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Characterizing Patterns and Drivers of Single-Family Household Water Uses in Arizona Using High-Resolution Smart-Metered Data

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ABSTRACT

This study aims to characterize single-family household water consumption utilizing smart-metered subdaily water use data from more than 700 single-family households across the state of Arizona in the United States for the water year 2022. Using statistical evidence, we identify factors that drive household water consumption such as the number of occupants, appliance efficiency, and the presence of a swimming pool. Furthermore, climate and other regional drivers of water use are investigated. The analysis encompasses mixed-effects regression models to assess water use patterns on daily, weekly, monthly, and seasonal time-steps. The findings show that approximately 64% of water consumption in Arizona was used for outdoor purposes. Households with a swimming pool use approximately 56% more water overall than those without a pool. Even indoor water use is nearly 26% greater in households with a swimming pool. Deep analysis of smart-metered water use data offers greater insights into the efficiency levels of appliances in a household. Households with high-efficiency appliances use about 18.5% less water than households without high-efficiency appliances. Analysis indicates that log-linear mixed-effects regression models provide the most robust assessments for relating water consumption with household and regional factors. This study helps water managers identify and implement water conservation and demand reduction strategies in single-family neighborhoods.

1 | Introduction

This study focuses on characterizing single-family household water use patterns and drivers utilizing high-resolution, smart-metered water use data collected from more than 700 single-family households across the state of Arizona in the United States for the water year 2022 (WY-2022; October 01, 2021 to September 30, 2022). In many parts of the western United States, especially the southwestern U.S., water is becoming a scarce resource and yet, these regions are witnessing high urban population growth (Gleick 2010). This has huge implications for the economic productivity and the livelihood of millions of people in this region (Kyl Center 2023; Wang and Vivoni 2022). Research and technological advancements for monitoring water use patterns with high resolution (in minutes or seconds), at individual building or land parcel levels, provide greater scope to uncover critical nuances in water usage drivers and to influence decision-making for a sustainable future (Cominola et al. 2023; Gleick 2003, 2010; Marston et al. 2018; Mekonnen and Hoekstra 2016; Sanchez et al. 2018).

Summary

- By utilizing advanced smart water metering data, this research advances statistical methods to better assess residential end uses of water, enabling more effective conservation efforts.

Arizona, a land of stunning desert landscapes and vibrant cities, grapples with pressing water resource challenges. In the early twentieth century, the development of large-scale irrigated agriculture attracted a surge of population growth, which eventually led to large-scale urban development (Baker et al. 2004; Gober and Kirkwood 2010). Over time, this growth trend necessitated the construction of dams, reservoirs, and the transfer of water over long distances from other watersheds (Eden et al. 2011; Wang and Vivoni 2022). The Central Arizona Project (CAP) is one such mega project that was designed to transport Colorado River water over 336 miles to southern Arizona (Figure 1) in order to protect the groundwater resources in the state from being overexploited (Witcher 2022). The CAP project, completed in 1993, supports nearly a million acres of irrigated agricultural land and plays a pivotal role in the state's water supply and economy. Phoenix and Tucson, which are home to a total of 2.2 million people (as per 2020 Census data for those cities), along with several tribal nations within the state, rely on CAP deliveries for their water needs.

Currently, Arizona receives approximately 36% of its water supply from the Colorado River, with the remainder sourced from groundwater aquifers, in-state rivers, and a small fraction from reclaimed water (ADWR 2020). Arizona is one of the seven states in the United States that rely on the Colorado River Basin along with Mexico and many Native American tribes (Figure 1). However, prolonged droughts, rapid urban developments, and agricultural land expansion, and interstate disputes over water allocation have put huge stress on the Colorado River, resulting in mandated cuts to CAP water allotments (Ault et al. 2016; Baker et al. 2004; Bureau of Reclamation 2023; Folger 2017; Mekonnen and Hoekstra 2016; Rajagopalan et al. 2009; Udall and Overpeck 2017; Warziniack and Brown 2019).

In the southwest U.S., such cuts to water allocation are prophesied to reoccur in the future due to climate change impacts on water yield (Brown et al. 2013; Cosgrove and Loucks 2015; Donkor et al. 2014; Gober et al. 2011; Salehabadi et al. 2020; Sanchez et al. 2018; Udall and Overpeck 2017; Warziniack and Brown 2019). The relationship between the development of Arizona's water resources and its urban growth is likely to become more controversial in the future as urban residents face increasing competition over scarce resources (Baker et al. 2004;

FIGURE 1 | Map of the Colorado River Basin with Lake Mead and Lake Powell, and the major U.S. cities receiving the Colorado River water in the lower basin. The Central Arizona Project canal is represented using a red line.

Bolin et al. 2013; Heidari et al. 2021; Kupel 2003; Larson et al. 2013; Wang and Vivoni 2022). The reliance on Colorado River water raises concerns about the long-term feasibility of maintaining such growth patterns in Arizona without jeopardizing the environment and the livelihood of future generations (Sprigg and Hinkley 2000; Yigzaw and Hossain 2016).

In 2019, approximately 22% of the total water consumption within the state of Arizona was by the municipal sector (ADWR 2020). In particular, the issue of residential water use, especially in single-family households, is of utmost importance. It has been established that single-family households are the largest end users and drivers of demand in the municipal water system of the United States (Chinnasamy et al. 2021; DeOreo et al. 2016). The Phoenix metropolitan area in Arizona particularly has been reported to be single-family household dominant in its urban growth patterns with high water demands, compared to other urban areas within the United States (Balling et al. 2008; Mayer et al. 1999; Ouyang et al. 2014). Private swimming pools, high water use for landscape irrigation, and sprawling development patterns with a high percentage of single-family households are the biggest challenges that Arizona faces regarding the future of water sustainability (Gleick 2010; Gober and Kirkwood 2010; MacDonald 2010).

In January of 2023, a developing community's water supply was cut off from the municipal system in the city of Scottsdale, which gets most of its water from the Colorado River (Partlow 2023). If such incidents are to be prevented from reoccurring in the future, it is imperative to recognize the importance of ongoing investigation into end water use and the forces that shape it. By continuously studying changes in residential water use, we can effectively plan for future water demand and implement policy-level changes to promote conservation and more efficient utilization of this precious resource. Therefore, urban water demand research and studies are vital to stay abreast of evolving trends, anticipate shifts in water consumption patterns, and facilitate informed decision-making that aligns with long-term sustainability goals.

With the development of advanced water metering technologies, it is now possible to take a closer look at water uses on a granular level (building and appliance levels), identify leaks, model the different parameters that cause variation in water uses, and use that knowledge to curb excess water consumption (Schultz et al. 2018; Sønderlund et al. 2016; Yang et al. 2017). High-resolution, high-frequency flow monitoring smart meters and technological advancements in the Internet-of-Things (IoT), machine learning, and big data analytics have enabled improved water demand management in urban settings (Pesantez et al. 2020; Romano and Kapelan 2014; Walker et al. 2015).

Advances in flow monitoring and smart metering can empower homeowners with real-time data for better consumption management, and it holds immense potential for utilities. Data analytics derived from household-level monitoring enable informed decisions on water resources, infrastructure, and conservation planning. Furthermore, this technology has a tangible impact on water conservation efforts, as leaks can be swiftly identified, usage patterns comprehensively analyzed, and proactive steps taken toward a more water-efficient future.

This study uses high-resolution, smart-metered water use data obtained at the individual consumer level to characterize the patterns and drivers of single-family household water use. Specifically, the objectives of this study are to:

1. Explore the relationship between water use intensity metrics and household occupancy.
2. Assess the effects of household appliance efficiency levels and swimming pools on indoor, outdoor, and total water consumption.
3. Develop robust statistical models to relate single-family household water consumption to important household and regional parameters to identify key drivers of water consumption.

The study provides a robust assessment of the effects of occupancy level, appliance efficiencies, swimming pools, and other household characteristics on water consumption patterns by controlling the effects of regional climatic diversities. By utilizing advanced smart water metering data, this research advances statistical methods for improved assessment of residential end uses of water in single-family households and adds to the previous efforts in characterizing municipal water uses by Mayer et al. (1999), Balling et al. (2008), Ouyang et al. (2014), DeOreo et al. (2016), Chinnasamy et al. (2021). The large sample of metering locations in the study area comprehensively represents single-family households in Arizona (Figure 2). The statistical assessments conducted in this study can guide the development and adoption of data-driven strategies for sound water demand management in the state and across the Colorado River Basin. Similarly, the methodology developed in this study can be used for water use assessments using Flume's or other advanced metering system data across the United States and worldwide.

The terms "water consumption" and "water use" are used interchangeably in this article, and both terms refer to the amount of water taken up by a household or person for various water needs. A common assumption in municipal water systems is that approximately 20% of the total water supplied to households is permanently lost through leaks in pipes, evapotranspiration by landscape vegetation, evaporation from swimming pools, washing cars and driveways, and irrigation system leaks.

2 | Data

The availability of high-resolution, smart-metered data from Flume Inc., a smart water consumption sensor company based in San Luis Obispo, California, United States, provides a unique opportunity to examine the study objectives. As of June 2023, Flume's smart water meter sensors are deployed in over 68,000 single-family households across the United States. The Flume system provides real-time leak alert notifications to the client and enables a better understanding of indoor and

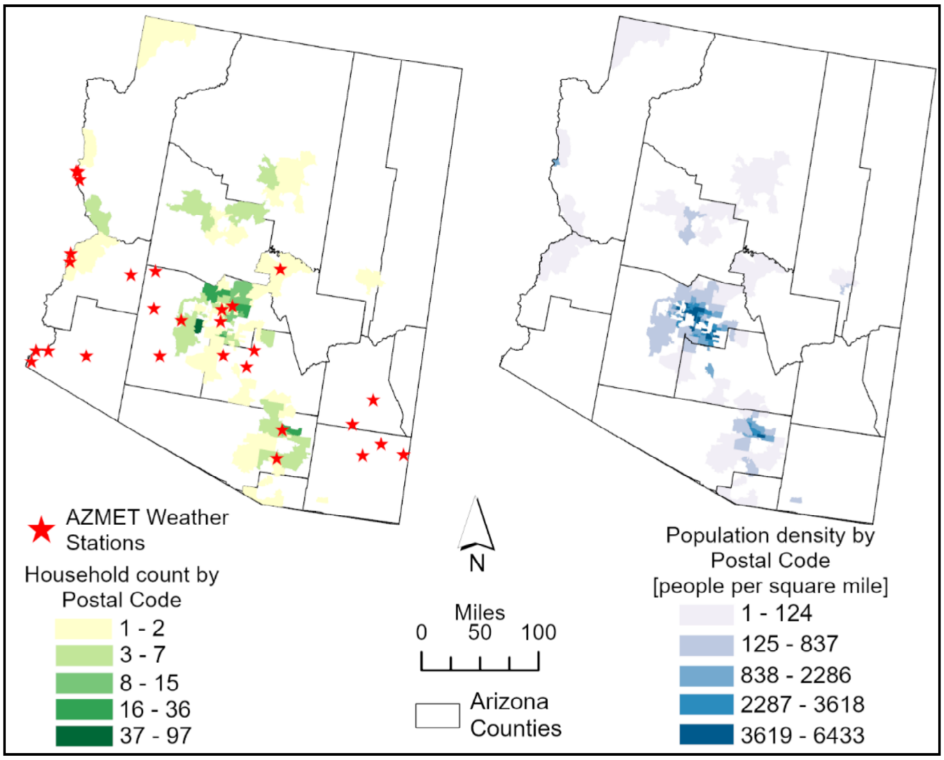

FIGURE 2 | Map of Arizona showing the postal codes with number of flume households used in this study on the left panel. Daily weather information was obtained from the Arizona Meteorological Network (AZMET) weather stations highlighted using red stars. On the right panel, population density of those corresponding postal codes with flume sensors are presented using the 2020 Census information.

outdoor water use patterns at the household and appliance levels.

The single-family household water consumption dataset provided by Flume for this study covered the WY-2022 from October 01, 2021, to September 30, 2022 (referred to as WY-2022). The primary water consumption dataset includes 5-s interval water metering data, categorized as indoor and outdoor water use, from over 900 households with active Flume sensors in Arizona. The water metering time series are subsequently aggregated for assessments at daily, weekly, monthly, and seasonal time-steps, under the indoor and outdoor household water use categories. Two other datasets provided by Flume represent building/household characteristics and appliance flow characteristics.

The households in these datasets were geographically identified only by their postal code designation in order to protect the privacy of Flume's customers. Figure 2 (left panel) shows the number of single-family households with active Flume sensors within Arizona by postal code polygons. The right panel illustrates population density in the study area. More household smart sensors are located in areas with higher population density.

A subset of the primary water consumption dataset was included in the analysis to improve the robustness of the statistical analyses. Households were included in the analysis only if they had water use data available for a minimum of 3 months or 90 days, and indoor and outdoor water use volumes were above 10.0 gallons per household per day (GPHD) on any given day. This process aimed to exclude low leak volumes from the analysis. However, distinguishing large leak volumes from lawn irrigation or swimming pool fill volumes proved challenging, and thus, these large leak volumes were not identified or removed during the data processing stage. After data processing, a final set of 706 households was identified for the subsequent data analysis.

The building and demographic characteristics for the selected households that were considered in the analysis include number of bathrooms, number of occupants, irrigation type (drip, garden hose, soaker hose, sprinkler, or none), irrigation frequency (once per week, twice per week, thrice per week, more than 4 times per week, or none), swimming pool (Yes/No), home value ($), year built, lot size (square feet), home size (square feet), and postal code.

The household-appliance characteristics for the selected households that were considered in the analysis include per event average flow characteristics—duration (minutes), volume (gallons), and flow rate (gallons per minute [gpm]), for clothes washer, dishwasher, faucet, indoor, irrigation, leak, shower, softener, and toilet. Flume Inc. and Mayer (2022) elaborate in detail on the disaggregation process and methodology used to obtain the appliance-level water consumption information from the original 5-s interval water consumption data.

Finally, daily weather information for every household in the Flume dataset was collected from the University of Arizona's Arizona Meteorological Network (AZMET) stations (accessed January to March 2023, https://ag.arizona.edu/azmet/), which are positioned across the state (Figure 2). Daily precipitation (inches), daily evapotranspiration (inches) calculated using the Penman-Monteith method, and daily minimum, maximum, and mean air temperatures (degrees Fahrenheit) were gathered for all the active AZMET stations in WY-22. Using ArcGIS Pro software's "Find the nearest feature" tool, all the active AZMET stations were matched by proximity with the nearest postal codes containing households with active Flume sensors (Figure 2).

3 | Statistical Methods

The statistical analyses in this study include characterization of water use intensity, assessment of swimming pool's impact on water consumption patterns, estimation of household appliance efficiencies and their impact on water consumption, and the mixed-effects modeling of household water consumption at different time steps. The statistical methods and data visualization were conducted using the R/RStudio software.

3.1 | Characterization of Water Use Patterns

Water use metrics in GPHD, gallons per capita per day (GPCD), and gallons per square foot (GPSF) are used in this study to characterize indoor, outdoor, and total water uses. The GPSF metric is specifically used to characterize outdoor water use. Indoor and outdoor GPCD was calculated by dividing the daily indoor and outdoor GPHD of a household by the "number of occupants" specifically reported to be in that household, and the daily GPSF of a household was obtained by dividing the aggregate outdoor GPHD of a household by its "lot size."

Temporal patterns in indoor and outdoor water consumption were estimated using the average indoor and outdoor GPCD of all households at a monthly time step. Using the aggregated daily household water consumption data, the percent indoor and outdoor water use to total household water use was computed. This representation offers insights into the total percentage of water used indoors versus outdoors in single-family households in Arizona.

Relationships were then estimated for household water use and household occupancy level (number of residents in a household). Average total water use characterized by GPCD and GPHD was estimated for every household, and a simple univariate regression was conducted to estimate the linear or non-linear (power, exponential, logarithmic, or polynomial) nature of the relationship between these total water use intensity metrics and household occupancy level, taking into account all the 706 households as the sample size (N). These relationships were tested using the coefficient of determination (R^2). Relationships between total household water use metrics and household occupancy levels were also estimated by grouping the 706 single-family households into those (i) having a swimming pool ($N=419$) and (ii) those without a pool ($N=287$).

3.2 | Impact of Swimming Pools

The impact of swimming pools on household-level water use is further assessed by the end-use category—indoor, outdoor, and total. Average indoor, outdoor, and total water use in GPCD separated by two groups—households with and without a swimming pool, is estimated using the statistical box plot method or whisker plot method (Chambers et al. 1983; Becker et al. 1988; Murrell 2005). ANOVA test of significance is then applied to test whether the patterns observed in indoor, outdoor, and total water uses for households with and without a swimming pool are significant.

3.3 | Appliance Efficiency

Box plots are used to categorically compare indoor and outdoor water use based on appliance efficiencies. This comparison is based on the combined water efficiencies of all appliances in each home, using the GPCD and GPSF metrics. Data from all 706 households are analyzed. This process is described in the following paragraphs in detail.

Cluster analysis on the appliance flow characteristics data was conducted to primarily identify water usage patterns of the individual appliances, thereby giving an estimation of whether those appliances met the U.S. plumbing code standards of efficiency. Conducting this cluster analysis was essential because Flume customers did not provide information about their household appliances (such as low-flow or high-flow toilets or faucets, and top-loading or front-loading clothes washers) in the survey when installing the smart sensor. It was hypothesized that cluster analysis of appliance flow characteristics can offer deeper insights into the water consumption patterns of a household.

The household appliances of particular interest in this study were toilets, showerheads, clothes washers, dishwashers, and faucets. These end-water-using appliances are standard fixtures in any household within the United States and have been well studied in the past, especially by the "Residential End Uses of Water" study groups (DeOreo et al. 1996, 2016; Deoreo and Mayer 2012; Mayer et al. 1999). Although there are other appliances used within a household, like the water softener, water heater, and different types of irrigation systems, they were not considered in the end-use appliance analytics.

Average gallons per event for toilets, average gpm per event for shower heads, average gallons per event for clothes washers, average gallons per event for dishwashers, and average gpm per event for faucets were the flow characteristics analyzed through the cluster analysis.

The U.S. Environmental Protection Agency's guidelines for WaterSense and the Department of Energy's ENERGY STAR programs were considered in evaluating the efficiency of a household appliance. These programs are generally used as plumbing code standards for water use efficiencies within the United States. The Energy Policy Act of 1992 (EPAct 1992) established the maximum flush volume for toilets at 1.6 gallons per flush (gpf) and the maximum flow rate for bathroom sink faucets, kitchen faucets, and showerheads at 2.5 gpm. Subsequently, in 1998, the U.S. Department of Energy (DOE) adopted a maximum flow rate standard of 2.2 gpm for all faucets. In 2012 and 2016, respectively, the DOE issued new regulations mandating minimum water efficiency requirements for clothes washers and dishwashers (DOE 2012, 2016; EPA 2021). DOE (2016) regulates that dishwashers with annual energy use of 307 kWh/year must use not more than 5 gallons per cycle and systems with 222 kWh must not use more than 3.5 gallons per cycle. DOE (2012) regulates that clothes washers that are top-loading must not use more than 14.4 gallons per load (gpl) per cubic foot capacity of the system, and front-loading washers must not use more than 8.3 gpl per cubic foot capacity of the system. Due to the unknown information about the cubic feet capacity of the clothes washers in the Flume datasets, 30 gpl is used in this study as a threshold for establishing efficiency in a clothes washer system as determined by DeOreo and Mayer (2012).

Partitioning Around Medoids (PAM) or k-medoids clustering method (Kaufman and Rousseeuw 1990) is used to cluster the flow characteristics of household appliances. The PAM method was chosen over the commonly used k-means method for its capability of creating groups around the medoids, which are an actual entity of the dataset that represents the group in which it is inserted, while the centroids of the k-means method are an artificial entity of the dataset (Kaufman and Rousseeuw 1990). Kaufman and Rousseeuw (1990) elaborate that the medoid estimated using the PAM method is a data point with minimal average dissimilarity to all objects of the cluster, and they affirm that the PAM method is most suited for characterization purposes through clustering that relies on the representative objects used. Also, the k-means estimation of centroids is sensitive to the outliers, while the PAM method of estimating the medoids makes it possible to isolate the outliers while determining the medoids (Kaufmann and Rousseeuw 1987).

In performing a cluster analysis, it is essential to predetermine the optimal number of output clusters, k. Here, the Silhouette method is used to identify the optimal k. This Silhouette method proposed by Rousseeuw (1987) is a graphical display method to represent each cluster as a silhouette, which is based on the comparison of tightness and separation of the medoid clusters. The average silhouette width provides an evaluation of clustering validity and might be used to select an "appropriate" number of clusters, k (Rousseeuw 1987).

Once the flow characteristics of the appliances of every household were individually clustered using the PAM method after identifying k, cluster medoids of each appliance were then compared with the efficiency thresholds of that particular appliance as determined by the WaterSense and ENERGY STAR programs. If a household appliance's cluster characteristics met the WaterSense and ENERGY STAR thresholds, the appliance was classified as having "High" efficiency, and if it did not meet the WaterSense and ENERGY STAR thresholds, it was classified as having "Low" efficiency. Finally, based on the efficiency levels of individual appliances, each household was then determined to be efficient or not by looking at the combined efficiencies of all the individual appliances—if all the appliances and fixtures were "High" in efficiency, then the household was classified as "High" efficiency household. If even one of the appliance or fixture categories was "Low" in efficiency, then that household was classified as a "Low" efficiency household.

3.4 | Drivers of Water Uses

The drivers of indoor, outdoor, and total water use in single-family households in Arizona were estimated by using multivariate mixed-effects models (Equation 1) regressed with household demographics, building characteristics, and weather response variables:

$$Y = \alpha X + \beta Z + \varepsilon \tag{1}$$

where Y is a response variable or a vector of known observations (i.e., household water consumption); X represents a design matrix of all the fixed effects (e.g., time-varying weather variables); α represents an unknown vector of the fixed effects coefficients; Z represents a design matrix of all the random effects (i.e., time-constant, independent household/building characteristic variables); β represents the vector of the random effect coefficients; and ε is an unknown vector of random errors, which are assumed to be normally distributed.

The exploratory variables used in the mixed-effects modeling process are presented in Table 1. Regional parameters, like temperature and precipitation, have consistent effects over all the households identified close to an AZMET weather station and therefore are considered to have fixed effects in estimating the water use for that population. However, household/building characteristics, like number of occupants, lot size, and presence of a pool, are independent and unique for each household and therefore are considered to cause random effects in the modeling of household water use. This way of combinedly modeling water uses based on fixed and random effects is referred to as mixed-effects modeling (Lindstrom and Bates 1990; Pinheiro et al. 1995; Pinheiro and Bates 1996).

TABLE 1 | Variables used in the mixed-effects modeling of water use in gallons per single-family household (GPH) in Arizona.

Response variables (Y)	Fixed effect variables (X)	Random effect variables (Z)
Total GPH Indoor GPH Outdoor GPH	Month Season Year Evapotranspiration (ET) precipitation Air temperature (min, max, mean)	Year built, postal code, home size, lot size, home value, number of bathrooms Number of residents, has pool, irrigation frequency, irrigation type, toilet efficiency, showerhead efficiency, laundry efficiency, dishwasher efficiency, irrigation efficiency, faucet efficiency

The mixed-effects modeling approach was developed using linear, log-linear, and exponential transformation at the daily, weekly, monthly, and seasonal time-steps of household water consumption. In the log-linear mixed-effects model, Equation (1) is represented by transforming the response variable (Y) and the fixed and random effects matrices (X, Z) to a natural logarithmic scale. In the exponential mixed-effects model, only the response variable (Y) in Equation (1) is transformed to a natural logarithmic scale. In both the log-linear and exponential mixed-effects models, the fixed and random effects are used in their additive form.

Model selection was performed using evaluation criteria including the adjusted coefficient of determination (adjusted R^2) and the Variable Inflation Factor (VIF). The VIF is used to ensure that there is no overfitting and multicollinearity among the variables identified in the final model. For this study, 2.5 is set as the maximum VIF factor threshold for all variables identified in the finalized mixed-effects model for different time steps.

4 | Results

Based on the 706 sample of households used in this study, water consumption patterns in single-family households in Arizona are highly skewed toward outdoor uses. Strong correlations exist between household occupancy levels and water use intensity metrics. Swimming pools and household appliance efficiencies strongly influence water consumption patterns and are driving forces behind variations in household water consumption patterns. The percentage of outdoor to total water use varies significantly based on the conservation mindset of the householders. Overall, household water consumption can be reliably modeled using a log-linear mixed-effects model that incorporates household and regional climatic factors.

4.1 | Single-Family Household Water Consumption Patterns by Indoor/Outdoor Category

For the 706 single-family households analyzed in this study, a strong seasonality is observed in outdoor water consumption throughout WY-2022 (Figure 3, top-left panel). The bottom-left panel of that figure shows that, on average, outdoor water usage accounts for nearly 64% of the total water consumed in these households. Indoor water usage remains relatively consistent throughout the year, averaging around 50 GPCD.

Further statistical analysis of the percentage of indoor and outdoor water uses to total household water use revealed a normal distribution (Figure 3, right panel). 95% confidence interval testing showed the expected outdoor water use ranges from 62% to 65% of total water use, skewing to the higher end of that range (skewness = −0.45). The expected indoor water use ranges from 35% to 38% of total water use, skewing to the lower end (skewness = 0.45). Both the indoor and outdoor percentages of total water use have a large standard deviation of 17.5%.

4.2 | The Effects of Household Occupancy

For single-family households in Arizona, household occupancy level and the presence of a swimming pool strongly influence water use patterns. There is a statistically significant relationship between the average total water consumed across the 706 households and the household occupancy level (Figure 4).

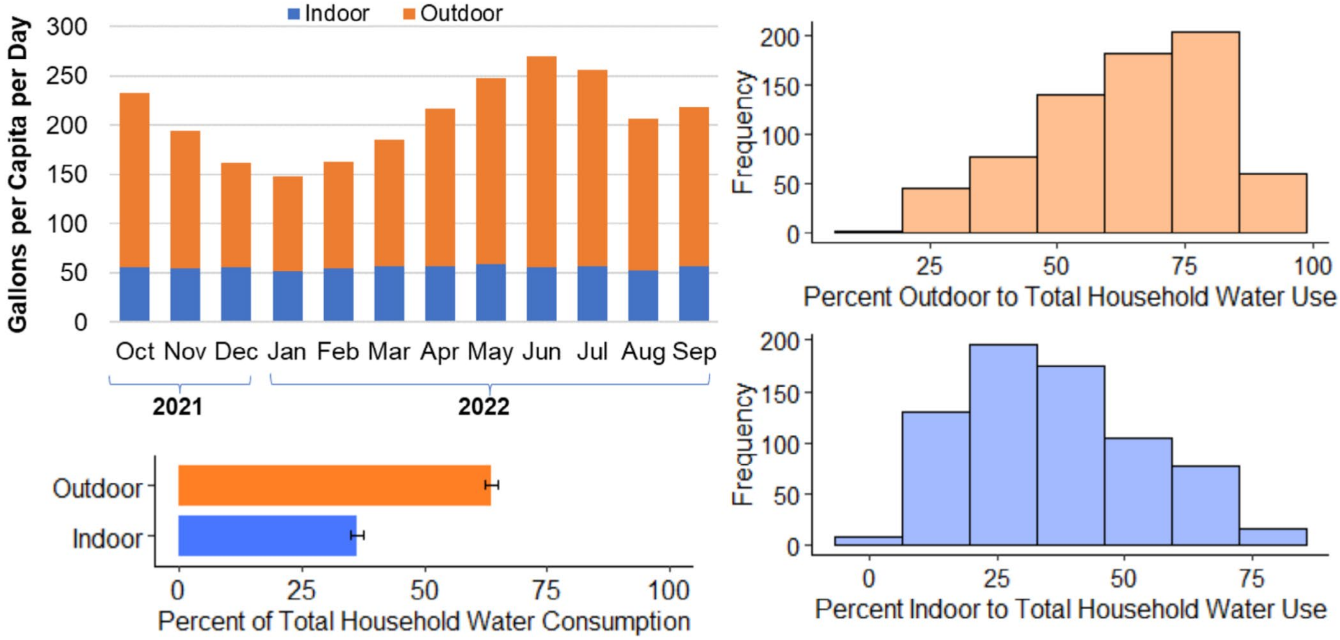

FIGURE 3 | (Top-left panel) Monthly trends in GPCD of indoor and outdoor water uses in those 706 single-family households in Arizona for the water year 2022 (WY-2022). (Bottom-left panel) Percent indoor and outdoor water uses of total household water consumption with error bars. (Right panel) Histogram of percent indoor and outdoor water uses to total household water consumption.

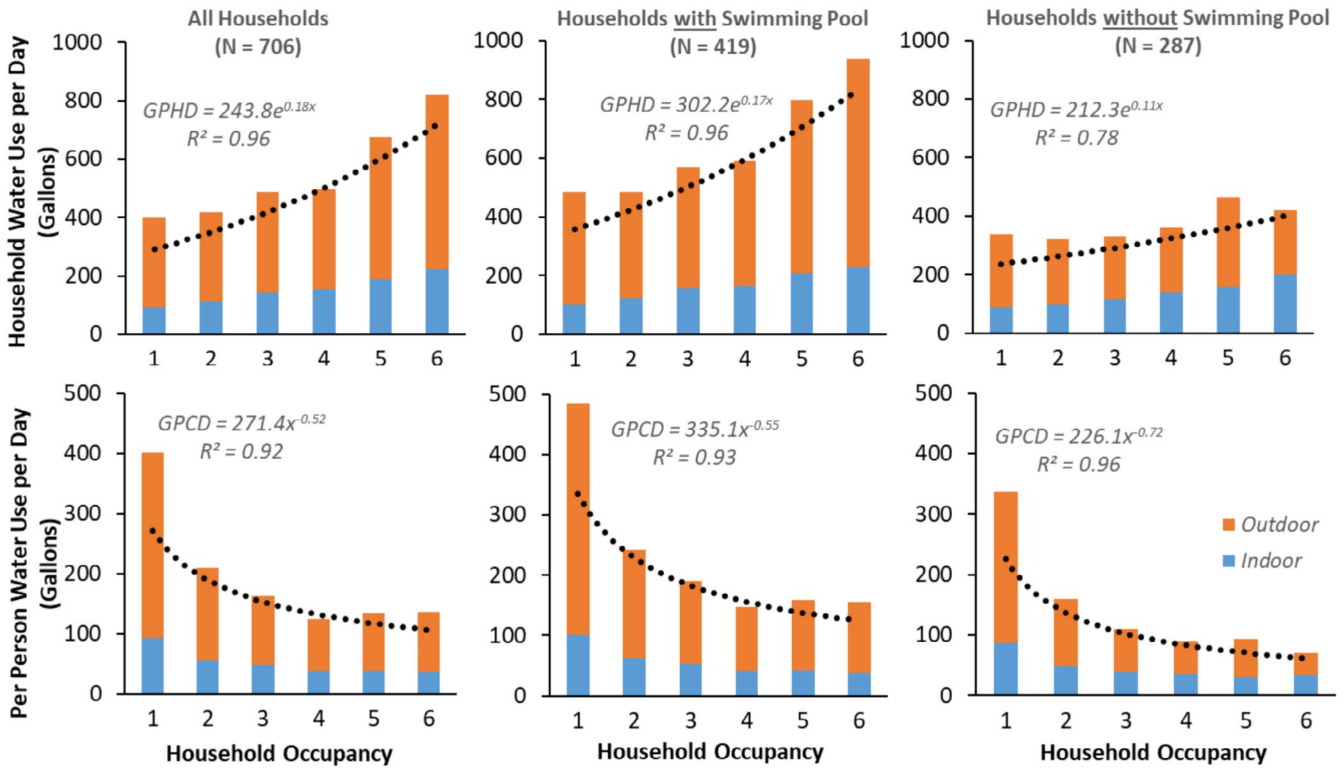

FIGURE 4 | Relationships between average total water consumption in gallons per household per day (GPHD) and gallons per capita per day (GPCD) with household occupancy level (x) for single-family households in Arizona.

Relationship fitness testing, using R^2, indicates that an exponential relationship best explains the variation in GPHD and the household occupancy level. Similarly, a sublinear power relationship most effectively captures the variation in GPCD.

Figure 4 presents the mathematical trendline relationships, along with the goodness of fit (R^2), for the total water use category in GPHD and GPCD metrics regressed with household occupancy levels for all the 706 households, and also by grouping those households based on the presence/absence of a swimming pool. This figure also shows the relative variability in indoor and outdoor water use in GPHD and GPCD based on the household occupancy level. On average, there is about a 56% difference in total water used by households with a swimming pool compared to those that do not have a pool.

4.3 | The Effects of Swimming Pool

Indoor water usage is substantially higher in single-family households with a swimming pool. Figure 4 clearly shows that the presence of a swimming pool greatly increases a household's total and outdoor water use compared to households without a pool. Further categorical assessment of water uses in GPCD between households with and without a swimming pool reveals that indoor water use is also significantly influenced (Figure 5). Households having a swimming pool use about 26% more water indoors than households without a pool. The reason for this difference in indoor water use was not examined as part of this study and could be a topic of future research.

4.4 | The Effects of Efficient Appliances

Clustering of appliance flow characteristics, enabled by Flume's smart sensor technology, offers a novel way to estimate appliance efficiency and overall household efficiency. Using the household-level appliance flow characteristics dataset, it was possible to cluster appliance characteristics into the medoid groups that were identified using the PAM method. The silhouette method results presented in Figure 6 show that the flow characteristics of toilets, showerheads, clothes washers, dishwashers, and faucets for all the 706 households could be clustered into just two optimal groups, that is, $k = 2$. Table 2 provides the two medoids that were estimated by the PAM method for the flow characteristics of each appliance. Appliance characteristics of each household clustered in the Medoid-1 group were classified as "High" efficiency fixtures, and those clustered in the Medoid-2 group were classified as "Low" efficiency fixtures.

Figure 7 shows the median value and range of the household appliance's flow characteristics clustered as "High" or "Low" efficiency fixtures based on the medoid estimates in Table 2. PAM method identifies "High" efficient toilets as 1.78 gpf system which is pretty close to the WaterSense standard of 1.6 gpf. Both the medoids of flow characteristic of showerheads in these sample single-family households meet the efficiency standard of 2.2 gpm (Table 2); however, due to the presence of outliers around the medoid-2 group of the showerheads (Figure 7), all the household showerheads clustered around medoid-2 are considered "Low" in efficiency. Clothes washers with "High" efficiency are clustered around the 25.4 gpl medoid. Following

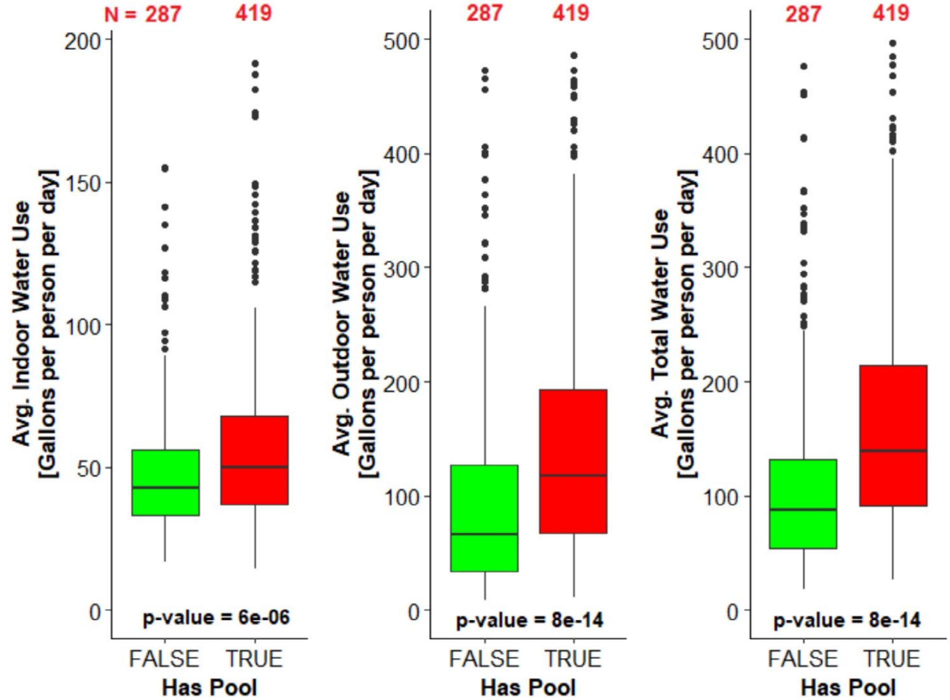

FIGURE 5 | Impact of swimming pool on average household indoor, outdoor, and total water uses in GPCD. The numbers in red above the box-plots show the total number of households under that category.

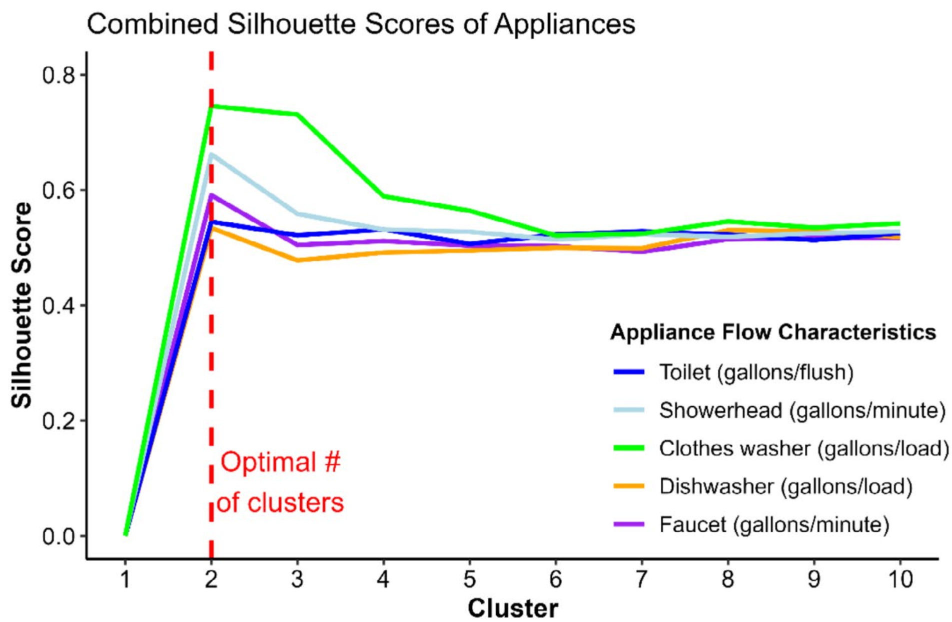

FIGURE 6 | Visual representation of the optimal number of clusters identified for the individual household appliances using the Silhouette method.

Deoreo and Mayer's (2012) findings, all the "High" efficiency clothes washer systems use less than 30 gpl. Similarly, for dishwashers, the medoid 3.28 gpl is considered a "High" efficiency system, and anything around 5 gpl or more is considered to be "Low" in efficiency. The PAM method again identified the "High" efficiency dishwasher system as having 3.38 gpl and the "Low" efficiency medoid for dishwashers as 5.42 gpl, both of which are close to the DOE (2016) standards for efficient dishwashers. The faucet flow characteristic, however, was unusually small for both the medoid clusters (<< 2.2 gpm). It was assumed to be an effect of measurement error within the Flume sensor algorithm. Faucets in the households were still classified as "High" and "Low" efficient fixtures based on the medoid groups in Table 2.

Overall, it is optimistic to note that more than 50% of the sample single-family households considered for this study have "High" efficiency toilets, dishwashers, and faucets, and similarly, a little over 50% of the households have "High" efficiency shower heads and clothes washers (Figure 7).

After determining appliance efficiencies in every sample household, indoor and outdoor water uses were then characterized based on the household efficiency level. In Figure 8, Household Efficiency is determined by the combined efficiency classifications of toilets, showerheads, dishwashers, clothes washers, and faucets. Per capita indoor water use was about 18.5% less in homes classified as "High" efficiency. Homes classified as "Low" efficiency used about 18.5% more water per person. Outdoor use (in GPSF) was not different between these two groups, even as indoor use varied. Therefore, indoor efficiency alone is not necessarily predictive of reduced outdoor water use.

TABLE 2 | Medoids of individual household appliances' flow characteristics, of all the 706 sample single-family households from Arizona, estimated using the PAM method.

Appliance	Medoid-1 (high efficiency)	Medoid-2 (low efficiency)
Toilet (avg. gallons per flush)	1.78	2.42
Showerhead (avg. gallons per minute)	1.61	2.24
Clothes washer (avg. gallons per load)	25.40	33.97
Dishwasher (avg. gallons per load)	3.28	5.42
Faucet (avg. gallons per minute)	0.015	0.070

4.5 | Conservation Mindset and Its Impact on Outdoor Water Consumption

With the outdoor water use being highly skewed, and the presence of swimming pools and appliance efficiency levels having a significant impact on its variation across single-family households in Arizona, outdoor water use was further analyzed using the consumption mindset framework. Households were grouped by those that (i) have a swimming pool and a low overall household efficiency ($N = 377$) and (ii) do not have a swimming pool and have a high overall household efficiency ($N = 32$). These two groups represent in volume the highest and lowest outdoor water users, respectively, among the 706 single-family households analyzed in this study. Thus, the households grouped in the latter were assumed to have a "high" conservation mindset, while the former group was assumed to have a "low" conservation mindset.

Statistical analysis of these two household groups again revealed a normal distribution in the percentage of outdoor to total water use (Figure S3). Table S1 presents their statistical characteristics with the 95% confidence interval range of expected values. Households with a low conservation mindset used up to 70% of total water outdoors, while those with a high conservation mindset used as little as 46% outdoors. An ANOVA test confirmed a significant difference in the outdoor to total water use percentages between these two groups. Figure 9 shows the relative comparison of these two groups to the percent outdoor water use ratio of all 706 households grouped together.

4.6 | Quantification of Water Consumption Using Household Characteristics and Regional Factors

Log-linear mixed-effects models perform the best in explaining the single-family household water use variation. Figure 10

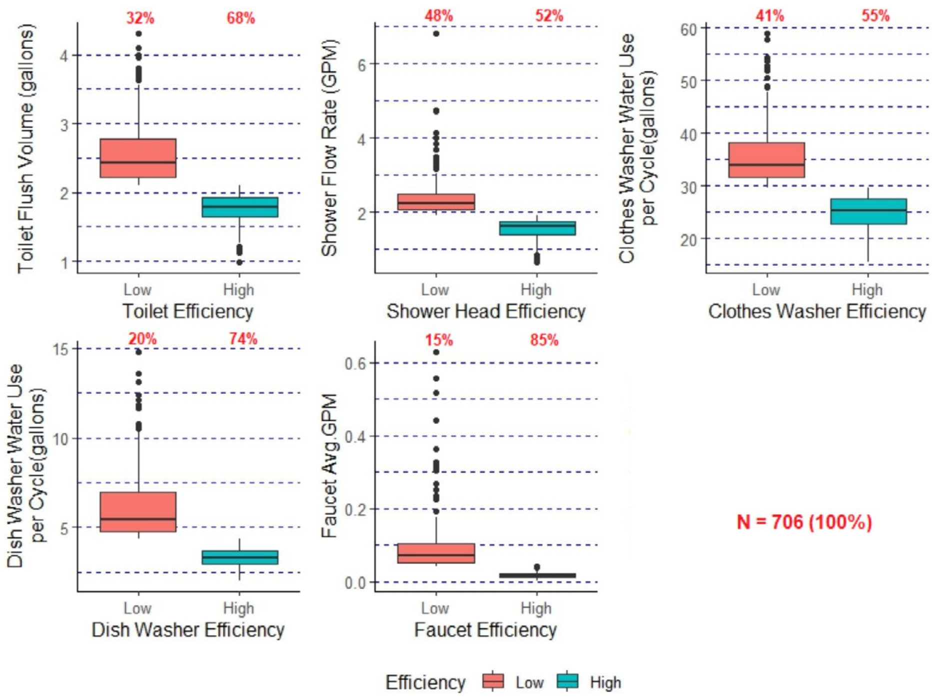

FIGURE 7 | The state of household appliance efficiencies for the 706 sample single-family households in Arizona. Percentage numbers in red color over the boxes represent the percent households within each efficiency level.

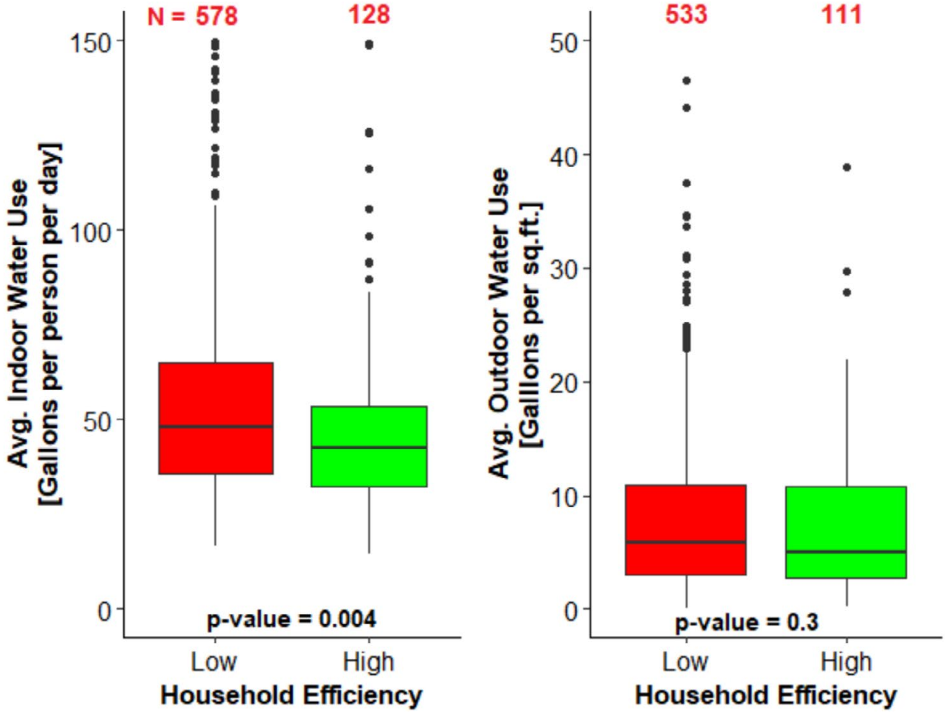

FIGURE 8 | Average household-level indoor and outdoor water uses differ based on household appliance efficiency levels. The numbers in red over the boxes represent the total number of households within that efficiency level.

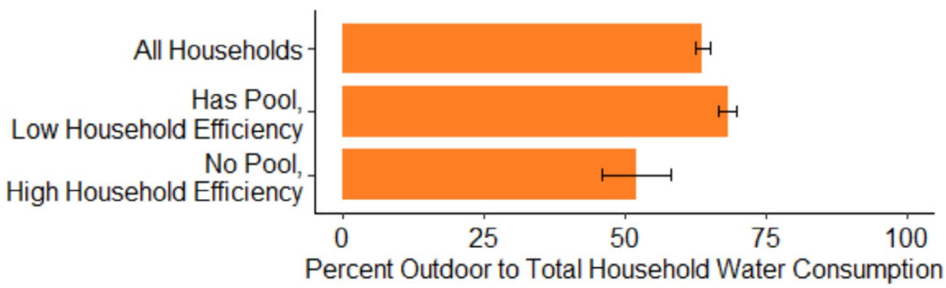

FIGURE 9 | Comparison of variation in the percent outdoor to total water use among the households grouped based on their conservation mindset.

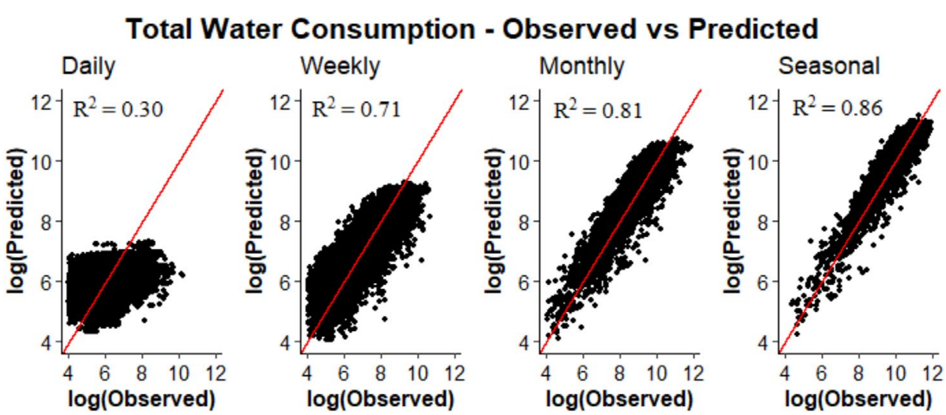

FIGURE 10 | Goodness-of-fit plots of observed versus predicted household level total water consumption data at different time-steps using the log-linear mixed effects model. Model prediction improves with larger time-steps.

shows the goodness-of-fit for the log-linear mixed-effects modeling of the total household water consumption at different time steps. Figures S1 and S2 show the goodness-of-fit for the log-linear mixed-effects modeling of indoor and outdoor household water uses, respectively. Log-linear mixed-effects model prediction significantly improves with increasing time steps.

The performance metric for all the linear, log-linear, and exponential mixed-effects models built for different time steps of household water consumption is presented in Table 3. Adjusted R^2 greater than 0.70 and p-value less than 0.05 were the criteria used in selecting the best performing mixed-effects models that have good prediction capabilities on household water use. While all the models were significant (p-value <0.05) in modeling household water use, only the log-linear mixed-effects models showed strong (adjusted $R^2 > 0.7$) predictive capabilities.

The weekly time-step log-linear model produces strong (adjusted $R^2 > 0.70$) and significant (p-value < 0.05) results in modeling the variations in total household water consumption only, while the monthly and seasonal time-step log-linear models are strong and significant in modeling all categories of household water consumption. However, at the daily time-step, the log-linear models remain significant (p-value < 0.05) but lack strong predictive power (adjusted $R^2 < 0.70$) and are noisy (Figure 10). This was also the case with modeling indoor and outdoor water uses at daily and weekly time-steps using the log-linear model (Figures S1 and S2).

4.7 | Drivers of Single-Family Household Water Uses in Arizona

The fixed and random effect variables (or drivers), X and Z, (Table 1) that are significant in modeling the single-family household's total water consumption, Y, at the monthly and seasonal time-step using the mixed-effects model are presented in Table 4. The drivers of indoor and outdoor water use at the monthly and seasonal time-steps are presented in Table S2. The direction and magnitude of variables in the model depended on the modeling time-step. All the variables and their estimates presented in these tables have a p-value of less than 0.05 and their VIF of less than 2.5. Note that the model intercept estimates presented in Table 4 and Table S2 are independent of fixed and random effects.

TABLE 3 | Adjusted coefficient of determination (adjusted R^2) for mixed-effects modeling of household water consumption categories at different time steps. All these models have a p-value of less than 0.05.

Time-step	Mixed-effects model type	Adjusted R^2		
		Indoor GPH	Outdoor GPH	Total GPH
Daily	Linear	0.02	0.23	0.22
	Log-linear	0.12	0.27	0.30
	Exponential	0.12	0.28	0.30
Weekly	Linear	0.21	0.41	0.44
	Log-linear	0.58	0.66	0.71
	Exponential	0.47	0.59	0.63
Monthly	Linear	0.38	0.47	0.52
	Log-linear	0.74	0.77	0.81
	Exponential	0.56	0.66	0.68
Seasonal	Linear	0.48	0.48	0.53
	Log-linear	0.81	0.82	0.86
	Exponential	0.61	0.68	0.70

For indoor water use, the number of residents, home features like pool ownership, the number of bathrooms, and the efficiency of appliances were important drivers. Outdoor water use was driven by irrigation factors like efficiency, frequency, and type, along with weather parameters (temperature and ET), socioeconomic attributes (home value, postal code), lot size, and pool ownership. The most significant drivers of total water use aligned with those for indoor and outdoor water use. Weather parameters impact all categories of single-family household water uses in Arizona and are speculated to be due to the overall arid climate type experienced within the state.

5 | Conclusion

This analysis highlights the pronounced impact of critical factors influencing single-family household water consumption patterns in Arizona. The analysis demonstrates a strong correlation between household occupancy and water usage, with the presence of a swimming pool further amplifying water consumption. The distinct relationship between household occupancy level and water consumption paves the way forward for policy-based and urban planning-related measures to target water conservation practices. This may involve changing housing density and associated land use patterns, and increased attention to the relationship between water use and urbanization (Gordon and Richardson 1997; Sampson et al. 2022; Stoker et al. 2022).

Furthermore, high seasonal variation in outdoor water use emphasizes the need to manage water resources in a sustainable manner, particularly in arid regions like Arizona. The percent of outdoor water use for Arizona estimated in this study shows some efficiency gains compared to the estimates for the percent outdoor water use that Balling et al. (2008) presented in their report, based on the trends and patterns they observed between 1995 and 2004 just for the Phoenix metropolitan area. However, outdoor water usage remains one of the biggest end-use categories of water in Arizona's single-family homes and is particularly high for homes with swimming pools, which use about 56% more water than homes without a pool. Given the role of swimming pools in mitigating the effects of extreme heat, perhaps no other use highlights the trade-offs between reducing water use and human comfort.

The investigation of appliance flow characteristics using Flume's smart sensor technology provides insights into the state of efficiency of the household fixtures. Clustering of appliance flow characteristics unveils that a significant portion of households possess high-efficiency toilets, dishwashers, and faucets. Notably, the study shows that indoor water use is influenced and reduced by better appliance efficiency. Overall, household efficiency and the presence of a swimming pool have a huge impact on a household's outdoor water consumption. Furthermore, grouping households based on their conservation mindset shows the existence of a wide range of

TABLE 4 | Important factors of single-family household's total water consumption in Arizona at the monthly and seasonal time-steps, and their corresponding coefficient estimates in the mixed-effects log-linear models. “NA” denotes variable insignificance in that time-step.

Variables	Fixed effect coefficients (α)		Random effect coefficients (β)	
	Monthly	Seasonal	Monthly	Seasonal
Air temperature (max)	−3.32	−2.16	[a]	[a]
Dishwasher efficiency	[a]	[a]	0.07	0.07
Evapotranspiration	1.10	1.11	[a]	[a]
Faucet efficiency	[a]	NA	−0.06	NA
Has pool	[a]	[a]	0.13	0.12
Home value	[a]	[a]	0.19	0.20
Irrigation efficiency	[a]	[a]	0.84	0.84
Irrigation frequency	[a]	NA	0.07	NA
Irrigation type	[a]	[a]	0.45	0.49
Laundry efficiency	[a]	[a]	0.08	0.07
Lot size	[a]	[a]	0.10	0.08
Month of year	0.32	NA	[a]	NA
Number of bathrooms	[a]	NA	−0.07	NA
Number of residents	[a]	[a]	0.24	0.23
Postal code	[a]	[a]	−38.03	−32.89
Showerhead efficiency	[a]	[a]	0.12	0.11
Toilet efficiency	[a]	[a]	0.11	0.12
Year	NA	−1124.03	NA	[a]
Year built	[a]	[a]	5.69	6.73
Intercept	492.35	8992.92	[a]	[a]

[a]Under the random-effect column if that variable has a fixed-effect nature, and vice versa.

outdoor water usage patterns across the single-family households in Arizona.

The mixed-effects modeling efforts undertaken in this study mostly reiterate the learnings from past studies (Balling et al. 2008; Deoreo and Mayer 2012; DeOreo et al. 2016; Ouyang et al. 2014; Stoker and Rothfeder 2014). This study builds on previous efforts by estimating household appliance efficiency using smart-metered data to improve the predictive power of water use/demand models, thus enhancing our understanding of water demand management.

To achieve significant scientific progress and make meaningful contributions to municipal water demand management in the United States, it is crucial to expand this analysis beyond the state of Arizona or the “Arizona Sun Corridor”. With the continuous growth of urban populations across the country, urban water usage is on the rise. This demographic shift has profound implications for how water is sourced, transported, and consumed, thereby necessitating a comprehensive understanding of the factors influencing water use. Smart-metered data, such as Flume's, can offer many nuanced insights into these variations in water uses, and their cobenefits for a diverse set of water management practices are yet to be realized (Monks et al. 2019).

Furthermore, the complex interplay between land use management, urban development, and climate variability impacts water supply and demand patterns across regions. Gathering nationwide, high-resolution, smart-metered data is therefore increasingly important to understand water usage dynamics. This study has thus offered a statistical framework to enable such future research using smart metering data. We hope this paves the way for more robust analysis and modeling of urban water demand across socioeconomic groups, promoting equitable and sustainable water management on a national scale.

Author Contributions

Cibi Vishnu Chinnasamy: conceptualization, methodology, formal analysis and investigation, writing – original draft, writing – review and editing. **Mazdak Arabi:** conceptualization, methodology, investigation and validation, writing – original draft, visualization, writing – review and editing, funding acquisition, research supervision, finalization and approval of the contents. **Peter Mayer:** conceptualization, methodology, data curation, investigation and validation, writing – review and editing, research supervision, finalization and approval of the contents. **Grant Bernosky:** data curation, formal analysis, writing – review and editing, validation of methods and results, finalization and approval of the contents. **Travis Warziniack:** investigation, funding acquisition, supervision, writing – review and editing, research supervision, validation of methods and results, finalization and approval of the contents.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Water use data for this research work was provided by Flume Inc., a smart water sensor company that collects real-time water use data from their customers who install Flume Sensors in their households. Due to the proprietary nature of the data (owned by Flume Inc.), those interested in obtaining data must contact Flume directly via https://www.flumedatalabs.com/contact-us. Weather data collected from the Arizona Meteorological Network (AZMET) stations positioned across the state can be accessed online at https://ag.arizona.edu/azmet.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.