list of properties in an agency's service territory and attributes of age and number of fixtures and appliances.

The efficiency of fixtures and appliances within a household was assumed based on building age derived from parcel data and the efficiency of fixtures during the time of the household's construction.

The end-use modeling used a vintage stock modeling approach (Muth 1973; Riedy 2003) to track the number and efficiency of fixtures within bins of houses associated with housing stock, including the number of fixtures that could still be replaced with more efficient ones through code-based or incentivized replacement. Code-based replacement rates were estimated using standard appliance lifetimes to estimate the average efficiency of a fixture in a household of a given age considering replacement over time (Table S5). The end-use model incorporated efficiency improvements for toilets, kitchen and bath faucet fixtures, showerheads, clothes washers, and dishwashers.

Effects of incentivized replacement were estimated for clothes washers and toilets by reducing the lifetime of each appliance by a percentage equal to the estimated annual rate of replacement. An exponential decay function was used to model replacement rates based on the estimated lifetime of a fixture (Diringer et al. 2018). While some literature indicates that other functions such as lognormal better represent the distribution of market penetration over time, for the mean and standard deviation values of device lifetimes used in the analysis, a lognormal distribution was deemed to overpredict the percentage of fixtures remaining after several decades. For instance, for toilets with an assumed average lifetime of 22 years (st. dev = 3.8 years), a lognormal distribution resulted in 15% of originally toilets remaining after 50 years and 10% of toilets remaining after 60 years. In the exponential decay functions that were used, lambda values can be interpreted as an annual rate of replacement, with the inverse equal to the length of operation of a fixture before failure. The lambda value is driven by two factors: fixture replacement from code-based efficiency improvements and incentivized efficiency improvements.

For code-based improvements, toilets have an estimated lifetime of 23.75 years ($\lambda = 0.4$), while clothes washers have an estimated lifetime of 14 years ($\lambda = 0.71$). For incentivized improvements, peak and annual replacement rates were estimated from data for water use efficiency rebate programs for water supply in Southern California, the San Francisco Bay Area, and the Sacramento region from 2012-2020 covering 16 million people (Porse et al. 2025). The rate of incentivized replacement was calculated as the ratio of reported rebates in an agency and the total number of fixtures in that agency based on land use parcel data. Peak replacement rates usually corresponded with drought

(2014–2016), when water management agencies boosted local or regional water use efficiency programs. As shown in Figure 1, for toilets, the average annual rate of replacement in an agency for areas with available data was 0.3% (range = 0% - 2.9%), while the average annual peak replacement rate was over 1% (range = 0.1% - 18.8%). For clothes washers, the average annual rate of replacement was 0.5% (range = 0.1% - 3.8%), while the annual peak replacement rate was nearly 1% (range = 0.2% - 7.9%). Lambda values for toilets and clothes washers used in the end-use modeling included both code-based and incentivized efficiency improvements, with incentivized efficiency based on the average annual rate of incentivized replacements. The cumulative effects of annual efficiency replacements can result in saturation of efficient fixtures, whereby nearly all older fixtures in an agency’s territory have been replaced. The theoretical rate of replacement of indoor fixtures was estimated as the ratio of the number of highly efficient fixtures to the number of all fixtures in an agency.

To incorporate uncertainty in fixtures, the end-use model was run 1,000 times by sampling from device lifetimes assumed to be normally distributed with mean and standard deviations equal to average and standard deviation values of lifetimes reported in the literature (data provided as a supplemental worksheet). Each scenario yielded a different percent decline in overall indoor water demand from 2020 to 2030, which was applied to the estimated 2020 demand to create 1,000 scenarios of indoor per capita demand.

Changes in Outdoor Water Use Efficiency ($e_{g,c,n}$): Outdoor efficiency results from improvements to irrigation systems, conversion to drought-tolerant landscapes, and changes in behavior regarding irrigation practices. Many water suppliers offer rebate programs that encourage households to replace turf lawns with water-efficient landscapes, including plants such as low-water perennials, shrubs, and trees, which can save as much as 75 gallons per square ft annually (AWE 2019; Chesnutt 2020). Additionally, evidence indicates that when a household replaces a turf lawn through a rebate program, neighbors may convert lawns without participating in the program, and this “neighbor effect” acts as a water savings multiplier for water agencies’ rebate investments (Pincetl et al. 2019a; Green et al. 2024). However,

outdoor irrigation is also highly dependent on behavior and climate. Residents control the frequency and duration of irrigation times, sometimes moderated by local codes and ordinances, and may adjust irrigation schedules based on conditions of drought, heat, or precipitation.

Future outdoor water demand was estimated based on methods used in urban areas of California through its Model Water Efficient Landscape Ordinance, or MWELo (State of California 2019). Total outdoor water demand ($T_{cur_{g,o}}$) for a water supply agency can be modeled as the product of irrigated landscape area (A); a reference evapotranspiration (ET_{Ref_g}) that is based on turf; an effective precipitation factor (C_g) that reduces the estimated evapotranspiration loss, assuming that soil water is used by vegetation; and an adjustment factor that incorporates irrigation efficiency and landscape vegetation that uses less water than turf (e_{adj_g}):

$$T_{cur_{g,o}} = A_g * (ET_{Ref_g} - C_g) * e_{adj_g} \quad (6)$$

From Equation 6, agency-specific adjustment factors were estimated from total outdoor demand, landscape area measurements, and reference evapotranspiration of turf derived from statewide reporting (Hart et al. 2009; DWR 2022). Current per capita demand in an agency was also estimated from the current total demand and population (Equation 7):

$$D_{cur_{g,o}} = \frac{T_{cur_{g,o}}}{p_{cur_g}} \quad (7)$$

Future per capita demand in simulation n becomes the product of the input values sampled from empirical parameter distributions (Equation 8):

$$D_{fut_{g,o,n}} = \frac{A_{g,n} * (ET_{Ref_{g,n}} - C_g) * e_{adj_g}}{p_{fut_{g,n}}} \quad (8)$$

Equation 8 is the future per capita demand $D_{fut_{g,o,n}}$ used to estimate total future demand represented in Equation 1.

The efficiency of outdoor demand considered two calculations. First, the change in total water demand was calculated by applying an assumed rate of water savings from replacing turf (gallons per

capita per day, per square-foot) from the Alliance for Water Efficiency’s proprietary *Water Conservation Tracking Tool* to the annual area assumed to be replaced through routine property redevelopment that must comply with MWELo requirements to limit turf (AWE 2020a; DWR 2025). The annual area of redeveloped property had an assumed rate of redevelopment of 0.2% during the 10-year period. The change in total water demand was calculated by applying an assumed rate of water savings from the literature from replacing turf (gallons per capita per day, per square-foot) to the annual area replaced. This yielded a 2% decline in demand during the 10-year period. Second, the effects of turf replacement rebate programs were considered. Data collected from water supply indicated that the average annual replacement rate of turf in an agency from 2011 to 2018 was 0.2% (0.0%–0.3%) of irrigated area replaced annually (Figure 1), while the peak average annual replacement rate of turf in an agency was 0.4% (0.0%–1.3%) (Porse et al. 2025). Combining these results using a normal distribution yielded distributions with percent declines in demand that ranged from 2.4% to 3.8%.

Drought Effects ($e_{g,d,n}$): During drought, significant reductions in water demand can occur (AWE 2020b). Drought can also result in lasting reductions in water demand after drought ends. California has experienced four major periods of drought in recent decades: 1976–1977, 1987–1992, 2007–2009, and 2012–2016. In each period, urban water demand dropped measurably to accommodate supply shortages, and, after drought, demand remained below predrought levels (Lee et al. 2021). For the recent drought from 2012–2016, a set of agency-specific statistical models was used to quantify a net effect of drought, defined as the difference in the estimated percent reduction in an agency in the 2014–2016 drought period and the estimated percent increase in an agency after the drought from 2016–2018 (Porse 2021). The average net drought effect across all water supply agencies was used as an estimate of a statewide reduction associated with the assumed period of extended drought incorporated into the forecast (Table S10). The statewide average net drought effect per agency was -5% in per capita residential demand (median = 7% decrease), which the average value of the net drought effect in an agency ranged from -

11% to 4% across regions. These values were used to develop a probability distribution of net drought effect values for random sampling as an input parameter for demand forecasting.

Efficiency in Commercial, Industrial and Institutional Properties ($e_{g,c,n}$, $e_{g,d,n}$): Water use efficiency in commercial, industrial, and institutional properties varies widely across businesses, institutions such as colleges and schools, and industrial sites. Given heterogeneity, a simple approach was used that assumed that indoor water demand in CII properties would grow more efficient at the same rate as the residential sector given improvements in fixtures, appliances, irrigation, and landscape change. California recently passed legislation to prohibit “non-functional” turf defined as turf that is not used regularly for activities such as sports or recreation, but current data is limited to estimate the effects of this requirement and CII water demand will be an area for further research in future forecasting studies (State of California 2022).

Network Modeling of Water Supply and Wastewater System Connectivity

There are approximately 1,300 regulated wastewater treatment facilities (WWTFs) in California that serve domestic needs. A portion of these serve larger urban retail water suppliers. In many California cities, multiple WWTFs may serve a metropolitan region, and influent and effluent flows can be interconnected.

To represent this diversity, a network connectivity model of water supply agencies, wastewater collection systems, and WWTFs was developed for all urban areas of the state served by one or more urban retail water suppliers. The connectivity between water supply agencies, wastewater collection systems, and WWTFs across California’s metropolitan areas was represented as a series of nodes and links. Generalized network flow depictions are widely used in modeling and have been applied to numerous water management studies, including in California (Bazaraa and Jarvis 1977; Jensen and Barnes 1980; Ahuja et al. 1993; Draper et al. 2003; Harou et al. 2009; Porse et al. 2017). Here, the network of connections between water supply, wastewater collection, and wastewater treatment systems in California is not a single large network, but instead many smaller networks with directed (one-way)

flows of wastewater effluent from water supply agencies to wastewater collection and treatment systems. The total volume (V_W) of wastewater effluent that flows from all source nodes i (supply agencies) to destination node j (wastewater collection systems and treatment plants) over link k is represented mathematically as:

$$V_{W_j} = \sum_{i=1}^I \sum_{k=1}^K (V_{W_{ijk}}) \quad (9)$$

WWTFs, collection systems, and water supply agencies can be connected in several ways. First, a WWTF may collect influent from a single water supply agency through a single collection system, yielding a one-to-one relationship between water supply and wastewater systems. Second, a WWTF may treat influent from multiple water supply agencies through one or more collection systems, representing a many-to-one relationship. Third, the service areas of multiple collection systems and WWTFs can overlap with the service area of a single agency, yielding a one-to-many relationship. Finally, the service areas of multiple collection systems and WWTFs can overlap with service areas of multiple water supply agencies, yielding a many-to-many relationship. Within the network model, water supply agencies are always source nodes (i), while collection systems and water treatment facilities may be either source (i) or destination (j) nodes. For the one-to-many or many-to-many relationships, we assume that the percentage of effluent flows from source i to each of its destination nodes j remains constant.

For each source node i , only the estimated volume of indoor demand was assumed to generate influent to wastewater systems. Per capita values of indoor residential and commercial, industrial, and institutional values were converted to volume by multiplying by the population of a water supply agency. For residential, indoor demand that becomes wastewater was estimated based on the procedures to split indoor and outdoor demand described previously. For Commercial, Industrial, and Institutional demands, 70% was assumed to be indoor and the volume of CII demand converting to wastewater in an agency was equal to total CII demand multiplied by 0.7. Limited data exists for agency-specific values for this metric. The value of 70% from indoor uses was assumed based on historical studies that noted greater than 50% of demand in the CII sector was indoor prior to 2014, and through 2030, recent drought and upcoming

bans on non-functional turf were assumed to have significantly reduced the % of CII as outdoor demand through 2030 (Herberger et al. 2014). This assumption may be an overestimate in areas with significant large CII buildings that use evaporative cooling and would be a consumptive use.

For each WWTF as a destination node, j , the Demand Change Factor (DCF_W) can be estimated by comparing current influent volume ($V_{W_j,current}$) with future influent volume ($V_{W_j,future}$) given water use efficiency and conservation in connected water supply agencies. DCF_W of a water treatment facility j is equal to the ratio of the total sum of future influent to that WWTF from all water supply agencies (via collection systems) divided by total sum of current influent:

$$DCF_{W_j} = \frac{V_{W_j,future}}{V_{W_j,current}} \quad (10)$$

In Equation 10, the wastewater influent flow to a WWTF facility j ($V_{W_j,future}$) from all source node i through link k is equal to the product of the Demand Change Factor associated with the connected water supply agency (DCF_{S_i}) and the current volume of influent flow from that water supply agency through a collection system ($V_{W_{ijk},current}$). Summing across all source nodes and links yields the total future wastewater effluent inflow to facility j (Equation 11):

$$V_{W_j,future} = \sum_i^I \sum_k^K DCF_{S_i} V_{W_{ijk},current} \quad (11)$$

In practice, only one link k exists for connectivity between a water agency and a wastewater collection system, and similarly between a collection system and WWTF. Collection systems are assumed to have no impact on the Demand Change Factor, though collections systems may affect influent quality.

The network modeling was created from three sources of data: Urban Water Management Plans that are submitted by water supply agencies every five years and compiled by the California Department of Water Resources (DWR); metadata from the California Integrated Water Quality System (CIWQS) managed by the California State Water Resources Control Board (SWB); and the SWB's Volumetric Annual Report (VAR) survey that began in 2019. The network connectivity between water supply

agencies, wastewater collection systems, and wastewater treatment and reuse systems is publicly-available (Porse et al. 2022).

The network model could track influent flows for scenarios of current and future water demand. The network model software was developed in *Python*. The estimated volume of wastewater generated by customers within an agency and sent to a collection system (and later a wastewater treatment plant) was based on reported data from several sources, including values recorded in Table 6-2 of UWMPs and the VAR survey. Influent volumes to a collection system and WWTF were tracked on an annual basis. The network model represented 329 wastewater facilities in California that serve urban retail water suppliers, of which available data was able to resolve results for 225 facilities wastewater treatment and reuse systems connected to modeled water supply systems.

Results

Results from the scenario modeling indicate that each factor included in the modeling (efficiency, price, and drought effects) reduces future water demand, with efficiency from fixtures, appliances, and landscapes having the largest influence. Results are presented for statewide average values (weighted by population in an agency), agency-specific values, and summary values of Demand Change Factors for water supply agencies and wastewater facilities.

Statewide Per Capita and Volumetric Demand

Historic statewide per capita demand is 129 gpcd for all sectors and 89 gpcd for the residential sector (Table 2). In both cases, indoor demand was most of the demand for nearly all scenarios. In all future forecasted scenarios, total and residential per capita demand were equivalent or lower than current demand. In the baseline scenario that incorporated only population growth, total per capita demand across all sectors dropped by 1.5% to 127 gpcd due to reductions in CII per capita demand, while in the scenario that includes efficiency, drought, and price factors, future demand dropped by 13% across the modeled period to 112 gpcd as a result of reductions in both residential and CII demand (*s.d.* +/- 3.9 gpcd). Among

the modeled factors, efficiency (indoor and outdoor) from existing codes and agency incentives had the greatest effect, reducing demand by 7%, while price and drought effects together decreased future water demand by 6%. Within the residential sector only, statewide average per capita water demand decreases by 7 gpcd (7.9%) due to indoor and outdoor fixture efficiency improvements from codes, standards, and rebates. Comparing ranges of forecasted statewide average per capita use across scenarios within 95% confidence intervals revealed that the scenarios yielded distinct outcomes. Efficiency and price factors introduce the greatest uncertainty into forecasts. Table 2 summarizes results for statewide forecasted indoor and outdoor per capita demand across the modeled scenarios.

While forecasted per capita demand decreased in nearly all scenarios, the forecasted total volume of demand for the included water supply agencies increased or decreased depending on the scenario. In the future forecasted scenario with only population change, total demand in the water supply agencies with data increased slightly from 7.7 million acre-feet to 7.8 million acre-feet because of population growth. Alternatively, when incorporating all factors that influence efficiency into the forecast, future forecasted volume decreased by 11% to 6.8 million acre-feet. When more factors were incorporated into the forecast, efficiency gains outpace population growth, leading to an overall decrease in total volumetric demand.

The 2020 total indoor demand noticeably increases in the *Baseline* scenario (Table 2). This likely occurs due to the assumption of 70% CII demand as indoor. In the analysis procedures, residential per capita demand is multiplied by the future population, to which the 2020 indoor CII demand is added (70% of total CII). When combining the increased total volume of residential demand with steady indoor CII demand and dividing by the 2030 population, the result is in an overall increase for indoor demand likely rooted in both the population increase and the 70% assumption of CII demand as indoor. Similarly, the outdoor estimate for total outdoor per capita demand decreases due to the assumption that 70% of CII demand is indoors.

Agency-Specific Per Capita Demand Trends

Within scenarios, agency-specific per capita demand varied significantly. In the future forecasted scenario that includes all factors, while the median value of mean per capita demand in an agency was 102 gpcd (all sectors), the 25th and 75th percentiles ranged from 80 to 130 gpcd (Figure S8). The range of per capita values was similar for each of the modeled scenarios, with the baseline scenario that only included population having the highest median value.

Results indicated that future per capita demand is likely to decrease in many water supply agencies after incorporating price, efficiency, and drought effects, though agency-specific factors such as managerial approaches, geography, and customer income could be influential between different water supply agencies. Plotting current versus future demand for all water supply agencies by scenario, the slopes of trend lines were all less than 1.0. (Figure 2b). Only in the *Baseline* scenario did a portion of forecasted simulations consistently result in future values that were higher than historic for some water supply agencies (Figure S8). Thus, future per capita water demand would be expected to decrease across water supply agencies even when considering the variability introduced through the Monte Carlo simulations that simulate stochastic factors as well as agency-specific demographics.

Underlying factors of geographic region and population drove forecasted future per capita demand, but in varying ways (Figure S9). In some regions, such as California's South Coast and the San Francisco Bay Area, per capita demand was relatively consistent across water supply agencies of varying population sizes. In other regions, distinct trends emerged. In the Sacramento metropolitan area, per capita water demand was highest in mid-sized water supply agencies (25,000-50,000 residents) but lower for small and large systems. The Central Coast and Tulare Lake regions showed wide variability in per capita demand both across and within population categories.

Demand Change Factors: Water Supply Agencies

The forecasted Demand Change Factor (*DCF*) of an agency ranged from 0.82 to 1.95 depending on the agency and modeled scenario. In the *Baseline* scenario that only considered population changes, 21% of

water supply agencies expect to see lower future total (volumetric) demand. The percentage increased significantly when incorporating any or all of the modeled factors. In the scenario that included *Price* and *Drought* factors, 58% of water supply agencies would be expected to have lower future per capita demand. Incorporating *Efficiency* factors in scenarios increased the percent of water supply agencies with DCF values less than 1.0 to 78%. Finally, when incorporating all modeled factors into the forecasting scenario, over 85% of water supply agencies would expect future per capita demand values less than current.

Efficiency had the largest contribution to lower DCF values. In the scenarios that include efficiency in forecasting, 50% of water supply agencies had DCF values of 0.90 to 0.92 or less. In the scenarios that did not incorporate efficiency, however, the DCF values of this 50th percentile was 0.98 to 1.02. In other words, without incorporating efficiency in forecasts, more than 50% of water supply agencies in California could be planning for future per capita demand that is equal to or greater than historic values (Figure 2a). The geographic distribution of DCF values was relatively even across cooler coastal areas with greater population density and hotter inland areas with less urbanization (Figure 2c).

Demand Change Factors: Wastewater Treatment Facilities

Results from the network modeling of water supply and wastewater system connectivity varied between the water supply and wastewater sectors. The average DCF value for a wastewater treatment facility across the state was 1.12 in the baseline forecast scenario considering only population change, while the value was 0.89 in the scenario that includes all factors in the forecast. DCF factors vary across geographic regions in the baseline forecast scenario, with the highest values seen in the Colorado River Basin and Central Valley regions (1.19 through 1.29), and the lowest values in the San Francisco Bay Area and San Diego regions (1.03-1.05), as shown in Table 3. There were no significant differences in the DCF values across treatment plants categorized either reported level of treatment (Secondary/Tertiary) or Design Flow (0 – 500 million gallons per day), with values ranging from 1.12 through 1.15. Figure 2d, Table 3, and Tables S14 through S15 in the *Supplemental Data* section provide further details.

Economic Impacts of Demand Forecasting Uncertainty

The consequences of overestimating future water demand can impact utility finances. The difference in estimated annual water demand between the baseline forecast scenario (only population change) and the forecast scenario with all factors (population, efficiency, drought, and prices) was 860,000 acre-feet. If water supply agencies planned for future demand in the *Baseline* scenario, but future demand was closer to the values estimated in the *All Factors* scenario, water supply agencies would be paying for 860,000 acre-feet of excess capacity. The economic cost of planning for this can be roughly estimated using the unit cost of new water supplies. The California Department of Water Resources publishes a data set of marginal production unit costs for urban water supply for all large urban water agencies (DWR 2020). Using these values, the California urban water agencies in this case study could spend up to \$860 million over the modeled period for excess water supply capacity, or a statewide average per capita increase of \$27 on water utility bills based on the 31 million people in the study area. This would translate to a 1-2% increase for many residents during the modeled period. This value does not, however, consider the costs of those investments or the effects on linked systems such as wastewater that may be affected by changes in flows or concentrations. A full life-cycle cost evaluation would be necessary to evaluate such changes, which is out of the scope of this study (OWP at Sacramento State 2022). Alternatively, if water supply agencies planned for the *All Factors* scenario, but the *Baseline* scenario materialized, agencies would need to adapt over time to acquire 860,000 of new water sources, which could present fiscal and managerial challenges if changes happened quickly.

Discussion

Results of the analysis show how the forecasted value of per capita water demand in California varies based on the factors included in the forecasting scenario. Efficiency, including both baseline and incentivized sources, had the most significant influence on decreasing future per capita water demand. Changes in water rates and drought also decreased water demand, but at a lower rate than efficiency.

Finally, the scenario that included all factors in the forecast reduced future per capita demand at rates significant to future water supply reliability planning (>10% during the forecasting period).

The analysis offers novel methods to consider stochastic parameters for multiple unrelated factors in demand forecasting. In the water sector, existing best practices for demand forecasting detail how to estimate a range of outcomes, with lower and upper boundaries corresponding to deterministic scenarios (Diringer et al. 2018; Maddaus Water Management, Inc. 2020). Both overestimating and underestimating water demand can have implications for long-term planning and retail water rates. Past planning documents by state and regional water agencies in California have often overestimated future water demand and population growth (Abraham et al. 2020; Capone and Marston 2025). For example, the 1998 California Water Plan Update forecasted that in 2020, 47 million people would live in California and use between 227 and 256 gallons per capita per day (gpcd) in cities and suburbs (DWR 1998). Instead, approximately 39 million people live in California today and, in 2020, the state's urban per capita water demand rate was approximately 130 gpcd (Census 2021; SWB 2024). Similarly, over the course of five Integrated Resource Plans since 2009, the Metropolitan Water District of Southern California has forecast future water demand greater than what materialized (MWD 2022). Future water demand (total gallons) is influenced by changes in rates of both per capita demand and population growth (or decline). While per capita water demand decreased significantly over three decades, populations continued to grow, resulting in relatively stable or slightly decreasing total water demand. For linked wastewater systems, failing to estimate and communicate likely scenarios of future water demand can result in oversized wastewater treatment facilities that face operational and regulatory challenges if they cannot meet water quality requirements for discharges.

Several noted emerging trends may influence long-term outcomes for water demand. For instance, population growth has flattened or decreased in many urban areas of California (Cain and Hehmeyer 2023). If per capita demand decreases, and some urban water agencies also see stable or declining populations, there could be an overall decrease in water demand in these agencies. This would leave agencies, both water and wastewater, to operate aging infrastructure with shrinking ratepayer bases,

likely requiring increased water rates (Faust et al. 2016). Separately, in 2025, the U.S. federal government eased water use efficiency standards for some fixtures and devices under its *WaterSmart* program. This program sets national standards for certain fixtures and devices. The end-use modeling in this analysis was based on a mixture of changes in federal and state standards over time. Presently, California has adopted standards for fixtures and devices that are equal to or more efficient than federal standards, so in California, the impact will likely be minimal if standards previously enacted by the California Energy Commission and through the *CalGreen* program remain in place (Table S5).

The findings of this analysis are subject to limitations. First, as with most forecasting exercises, future projections include some level of assumptions with stationarity, which may not hold true as future conditions emerge. Second, there were limited data available to develop parameter distributions for several of the factors used in the demand forecasting, including long-term rates of water use efficiency for outdoor irrigation. Assuming normal distributions for some parameters may skew the outcomes and underemphasize the role of long-tailed distributions. Third, while summary metrics reported mean values, some underlying parameters included in the forecast, especially drought effects, are likely to become more extreme in coming decades. The modeled effects may not reflect the impacts of future climate extremes on water demand. Finally, while the model of water supply and wastewater network connectivity is based on best available data at a statewide scale, some data gaps exist. Indoor water demand in commercial, industrial, and institutional (CII) properties supports baseflow, but precise values for every water agency across the state are not known. The estimate used in modeling may under- or over-estimate indoor water use percentages, which contribute to baseflow that can stabilize influent to wastewater collection systems and treatment facilities. Finally, the available data may not capture all influent to a wastewater facility. For instance, while the analysis especially emphasized residential water demand, urban water agencies also support CII demands. In service areas that have a higher proportion of these land use types, cuts in residential demand could be moderated by sustained demand in CII properties. Local retail water agency data available at the time of this analysis did not allow for full accounting of CII demands in estimates of wastewater influent.

Conclusions

This study used a systems-based approach to forecast changes in urban water demand and model the effects of these changes on wastewater management systems. Results indicate that in all future forecasted scenarios, total and residential per capita demand are equivalent to or lower than current demand. The study methodology highlights the importance of including multiple factors of population, efficiency, price, and drought in future forecasts. The percent of water supply agencies that would expect to see lower future demand ranges from 21% to 78% percent depending on which factors are included in forecasts. The Demand Change Factor (DCF) is introduced as a simple metric to interpret demand forecasting scenarios, where DCF values less than 1.0 indicate agencies that may likely experience future demand that is less than current demand. In the scenario incorporating *All Factors* in the forecast, 85% of agencies have an DCF value of less than 1.0. The DCF can also extend to systems and facilities connected to water supply agencies. For wastewater facilities, the average DCF value for a treatment plant is 1.12 in the baseline forecast scenario considering only population change, while the value is 0.9 in the scenario that includes all factors in the forecast. In the absence of incorporating efficiency into future forecasts, urban water agencies could plan to spend up to \$860 million for new water supply capacity that would not be needed, though risk averse planning by an agency might still support projections of future water sales at the level of the baseline to ensure sufficient supplies no matter the true future. The results indicate the value of incorporating multiple and detailed factors into future forecasts for cost-effective operational and long-term planning.

Data Availability Statement

Data, models, and code are available in multiple Hydroshare repositories, including: descriptions to process data from California's electronic Annual Report on annual water demand and supply (Porse 2023), the network model of water supply and wastewater agency connectivity (Porse et al. 2022), urban water demand regression modeling (Porse 2021), end-use modeling of fixture efficiency improvements,

and processed data for water supply and demand by urban water retailers in California (Philine-Gross et al. 2024). Additional data and code are available by contacting the corresponding author.

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Supplemental Data

A Supplemental Data file is included with further details on literature review, end-use modeling, drought effects on water supply, network modeling of water and wastewater connectivity, and results.

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Tables

Table 1: Factors included in each scenario. Parameters in italics are distinct in each simulation by incorporating randomly sampled values from probability distributions. Factors in the Baseline scenario (in italics) are included in all scenarios.

Scenario	Factors Included in Scenario
<i>Baseline Factors</i>	Current water use <i>Future population projections</i> <i>Changes in land use density</i> <i>Evapotranspiration rates</i> <i>Irrigated land area</i>
<i>Baseline</i> + Efficiency Improvements + Retail Water Rate Changes	<i>Baseline Factors</i> Impacts of changes in retail water rates Indoor efficiency (technology, codes, device lifetimes) Outdoor irrigation efficiency
<i>Baseline</i> + Drought Effects + Retail Water Rate Changes	<i>Baseline Factors</i> Impacts of changes in retail water rates Net drought effect on demand
<i>Baseline</i> + Efficiency Improvements + Drought Effects	<i>Baseline Factors</i> Indoor efficiency (technology, codes, device lifetimes) Outdoor irrigation efficiency Net drought effect on demand
All Factors	<i>Baseline Factors</i> Impacts of changes in retail water rates Indoor efficiency (technology, codes, device lifetimes) Outdoor irrigation efficiency Net drought effect on demand

Table 2: Population-weighted statewide average per capita demand by scenarios (in gallons per capita per day), with indoor & outdoor contributions: 2020 vs 2030. Ranges of values (95% confidence intervals) are noted for indoor, outdoor, and total average per capita demand. Population values represent agencies included in the analysis out of approximately 31 million total California residents.

Parameter	Historic (2020)	Future Scenarios (2030)				
		Baseline	Efficiency and Drought (No Price Factors)	Efficiency and Price (No Drought Factors)	Price and Drought (No Efficiency Factors)	All Factors
Population	28,139,232	30,145,780				
Per Capita Use: All Sectors (Residential, Commercial, Industrial, and Institutional)						
Total (standard dev.)	129.0	126.9 (+/- 0.52)	114.4 (+/- 3.65)	114.5 (+/- 0.85)	121.2 (+/- 3.88)	111.5 (+/- 3.94)
Indoor	68.9	74.0	59.7	58.2	66.1	58.2
Outdoor	60.1	52.8	54.6	56.2	56.4	58.6
Per Capita Use: Residential Sector Only						
Total (standard dev.)	89	89.2 (+/- 0.21)	79.3 (+/- 0.21)	79.5 (+/- 0.56)	83.5 (+/- 0.56)	76.5 (+/- 0.59)
Indoor	49.8	49.7	44	42.4	49.7	42.4
Outdoor	39.2	39.5	35.3	37.1	33.8	34.1

901 **Table 3: Average values of Demand Change Factors (DCFs) for wastewater treatment facilities in the baseline**
902 **scenario and in the scenario with all factors incorporated into the forecast, by region.**

Region Name	Scenario: Baseline	Scenario: All Factors	Number of Facilities in Region
<i>North Coast</i>	1.12	0.90	8
<i>San Francisco Bay Area</i>	1.03	0.82	28
<i>Central Coast</i>	1.12	0.90	25
<i>Los Angeles</i>	1.04	0.82	25
<i>Central Valley South</i>	1.21	0.97	22
<i>Central Valley North</i>	1.19	0.89	2
<i>Central Valley Sacramento</i>	1.23	1.00	28
<i>Lahontan</i>	1.13	0.88	6
<i>Colorado River/Imperial</i>	1.29	1.04	10
<i>Orange</i>	1.12	0.90	16
<i>San Diego</i>	1.05	0.86	21
<i>n/a</i>	1.10	0.88	32
Total	1.12	0.90	225

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Figure Captions

Figure 1: Annual and peak replacement rates of toilets, clothes washers, turf, and smart irrigation controllers associated with agency-funded water efficiency rebates from 2012–2020.

Figure 2: Illustrating changes in per capita use and Demand Change Factor (DCFs) for water supply and wastewater agencies in forecasted scenarios: (a) cumulative distributions of DCF values in an agency by scenario; (b) Historic vs. future (forecasted) per capita demand for indoor and outdoor use in all sectors (Residential and CII) by scenario, with all 1,000 simulations in a scenario plotted; (c) Geographic distribution of DCF values in agencies for the scenario that included all factors influencing future demand; (d) Demand Change Factors for Wastewater Treatment Facilities in the forecasted scenario that included all factors influencing future demand

Figure 1

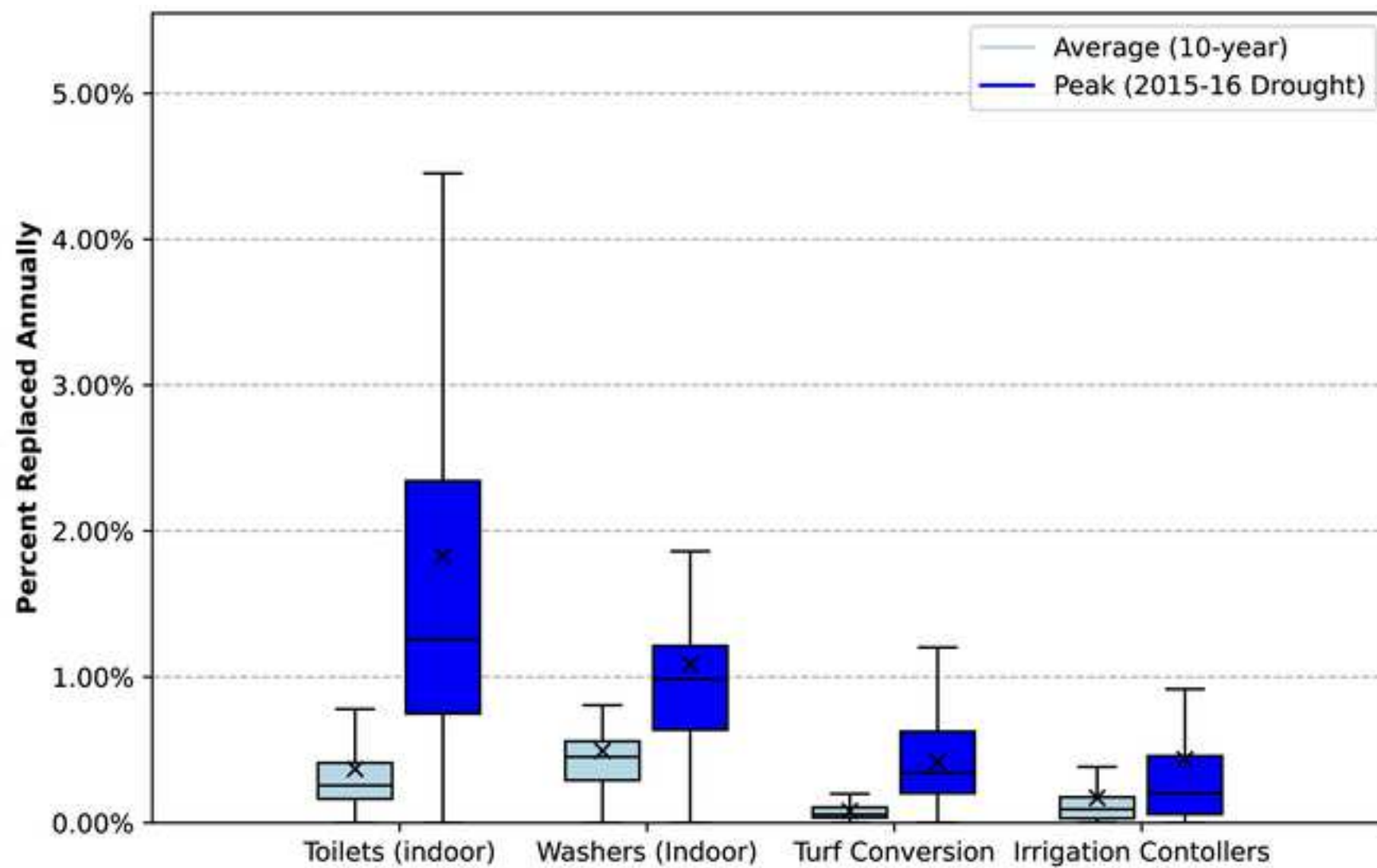
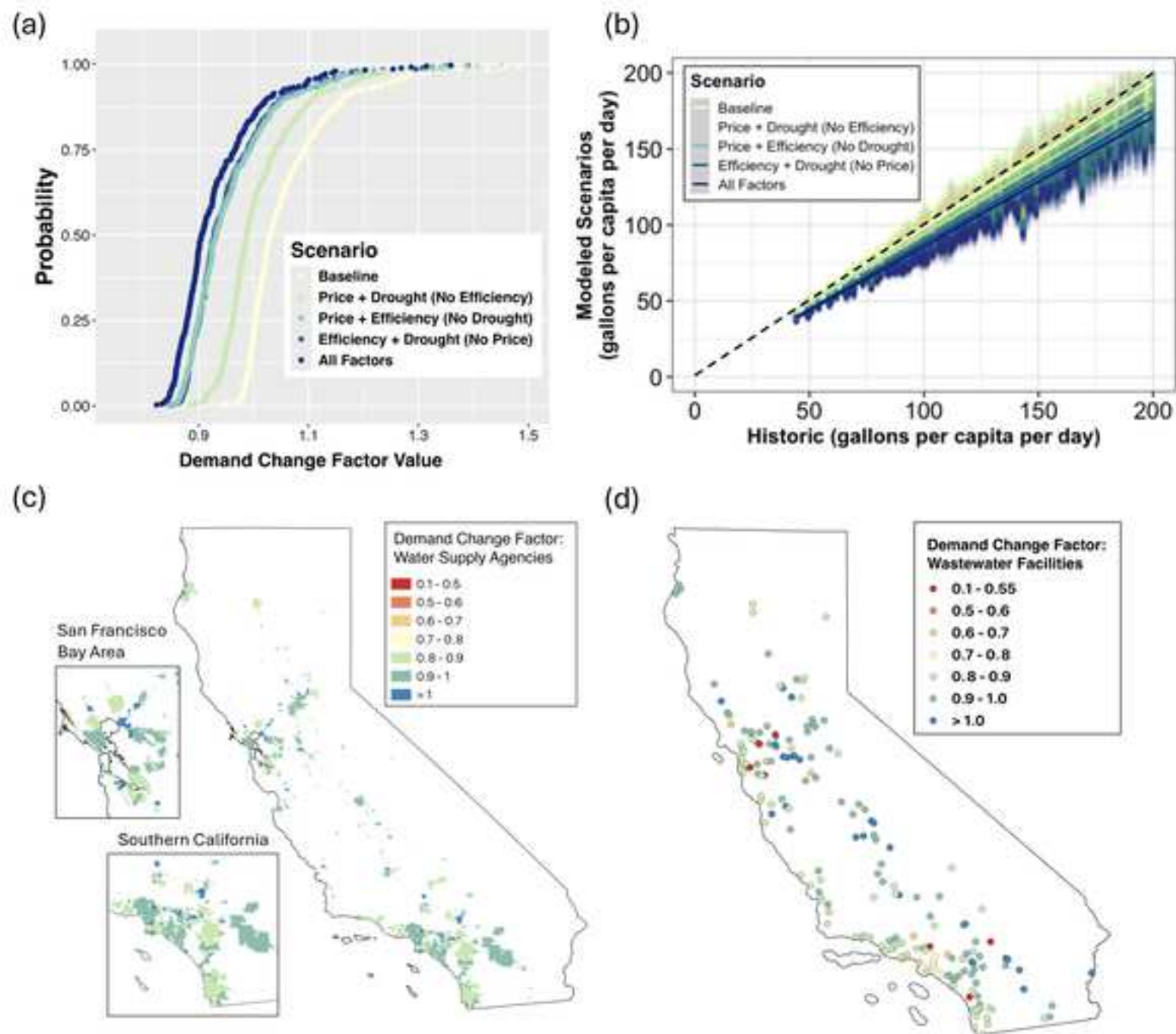


Figure 2



SUPPLEMENTAL INFORMATION FOR:
**Forecasting Urban Water Demand and Effects on Wastewater Management: An
Integrated Systems Approach with Uncertainty**

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29	Contents	
30		
31	1. Water Demand Forecasting Methods	3
32	2. Current Indoor Water Use Estimates.....	4
33	3. Population Projections.....	6
34	4. End-Use Modeling of Indoor Efficiency	8
35	4.1. Overview of Model Approach.....	8
36	4.2. Model Steps.....	9
37	4.3. Cumulative Effects of End-Use Modeling on Efficiency Gains	34
38	5. Drought Effects on Indoor and Outdoor Water Use.....	35
39	6. Network Modeling of Water Agency and Wastewater System Connectivity.....	37
40	7. Results.....	39
41	8. Summary of Data Sources	43
42	9. References	46
43		
44		

1. Water Demand Forecasting Methods

Existing literature on water demand modeling and forecasting is significant and several studies provide detailed reviews of conceptual frameworks, methods, and approaches (Billings and Jones 2008; House-Peters and Chang 2011; Rinaudo 2015; Diringer et al. 2018). Multiple approaches are used in the literature and in practice. First, future water demand can be estimated based on simple extrapolations with assumptions of population growth or aggregate demand increases. Second, future water demand can be estimated based on statistical and econometric modeling that uses explanatory factors to estimate water demands through regression. Explanatory factors of water demand generally include: land use, such as the types of properties in an area; landscape characteristics, such as lot size and landscaping; building age as an indication of appliance and fixture efficiency; seasonal water use patterns and irrigation habits; economic factors, such as retail water rates, unemployment, and price elasticity of residential water; sociodemographic characteristics and behavioral changes; and agency-specific investments in conservation programs (Howe and Linaweaver 1967; Wong 1972; Young 1973; Willsie and Ratt 1974; Morgan and Smolen 1976; Cassuto and Ryan 1979; Maidment and Parzen 1984; Maidment and Miaou 1986; Breyer et al. 2018; Heydari et al. 2022; Cominola et al. 2023). Third, future water demand can be estimated with end-use (component) modeling. End-use modeling is a mechanistic approach that sums water demand based on granular data for the volume and frequency of consumption for fixtures, appliances, and irrigation. Detailed data is compiled for factors including, but not limited to, building types, building ages, population and population density, number and efficiency of fixtures and appliances, and number of connections. Water use of each building type and age is summed and calibrated to simulate water use in a water agency. Finally, emerging approaches such as remote sensing, wavelet analysis, machine learning algorithms, and agent-based modeling have all been used to model aspects of indoor and outdoor urban water demand (Mini et al. 2014; Hemati et al. 2016; Gonzales and Ajami 2017; Lu et al. 2020). Incorporating multiple factors into urban water demand forecasting within complex socioecological systems likely requires a mix of methods (Baumann et al. 1998; House-Peters and Chang 2011; Rinaudo 2015). The difference in forecasted amounts and what develops to be actual future water use can impact water utility investments (Figure S1)

Drivers of Water Use
Efficiency and Conservation

Increased fixture efficiency
Local municipal codes
Landscape change
Utility rebates
Drought
Water rates
Behavior change
Education and awareness

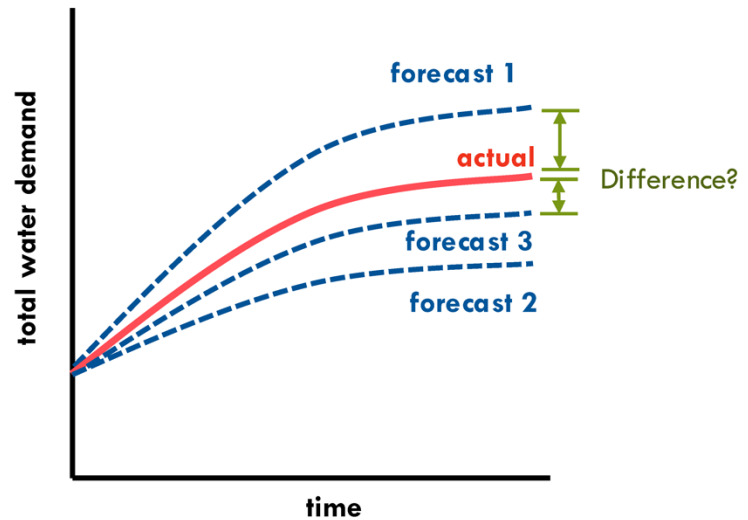


Figure S1: Factors that influence long-term changes in demand in forecasting water use. These factors influence future forecasts. Having an associated likelihood with various forecasts (1, 2, and 3) can help managers identify prudent investments that balance benefits and costs with uncertainty.

2. Current Indoor Water Use Estimates

Indoor water use values were identified for 158 agencies from an existing study of large water agencies in California (DWR 2021). The statewide average value of demand for this group was 51 gallons per person per day (gpcd) and the median value was 48 gpcd. For those agencies, this value was assumed to represent current indoor water use.

For other agencies in the study set, three methods were available to estimate indoor water use. First, recent Minimum Month demand (2-month average) estimates were available based on 2019 data from the California State Water Resources Control Board's (SWB) electronic Annual Report (eAR) (Method 1). Second, seasonally adjusted indoor demand was available based on a linear transfer function (Figure S2) that related indoor demand and minimum month demand for the 158 agencies with values for indoor water use data derived from a seasonal adjustment method that derived the portion of indoor and outdoor uses in a month based on reported data for dedicated landscape irrigation in an agency (Method 2) (DWR 2021). Third, indoor use estimates were available based on a multivariate linear regression model, which was developed based on the 158 agencies and could be applied to over 300 agencies with available data for explanatory factors (Method 3).

The preferred method for estimating indoor use based on the multiple methods was based on summary statistics that best represented known observed and available data. In most cases, Method 2 was preferred as it yielded reasonable results. If the value was unreasonable or out of range, Method 1 was used if it was a reasonable value.

From Method 2, the linear transfer function provided an estimate of indoor demand that was deemed the most appropriate because it adjusted observed values rather than estimating predicting values based on a series of factors that may not best capture site-specific influences of residential demand in an agency.

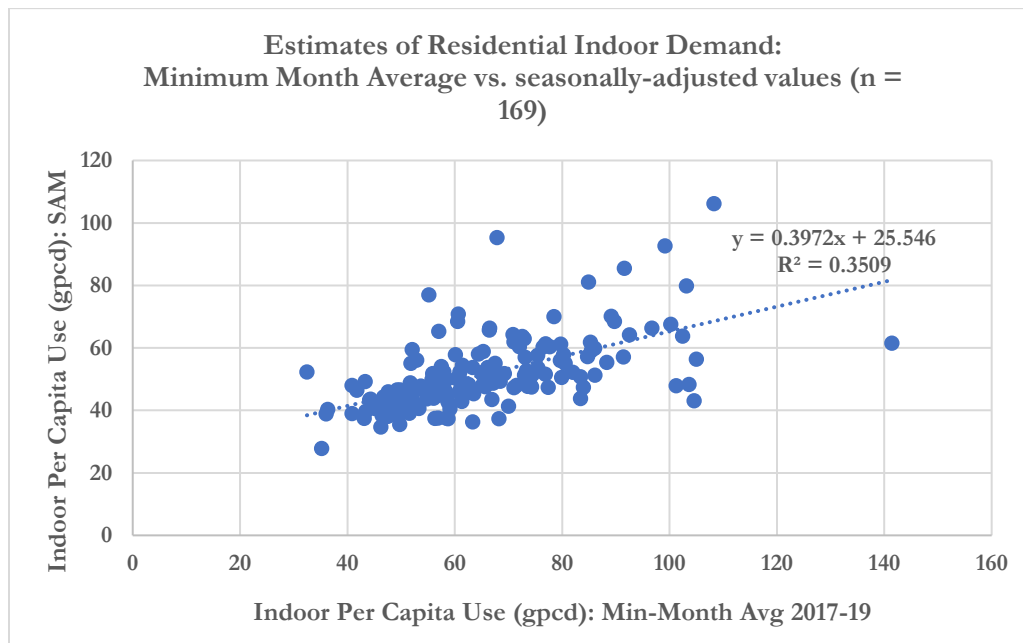


Figure S2: Transfer function to relate observed indoor residential demand with estimated demand from the minimum month method for agencies with available data (n = 169)

After applying the technique from Method 2 to all agencies, the resulting distribution of indoor demand was compared to the observed values (Figure S3). Measures of central tendency (mean, median, and standard deviation) were used to evaluate if the resulting population of agencies with extrapolated values resembled the observed population of agencies with seasonally adjusted data. The average, median, and standard deviation were similar (Table S1).

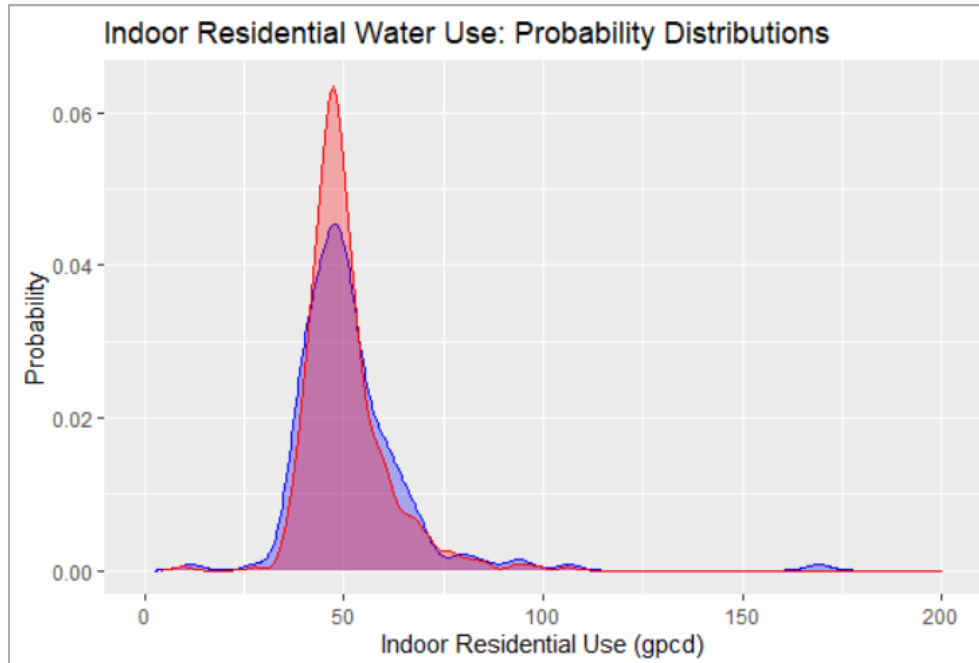


Figure S3: Comparing the distributions of: a) observed indoor residential water use for a set of agencies (n = 169), shown in red, and b) extrapolated indoor residential water use for all agencies, shown in blue.

Table S1: Estimated statistics for current indoor water use based on observed data (n = 154) and extrapolated data (n = 196). Estimates were based on either Method 1 (seasonally adjusted demand) or Method 2 (linear transfer function of minimum month demand and seasonally adjusted demand).

Value	Average	Median	St. Dev.	Count
<i>Method 1:</i> Seasonally Adjusted Indoor Use (gpcd)	51.2	48.8	11.5	154
<i>Method 2:</i> Linear Transfer Function: Minimum Month and Seasonally Adjusted Demand (gpcd), ($R^2 = 0.351$, <i>adjusted</i> $R^2=0.347$)	49.7	48	7.7	196
<i>Final:</i> Combined results (gpcd)	50.7	48.2	9.9	350

3. Population Projections

Population projections for agency service areas in California were evaluated from two sources: self-reported estimates through 2045 within required Urban Water Management Plans (UWMPs) and county-level estimates from the Department of Finance (DoF) through 2030 (Figure S4).

Comparing the projected populations from both sources, self-reported estimates were approximately 4.5% larger than estimates from DoF data (Table S2). The range of uncertainty

considered in the analysis incorporated the discrepancies in future estimates from these two sources as upper and lower values for the percent change in demand for an agency.

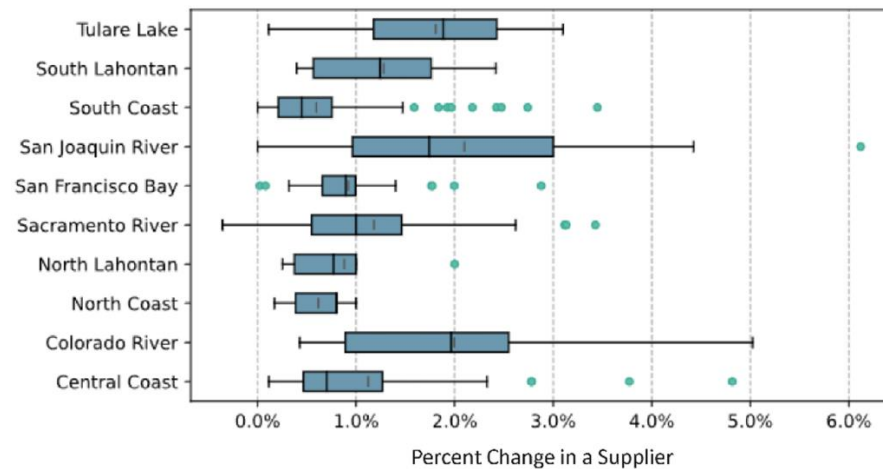


Figure S4: Unadjusted average annual percent change in population for a retailer (2020–2030)

Table S2: Comparison of population projections for agencies based on agency-level estimates reported in 2015 & 2020 Urban Water Management Plans (UWMP) and county-level estimates from the Department of Finance (DoF).

Parameter	2020 Population	2030 Population
Agency Population: UWMP Data (2015 or 2020, as available)	37,458,000	41,445,000
Statewide Total Population: U.S. Census (2020)	39,538,000	n/a
Statewide Total Population: DoF Estimates (2021)	39,953,000	41,860,000
Percent of Statewide Population Living in Agencies' Territories	95%	95% (assumed)
Agency Population: Estimated Total Using DoF Projections	n/a	39,658,301
Percent Difference in Agency and DoF Projections	n/a	4.5%

This population trend has the potential to create revenue challenges for water agencies, whereby agencies must maintain and upgrade aging infrastructure, and invest in new infrastructure, with revenues from stable or even declining populations. The implications could be significant. For example, the difference in estimated annual water demand between the baseline forecast scenario

(only population change) and the forecast scenario with all factors (population, efficiency, drought, and prices) is 860,000 acre-feet as noted in the main text. If water agencies planned for baseline future demand, but the “all factors” scenario occurs, agencies could pay for 860,000 acre-feet of excess capacity.

4. End-Use Modeling of Indoor Efficiency

4.1. Overview of Model Approach

As part of modeling indoor urban water use efficiency, an end-use model was developed to quantify changes in the saturation rate of efficient fixtures within agency service territories. The end-use modeling combined estimates of fixture efficiency from literature with assumptions the number of fixtures in agencies’ territories based on land use and tax assessor data.

Values for water use by appliance and fixture were obtained from a variety of sources including residential end use studies and flow tracing analyses (Mazzanti and Montini 2006). Additionally, studies using Flow Trace Analysis (FTA), have allowed indoor residential water use literature to parse out individual appliance uses (DeOreo, 1996), further enabling demand-side management programs to verify applicable water savings.

The residential indoor use estimates rely on two main components – Determining the indoor use values and estimating the type of or stock of appliances and fixtures within homes. The former relies on previous use literature studies and the later incorporates legislative timelines, turnover, and available saturation data. To develop a method of calculating residential indoor water use savings for different efficiency measures, a series of several steps was required and is outlined below:

- 1) Determine appliance and fixture water use using techniques commonly found in other residential indoor water use estimations. These fixture values are found in literature (Mayer et al. 1999; DeOreo et al. 2011, DeOreo et al. 2016)
- 2) Establish several housing vintage bins based on water efficient standards for the state of California and federally while incorporating saturation data resulting from such sources as WaterSense and EnergyStar.
- 3) Incorporate fixture and appliance turnover, including Senate Bill (SB) 407 impacts.

- 4) Create a vintage portfolio for each agency by incorporating service parcel data and grouping parcels together into vintages.
- 5) Calculate a weighted-water savings value for each measure for each agency using the characteristic and parcel make-up of each area.

4.2. Model Steps

The end-use modeling procedure for indoor fixture efficiency used three steps.

Step 1 – Determine Water Using Fixtures and Related GPCD Formulations:

To estimate the GPCD for each vintage and appliance or fixture, a typical use value per person per household was taken from water demand literature and applied to the estimated vintage gallons per use. The vintage usage values incorporated saturation data from WaterSense and EnergyStar. Equations are shown below:

$$GPCD_{Vintage\ i} = \frac{\#Uses}{Person \cdot Day} \times \left[\frac{Gallons}{Use} \right]_i$$

$$\text{Where, } \left[\frac{Gallons}{Use} \right]_i = \text{Gallons per use within each vintage, } i$$

The number of uses per person per day for each use fixture and appliance was rooted in water use pattern literature, ultimately making use of the Water Research Foundation’s 2016 *Residential End Uses of Water, Version 2* study (DeOreo et al. 2016). This study is a follow up of a previous American Water Works Association (AWWA) study, *Residential End Uses of Water* (1999) along with the CA Department of Water Resources sponsored *California Single Family Water Use Efficiency Study* (2011).

To calculate the GPCD values for all water uses, not including leaks and the “other” category, and bathtubs, use values and behaviors were taken from WRF (DeOreo et al. 2016). Equations for these fixtures and appliances along with their related assumptions are described in detail below. A summary of the GPCD for each indoor appliance and fixture is shown in Table S3 below. This analysis also assumes that each household has at least one of the fixtures or appliances in the home with a “presence” value equal to 1.

The GPCD for toilets was calculated as:

$$\textit{Toilet} = (\textit{Uses per person per day}) \times (\textit{Gallons per use})$$

This study assumes there are 5.0 flushes per person per day for all vintages. Gallons per use was determined by the estimated gallons per flush for each vintage.

The GPCD for showerheads was calculated as:

$$\begin{aligned} \textit{Showerhead} = & (\textit{Average minutes of use}) \times (\textit{Uses per person per day}) \\ & \times (\textit{Gallons per minute}) \times (\textit{Throttling Assumption}) \end{aligned}$$

It is assumed that the length of shower use is 7.8 average minutes of use and 0.69 uses per person per day (DeOreo et al. 2016). Gallons per minute were determined by multiplying the estimated flow rates for each vintage by two-thirds. Consistent with previous studies (Brown & Caldwell 1984; Maddaus 1987; Vickers 2001), it is assumed that a showerhead is used at two-thirds of its rated capacity. The two-thirds assumption may underestimate flow for showers. In more recent end use studies, measured flow rates ranged from 84% to 86% of the rated fixture capacity, with a mean of 85% (Mayer et al. 1999; DeOreo et al. 2011, 2016).

The GPCDs for bathroom and kitchen faucets were calculated as:

$$\begin{aligned} \textit{Faucets} = & (\textit{Average minutes of use}) \times (\textit{uses per person per day}) \\ & \times (\textit{average gallons per minute}) \times (\textit{Throttling Assumption}) \end{aligned}$$

It is assumed that the length of faucet use is 0.5 average minutes of use and 20 uses per person per day (DeOreo et al. 2016). The average gallons per minute was calculated by averaging the kitchen and bathroom flow rates for each vintage and multiplying by two-thirds. Consistent with previous studies (Brown & Caldwell 1984; Maddaus 1987; Vickers 2001), we assume faucets are used at two-thirds of their rated capacity. The two-thirds assumption may be somewhat conservative, i.e. overestimating flow. In more recent end use studies, measured flow rates ranged from 50% to 58% of the rated fixture capacity, with a mean of 54% (Mayer et al. 1999; DeOreo et al. 2011, 2016). Bathroom faucets and kitchen faucets are grouped together because

they are difficult to differentiate in the flow Trace Wizard analysis. Their water-use standards have deviated from one another at times and for this analysis, the average of the two specifications was incorporated into the fixture GPCD calculation.

The GPCD for dishwashers was calculated as:

$$Dishwasher = (uses\ per\ person\ per\ day) \times (gallons\ per\ use)$$

Dishwasher use was assumed to be 0.1 uses per person per day, or one load per every 1.5 weeks (DeOreo et al. 2016).

The GPCD for clothes washers was calculated as:

$$CW = (uses\ per\ person\ per\ day) \times (weighted\ average\ gallons\ per\ cycle)$$

Clothes washer use was assumed to be 0.3 uses per day, or about two loads per week (DeOreo et al. 2016).

The GPCD for leaks was taken from literature values and was assumed to be greater for older housing vintages and smaller for new vintages. Values for leak GPCD came from DeOreo et al. (2016) where the average reported value of 7.9 GPCD was assumed for all vintages prior to 2014. A value of 4.3 GPCD was assumed for the vintages of 2014 to 2017 because it is the median value reported in DeOreo et al. (2016) and matches the general leak assumption that younger houses will have a lower number of leaks. For the most recent vintage, a leak volume of 1.6 GPCD is assumed and is the result of dividing the median leak value (4.3) by the average number of household residents reported (2.65).

The GPCD for Other is assumed to be 2.5 GPCD for all vintages and includes evaporative cooling, humidification, water softening, and other uncategorized indoor uses. It is taken from DeOreo et al. (2016).

The GPCD for baths is assumed to 1.5 GPCD for all vintages and is taken from DeOreo et al. (2016).

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270 Ultimately, GPCD was calculated for each of fixtures or appliances within each vintage and is
271 shown in Table S4 below. The highlighted vintage periods indicate that there was a reduction in
272 the GPCD for the appliance or fixture with yet to be discussed incorporation of replacement and
273 saturation data. The progressively lower GPCD has been the result of more efficient water use
274 measures.

Table S3. Calculations for Indoor Water Use

		Applicable Vintage Period										
Water Use	Use Assumptions	Pre-1950	1950-1977	1978-1993	1994-2006	2007-2009	2010	2011-2013	2014	2015	2016-2017	2018-Present
Toilet	Flushes per person per day	5	5	5	5	5	5	5	5	5	5	5
	Gallons per Flush	7.0	5.0	3.5	1.6	1.56	1.54	1.50	1.28	1.28	1.28	1.28
	GPCD	35	25	17.5	8	7.8	7.7	7.5	6.4	6.4	6.4	6.4
Showerhead	Average Minutes of Use	7.8	7.8	7.8	7.8	7.8	7.8	7.8	7.8	7.8	7.8	7.8
	Uses per Person per Day	0.69	0.69	0.69	0.69	0.69	0.69	0.69	0.69	0.69	0.69	0.69
	Fixture Gallons per Minute	7	7	2.75	2.5	2.4	2.4	2.3	2	2	2	1.8
	Use Throttling Assumption	67%	67%	67%	67%	67%	67%	67%	67%	67%	67%	67%
	GPCD	25.1	25.1	9.9	9.0	8.6	8.6	8.3	7.2	7.2	7.2	6.5
Bathroom Faucet	Average Minutes of Use	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	Uses per Person per Day	20	20	20	20	20	20	20	20	20	20	20
	Gallons per minute	5	5	2.63	2.2	2.1	2.1	2	1.7	1.7	1.5	1.5
	Use Throttling Assumption	67%	67%	67%	67%	67%	67%	67%	67%	67%	67%	67%
	GPCD	33.3	33.3	17.5	14.7	14.0	14.0	13.3	11.3	11.3	10.0	10.0
Kitchen Faucet	Average Minutes of Use	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	Uses per Person per Day	20	20	20	20	20	20	20	20	20	20	20
	Gallons per Minute	5	5	2.63	2.2	2.1	2.1	2	1.7	1.7	1.5	1.5
	Use Throttling Assumption	67%	67%	67%	67%	67%	67%	67%	67%	67%	67%	67%
	GPCD	33.3	33.3	17.5	14.7	14.0	14.0	13.3	11.3	11.3	10.0	10.0
Clothes Washer	Gallons per Load	56.0	56.0	51.0	37.3	31.8	31.3	28.1	27.3	21.5	20.9	18.8

	Use per Person per Day	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
	GPCD	16.8	16.8	15.3	11.2	9.5	9.4	8.4	8.2	6.5	6.3	5.6
Dishwasher	Gallons per Load	14	14	14	9	7.7	5.8	4.9	4.3	4.4	3.7	3.6
	Use per Person per Day	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
	GPCD	1.4	1.4	1.4	0.9	0.8	0.6	0.5	0.4	0.4	0.4	0.4
Bath	GPCD	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5
Leaks	GPCD	7.9	7.9	7.9	7.9	7.9	7.9	7.9	4.3	4.3	4.3	1.6
Other**	GPCD	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5

**Other includes: evaporative cooling, humidification, water softening, and other uncategorized indoor uses.

Table S4. Visualization of changes in water use for specific appliance or fixtures.

Water Use (GPCD)	Vintage Period										
	Pre-1950	1950-1977	1978-1993	1994-2006	2007-2009	2010	2011-2013	2014	2015	2016-2017	2018-Present
Toilet	35.0	25.0	17.5	8.0	7.8	7.7	7.5	6.4	6.4	6.4	6.4
Clothes Washer	16.8	16.8	15.3	11.2	9.5	9.4	8.4	8.2	6.4	6.3	5.7
Shower	25.1	25.1	9.9	9.0	8.5	8.4	8.1	7.2	7.2	7.2	6.5
Faucet	33.3	33.3	17.5	14.7	14.2	14.0	13.5	11.0	11.0	10.0	10.0
Leak	7.9	7.9	7.9	7.9	7.9	7.9	7.9	4.3	4.3	4.3	1.6
Other	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5
Bath	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5
Dishwasher	1.4	1.4	1.2	0.9	0.8	0.6	0.5	0.4	0.4	0.4	0.4
Total	123.5	113.5	73.3	55.6	52.7	52.0	49.8	41.5	39.7	38.5	34.5

Step 2 – Establish Vintages based on Legislation and Incorporate Available Market Data:

To establish vintages that better represent the likely differences of water fixtures between older housing stock and newer housing stock, vintages were created to reflect legislative changes affecting these fixtures and appliances. These are meant to mark intervals of significant changes at both the federal and California state level. Table S5 presents a summary of the legislative findings and how they relate to the vintage periods. For each vintage, GPCD of each fixture or appliance was calculated at the time of the housing construction and does not yet incorporate the effects of turnover.

The following section lists the vintage period with accompanying text explaining the related legislation and industry saturation data that determines the different vintages. See Table S5 for a summary of vintage specific values for GPCD and assumed use metrics like gallons per flush, load, or minute. Vintages after 1994 to 2006 incorporate market saturation data of WaterSense and ENERGYSTAR labeled fixtures and appliances. WaterSense specifications are not standards and ENERGYSTAR specifications were not adopted by the DOE until 2011, but the program was in place before that time.

Table S5. Legislation and Programs Timeline for Determining Vintages

Vintage Period	Legislation and Programs in Effect	Toilet	CW	Shower	BF/KF	DW
Pre-1950	No Legislation – Baseline Vintage					
1950-1977	No Legislation – Vickers (2001)	Y				
1978-1993	CEC 1978	Y	Y	Y	Y	Y
1994-2006	EPA 1992, 63 FR 13308 (1998), ENERGYSTAR (1996, 2004), WaterSense (2006)	Y	Y	Y	Y	Y
2007-2009	WaterSense (2006), EISA (2007), ENERGYSTAR (2008)	Y	Y	Y	Y	Y
2010	AB 715**, EISA (2007), ENERGYSTAR (2008)	Y	Y	Y	Y	Y
2011-2013	AB715**, 77 FR 31918 (2013), EISA (2007), ENERGYSTAR (2009, 2011, 2012)	Y	Y	Y	Y	Y
2014	AB715**, CALGreen2013	Y	Y	Y	Y	Y
2015	77 FR 32307, ENERGYSTAR (2015)		Y			
2016-2017	CEC Title 20 (2016), ENERGYSTAR (2016)		Y		Y	
2018-Present	77 FR 32307, CEC - Title 20 (2016)		Y	Y		

** As stated in California Assembly Bill 715, sales for high-efficiency toilet models should have reached 67% by January 1, 2011, 75% by January 1, 2012, and 85% by January 1, 2013.

Pre-1950

Houses built before 1950 were assumed to have fixtures and appliances water use values from Vickers' Handbook of Water Use and Conservation (2001) while GPCD values for leaks, other, and baths are from DeOreo et al.'s *Residential End Uses of Water, Version 2* (2016).

1950 – 1997

Houses built between the period of 1950 and 1977 were assumed to have fixtures and appliances water use values from Vickers' Handbook of Water Use and Conservation (2001) while GPCD values for leaks, other, and baths are from DeOreo et al. (2016). Changes from the previous vintage were seen in toilets (7 to 5 Gallons per Flush, or gpf).

1978 – 1993

Houses built between the period of 1978 and 1993 had appliance and fixture value changes for toilets, clothes washers, showerheads, faucets, and dishwashers. In 1978, the California Energy Commission (CEC) adopted the *Conservation Division Regulations for Appliance Efficiency Standards*, which required all toilets sold in California to use no more than 3.5 gallons of water per flush (gpf) and all faucets to use no more than 2.75 gallons per minute (gpm). The standards for clothes washers and dishwashers came from Vickers' Handbook of Water Use and Conservation (2001). GPCD values for leaks, other water uses, and baths came from De Oreo et al. (2016).

1994 – 2006

Houses built between the period of 1994 and 2006 had appliance and fixture value changes for toilets, clothes washers, showerheads, faucets, and dishwashers. GPCD values for leaks, other water uses, and baths came from De Oreo et al. (2016). The Energy Policy Act of 1992 (EPA 1992) became effective on January 1, 1994, with additional stricter efficiency standards becoming effective on April 17, 1998, due to Department of Energy (DOE) standards in 63 FR 13308. Relevant changes are listed in Table S6 below. These standards changed efficiencies for faucets, toilets, and showerheads and some testing procedures.

In 1996, the U.S. EPA and the U.S. Department of Energy announced their [ENERGY STAR](#) partnership, establishing voluntary performance standards for many appliances, including dishwashers (in 1996 and again in 2004) and clothes washers (in 1997). While ENERGYSTAR did not explicitly require a certain level of water efficiency (dictated by what is now called the Integrated Water Factor, or IWF), ENERGYSTAR water-using appliances were typically 20-30% more water efficient. The Pacific Institute estimated that efficient clothes washers at this time used as little as 24.2 gallons per load while conventional machines used as many as 44 gallons per load; and that efficient dish washers at this time used as little as 2.2 gallons per load while conventional machines used as many as 9.1 gallons per load (Gleick et al. 2003). Clothes washers and dishwashers subject to regulation at a federal level while toilets, faucets, and showerheads are subject to regulation at both the state and federal level.

Table S6: Summary of the efficiency standards established in 1992 and 1998.

Fixture	Standard	
	EPA 1992 <i>Effective January 1, 1994</i>	63 FR 13308 <i>Effective April 17, 1998</i>
Lavatory faucets	2.5 gpm	2.2 gpm
Lavatory aerators	2.5 gpm	
Kitchen faucets	2.5gpm	2.2 gpm
Kitchen aerators	2.5gpm	
Metering faucets	0.25 gallons per cycle	
Gravity tank-type toilets	1.6gpf	1.6gpf
flushometer tank toilets	1.6gpf	
Blowout toilets	3.5gpf	3.5gpf
showerhead	2.5 gpm	2.5gpm
Urinals	1.0gpf	1.0gpf

The ENERGYSTAR specifications are not standards. While some homes constructed in California between 1996 and 2006 installed ENERGYSTAR clothes washers and dishwashers, CA-specific saturation rates for this period could not be located and therefore used ENERGY STAR’s appliance sales data for California (ENERGY STAR 1998-2006 data). Based on a weighted average, clothes washers and dishwashers used 37.3 GPL and 9.0 GPL, respectively, for this vintage.

2007 – 2009

Houses built between 2007 and 2009 had changes in efficiencies for toilets, faucets, showerheads, clothes washers, and dishwashers. GPCD values for leaks, other water uses, and baths came from De Oreo et al. (2016).

To capture the market share from WaterSense-labeled or ENERGYSTAR products within a vintage, a weighted average efficiency was applied and is in the equation below.

Weighted Average

$$\begin{aligned} &= (\text{WaterSense or ENERGYSTAR Water Use Efficiency}) \\ &\quad * (\text{Market Share of high efficient products}) + \left(\frac{\text{Gallons}}{\text{use}} \right)_i * (1 \\ &\quad - (\text{WaterSense or ENERGYSTAR Water Use Efficiency})) \end{aligned}$$

Toilets

[California Assembly Bill 715](#) (2007) required “all water closets sold or installed in this state shall use no more than an average of 1.6 gallons per flush,” starting at 50% of all models offered in the year 2010 and contributing to a shift towards more appliance efficiency. The [EPA WaterSense program](#) also launched on June 12, 2006. In April 2006, the EPA released the [high-efficiency plumbing fixture draft specifications for toilets](#); final specifications were published in 2007. These set the specification for high-efficiency toilets (HET) as follows:

Single flush toilet: 1.28 gpf or less

Dual flush toilets: 1.6 gpf and a reduced flush no more than 1.1 gpf

The WaterSense specifications are not standards. While some homes constructed between 2007 and 2009 likely installed WaterSense toilets, CA-specific saturation rates could not be located for this time period and therefore relied on estimates developed by GMP Research. Between 2007 and 2014, only 5.5 percent of California’s toilets used 1.28 fewer GPF ([GMP Research, 2015](#)). According to GMP Research 2019 update, 56 million (or 48%) of the 118 million toilets sold between 2007 and 2018 used 1.8 or fewer GPF ([GMP Research, 2019](#)). It is assumed that the WaterSense toilet market share in new homes increased by 4.4% per year starting in 2007 or 48% taken of the 11-year period. For the 2007-2009 vintage, it is assumed 13% (4.4%/year * 3 years) of new homes had WaterSense toilets, equating to a weighted average of 1.52 GPF.

Faucets

On October 1, 2007, EPA released a final specification, for bathroom sink faucets and faucet accessories (e.g., aerators). WaterSense-labeled bathroom sink faucets and accessories that use a maximum of 1.5 gallons per minute can reduce a sink's water flow by 30 percent or more from the standard flow of 2.2 gallons per minute.

CA-specific saturation rates could not be located for this time and therefore relied on estimates developed by GMP Research, Inc. Between 2007 and 2014, 21 percent of faucets used 1.5 GPM or less ([GMP Research, 2015](#)). According to GMP’s 2019 update, 195.672 million (or 80.1%) of the 242.5 million faucets sold between 2007 and 2018 met WaterSense criteria ([GMP Research, 2019](#)). It is assumed the WaterSense faucet market share for new homes increased by 7.3% per year starting in 2007. For the 2007-2009 vintage, it is assumed 22% ($7.3\% \times 3$) of new homes had WaterSense faucets, equating to a weighted average of 2.05 GPM.

Showerheads

While the WaterSense specification for showerheads had not yet been finalized, Californians could purchase showerheads meeting the future requirement of no more than 2.0 GPM during this time. According to GMP Research, Inc., between 2007 and 2014, 23.9 percent of showerheads used 2.0 GPM or less ([GMP Research, 2015](#)). For this vintage, we assumed 23.9% of new homes had efficient showerheads, equating to a weighted average of 2.38 GPM.

Washing Machines

Between 2007 and 2009, the ENERGYSTAR IWF, “quotient of the total weighted per-cycle water consumption for all wash cycles, Q_A , divided by the capacity of the clothes washer, C ,” ([ENERGYSTAR](#)) for residential clothes washers was no more than 8 gallons/cycle/ft³ ([ENERGY STAR, 2008](#)). Assuming an average tub size of 3.24 cu. ft., the GPL is 25.9. The California Single Family Water Use Efficiency Study analyzed water use data from 2007. De Oreo et al. (2016) found that ENERGYSTAR clothes washers use as little as 14.9 GPL and the average clothes washer efficiency was 36 GPL. While some homes constructed between 2007 and 2009 likely installed ENERGYSTAR appliances, we could not locate CA-specific saturation rates for this time and therefore relied on ENERGYSTAR’s California appliance sales data. Based on a weighted average, washing machines in new homes built between 2007 and 2009 used 31.8 gallons per load (ENERGY STAR 2007-2009 data).

2010

Houses built in 2010 had changes in efficiencies for toilets, faucets, showerheads, clothes washers, and dishwashers. GPCD values for leaks, other water uses, and baths came from De Oreo et al. (2016).

Toilets

Per [California Assembly Bill 715](#), “all water closets sold or installed in this state shall use no more than an average of 1.6 gallons per flush.” In addition, manufacturers selling water closets or urinals in the State of California were required “to offer high-efficiency models for sale in a specified percentage of all models offered, including 50% by January 1, 2010, 67% by January 1, 2011, 75% by January 1, 2012, 85% by January 1, 2013, and 100% by January 1, 2014.”

According to GMP Research (2019), 56 million (or 48%) of the 118 million toilets sold between 2007 and 2018 used 1.8 GPF or less. It is assumed WaterSense toilet market share increased by 4.4% per year starting in 2007 and that newly constructed homes would install WaterSense toilets at the same rate as existing homes. For the 2010 vintage, we assumed 17% (4.4×4) of new homes had WaterSense toilets, equating to a weighted average of 1.54 GPF.

Washing Machines

During this period, the federal standard for residential clothes washers remained the same. Effective 2009, The ENERGYSTAR specification for residential clothes washers required a water factor of no more than 7.5 ([ENERGY STAR, 2008](#)). Assuming an average tub size of 3.46 cu. ft., ENERGYSTAR clothes washers used 26 GPL.

While some homes constructed in 2010 likely installed ENERGYSTAR appliances, CA-specific saturation rates for this time could not be located and therefore relied on ENERGYSTAR’s unit shipment data, which reported that ENERGYSTAR clothes washers held a 47% market share. Based on a weighted average, washing machines in new homes built in 2010 used 31.3 gallons per load (ENERGY STAR 2010 data). While ENERGYSTAR washing machines represented a larger portion of units sold, tub sizes also increased, slightly driving up washing machine-related water use.

Showerheads

In March 2010, EPA released the WaterSense Specification for Showerheads. According to GMP Research (2019), 141.1 million (or 45%) of the 313.6 million showerheads sold between 2010 and 2018 met WaterSense criteria. It is assumed WaterSense showerhead market share increased by 5.6% per year (quotient of 45% WaterSense sold and time period of 8 years) starting in 2010. 23.9% of showerheads in California met the WaterSense standard of 2.0 GPM (PMI 2015). For the 2010 vintage, we assumed 29.52% (5.6 + 23.9) of new homes had WaterSense showerheads, equating to a weighted average of 2.31 GPM.

Faucets

CA-specific saturation rates could not be located for this vintage and therefore relied on estimates developed by GMP Research, Inc. Between 2007 and 2014, 21% of faucets used 1.5 GPM or less ([GMP, 2015](#)). According to GMP's 2019 update, 195.672 million (or 80.1%) of the 242.5 million faucets sold between 2007 and 2018 met WaterSense criteria ([GMP, 2019](#)). It is assumed the WaterSense faucet market share for new homes increased by 7.3% per year starting in 2007. For the 2010 vintage, it is assumed 29% (7.3%*4) of new homes had WaterSense faucets, equating to a weighted average of 1.99 GPM.

Dishwashers

Per the [Energy Independence and Security Act of 2007](#), conventional dishwashers manufactured on or after January 1, 2010 should not exceed:

- 6.5 gallons per cycle (Standard)
- 4.5 gallons per cycle (Compact)

By 2010, the ENERGY STAR program had been present for 14 years. More water efficient dishwashers had been on the market since 1997. [Per the 2008 specification](#), by Fall 2009, ENERGYSTAR dishwashers should not exceed:

- 5.8 gallons per cycle (Standard)
- 4.0 gallons per cycle (Compact)

While some homes constructed in 2010 likely installed ENERGYSTAR appliances, CA-specific saturation rates could not be located for this time and therefore relied on ENERGYSTAR's unit shipment data. It is assumed that in 2010, ENERGYSTAR dishwashers held a 100% market share. It is also assumed dishwashers in new homes built in 2011 used 4.9 GPL, or the average of 5.8 and 4.

2011 – 2013

Houses built between 2011 and 2013 had changes in efficiencies for toilets, faucets, showerheads, clothes washers, and dishwashers. GPCD values for leaks, other water uses, and baths came from De Ore et al. (2016).

Toilets

Per [California Assembly Bill 715](#), “all water closets sold or installed in this state shall use no more than an average of 1.6 gallons per flush.” In addition, manufacturers selling water closets or urinals in the State of California were required “to offer high-efficiency models for sale in a specified percentage of all models offered, including 50% by January 1, 2010, 67% by January 1, 2011, 75% by January 1, 2012, 85% by January 1, 2013, and 100% by January 1, 2014.”

According to GMP Research (2019), 56 million (or 48%) of the 118 million toilets sold between 2007 and 2018 used 1.8 GPF or less. It is assumed WaterSense toilet market share increased by 4.4% per year starting in 2007 and that newly constructed homes would install WaterSense toilets at the same rate as existing homes. For the 2011-2013 vintage, it is assumed 30% (4.4*7) of new homes had WaterSense toilets, equating to a weighted average of 1.5 GPF.

Showerheads

In March 2010, EPA released the WaterSense Specification for Showerheads. According to GMP Research (2019), 141.136 million (or 45%) of the 311.173 million showerheads sold between 2010 and 2018 met WaterSense criteria. It is assumed WaterSense showerhead market share increased by 5.6% per year (quotient of 45% WaterSense sold and time period of 8 years) starting in 2010. 23.9% of showerheads in California met the WaterSense standard of 2.0 GPM

(PMI 2015). For the 2011 to 2013 vintage, we assumed 46.32% ($3 \times 5.6\% + 29.52\%$) of new homes had WaterSense showerheads, equating to a weighted average of 2.23 GPM.

Faucets

CA-specific saturation rates could not be located for this vintage and therefore relied on estimates developed by GMP Research, Inc. Between 2007 and 2014, 21% of faucets used 1.5 GPM or less ([GMP, 2015](#)). According to GMP's 2019 update, 195.672 million (or 80.1%) of the 242.5 million faucets sold between 2007 and 2018 met WaterSense criteria ([GMP, 2019](#)). It is assumed the WaterSense faucet market share for new homes increased by 7.3% per year (80.1% over 11 years) starting in 2007. For the 2011 to 2013 vintage, it is assumed 51% ($7.3\% \times 7$) of new homes had WaterSense faucets, equating to a weighted average of 1.81 GPM.

Washing Machines

During this period, the federal standard for residential clothes washers required a water factor of no more than 9.5 (gal/cycle/ft³). Effective 2011 ([ENERGY STAR, 2009](#)), the ENERGYSTAR water factor was 6.0. Effective 2012 ([ENERGY STAR, 2012](#)), the ENERGYSTAR specifications began to be based on tub-size (in cubic feet, cu-ft). For machines with a tub size greater than 2.5 cu-ft, the IWF was no more than 4.5 and for machines with the tub size less than 2.5 cu-ft, the IWF was no more than 3.3, assuming an average tub size of 3.66 cu-ft, the GPL ranged from 34.8 (conventional) to 22.0 (ENERGYSTAR).

While some homes constructed during this time likely installed ENERGYSTAR appliances, CA-specific saturation rates for this time could not be located and therefore relied on ENERGYSTAR's unit shipment data, which reported that ENERGYSTAR clothes washers held a 50, 53 and 55% market share in 2011, 2012, and 2013, respectively. Based on a weighted average, washing machines in new homes built between 2011 and 2013 used 28.1 gallons per load. While ENERGYSTAR washing machines represented a larger portion of units sold, tub sizes also increased, slightly driving up washing machine-related water use.

Dishwashers

Per the [Energy Independence and Security Act of 2007](#), conventional dishwashers manufactured on or after January 1, 2010 should not exceed:

- 6.5 gallons per cycle (Standard)
- 4.5 gallons per cycle (Compact)

Then, effective May 2013, the U.S. Department of Energy (DOE) amended and adopted energy conservation standards for residential dishwashers. As shown in ([77 FR 31918](#)):

- Standard residential dishwashers should not exceed 5.0 gallons per cycle
- Compact residential dishwashers should not exceed 3.5 gallons per cycle

Effective 2012 ([ENERGY STAR, 2011](#)), an ENERGYSTAR dishwasher should not exceed:

- More than 4.25 gallons per cycle (Standard)
- More than 3.5 gallons per cycle (Compact)

While some homes constructed between 2011 and 2013 likely installed ENERGYSTAR appliances, we could not locate CA-specific saturation rates for this time and therefore relied on ENERGYSTAR's unit shipment data, which reported that ENERGYSTAR dishwashers held a 96, 89 and 90% market share in 2011, 2012, and 2013, respectively. For this vintage, it is assumed dishwashers used 4.3 GPL, or the weighted average of the dishwashers meeting the federal standards and ENERGYSTAR specification over the three-year period.

2014

Houses built between 2014 had changes in efficiencies for toilets, faucets, showerheads, clothes washers, and dishwashers. GPCD values for leaks, other water uses, and baths came from De Oreo et al. (2016). Leaks were assumed to be 4.3 GPCD, the median household leak volume and lower than older vintages because newer homes are assumed to have fewer substantial leaks.

Toilets, Showerheads, and Faucets

Effective January 1, 2014, the California Green Building Code (CALGreen 2013) included amendments to Title 20, “which dictates the allowable water consumption values for products for sale or offered for sale in California and provides a means for enforcement of those standards.”

These efficiency standards applied to new and renovated buildings, and were as follows:

- Toilets: 1.28 gpf or less.
- Bathroom faucets: maximum flow rate of 1.5 gpm at 60 psi.
- Kitchen faucets: Maximum flow rate of 1.8 gpm measure at 60 psi.
- Showerheads: 2.0 gpm.

For faucets, it is assumed the average of the kitchen and bathroom faucet flow standards (1.65 gpm).

Clothes Washers

While the federal standard and the ENERGYSTAR specification for clothes washers remained the same, ENERGYSTAR clothes washers held a slightly larger market share, leading to a smaller GPL estimate (27.3). According to ENERGYSTAR’s unit shipment data, ENERGYSTAR clothes washers held a 58% market share in 2014.

Dishwashers

While the federal standard and the ENERGYSTAR specification for dishwashers remained the same, ENERGYSTAR dishwashers held a slightly larger market share in 2014, leading to a smaller GPL estimate (4.0 GPL). According to ENERGYSTAR’s unit shipment data, ENERGYSTAR dishwashers held a 92% market share in 2014.

2015

Houses built in the year 2015 had changes in efficiencies for clothes washers and dishwashers. GPCD values for leaks, other water uses, and baths came from De Oreo et al. (2016).

Clothes Washers

Effective 2015 per [77 FR 32307](#), new federal standards for clothes washers required a maximum water factor (WF) of 8.0 for top-loading machines, and a maximum water factor (WF) of 4.5 for

front loading machines,. Effective 2015, the ENERGYSTAR energy and water factors began to be based on tub-size and design (i.e. top v front-loading) ([ENERGY STAR, 2015](#)):

- For front-loading machines with a tub size greater than 2.5 cu-ft, an IWF of 3.7 or less.
- For top-loading machines with a tub size greater than 2.5 cu-ft, an IWF of 4.3 or less.
- For a machine with a tub size less than or equal to 2.5 cu-ft, an IWF of 4.2 or less.

Assuming an average tub size of 4.05 cu-ft, the GPL ranged from 28.8 (conventional) to 16.8 (ENERGYSTAR).

While some homes constructed between 2015 likely installed ENERGYSTAR appliances, CA-specific saturation rates for this time could not be located and therefore relied on ENERGYSTAR's unit shipment data, which reported that ENERGYSTAR clothes washers held a 61% market share 2015. Furthermore, based on 2018 AHAM shipment data, it is assumed top-loaders and front-loaders held 74% and 26% market shares, respectively. For this vintage, it is assumed clothes washers used 21.45 GPL, or the weighted average of the clothes washers meeting the federal standards and ENERGYSTAR specifications for front- and top-loading machines.

Dishwashers

While the federal standard and the ENERGYSTAR specification for dishwashers remained the same, ENERGYSTAR dishwashers held a smaller market share in 2015, leading to a slightly larger GPL estimate (4.1 GPL). According to ENERGYSTAR's unit shipment data, ENERGYSTAR dishwashers held an 84% market share in 2015.

2016 – 2017

Houses built in the between 2016 and 2017 had changes in efficiencies for clothes washers, showerheads, and faucets. GPCD values for leaks, other water uses, and baths came from De Oreo et al. (2016).

Showerheads and Faucets

In 2016, the California Energy Commission published the *Appliance Efficiency Regulations* ([California Code of Regulations, Title 20, Sections 1601 through 1609](#)). The new efficiency standards are as follows:

- Bathroom faucets: **1.2gpm**
- Kitchen Faucets: **1.8gpm**

For faucets, it is assumed the average of the kitchen and bathroom faucet flow standards (1.5).

Clothes Washers

While the federal standard and the ENERGYSTAR specification for clothes washers remained the same, ENERGYSTAR clothes washers held a larger market share in 2016 and 2017, leading to a slightly smaller GPL estimate (20.9 GPL). According to ENERGYSTAR's unit shipment data, ENERGYSTAR clothes washers held a 64 and 67% market share in 2016 and 2017, respectively.

Dishwashers

While the federal standard remained the same, the ENERGYSTAR specification for dishwashers became more efficient. Effective 2016 ([ENERGY STAR, 2016](#)), an ENERGYSTAR dishwasher should not exceed:

- More than 3.5 gallons per cycle (Standard)
- More than 3.10 gallons per cycle (Compact)

While some homes constructed between 2016 and 2017 likely installed ENERGYSTAR appliances, CA-specific saturation rates could not be located for this time and therefore relied on ENERGYSTAR's unit shipment data. They reported ENERGYSTAR dishwashers held an 87 and 91% market share in 2016 and 2017, respectively. For this vintage, it is assumed dishwashers used 3.54 GPL, or the weighted average of the dishwashers meeting the federal standards and ENERGYSTAR specification over the two-year period.

2018 – Present

Houses built in the year 2018 had changes in efficiencies for clothes washers and showerheads. GPCD values for leaks, other water uses, and baths came from De Oreo et al. (2016). For this vintage, a leak volume of 1.6 GPCD is assumed. This leak volume is the median household leak volume divided by the average number of persons per household in the 2016 study (2.65). It is assumed a recently constructed houses would have minimal leaks.

Clothes Washers

Effective 2018 per [77 FR 32307](#), new federal standards for clothes washers required a maximum water factor (WF) of 6.0. for top-loading machines Effective 2018 ([ENERGYSTAR, 2017](#)), the ENERGYSTAR water factors for front-loading machines with a tub size greater than 2.5 cu-ft decreased from 3.7 to 3.2 or less. Assuming an average tub size of 4.22 cu-ft, the GPL ranged from 23.7 (conventional) to 17.0 (ENERGYSTAR).

While some homes constructed between 2018 and today likely installed ENERGYSTAR appliances, CA-specific saturation rates could not be located for this time and therefore relied on ENERGYSTAR’s unit shipment data, which reported that ENERGYSTAR clothes washers held a 70 and 73% market share in 2018 and 2019, respectively— and are projected to hold a 75% market share for 2020. As with the previous two vintages, we assumed top-loaders and front-loaders hold 74% and 26% market shares, respectively. For this vintage, we estimate washers use 18.8 GPL.

Showerheads

Effective 2018 per the California Energy Commission’s *Appliance Efficiency Regulations* ([California Code of Regulations, Title 20, Sections 1601 through 1609](#)), showerheads must meet an efficiency standard of 1.8 gpm at 80 psi.

Step 3 –Incorporate fixture and appliance turnover. Apply to vintage efficiency rates.

Vintage efficiency rates determined for the fixtures and appliance in the previous section were adjusted to incorporate turnover rates. As appliances and fixtures get older, they will fail and need to be replaced at some point, t years. Each appliance and fixture have an average lifetime

along with standard deviation seen in Table S7. An appliance or fixture that failed outside of a vintage period, i.e. a toilet failing 20 years an unrenovated house was built 1985 would have its 3.5 GPF water use replaced with the 2005 water use toilet of 1.6 GPF.

Table S7. Fixture and appliance average lifetime and standard deviation from code-based improvements before considering additional replacement from rebates. Values below are the averages of reported device lifetimes from multiple sources in literature.

Fixture/Appliance	Average Lifetime	Standard Deviation
Toilet	23.75 years	4
Faucets	17.5 years	2.5
Clothes Washer	14 years	3.1
Showerhead	8.5 years	3
Dishwasher	11.5 years	2.1

Vintage efficiency rates from were adjusted to account for fixture and appliance turnover rates over time. Two replacement functions were used to model device turnover, a lognormal decay function and an exponential decay function. The two replacement functions demonstrate how GPCD calculations vary depending on how replacement rates are modeled.

The lognormal decay was calculated using the lognormal distribution:

$$N(t) = \frac{1}{t} * \frac{1}{\sigma\sqrt{2\pi}} * \exp\left\{\frac{-[\ln(t) - \mu]^2}{2\sigma^2}\right\}$$

where $N(t)$ is the proportion of devices that fail t years after installation based on the mean (μ) and the spread (σ). The mean is defined as the natural log of the average device lifetime and the spread is defined as the natural log of the device lifetime standard deviation. Average device lifetimes and standard deviations were calculated from the range of lifetimes in the Water Research Foundation's *Integrating Water Efficiency into Long-Term Demand Forecasting's Appendix E* (WRF4495, 2018) for toilets, faucets, clothes washers, showerheads, and dishwashers. Alternative lifetime estimates were also found in several company websites (OnTime Service, Total Comfort Solutions).¹

¹ OnTime Service (<https://ontime59.com/faucet-lifespan-repair-or-replace/>); Total Comfort Solutions (<https://www.wallawallahvaccontractor.com/blog/2018/september/is-it-time-to-replace-your-plumbing-fixtures-/>).

In general, the lognormal decay function is skewed to the right and predicted a higher presence of older devices. The exponential decay function is:

$$N(t) = N_0 e^{-\lambda t}$$

where $N(t)$ is the number of devices of a given efficiency at year t , N_0 is the number of devices at year 0, and λ is the percent of device failing each year. The turnover rate, λ , is calculated as the inverse of the device lifetime.

$$\lambda = \frac{1}{\text{Device Lifetime}}$$

The exponential decay function assumes a constant percentage, λ , of remaining stock is replaced each year. Because of this, the greatest replacement occurs in year one, when the remaining stock is the largest. In general, the exponential decay function modeled quicker device turnover and thus lower GPCD values than the lognormal decay function, but the lognormal decay function yielded unrealistic percentages of remaining devices after 50 and 60 years, so the exponential function was used. To align with literature lifetime values for exponential replacement, the same device lifetimes were used as for the lognormal decay function except for the following.

The Saturation Study for Non-Efficient Water Closets uses a 25-year lifetime for toilets and assumes a natural replacement rate of four percent annually of the remaining installed stock each year of non-efficient fixtures (Koeller 2017). To more closely replicate Koeller 2017, we use a lifetime of 25 years for toilets. The Residential Energy Consumption Survey (RECS) has appliance lifetime data in U.S. homes disaggregated by year of construction. The latest survey data was used to calibrate the device lifetime and turnover rate in the exponential decay function for clothes washers (EIA 2013). The California Urban Water Agencies Phase 1 Water Savings Study documents a device lifetime of 8-14 years for clothes washers. The RECS-calibrated exponential decay function for clothes washers uses a device lifetime of 9 years.

In addition, the analysis takes into consideration impacts of [Senate Bill \(SB\) 407](#), passed by the legislature in 2009. Among other requirements, SB 407 required single-family homes sold after 2017 to be retrofitted with more efficient plumbing fittings and fixtures. While SB 407 also

established efficiency requirements for remodeled single-family homes, multi-family residences, and commercial buildings, this analysis did not attempt to quantify those prospective impacts.

To analyze the prospective impact of SB 407 on single-family homes sold or transferred after 2017, parcel data for California was acquired from LandVision, a map-based real estate application with a nationwide parcel database that ties parcel boundaries to several property and tax attributes, such as the most recent sale date. For single-family homes, SB 407 required the upgrading of toilets, showerheads, and faucets and identified specific efficiency factors for those fixtures. In estimating its impact, it is assumed SB 407 only resulted in houses sold in 2017 and after retrofitting these fixtures. By 2017 and 2018, the 2009 factors became irrelevant, as Californians could no longer purchase products reflecting the older standards. Inasmuch, this analysis incorporates contemporary standards. Table S8 below summarizes the differences.

Table S8: Comparing the 2009 SB 407 efficiency requirements with contemporary efficiency standards.

	SB 407 requirements	2017 CA requirements	2018 CA requirements
Toilets	1.6 GPF	1.28 GPF	1.28 GPF
Showerheads	2.5 GPM	2 GPM	1.8 GPM
Kitchen faucets	n/a	1.8	1.8
Bathroom faucets	2.2	1.2	1.2

If a single-family home were sold or transferred after 2017, we considered the impacts of SB 407 on pre-2016 vintages by adjusting the efficiency values of toilets, showerheads, and faucets—from their baseline to their contemporary flow rate. For example, if a 1940s home were sold in 2018, we assumed that home's toilet would now use 1.28 GPF rather than 7 GPF. For the appliances unaffected by the SB 407 directive (i.e., clothes washers and dishwashers), we assumed natural turnover rates as described above.

For each vintage, the graphs below show how turnover (assuming an exponential decay function) and the impacts of SB 407 affect total and fixture specific GPCD rates as well as fixtures efficiencies.

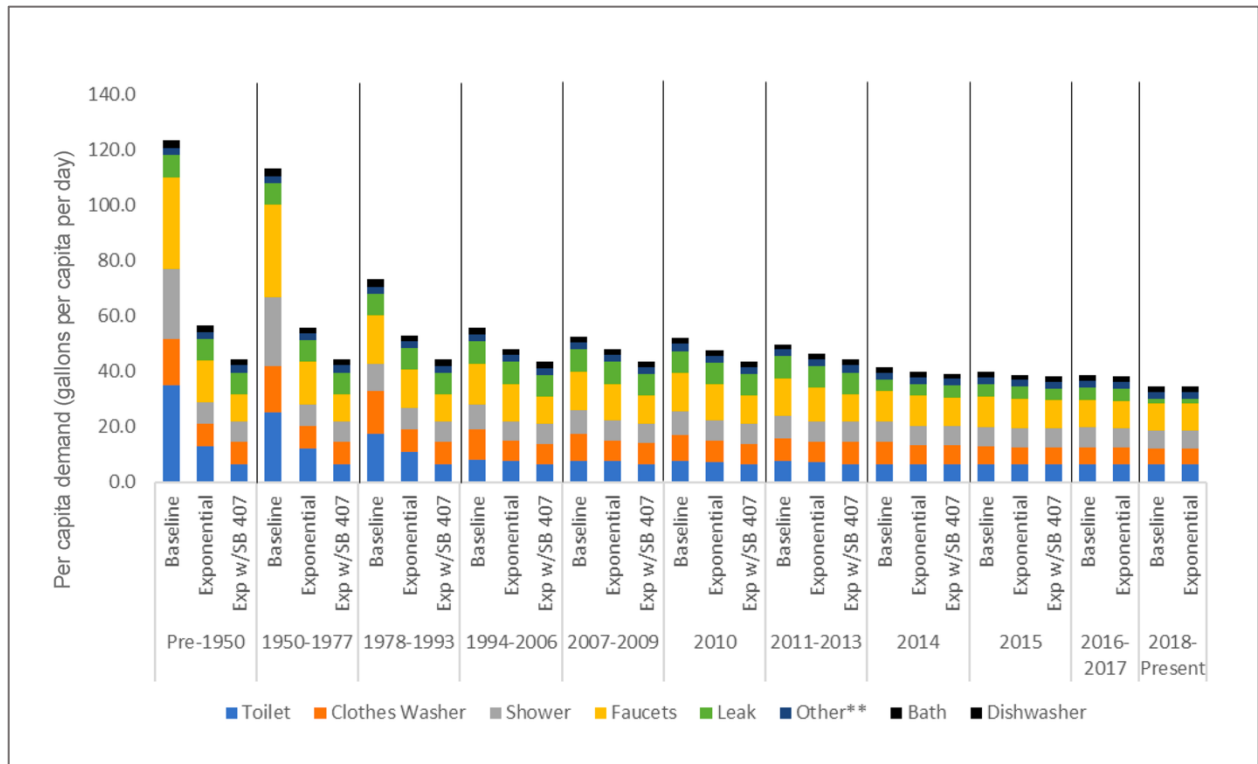


Figure S5: Comparing the 2009 SB 407 efficiency requirements with contemporary efficiency standards.

For each vintage, a weighted average for each appliance or fixture efficiency was created as is common in stock modeling. The final water use for each fixture or appliance is calculated as:

$$\text{Weighted Water Use within a Vintage} = \sum_{i=1}^n c_i X_i$$

Where n is the number of appliances or fixtures use efficiencies within each vintage, X_i is the water use for each appliance or fixture, and c_i is the determined weight for each appliance or fixture water use efficiency within each vintage after incorporating turnover.

An important caveat is that this analysis only takes into consideration natural or passive, not incentivized, turnover rates. For many URWS in California, long-term investments in conservation programming have resulted in substantially higher turnover rates than those we modeled to estimate current statewide IR-GPCD. For example, for the City of Santa Cruz, this model predicts IR-GPCD to be no lower than 52 GPCD. The city itself calculates their IR-GPCD

is currently 34 GPCD. To predict an IR-GPCD value of 34 for Santa Cruz, the turnover rates for fixtures and appliances would have to be multiplied by 8 and leaks across all housing vintages would have to be set at 1.6 GPCD to come close at 35.2 IR-GPCD. This highlights how impactful conservation programs can be at residential adoption of water efficient appliances. See Table S9 below.

Table S9. City of Santa Cruz example

Water Use	Assumed turnover rates in model	Turnover rates to optimize efficiency
Toilet	4%	32%
Clothes Washer	11.1%	89%
Shower	11.8%	94%
Bathroom Faucet	5.7%	46%
Kitchen Faucet		
Dishwasher	8.7%	70%
Leaks	7.9 – 1.6 GPCD	1.6 GPCD
Modeled RI-GPCD for the City of Santa Cruz	52	35.2

According to the City of Santa Cruz’s Water Conservation Master Plan’s 2011 Baseline Survey results, 90% of toilets in Single Family homes were 1.6 gpf or less. The city models that 1.28 gpf toilets have a 100% replacement fixture market share beginning in 2015 and a 100% new fixture market share beginning in 2012. In contrast, the exponential decay function with a natural turnover rate of 4% predicts approximately 60% of toilets were 1.6 gpf or less in 2011. The model for this analysis uses a 100% replacement and new fixture market share for 1.28 gpf toilets beginning in 2014.

4.3. Cumulative Effects of End-Use Modeling on Efficiency Gains

Through 2030, statewide indoor water use from code-based improvements was estimated to decline in an agency by 0.6 gpcd (range = 0.3-0.7 gpcd) from indoor fixture efficiency, which is equivalent to a 1.1% annual change and aligned with previous studies (Mitchell 2016). Incentivized rates of replacement resulted in an average annual decline in an agency of 0.4 gpcd

(range = 0.3–0.6 gpcd). Over the entire period from 2020 to 2030, the estimated average value (unweighted) of per capita water demand decrease from indoor fixture efficiency improvements in an agency is 5.8 gpcd and 4.2 gpcd for the natural and enhanced rates of replacement, respectively.

5. Drought Effects on Indoor and Outdoor Water Use

The analysis of dynamically downscaled GCMs and results from the regression modeling informed the quantification of the “net drought effect” on urban water demand through 2030.

For the recent drought from 2012–2016, a set of agency-specific statistical models was used to quantify a net drought effect as the net change in demand during and after the 2013–2018 drought. The net drought effect was the difference in the estimated percent reduction in an agency in the 2014–2016 drought period and the estimated percent increase in an agency in the 2016–2018 period. The net drought effect attempts to capture and quantify the influence of several potential policy actions on water demand, such as restricted watering days, conservation messaging, increases in indoor fixture rebates, and others. The influence of both drought and subsequent rebound on total urban water demand, quantified as a percent change, was estimated using the agency-specific regression modeling (2013–2018) with Ordinary Least Squares, which controlled for changes in climate (temperature, precipitation), population, and water rates as data allowed. Average and median values of the net drought effects are listed in Table S10.

Model fit statistics generally validated use of the model. Out of the supplier-specific regression models, 98% of the models yielded f-statistic values sufficient to negate the null hypothesis that the independent variables in the models did not explain actual water demand. Then, across all models, 72% had R^2 values over 0.8 and 88% had R^2 values over 0.6, indicating that most models were of good fit (Figure TA-1.4). Finally, visual inspection of plots of actual and modeled values across the time series demonstrated that for most Suppliers, the models had reasonable accuracy in representing seasonal and annual changes in demand.

Table S10: Average and median values by region of the change in total per capita demand in an agency during drought (2014–2016), rebound (2017–2018), and the net drought effect derived from agency-specific modeling with multivariate linear regression (Porse 2021).

	Drought Period (2014–16)		Rebound Period (2017–18)		Net Drought Effect	
Region	<i>Average</i>	<i>Median</i>	<i>Average</i>	<i>Median</i>	<i>Average</i>	<i>Median</i>
Central Coast	-11%	-10%	9%	4%	-2%	-5%
Colorado River	-13%	-13%	-1%	-2%	-14%	-16%
North Coast	-10%	-5%	-7%	2%	-17%	-3%
North Lahontan	-14%	-15%	10%	10%	-4%	-5%
Sacramento River	-9%	-10%	14%	8%	4%	-2%
San Francisco Bay	-12%	-13%	3%	0%	-9%	-13%
San Joaquin River	-9%	-8%	0%	6%	-9%	-3%
South Coast	-10%	-8%	-1%	-1%	-11%	-9%
South Lahontan	-5%	-7%	5%	4%	1%	-3%
Tulare Lake	-2%	-9%	7%	6%	5%	-4%

A net drought effect taken from a distribution of potential values was applied to all agencies based on a conservative estimate using the average value across the distribution of agencies. Out of all agencies, 277 had estimates of the net drought effect in a reasonable range, from -20% to 20% change over the course of 2014 to 2018 (Figure S6). The statewide average net drought effect in an agency was a 5% decrease in per capita residential demand (median = 7% decrease). The average value of the net drought effect of an agency within a region ranged from -11% to 4% across regions. The statewide average value was applied to all agencies as a conservative estimate of the assumed percent decrease in per capita demand through 2030, which results from the 3-year period of below average precipitation within the climate forecast. This estimate is less than (i.e. more conservative than) recent related research that identified similar effects of drought to decrease residential water demand across each of California’s major recent drought periods (Lee et al. 2021).

The analysis of net drought effects was subject to several limitations. First, the values of the indicator variables for drought and post-drought periods were subject to errors for some agencies. Data inconsistencies in eAR values could cause erratic values in the indicator variables. This occurred when reporting errors or missing data was not identified and corrected

in the data records. As noted, data errors were identified and corrected for approximately 70 agencies, but in some cases, were likely still missed.

Second, even in the absence of data errors, the balance between the drought and post-drought indicator variables that informed net drought effect estimates was subject to site-specific factors. Changes in population, water use, and other factors during the modeled period could have led to changes in water use that would be inappropriately attributed to the indicator variables.

Third, the statistical controls to estimate values of the drought and post-drought indicator variables do not control for changes over time in fixture efficiency. The effects of such changes are likely minimal during the short period of modeling used in this analysis (5 years) for each agency.

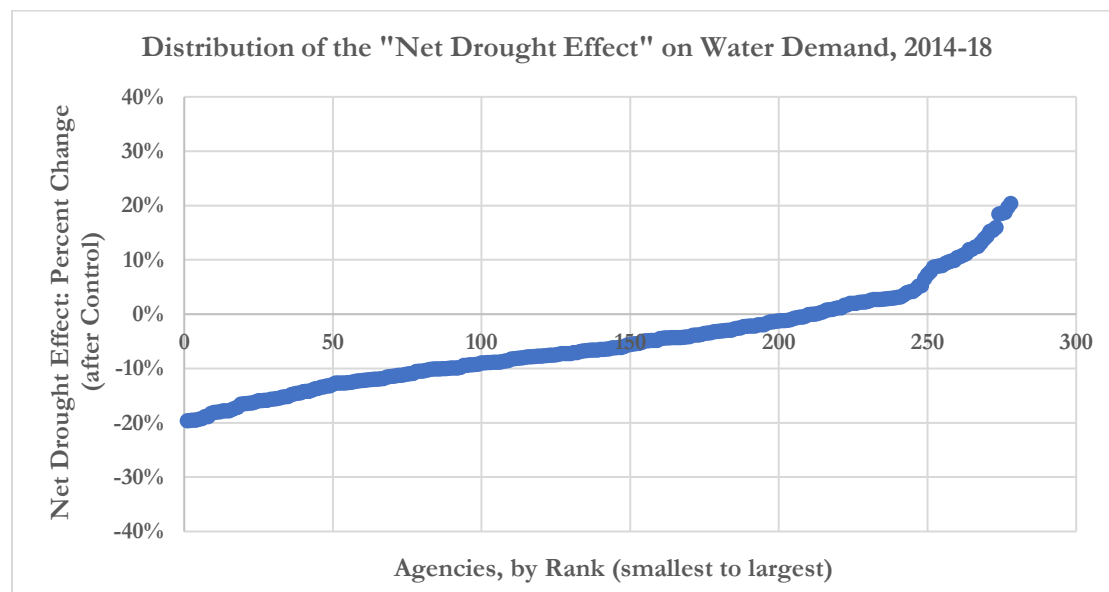


Figure S6: Distribution of Net Drought Effect values across agencies, ranked from lowest to highest. The values center on a 5% decrease in an agency from 2014-2018 after statistical controls

6. Network Modeling of Water Agency and Wastewater System Connectivity

No existing database identifies relationships or estimates flows between Suppliers and wastewater management systems. The only sources of data for this purpose are Tables 6-2 through 6-4 of Urban Water Management Plans (UWMPs) collected and published by the

California Department of Water Resources (DWR). These tables compile self-reported data from the UWMPs and link between water sector systems. Table 6-2 describes connections between urban water supply retailers, wastewater collection systems, and wastewater treatment facilities. The tables, however, are based on self-reported data and include errors. Further, the reported names do not match names in other state databases such as the California Integrated Water Quality System (CIWQS), and common identifiers are not included. For this project, the database in Table 6-2 was converted into a network model representation to connect water supply agencies, collection systems, and wastewater treatment facilities.

A multistep procedure was used to link Suppliers with wastewater management systems and identify systems of interest. First, we rectified name discrepancies between DWR's Table 6-2, CIWQS, and the AVR. Second, after identifying wastewater systems and facilities of interest, characteristics (attributes) of those systems and facilities were collected and compiled to create a database of attributes associated with both collection systems and treatment systems. Third, historical records for operations and monitoring were collected from CIWQS and DWR's Table 6-2 for collection systems and WWTFs with available data (Figure S7). Fourth, using the AVR and data from DWR's Urban Water Management Plans, the volume of recycled water produced by a WWTF was estimated and linked to receiving Suppliers.

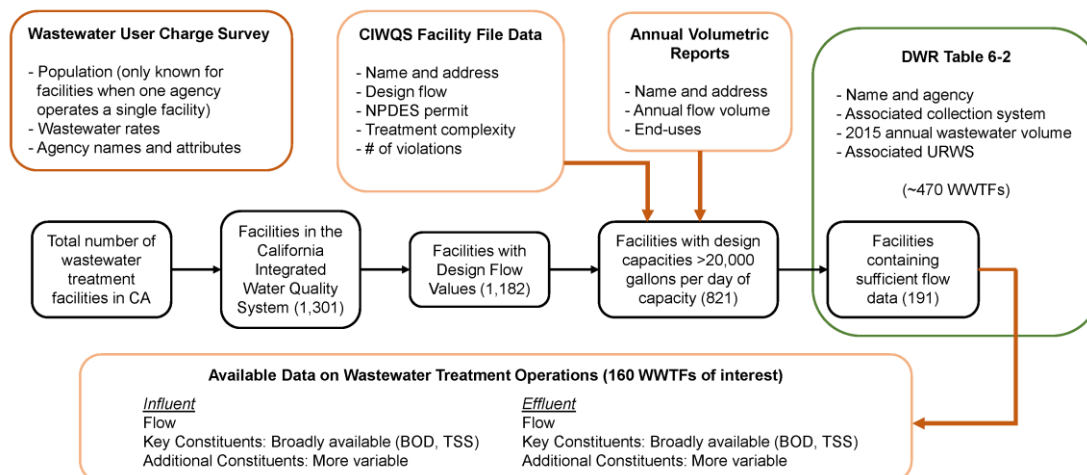


Figure S7: Summarizing the process to develop time series records of operations and monitoring for WWTFs with available data in the California Integrated Water Quality System (CIWQS)

7. Results

The tables and figures below supplement data presented in the main article text related to historical per capita demand, demand change factors of water supply agencies in forecasted scenarios, and demand change factors of wastewater treatment facilities in forecasted scenarios (Figures S8 through S10 and Tables S11 through S16).

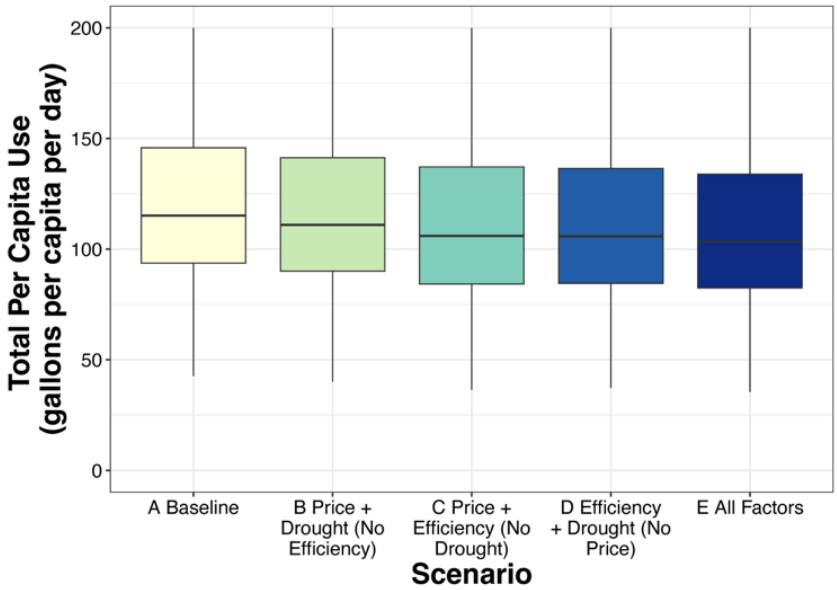


Figure S8: Forecasted future total per capita water use (indoor and outdoor) across all sectors, by scenario.

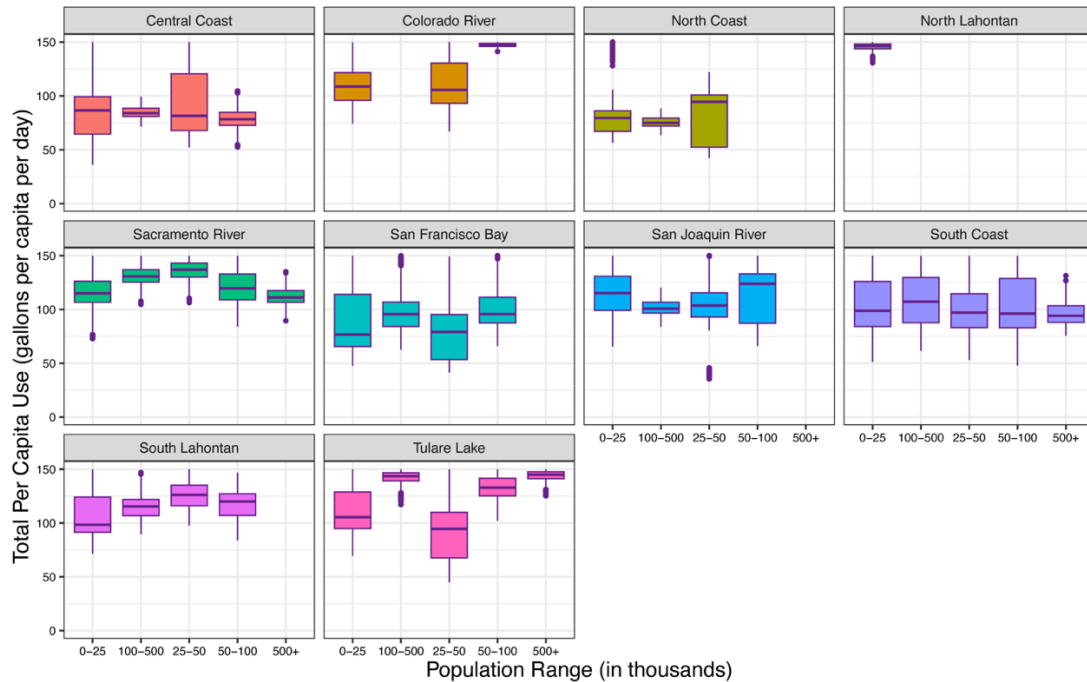


Fig S9: Future (forecasted) per capital demand for indoor and outdoor use (all sectors), by region and population.

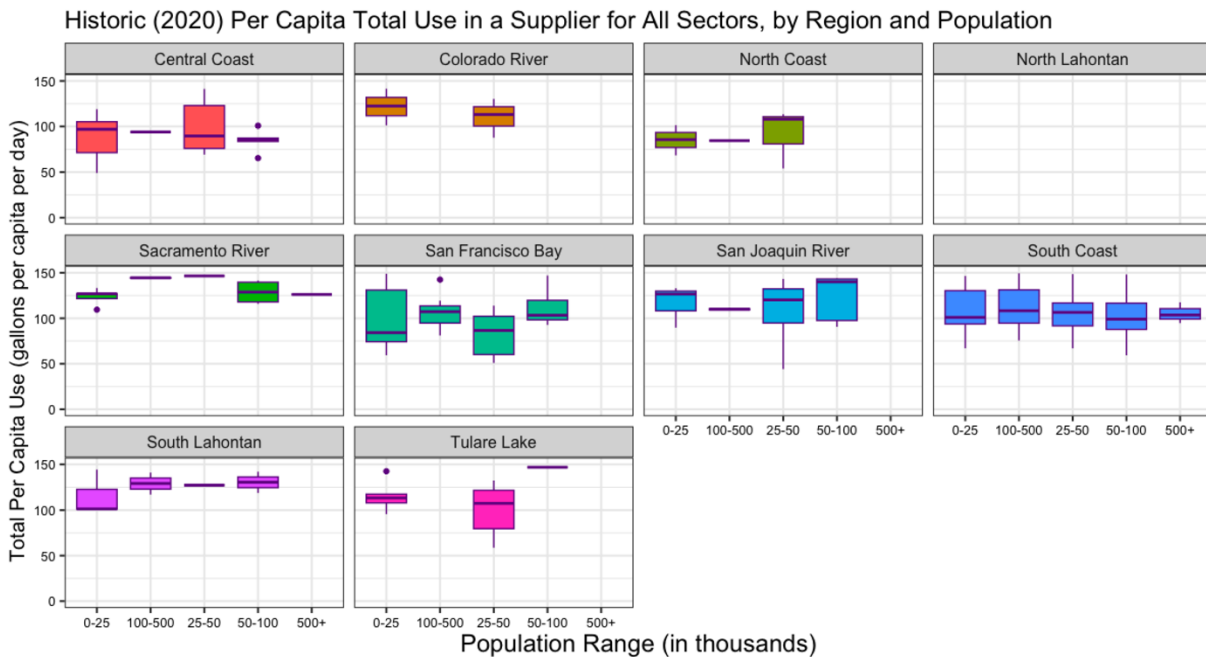


Fig S10: Historic (2020) per capital demand for indoor and outdoor use (all sectors), by region and population

Table S11: Average Demand change factor of Water Supply Agencies, by Scenario and Population Served

Population (in thousands)	Future Scenarios				
	<i>Baseline</i>	<i>Price and Efficiency</i>	<i>Drought and Efficiency</i>	<i>Drought and Price</i>	<i>All Factors</i>
<i>Not Available</i>	1.06	0.94	0.94	1.01	0.92
<i>0-25</i>	1.07	0.96	0.96	1.01	0.93
<i>25-50</i>	1.08	0.98	0.98	1.03	0.95
<i>50-100</i>	1.05	0.95	0.95	1.00	0.92
<i>100-500</i>	1.05	0.94	0.94	1.00	0.92
<i>500+</i>	1.07	0.97	0.97	1.03	0.95
<i>All</i>	1.06	0.96	0.96	1.01	0.93

Table S12: Average Demand change factor of Water Supply Agencies, by Scenario and Median Household Income in district

Median Household Income	Future Scenarios				
	<i>Baseline</i>	<i>Price and Efficiency</i>	<i>Drought and Efficiency</i>	<i>Drought and Price</i>	<i>All Factors</i>
<i>Not Available</i>	1.10	0.99	0.99	1.05	0.96
<i>\$0-\$25,000</i>	0.98	0.90	0.87	0.89	0.84
<i>\$25,000-50,000</i>	1.08	0.97	0.97	1.03	0.95
<i>\$50,000-\$75,000</i>	1.07	0.96	0.96	1.02	0.93
<i>\$75,000-\$100,000</i>	1.06	0.95	0.95	1.00	0.93
<i>>\$100,000</i>	1.05	0.95	0.94	0.99	0.92
<i>All</i>	1.06	0.96	0.96	1.01	0.93

656 **Table S13: Average Demand change factor of Water Supply Agencies, by Scenario and Region**

Region	Future Scenarios				
	<i>Baseline</i>	<i>Price and Efficiency</i>	<i>Drought and Efficiency</i>	<i>Drought and Price</i>	<i>All Factors</i>
<i>North Coast</i>	1.06	0.96	0.97	1.02	0.94
<i>North Lahontan</i>	1.03	0.94	0.93	0.97	0.90
<i>Sacramento River</i>	1.11	1.01	1.00	1.05	0.98
<i>San Francisco Bay</i>	1.05	0.94	0.94	1.00	0.92
<i>Central Coast</i>	1.06	0.95	0.95	1.01	0.93
<i>San Joaquin River</i>	1.14	1.04	1.03	1.08	1.01
<i>South Coast</i>	1.03	0.93	0.92	0.98	0.90
<i>South Lahontan</i>	1.05	0.95	0.95	0.99	0.92
<i>Tulare Lake</i>	1.14	1.03	1.02	1.08	1.00
<i>Colorado River</i>	1.15	1.05	1.04	1.09	1.02
<i>All</i>	1.06	0.96	0.96	1.01	0.93

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658 **Table S14: Average Water Use Demand change factor on Wastewater Treatment Facilities, by**
659 **Scenario and Facility Level of Treatment**

Treatment Level	Future Scenarios				
	<i>Baseline</i>	<i>Price and Efficiency</i>	<i>Drought and Efficiency</i>	<i>Drought and Price</i>	<i>All Factors</i>
<i>Secondary, No Disinfection</i>	1.13	0.91	0.94	1.03	0.91
<i>Secondary, Disinfected</i>	1.12	0.91	0.93	1.02	0.91
<i>Tertiary</i>	1.12	0.89	0.92	1.01	0.89
<i>All Facilities</i>	1.12	0.90	0.92	1.01	0.90

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661 **Table S15: Average Water Use Demand Change Factors (DCF) on Wastewater Treatment**
662 **Facilities, by Scenario and Facility Design Flow (MGD = Millions of Gallons per Day)**

Design Flow (MGD)	Future Scenarios				
	<i>Baseline</i>	<i>Price and Efficiency</i>	<i>Drought and Efficiency</i>	<i>Drought and Price</i>	<i>All Factors</i>
<i>0-5</i>	1.21	1.01	1.04	1.14	1.01
<i>6-25</i>	1.13	0.91	0.94	1.02	0.91
<i>26-50</i>	1.15	0.92	0.95	1.04	0.92
<i>51-100</i>	1.15	0.92	0.94	1.04	0.92
<i>101-500</i>	1.13	0.89	0.91	1.01	0.89
<i>Not Available</i>	0.91	0.71	0.72	0.80	0.70
<i>All Facilities</i>	1.07	0.85	0.87	0.96	0.85

663 **8. Summary of Data Sources**

664 **Table S17: Data sources integrated into the analysis of water demand and forecasting**

Name	Source	Parameters Used	Timeframe
electronic Annual Report (eAR)	California State Water Resources Control Board	-Agency Information -Demand, by Sector (single-family residential, multi-family residential, commercial, industrial, institutional, landscape irrigation, other) -Population -Connections -Retail water rates -Conservation program activities	06/2013 – 12/2019
Urban Water Management Plans (UWMP)	Department of Water Resources	-Region -Location -Demand by sector (every 5 years) -Population (2020 and 5-year projections) -Supply by sector	2015, 2020
Population Projections	California Department of Finance	-Current population, by county -Future population projections, by county	2020-2035
Water Conservation Tracking Tool	Alliance for Water Efficiency	-Estimated water savings from water use efficiency replacements -Unit cost of water use efficiency rebates	2020
California Parcel and Tax Assessor Data	Digital Map Products (2021)	-Parcel ID -Address -Number of bathrooms -Number of bedrooms -square footage -Lot size -	2019
Landscape Area Measurements (Irrigated Turf Area)	California Department of Water Resources (DWR 2022)	-Irrigable, irrigated, and non-irrigable area in a supplier	2017-2018
Water Use Efficiency Rebate Program Data	Various (agencies in Southern California, San Francisco Bay Area, and Sacramento metropolitan area) (Porse et al. 2025)	-Number of water use efficiency rebates by type (washers, toilets, sq-ft of replaced turf, irrigation controllers)	2010-2020
Water Use of Fixtures and Devices	Various (detailed in Supplemental Information)	-Estimated water consumption per use	1999-2016

	description of end-use modeling)	based on collection and analysis of field data	
Median Household Income	U.S. Census, American Community Survey (2019)	-Median Household Income by Census tract	2018

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667 **Table S18: Data sources used to evaluate wastewater flow, systems, facilities, and demand change**
668 **factors.**

Name	Source	Parameters	Timeframe
2017 Wastewater User Charge Survey	California State Water Resources Control Board (file was given)	-Agency Information -Service Area -Name(s) and location(s) of the treatment facilities your agency is responsible for	06/22/2020 – 07/31/2020
California Integrated Water Quality System Project (CIWQS) eSMR Flat File	California State Water Resources Control Board (file was given)	-Region -Location -Location_Place_ID -Location_Place_Type -Parameter -Result -Units -Sampling_Date -Facility_Name -Facility_Place_ID -Latitude/Longitude	02/14/2020 – 06/22/2020
California Integrated Water Quality System Project (CIWQS) eSMR Facility Export	California State Water Resources Control Board (file was downloaded from the website)	-Agency -Agency Address -Facility Name -Facility Address -Latitude/Longitude -County -Region -WDID -Design Flow	06/22/2020 – 07/31/2020
Table 6-2 Retail: Wastewater Collected Within Service Area in 2015, and Table 6-3 Retail: Wastewater Treatment and Discharge Within Service Area in 2015 (compiled data associated with urban water management plans)	California Department of Water Resources (DWR)	-DWR Supplier Org ID -Water Supplier Name -Wastewater Collection Agency -Volume of Wastewater Collected (2015) -Volume of Wastewater Treated (2015) -Volume of Wastewater Discharged (2015) -Wastewater Treatment Agency -Treatment Plant Name	2015
Volumetric Annual Report (VAR)	California State Water Resources Control Board	-Facility name -Facility location -Volume of influent (monthly) -Volume of treated effluent (monthly) -Level of treatment	2019 (data may be available for some facilities as early as 2017)

		-Volume of water reuse production	
Sewer System Overflow (SSO) database	California State Water Resources Control Board	-System name -System location -Length of pipes by type of pipe (gravity main, lateral line) -Number of pumps -Number of operators -Operator training levels -Operator certifications -Violation reports (Sewer System Overflows) and reported causes	various, based on last year of available reporting

9. References

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771