Case Study

Variability in Consumption and End Uses of Water for Residential Users in Logan and Providence, Utah, US

Camilo J. Bastidas Pacheco, Aff.M.ASCE[1]; Jeffery S. Horsburgh, Ph.D., Aff.M.ASCE[2]; and Nour A. Attallah, Ph.D., A.M.ASCE[3]

Abstract: Variations in water fixtures and appliances coupled with different routines and preferences of users result in high levels of variability in residential water consumption. This study assessed differences in residential water use in terms of the timing and distribution of end uses across residential properties. Past studies analyzing residential end use of water have collected data for periods of time that may prevent the observation of temporal variations in indoor and outdoor water use practices. We examined indoor and outdoor residential water use at the household level by analyzing four to 23 weeks of 4-s resolution water use data at 31 single family residential properties in Logan and Providence, Utah, between 2019 and 2021. We identified and classified end uses of water for each property and analyzed monthly water use records to understand how water use varied for users at different levels of consumption. Our results indicated that indoor water use is influenced more by frequency of use than by the characteristics of water fixtures. At sites with longer data collection periods, indoor water use volume, timing, and distribution across end uses varied across homes and across weeks for which we collected data, indicating that short duration data collection intervals used by past studies may not have adequately characterized these variables. The paper presents opportunities to conserve water indoors and outdoors by adopting more efficient fixtures (particularly toilets) and promoting conservation behaviors. All the data and tools used in this study are freely available online for reuse. **DOI: 10.1061/(ASCE)WR.1943-5452.0001633.**

Author keywords: Water end uses; Residential water use; Water demand; Indoor water use; Outdoor water use.

Introduction

Residential water use in the state of Utah has been estimated at approximately 640 L per capita per day, the second largest volume in the US (Dieter et al. 2018). Approximately 98% of the state's population is served by public water suppliers, one of the highest percentages in the country (Dieter et al. 2018). It is estimated that Utah will need a $4.4 billion investment over a 20-year period to maintain current service and meet future demands (EPA 2018). It was estimated in 2010 that 91% of Utah's population lived in urban areas (The University of Utah 2016). This pattern is repeated in many areas within the US; the urban population has grown much faster (500%) than the rural population (19%) between 1910 and 2010 (EPA 2016). The percent of the world's population living in urban areas increased from 43% to 54% between 1990 and 2015 (UN-Habitat 2016). With this increase in urban density and the costs associated with delivering water to urban populations, managing and reducing demand is vital for providing a clean and safe water supply for the world's growing urban populations.

[1]Postdoctoral Researcher, Dept. of Civil and Environmental Engineering and Utah Water Research Laboratory, Utah State Univ., 8200 Old Main Hill, Logan, UT 84322-8200 (corresponding author). ORCID: https://orcid.org/0000-0001-6634-439X. Email: camilo.bastidas@usu.edu

[2]Associate Proffesor, Dept. of Civil and Environmental Engineering and Utah Water Research Laboratory, Utah State Univ., 8200 Old Main Hill, Logan, UT 84322-8200. Email: jeff.horsburgh@usu.edu

[3]Graduate Research Assistant, Dept. of Civil and Environmental Engineering and Utah Water Research Laboratory, Utah State Univ., 8200 Old Main Hill, Logan, UT 84322-8200. Email: nour.atallah@usu.edu

Note. This manuscript was submitted on November 4, 2021; approved on August 29, 2022; published online on November 3, 2022. Discussion period open until April 3, 2023; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Water Resources Planning and Management***, © ASCE, ISSN 0733-9496.

In order to accurately estimate and forecast urban water consumption, it is important to know the different daily patterns in consumption, the distribution of water use across end uses, how that distribution varies across time, and potential savings from different conservation programs or demand side measures (Willis et al. 2011). Conventional water use data (collected at monthly, bimonthly, or coarser resolutions) analyses leave knowledge gaps with regard to water use peak times and volumes and detailed estimates of indoor versus outdoor water use. By one estimate, per capita water use decreased by 4.4% between 2010 and 2015 in the US (Dieter et al. 2018). It is commonly assumed that decreases in residential water use are produced by the use of more efficient fixtures (DeOreo and Mayer 2012), yet few definitive statements can be made about this because few data exist that directly measure the performance and impact of retrofitted fixtures (Rockaway et al. 2010). In addition, behavior may change over time as the demographics of water users change. These types of gradual and pervasive changes are difficult to track with monthly data. Analyses derived from high temporal resolution data aimed at demand management, understanding behavior, evaluation of fixture performance, or evaluation of conservation potential can address these gaps, yet this type of data has only been collected sporadically and over short periods of time, resulting in uncertainty with regard to how generalizable and applicable the results obtained are.

Researchers are increasingly using smart meters and advanced analytics to monitor water use at finer temporal resolutions at the household level (Cominola et al. 2015). The potential for these technologies to address the existing gaps in residential water use knowledge is well recognized (Boyle et al. 2013). Higher temporal resolution data can aid in the identification and quantification of individual water end use, reveal water use behavior, improve the reliability of water quality predictions, assist in the design of water service lines, and help detect and reduce the volume of leaks

(Buchberger et al. 2003; Buchberger and Wells 1996; Cominola et al. 2018). Furthermore, feedback to water users on their water use (derived from high temporal resolution data) has the potential to motivate conservation behaviors (Cominola et al. 2021). For example, Fielding et al. (2013) noted significant differences in water usage for users receiving water use feedback derived from 5-s data.

End uses of water refers to the distribution of water usage across different uses (e.g., faucets, showers, toilets). Such information is needed to produce more accurate demand forecast modeling and to identify opportunities to improve water use efficiency (White et al. 2003). Water end use information can increase our understanding of water use behavior, inform future water projections, and aid in the design and assessment of water conservation efforts. For example, incentives to upgrade inefficient fixtures/appliances (Mayer et al. 2004; Suero et al. 2012) or awareness campaigns targeting specific end uses would benefit from this information (Abdallah and Rosenberg 2014; Willis et al. 2010) by quantifying behavioral (frequency, duration) and technological (flow rate, volume) parameters for individual water use appliances. These parameters can be used to calculate potential or actual benefits of conservation measures and to identify the most effective strategies. In addition, high resolution water use data can enable verification and calculation of accurate price elasticity estimations (Marzano et al. 2018).

High resolution (subminute) data are required to record and quantify end uses that have short durations (Nguyen et al. 2015). Typically, end use information is derived from high temporal resolution water use data using algorithms that differentiate between the characteristics or features (e.g., duration, average flow rate, mode flow rate) of water use events. Several algorithms for disaggregating and classifying end uses of water have been developed by private companies (Aquacraft 1996) and by researchers (Attallah et al. 2022; Froehlich et al. 2009; Nguyen et al. 2018; Pastor-Jabaloyes et al. 2018). Despite the number of algorithms described in the literature, opportunities to replicate or build from these tools are limited due to the unavailability of code and/or data. Di Mauro et al. (2020) found that, of 41 data sets collected for assessing end uses of water at residential properties, only four (Beal and Stewart 2011; Makonin 2016; Vitter and Webber 2018; Kofinas et al. 2018) had an open access policy. In limited instances, flow trace data (i.e., the raw, high resolution data collected) and event files (i.e., end use events and their attributes extracted from raw data) from past studies were available for purchase (Aquacraft 2016), including the events table resulting from the one of the largest studies of water end uses conducted to date (DeOreo et al. 2016).

While the lack of available data sets is limiting, so is the duration of many of the collected data sets. Several past residential water use studies (Beal and Stewart 2011; DeOreo et al. 2016; Mayer et al. 1999) collected data for a period of two weeks. This relatively short data collection window does not necessarily allow observation of temporal variations in indoor water use volume, timing, and distribution across end uses. It is likely also insufficient to assess outdoor water use practices. Furthermore, previous data were collected in small samples across a limited number of cities. Given that there are differences in how people use water at the neighborhood, city, and country levels (e.g., Inman and Jeffrey 2006), exploring temporal changes in water use and expanding the available data sets for urban water planning and management motivates conducting local case studies. High temporal resolution water use data are not available for Utah; this has, to date, limited the analyses that can be conducted to explain the large per capita water use observed at the state level (Dieter et al. 2018).

To build on the results of prior studies, this study focused on the following research questions. (1) How do the distribution of indoor water use, frequency of use of indoor water fixtures, indoor water use timing, and outdoor practices vary for users at different water consumption levels (i.e., when ranked based on water use volumes)? (2) What is the performance of water fixtures among the sample of residential homes analyzed when compared with plumbing standards for fixtures in the US, and how do these values compare with previous studies? (3) How do estimates of volume, distribution across end uses, and timing of indoor water use change as the data collection period is increased beyond the two weeks observed in the past? We analyzed water use at different temporal aggregations (monthly, daily, hourly, weekdays versus weekends), its subdivision between indoor and outdoor use, and the distribution of end uses to address these questions. In this paper, we show how the high temporal resolution data collected as part of this project can help researchers answer other questions. The data used are openly and freely available for reuse, providing an opportunity to expand the analyses and extend the research presented in this paper. The analyses we conducted convey new and key information that can assist water utilities and decision makers in Utah and potentially other areas with similar characteristics (climate, landscape sizes, household occupancy, level of water use) in understanding water use.

Methods

Fig. 1 illustrates the research methodology workflow, which was divided into seven main steps and is described in the following subsections.

Study Area and Data Used

This study combined data from multiple sources (Table 1). The area of study comprised the cities of Logan and Providence in northern Utah, which have about 7,500 and 2,100 single family residential (SFR) connections, respectively. Monthly water use data was provided by the municipalities, and we collected high temporal resolution (4 s) data for 31 SFR properties, 19 in Logan and 12 in Providence. These data were a superset of the data used by Attallah et al. (2022), who used data from five of the 31 properties in the development and testing of the end use disaggregation and classification algorithm we used for our analyses (see "End Use Classification").

Meter readings provided by the cities of Logan and Providence were collected on different days of the month, depending on the utility's working schedule. Therefore, the volume of water used within a given month had to be estimated from two meter readings. We calculated standardized monthly water use, from the first to the last day of each month, as follows:

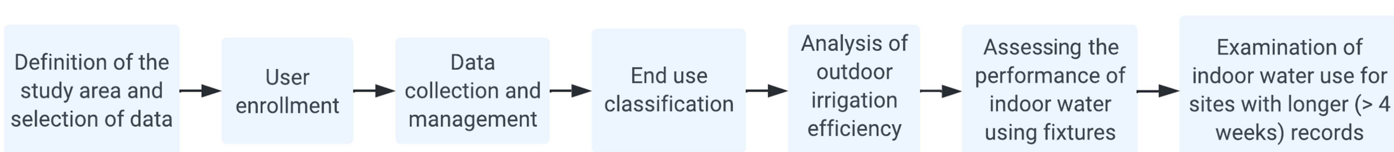

Fig. 1. General methodology workflow.

J. Water Resour. Plann. Manage., 2023, 149(1): 05022014

Table 1. Data sets used in the present study—source, coverage, and availability

Data set	Source	Coverage	Availability
Monthly water use for Logan Monthly water use for Providence	Logan Providence	January 2017–December 2018 January 2018–December 2019	Anonymized and standardized monthly values are available in HydroShare (Bastidas Pacheco and Horsburgh 2021)
Parcel and building area for properties in Logan and Providence	Cache County	Updated and maintained by Cache County	Available in HydroShare for participant sites (Bastidas Pacheco et al. 2021a)
Aerial photography for the area. Hexagon (24 cm or 15 cm) and Google (15 cm) licensed imagery, and high resolution orthophotography (24 cm or better) (UGRC 2021)	Utah Geospatial Resource Center	Collected between 2012 and 2021	Available for use by Utah agencies and educational institutions in web and desktop mapping applications
High temporal resolution (4-s) water use data	Collected by the authors	Collected from 2019 to 2021	Anonymized version available in HydroShare (Bastidas Pacheco et al. 2021a)
Characteristics of each residence participating in the study	Surveyed by the authors, combined with county data	Surveys conducted during enrollment	
Daily rainfall and evapotranspiration data for the USU Environmental Observatory and Evans Farm weather stations	Utah Climate Center	January 2019–April 2021	Publicly available in HydroShare (Bastidas Pacheco and Horsburgh 2022)

$$V_n = \frac{V_{MR1}}{D_{MR1}} \times D_{n-MR1} + \frac{V_{MR2}}{D_{MR2}} \times D_{n-MR2} \qquad (1)$$

where V_n = volume of water used for a month n; V_{MR1} = water volume from the first meter reading ($MR1$) that contains water use for month n; D_{MR1} = number of days covered by $MR1$ (i.e., the number of days since the previous meter reading); D_{n-MR1} = number of days within month n to which $MR1$ applies; and V_{MR2}, D_{MR2}, and D_{n-MR2} = same information for the second meter reading ($MR2$) that contains water use for month n. User ranking, monthly variation, and annual averages used when selecting participants to enroll in the study were derived from these standardized monthly values.

User Enrollment

Participants were enrolled in this study using multiple methodologies. First, four households were enrolled by word of mouth to deploy and test data collection hardware and software (Bastidas Pacheco et al. 2020, 2021b). The longest data records were from these users. Second, we invited users based on their annual average water use (computed from monthly records) in an attempt to create a sample with participants from different water consumption levels so we would have representatives ranking in the lower, middle, and higher end of water consumption. Prospective participants were sent a letter in the mail inviting them to participate. Of 200 letters sent, 11 participants responded positively and enrolled. Given the low response rate to the mailed letters, an additional 16 participants were recruited and enrolled by word of mouth and targeted invitations. Originally, we intended to enroll 50 participants, but due to public health conditions associated with the COVID-19 pandemic, additional participation was limited.

Participation in this study was voluntary. Residents agreed to participate but did not necessarily know when data were being collected. In all cases, we conducted multiple data collection periods for each household (referred to as *sites* in this study). During enrollment, information was collected on the water fixtures in each home, the age of appliances, common times of the day for irrigation, and typical timing for the use of clothes washers. High temporal resolution data were collected, and a small set of short duration events were registered (toilet flushes, opened and closed showerheads, faucets, bathtub faucets). The information and event data collected during enrollment were collected to support and evaluate the accuracy of the end use events generated. Study sample household characteristics ($n = 31$) are reported in Table 2, including length of the data record, number of occupants, irrigable area, building area, irrigation mode, volumetric pulse resolution of the meter, and average annual water use. The information for each site was obtained through different sources: (1) the survey conducted during enrollment, (2) publicly available data from the county, (3) analysis of the monthly water use records provided by each city, and (4) geographic information systems (GIS) analysis of high resolution imagery for Utah available from the Utah Geospatial Resource Center (UGRC 2021).

Data Collection and Management

High temporal resolution water use data for all sites were collected using the Cyberinfrastructure for Intelligent Water Supply (CIWS)-Datalogger (Bastidas Pacheco et al. 2020) or the CIWS-Node Datalogger (Attallah et al. 2021), which were attached to the existing meters at each site. These external dataloggers measured the magnetic field around magnetically-driven residential water meters and counted peaks in the magnetic field associated with the movement of the measurement element within the meter. They registered peaks as pulses that represented a fixed volume of water passing through the meter. The volumetric pulse resolution (L/pulse) used in this study was determined in the laboratory (Bastidas Pacheco et al. 2020) and was used for all meters of the same size and brand found in the field deployments. Other studies self-calibrated this parameter for each meter when volumes (from the meter and datalogger) did not match (DeOreo et al. 2016), resulting in accuracies that are not directly comparable with ours. While we did not calibrate pulse resolution in this study, instead choosing to use only data that passed the quality control (QC) procedure described subsequently, our field data logs provided the volumes recorded by the meters' registers and the raw pulse data we collected so that calibration methods could be applied to this data, if warranted, for other studies.

Data were collected over a period of three years before and during the COVID-19 pandemic. We recorded the number of residents in each home during enrollment but did not collect any information related to the participants' schedules or employment status, nor did we assess any changes in these parameters due to the COVID-19

Table 2. Data collection period and characteristics of each site where data was collected

Site ID	Length of QC data record (weeks)	Number of occupants	Irrigable area (m^2)	Building area (m^2)	Irrigation mode	Volumetric pulse resolution (L/pulse)	Annual average water use (m^3)
2	21.6	2	643	140	Sprinkler system	0.1257	397.9
3	22.5	2	1,408	138	Hose	0.0329	234.9
4	9.3	4	1,015	136	Sprinkler system	0.0329	647.7
5	16.4	2	3,118	169	Sprinkler system	0.1257	1,786.0
6	6.2	3	294	101	Hose	0.0329	96.2
7	16.8	3	241	104	Hose	0.1257	55.2
8	6.4	2	1,789	160	Hose	0.1257	720.6
9	9.3	2	509	173	Sprinkler system	0.1257	602.4
10	6.2	2	824	102	Hose	0.1257	149.0
11	12.4	4	827	136	Sprinkler system	0.1257	401.3
12	9.9	2	1,744	156	Sprinkler system	0.1257	181.2
13	7.8	2	742	239	Sprinkler system	0.1257	1,507.5
14	10.4	2	2,005	315	Sprinkler system	0.1257	1,099.8
15	9	6	405	171	Sprinkler system	0.1257	392.2
16	7.4	3	1,162	151	Hose	0.0329	247.4
17	8.5	3	1,451	92	Hose	0.0329	341.0
18	8.7	1	410	74	Hose	0.0329	233.5
19	23.1	5	982	128	Sprinkler system	0.1575	854.1
20	5.2	4	1,202	177	Sprinkler system	0.1575	942.2
21	6.8	6	N/A	N/A	Sprinkler system	0.1575	N/A
22	8	7	N/A	N/A	Sprinkler system	0.1575	N/A
23	5.7	6	1,108	144	Sprinkler system	0.1575	809.2
24	8.1	8	1,276	279	Sprinkler system	0.1575	1,308.0
25	7.4	6	914	282	Sprinkler system	0.1575	614.4
26	6.7	6	3,592	117	Sprinkler system	0.0962	644.0
27	6.7	7	3,842	299	Sprinkler system	0.0962	2,248.6
28	4.8	6	1,846	337	Sprinkler system	0.1575	1,747.6
29	4.8	3	700	133	Sprinkler system	0.1575	573.3
30	5	6	1,250	137	Sprinkler system	0.1575	716.2
31	4.6	3	827	154	Sprinkler system	0.1257	695.7
32	4.6	2	862	104	Sprinkler system	0.0329	730.1

Note: The length of the record presented here is the sum of all individual data collection periods that passed quality control. Water use records for Sites 21 and 22 were not available (N/A).

pandemic. We did not anticipate the COVID-19 pandemic; therefore, collecting data that would allow us to fully assess the impact of the COVID-19 pandemic on participants' schedules was not part of the study design. We were limited in our ability to modify the institutional review board (IRB) protocol governing this study and were also constrained by a complete pause of all human subject research implemented by our institution early in the pandemic. While we did not assess the impact of the COVID-19 pandemic on participants of this study, recent studies evaluating the impact of the COVID-19 pandemic on water demand suggested that residential water use increased, and some nonresidential use (e.g., bars, restaurants, hotels, schools) decreased when stay-at-home orders were issued (Cooley et al. 2020; Menneer et al. 2021; Cahill et al. 2021; Lüdtke et al. 2021). Other studies found changes in residential diurnal water use patterns resulting from COVID-19 lockdowns (Alvisi et al. 2021; Balacco et al. 2020). The COVID-19 pandemic changed the way water was consumed (Berglund et al. 2021), and it is likely that these changes were evident in some of the data we collected, but such changes were not specifically analyzed.

We collected at least two weeks of data during months when irrigation was expected to occur (referred to as summer months, including May through October), and two weeks during the rest of the months (referred to as winter months) at each site. In December, January, and February, access to meter pits was restricted by the municipalities due to cold temperatures, resulting in shorter records for those months. Log files included within the LogFiles folder in the HydroShare data repository (Bastidas Pacheco et al. 2021a) contain information about the data collection periods at each site, including the exact start and end time of each period, the volume registered by the meter's register and by our datalogger for each period, the percent error in volume for each period, the number of expected data values (computed using the start and end times of each data collection period, assuming one value was collected every 4 s), the number of recorded data values, the percent error in the number of values logged, and an indicator of whether outdoor water use was expected or not. The HydroShare resource also contains the high temporal resolution data for each site. The data were managed using cyberinfrastructure described in Bastidas Pacheco et al. (2021b). The data management process involved collection and processing of raw 4-s resolution data, QC to ensure validity of the data, and storage in a centralized database for analysis. QC was conducted using the following procedure:

1. The volume recorded by the meter's register was compared with the volume recorded by the installed datalogger for each data collection period. The volume recorded by the meter's register was calculated by subtracting manual meter readings made at the beginning and end of each data collection period. The volume of water registered by the dataloggers was calculated by multiplying the number of pulses recorded during each data collection period by the volumetric pulse resolution.
2. If the percent error of the volume was less than 5%, associated values were finalized without further review. In the opposite case, additional steps were performed to determine whether portions of the data could be included in the analysis.

J. Water Resour. Plann. Manage., 2023, 149(1): 05022014

3. When the datalogger recorded more water than the meter, the raw data and hourly volumes were inspected for anomalous values (larger than those observed in validated days at the same site). If an anomalous period (lasting less than a day) was identified, the day on which it occurred was removed and the remaining data were evaluated as indicated in Steps 4 and 5. If no anomalous period was identified, the data were rejected.
4. When the datalogger recorded less water than the meter, the percent error of the number of values was compared with the percent error of the volume. In some cases, partial records of good data were recorded (e.g., the datalogger stopped working before the end of a deployment). If the percent error of the volume and the number of values were within 10% of each other (e.g., only 50% of the values were recorded, resulting in a percent error of −50%), full days of data were further inspected as indicated in Step 5.
5. The data were reviewed on a daily basis by visually examining the characteristics of the data (by plotting and visually inspecting the raw data and by calculating and plotting hourly and daily volumes) for the period in question and comparing them with similar data (i.e., raw data, hourly and daily volumes for data from the same site that were already validated). Days of questionable data were accepted if the observed raw data and hourly and daily volumes were within the same range as the validated data.

Analysts considered all the aforementioned elements in accepting or rejecting the raw data collected. Only data that passed these QC checks were used.

End Use Classification

In many past studies that have analyzed end uses of water, a single device measured total water use for a site, and the data were later disaggregated and classified (Al-Kofahi et al. 2012; Beal and Stewart 2011; DeOreo et al. 2011, 2016; Mayer et al. 1999, 2020; Otaki et al. 2011; Roberts 2005). Less commonly, water use for each individual fixture was measured (Kofinas et al. 2018; Di Mauro et al. 2019). We adopted the first approach and used a single device (Attallah et al. 2021; Bastidas Pacheco et al. 2020) to measure total water use; data were disaggregated using an open source algorithm described in Attallah et al. (2022). In summary, the disaggregation and classification process worked in the following way: (1) an algorithm filtered the raw data using a low-pass filter, facilitating the identification of single and overlapping events; (2) overlapping events were separated into single events using an iterative splitting process; (3) several features (e.g., average flow rate, mode flow rate, duration) were calculated for each event; and (4) the events were classified using a combination of clustering to identify atypical or outlier events that were later labeled as unknown and a semisupervised machine learning methodology to assign labels to the remaining events (Attallah et al. 2022). The machine learning model used a random forest classifier (Liaw and Wiener 2002) trained using a set of events manually labeled by a resident at one of our data collection sites to classify new events for individual residential homes.

Using the disaggregation and classification tool described by Attallah et al. (2022), water use was classified among the following end uses—irrigation, faucet, shower, toilet, clothes washer, bathtub, and unknown—using features of each event (mode, average, root-mean square, and peak flow rate, duration, and volume). A detailed description of the end use classification process, included to ensure this paper stands alone, is presented in Appendix I.

Estimating Outdoor Irrigation Efficiency

The time period for which data were collected at a site influenced the amount of outdoor water use captured. In order to obtain an estimate of outdoor irrigation efficiency comparable across different time periods of the year, the landscape irrigation ratio (LIR) (Glenn et al. 2015) was calculated at weekly intervals for each site. The LIR is defined as the ratio between landscape water use and landscape water needs [Eq. (2)]

$$\mathrm{LIR} = \frac{\text{landscape water use}}{\text{landscape water need}} \tag{2}$$

Landscape water needs were determined for each site based on a water budget [Eq. (3)], similar to what was used in Glenn et al. (2015):

$$\text{Landscape water need} = (K_c \times ETo_i - P_i) \tag{3}$$

where K_c = crop coefficient; and ETo_i and P_i = reference evapotranspiration and precipitation for a given week i, respectively (in mm). Daily rainfall data and estimates of evapotranspiration from the Utah State University (USU) Environmental Observatory weather station were used to estimate the landscape water need for all properties in Logan, and data from the Evans Farm weather station was used for properties in Providence (Bastidas Pacheco and Horsburgh 2022). The crop coefficient represents the ratio between reference evapotranspiration and actual crop evapotranspiration (Doorenbos and Pruitt 1977). To determine this value, we assumed a uniform turfgrass surface for all sites and used $K_c = 0.8$, similar to what was done in Endter-Wada et al. (2008). Typically, residential landscapes are composed of turfgrass and trees immersed in a turfgrass landscape (Kjelgren et al. 2000). However, there is limited information about crop coefficients for turfgrass (Romero and Dukes 2015) or landscapes with multiple plant species (White et al. 2004). Therefore, the actual K_c value for each site was most likely lower than 0.8.

Landscape water use for a given week i (in m) was computed for each site using Eq. (4):

$$\text{Weekly landscape water use}_i = \frac{\text{weekly outdoor volume}_i}{\text{landscape area}} \tag{4}$$

where weekly outdoor volume$_i$ = total volume of water used outdoors for week i (in m^3); and landscape area = area being irrigated (in m^2) at each site. Landscape areas were identified and manually digitized from high resolution aerial imagery for each site, and the areas were calculated using GIS. Using LIR helps classify outdoor water use (Table 3).

Of the 31 sites enrolled in this study, participants at two sites (Sites 21 and 22) moved into newly built homes between the times when we collected winter and summer data. These sites had not yet developed their landscape when summer data were collected and so outdoor water use was not assessed for those sites. All outdoor analyses presented in this paper were for the remaining 29 sites.

Performance of Indoor Water Use Fixtures

To assess the performance of indoor water fixtures, we compared the characteristics (showerhead and faucet flow rates, toilet volume

Table 3. Category benchmarks for the LIR (Glenn et al. 2015)

Benchmark category	LIR value
Justifiable water use	
Efficient	LIR ≤ 1
Acceptable	1 < LIR ≤ 2
Unjustifiable water use	
Inefficient	2 < LIR ≤ 3
Excessive	LIR > 3

Table 4. Federal standard and WaterSense criteria for toilets, faucets, and showerheads

End use	Criterion	Federal standard (DOE 1992)	EPA WaterSense (EPA 2021)
Toilet	Volume per flush	<6.1 L/flush	<4.8 L/flush
Shower	Flow rate	<9.5 L/min	<7.6 L/min
Faucet	Flow rate	<8.3 L/min	<5.7 L/min

used per flush) of existing fixtures at the 31 sites enrolled with the federal standard defined in the US Energy Policy Act of 1992 (DOE 1992) and the USEPA's WaterSense efficient fixtures (EPA 2021) (Table 4). The Energy Policy Act of 1992 (DOE 1992) set national water efficiency standards for toilets, faucets, and showerheads and has been in effect since 1994. The EPA WaterSense program labels water fixtures using higher efficiency standards than the 1992 Energy Policy Act, aiming to achieve 20% more efficiency than average products in the same category (EPA 2021).

We divided faucet, toilet, and shower events into three categories: efficient (flow rate or volume per flush less than or equal to WaterSense specifications), compliant (flow rate or volume per flush greater than WaterSense specifications but less than or equal to federal standards), and inefficient (flow rate or volume per flush greater than federal standards). Events with small frequencies (<5%) were not accounted for in the final assessment in order to reduce the impact of double toilet flushes, errors in classification, or unintended use. We did not assess the performance of clothes washers, because it would have required information about load sizes. We also did not assess bathtub events, because there was no defined criterion for an efficient bathtub event.

Examination of Indoor Water Use

We examined indoor water use for sites with records longer than four weeks (18 sites, including five sites with record lengths varying between 11 and 19 weeks). For this analysis, we used data collected during summer and winter months and removed irrigation events to focus on indoor water use. We quantified the total volume used for indoor water use, the distribution across end uses, and hourly aggregated water use estimations at the weekly level for each site. In addition, we quantified differences in the mean volumes (for faucet, shower, and bathtub events) and frequency of end use events (for all end uses) in winter versus summer months using Student's t-test (Student 1908) for sites that had at least 4 weeks of data during summer and winter months (10 sites).

Results and Discussion

For completeness and to allow our results to be compared with other studies, Appendix II provides information about participants' rankings in terms of annual water use, additional water use statistics, the distribution of end uses, comparison of water use between this study and other studies, and additional information about the duration and flow rate of events. We believe that this information may be of interest for decision makers and water managers. However, for the sake of brevity and in light of the fact that it was not strictly related to the research questions in the current work, we placed it in an appendix.

Distribution of Indoor Water Use and Frequency of Use for Indoor Water Fixtures

Our analysis of indoor water use frequency and end use distribution showed the following:

- The distribution of events across end uses was similar for users at different overall consumption levels.
- The frequency of per capita events was larger for users at higher consumption levels even though the average volume per event was similar, indicating that frequency had a larger influence on per capita water consumption at the group level.

To address our first research question, we used the per capita daily average indoor water consumption to rank sites as low (<33rd percentile), medium (33rd–66th percentile), or high (>66th percentile) water users depending on their percentile ranking of per capita daily average indoor water consumption. Fig. 2 shows the average volume per event, the number of events per capita, and the per capita average water use for all groups across end uses. There was less than a 13% difference in the average volume used for all events across the three groups. A Kruskal-Wallis test (Kruskal and Wallis 1952) with $p > 0.05$ showed that these differences were not statistically significant. Fig. 2 shows that high consumption sites had larger numbers of events per capita per day across all end uses. A Kruskal-Wallis test (Kruskal and Wallis 1952) with $p < 0.05$ showed that the differences in frequency across all end uses were significant. These results indicate that event frequency, which is an

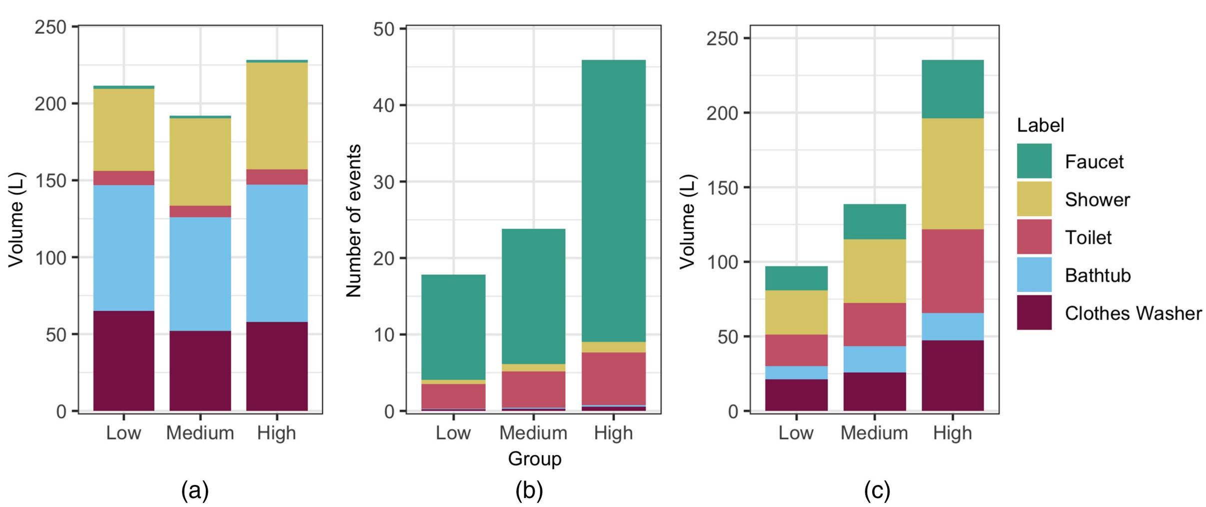

Fig. 2. Indoor water use summary by group for low, medium, and high water users: (a) average water use volume per event occurrence; (b) average number of events per capita per day; and (c) average daily indoor water use per capita and distribution among end uses.

indicator of behavior, had the largest influence on per capita daily water consumption at the group level.

The distribution among end uses remained relatively constant across consumption levels. As the largest indoor water use category, shower events accounted for 30.3%, 30.8%, or 31.6% of total indoor per capita daily water use (for low, medium, and high consumption sites, respectively). Toilet events accounted for 21.8%, 20.8%, or 23.8% of total indoor volume across the three levels (low, medium, and high, respectively). Faucets accounted for 17% of total indoor water use across all categories.

Indoor Water Use Timing

The analysis of indoor water use timing found the following:

- There were different diurnal water use patterns (i.e., one, two, or no periods of higher consumption during the day) across the sites investigated, and these timing patterns were independent of water consumption level.
- Participants in lower consumption categories had a larger increase in weekend versus weekday use compared to larger consumption sites, suggesting that lower consumption sites had shorter participant presence at home on weekdays.

Hourly and daily aggregated values were considered to further address our first research question and assess indoor water use timing and its variations across users of different consumption levels. Indoor water use timing is behavioral and is determined by personal preferences and schedules. Fig. 3 shows the hourly distribution of indoor water use across all users. Some sites had distinctive periods of water consumption during the day, while other sites had relatively similar water use throughout most of the day. Water use was larger in the morning than in the afternoon at most sites. The bimodal distribution with peaks in the morning and in the evening observed in the past (Buchberger and Wells 1996) was visible only at a few sites (e.g., Sites 6, 20, and 29). Timing patterns were independent of water consumption levels. Sites within the low, medium, and high consumption categories followed different patterns indistinctively.

Participants consumed, on average, 21% more water on weekend days (Saturday and Sunday) than on weekdays (Monday to Friday). High consumption sites used 15.7% more water on weekend days compared with weekdays, while medium and low users

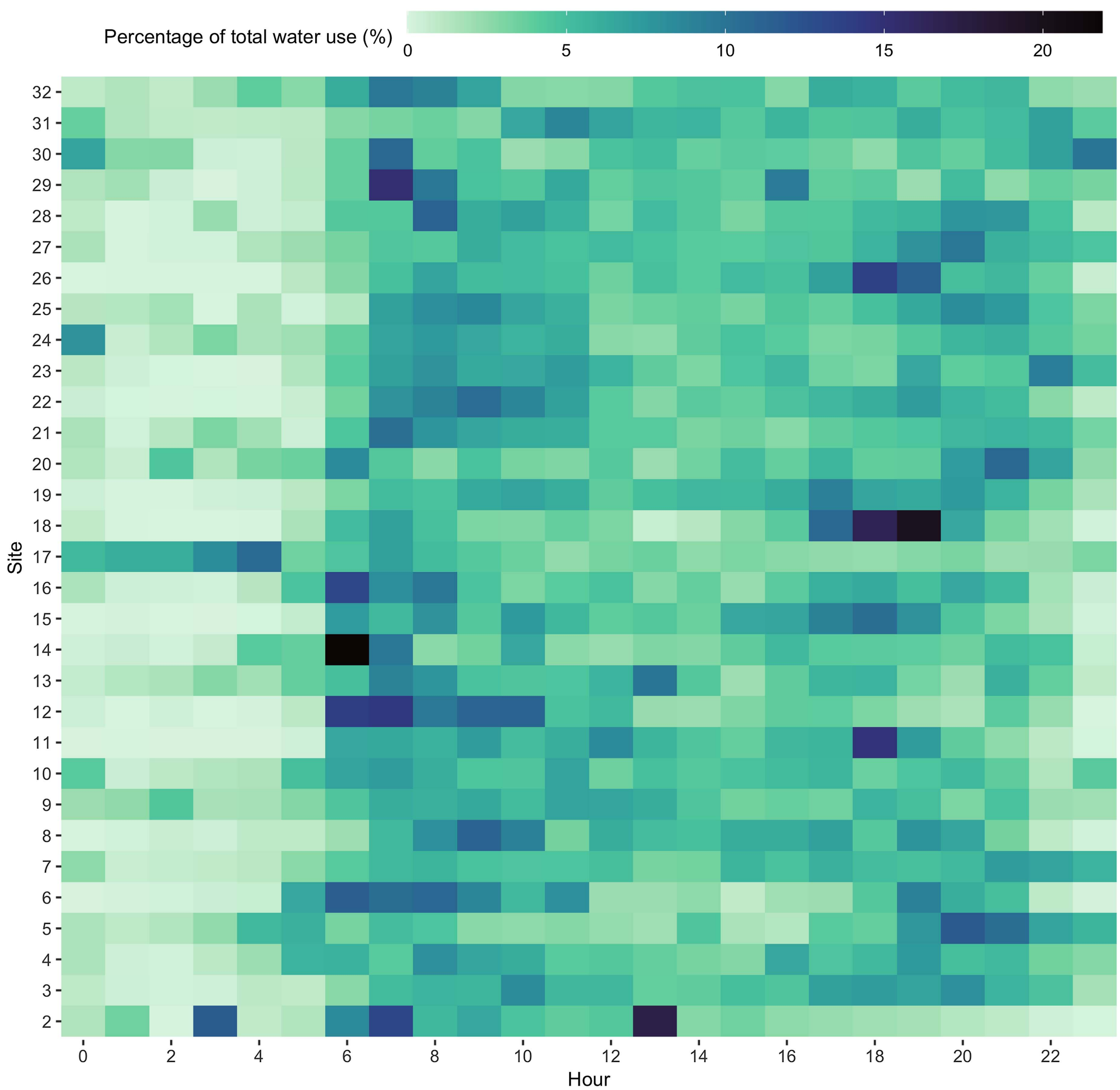

Fig. 3. Hourly distribution (in percentage) of total indoor water use for all participant sites.

used 19.6% and 28.9% more water on weekend days than on weekdays, respectively. Smaller increases in weekend versus weekday average per capita daily volume likely indicate longer participant presence at home on weekdays. This partially explains the results observed in Fig. 2. In general, the differences in the observed hourly and daily patterns were most likely dictated to a large degree by the heterogeneity in the schedules of the occupants.

Outdoor Water Use

The analysis of outdoor water use found the following:

- The volume of water used outdoors was approximately 83% of all water use, with differences among sites primarily determined by the irrigated area and the method used to irrigate.
- Most of the time, irrigation was acceptable or efficient, according to the LIR, and the largest outdoor water conservation potential with existing landscapes could be achieved by adjusting irrigation settings when rainfall occurs.
- Additional outdoor water conservation would require reductions in the size of the irrigated landscapes.
- Most participants irrigated in the early morning or late evening, which matched regional guidelines for water conservation.

To address outdoor water use for our first research question, we used a combined 278 weeks of data collected between May and October at the 29 sites where outdoor water use was analyzed, recording 4,533,939 L of water use during these months. Approximately 83% of this volume was used for outdoor irrigation. Outdoor water use is largely driven by personal preferences, but in some instances may be required by homeowner's associations. The volume used may also be impacted by the type of system used for irrigation (i.e., hose, sprinkler system, automated timer, smart weather controller, soil sensors). While the level of technology used for irrigation is a personal preference, each type of system has a potential technological impact related to device performance. In our sample, the eight sites that irrigated using a hose (Sites 3, 6, 7, 8, 10, 16, 17, and 18—some with an automated timer, others manually) ranked below the 40th percentile for annual water use in Logan City (see Appendix II). The rest of the participants used sprinkler systems with automated controllers, and 88% of those sites ranked above the 40th percentile. These results are similar to results from past studies, which have found a strong correlation between automated sprinkler systems and higher water use (DeOreo et al. 2016; Endter-Wada et al. 2008; Mayer et al. 1999).

Fig. 4(b) shows the average weekly outdoor volume for each site. Sites 27 and 5 had the largest outdoor water use, consuming, on average, more than 80,000 L per week, and had the largest and the third largest landscape areas (3,843 m^2 and 3,118 m^2, respectively). During six weeks (five in 2019 and one in 2020) the landscape irrigation needs were zero (rainfall supplied all the water the landscapes needed), and any outdoor water use that occurred was unnecessary. Given that the LIR had an undefined value during these weeks [Eq. (2)], these six weeks were not included in Fig. 4 but are addressed in the following paragraph. All hose irrigators used less than 8 m^3 of water per week, while 80% of sites with automated sprinkler systems used more than this value (Fig. 4). The landscape areas for hose irrigators were not all smaller than the sprinkler irrigated sites (ranking 1st, 2nd, 4th, 9th, 17th, 21st, 22nd, and 24th among the 28 sites presented in Fig. 4). Using the LIR values determined for each week of irrigation [Fig. 4(c)], irrigation was excessive at Sites 2, 9, 11, and 14 during week 36 of 2019, and at Site 14 during week 38 of 2019. During week 36 of 2019, a rainfall event that supplied 97% of landscape water needs was registered by the USU Environmental Observatory station, making outdoor water use inefficient during that time period at those sites. In summary, outdoor water use was either efficient (62%) or acceptable (27%) during most the weeks in which data were collected and was excessive (5%) or inefficient (6%) the rest of the time. Given the large percentage of time that irrigation fell in the efficient or acceptable categories, it is likely that larger reductions in outdoor water use would require reductions in irrigated landscape area.

During the six weeks in which landscape water needs were zero (the LIR was undefined), we collected 33 full weeks of data across 20 sites. Fig. 5 shows the number of full weeks of data collected at each of these 20 sites and the volume (average when more than one week was available) used during weeks in which landscape irrigation needs were zero. Most sites (80%) reduced their outdoor water use between 11% and 90% in response to precipitation compared to the remainder of the weeks. Nevertheless, precipitation can occur at the end of a week after all outdoor water has been applied, and the regular weekly intervals we used for our analysis did not attempt to account for this. Furthermore, homeowners would have needed additional information (landscape water needs, rainfall data, usage from their irrigation system) to accurately respond to precipitation events. Even with the reduction in outdoor water use observed, the volume used for outdoor irrigation during weeks when landscape water needs were met by precipitation (366 m^3) represented a large water conservation potential without changing existing irrigated landscape area at participant sites.

Separating indoor from outdoor water use was more accurate when automated sprinkler systems were present, because the flow rates for automated irrigation events can be as much as twice the values observed for indoor events. In addition, irrigation events produced by automated irrigation controllers have similar timing, flow rates, and durations. The flow rate of irrigation events was the highest among all end uses. At five sites (Sites 2, 5, 9, 19, and 27), flow rates of irrigation events exceeded 70 litres per minute (Lpm). Irrigation events also had the longest duration among all end uses, with an average of 42.1 min across all sites. Participants with automated sprinkler systems irrigated in the early morning or late evening, which was within the recommended irrigation timing for reducing losses from evaporation; the exceptions were Sites 25 and 26, at which a few irrigation events were detected close to noon.

Individual sites were classified as low, medium, or high according to their monthly outdoor water use ranking, dividing at the 33rd and 66th percentile (computed for all SFR users by city, using the entire record of monthly data available, shown in Table 1). Monthly outdoor water use was computed as the difference between the average monthly water use during months when irrigation occurs (May through October) and the average monthly water use during months when irrigation was not expected (November through March). Using this procedure, eight sites were ranked as low, 11 sites were ranked as medium, and the remaining 10 sites were ranked as high (Fig. 6). Fig. 6(a) shows average monthly outdoor water use per landscape area, in mm. We collected two full weeks of data at Site 13 during the summer months, shown in Figs. 5 and 6, in which outdoor water use was inefficient and unnecessary. Fig. 6(b) shows average outdoor monthly water use. Hose irrigators generally ranked lower than irrigators who used sprinkler systems, and they applied less water per unit area. Broadly, sites classified as medium and high applied water at similar rates per unit of area; this result was similar to results of previous studies (DeOreo et al. 2016; Mayer et al. 1999; Endter-Wada et al. 2008). This indicates that the differences in outdoor water use observed were, in most cases, the result of the irrigation method used or the landscape area irrigated. Fig. 6 shows that Providence residents consumed more water than Logan residents (the 33rd and 66th percentiles of outdoor water use were higher).

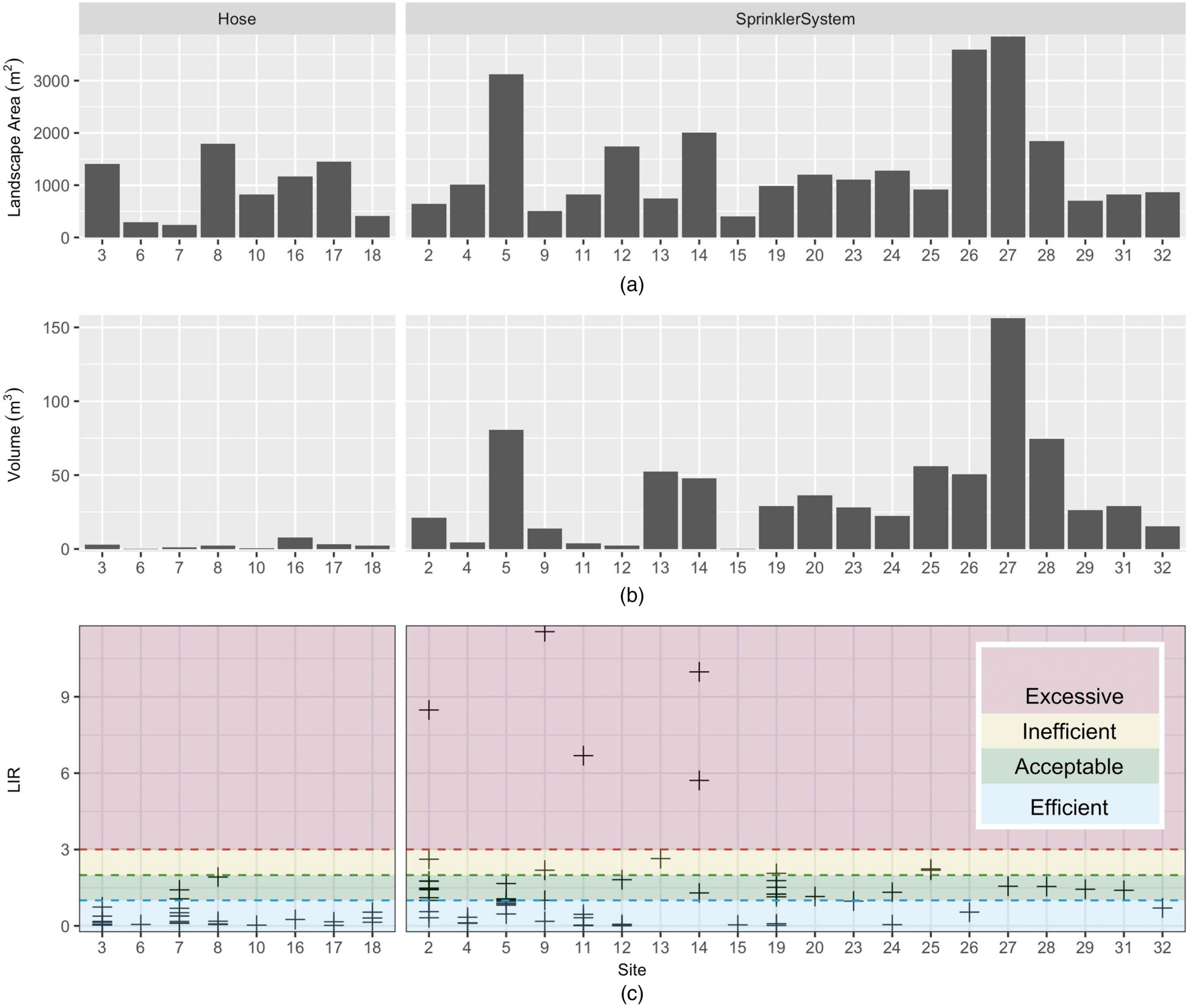

Fig. 4. Weekly outdoor water use information (excluding weeks in which landscape water needs were zero) and landscape area: (a) landscape area; (b) average weekly outdoor water use volume; and (c) weekly LIR values for each site.

Performance of Indoor Water Use Fixtures

Our review of the performance of indoor water use fixtures found the following:

- Despite technology standards that have been in place since 1994, there is still opportunity for indoor water conservation by replacing or adjusting toilets and showerheads and promoting behavior changes to reduce shower duration.
- While the average shower duration from this study was similar to that of the 2016 Residential End Uses of Water Study (REUWS), we observed a greater number of shorter duration showers, which may reflect regional differences in behavior.
- Faucets were the highest performance fixture, with the highest number of events falling into the efficient category according to WaterSense standards.

To analyze the performance of water fixtures among participant sites—our second research question—we examined the features of shower, toilet, and faucet events at each of the participant sites. Our analyses focused primarily on the technological performance of fixtures (e.g., flow rates of showers and faucets and volume per flush for toilets) rather than on behavior (e.g., frequency or duration of events). As an exception, we analyzed shower durations to highlight potential opportunities for conservation related to behavior. Most of our participant sites (28) had more than one bathroom. The performance analysis was conducted on individual events and not on average characteristics in order to observe differences in the performance of different fixtures at the individual level. The results are presented in Fig. 7.

For showerhead flow rates, we found inefficient shower events at 14 sites, compliant shower events at 29 sites, and efficient shower events at all sites. Two sites (Sites 14 and 17) had only efficient events, indicating all showerheads at those sites operated below the WaterSense standard. While most sites had a mix of shower events across two or all three of the efficiency categories defined, the percentage of inefficient shower events was below 25% at all sites with three exceptions (Sites 12, 29, and 31). Shower durations are related to social norms, and, because of this, there is no consistent

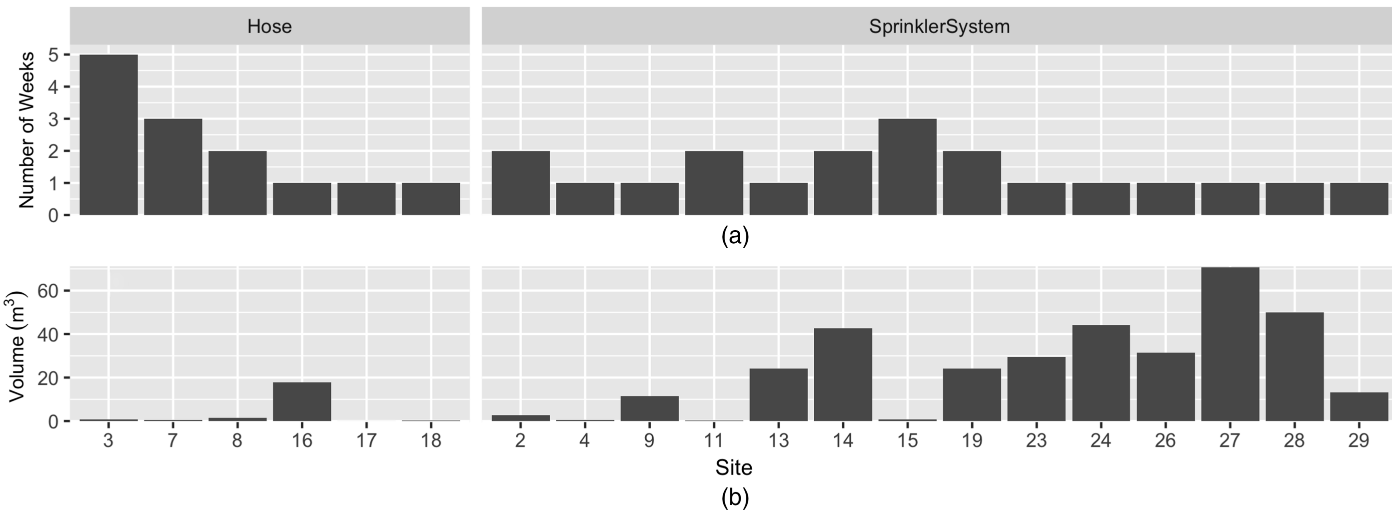

Fig. 5. Outdoor water use measured during weeks when landscape irrigation needs were zero: (a) number of weeks of data collected; and (b) average volume used.

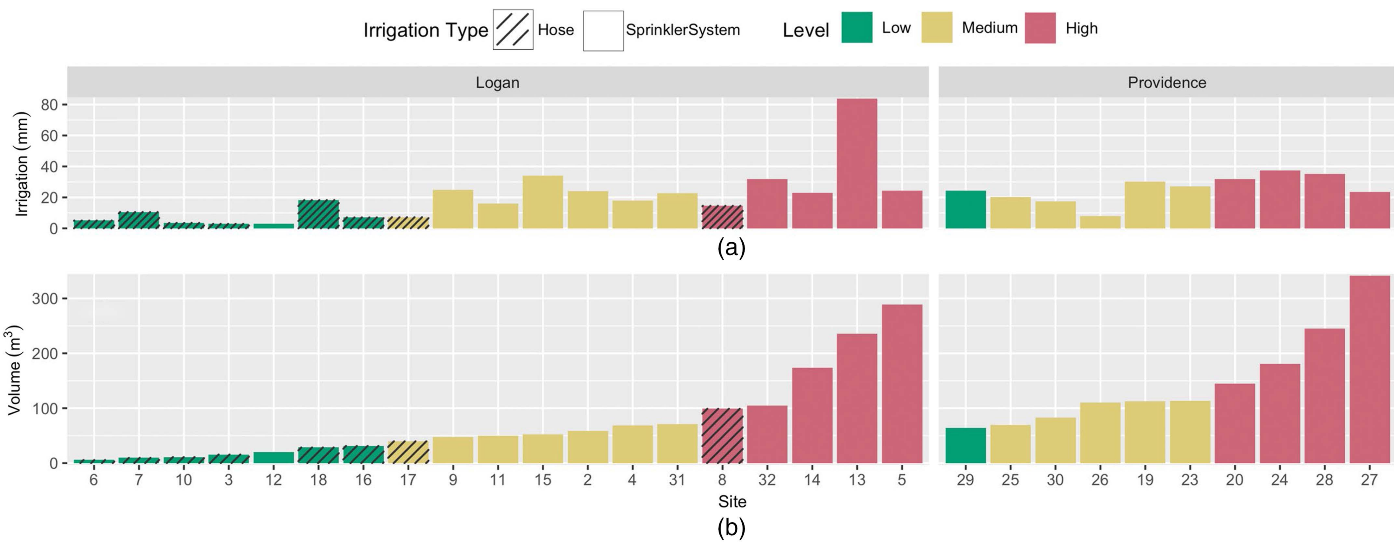

Fig. 6. Outdoor water use analysis from monthly records: (a) outdoor water use per unit area; and (b) average monthly outdoor water use.

standard or guidance as to what shower duration is considered efficient. In these data, the distribution of shower durations was as follows: 25% of showers lasted less than 3.2 min, 25% lasted between 3.2 min and 5.87 min, 25% lasted between 5.87 min and 10 min, and the top 25% were longer than 10 min. The average duration across all sites was 7.5 min, which was similar to the 7.8 min found in the 2016 REUWS (DeOreo et al. 2016). However, the distribution of shorter showers was different, for example. The first quartile of shower durations in the 2016 REUWS was 6 min (compared to 3.2 min in our study). The different methods used for analysis, the varied households characteristics, or geographical factors could explain these differences.

The EPA allows some flexibility (± 0.38 L $= 0.1$ gallon) in the values used for certifying toilets (EPA 2014). We added this 0.38 L to the threshold definitions shown in Table 4. We found inefficient toilet events at all sites, compliant toilet events at 26 sites, and efficient toilet events at only 8 sites. The percentage of inefficient toilet events was greater than 50% at 23 of the 31 sites (Fig. 7). The 2016 REUWS classified individual toilet events as efficient if they used less than 8.3 L. Using this higher threshold, they found that 48% of toilet events were in this efficient category, compared to 16% in 1999 (DeOreo et al. 2016). When comparing toilet events in our sample with the 8.3-L threshold, we found that about 58% of toilet events were in this range, suggesting that there has been continuous improvement in toilet performance in the last few decades. However, the percentage of efficient toilets in the 2016 REUWS varied from 38% to 61% across participant cities (DeOreo et al. 2016), indicating that geographical factors influenced the values observed. Further studies across different cities are needed to discern between temporal and geographical effects on toilet performance.

The disaggregation and classification algorithm we used was unable to separate kitchen and bathroom faucets, and, while it is possible that higher flow rate faucet events occur in the kitchen, this cannot be guaranteed. A total of 90% of the faucet events identified across all sites lasted less than 48 s and had a flow rate less than 5 L/min. Only 0.14% (1,136 occurrences) of faucet events

Fig. 7. Performance of showerheads, toilets, and faucets expressed as percentage of events falling into efficient, compliant, or inefficient categories.

had a flow rate larger than 8.3 L/min, indicating that faucet events exceeding the federal standard for maximum flow rate were rare. Faucets were the highest-performance category among those analyzed (Fig. 7). Faucets are most likely replaced more frequently than other water-using appliances in a home, and the growing presence of water efficient faucets may explain why this category exhibited higher performance. The 2016 REUWS found similar results in terms of faucet event flow rates, with 99% of faucet events in that study having a flow rate less than 8.7 L/min.

Indoor Water Use over Longer Data Collection Periods

When analyzing water use at sites with more than four weeks of data, we observed the following:

- Diurnal water use patterns and the distribution of events across end uses varied between weeks at individual sites.
- Short term observations of water use (e.g., two weeks or less) may be adequate for assessing the performance of some water fixtures but do not adequately represent longer term behavior.
- There were differences in summer versus winter water use frequency and volume for events at some sites; however, these differences were not generalizable across sites.

To assess how estimates of volume, distribution across end uses, and timing of indoor use may change with longer data collection periods—our third research question—we focused on sites for which we had four or more weeks of data. Indoor water use was relatively constant across weeks at some sites (e.g., Sites 7, 12, and 22), whereas relatively drastic differences in week-to-week volumes were observed at others (e.g., Sites 2, 9, 18, and 19) (Fig. 8). In some cases, these variations occurred within the same period of the year; this can be observed by analyzing the separation of points of similar shape across sites in Fig. 8. Some of these variations may have been the result of changes in occupancy. For example, there were weeks with minimal water use at Sites 5, 14, and 15, which indicates that the occupants were likely not at home during these weeks. In addition, changes in weekly schedules and personal preferences may have affected the amount of water used.

The daily timing of water use also varied significantly between weeks. Fig. 9 shows total hourly water use week by week for Site 19, that is, the total water used within each hour summed across all the days of each week. The time of occurrence and the magnitude of peaks in water use varied significantly from week to week, and this lack of patterns in hourly and weekly water use data was observed at most of the study sites. There were weeks at this site that had one or more distinctive periods of high water use, but in other weeks water

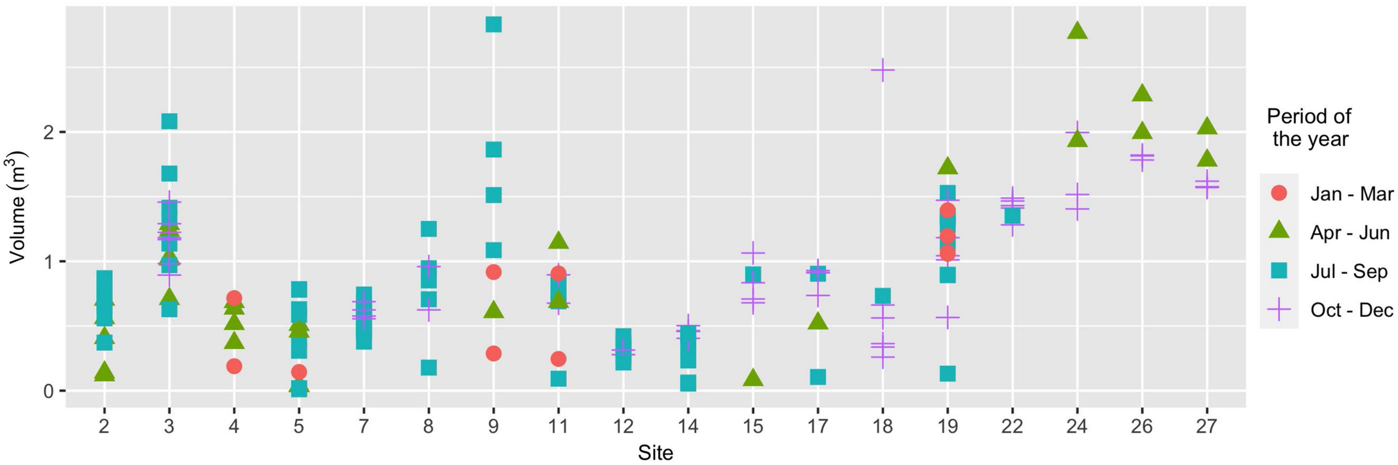

Fig. 8. Indoor weekly water use volumes for sites with a data record longer than four weeks.

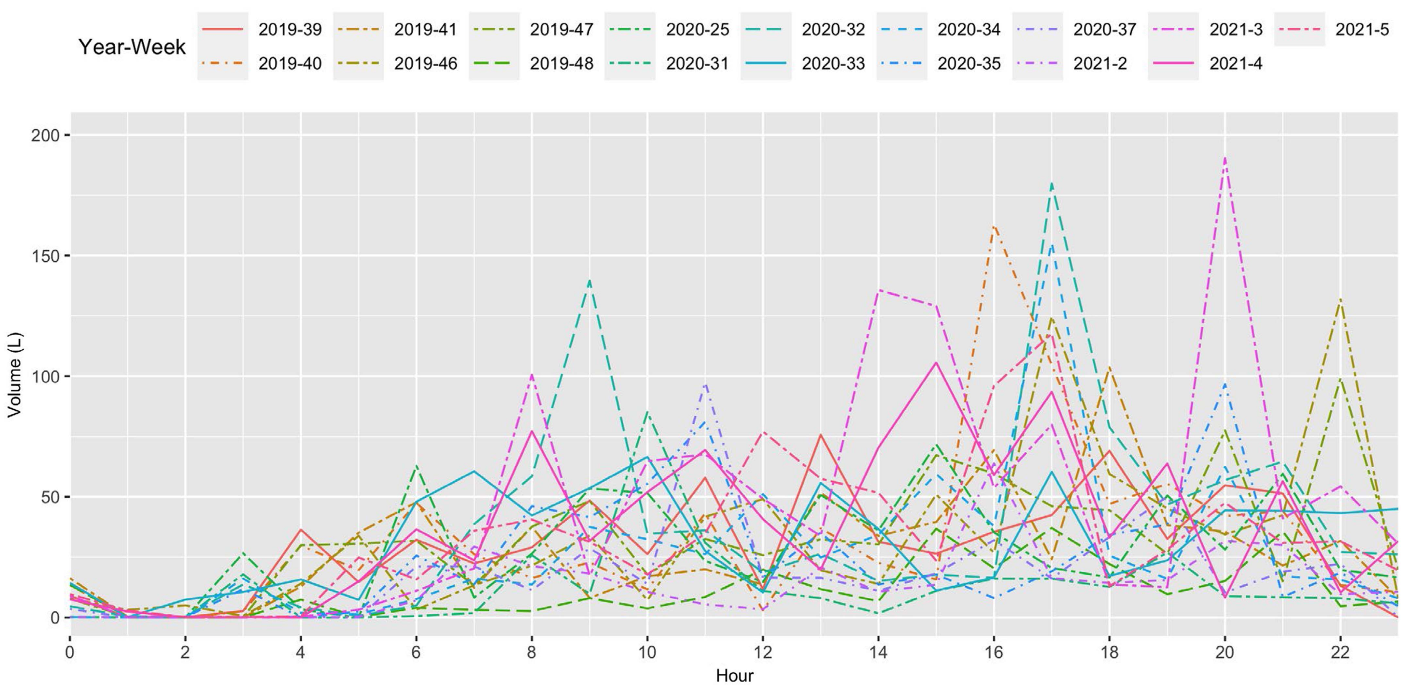

Fig. 9. Total hourly indoor water use for the 17 full weeks of data at Site 19. Values for each hour include all water used during that hour—for example, the value plotted at 4:00 a.m. includes all water use between 4:00 a.m. and 5:00 a.m. The week of the year is indicated in the labels (YYYY-WW).

use was relatively constant across the day, indicating that the distribution of use varied over time. Fig. 10 shows weekly variations in indoor water use across end uses for the same site and the same weeks. The percent of indoor volume used for shower events varied the most from week to week, from over 40% to 16% of total water use; it ranked as the largest end use in some weeks but ranked 4th in others. The percent of indoor water use dedicated to bathtub events also exhibited changes, ranging from 6% to 20% and ranking from 2nd highest to 5th highest. The percentage of indoor water use dedicated to toilets varied between 25% and 36%. While we have generally reported use in terms of percentage of volume, the frequency with which end use events occurred also varied depending on the week.

Of the 10 sites selected for indoor winter and summer comparison, four did not have bathtub events. We compared eight (or six, when bathtub events were not present) parameters at each site between winter and summer months. Of the 72 parameters analyzed across these 10 sites, there were significant differences (p value < 0.05) in the mean of 19 (26% of the cases) of them, according to t-test results. In 11 cases, we observed changes in the mean frequency, and in eight cases we observed differences in the mean volume. The direction of these differences by event type is reported in Table 5 (for frequencies) and Table 6 (for volumes). The inconsistency in the differences between frequency and volume of end use events suggests that the observed differences are not generalizable. In some cases, the number of events or the volume was larger in the

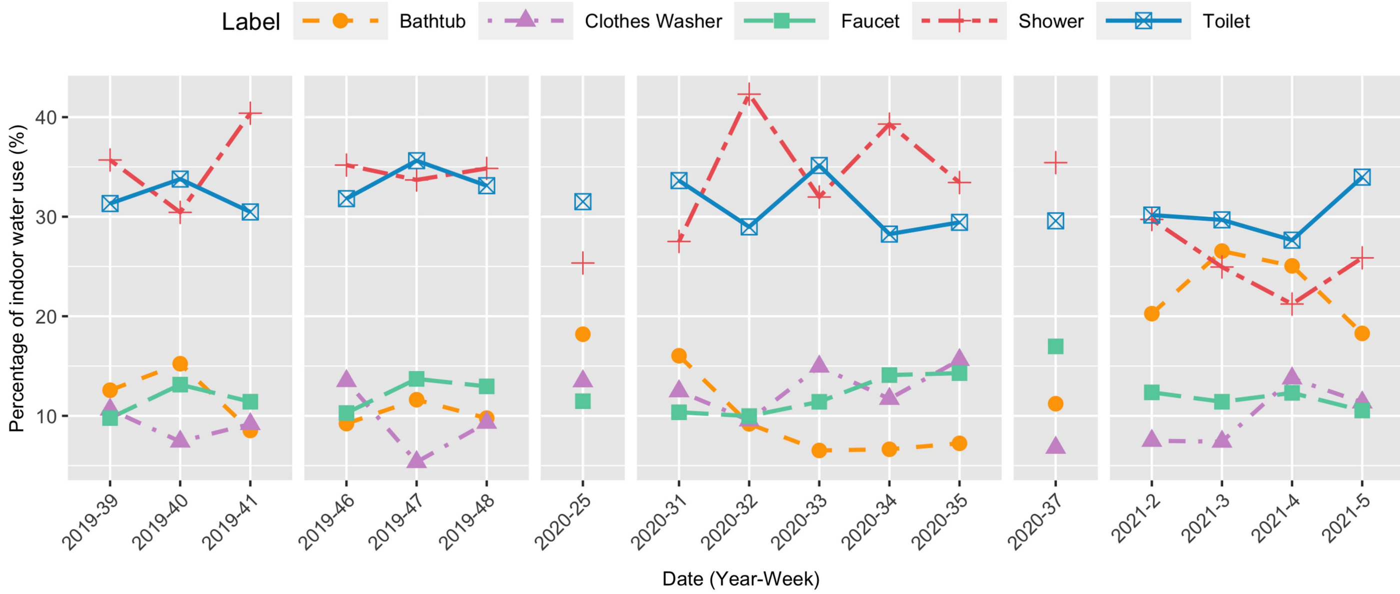

Fig. 10. Weekly percentages of indoor water use by end use for the 17 full weeks of data at Site 19. The *x*-axis of the plot is broken for instances in which data collection weeks were not immediately adjacent.

Table 5. Number of sites and changes observed in the mean frequency of events (summer versus winter)

Change observed	Faucet	Shower	Toilet	Bathtub	Clothes washer
Larger frequency of events (summer versus winter)	4	1	2	0	2
Smaller frequency of events (summer versus winter)	1	1	0	0	0
No significant change	5	8	8	6	8

Table 6. Number of sites and changes observed in the mean volume of events (summer versus winter)

Change observed	Faucet	Shower	Bathtub
Larger mean volume (summer versus winter)	2	0	1
Smaller mean volume (summer versus winter)	4	1	0
No significant change	4	9	5

summer, and the opposite occurred at other sites. In addition, with the exception of faucets, no significant changes were observed at the majority of the sites analyzed.

As the number of weeks of data increased for a site, we observed only small variations in the average, mode, and peak flow rates for showerheads and faucets and in the volume per flush used in toilets. Therefore, it appears that the technological performance of indoor fixtures can be accurately assessed with short data collection periods unless a fixture is replaced. However, capturing behavioral changes in indoor water use volume and timing and developing a comprehensive representation of the distribution of indoor water use across end uses that were evident in our data requires longer data collection periods or a different study design than has been typically used. The lack of consistency in indoor water use patterns cannot be characterized using coarser resolution (e.g., monthly) data or when analyzing indoor and outdoor water use together. Other studies have pointed to similar results. For example, Rathnayaka et al. (2015) found differences in shower durations and frequencies in summer versus winter months in 117 houses across two municipalities in Australia. Suero et al. (2012), who analyzed two weeks of data before and four weeks of data after retrofitting with efficient appliances in 96 homes in the US, found differences in the frequency of use of toilets and clothes washers between the pre- and post-retrofit data sets. The seasonal differences we observed and those observed in prior studies indicate that there are seasonal and shorter-term changes in the frequency, timing, and distribution of end uses. Longer, and continuous, periods of data collection are required to characterize these types of temporal variations (Fig. 9), including changes in the distribution of water use across end uses (Fig. 10) and the seasonal component of indoor water use (Rathnayaka et al. 2015). In addition, we observed that indoor water use varies differently across sites (Fig. 8), suggesting that the record length needed to characterize indoor water use variability may be different across sites.

Collecting indoor water use data for short periods of time can generate parameters (volume, timing, and distribution across end uses) that may not be representative of water consumption at a site given that water use depends on behavioral factors in addition to fixture performance. End use level data provide a basis for evaluating and designing water demand strategies (Beal and Stewart 2014), demand and infrastructure modeling (Blokker et al. 2010), and general planning (Willis et al. 2013). Using water use estimations resulting from data that do not capture a representative sample of water use may impact the accuracy of such applications and lead to the implementation of ineffective water management strategies, under- or over-dimensioning of infrastructure, and other issues. However, defining a fixed record length that secures a complete characterization of indoor water use across multiple residential properties is infeasible using currently available data, most of which are short duration data.

J. Water Resour. Plann. Manage., 2023, 149(1): 05022014

Conclusions

The results presented in this paper were derived from analysis of monthly water use data provided by two municipalities in northern Utah and from 4-s temporal resolution data collected by the authors over a time span of three years at 31 homes in the two cities. Related to indoor water use, we found that total water use volume and the distribution across end uses varied across hours, days, and weeks. Our analysis of water usage across high, medium, and low water users revealed behavioral differences. Although the distribution of indoor water use across end uses was similar for sites at all levels of consumption, sites with higher usage had higher numbers of events per capita. Additional data, which could be collected via an additional survey, is needed to characterize the determinants of this behavior. Showers and toilets were the largest indoor water use categories. All sites used more water on the weekends than on weekdays; however, sites at lower consumption levels had a higher percentage increases from weekday to weekend use.

The data from this study demonstrated opportunities to improve toilet water use efficiency by either adjusting existing toilets or replacing them with more efficient toilets at all participant sites. This could be done through educational campaigns targeted at homeowners, explaining how to adjust existing toilets, or through rebate programs that encourage homeowners to replace existing toilets with efficient ones. Toilet age, installation characteristics, and valve status affect the volume used per flush. Even toilets manufactured under Federal standard specifications can perform outside their target range.

Most participant sites had efficient showerheads relative to high efficiency standards such as EPA WaterSense (EPA 2020). Therefore, the largest opportunity for reducing shower water use would be through promoting shorter duration showers, given that 25% of all shower events lasted longer than 10 min. This may be difficult for a number of reasons, including identifying those with the highest opportunity to conserve and presenting them with effective information to encourage conservation. There is a shortage of longitudinal studies in the literature assessing the effectiveness and long-term effects of these types of campaigns. Bathtub events used significantly more water than showers but were also less frequent and were not found or not used at 35% of the sites. Faucets had the highest performance compared to existing efficiency standards.

In summer months, outdoor water use was the largest component of residential water use. Generally, outdoor water use volume per unit of irrigated area was similar across users at all consumption levels. Users that irrigated with automated sprinkler systems used larger volumes (in total and per unit of area) of water than those who irrigated with hoses. The total volume of outdoor water used at a given site was mainly influenced by the irrigated area and the method used for irrigation.

Outdoor water use was efficient or acceptable according to LIR categories during 89% of user weeks, despite the large volumes used for outdoor irrigation. This indicates that most users were not significantly overwatering their landscapes according to the LIR. While we do not want to discount informational campaigns targeted at ensuring that people are not overwatering their landscapes, more significant water savings may be achieved through campaigns aimed at reducing landscape water need by changing landscape size or composition. Furthermore, we found significant conservation potential (366 m^3 in a week across 20 sites) that would be realized if users did not irrigate when rainfall sufficient to meet landscape needs occurs.

The total volume of water used, the distribution of use across end uses, and the timing of indoor water use varied from week to week such that data collection periods longer than those used in previous studies and, likely, even those used in this study are needed to fully characterize these changes. The temporal patterns of water use (peaks, timing of peaks) varied between weeks at all sites independent of water consumption levels. Daily indoor water use timing patterns can be difficult to determine, because they depend on personal and often variable schedules; this was evident in our data. Further research is needed to define the effect of data record length on indoor water use temporal variability is also not well represented in existing water demand modeling approaches, and doing so presents an opportunity to improve these models.

Some of the general results of this study and the analyses included in Appendix II were similar to those of previous studies, indicating that some aspects of residential water use are generalizable. However, our analyses conveyed new and key information that can assist water utilities and decision makers in Utah and potentially other areas with similar characteristics (climate, landscape sizes, household occupancy, level of water use) in better understanding how water is being used, including changes over time in the distribution of indoor water use across end uses, differences in weekly total use, variabilities in timing, and differences in outdoor water use across longer data collection periods. Participants in this study received detailed water use feedback comparing their annual usage with the rest of the SFR clients in their cities; the performance of individual fixtures at their home; shower durations; outdoor water use; and opportunities for water conservation. Prior studies have shown that this type of specific information can motivate conservation behavior. Water managers in these cities can use the types of information generated by this study to assess demand, promote conservation, obtain insights into the real operational efficiency of fixtures within residential homes in Utah, design rebate programs, determine the effectiveness of such programs or other commonly applied strategies for managing demand, or simply gain further insights into how and when are people using water. In addition, engineers and city planners can use the type of information we derived from the data we collected to increase the accuracy of water use estimations and assess infrastructure needs for future urban developments.

Appendix I. Water End Uses: Disaggregation and Classification

End uses in addition to those mentioned in the main article (irrigation, faucet, shower, toilet, clothes washer, bathtub, and unknown) were not individually identified for several reasons. Dishwasher events were lumped in with faucet events, because the features of these two categories of events were indistinguishable in our sample. A swimming pool was only present at one of the participant sites, and pool-related events were likely labeled as irrigation by our algorithm. Additional uses, such as hose events, leaks, or those not described here were placed in the category that their features most closely resembled or were labeled unclassified. We manually labeled all events with a duration of 4 s (the temporal resolution of the data) and volume equal to the meter pulse resolution (i.e., single pulse events) as unclassified. Indoor water use estimates were computed after filtering out irrigation events. Outdoor water use included only events labeled as irrigation. The accuracy of the method was characterized using data for a single site, and, under those conditions, the overall accuracy of the classification method was around 98%. This accuracy was expected to be maximal, because the training and testing data set for the machine learning algorithm contained events for the same site.

When using the algorithm to label events for new sites (those for which no manually labeled user events existed) it was expected that accuracy would decrease, given that the features of the unlabeled events may have been different from the ones included in the training data set. We used a self-learning approach to classify data from sites at which no manually labeled events were available (30 of 31 sites). Using this approach, events were initially classified using a random forest algorithm trained using manually labeled events. Events with a similarity score larger than 90% were then added to the training data set. This process was repeated iteratively until there were no events with a similarity score larger than 90%. The revised random forest model for a site based on the enhanced training data set was then used to classify all events for that site.

Without manually labeled events for each site, it was not possible to evaluate the accuracy of the classifications. Consequently, we applied a manual verification procedure that consisted of examining the characteristics and raw data for a number of events of each end use type at each site. Events within each type were sorted according to their features in a step-by-step procedure (e.g., first sorting shower events by the flow rate feature in descending order and then by ascending flow rate) to observe how similar events at the endpoint of each end use's feature distributions were to those in the middle. This verification method assumed that events were generally labeled correctly and was based on our observation that labeling errors were more likely to occur at the endpoints of the feature distributions of each end use. We are confident that the majority of events in each category were labeled correctly; yet, at the endpoints of each feature distribution, at which overlapping (similar features) exist (e.g., the lowest flow rate shower may overlap with the highest flow rate faucet events), there was uncertainty in the labeling process.

The number of events examined varied depending on how similar events at the endpoints of each end use's distribution were to the rest. Generally, we examined between 10 and 30 events per end use and sort direction. The raw pulse data for a number of events (in the same 10-to-30 event range) were examined visually to verify similarities in events with the same label. The information and a small set of labeled events for each site registered during enrollment allowed us to verify event labels (e.g., volume and flow rates observed in toilets and showers) and to find errors (e.g., the algorithm labeling bathtub events that were similar to clothes washer events in homes where bathtubs were not present or used). Events collected during enrollment were not included as training data, because they did not represent real events (with the exception of toilets), yet they provided an idea of the flow rate ranges for each site. In addition, Attallah et al.'s (2022) method sought to classify end uses of water without the need for labeled events at each property. Therefore, the manual evaluations we did were aimed at ensuring the quality of our analyses.

In some cases, events of different types may have similar features (e.g., short duration showers with low flow rates may appear similar to faucet events). When two events of different types have similar characteristics, it is not possible to differentiate them using existing methods, and they were assigned the same label. Metering of individual end uses could produce further data about the frequency at which such situations occur and provide further details about how this affects the accuracy of single point measurement and disaggregation methods. Without meter data for individual end uses, it is not possible to assess how often or where such events occur. However, the trade-off is that the metering of individual end uses is expensive, invasive, and largely impractical at any scale.

As a last step in the verification procedure, we corrected the labels for some events using the following criteria: (1) misclassified events were relabeled according to the category in which they were most likely to belong, based on the analyst's decision, considering all the elements described in the foregoing; and (2) when events were routinely misclassified by the algorithm, we filtered events with similar characteristics and applied the same corrected label to all. Without considering unclassified events, on average, changes were made to 6.3% of the labels assigned by the algorithm at each site. At Sites 2, 4, 14, and 31, 15% to 18% of the algorithm-assigned labels were reclassified. At these sites, the algorithm systematically made errors because of differences in the features of the events that occurred at these sites versus the manually labeled events used for training the algorithm.

Appendix II. Additional Water Use Information

Monthly Water Use Records

Logan City reads meters once per month, and Providence City reads meters once per month from April through September. We calculated volumes for October through March for Providence by dividing the total winter volume measured (calculated using the September and May meter readings) by six, resulting in the constant values shown in Fig. 11 during those months.

Single family residential water use varied throughout the year in Logan and Providence, peaking in July with average monthly values, across all connections, per household, close to 125,000 L in Logan and 220,000 L in Providence (as shown in Fig. 11). During winter months, SFR water use remained relatively constant in Logan, with per household monthly averages just below 20,000 L and below 30,000 L in Providence. Sociodemographic variables like differences in household and landscape sizes could account for the differences observed in water use between the two cities during

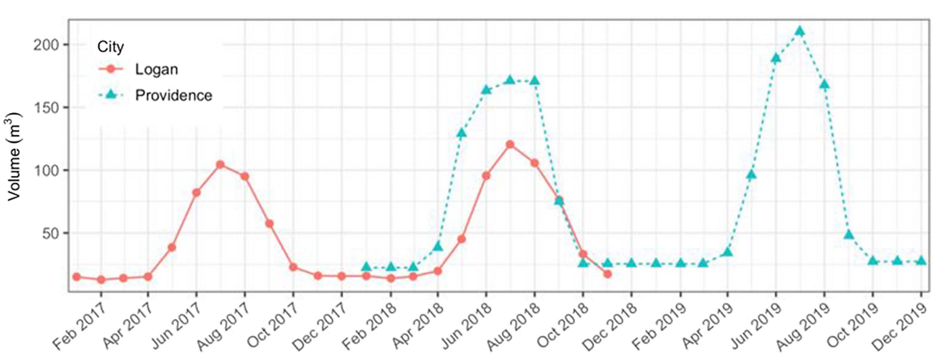

Fig. 11. Average monthly water use per household across all residential customers in Logan and Providence, Utah, between 2017 and 2019, calculated from billing data for 7,522 and 2,113 connections, respectively.

winter months. However, we did not collect data at the city level, and the monthly data provided by the cities did not contain information that would have allowed us to further assess these differences. Outdoor water use drives the increase in residential water use observed during summer months, constituting the largest component of residential water use. Total annual water use did not vary significantly from one year to the next during the period of data available for each city. Winter water use for Logan (Fig. 11) showed some variations that were likely due to differences in indoor water use; however, when compared with the magnitude of the annual variations, changes during winter months appear to be minimal.

Water Use Rankings, Indoor Water Use Statistics, and Comparison with Previous Studies

In order to place our sample of households in the context of single family residential water use in their cities and of other residential water use studies, we report brief general statistics about ranking and water use. Participant sites ranked between the 4th and 95th percentiles of annual SFR water use in each city (computed from monthly meter records). Figs. 12(a and b) show the percentile rankings of annual water use for each participating site, computed for the last two years of data available in each city—2017 and 2018 for Logan, and 2018 and 2019 for Providence. Despite the combined user sampling approach used (targeted invitations, word of mouth) and the relatively small number of participating homes, the samples contained a broad range of percentile rankings and annual water use volumes. Percentile rankings were not consistent from year to year, indicating that there is significant interannual variability in water use that is not determined solely by the climatic conditions that drive outdoor use. Fig. 12(c) presents the participating sites' per capita daily average water use for the same two years. Occupancy was registered during enrollment (2019–2021), and monthly water use data were recorded during previous years; therefore, changes in occupancy during this period were not accounted for.

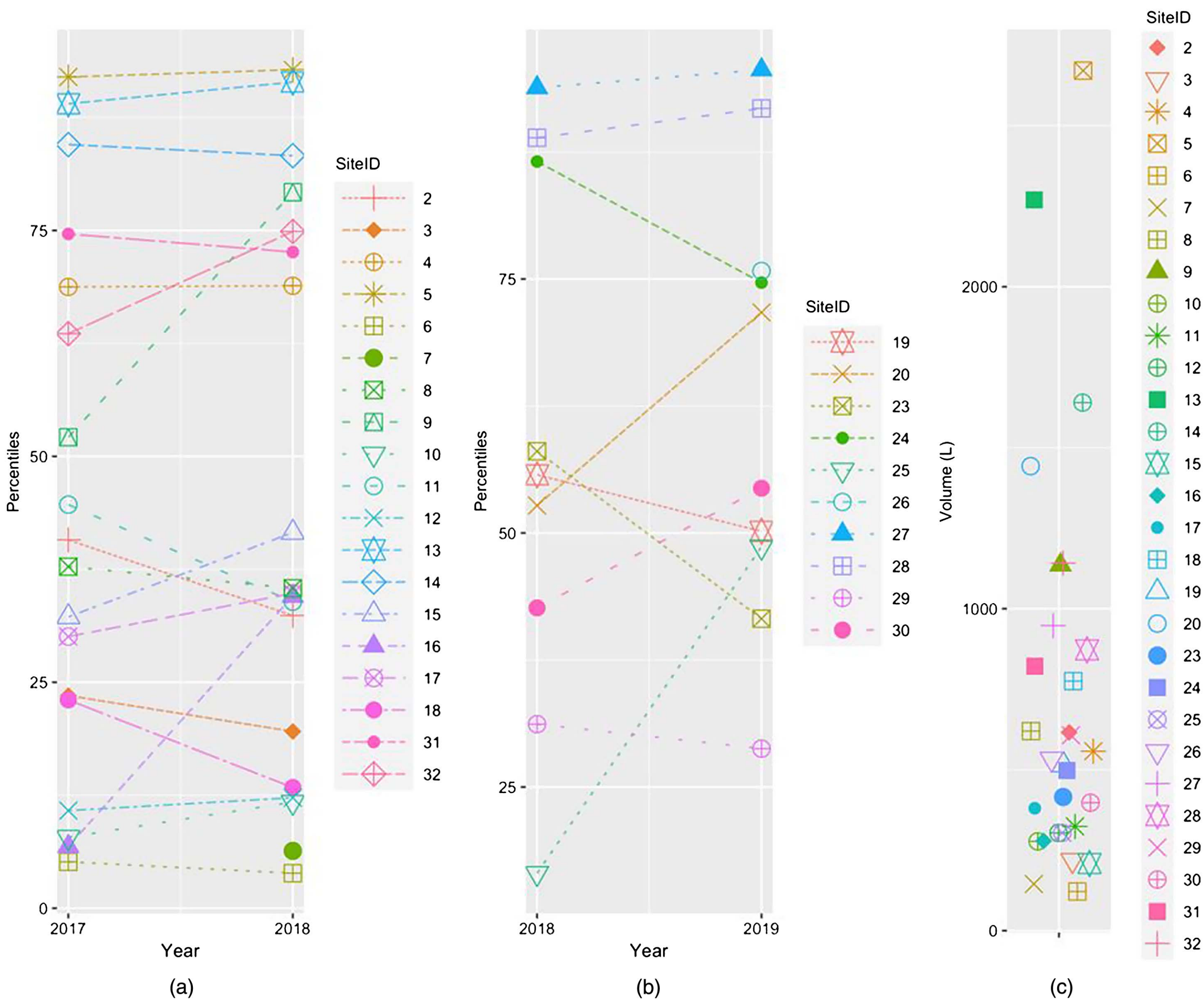

Fig. 12. Annual water use rankings of the participants in the high-temporal resolution study in (a) Logan (2017–2018); (b) Providence (2018–2019); and (c) average per capita daily water use volume in L for all participants computed from monthly records. Participants for which we had less than one year of monthly billing data (Sites 21 and 22—participants moved during the study) were removed from all plots.

Fig. 12(c) shows that our sample included users that differed from the per capita average values presented here. The average per capita daily water use among participants in this study, computed from monthly water meter data, was 695 L per capita per day (Lpcd), and the same figure computed from the high temporal resolution data we collected was 754 Lpcd. A total of 73% of our high temporal resolution data were collected in summer months, which could explain the differences between the estimations from monthly records and the high temporal resolution water use data collected. One recent estimate places per capita daily average residential water consumption in Utah at approximately 640 Lpcd (Dieter et al. 2018). However, this value was calculated by compiling data from different agencies, using coefficients in areas of the state where supply is not measured, and using population estimates that may have impacted the accuracy of this estimation (Milligan 2018)—these factors may have hidden a lot of variability within Utah. The Utah Division of Water Resources (DWR) estimated that in 2015, residential water use in Cache County, where Logan and Providence are located, was 784 Lpcd and that there were differences in water use across counties in the state (Utah DWR 2020).

It is well known that per capita averages, while useful for estimating total water demand at aggregated scales, provide little information about water use patterns or behavior within individual households—in particular, because outdoor water use is not dependent on the number of occupants of a house. A household with a small number of occupants and a large landscape will have a larger per capita consumption. The average daily per capita indoor water use among participants in this study was 174 Lpcd.

Table 7 shows the average per capita daily volume used for each indoor category and the percentage of indoor water use that each category represents. Short events lasting less than 4 s with a single recorded pulse (unclassified) were the most common indoor event (79.2% of all indoor events were in this category) but represent only 4.73% of average indoor water consumption. This category included leaks, very short duration events (e.g., faucets and refrigerators with ice makers), and other events that we were not able to separate or identify because they all had the same volume and duration. Unknown events included outlier events identified during clustering that we were unable to classify and represented approximately 1.51% of total indoor volume.

Showers were the largest indoor water use in our study, representing 31.2% of total indoor water use. Toilets were the second largest end use across all sites, representing 25.6% of total indoor use, although toilets were the largest water end use in 13 of the 31 homes. In contrast, the 2016 REUWS (DeOreo et al. 2016) found that toilets were the largest indoor end use, consuming 24% of indoor volume, followed by showers (19%). The South East Queensland Residential End-Use Study (SEQREUS) (Beal and Stewart 2011) conducted in Australia found that showers consumed 29.5% of indoor volume and toilets 16.5%. These results indicated that the distribution of water use across end uses is different across individual residential homes and regionally. The distribution among end uses remained relatively constant across the three consumption levels described in the main article. As the largest indoor water use category, shower events accounted for 30.3%, 30.8%, or 31.6% of total indoor per capita daily water use (for low, medium, and high consumption sites, respectively). Toilet events accounted for 21.8%, 20.8%, or 23.8% of total indoor volume across low, medium, and high consumption sites, respectively. Faucets accounted for 18% of total indoor water use across all categories.

Table 7. Indoor per capita end use expressed in L per capita a day (Lpcd) and percent of indoor use by end use

End use	Average per capita use (Lpcd)	Percent of indoor water use (%)
Shower	54.3	31.2
Toilet	44.6	25.6
Faucet	32.4	18.9
Clothes washer	24.1	13.62
Bathtub	7.72	4.44
Unclassified	8.23	4.73
Unknown	2.62	1.51

The number of per capita faucet events, showers, and toilet flushes in our study was 23.2, 0.97, and 5, respectively. The 2016 REUWS found similar results in terms of per capita daily frequency of toilet flushes (5) and faucet events (20) but lower shower frequency (0.69) per capita per day. The 2016 REUWS used a much larger sample of homes (763 homes across nine cities in the US versus 31 homes in two neighboring cities in this study), but the average household occupancy was 2.7, which was much lower than the 3.8 in our study. The number of bathtub events per capita per day in our study was 0.12, higher than the 0.05 encountered in the 2016 REUWS. The frequency of clothes washer events in our study was considerably less than that of the 2016 REUWS. Assuming each load had 2 cycles (wash and rinse), we estimated 0.19 clothes washer events per capita per day versus 0.3 in the 2016 REUWS.

Showers

High use associated with showers can be the result of personal preferences (longer and/or more frequent showers) or the presence of less efficient fixtures (showerheads operating at higher flow rates). Fig. 13 shows the average flow rate and duration of shower events for each site. Site 31 had the largest average shower flow rate and the largest per capita daily average shower use, despite having shorter shower durations. Site 18 had the second largest daily per capita shower consumption. This site had a much lower shower flow rate but higher shower durations. Site 17 had lower durations and shower flow rate but a higher number of showers per day, ranking in third place for daily shower volume. At Site 27, median shower duration was 15 min. The average shown in Fig. 13 was increased by three events that had durations longer than 80 min at flow rates in the same range as all showers. Without additional information, it was not possible to identify if these were erroneous events (i.e., incorrectly labeled as showers), and they remained labeled as showers.

Toilets

Fig. 14 shows the volume distribution of toilet flushes for all sites. Toilets are a mechanical end use (i.e., the flow rate and duration do not depend on user preferences and are expected to be similar for each flush). We observed some variability in the volumes shown in Fig. 14. Some sites had a multimodal distribution (e.g., Sites 16, 19, and 30) that was the result of having multiple toilets with different characteristics. For example, Site 19 had toilets that used approximately 8.3 and 13.2 L/flush. The average flush at this site used 10.8 L, but this value ranged lower or higher depending on which toilet was used more frequently. This was true for every site with a multimodal distribution.

The values at the extremes of each violin plot are typically events with flow rates similar to most toilet events but with different durations. These may be half flushes, double flushes, a toilet valve remaining open longer than normal due to flapper valve malfunction, or other misclassified uses. At some sites with multiple toilets, the distribution showed a single mode with higher variability.

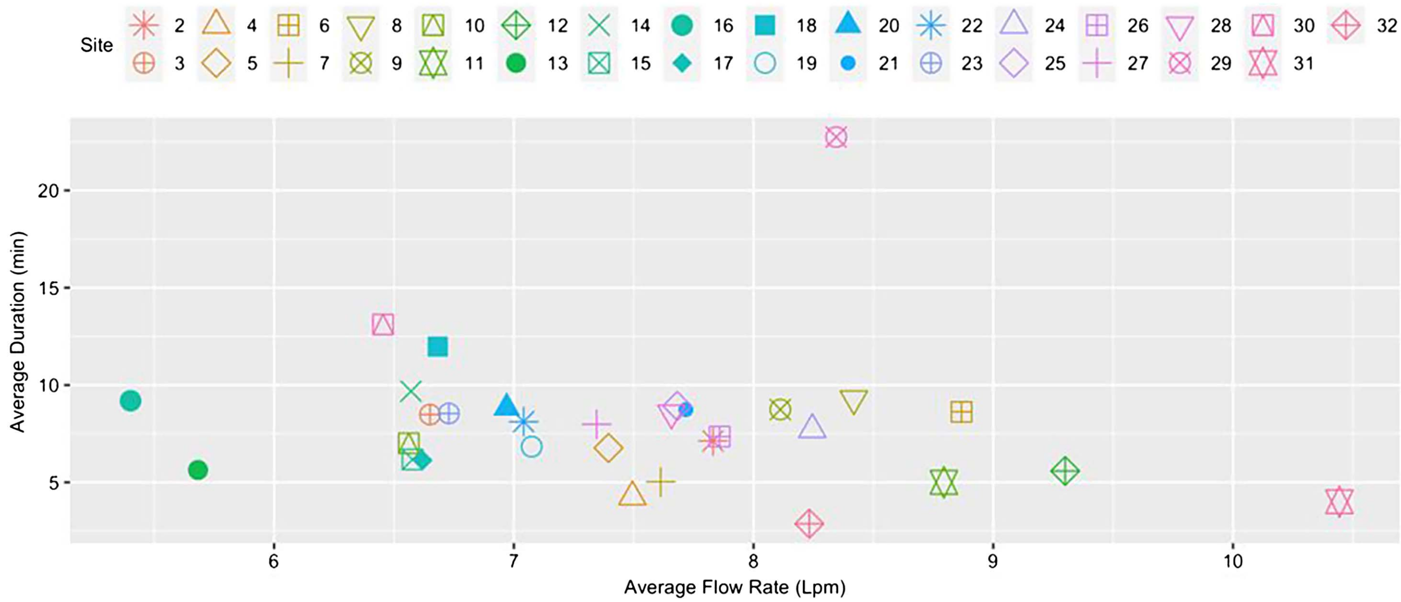

Fig. 13. Average flow rate and duration of shower events.

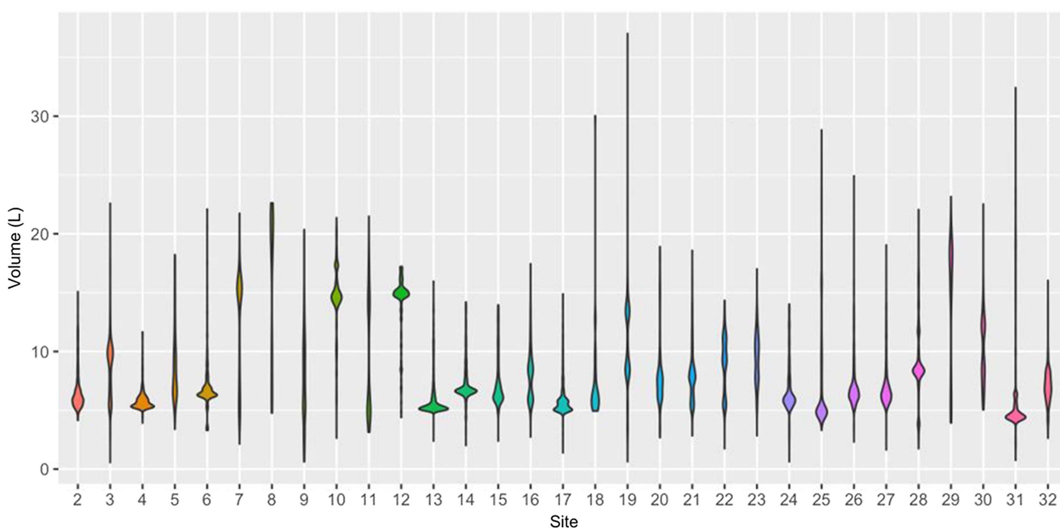

Fig. 14. Volume distribution of toilet flush events for all sites.

This was the case at Sites 20 and 23, which had 3 and 4 toilets, respectively. In these cases, it was likely that the toilets performed similarly enough that the volumes mixed, giving the appearance of a single mode distribution.

Toilet and faucet events that happened simultaneously (i.e., washing hands before the toilet tank is done refilling) were common and can be identified when examining the raw data. However, given the low flow rate of faucets, attempting to automatically separate such events tends to make the algorithm too sensitive toward classifying single events as overlapping. For the purposes of this study, we decided to not separate toilet events from simultaneous short duration faucet events, which meant that these events were lumped in with toilet events.

Faucets

Faucet events were the third largest category of indoor water use by volume. This category included kitchen and bathroom faucets, hose bibs, and other short duration and low flow rate events that did not fit other categories. Faucet events were the second most common events behind the unclassified category, which can also include very short duration faucet events. The characteristics of dishwasher cycles were indistinguishable from faucet events. Therefore, they were labeled as and lumped in with faucet events. Future improvements of our classification method could include identification of cycles for dishwashers and clothes washer events, as has been described in other methods (Nguyen et al. 2018). Most faucet events

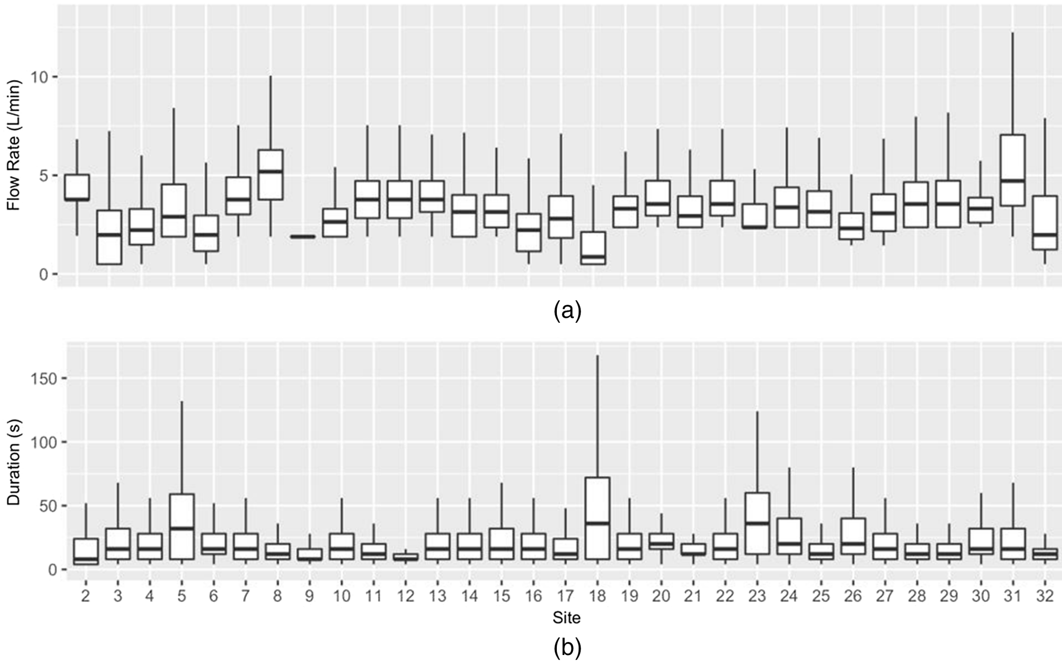

Fig. 15. Boxplots of (a) flow rate; and (b) duration of faucet events across all participant sites. Outliers were removed for visualization purposes.

were short (93% lasted less than 1 min) and low volume (80% used less than 2 L). Fig. 15 shows the flow rates and duration of faucet events across all sites. Sites 5, 18, and 23 had the largest faucet event durations. Site 9 had the smallest flow rate variability for faucet events; 91% of the faucet events at this site had a flow rate less than 2.2 L/min. Sites 8 and 31 had the highest median faucet flow rates among all participants.

Clothes Washers

Despite clothes washers being a mechanical end use, the identification and classification of clothes washer events is not straightforward. Clothes washers can have different configurations such that the volume of water used can vary depending on the load size and cycle selected. In addition, the flow rate can vary depending on the temperature of water used—hot, cold, or both. According to DeOreo et al. (2016), the average per load volume decreased from 155 L in 1996 to 117 L in 2016, and this change was attributed to the adoption of more efficient appliances. However, it is not clear how clothes washer cycles were grouped in these studies. Other methods used to classify end uses of water use a time span of two hours to aggregate and identify clothes washing cycles (Nguyen et al. 2018), adding all events with clothes washer characteristics in this time span to a single load. How clothes washer events are aggregated to loads has a significant impact on the statistics reported.

For this study, we did not aggregate clothes washer cycles (i.e., we identified individual clothes washer cycles but did not aggregate them into multicycle loads). The average water consumption per clothes washer cycle was 60 L. If we assume a load consists of one wash and one rinse cycle, the average (120 L) is close to the 117 L reported by DeOreo et al. (2016). Fig. 16 shows the volume distribution of clothes washer events for all sites. We observed large

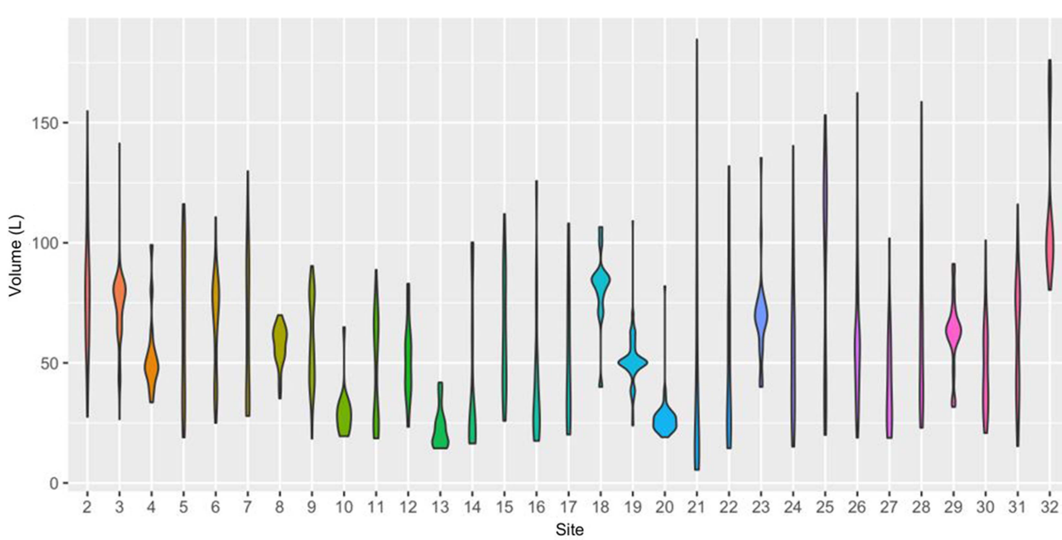

Fig. 16. Volume distribution of clothes washer events for all sites.

variability in the volume used in clothes washer events at most sites, which we attributed to different load sizes and clothes washer settings. Site 24 had two clothes washers; all other sites had a single clothes washer. Sites with large numbers of events with similar volumes (e.g., Sites 19, 20, and 29) were likely doing laundry without constantly modifying appliance settings. Site 32 had the highest volume per clothes washer event among all sites (Fig. 16) and ranked fifth overall for average per capita daily clothes washer use.

Bathtubs

Bathtub events can use up to 265 L of water, and the time at which the drain is plugged (before or after the temperature is adjusted) can increase this volume (EPA 2021). Bathtub events were not found at 11 sites (35% of participating homes). The average volume used in bathtub events among the remaining participants was 77 L, similar to the 76 L per bath found in the 2016 REUWS study (DeOreo et al. 2016). The average flow rate at which bathtubs were filled was 14.5 L/min, and the average duration of these events was 5.6 min.

Data Availability Statement

The high resolution water use data set containing data for all 31 participant sites, anonymized information collected for each site, final end use events file, and log files indicating key information about each data collection period are publicly available in the HydroShare repository (Bastidas Pacheco et al. 2021a). The data set with events manually labeled by a resident of Site 19, from which our classification model was trained and tested, is also available in HydroShare (Bastidas Pacheco and Horsburgh 2022).

Reproducible Results

The code used to generate all the results presented in this paper is available in HydroShare (Bastidas Pacheco and Horsburgh 2022). Patricia Ayaa (Utah State University, Utah) downloaded and ran the code and reproduced the results presented.

Acknowledgments

This research was funded by the US National Science Foundation under Grant No. 1552444. Any opinions, findings, conclusions, or recommendations expressed are those of the authors and do not necessarily reflect the views of the National Science Foundation. Additional financial support was provided by the Utah Water Research Laboratory at Utah State University. We acknowledge the cities of Logan and Providence for their cooperation in the realization of the field data collection campaigns. The authors also gratefully acknowledge the homeowners who participated in our data collection efforts.

References

Abdallah, A. M., and D. E. Rosenberg. 2014. "Heterogeneous residential water and energy linkages and implications for conservation and management." *J. Water Resour. Plann. Manage.* 140 (3): 288–297. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000340.

Al-Kofahi, S., C. Steele, D. VanLeeuwen, and R. St. Hilaire. 2012. "Mapping land cover in urban residential landscapes using very high spatial resolution aerial photographs." *Urban For. Urban Green* 11 (3): 291–301. https://doi.org/10.1016/j.ufug.2012.05.001.

Alvisi, S., M. Franchini, C. Luciani, I. Marzola, and F. Mazzoni. 2021. "Effects of the COVID-19 lockdown on water consumptions: Northern Italy case study." *J. Water Resour. Plann. Manage.* 147 (11): 05021021. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001481.

Aquacraft. 1996. "Trace Wizard description." Accessed June 28, 2021. https://aquacraft.com/data-downloads/trace-wizard/.

Aquacraft. 2016. "Project downloads." Accessed May 3, 2021. https://aquacraft.com/data-downloads/.

Attallah, N. A., J. S. Horsburgh, C. Bastidas, and C. J. Bastidas Pacheco. 2022. "An open-source, semi-supervised water end use disaggregation and classification tool." *J. Water Resour. Plann. Manage.*

Attallah, N. A., J. S. Horsburgh, A. S. Beckwith, and R. J. Tracy. 2021. "Residential water meters as edge computing nodes: Disaggregating end uses and creating actionable information at the edge." *Sensors* 21 (16): 5310. https://doi.org/10.3390/s21165310.

Balacco, G., V. Totaro, V. Iacobellis, A. Manni, M. Spagnoletta, and A. Ferruccio Piccinni. 2020. "Influence of COVID-19 spread on water drinking demand: The case of Puglia region (Southern Italy)." *Sustainability* 12 (15): 5919. https://doi.org/10.3390/su12155919.

Bastidas Pacheco, C. J., N. A. Attallah, and J. S. Horsburgh. 2021a. "High resolution residential water use data in Cache County, Utah, USA." Accessed October 10, 2022. http://www.hydroshare.org/resource/0b72cddfc51c45b188e0e6cd8927227e.

Bastidas Pacheco, C. J., J. C. Brewer, J. S. Horsburgh, and J. Caraballo. 2021b. "An open source cyberinfrastructure for collecting, processing, storing and accessing high temporal resolution residential water use data." *Environ. Modell. Software* 144 (Oct): 105137. https://doi.org/10.1016/j.envsoft.2021.105137.

Bastidas Pacheco, C. J., and J. S. Horsburgh. 2021. "Standardized monthly water use data for Logan and Povidence Cities, Utah, USA." *HydroShare*. Accessed October 10, 2022. http://www.hydroshare.org/resource/16c2d60eb6c34d6b95e5d4dbbb4653ef.

Bastidas Pacheco, C. J., and J. S. Horsburgh. 2022. "Supporting data and tools for 'variability in consumption and end uses of water for residential users in Logan and Providence, Utah, USA'." Accessed October 10, 2022. http://www.hydroshare.org/resource/379d9e7037f04478a99d5aec22e841e6.

Bastidas Pacheco, C. J., J. S. Horsburgh, and R. J. Tracy. 2020. "A low-cost, open source monitoring system for collecting high temporal resolution water use data on magnetically driven residential water meters." *Sensors* 20 (13): 3655. https://doi.org/10.3390/s20133655.

Beal, C., and R. A. Stewart. 2011. "South east Queensland residential end use study: Final report." Accessed October 15, 2021. http://www.urbanwateralliance.org.au/publications/UWSRA-tr47.pdf.

Beal, C. D., and R. A. Stewart. 2014. "Identifying residential water end uses underpinning peak day and peak hour demand." *J. Water Resour. Plann. Manage.* 140 (7): 4014008. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000357.

Berglund, E. Z., et al. 2021. "Water and wastewater systems and utilities: Challenges and opportunities during the COVID-19 pandemic." *J. Water Resour. Plann. Manage.* 147 (5): 02521001. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001373.

Blokker, E. J. M., J. H. G. Vreeburg, and J. C. Van Dijk. 2010. "Simulating residential water demand with a stochastic end-use model." *J. Water Resour. Plann. Manage.* 136 (1): 19–26. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000002.

Boyle, T., D. Giurco, P. Mukheibir, A. Liu, C. Moy, S. White, and R. Stewart. 2013. "Intelligent metering for urban water: A review." *Water* 5 (3): 1052. https://doi.org/10.3390/w5031052.

Buchberger, S. G., J. T. Carter, Y. H. Lee, and T. G. Schade. 2003. *Random demands, travel times and water quality in dead-ends*. AWWARF Rep. No. 294. Denver, CO: American Water Works Association Research Foundation.

Buchberger, S. G., and J. G. Wells. 1996. "Intensity, duration and frequency of residential water demands." *ASCE J. Water Resour. Plann. Manage.* 122 (1): 11–19. https://doi.org/10.1061/(ASCE)0733-9496(1996)122:1(11).

Cahill, J., C. Hoolohan, R. Lawson, and A. L. Browne. 2021. "COVID-19 and water demand: A review of literature and research evidence." *Wiley Interdiscip. Rev. Water* 9 (1): e1570. https://doi.org/10.1002/wat2.1570.

Cominola, A., M. Giuliani, A. Castelletti, P. Fraternali, S. L. H. Gonzalez, J. C. G. Herrero, J. Novak, and A. E. Rizzoli. 2021. "Long-term water conservation is fostered by smart meter-based feedback and digital user engagement." *Clean Water* 4 (1): 29. https://doi.org/10.1038/s41545-021-00119-0.

Cominola, A., M. Giuliani, A. Castelletti, D. E. Rosenberg, and A. M. Abdallah. 2018. "Implications of data sampling resolution on water use simulation, end-use disaggregation and demand management." *Environ. Modell. Software* 102 (Apr): 199–212. https://doi.org/10.1016/j.envsoft.2017.11.022.

Cominola, A., M. Giuliani, D. Piga, A. Castelletti, and A. E. Rizzoli. 2015. "Benefits and challenges of using smart meters for advancing residential water demand modeling and management: A review." *Environ. Modell. Software* 72 (Oct): 198–214. https://doi.org/10.1016/j.envsoft.2015.07.012.

Cooley, H., P. H. Gleick, S. Abraham, and W. Cai. 2020. "Water and the COVID-19 pandemic: Impacts on municipal water demand." Accessed May 7, 2021. https://pacinst.org/wp-content/uploads/2020/07/Water-and-COVID-19_Impacts-on-Municipal-Water-Demand_Pacific-Institute.pdf.

DeOreo, W. B., and P. W. Mayer. 2012. "Insights into declining single-family residential water demands." *J. Am. Water Works Assoc.* 104 (6): E383–E394. https://doi.org/10.5942/jawwa.2012.104.0080.

DeOreo, W. B., P. W. Mayer, B. Dziegielewski, J. Kiefer, and Water Research Foundation. 2016. *Residential end uses of water, version 2*. Denver, CO: Water Research Foundation.

DeOreo, W. B., P. W. Mayer, L. Martien, M. Hayden, A. Funk, M. Kramer-Duffield, R. Davis, J. Henderson, B. Raucher, and P. Gleick. 2011. *California single-family water use efficiency study, Report prepared for the California Department of Water Resources*. Boulder, CO: Aquacraft.

Dieter, C. A., M. A. Maupin, R. R. Caldwell, M. A. Harris, T. I. Ivahnenko, J. K. Lovelace, N. L. Barber, and K. S. Linsey. 2018. *Estimated use of water in the United States in 2015. US geological survey circular 1441*. Washington, DC: USGS. https://doi.org/10.3133/cir1441.

Di Mauro, A., A. Cominola, A. Castelletti, and A. Di Nardo. 2020. "Urban water consumption at multiple spatial and temporal scales. A review of existing datasets." *Water* 13 (1): 36. https://doi.org/10.3390/w13010036.

Di Mauro, A., A. Di Nardo, G. F. Santonastaso, and S. Venticinque. 2019. "An IoT system for monitoring and data collection of residential water end-use consumption." In *Proc., 28th Int. Conf. on Computer Communication and Networks (ICCCN)*, 1–6. Valencia, Spain: IEEE. https://doi.org/10.1109/ICCCN.2019.8847120.

DOE. 1992. *Energy policy act*. Washington, DC: DOE.

Doorenbos, J., and W. O. Pruitt. 1977. *Guidelines for predicting crop water requirements. FAO irrigation and drainage paper 24*. Québec City: FAO.

Endter-Wada, J., J. Kurtzman, S. P. Keenan, R. K. Kjelgren, and C. M. U. Neale. 2008. "Situational waste in landscape watering: Residential and business water use in an urban Utah community." *J. Am. Water Resour. Assoc.* 44 (4): 902–920. https://doi.org/10.1111/j.1752-1688.2008.00190.x.

EPA. 2014. "WaterSense ® specification for tank-type toilets version 1.2." Accessed September 29, 2021. https://www.epa.gov/sites/default/files/2017-01/documents/ws-products-spec-toilets.pdf.

EPA. 2016. "Urbanization and population change." Accessed October 10, 2022. https://cfpub.epa.gov/roe/indicator.cfm?i=52.

EPA. 2018. "Drinking water infrastructure survey and assessment." Accessed May 3, 2021. https://www.epa.gov/dwsrf/epas-6th-drinking-water-infrastructure-needs-survey-and-assessment.

EPA. 2020. "The WaterSense label." Accessed May 3, 2021. https://www.epa.gov/watersense.

EPA. 2021. "WaterSense products." Accessed May 7, 2021. https://www.epa.gov/watersense/watersense-products.

Fielding, K. S., A. Spinks, S. Russell, R. McCrea, R. Stewart, and J. Gardner. 2013. "An experimental test of voluntary strategies to promote urban water demand management." *J. Environ. Manage.* 114 (Jan): 343–351. https://doi.org/10.1016/j.jenvman.2012.10.027.

Froehlich, J. E., E. Larson, T. Campbell, C. Haggerty, J. Fogarty, and S. N. Patel. 2009. "HydroSense: Infrastructure-mediated single-point sensing of whole-home water activity." In *Proc., 11th Int. Conf. on Ubiquitous Computing*. Orlando, FL: Association for Computing Machinery. https://doi.org/10.1145/1620545.1620581.

Glenn, D. T., J. Endter-Wada, R. Kjelgren, and C. M. U. Neale. 2015. "Tools for evaluating and monitoring effectiveness of urban landscape water conservation interventions and programs." *Landscape Urban Plann.* 139 (Jul): 82–93. https://doi.org/10.1016/j.landurbplan.2015.03.002.

Inman, D., and P. Jeffrey. 2006. "A review of residential water conservation tool performance and influences on implementation effectiveness." *Urban Water J.* 3 (3): 127–143. https://doi.org/10.1080/15730620600961288.

Kjelgren, R., L. Rupp, and D. Kilgren. 2000. "Water conservation in urban landscapes." *HortSci.* 35 (6): 1037–1040. https://doi.org/10.21273/HORTSCI.35.6.1037.

Kofinas, D. T., A. Spyropoulou, and C. S. Laspidou. 2018. "A methodology for synthetic household water consumption data generation." *Environ. Modell. Software* 100 (Feb): 48–66. https://doi.org/10.1016/j.envsoft.2017.11.021.

Kruskal, W. H., and W. A. Wallis. 1952. "Use of ranks in one-criterion variance analysis." *J. Am. Stat. Assoc.* 47 (260): 583–621. https://doi.org/10.1080/01621459.1952.10483441.

Liaw, A., and M. Wiener. 2002. "Classification and regression by randomForest." *R News* 2 (3): 18–22.

Lüdtke, D. U., R. Luetkemeier, M. Schneemann, and S. Liehr. 2021. "Increase in daily household water demand during the first wave of the Covid-19 pandemic in Germany." *Water* 13 (3): 260. https://doi.org/10.3390/w13030260.

Makonin, S. 2016. "AMPds2: The almanac of minutely power dataset (Version 2)." Accessed May 3, 2021. https://doi.org/10.7910/DVN/FIE0S4.

Marzano, R., C. Rougé, P. Garrone, L. Grilli, J. J. Harou, and M. Pulido-Velazquez. 2018. "Determinants of the price response to residential water tariffs: Meta-analysis and beyond." *Environ. Modell. Software* 101 (Mar): 236–248. https://doi.org/10.1016/j.envsoft.2017.12.017.

Mayer, P., W. DeOreo, E. Towler, L. Martien, and D. Lewis. 2004. *Tampa water department residential water conservation study: The impacts of high efficiency plumbing fixture retrofits in single-family homes*. Denver: American Water Works Association.

Mayer, P. W., W. B. DeOreo, E. M. Optiz, J. C. Kiefer, W. Y. Davis, B. Dziegielewski, and J. O. Nelson. 1999. *Residential end uses of water*. Denver, CO: American Water Works Association.

Menneer, T., Z. Qi, T. Taylor, C. Paterson, G. Tu, L. R. Elliott, K. Morrissey, and M. Mueller. 2021. "Changes in domestic energy and water usage during the UK COVID-19 lockdown using high-resolution temporal data." *Int. J. Environ. Res. Public Health* 18 (13): 6818. https://doi.org/10.3390/ijerph18136818.

Meyer, B. E., H. E. Jacobs, and A. Ilemobade. 2020. "Extracting household water use event characteristics from rudimentary data." *J. Water Supply Res. Technol.* 69 (4): 387–397. https://doi.org/10.2166/aqua.2020.153.

Milligan, M. 2018. "Glad you asked: Does Utah really use more water than any other state?—Utah geological survey." Accessed October 19, 2021. https://geology.utah.gov/map-pub/survey-notes/glad-you-asked/does-utah-use-more-water/.

Nguyen, K. A., R. A. Stewart, H. Zhang, and C. Jones. 2015. "Intelligent autonomous system for residential water end use classification: Autoflow." *Appl. Soft Comput.* 31 (Jun): 118–131. https://doi.org/10.1016/j.asoc.2015.03.007.

Nguyen, K. A., R. A. Stewart, H. Zhang, and O. Sahin. 2018. "An adaptive model for the autonomous monitoring and management of water end use." *Smart Water* 3 (1): 5. https://doi.org/10.1186/s40713-018-0012-7.

Otaki, Y., M. Otaki, H. Sugihara, L. Mathurasa, P. Pengchai, and T. Aramaki. 2011. "Comparison of residential indoor water consumption patterns in Chiang Mai and Khon Kaen, Thailand." *J. AWWA* 103 (5): 104–110. https://doi.org/10.1002/j.1551-8833.2011.tb11457.x.

Pastor-Jabaloyes, L., F. J. Arregui, and R. Cobacho. 2018. "Water end use disaggregation based on soft computing techniques." *Water* 10 (1): 46. https://doi.org/10.3390/w10010046.

Rathnayaka, K., H. Malano, S. Maheepala, B. George, B. Nawarathna, M. Arora, and P. Roberts. 2015. "Seasonal demand dynamics of residential water end-uses." *Water* 7 (1): 202–216. https://doi.org/10.3390/w7010202.

Roberts, P. 2005. *Yarra Valley water 2004 residential end use measurement study*. Mitcham, VIC, Australia: Yarra Valley Water.

Rockaway, T. D., P. Coomes, J. Rivard, B. Kornstein, and Water Research Foundation. 2010. *North America residential water usage trends since 1992*. Denver, CO: The Water Research Foundation.

Romero, C. C., and M. D. Dukes. 2015. "Review of Turfgrass evapotranspiration and crop coefficients." In *Proc., 2015 ASABE/IA Irrigation Symp*. St. Joseph, MI: American Society of Agricultural and Biological Engineers. https://doi.org/10.13031/irrig.20152145395.

Student. 1908. "The probable error of a mean." *Biometrika* 6 (1): 1–25.

Suero, F. J., P. W. Mayer, and D. E. Rosenberg. 2012. "Estimating and verifying united states households' potential to conserve water." *J. Water Resour. Plann. Manage.* 138 (3): 299–306. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000182.

The University of Utah. 2016. "Fact sheet August 2016." Accessed October 10, 2022. https://gardner.utah.edu/wp-content/uploads/2016/08/UtahAtAGlance-Final1.pdf.

UGRC (Utah Geospatial Resource Center). 2021. "Aerial photography products for Utah." Accessed May 3, 2021. https://gis.utah.gov/data/aerial-photography/.

UN-Habitat. 2016. *Urbanization and development: Emerging futures*. World Cities Rep. No. 2016. Nairobi, Kenya: UN-Habitat.

Utah DWR (Utah Division of Water Resources). 2020. *2015 Municipal and industrial water use data: 2020 version 3*. Salt Lake City, UT: Utah DWR.

Vitter, J. S., and M. Webber. 2018. "Water event categorization using sub-metered water and coincident electricity data." *Water* 10 (6): 714. https://doi.org/10.3390/w10060714.

White, R., R. Havalak, J. Nations, J. Thomas, D. Chalmers, and D. Dewey. 2004. *How much water is enough? Using PET to develop water budgets for residential landscapes.* College Station, TX: Texas A&M Univ.

White, S., J. Robinson, D. Codell, M. Jha, and G. Milne. 2003. *Urban water demand forecasting and demand management: Research needs review and recommendations*. Melbourne, Australia: Water Services Association of Australia.

Willis, R. M., R. A. Stewart, D. P. Giurco, M. R. Talebpour, and A. Mousavinejad. 2013. "End use water consumption in households: Impact of socio-demographic factors and efficient devices." *J. Cleaner Prod.* 60 (Dec): 107–115. https://doi.org/10.1016/j.jclepro.2011.08.006.

Willis, R. M., R. A. Stewart, K. Panuwatwanich, S. Jones, and A. Kyriakides. 2010. "Alarming visual display monitors affecting shower end use water and energy conservation in Australian residential households." *Resour. Conserv. Recycl.* 54 (12): 1117–1127. https://doi.org/10.1016/j.resconrec.2010.03.004.

Willis, R. M., R. A. Stewart, P. R. Williams, C. H. Hacker, S. C. Emmonds, and G. Capati. 2011. "Residential potable and recycled water end uses in a dual reticulated supply system." *Desalination* 272 (1–3): 201–211. https://doi.org/10.1016/j.desal.2011.01.022.