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Novel bottom-up urban water demand forecasting model: Revealing the determinants, drivers and predictors of residential indoor end-use consumption

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ABSTRACT

The purpose of this comprehensive study was to explore the principal determinants of six residential indoor water end-use consumption categories at the household scale (i.e. namely clothes washer, shower, toilet, tap, dishwasher, and bath), and to find an overarching research design and approach for building a residential indoor water end-use demand forecasting model. A mixed method research design was followed to collect both quantitative and qualitative data from 210 households with a total of 557 occupants located in SEQ, Australia, utilising high resolution smart water metering technology, questionnaire surveys, diaries, and household water stock inventory audits. The principal determinants, main drivers, and predictors of residential indoor water consumption for each end-use category were revealed, and forecasting models were developed this study. This was achieved utilising an array of statistical techniques for each of the six end-use consumption categories. Cluster analysis and dummy coding were used to prepare the data for analysis and modelling. Subsequently, independent *t*-test and independent one-way ANOVA extended into a series of bootstrapped regression models were used to explore the principal determinants of consumption. Successively, a series of Pearson's Chi-Square tests was used to reveal the main drivers of higher water consumption and to determine alternative sets of consumption predictors. Lastly, independent factorial ANOVA extended into a series of bootstrapped multiple regression models was used for the development of alternative forecasting models. Key findings showed that the usage physical characteristics and the demographic and household makeup characteristics are the most significant determinants of all six end-use consumption categories. Further, the appliances/fixtures physical characteristics are significant determinants of all end-use consumption categories except the bath end-use category. Moreover, the socio-demographic characteristics are significant determinants of all end-use consumption categories except the tap and toilet end-use categories. Results also demonstrated that the main drivers of higher end-use water consumption were households with higher frequency and/or longer end-use events which are most likely to be those larger family households with teenagers and children, with higher income, predominantly working occupants, and/or higher educational level. Moreover, a total of 14 forecasting model alternatives for all six end-use consumption categories, as well as three total indoor bottom-up forecasting model alternatives were developed in this study. All of the developed forecasting model alternatives demonstrated strong statistical power, significance of fit, met the generalisation statistical criteria, and were cross-validated utilising an independent validation data set. The paper concludes with a discussion on the most significant determinants, drivers and predictors of water end-use consumption, and outlines the key implications of the research to enhanced urban water planning and policy design.

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1. Introduction

1.1. Urban water security and demand management

Availability of water is becoming more variable due to the rising severity of climate change conditions. Consequences of such changing conditions are the unpredictable changing rainfall patterns and the increasing frequency and severity of droughts. This coupled with growing populations and expanding economic development, results in escalating urban water demands, making water a scarce resource in many regional and urban centres (Gleick, 2011; Jorgensen et al., 2009; Willis et al., 2010a, 2011b). Therefore, scarcity of water and the ability to meet future water demands is one of the greatest concerns for many governments and public utilities, considering the costs associated with sourcing new water supplies. This issue necessitates water being very carefully managed on both the supply and demand sides across the residential, commercial and industrial sectors. This is a common concern in South East Queensland (SEQ) where this study took place, most of the dry Australian continent and also to many other water scarce or variable regions internationally (Bates et al., 2008; Beal and Stewart, 2011; Commonwealth of Australia, 2013b,c; Inman and Jeffrey, 2006; Jiang, 2009; Turner et al., 2010).

Residential water consumption represents a significant component of overall water consumption (Sadalla et al., 2012), forcing water authorities to invest significantly in the development and implementation of a range of integrated urban water management (IUWM) strategies and programmes in an attempt to ensure urban water security (Beal and Stewart, 2011; Correljé et al., 2007; Stewart et al., 2010). Such strategies include the initiation of water-saving measures, imposing water restrictions, rebate programmes for water-efficient fixtures, dual-supply schemes (Beal and Stewart, 2011; Mitchell, 2006; Price et al., 2014; Willis et al., 2011b), visual display shower monitors (Stewart et al., 2011; Willis et al., 2010b), the installation of rainwater tanks (Beal et al., 2011a, 2012c; Coultas et al., 2012), source substitution for toilet flushing and laundry (Anand and Apul, 2011; Chen et al., 2013; Mourad et al., 2011; Stewart et al., 2010), promoting water efficiency labelling schemes, pricing, and conservation awareness programmes (Arbués et al., 2010; Inman and Jeffrey, 2006; Mayer et al., 2004; Nieswiadomy, 1992). These strategies and programmes aim at improving urban water security through wiser, more conservative and sustainable water consumption to enable future water demands to be met (Beal and Stewart, 2011).

In SEQ, the implementation of such IUWM strategies and programmes has resulted in large water consumption reductions and in greater social awareness of the value of water as a precious resource. However, water-regulating authorities usually follow a reactionary-based approach in the design and implementation of water-regulating strategies, such as setting a target consumption value to reduce water consumption during insecure water periods (Beal and Stewart, 2011). The effectiveness of such approaches depends on differences in location, community attitudes and behaviours (Corral-Verdugo et al., 2003; Turner et al., 2005). In addition, due to the lack of data at the end-use level, water savings associated with their implementation are often estimated on the basis of limited evidence and with many assumptions, leading to understated or grossly inaccurate values (Beal and Stewart, 2011; Stewart et al., 2010). This highlights the need for more detailed information about residential water consumption at the end-use level (Stewart et al., 2010).

Disaggregation of residential water use improves understanding about how water consumption is proportioned in households, and identifies determinants of water consumption to allow an analysis of links between them based on subsets of consumers and end-use consumption (Beal and Stewart, 2011). Further, improved understanding about spatial and temporal residential water consumption variability at the end-use level enables the development and implementation of more effective IUWM strategies, programmes and forecasting models (Beal and Stewart, 2011, 2013). This can provide useful insights enabling water authorities to pursue more proactive approaches to better manage urban water demand and resources.

1.2. Water smart metering

More detailed information about how and where residential water is consumed (e.g. shower, washing machine, dishwasher, tap, bathtub), is an essential requirement for the development of more effective IUWM strategies and programmes, and for a better evaluation of water savings associated with their implementation (Beal and Stewart, 2011; Cole and Stewart, 2012; Willis, 2011; Willis et al., 2011b, 2013). Moreover, such detailed knowledge about water consumption can improve understanding of the key determinants of each end use to form the basis of water consumption predictions and the development of improved demand forecasting models (Blokker et al., 2010; Stewart et al., 2010). The development of such forecasting models at an end-use scale is vital, but essential micro-component level models created from detailed empirical water end-use events data registries (i.e. micro-level bottom-up models) (Kenney et al., 2008; Willis et al., 2009c) are currently lacking. Improved forecasting of total urban residential connection demands will be possible using the models presented in this study.

The emergence of advanced technologies such as water smart-metering enables the creation of the required detailed data registries through real-time or near-real time-monitoring, high-resolution interval metering, automated water meter reading (e.g. drive by GPRS) and access to data from the Internet (Beal and Stewart, 2011). Smart water metering technology comprises high-resolution data capturing, logging and wireless communication technologies, which facilitate the collection, storage, wireless transfer and subsequent analysis of abundant and detailed data (i.e. water consumption flow quantities and time of disaggregated end-use events) using computer software (Beal and Stewart, 2011; Cole and Stewart, 2012; Willis et al., 2009e; Nguyen et al., 2014, 2013a,b). Such detailed and accurate water end-use data, when combined with socio-demographic, water stock inventory, and residential attitude and behavioural factors, will facilitate the creation of models capable of identifying determinants of residential water end-use consumption. Knowledge of these determinants and consumption of each end use will explain aggregate residential consumption and form the foundation for more robust demand forecasting models.

1.3. Water end-use studies

Due to the emerging necessity for residential water consumption disaggregation, a number of end-use studies and forecasting models have been developed, aiming at quantifying and predicting water demand for each end-use category (e.g. shower or washing machine). Such studies and models have been mostly developed using mixed method approaches with some degree of technology for water volume data capturing and social surveys and/or sourced statistical information from available documents (e.g. historical billing data, existing statistical reports or technical information from stock appliance manufacturers) to estimate water end-use consumption using mathematical modelling methods (Beal and Stewart, 2011). Despite the undeniable usefulness of such studies and models in water demand management and prediction, their ability to disaggregate consumption into water end-use categories is limited in accuracy, thereby limiting prediction accuracy. Therefore, utilising a combination of long-term actual measurement

Table 1
Previous residential water end use studies conducted in Australia (Beal and Stewart, 2011).

Author(s)	Loh and Coghlan (2003)	Roberts (2005)	Willis et al. (2009c)	Mead (2008)
Study title	Domestic Water Use Study	REUMS	Gold Coast Watersaver End Use Study	Investigation of domestic water end use
Region	Perth	Melbourne	Gold Coast	Toowoomba
Reporting year	1998–2001	2004	2009	2008
Sample size (no. homes)	120	100	151	10
Average indoor consumption (L/p/d)	155	169	139	111.6
Average total consumption (L/p/d)	335	226	157	112
Bath/shower (%)	33	31	42	46
Washing machine (%)	28	26	22	24.8
Toilet (%)	22	18	15	12.76
Tap (%)	15	17	20	15.5
Leaks (%)	2	8	1	0.4

and disaggregation of water end-use data (i.e. micro-component analysis), collected by high-resolution water smart-metering technology and computer software, along with household surveys, self-reported water usage diaries, and water appliances and fixtures audits collected from metered households is considered the most robust and accurate foundation for the development of urban water demand forecasting models. Although only a small number of residential water end-use studies have been conducted using the combination of high-resolution smart-metering technologies, end-use software (e.g. Trace wizard®, Aquacraft, 2010) and household surveys, such studies are becoming more popular (Beal and Stewart, 2011; Parker and Wilby, 2013).

A number of end-use studies have been conducted in the United States of America (DeOreo et al., 1996; Mayer and DeOreo, 1999; Mayer et al., 2004), and more recently in New Zealand (Heinrich, 2007) and Sri Lanka (Sivakumaran and Aramaki, 2010). Moreover, a number of water micro-component studies have been conducted in the United Kingdom (Barthelemy, 2006; Creasey et al., 2007; Kowalski and Marshallsay, 2005; Parker and Wilby, 2013; Sim et al., 2007).

In Australia, only a few water end-use studies have been completed to date. Major studies have been conducted in Perth, Western Australia (Loh and Coghlan, 2003; Water Corporation, 2011) and in Melbourne, Victoria (Roberts, 2005; Gato-Trinidad et al., 2011). In Queensland, an end-use study recently was conducted in Gold Coast City (Willis, 2011; Willis et al., 2009a,b,c, 2010a,b, 2011a,b, 2013) in addition to a small study in Toowoomba, west of Brisbane (Mead, 2008). A summary of established averages of total and indoor daily per capita water consumption volumes, along with indoor water end-use breakdown percentages reported in previous Australian studies is provided in Table 1.

Another major study in Queensland was the South-East Queensland Residential End Use Study (SEQREUS), commissioned in 2010 to gain a greater understanding of water end-use consumption in the SEQ urbanised region. This study was funded by the Urban Water Security Research Alliance (UWSRA)—a partnership between the Queensland Government, CSIRO's Water for Healthy Country Flagship, Griffith University and the University of Queensland. The main aim of this alliance was to address urban water issues emerging in SEQ and inform the implementation of an enhanced water strategy (Beal et al., 2011b; Beal and Stewart, 2011). The primary objective of the SEQREUS was to quantify and characterise mains water end uses in single detached dwellings across four main regions (Sunshine Coast Regional Council, Brisbane City Council, Ipswich City Council, and Gold Coast City Council) in SEQ. More information about the SEQREUS can be found in Beal and Stewart (2011).

This paper describes a component of the greater SEQREUS and utilises a subset of information collected during four different periods over two years: winter 2010 (baseline data for model development); and summer 2010, winter 2011 and summer 2011 data for validation of developed models. These data were obtained through long-term actual measurement and disaggregation of water end-use data (i.e. micro-component analysis) using high-resolution smart-metering technology and computer software, along with household surveys, self-reported water usage diaries, and water appliances and fixtures audits collected from metered households in SEQ. More information about the data collected in SEQREUS is provided below. Utilising a subset of the available information, the objectives of current research study are as presented next.

1.4. Research objectives

The key objectives of this study are to:

- Explore the principal determinants of consumption at the household scale for each of the six residential indoor water end-use consumption categories, namely shower, clothes washer, toilet, tap, dishwasher and bath.
- Create a series of forecasting models for each of the six residential indoor water end-use consumption categories that are capable of generating average daily per-household consumption predictions for each end-use category, where their summation can provide a bottom-up evidence-based forecast of domestic water demand.

2. Residential water end uses

Residential household water-use components comprise indoor consumption, outdoor consumption (e.g. irrigation, and activities such as swimming pool filling and car washing) and leakage. This herein study scope purposely focuses only on the indoor water consumption and its end-uses. Outdoor end uses and leakage categories have been excluded from this present study since they are characterised by having much greater variability and uncertainty and correlate with a largely different suite of determinants (Beal and Stewart, 2013; Britton et al., 2009, 2013), thereby requiring alternative modelling approaches and longitudinal end use datasets (i.e. 5–10 years) to develop sufficiently robust relationships. Residential household indoor water end-use consumption is dominated by showers, clothes washers, toilets, indoor taps, dishwashers and baths (Mayer and DeOreo, 1999). Information about these typical six indoor water end-use consumption categories collected in SEQREUS provides the focus of the current research.

As discussed above, conducting end-use studies utilising smart-metering technology and computer software enables the collection and accurate disaggregation of end-use flow data, creating a repository of all residential water end-use events. Such detailed information allows the study of influencing factors and their relationship with water consumption, to improve current understanding of primary determinants for each residential water end use, as well as improving the accuracy of demand forecasting models. This aids the design and implementation of better targeted and more effective IUWM strategic plans (e.g. showerhead rebate/replacement programmes and social behaviour marketing) to reduce overall residential consumption during insecure water periods, in addition to the flow-on energy and greenhouse gas (GHG) conservation benefit associated with such consumption reductions (Beal et al., 2012a; Bertone et al., 2012; Lee and Tansel, 2012; Zhou et al., 2013). A discussion on indoor residential water end-use modelling and consumption-influencing factors follows.

3. Residential water demand modelling and forecasting

Water demand modelling and consumption prediction is complicated (Donkor et al., 2014; Hanif et al., 2013; House-Peters and Chang, 2011) due to the nature of water demand as a process. Residential water demand is an outcome of relationships and their interactions between humans and urban natural systems, which are both multi-scale (e.g. individual, household, regional and national) and cross-scale (i.e. spatial and temporal) in nature (House-Peters and Chang, 2011). This results in a large number of variables that can be hypothesised to affect water demand, adding to the complexity of residential water demand forecasting modelling (Donkor et al., 2014). Such variables range from micro-variables at the individual scale (e.g. individual motivations and attitudes) to macro-variables at the national scale (e.g. population growth and tourism). This complex nature requires the development of criteria for the selection of an appropriate set of factors influencing water consumption to be used for modelling residential water demand at a specific scale of consumption; in this case the household scale. A discussion of such criteria in relation to the water consumption-influencing factors covered in this study follows.

3.1. Selection of consumption scale and unit of analysis

When conducting a study, it is necessary to have a clear understanding of level or scale, and unit of analysis, for describing the context and structure of the problem under study. Both scale and unit of analysis are important elements of the study design and subsequent data analysis (Babbie, 2012; Yurdusev, 1993). Therefore, studying factors influencing water consumption for the purpose of selecting those most appropriate for modelling residential water demand at a specific scale (i.e. individual, household, district or regional) is critical. For instance, Jorgensen et al. (2013a,b) found that some variables measured at the individual scale (i.e. individual motivations and attitudes) were not significant predictors of household water consumption, but did predict individual consumption. Therefore, ensuring consistent use of scales, both of factors hypothesised to be influencing water consumption and collected actual metered water consumption flow data, is important for identifying the principal determinants of consumption and predictors of demand at the selected scale (Jorgensen et al., 2013b). Thus, when predicting water demand for individuals, attitudes and motivations ideally would play a bigger role in explaining consumption than they do for household demand predictions, and similarly with other scales.

It might be considered that identifying residential water consumption drivers and predictors of water demand for individuals would provide the best understanding of such a complex natural system, as individual consumption represents the basic component shaping water consumption at other scales in an ascending way (i.e. household, district, regional and national). However, because of the difficulty of collecting water-consumption data at an individual scale, neither (1) rescaling the unit of analysis from that at which actual metered water consumption flow data were collected (e.g. litres per household L/hh) to another unit (e.g. average litres per person L/p) by simply dividing collected consumption data at a particular scale (e.g. household consumption) by number of persons in the household or number of households in the region, for the purpose of studying consumption factors (e.g. individual motivations and attitudes) or (2) modelling demand at another scale (e.g. individual scale), will reconcile the different scales (Jorgensen et al., 2013b).

It has been reported in previous studies that the increase in household water consumption is associated with an increase in the number of people in the household (Beal et al., 2011b; Beal and Stewart, 2011; Gato-Trinidad et al., 2011; Gato, 2006; Turner et al., 2009; Willis et al., 2009c). However, such an increase is not linear, that is, the increase in water consumption associated with an increase in household size by one person does not follow a fixed rate of increment (Bennett et al., 2012). This could be due to differing characteristics of households (e.g. single adults, couple, family that might include younger children and teenagers, males, females) in each household size category (number of occupants), in addition to other socio-demographic characteristics (e.g. existence of a retired person in household) (Beal and Stewart, 2011). In contrast, it has been found that household per capita consumption (PCC) decreases as household size increases, due to economies of scale (Arbués et al., 2003; Beal et al., 2011b; Beal and Stewart, 2011; Russell and Fielding, 2010; Turner et al., 2009).

Arbués et al. (2000) demonstrated an optimum household size beyond which such economies of scale vanish (Arbués et al., 2003). However, calculating average household consumption on a per capita basis by simply dividing household consumption by the number of people in the household involves an inherent assumption of equally apportioned PCC for each household occupant, which does not account for the non-proportional nature of differences in consumption associated with their different characteristics (e.g. age). Such paradoxical assumptions when rescaling household consumption to average household PCC work against identifying significant household characteristics associated with water consumption at the household scale. This is simply due to distributing the non-equal portions of household consumption contributed by each household occupant equally among all occupants, diminishing the effect of their consumption characteristics.

Therefore, such rescaling might prevent capturing of the significance of household makeup and socio-demographic characteristics (e.g. age, gender and retirement status) as determinants of consumption at the household scale, and might be misleading in relation to the direction of relationships between them and water consumption. For this reason, PCC data are not considered to be the best for identifying determinants of residential water consumption at the household scale, and would limit prediction accuracy of models developed for that consumption scale (Hanif et al., 2013). However, it is worth mentioning that after ensuring consistency of scales between predictors and metered water flow consumption data at the modelling stage of water demand, predictions generated from such forecasting models can be converted to a more standardised unit (such as average L/p) for comparison with other reported studies. This also adds to the complexity of residential water demand forecasting modelling, due to its implications for data-collection requirements, quality, availability and the forecasting approach to be used.

Despite the importance of individual householder attitudes as a key determinant category of residential water end-use consumption, such information has not been included in the current study due to the above constraints. This will ensure consistency of scales between metered water consumption and the consumption factors to be studied. The purpose of this study is to identify the determinants of consumption, as well as develop end-use forecasting models at the household level. As the utilised data have been collected at the household scale, average L/hh was used as the unit of analysis in this case.

In addition to the importance of ensuring consistency of scales when modelling water demand, there are two other reasons for selecting the household, rather than the individual scale, in this study. The first is the higher feasibility of water businesses collecting data on household-scale determinants or predictors as input parameters in the developed end-use forecasting models in this study, increasing their usability for future residential prediction and planning. Water businesses have only limited ability to collect data on householder motivations and attitudes, due to privacy concerns, difficulties in obtaining reliable attitude data, and the likelihood that attitudes might be latent variables of other household demographic characteristics, to name a few. The second reason for selecting the household scale, as argued by Hanif et al. (2013), is that water consumption estimates made by water suppliers based on PCC data usually vary significantly; thereby affecting the veracity of models whose development is based on them.

3.2. Consumption-influencing factor relationships within and between consumption scales

It is important to account for relationships and interactions between variables within the same scale or between different scales of consumption when used as predictors in water demand forecasting models to ensure prediction accuracy, especially when using statistical modelling approaches such as regression (Billings and Jones, 2008), as in this study. This will also ultimately identify the complexity of such multi-scale relationships and interactions, and their role in shaping residential water demand (House-Peters and Chang, 2011). However, this adds to the complexity of water demand modelling in terms of the forecasting approach to be used, as well as methods of dealing with such relationships and interactions.

As consumption-influencing factors of other scales (i.e. individual, regional and national) were not included in this study (for the reasons discussed above and because of the specified scale and purpose of the models developed in this study), their relationship with the household consumption-influencing factors covered in this study were not included. Nevertheless, it is worth mentioning that studying household consumption-influencing factors such as the ones covered here might enable the identification of some potential associations with consumption-influencing factors at other scales. For instance, studying the influence of the makeup of households (including gender, age and income profiles) on water consumption at the household scale enables the capturing of differences in household consumption between different typologies of consumers that might be attributed to the attitudes of a specific group of consumers. For example, this may enable exploration of the idea that teenagers might have higher volume showers than adults, which could be inherently attributed to their attitudes as influencing factors of shower consumption at the individual scale. Therefore, the inclusion of such profiles when studying water consumption at the household scale increases the capability of spatial end-use models in representing water demand behavioural variability among different typologies of consumers. Such representation helps overcome the difficulty of identifying, observing or measuring influential behavioural factors to be studied or used as predictors of consumption at the individual scale (Rathnayaka et al., 2011).

Relationships between consumption-influencing factors within the same scale (in this case, the household scale) were accounted for and studied before including them as predictors in the developed end-use forecasting models in the current study. Studying such relationships enabled exploration of consumption drivers, which enabled the design of better conservation targets. For instance, in the previous example that teenagers might have higher volume showers than adults, studying the association between influencing factors enabled the exploration of whether such higher consumption volume is due to more frequent or longer showers by teenagers, or both. Further, studying such associations before including factors as predictors in the demand forecasting models, helped to avoid multicollinearity issues in the statistical modelling process. In addition, it provided a framework for the criteria of building alternative forecasting models for each end-use category, as some predictors could act as proxies for each other.

3.3. Demand forecasting modelling purpose, periodicity and horizon

Determinants of consumption to be used as demand predictors should be specified in light of the purpose of the demand forecasting model to be developed. Donkor et al. (2014) provided evidence that determinants of consumption and demand predictors might be completely different at different forecasting periodicities (e.g. hourly, daily, monthly or annual) and horizons (e.g. short-, medium- or long-term) when utilised at different planning levels (e.g. strategic, tactical or operational), even when using the same unit of analysis (e.g. PCC). This adds further to the complexity of residential water demand forecasting modelling, especially at an end-use level. This complexity is due to implications of data-collection requirements (i.e. data periodicity and horizon), quality, availability, and selection of suitable determinants and the forecasting approach (Donkor et al., 2014; House-Peters and Chang, 2011). Further, depending on the purpose of the forecasting model to be developed (i.e. periodicity, horizon and planning level), forecasting approaches could range from simplistic to complex, static to dynamic, deterministic to fuzzy or stochastic, parametric to non-parametric, or hybrids thereof (Baumann et al., 1997; Billings and Jones, 2008; Donkor et al., 2014; Fyfe et al., 2010; Galán et al., 2009; House-Peters and Chang, 2011; Qi and Chang, 2011). The forecasting method used in this study is discussed in the supplementary material S–A.

Since the study described herein focuses on the spatial (rather than the temporal) side of residential water consumption, and utilises a cross-sectional data set (i.e. average daily consumption per household of metered household consumption across two-week periods in winter 2010) collected in SEQREUS, it aims to identify the principal determinants of consumption for each end-use, as well as to develop end-use forecasting models at the household scale, facilitating predictions of very short-term water end-use average daily demand. Therefore, factors influencing residential consumption that could be better captured on a temporal or a longitudinal scale (e.g. population, water price, awareness, restrictions, rebates, technology take-up rates, seasonality, temperature or rainfall) (Jacobs and Haarhoff, 2004b; Rathnayaka et al., 2011) were not covered in this study due to the specified purpose of the models in terms of their horizon and periodicity, as well as the nature of the available data. In addition to the reasons discussed above for excluding factors associated with climate and seasonality, previous studies reported a low level of fluctuation between summer and winter indoor water end-use consumption (Beal and Stewart, 2011; DeOreo et al., 1996; Heinrich, 2009; Howe and Linaweaver, 1967; Jacobs and Haarhoff, 2004a,b; Loh and Coghlan, 2003; Loh et al., 2003; Willis et al., 2011b). Further, Roberts (2005) reported that the six household indoor water end-use categories daily consumption covered in this study (shower, clothes washers, toilets, indoor taps, dishwashers and baths) were non-seasonal.

To confirm non-seasonality in the indoor residential end use data used in the current study, a series of one-way repeated measures analysis of variance (ANOVA) and Friedman's ANOVA tests were conducted for dependent means comparisons, using data collected in the SEQREUS from 30 households' metered average daily end-use consumption (i.e. average L/hh/d) across four

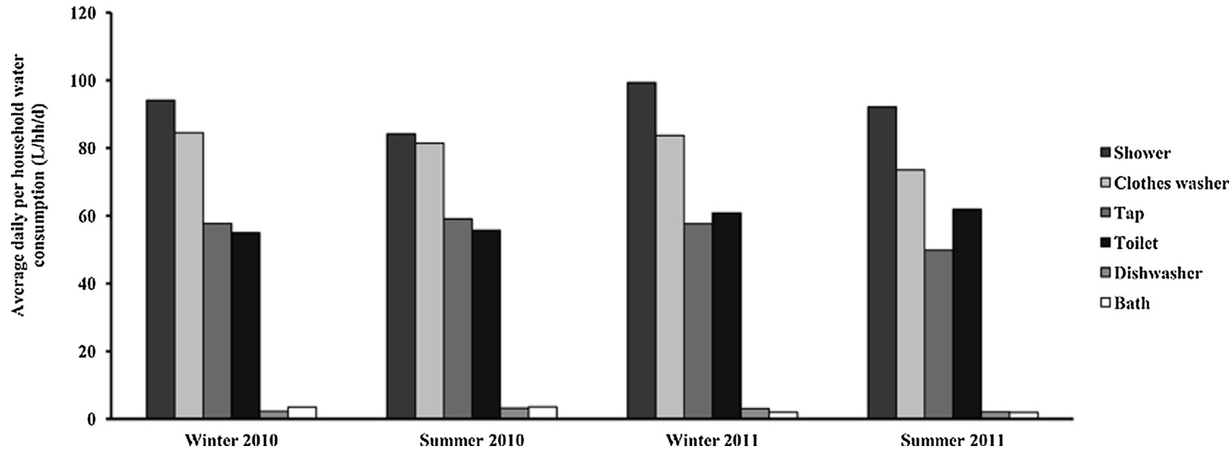


Fig. 1. Summer versus winter daily per household average water end use consumption of four two-week monitoring periods across two years (2010 and 2011) of same 30 households.

Table 2
Dependent mean comparisons of daily per household average water end use consumption of summer versus winter four two-week monitoring periods across two years (2010 and 2011) of same 30 households.

	Winter 2010	Summer 2010	Winter 2011	Summer 2011	Average	Test	Test type	*df*	F[a,b]	χ^2 [c]
N	30	30	30	30						
Shower (ave. L/hh/d)	94.2	84.2	99.4	92.2	92.5	Repeated measures ANOVA	Parametric	3	0.840[n.s.]	
Clothes washer (ave. L/hh/d)	84.5	81.5	83.7	73.5	80.8	Friedman's ANOVA	Non-parametric	3		4.680[n.s.]
Tap (ave. L/hh/d)	57.8	59.1	57.7	49.9	56.1	Repeated measures ANOVA	Parametric	3	1.252[n.s.]	
Toilet (ave. L/hh/d)	55.0	55.7	60.9	61.9	58.4	Friedman's ANOVA	Non-parametric	3		2.200[n.s.]
Dishwasher (ave. L/hh/d)	2.3	3.2	3.0	2.1	2.7	Friedman's ANOVA	Non-parametric	3		5.006[n.s.]
Bath (ave. L/hh/d)	3.5	3.5	2.0	1.9	2.7	Friedman's ANOVA	Non-parametric	3		7.027[n.s.]

[a] Sphericity is assumed: Mauchly's test was conducted for shower four reads ($W = 0.937$, approximated $\chi^2 = 1.801$, $df = 5$, $p = .876 > .05$).
[b] Sphericity is assumed: Mauchly's test was conducted for tap four reads ($W = 0.847$, approximated $\chi^2 = 4.641$, $df = 5$, $p = .465 > .05$).
[c] χ^2 statistical significance level was calculated utilising *Monte Carlo* method using 10,000 samples and 99% CI.
[n.s.] Statistically non-significant ($p > .05$).

periods (winter 2010, summer 2010, winter 2011 and summer 2011) (Fig. 1 and Table 2). This was done to test for the significance of any change in average end-use consumption of the same 30 households across different conditions (in this case, four periods including two summer and two winter seasons). Further, a series of Kruskal–Wallis tests were conducted for an independent means comparison of average metered end-use consumption (L/hh/d) between 210 households in winter 2010 (collected in the SEQREUS) and different households metered across the other three periods (48 households in summer 2010, 49 in winter 2011 and 53 in summer 2011, collected in the SEQREUS), excluding the 30 households utilised in the previous test, to ensure independent comparisons (Fig. 2 and Table 3). This was done to test whether the end-use consumption data set (consisting of 210 households' metered consumption in winter 2010) used for models development in the current study is representative of the other three data collection periods. The resulting F and χ^2 statistics (see Tables 2 and 3) revealed no significant differences (all $p > .05$) between means of

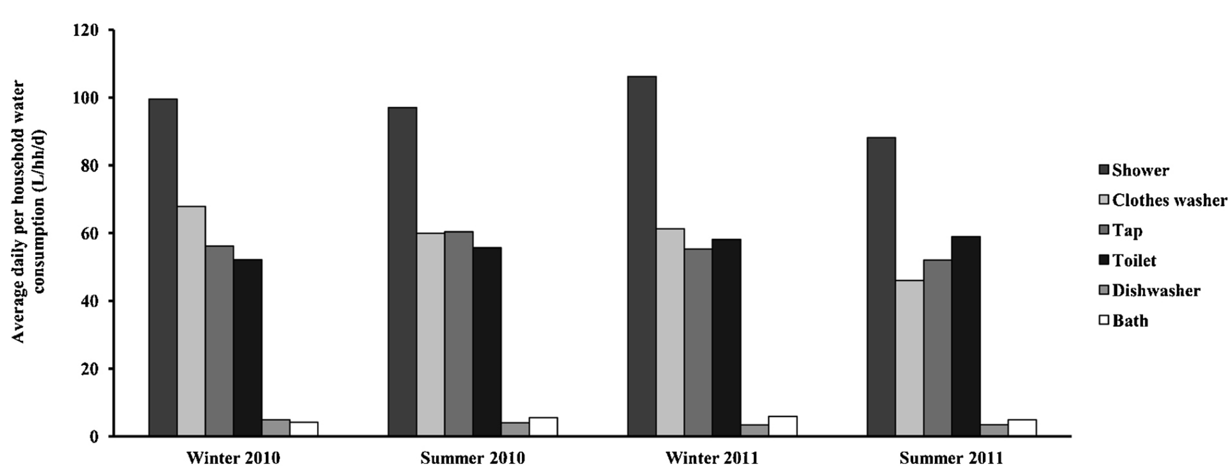


Fig. 2. Summer versus winter daily per household average water end use consumption of four two-week monitoring periods across two years (2010 and 2011) of different households.

Table 3
Independent mean comparisons of daily per household average water end use consumption of summer versus winter four two-week monitoring periods across two years (2010 and 2011) of different households.

	Winter 2010[a]	Summer 2010	Winter 2011	Summer 2011	Average	Test	Test type	*df*	χ^2 [b]
N	210	48	49	53					
Shower (ave. L/hh/d)	99.5	97.0	106.2	88.2	97.7	Kruskal Wallis	Non-parametric	3	3.588[n.s.]
Clothes washer (ave. L/hh/d)	67.9	60.0	61.3	46.0	58.8	Kruskal Wallis	Non-parametric	3	6.235[n.s.]
Tap (ave. L/hh/d)	56.2	60.4	55.3	52.0	56.0	Kruskal Wallis	Non-parametric	3	4.002[n.s.]
Toilet (ave. L/hh/d)	52.2	55.7	58.1	59.0	56.2	Kruskal Wallis	Non-parametric	3	6.639[n.s.]
Dishwasher (ave. L/hh/d)	4.9	4.1	3.4	3.5	4.0	Kruskal Wallis	Non-parametric	3	2.915[n.s.]
Bath (ave. L/hh/d)	4.2	5.5	5.9	4.9	5.1	Kruskal Wallis	Non-parametric	3	0.806[n.s.]

[a] Utilised for models development in the herein described study.
[b] χ^2 statistical significance level was calculated utilising *Monte Carlo* method using 10,000 sampled tables and 99% CI.
[n.s.] Statistically non-significant ($p > .05$).

average demand (L/hh/d) for each of the six indoor end-use consumption categories across the four periods, for both dependent and independent tests. This confirms that the six indoor water end-use consumption categories are non-seasonal, and justifies the exclusion of climatic and seasonal factors from this study. Further, this has ensured that the 210 households' metered consumption in the winter 2010 dataset used for models development in the current study is representative of end-use consumption across the other three periods.

The factors chosen for this study are now discussed in relation to the criteria presented above for selecting factors influencing water consumption.

4. Factors influencing residential indoor water end-use consumption

A number of factors have been found to influence residential indoor water consumption. Such factors are mainly related to demographic, socio-demographic and water stock efficiency characteristics. Demographic and socio-demographic factors such as household occupancy and household income have been found to influence water consumption (Beal et al., 2012b, 2013; Beal and Stewart, 2011; Fielding et al., 2012; Kim et al., 2007; Matos et al., 2014; Mayer and DeOreo, 1999; Renwick and Archibald, 1998; Turner et al., 2009; Willis et al., 2009e, 2013). In addition, other studies have reported associations between the use of water-efficient technologies in residential dwellings, and reduced water consumption (Athuraliya et al., 2008; Beal and Stewart, 2011; Beal et al., 2013; Heinrich, 2007; Inman and Jeffrey, 2006; Lee et al., 2011; Mayer et al., 2004; Water Corporation, 2011; Willis et al., 2009e, 2013).

Factors influencing water end-use consumption that are covered in the current study generally fall into two main groups. The first encompasses the physical characteristics of *how* water is consumed by household occupants, and water end-use fixtures and appliances, and it comprises two categories of factors. The first category includes factors describing usage physical characteristics and subjective or manual practices of end-use water consumption at the household scale, which inherently and indirectly describe human consumption habits of households when modelling residential indoor water demand as classified by Jacobs and Haarhoff (2004b). Such factors represent the physical actions of consumers' decisions about how water is consumed, in terms of frequency, duration, volume and/or selection of programme or operating modes for both discretionary (i.e. shower, bath and tap) and automated/programmed (i.e. clothes washer, dishwasher and toilet) end uses. The second category includes factors describing the physical characteristics of water end-use appliances and fixtures installed and used in the residential dwelling. Such factors represent the water stock efficiency level, type, capacity, size, number of fixtures and appliances used in residential dwelling, and also the use of fixture add-ons (which are set or programmed by manufacturers, making them out of the consumer's control beyond the purchasing and installation decision). These factors were included to study the role of the physical characteristics of installed water end-use appliances and fixtures as well as fitted add-ons in shaping household consumption.

The second group of factors encompasses those describing characteristics of *who* is consuming water, which is represented by household characteristics and comprises two categories of factors. The first category includes factors describing demographic characteristics of household occupants including gender and age profiles. The second category includes factors describing household socio-demographic characteristics such as income level, predominant educational level and occupational status.

Detailed descriptions of the water consumption-influencing factors belonging to the four categories of characteristics described above are provided next, along with a discussion on the literature addressing relationships between them and each of the six indoor water end-use consumption categories covered in this study.

4.1. Usage physical characteristics

Frequency-, duration- and volume-related characteristics of each of the six residential water indoor end uses covered in this study are listed in Tables S1, S9, S16, S23, S30 and S36 in supplementary material S–B. As defined earlier, such characteristics describe the physical usage of water consumption for each end use, which is within the control of household consumers. The frequency-related characteristics include average number of clothes washer, shower, tap, toilet, dishwasher, and bath events.

The duration-related characteristics include average duration of shower and tap events per household (in minutes). However, it does not include duration of bath events or events related to other automated or programmed end uses (i.e. clothes washer, dishwasher and toilet). This is because bathing duration does not determine the volume of water used, and duration of water consumption for clothes washer, dishwasher and toilet events is programmed by manufacturers and is beyond the consumers' control.

The volume factor includes characteristics describing typical manual or subjective practices in discretionary end-use consumption, as well as the usual choice of mode or programme in automated or programmed ones that influence the amount of water consumed in the household. Such characteristics include rinsing dishes before using a dishwasher, rinsing food under running water, using a plug in the sink, average percentage of half flushes from total number of flushes per household per day, normally selected water volume mode or programme for clothes washer (i.e. auto, low, medium and full), water level used to fill the bathtub and selection of economy cycle programme or operating mode for dishwashers.

Usage physical characteristics are important for end-use consumption representation and demand modelling. It is obvious that the more frequent, longer and higher volume the water-consumption events, the higher the end-use consumption. However, such basic consumption-influencing factors (i.e. frequency, duration and volume) when quantified and studied with other factors (e.g. stock efficiency), could improve understanding about principal determinants of each water end-use consumption, enabling better targeted conservation strategies and more accurate potential saving estimations, and could be used as predictors for more accurate water end-use demand modelling. Therefore, such factors have been considered as essential input parameters for forming the mathematical structure in residential indoor water end-use demand modelling and spatial consumption variability representation (Beal and Stewart, 2011; Jacobs and Haarhoff, 2004b; Rathnayaka et al., 2011; Roberts, 2005). Additionally, the typical selection of economy cycle programmes when using a dishwasher reduces the dishwasher end-use water consumption (Beal and Stewart, 2011). Further, the use of dual flush toilets reduces toilet end-use water consumption (Beal and Stewart, 2011; Walton and Holmes, 2009). Therefore, consumption practices related to tap, clothes washer and bath end uses as described above were also included to study their influence on relevant end-use consumption categories.

4.2. End-use appliance and fixture physical characteristics

Characteristics related to water stock efficiency level, type, capacity or size, number of fixtures/appliances, and fitted add-ons for each of the six residential water indoor end uses covered in the current study are listed in Tables S1, S9, S16, S23, S30 and S36 in supplementary material S–B. Such physical characteristics of water end-use appliances/fixtures used in a residential dwelling were included to study their role in shaping household water end-use consumption, which is out of the consumer's control. Water stock efficiency level-related characteristics of all six end uses were categorised based on the standardised technical performance (star ratings, zero to six) of household appliances/fixtures developed by the Water Efficiency Labelling and Standards (WELS) scheme in Australia (Commonwealth of Australia, 2011). Such characteristics include stock efficiency star ratings for showerhead, tap and bathtub tap fixtures (based on average flow rate, L/min.), clothes washers (average litres per kilogram of clothes washed, L/kg), dishwashers (average litres per place setting) and toilets (average litres per flush).

Appliance/fixtures-related characteristics include type of clothes washer (i.e. front or top loader). However, type of toilets (i.e. single flush or dual flush toilets) was not included in this characteristics category. This is because, such characteristic was already represented by the average percentage of half flushes from total number of flushes described in this study in the usage physical characteristics category (see Section 4.1). Inclusion of both characteristics (type of toilet and percentage of half flushes to total number of flushes) in both categories (usage physical characteristics and appliance/fixtures physical characteristics) would be redundant and might cause a multicollinearity issue in the statistical analysis. The reason behind selecting this particular physical characteristic to represent the usage rather than the fixture, is the existing probability of consumers to select the full flushing mode every time even when a dual flush toilet is installed, as well as, the probability of double half or full flushing for one toilet event; thereby consuming similar amount of water as single flush toilets which was noted in previous studies (Jacobs and Haarhoff, 2004b; Loh and Coghlan, 2003). Another reason is to have a more accurate representation about the mode of flushing that is more frequently used in case both types of toilets (i.e. single flush and dual flush toilets) are installed in the same residential dwelling. Therefore, consumer's choice of the toilet water usage mode (i.e. flushing mode) caters for the type of the installed toilet fixture in a residential dwelling, and was considered more accurate for describing this characteristic.

The capacity- or size-related characteristics include clothes washer loading capacity (kg), dishwasher capacity (number of place settings) and bathtub size or capacity (L). The number of fixture/appliance-related characteristics includes number of showerhead fixtures, number of indoor tap fixtures (excluding bathtub tap), and number of toilets installed in household. However, the number of clothes washers, dishwashers and bathtubs was not included as a variable because multiple machines or bathtubs were not evident in the single-family households sample utilised in this study.

Characteristics related to add-ons were included to test for their influence on indoor tap end-use water consumption when installed in a residential dwelling. Such characteristics include fitted tap regulators (e.g. aerators, flow controllers or restrictors) on any indoor taps, installed insinkerator, installed separate tap for filtered/purified water and tap-plumbed ice maker on fridge. Further, the influence of having a dishwasher on the tap end-use water consumption was tested to account for differences in tap end-use consumption due to more or less dishes being hand washed. However, the effect on tap end-use consumption of having a clothes washer was not tested as there were no cases of households not owning a washing machine.

Associations have been reported in the literature between appliance/fixture physical characteristics and the six end-use consumption categories. For example, use of efficient showerhead fixtures results in significant reductions in shower end-use consumption (Beal et al., 2012b; Beal and Stewart, 2011; Gato-Trinidad et al., 2011; Jacobs and Haarhoff, 2004a; Loh and Coghlan, 2003; Makki et al., 2013, 2011; Mayer and DeOreo, 1999; Mayer et al., 2004; Roberts, 2005; Turner et al., 2007; Willis et al., 2013). Moreover, the use of efficient tap fixtures and low-flow tap add-ons such as flow controllers or restrictors reduces tap water end-use consumption (Beal and Stewart, 2011; Cooley et al., 2010; Fielding et al., 2012; Mayer and DeOreo, 1999; Roberts, 2005; Turner et al., 2005). Therefore, other tap-related add-ons described above were also included to study their influence on tap end-use consumption. It has been noted in previous studies that having a dishwasher influences tap end-use consumption (Gato, 2006; Mayer and DeOreo, 1999; Willis et al., 2009d). Hence, the influence of dishwasher ownership status in households on tap end-use consumption was studied.

It has been also reported that the use of efficient and front-loading washing machines can result in substantial water savings in clothes washer end-use consumption (Beal et al., 2012b; Beal and Stewart, 2011; Davis, 2008; Gato-Trinidad et al., 2011; Gato, 2006; Lee et al., 2011; Water Corporation, 2011; Willis et al., 2009e, 2013). Similarly, dual flush and efficient low-flow toilets consume less water than single flush and inefficient toilets (Beal and Stewart, 2011; Jacobs and Haarhoff, 2004a; Lee et al., 2011; Mayer and DeOreo, 1999; Roberts, 2005; Walton and Holmes, 2009). Further, the use of efficient dishwashers has been found to reduce dishwasher end-use water consumption. However, such reduction is insubstantial relative to the savings that can be achieved by utilising efficient appliances/fixtures for other end uses (e.g. efficient showerheads, clothes washers and toilets) (Beal and Stewart, 2011; Lee et al., 2011), as dishwasher end-use consumption usually represents a smaller proportion of total indoor water consumption (Beal and Stewart, 2011). In contrast to other end uses, efficient bathtub fixtures have not been found to reduce bath end-use consumption, as bathing usually requires a fixed amount of water (Mayer et al., 2004).

In relation to number-, capacity- or size-related characteristics of appliances and fixtures, Mayer and DeOreo (1999) used house size (i.e. square feet) as a proxy for its number of toilets and taps, and found that both are positively correlated with end-use consumption. Thus, number of showerhead fixtures, number of indoor tap fixtures (excluding bathtub tap), and number of toilets in household were included in this study as well. Moreover, Jacobs and Haarhoff (2004b) suggested that utilising parameters such as bathtub size could refine the description of the bath end-use event, therefore it was included in this study. Further, Loh and Coghlan (2003) also suggested that washing machine capacity has an influence on water consumption. Therefore, the influence of clothes washer and dishwasher capacity characteristics on their related water end-use consumption categories were studied as well.

4.3. Demographic and household makeup characteristics

Demographic and household makeup-related characteristics included in the current study to assess their influence on each of the six residential water indoor end-use consumption categories are listed in Tables S1, S9, S16, S23, S30 and S36 in supplementary material S–B. They include the number of people in the household belonging to particular age and gender profiles: adults, children or dependents, teenagers, children aged between four and 12 years, children aged three years or younger, and males and females. Such detailed household demographic information allowed for the investigation of a wide range of household size, age and gender combinations to explore the influence of different household makeup compositions on each of the six end-use consumption categories.

Generally, household size is one of the most influential characteristics on residential total indoor water consumption at the household scale. Therefore, it is an important forecasting parameter to be included for the development of reliable water demand forecasting models at that scale. Further, as discussed earlier, exploring the positive relationship between household size (represented by age and gender profiles) and residential water consumption at the household scale enables the capturing of variation in consumption of different household makeup characteristics belonging to each household size category. Such exploration, when conducted on an end-use level, identifies the principal demographic and household makeup characteristics influencing each of the six indoor end-use consumption categories.

Previous studies have reported that shower end-use consumption increases in larger families, particularly those with younger children and teenagers (Beal and Stewart, 2011; Gato, 2006; Makki et al., 2013, 2011; Mayer and DeOreo, 1999; Willis et al., 2013). Gender has also been found to have an influence on shower end-use consumption (Makki et al., 2013). Similarly, clothes washer end-use consumption is positively related to household size and number of teenagers and younger children in the household (Beal and Stewart, 2011; Gato, 2006; Mayer and DeOreo, 1999; Willis et al., 2009d). Tap and toilet end-use consumption is also positively related to household size, but in contrast to the case of shower and clothes washer consumption, it increases at a higher rate with the addition of higher age occupants such as adults, than with the addition of younger children (Beal and Stewart, 2011; Gato, 2006; Mayer and DeOreo, 1999). Household size has also been found to positively influence dishwasher end-use consumption, although the number of teenagers or younger children has only a weak influence (Gato, 2006; Mayer and DeOreo, 1999). Mayer and DeOreo (1999), indicated that household size is positively related to bath end-use consumption. However, in a study conducted in Australia, Willis et al. (2009d) found that only younger couples and families use bathtubs. Similarly, Beal and Stewart (2011) noted that bathing is commonly associated with families with younger children. Likewise, in the data set used for the current study, bath usage was reported only by households with couples and families that have younger children; not by single-adult, three-or-more-adult, or all-male households.

4.4. Socio-demographic characteristics

The socio-demographic characteristics examined in the current study for their influence on each of the six residential water indoor end-use consumption categories are listed in Tables S1, S9, S16, S23, S30 and S36 in supplementary material S–B. They include occupational status, predominant educational level and annual income level of household members. Occupational status was included to account for differences in consumption between households with any occupants staying at home during the day and those with occupants for whom some of their end-use consumption (e.g. tap and toilet) are partially displaced outside the house. The predominant educational and annual income level characteristics of households were included to study the effect of these groups lifestyle on each of the six end-use water consumption categories.

Total indoor water consumption in households with working residents is significantly higher than that in households with retired residents, and this is mainly due to shower, clothes washer and dishwasher end-use consumption categories (Beal et al., 2012b; Beal and Stewart, 2011). Makki et al. (2013) suggested that shower end-use consumption often represent a large proportion of residential indoor water consumption and it is positively correlated with occupation status, education level and income level. Similarly, Mayer and DeOreo (1999) reported positive correlations between the number of employed people in a household and shower, bath and clothes washer end-use consumption; but negative associations of this factor with tap, toilet and dishwasher consumption. They also reported a relatively weak positive relationship between income level and shower, bath, clothes washer and dishwasher end-use consumption categories. It might be expected that there is a level of association between socio-demographic characteristics (e.g. higher education working households are most likely to be the higher income households) when combined in end-use model development. Thus, such associations were accounted for in the model development process for each end use in this study.

All four categories of characteristics described above, and their related factors influencing each of the six indoor water end-use consumption categories covered in this study are the focus of the investigation process described below. The applied research design and method to achieve such objectives are discussed below.

5. Research approach

5.1. Research design

A mixed method research design was employed here to achieve the comprehensive objectives of the study. Both quantitative and qualitative approaches are used to obtain and analyse water end-use data. Such a complex design incorporates multiple methods to address research objectives (Creswell and Clark, 2007), and includes collection of both quantitative (water end-use consumption, water stock inventory data and socio-demographic survey) and qualitative (water consumption behavioural) data.

Water end-use consumption data were collected by fitting houses with high-resolution smart meters (0.014 L/pulse). These smart meters were connected to wireless data loggers that log (at 5-s record intervals) and store water flow data. Data loggers transfer water flow data to a central computer server via Water flow data were analysed and disaggregated into a registry of detailed

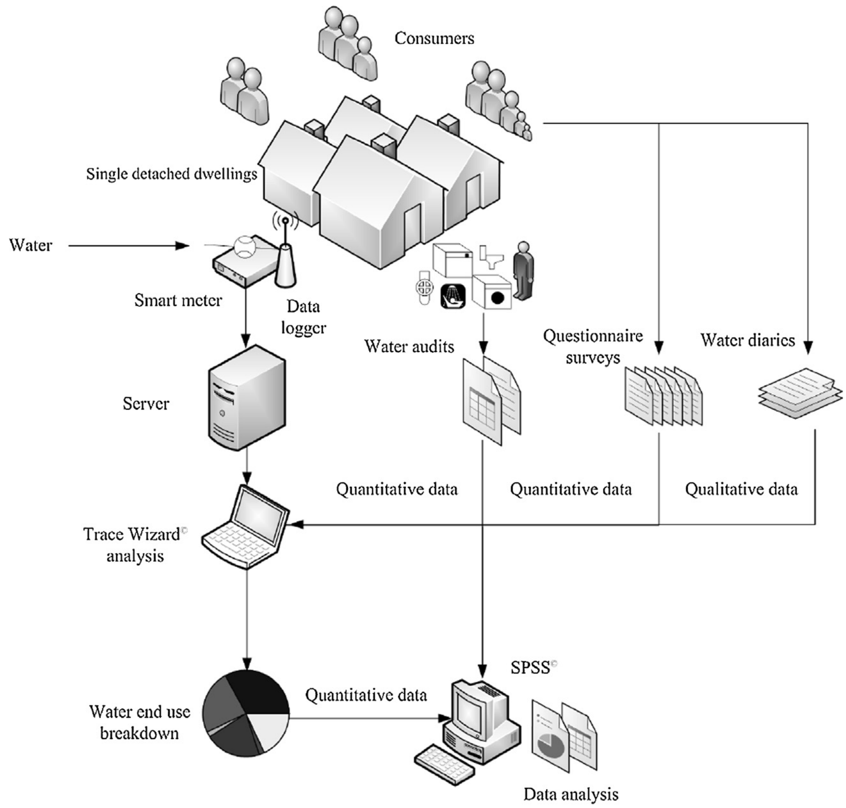


Fig. 3. Schematic illustrating the utilised water end use analysis process in the herein study (Makki et al., 2013).

end-use events (shower, washing machine, tap, etc.) using Trace Wizard® software version 4.1 (Aquacraft, 2010) on a personal or laptop computer.

Qualitative water consumption behavioural data were collected utilising self-reported water-use diaries for each household, which were developed for the study. The collected data were in the form of behavioural records of water usage over two-week sampling periods for each household in the sample.

In addition to the water diaries, quantitative data on appliance stock inventory (flow rate of fixtures, star ratings, etc.) were obtained using individual household audits. Both water-use diaries and appliance stock inventory audits assisted and ensured the validity of the Trace Wizard analysis by developing a qualitative understanding of where and when occupants are undertaking a certain water-consuming activity in their household.

Quantitative socio-demographic data were collected via developed questionnaire surveys distributed to each smart-metered household. The collected data were entered into SPSS for Windows, release version 21.0 (IBM_Corp, 2012) on a desktop computer, to enable analysis of results, particularly the determination and clustering of household makeup and socio-demographic groups, as well as household usage and appliance/fixture physical characteristic clusters for each end-use category (Tables S1, S9, S16, S23, S30 and S36 in supplementary material S–B). The detailed process for this mixed method water end-use study is presented in Fig. 3.

More detailed information about the instrumentation of data capture, data transfer and storage, Trace Wizard analysis, household stock audits, water diaries and socio-demographic surveys can be found in Beal and Stewart (2011).

5.1.1. Sampling criteria

Data used for this study were restricted to residential, single detached dwellings with mains-only water supply, which make up the majority of current residential stock in the SEQ region. This was designed to capture only single household data. Properties identified as having an internally plumbed rainwater tank or alternative supply source were not included in the sample, because end uses that could be sourced from the tank (e.g. toilet and/or clothes washer) could not be measured by the mains water meter. Another criterion in sample selection was that houses were occupied by their owners rather than renters, for reasons relating to consent, and to ensure that water bills are paid by the home owner. This is because rental households are typically transient and may move every 6–12 months, providing a poor sample for seasonal comparisons.

5.1.2. Situational context and sample characteristics

The residential households from which data were collected in this study are from four regions (Sunshine Coast Regional Council, Brisbane City Council, Ipswich City Council, and Gold Coast City Council) in SEQ, Australia (Fig. 4).

As mentioned earlier, the data utilised in this study were collected over two years (2010–11). The data were collected over four separate two-week sampling periods across winter 2010, summer 2010, winter 2011 and summer 2011 from 210, 48, 49 and 53 households, respectively. In the current study, the winter 2010 baseline data collected from the 210 households were used for model development and data collected in the other three sampling periods were used to validate the models. SEQ is a subtropical region with relatively mild winters (10–20 °C, compared with 17–32 °C the rest of the year) (Commonwealth of Australia, 2013a), which are expected to have little effect on indoor end-use consumption. However, in order to verify the representativeness of the indoor end-use data collected from the 210 metered households in winter 2010, they were compared with data from other households from three other periods, using statistical tests of means comparisons as discussed earlier in Section 3.3. The results are presented in Tables 2 and 3

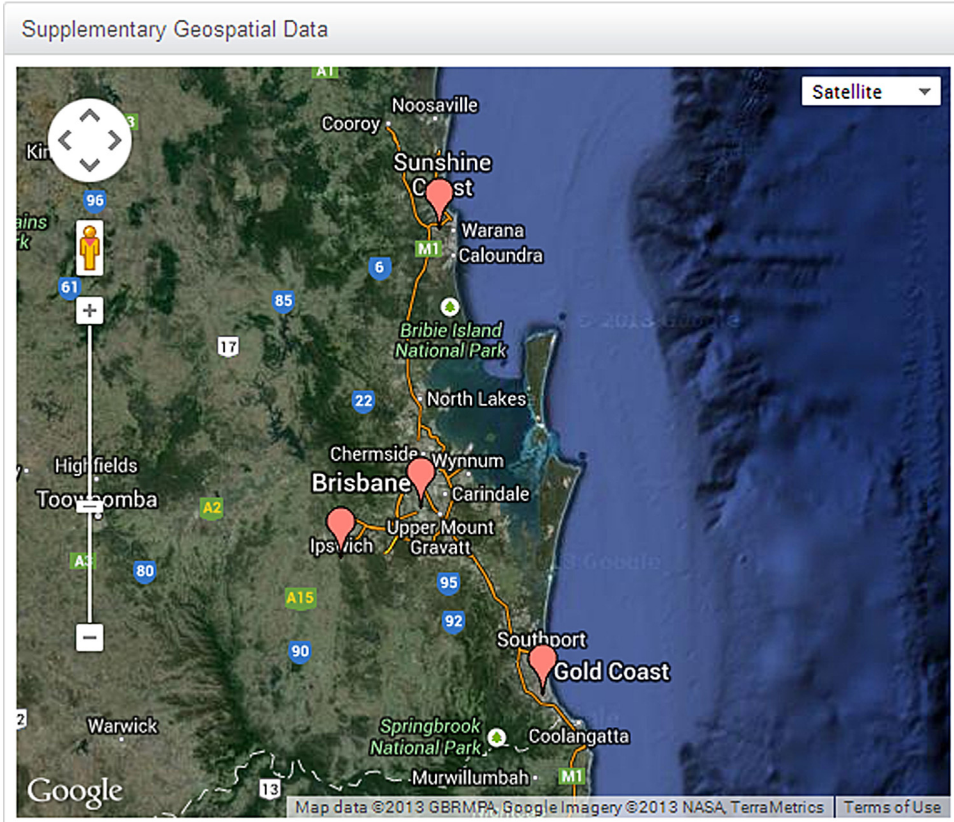
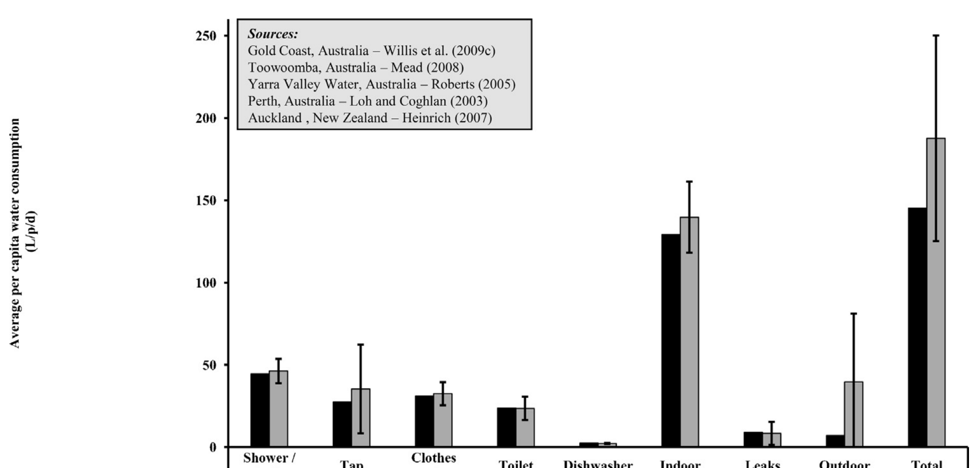


Fig. 4. Regions covered by SEQREUS (Beal and Stewart, 2011) and this study.

and Figs. 1 and 2, which show no significant differences between means of indoor end-use consumption averages across four reads. Further, a comparative study was conducted of average daily per capita water end-use consumption by 252 metered households in SEQREUS in winter 2010, from which the 210 samples utilised in the current study were drawn. These data were compared with those from a range of other studies recently conducted across Australia and New Zealand. As shown in Fig. 5, showers, clothes washer and tap indoor water end-use consumption categories consistently place the greatest demand on residential water supplies. Fig. 5 also shows that all indoor water end-use consumption categories, with the exception of tap, are relatively homogenous across regions, with the lowest per capita variance occurring for appliances which are programmed to use fixed water volumes (e.g. clothes washers, dishwashers and toilets). Finally, average daily per capita indoor consumption figures measured in the SEQREUS were well within the range reported elsewhere in Australia and New Zealand (see Fig. 5), ensuring the representativeness of the data set utilised herein (i.e. 210 metered households in winter 2010) for predictive purposes.



	Shower / bath	Tap	Clothes washer	Toilet	Dishwasher	Indoor	Leaks	Outdoor	Total
■ SEQREUS (Winter 2010, N=252)	44.5	27.5	31	23.7	2.5	129.2	9	7	145.2
□ Other studies	46.2	35.3	32.5	23.5	2.3	139.7	8.3	39.6	187.7

Fig. 5. Average daily per capita water end-use consumption results of SEQREUS (winter 2010) versus results of other Australian and New Zealand studies (Beal and Stewart, 2011).
Note: Error bars represent standard deviation between averages of daily per person water end-use consumption established by other studies cited in the chart.

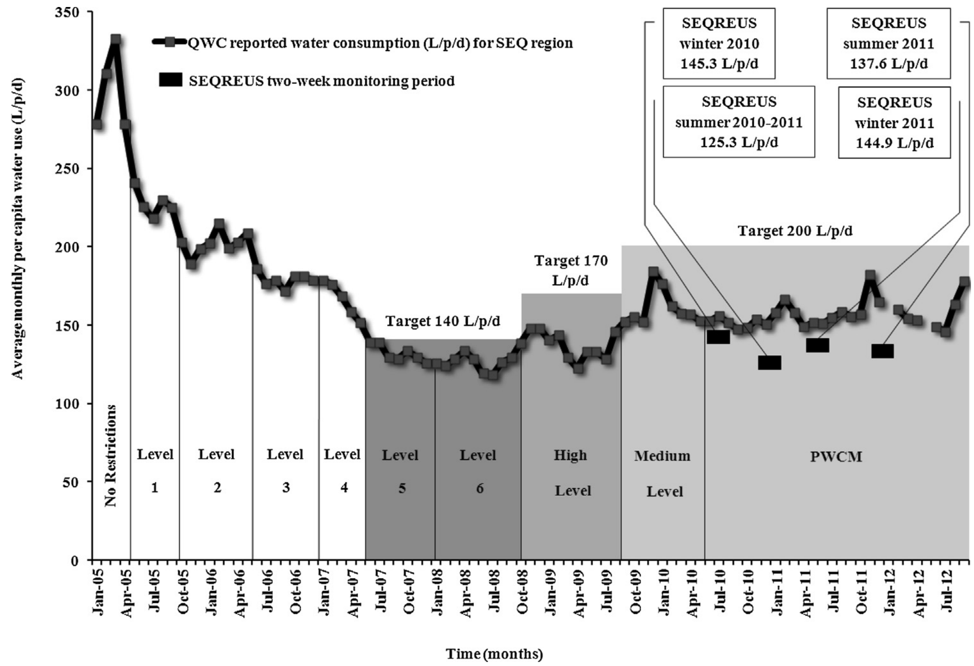


Fig. 6. Comparison between SEQREUS four reads total averages and government reported daily per capita water use of SEQ region (Beal and Stewart, 2011).

Water restrictions that could have directly influenced householders' indoor consumption were not in place at the time of data collection across the four monitoring periods used in this study, nor indeed the greater SEQREUS. Although a Permanent Water Conservation Measures (PWCM) daily target of 200 L per person per day (L/p/d) was set by the State Government during the data-collection period, PWCM targets are not considered restrictions. Instead, they are guidelines for the efficient use of potable water for irrigation purposes (e.g. irrigating lawns after 4 pm when there is less heat), which is outside the scope of this study, and provide only very broad guidance on efficient indoor consumption. Fig. 6 shows that both reported Queensland Water Commission (QWC) residential total water use averages and SEQREUS averages across winter 2010, summer 2010, winter 2011 and summer 2011 (145.3, 125.3, 144.9 and 137.6 L/p/d) fell well below the government's set target of 200 L/p/d (Beal and Stewart, 2011; QWC, 2010).

General characteristics of the sample utilised in the current study are presented in Figs. 7 and 8. Average household occupancy was relatively consistent across the four regions, averaging 2.65 people per household for all regions (see Fig. 7). Further, Fig. 8a–f provides a general overview of the proportions and mix of households' socio-demographic typologies and regional coverage that forms the structure of the sample utilised in this study.

5.2. Method overview

As outlined previously, utilising the combination of high-resolution smart-metering technology and computer software, along with household surveys, self-reported water usage diaries and water appliance/fixture audits facilitated the collection of detailed information for conducting comprehensive end-use studies. Such studies provide immense opportunity to advance

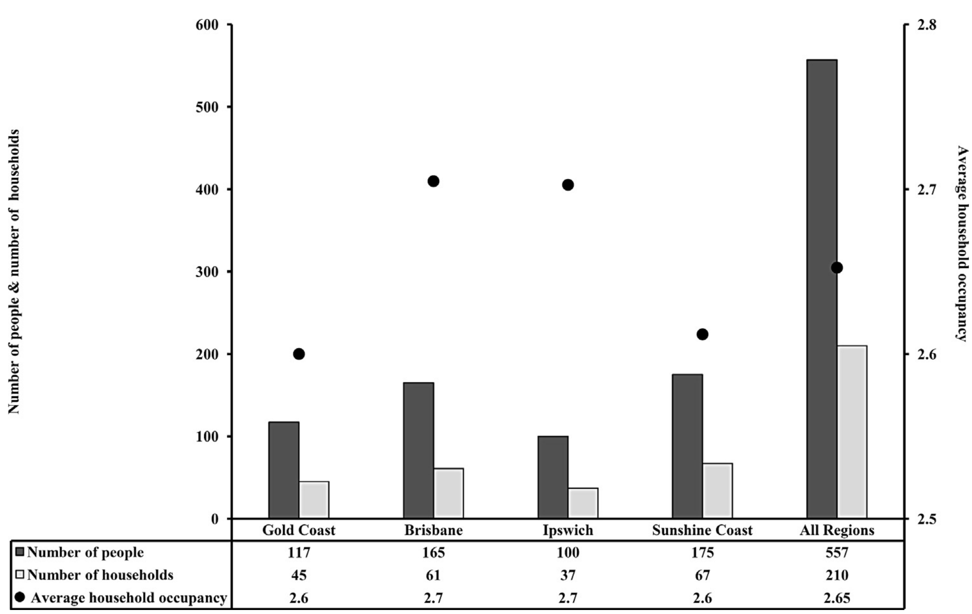


Fig. 7. Total and per region sample size and average household occupancy of the utilised sample in the herein study.

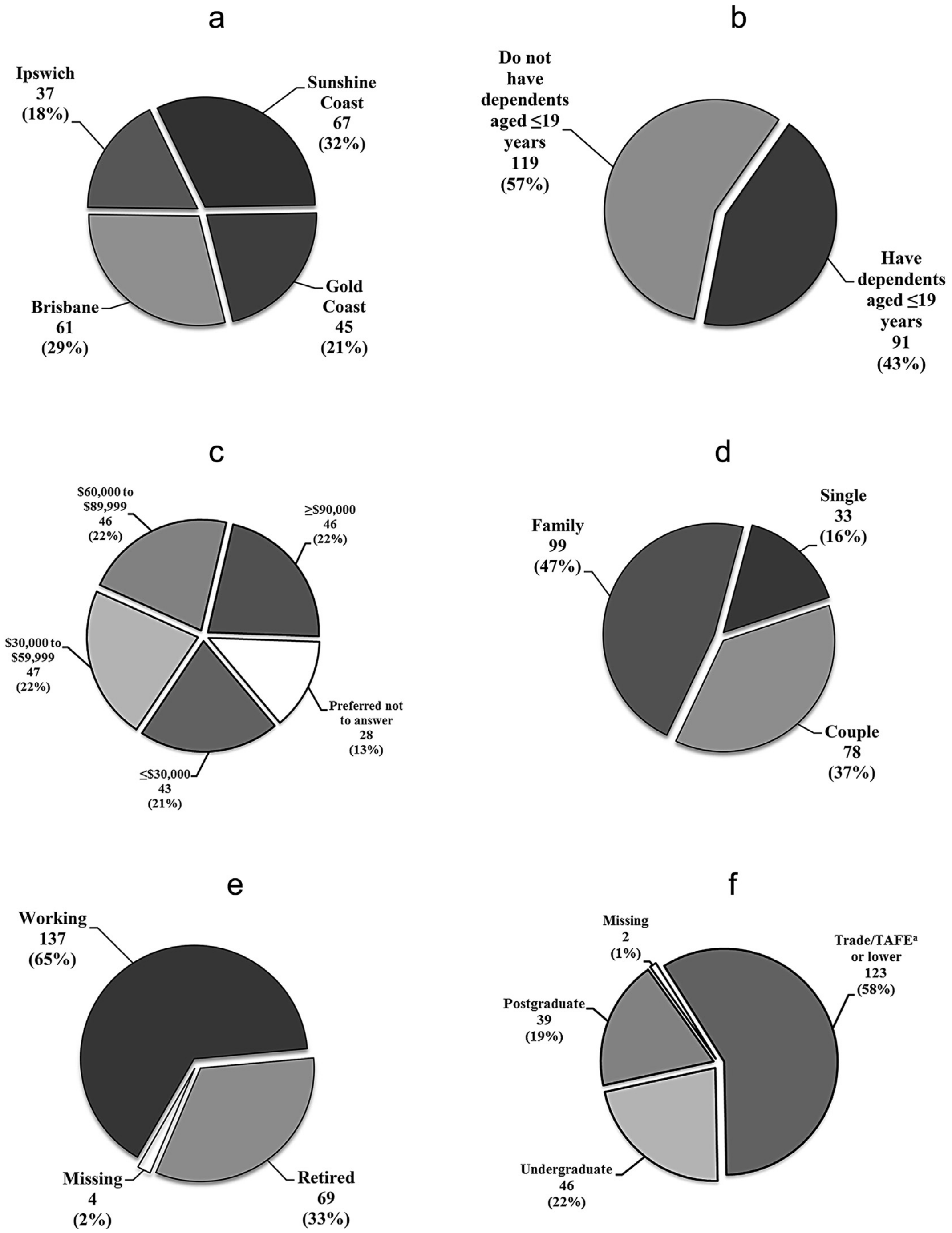


Fig. 8. General households characteristics forming the structure of the utilised sample in the herein study (N = 210 households). (a) Sampled households breakdown by region. (b) Sampled households breakdown by occupancy of dependents aged 19 years or less. (c) Sampled households breakdown by annual income level (AU$). (d) Sampled households breakdown by occupancy. (e) Sampled households breakdown by predominant occupational status. (f) Sampled households breakdown by predominant educational level.
[a]Technical and Further Education (Australia).

significantly understanding of residential water demand, and develop improved demand forecasting models. For the purposes of this study, this was done by examining correlations between detailed subsets of household characteristics and each of the end-use consumption categories to identify key determinants of consumption in each indoor water end-use category. Relationships among demand predictors for each end use were examined to determine the best grouping of predictors for the development of alternative forecasting models for each end-use category. The dominant consumption determinants for each water end-use consumption category were then used as demand predictors in development of forecasting models. Ultimately, the summation of demand predictions generated from the end-use forecasting models developed for each end-use category can provide a bottom-up evidence-based forecast of domestic water demand.

To achieve such comprehensive research objectives, cluster analysis, dummy coding, independent *t*-tests, independent one-way ANOVA, independent factorial ANOVA, multiple regression,

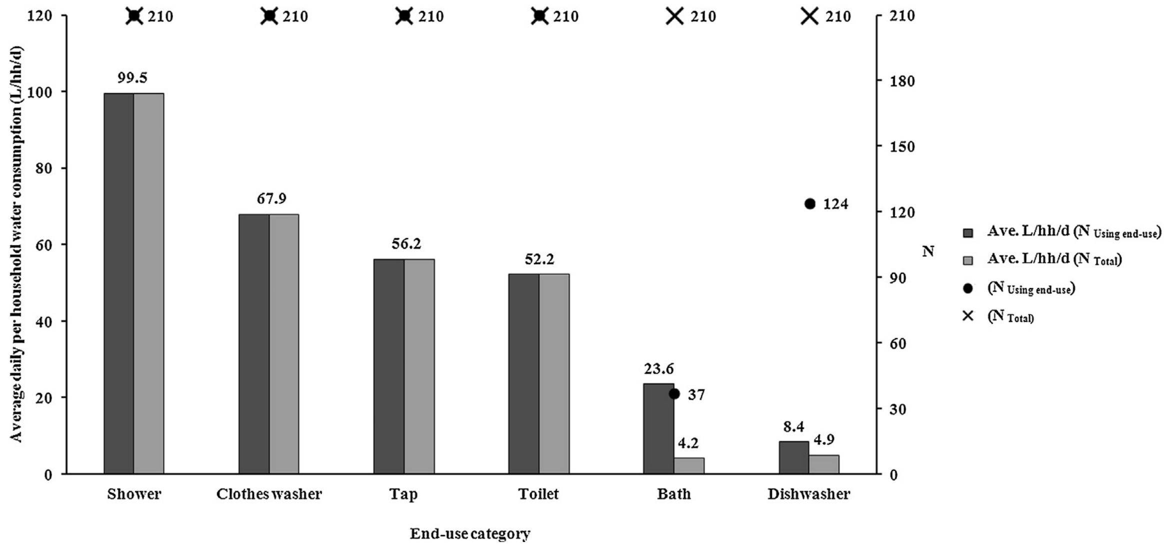


Fig. 9. Comparison between daily per household water end use consumption averages of total sampled households and averages of non-zero logged households (i.e. only households using end use) (Winter 2010).

Pearson's Chi-Square tests and bootstrapping statistical techniques were used. A comprehensive discussion on the use of each of these methods is presented in Sections 1–5 in supplementary material S–A.

6. Results and discussion

As shown in Figs. 9 and 10, end-use event disaggregation of water flow data collected in winter 2010 from $N_{Total} = 210$ households fitted with smart meters utilising flow trace analysis (Fig. 3), resulted in an average water consumption breakdown of 99.5, 67.9, 56.2, 52.2, 4.9 and 4.2 L/hh/d, respectively, for the shower, clothes washer, tap, toilet, dishwasher and bath end-use categories ranked from highest to lowest. This resulted in an average total indoor consumption of 284.9 L/hh/d. Thus, the shower, clothes washer, tap and toilet end-use categories represent the largest proportions of indoor consumption (34.9, 23.8, 19.7 and 18.3%) when compared to the dishwasher and bath end-use categories, which use 1.7 and 1.5% (Fig. 10).

As outlined in Section 3 in supplementary material S–A, only households with non-zero logged values for a given end-use, were included for analysis and model development for that end-use category. Figs. 9 and 10 show that consumption averages of households using the shower, clothes washer, tap and toilet end-use categories are the same as mentioned above for the total households in the sample, as $N_{Total} = N_{using\ end\ use} = 210$ households. However, Fig. 9 shows consumption averages of 32.6 and 8.4 L/hh/d for $N_{using\ end\ use} = 37$ and 124 households using the bath and dishwasher end-use categories.

To achieve the first and second objectives of this study (described in Section 1.4), the statistical methods described in Sections 1–5 in supplementary material S–A were applied to each end-use category. Average daily per household water consumption volumes of each end-use category representing the DV was studied against its associated set of IVs that belong to the four categories of characteristics described in Sections 4.1–4.4 and listed in Tables S1, S9, S16, S23, S30 and S36 in supplementary material S–B for the shower, clothes washer, tap, toilet, dishwasher and bath end-use categories, respectively.

Detailed data analysis and discussion on the resulting determinants of consumption, the utilised predictors and correlations between them, the drivers of consumption and the alternative forecasting models developed for each end-use category are provided in Sections 6–11 in supplementary material S–B accompanied with this paper. In the herein paper, a summary and discussion on key results of all end-use categories, along with the bottom-up total indoor forecasting model alternatives are provided in the following sections.

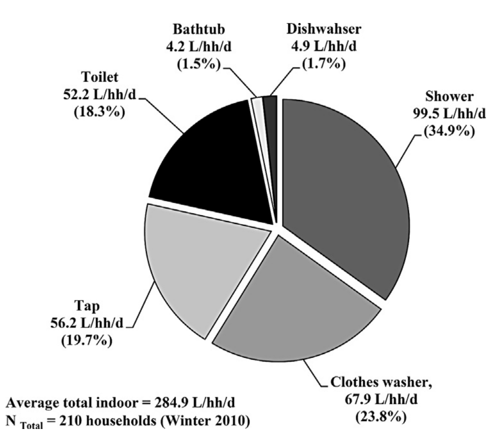


Fig. 10. Average daily per household indoor water end-use consumption breakdown.

6.1. Summary and discussion on key results of six indoor water end-use categories

6.1.1. Determinants of end-use consumption

A summary of the identified principal significant determinants of each of the six residential indoor water end-use consumption categories is presented in Table 4. The results show that the usage physical characteristic frequency of events (FQ) is the most important determinant of consumption for all categories and that average duration of events (D) is an important determinant of consumption for the shower and tap discretionary end-use categories only, which might be expected as other end-use categories are either automated to use a programmed water volume (clothes washer, toilet and dishwasher) or depend on filling to a limited water level (bath). Other usage physical determinants describing subjective and manual practices of end-use water consumption are also significant determinants of consumption of the tap, toilet, dishwasher

Table 4
Summary of the revealed principal determinants of six residential indoor water end-use consumption categories.

Determinants category	Shower	Clothes washer	Tap	Toilet	Dishwasher	Bath
Usage physical characteristics	FQ D	FQ	FQ D RDBDW RF PL	FQ HF	FQ ECO	FQ WL
Appliances/fixtures physical characteristics	S	S TYP CAP	S NIT DW ISE	S NT	S CAP	
Demographic and household makeup characteristics	$A+T+C_{4 \le Age \le 12y}+C_{Age \le 3y}$ $M+F$ HHS $A+C$ M C T F A $C_{4 \le Age \le 12y}$ $C_{Age \le 3y}$	HHS $A+T+C_{4 \le Age \le 12y}+C_{Age \le 3y}$ $A+C$ C $C_{Age \le 3y}$ $M+F$ M T A $C_{4 \le Age \le 12y}$ F	$HHS_{Age \ge 13y}$ $A+T$ $M_{Age \ge 13y}+F_{Age \ge 13y}$ A $M_{Age \ge 13y}$ T $F_{Age \ge 13y}$	$A+T+C_{4 \le Age \le 12y}$ $A+C_{Age \ge 4y}$ A $HHS_{Age \ge 4y}$ $C_{Age \ge 4y}$ T $C_{4 \le Age \le 12y}$	$C_{Age \le 3y}$ HHS M	HHS
Socio-demographic characteristic	I O E	O I			E I	I

Notes: Determinant symbols' definitions are provided in supplementary material (S–B). Determinants belonging to each category are presented in a cascading order based on their ability of explaining consumption (i.e. R^2) for each end use category.

and bath end-use categories. Such determinants include rinsing dishes before using the dishwasher (RDBDW), rinsing food under a running tap (RF) and using a plug in the sink (PL) for the tap end use; use of half flush mode (HF) in toilets; selection of economy cycle programme/mode (ECO) for dishwashers; and selected water level (WL) for the bath end use (Table 4).

Results presented in Table 4 also show that the stock efficiency (S) of appliances and fixtures in a residential dwelling is the most important appliances/fixtures physical determinant of consumption for all end-use categories other than baths. Moreover, capacity (CAP) of the appliance is a significant determinant of consumption for the clothes washer and dishwasher automated end-use categories, as is the type of the appliance (TYP) for the clothes washer end-use category. Number of indoor tap (NIT) and number of toilets (NT) are significant determinants of consumption of the tap and toilet end-use categories, respectively. Moreover, the use of dishwasher (DW) and insinkerator (ISE) characteristics were also found to be significant determinants of consumption of the tap end use category.

Results presented in Table 4 also suggest that the demographic characteristic household size generally is a significant determinant of consumption of all six end-use categories. Different household size representations using age and gender profiles were used, and revealed that all tested age and gender characteristics are significant demographic determinants of consumption of the shower and clothes washer end-use categories. Nevertheless, the identified significant age and gender demographic determinants of consumption of the tap end-use category include only occupants aged 13 years or more. Further, gender-related demographic characteristics were not significant determinants of consumption of the toilet end-use category, and its age-related determinants of consumption were restricted to households with occupants four or more years of age. The significant age- and gender-related determinants identified for consumption of the dishwasher end-use category only include existence of children aged three years or less in the household, household size in general and number of males in household. Household size, classifying households into two categories (being couples, and families with children) was the only significant demographic determinant of consumption of the bath end-use category.

Using the identified significant demographic determinants of each end-use category, three forms to fully represent the demographic household makeup characteristics of households were used whenever possible (household size in general, household makeup composite including age profiles with two levels of details, and household makeup composite including gender profiles). It was observed that the importance of such demographic and household makeup representations as significant determinants of consumption differs from one end-use category to another. Generally, gender-related household makeup composites are less capable of explaining all end-use consumption categories than household size in its general format and age makeup composites. As can be seen in Table 4, the most significant household makeup determinants of consumption of the shower, toilet and dishwasher end-use categories are based on age composites. Further, household size was the most significant demographic determinant of consumption of the clothes washer, tap and bath end-use categories. This indicates that shower, toilet and dishwasher use is more sensitive to age of household occupants than are other end-use categories. Similarly, shower water use is more sensitive to gender of occupants than all other end-use categories, whereas number of occupants in household is more important to the clothes washer, tap and bath end-use categories than their age or gender makeup, in order.

Results presented in Table 4 show that the household socio-demographic characteristics are determinants of consumption of the shower, clothes washer, dishwasher and bath end-use categories, but not the tap and toilet. Household annual income is a significant determinant of consumption of shower, clothes washer, dishwasher and bath water. This indicates that income might have two modes of influence on consumption in these categories. The first might be related to life style and leisure additional consumption purposes for the shower and bath end-use categories. The second might be related to affordability of detergents associated with the clothes washer and dishwasher end-use

Table 5
Summary of the developed residential water end-use demand alternative forecasting model predictors and input variables.

Forecasting model alternative	Shower	Clothes washer	Tap	Toilet	Dishwasher	Bath
ADHEUC 1	FQ + D + S	FQ + S + TYP + CAP	FQ + D + S	FQ + HF + S	FQ + ECO + S + CAP	FQ + WL
ADHEUC 2	$A + T + C_{4 \le Age \le 12y} + C_{Age \le 3y} + S$	HHS + I + S + TYP + CAP	$HHS_{Age \ge 13y} + D + S$	$A + T + C_{4 \le Age \le 12y} + HF + S$	$C_{Age \le 3y} + S + CAP$	I + WL
ADHEUC 3		HHS + O + S + TYP + CAP			$C_{Age \le 3y} + E + ECO + S + CAP$	

Notes: Predictor symbols' definitions are provided in supplementary material (S–B).
Sets of predictors of each alternative forecasting model are presented in a cascading order based on their prediction ability (i.e. highest R^2 and lowest *SE*) for each end use category.

categories. Occupational status is a significant determinant of consumption of only shower and clothes washer water, indicating that consumption in these categories is influenced the most by the predominant status of household occupants being at home or outside home during the day. Finally, predominant education level is a significant determinant of consumption only for the shower and dishwasher end-use categories.

6.1.2. Predictors of end-use consumption

A summary of the refined sets of significant predictors used for the development of forecasting model alternatives for each of the six residential indoor water end-use categories is presented in Table 5. This shows that the predictors of the first average daily household end-use consumption forecasting model alternative for all six end-use categories (ADHEUC 1) are a combination of both usage physical characteristics and appliance/fixtures physical characteristics, whereas, the predictors of the second and third forecasting model alternatives (ADHEUC 2 and ADHEUC 3) for each end-use category are combinations of appliance/fixtures physical characteristics, and either demographic and household makeup characteristics, socio-demographic characteristics, or both. In terms of the description of these characteristic categories discussed in Section 4 as being represented by predictors, these combinations indicate that the higher ability of explaining water end-use consumption (i.e. higher R^2 and lower *SE*) of ADHEUC 1 was achieved by using predictors describing *how* water is consumed, in terms of both occupants' usage and fixtures/appliances used by those occupants. In contrast, the ADHEUC 2 and ADHEUC 2 forecasting model alternatives are based on appliances/fixtures physical characteristics describing *how* water is consumed by the appliance/fixtures, together with demographic and socio-demographic predictors describing *who* is consuming water. These worked as surrogates to describe *how* water is consumed in terms of occupants' usage, as covered in the first alternative models. These sets of predictors were created by studying relationships among significant determinants of end-use consumption and were statistically refined using a method of entering predictors, indicating that end-use consumption is influenced by both appliances/fixtures and the occupants using them. Therefore, the appliances/fixtures characteristics should always be included in water end-use forecasting models to explain their partial role in shaping consumption, which is out of consumers' control, along with occupants' characteristics to explain their other partial role in shaping consumption, whether such characteristics are represented by their usage characteristics, their demographic and household makeup characteristics or socio-demographic characteristics, or both.

A discussion on how average daily per household water end-use consumption predictions could be derived from the developed end-use forecasting models (Eqs. S3–S16 in supplementary material S–B, also summarised in Table 6 in the herein paper), as well as how such models could be used to generate predictions of total indoor water consumption is provided in the following section.

6.2. Total indoor bottom-up forecasting model

Predictions of ADHEUC for each end-use category could be obtained using its related developed forecasting model alternatives (Eqs. S3–S16 in supplementary material S–B, Table 6) by identifying the required household characteristics as input parameters for each model. This could be achieved simply by assigning the membership of the household under which its end-use water consumption is to be predicted to its characteristics, using a value of 0 or 1. In this way, such values can be assigned to each variable in the equation, where a value of 1 refers to that household belonging to a particular characteristic group, and a value of 0 means no belonging. Given that the constant in the equations represents the average ADHEUC of households belonging to a particular set of its characteristics acting as the control group or the reference group, and that the coefficients in the equations represent differences in water consumption from the consumption of that control group, substituting values of 0 and 1 in the equation variables (i.e. household characteristics) to be multiplied by their related coefficients will retain consumption differences related to the household based on its assigned characteristics (i.e. coefficients multiplied by a value of 1) and will eliminate consumption differences of other characteristics to which it does not belong (i.e. coefficients multiplied by a value of 0). Based on the equation used, adding or subtracting the retained differences in consumption (i.e. retained coefficients) to or from, respectively, the consumption of the control group (i.e. the constant in the equation) will result in ADHEUC prediction of the household whose characteristics were determined. In this way, ADHEUC predictions of each of the six end-use categories could be generated using any of the relevant alternative forecasting models.

Towards a bottom-up evidence-based forecast of domestic water demand, the summation of water demand predictions generated from end-use forecasting models developed using one alternative model for each end-use category can provide predictions of average daily per household total indoor water consumption. As presented in Sections 6.3, 8.3, 9.3 and 11.3 in supplementary material S–B, two forecasting model alternatives were developed for each of the shower, tap, toilet and bath end use categories, and three alternatives were developed for each of the clothes washer and dishwasher end-use categories as presented in Sections 7.3 and 10.3 in supplementary material S–B. Using one of the forecasting model alternatives for each of the end-use categories selected based on the availability of required input parameters, the summation of predictions generated using any combination of models belonging to any of the alternatives (i.e. ADHEUC 1, ADHEUC 2 and ADHEUC 3) can provide predictions of average daily per household total indoor water consumption. Although the first alternative forecasting model for each of the six end-use categories is the most capable of explaining end-use consumption (i.e. showing higher R^2s and lower *SE*s) than the second and third alternative forecasting models (see Fig. 11 and Tables S8, S15, S22, S29, S35 and S41 in supplementary material S–B), the input parameters required for ADHEUC 2 and ADHEUC 3 to generate end-use

Table 6
Summary of developed residential indoor end-use demand forecasting models.

Consumption	ADHEUC forecasting model alternative	
Total indoor	$\mathrm{ADHEUC}_{\mathrm{Total\ indoor\ 1}} = \mathrm{ADHEUC}_{\mathrm{Shower\ 1}} + \mathrm{ADHEUC}_{\mathrm{Clothes\ washer\ 1}} + \mathrm{ADHEUC}_{\mathrm{Tap\ 1}} + \mathrm{ADHEUC}_{\mathrm{Toilet\ 1}} + \mathrm{ADHEUC}_{\mathrm{Dishwasher\ 1}} + \mathrm{ADHEUC}_{\mathrm{Bath\ 1}}$	(1)
	$\mathrm{ADHEUC}_{\mathrm{Total\ indoor\ 2}} = \mathrm{ADHEUC}_{\mathrm{Shower\ 2}} + \mathrm{ADHEUC}_{\mathrm{Clothes\ washer\ 2}} + \mathrm{ADHEUC}_{\mathrm{Tap\ 2}} + \mathrm{ADHEUC}_{\mathrm{Toilet\ 2}} + \mathrm{ADHEUC}_{\mathrm{Dishwasher\ 2}} + \mathrm{ADHEUC}_{\mathrm{Bath\ 2}}$	(2)
	$\mathrm{ADHEUC}_{\mathrm{Total\ indoor\ 2\&3}} = \mathrm{ADHEUC}_{\mathrm{Shower\ 2}} + \mathrm{ADHEUC}_{\mathrm{Clothes\ washer\ 3}} + \mathrm{ADHEUC}_{\mathrm{Tap\ 2}} + \mathrm{ADHEUC}_{\mathrm{Toilet\ 2}} + \mathrm{ADHEUC}_{\mathrm{Dishwasher\ 3}} + \mathrm{ADHEUC}_{\mathrm{Bath\ 2}}$	(3)
Shower	$\mathrm{ADHEUC}_{\mathrm{Shower\ 1}} = \begin{cases} 106.1 - 49.4(\mathrm{FQ}_{1^-}) + 63.7(\mathrm{FQ}_{3^+}) + 41.2(\mathrm{D}_{\geq 5}) - 46.9(\mathrm{S}_{3^+}) \pm 33.1^{a} \\ 0^{b} \end{cases}$	(S3)
	$\mathrm{ADHEUC}_{\mathrm{Shower\ 2}} = \begin{cases} 91.2 - 23.3(1\mathrm{A}) + 51.0(3\mathrm{A}^+) + 82.3(1\mathrm{T}^+) + 52.0\left(1\mathrm{C}^+_{4\leq \mathrm{Age} \leq 12\mathrm{y}}\right) + 32.4\left(1\mathrm{C}^+_{\mathrm{Age}\leq 3\mathrm{y}}\right) - 32.3(\mathrm{S}_{3^+}) \pm 48.5^{a} \\ 0^{b} \end{cases}$	(S4)
Clothes washer	$\mathrm{ADHEUC}_{\mathrm{Clothes\ washer\ 1}} = \begin{cases} 38.5 + 36.7(\mathrm{FQ}_{4\,\mathrm{to}\,7}) + 91.4(\mathrm{FQ}_{8^+}) - 19.4(\mathrm{S}_{3.5^+}) + 9.8(\mathrm{TYP}_{\mathrm{Top}}) - 7.8\left(\mathrm{CAP}_{<7\,\mathrm{kg}}\right) \pm 17.9^{a} \\ 0^{b} \end{cases}$	(S5)
	$\mathrm{ADHEUC}_{\mathrm{Clothes\ washer\ 2}} = \begin{cases} 58.4 + 24.0\left(3\mathrm{P}^+\right) + 27.2\left(\mathrm{I}_{\geq \$60,000}\right) - 26.1(\mathrm{S}_{3.5^+}) + 17.5(\mathrm{TYP}_{\mathrm{Top}}) - 16.4\left(\mathrm{CAP}_{<7\,\mathrm{kg}}\right) \pm 36.5^{a} \\ 0^{b} \end{cases}$	(S6)
	$\mathrm{ADHEUC}_{\mathrm{Clothes\ washer\ 3}} = \begin{cases} 73.6 + 24.0\left(3\mathrm{P}^+\right) - 31.2(\mathrm{O}_{\mathrm{R}}) - 19.9(\mathrm{S}_{3.5^+}) + 21.7(\mathrm{TYP}_{\mathrm{Top}}) - 14.2\left(\mathrm{CAP}_{<7\,\mathrm{kg}}\right) \pm 36.2^{a} \\ 0^{b} \end{cases}$	(S7)
Tap	$\mathrm{ADHEUC}_{\mathrm{Tap\ 1}} = \begin{cases} 20.2 + 23.0(\mathrm{FQ}_{19\,\mathrm{to}\,34}) + 55.3(\mathrm{FQ}_{35^+}) + 17.0(\mathrm{D}_{\geq 0.4}) - 18.0(\mathrm{S}_{6}) \pm 15.9^{a} \\ 0^{b} \end{cases}$	(S8)
	$\mathrm{ADHEUC}_{\mathrm{Tap\ 2}} = \begin{cases} 42.6 + 25.0\left(2, 3\mathrm{P}_{\mathrm{Age}\geq 13\mathrm{y}}\right) + 44.1\left(4\mathrm{P}^+_{\mathrm{Age}\geq 13\mathrm{y}}\right) + 16.0(\mathrm{D}_{\geq 0.4}) - 19.3(S_{6}) \pm 25.3^{a} \\ 0^{b} \end{cases}$	(S9)
Toilet	$\mathrm{ADHEUC}_{\mathrm{Toilet\ 1}} = \begin{cases} 31.0 + 15.3(\mathrm{FQ}_{6\,\mathrm{to}\,9}) + 44.7(\mathrm{FQ}_{10^+}) - 7.2(\mathrm{HF}_{>50\%}) - 17.1(\mathrm{S}_{3^+}) \pm 10.8^{a} \\ 0^{b} \end{cases}$	(S10)
	$\mathrm{ADHEUC}_{\mathrm{Toilet\ 2}} = \begin{cases} 53.1 - 13.9(1\mathrm{A}) + 20.9\left(3\mathrm{A}^+\right) + 16.0\left(1\mathrm{T}^+\right) + 9.7\left(1\mathrm{C}^+_{4\leq \mathrm{Age}\leq 12\mathrm{y}}\right) - 7.3(\mathrm{HF}_{>50\%}) - 11.2\left(\mathrm{S}^+_{3}\right) \pm 20.7^{a} \\ 0^{b} \end{cases}$	(S11)
Dishwasher	$\mathrm{ADHEUC}_{\mathrm{Dishwasher\ 1}} = \begin{cases} 5.6 + 5.5(\mathrm{FQ}_{4\,\mathrm{to}\,6}) + 12.3(\mathrm{FQ}_{7^+}) - 1.7(\mathrm{ECO}_{\mathrm{Yes}}) - 2.4(\mathrm{S}_{3.5^+}) + 2.4(\mathrm{CAP}_{>12\mathrm{PS}}) \pm 2.0^{a} \\ 0^{b} \end{cases}$	(S12)
	$\mathrm{ADHEUC}_{\mathrm{Dishwasher\ 2}} = \begin{cases} 9.0 + 3.1\left(1\mathrm{C}^+_{\mathrm{Age}\leq 3\mathrm{y}}\right) - 5.6(\mathrm{S}_{3.5^+}) + 3.0(\mathrm{CAP}_{>12\mathrm{PS}}) \pm 3.9^{a} \\ 0^{b} \end{cases}$	(S13)
	$\mathrm{ADHEUC}_{\mathrm{Dishwasher\ 3}} = \begin{cases} 9.1 + 3.8\left(1\mathrm{C}^+_{\mathrm{Age}\leq 3\mathrm{y}}\right) + 1.9(\mathrm{E}_{P}) - 2.0(\mathrm{ECO}_{\mathrm{Yes}}) - 4.0(\mathrm{S}_{3.5^+}) + 2.0(\mathrm{CAP}_{>12\mathrm{PS}}) \pm 3.9^{a} \\ 0^{b} \end{cases}$	(S14)
Bath	$\mathrm{ADHEUC}_{\mathrm{Bath\ 1}} = \begin{cases} 10.5 + 29.0(\mathrm{FQ}_{8^+}) + 18.3(\mathrm{WL}_{>70}) \pm 10.7^{a} \\ 0^{b} \end{cases}$	(S15)
	$\mathrm{ADHEUC}_{\mathrm{Bath\ 2}} = \begin{cases} 23.3 - 20.9\left(\mathrm{I}_{<\$60,000}\right) + 22.2(\mathrm{WL}_{>70}) \pm 14.9^{a} \\ 0^{b} \end{cases}$	(S16)

[a] If using the end use category e.
[b] If not using the end use category e.
Notes: Symbols' definitions are provided in supplementary material (S–B).

predictions are mainly based on household demographic and/or socio-demographic characteristics that are more easily collected by water businesses than the household physical usage input parameters (e.g. average frequency and duration of events) required by the ADHEUC 1 models, which must be estimated by household occupants themselves. However, having a smaller number of characteristic groupings was accounted for during the cluster analysis phase discussed in Section 1 in supplementary material S–A to ensure user friendliness of the models: fewer details are required for household characteristics to be assigned as input parameters, which was deemed suitable to increase the feasibility of the use of the forecasting model alternatives by both consumers and water utilities.

From this perspective (i.e. availability and type of required input parameters), three main total indoor bottom-up alternative model combinations could be used to generate predictions of average daily per household total indoor water consumption. The first combination includes the summation of predictions generated from the ADHEUC 1 models as presented in Eq. (1), Table 6. The second includes the summation of predictions generated from ADHEUC 2 models as presented in Eq. (2), Table 6. The third includes the summation of predictions generated from both ADHEUC 2 and ADHEUC 3 models (i.e. ADHEUC 2 and 3) as presented in Eq. (3), Table 6, because their required input parameters are based on demographic and/or socio-demographic characteristics.

Validation of each end-use forecasting model for each end-use category (Eqs. S3–S16 in supplementary material S–B, Table 6), and of bottom-up total indoor forecasting models using the three combinations of forecasting model alternatives presented above (Eqs. (1)–(3), Table 6) is outlined in the next section.

7. Validation

Initially, in order to visualise and perform preliminary checks of the daily average per household water consumption prediction coverage ranges of all forecasting models developed in this study, minimum and maximum achievable possible predictions were calculated for each of the forecasting model alternatives using Eqs. (S3)–(S16) in supplementary material S–B and Eqs. (1)–(3), Table 6. Fig. 11 presents these prediction ranges as well as *SE*s associated

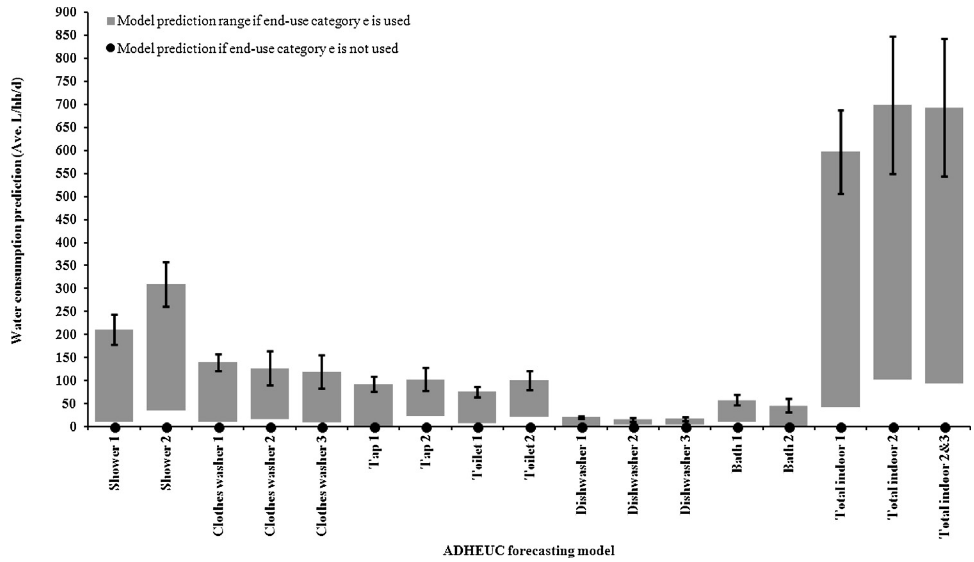


Fig. 11. Prediction ranges and *SE*s of developed ADHEUC forecasting models.
Notes: Error bars represent the *SE* of each of the developed ADHEUC forecasting model alternatives. Total indoor prediction ranges and *SE*s are obtained from the summation of lowest and highest achievable predictions and *SE*s of associated combination of developed forecasting model alternatives.

with each of the ADHEUC forecasting models. This shows that the models are capable of generating predictions that fall within these ranges, and are thus deemed acceptable, particularly because the observed average water end-use consumption averages of the data used for their development (presented in Figs. 9 and 10) fall well within these prediction ranges.

All of the forecasting models (Eqs. (S3)–(S16) in supplementary material S–B, Table 6) are a significant fit to the data used for their development, as determined by significant *F*-statistics for each model ($p < .001$), as well as the ability of the used predictors to predict and explain variation in end-use water consumption, assessed by having acceptable levels of R^2, *SE* and $CV_{Reg.}$ of each model (Tables S8, S15, S22, S29, S35 and S41 in supplementary material S–B). However, in order to go beyond having models that are a good fit to the data used, and to ensure the models and predictors used for their development can generalise to the population, regression analysis assumptions of model generalisation (Berry, 1993) as discussed in Section 3 in supplementary material S–A were tested and met. Moreover, given that the end-use forecasting models (Tables S8, S15, S22, S29, S35 and S41 in supplementary material S–B) are based on modelling significant consumption mean differences between different household characteristics, which are presented as the constants and coefficients in Eqs. (S3)–(S16) in supplementary material S–B (Table 6) as discussed in Section 3 in supplementary material S–A, the significance level of these constants and coefficients was calculated based on a stratified bootstrapped sample ($B = 1000$ samples, unless otherwise stated) in order to show their legitimate and genuine significance level if they were modelled from the population from which the data used for their development were drawn. This ensures that results can be generalised when used within their associated forecasting models to generate predictions. It is worth mentioning that most constants and coefficients were significant at $p < .001$ to the original sample (i.e. N = 210 households), but their adjusted significance levels based on the bootstrapped sample are lower ($p < .01$ and $p < .05$) as shown in Tables S8, S15, S22, S29, S35 and S41 in supplementary material S–B, which provide their estimated significance levels to the population from which the 210 households was drawn. Further, *Adj.* R^2 was calculated for each of the forecasting models (Tables S8, S15, S22, S29, S35 and S41 in supplementary material S–B) in order to estimate how well the developed forecasting models can explain variations in average daily per household end-use water consumption if they were derived from the population from which the data used for their development were drawn, showing the shrinkage in their predictive power. All developed models demonstrated strong *Adj.* R^2 values, with low loss of predictive power.

Having ensured the statistical robustness and generalisation capacity of the developed forecasting models, they were also cross-validated using another data set that was not used for their development. This was to test their usability and accuracy in generating average end-use water consumption predictions in other seasons, and to check if the predictors used in their development can accurately predict consumption at different points of time. In particular, the sets of predictors used in each of the developed models (summarised in Table 5) resulted from backward stepwise regression, which retained these predictors based on their significance to the utilised data. This will ensure that predictors were not retained in the models only due to their significance to the utilised data; rather, it will validate if their inclusion is due to their importance in explaining end-use consumption in another data set. Thus, as mentioned in Section 5.1.2, an independent data set collected over three separate two-week sampling periods across summer 2010, winter 2011, and summer 2011 from a randomly selected set of 51 different households was used for cross-validation of the developed forecasting models. These data were collected using the same sampling method and criteria (see Sections 5.1 and 5.1.1) employed to collect the data used for the forecasting models to be validated. This independent data set was used to validate all developed forecasting model alternatives by comparing observed ADHEUC to ADHEUC predicted using Eqs. (S3)–(S16) in supplementary material S–B and Eqs. (1)–(3), Table 6. These comparisons were assessed using R^2 and *SE* parameters in order to check how well the water consumption predictions generated using the developed models explain variation in observed consumption, where, $R^2 = 1$ and $SE = 0$ indicates perfect matching between observation and prediction.

In the validation data set, 51 households were using the shower, tap, and toilet end-use categories. However, only 49, 22 and six households of these 51 households were using the clothes washer, dishwasher and bath end-use categories, respectively. Although developed forecasting models can accommodate zero-logged households by giving them a value of zero as a consumption

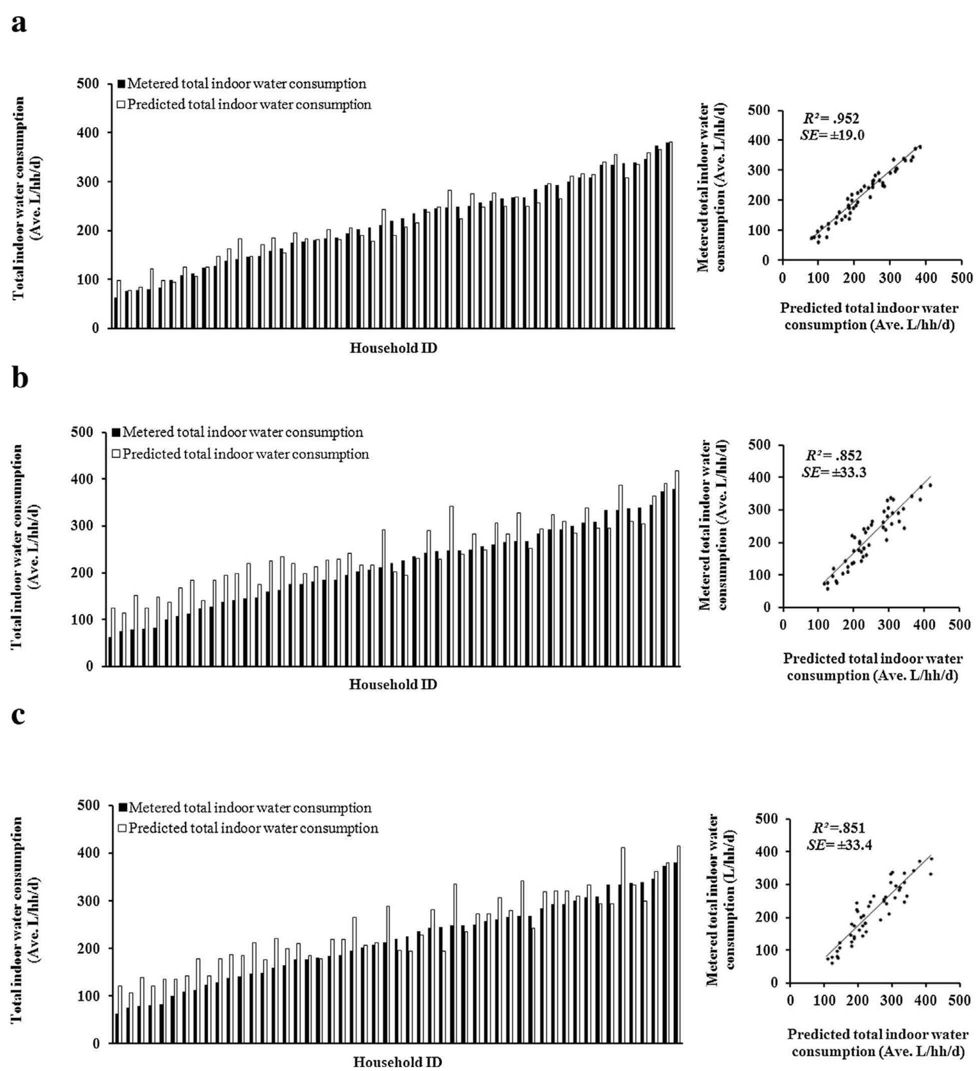
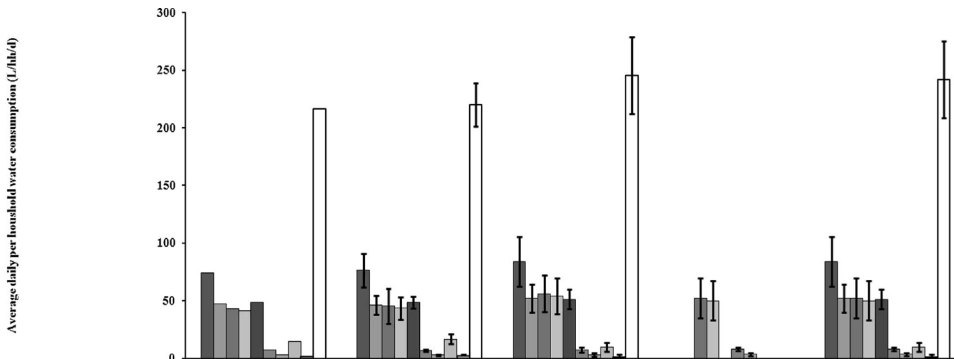


Fig. 12. Predicted versus metered average daily per household total indoor water consumption ($N_{Total} = 51$). (a) $ADHEUC_{Total\ indoor\ 1}$ predictions versus metered total indoor water consumption; (b) $ADHEUC_{Total\ indoor\ 2}$ predictions versus metered total indoor water consumption; (c) $ADHEUC_{Total\ indoor\ 2\&3}$ predictions versus metered total indoor water consumption.

prediction, the R^2 and *SE* parameters were calculated twice for the observed versus predicted comparisons. The first calculation is to validate the model when the full sample size of 51 households is used, including zero observed and zero predicted consumption, and the second is to validate the forecasting model by comparing observed versus predicted consumption of only households using the clothes washer, dishwasher and bath end-use categories. This is to genuinely validate the forecasting models developed for these end-use categories without taking advantage of zero variation between observations and predictions both having a value of zero L/hh/d water consumption that happened by chance in the used data set.

As shown in Figs. (S1)–(S6) in supplementary material S–C, the comparison analysis of observed (i.e. metered) versus predicted (calculated utilising Eqs. (S3)–(S16) in supplementary material S–B, Table 6) average daily per household water end-use consumption showed that all developed forecasting model alternatives fit the validation data set well, generating higher R^2 and lower *SE* values than the modelled values. Such R^2 and *SE* values range between $R^2 = .982$ and $SE = \pm 0.6$ L/hh/d of the $ADHEUC_{Dishwasher\ 1}$ forecasting model (Fig. S5a in supplementary material S–C), and $R^2 = .737$ and $SE = \pm 16.9$ L/hh/d of the $ADHEUC_{Clothes\ washer\ 3}$ forecasting model (Fig. S2c in supplementary material S–C). In general, the ADHEUC 1 models show more accuracy than do the ADHEUC 2 and ADHEUC 3, which is the case for the developed model and the original data set used for their development (i.e. N = 210, winter 2010). This indicates that the predictors used for each model alternative have similar importance to the validation data set (N = 51, summer 2010, winter 2011 and summer 2011). Further, Fig. 12a, b and c shows that the $ADHEUC_{Total\ indoor\ 1}$, $ADHEUC_{Total\ indoor\ 2}$, and $ADHEUC_{Total\ indoor\ 2\ and\ 3}$ forecasting models have higher R^2 values (.952, .852 and .851) and lower *SE* values (19.0, 33.3 and 33.4 L/hh/d), respectively. This result indicates that the developed forecasting models are capable of predicting total indoor consumption with relatively low error.

In addition, a comparison study between daily per household water consumption prediction averages using all forecasting model alternatives, and metered water consumption average of all households in the used validation data set was conducted. Fig. 13 shows that averages of water consumption predictions generated from the forecasting models developed for each end-use category, as well as total indoor consumption, were retained in the same proportion in the validation data set (i.e. predicted end-use breakdown is similar to actual metered breakdown, and falls within the *SE* ranges of predictions). Therefore, all forecasting model alternatives developed and presented in this study (Eqs. (S3)–(S16) in



		Metered	Prediction (ADHEUC 1)	Prediction (ADHEUC 2)	Prediction (ADHEUC 3)	Prediction (ADHEUC 2&3)
Shower	($N_{Total} = 51$)	73.8	76.3	83.8		83.8
Tap	($N_{Total} = 51$)	47.5	46.4	52.0		52.0
Clothes washer	($N_{Using\ end\text{-}use} = 49$)	43.1	45.4	56.1	52.0	52.0
Clothes washer	($N_{Total} = 51$)	41.4	43.6	53.9	49.9	49.9
Toilet	($N_{Total} = 51$)	48.7	48.6	51.3		51.3
Dishwasher	($N_{Using\ end\text{-}use} = 22$)	7.4	7.0	7.5	8.1	8.1
Dishwasher	($N_{Total} = 51$)	3.2	3.0	3.2	3.5	3.5
Bath	($N_{Using\ end\text{-}use} = 6$)	14.5	16.6	9.8		9.8
Bath	($N_{Total} = 51$)	1.7	2.0	1.2		1.2
Total indoor	($N_{Total} = 51$)	216.4	219.9	245.4		241.7

Fig. 13. Water end use consumption prediction averages versus metered water end use consumption averages.
Note: Error bars represent *SE* of predictions versus metered average daily per household consumption.

supplementary material S–B and Eqs. (1)–(3), Table 6) were deemed valid.

8. Conclusions

The study identified the most significant determinants belonging to the four categories of household characteristics for each end-use consumption category. The usage physical characteristics and the demographic and household makeup characteristics are the most significant determinants of all six end-use consumption categories. Further, the appliances/fixtures physical characteristics are significant determinants of the shower, clothes washer, toilet, tap and dishwasher end-use consumption categories, but not for the bath end-use category. Generally, socio-demographic characteristics are significant determinants of shower, clothes washer, dishwasher and bath water usage, but not for the tap and toilet end-use categories.

Correlations among the identified significant determinants of consumption for each end use category were examined, revealing that households with a higher frequency of shower events are most likely to be those with higher income, predominantly working occupants and larger families with higher numbers of adults, teenagers and children. Further, households with longer shower event duration are most likely to be higher income households with teenagers and children. Correlations among the determinants of clothes washer end-use consumption revealed that occupants of households with higher clothes washer event frequencies are most likely to have higher incomes, be predominantly working and consist of larger families. Also, households with higher tap event frequencies are most likely to be those with more occupants aged 13 years or over. Relationships among the determinants of toilet end-use consumption suggested that households with higher toilet event frequencies are most likely to be larger family households with higher numbers of occupants aged four or more years. Further, households with higher dishwasher event frequencies are most likely to be higher income households, higher education households and family households having children aged three years or less. Households normally using the economy cycle operating programme/mode on their dishwasher are most likely lower income households. Correlations among the determinants of bath end-use consumption indicate that households with higher bath event frequencies are most likely to be higher income and larger family households with children.

The correlations identified between determinants of each end-use consumption category have revealed the household demographic and socio-demographic drivers of higher end-use water consumption, deemed to be important conservation targets. This analysis process also identified predictors that work as proxies for each other, which enabled the choice of predictor sets to be used for the development of forecasting model alternatives for each end-use category. If water consumption is a function of appliances and occupants using them, the predictor sets identified in this study show that appliances/fixtures physical characteristics should always be included in end-use forecasting models as predictors, in order to explain the appliances/fixtures role in consumption along with other household characteristics explaining the role of occupants in consumption. The analysis suggests that occupants' roles in water end-use consumption can be explained by usage physical characteristics or demographic, household makeup and socio-demographic characteristics as predictors, because they work as proxies for each other. Based on the resulting predictor sets, forecasting model alternatives were developed for each end-use category using the most significant predictors. The developed models are capable of generating average daily per household end-use consumption predictions and have shown a significant level of fit to the data used for their development.

Towards an evidence-based forecast of domestic water demand, three total indoor bottom-up forecasting model alternatives were developed. These models are capable of generating average daily per household total indoor consumption predictions through the summation of predictions generated from three combinations of forecasting model alternatives for each of the six end-use categories. Such forecasting model alternatives provide flexibility of their utilisation in terms of required data input parameters by users, as well as user friendliness to generate predictions; this is since the method of entering such input parameters is based on assigning the household(s) being predicted with clustered characteristic memberships using binary codes (zeros, ones or combinations of both).

All developed forecasting models have met the generalisation statistical criteria, and have been cross-validated using an independent validation data set of 51 randomly selected households in SEQ, Australia, collected over three separate two-week sampling periods across summer 2010, winter 2011 and summer 2011. All forecasting model alternatives developed using the identified sets of predictors performed well in explaining variation in average daily per household end-use consumption, as well as total indoor water consumption. The models showed respectable prediction accuracy, which indicated the validity of the chosen predictors and their usability at different time points. As detailed in the next section, the urgent need for more robust micro-component level models created from detailed empirical water end-use event data registries (i.e. micro-level bottom-up model) is crucial for better urban water planning.

9. Study implications

This study advances current understanding on residential end-use water consumption, which are the fundamental building blocks for assisting water businesses and government policy officers in the design and implementation of better targeted and more effective water conservation strategies. Specifically, the identified determinants of each water end-use consumption category and significant correlations among them can assist planners in targeting particular subsets of household typologies for best-value water conservation initiatives due to their identified higher influence on that end use. This highly targeted water demand management approach can optimise water conservation efforts to achieve substantial water savings at least cost.

This study has also provided further empirical support to the growing body of knowledge highlighting that the replacement of lower efficiency appliances and fixtures with more efficient ones will result in considerable reductions in water consumption. Retrofit programmes using efficient water appliances and fixtures are confirmed herein as a least-cost potable water savings measure that can be easily implemented by water businesses and/or government agencies.

Finally, the suite of formulated end-use forecasting models developed in this study will be invaluable for urban water demand forecasting professionals when completing water balance or infrastructure planning reports. However, as a note of caution, the presented models should be considered in relation to the situational context of the research investigation (in this case, SEQ, Australia) and needs to be adapted for use elsewhere. Nonetheless, it is strongly believed that most of the determinants of consumption identified herein, the predictors of all end-use consumption categories, and their relative level of predictive power, will hold true in other regions, both elsewhere in Australia and in other developed nations.

10. Limitations and future research directions

Despite the higher accuracy of flow data collected in water end use studies utilising high resolution smart-metering technology, they are costly and time consuming; thereby prohibiting large and widespread sample sizes. Nonetheless, the cost of this technology will reduce over time and enable larger samples to be examined over longer time periods. This is to enhancing the statistical power of the forecasting model, as well as, increasing their ability to explain variations in consumption through utilising more detailed predictors. Although the utilisation of the bootstrapping technique has increased the statistical power and robustness of the developed models in the herein study, a larger sample size of the original data set will allow utilising a larger number of dummy coded determinant categories (e.g. the household size demographic determinant could be categorised into eight categories: one person household to eight or more person households, instead of being clustered into three categories due to lower sample size of households having six or more occupants), as well as, exploring more detailed household characteristics (e.g. female teenagers, male teenagers, female adults, male adults, etc.).

Despite that the developed forecasting models in the herein study are static and based on a snapshot of collected end use data, they could be used to derive predictions at different time points. This is to account for the change in end use water consumption over time. Ideally, data is collected remotely and stored over longer time periods and automatically disaggregated into water end use events as demonstrated to be possible by Nguyen et al. (2014) and Nguyen et al. (2013a,b); aligned household data is also updated over time. Such a dynamic micro-component model will be an ideal tool for just-in-time residential demand forecasting in the urban water context.

Finally, determinants of consumption have been explored in the herein study at the household scale. Determinants of consumption at other consumption scales including macro factors (i.e. government policy of region, environmental context, etc.), and micro factors (e.g. individual motivations, attitudes, etc.), and a range of other socio-demographic factors could be also explored in future studies. Furthermore, interactions between the revealed determinants within each of the consumption scales (e.g. interactions between environmental context and government policy), as well as, the interaction between the revealed determinants at different scales of consumption (e.g. interactions between government policy, environmental context and individual motivations attitudes) could be also explored to reveal their role in shaping urban water demand.

The next stage of this investigation is revealing determinants of consumption, as well as, developing modules for outdoor (i.e. irrigation) and leakage end uses by applying a range of complex prediction techniques, given their greater variability and uncertainty when compared to indoor end uses. Such models could be added to the developed models in the herein study. The summation of all end use predictions from such complex models (i.e. indoor, outdoor, and leakage) can provide an evidence-based forecast of urban residential connection demand. Furthermore, averaged daily diurnal pattern profiles based on revealed significant household characteristics will be linked to each of the developed end use models enabling the models to show how their generated predictions will be distributed over the day in hourly basis. Next to this, a web-based water end-use demand forecasting tool will be developed that is capable of generating demand predictions of each end use category, total indoor, outdoor, leakage, as well as, the diurnal pattern profiles associated with each of them. Such model and associated software tool has a number of purposes, including water demand forecasting, water infrastructure network planning, demand management scheme evaluation, social behavioural marketing scenario analysis, to name a few.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.resconrec.2014.11.009. These data include Google maps of the most important areas described in this article.

References

Anand C, Apul DS. Economic and environmental analysis of standard high efficiency, rainwater flushed, and composting toilets. J Environ Manage 2011;92(3):419–28.

Aquacraft. Trace Wizard® software, 4.1 ed. 1995–2010. Boulder, CO, USA: Aquacraft, Inc; 2010 http://www.aquacraft.com/

Arbués F, Barberán R, Villanúa I. Water price impact on residential water demand in the city of Zaragoza. A dynamic panel data approach. In: 40th European Congress of the European Regional Studies Association (ERSA) in Barcelona, Spain; 2000.

Arbués F, Garcıa-Valiñas MÁ, Martınez-Espiñeira R. Estimation of residential water demand: a state-of-the-art review. J Socio-econ 2003;32:81–102.

Arbués F, Villanúa I, Barberán R. Household size and residential water demand: an empirical approach*. Aust J Agric Resour Econ 2010;54:61–80.

Athuraliya A, Gan K, Roberts P. Yarra Valley Water 2007 appliance stock and usage patterns survey. Victoria: Yarra Valley Water; 2008.

Babbie E. The practice of social research. 13th ed.; 2012, CengageBrain.com.

Barthelemy OT. Untangling scenario components with agent based modelling. Manchester Metropolitan University; 2006.

Bates B, Kundzewicz ZW, Wu S, Palutikof J. Climate change and water. Intergovernmental Panel on Climate Change (IPCC); 2008.

Baumann DD, Boland JJ, Hanemann MW. Urban water demand management and planning; 1997.

Beal C, Bertone E, Stewart RA. Evaluating the energy and carbon reductions resulting from resource-efficient household stock. Energy Build 2012a;55:422–32.

Beal C, Gardner T, Sharma A, Barton R, Chong M. A desktop analysis of potable water savings from internally plumbed rainwater tanks in South East Qld. Urban Water Security Research Alliance. Technical Report No. 26; 2011a http://www.urbanwateralliance.org.au/publications/UWSRA-tr26.pdf

Beal C, Makki AA, Stewart RA. Identifying the drivers of water consumption: a summary of results from the South East Queensland residential end use study, Science Forum and Stakeholder Engagement: Building Linkages Collaboration and Science Quality. Urban Water Secur Res Alliance 2012b:126–32.

Beal C, Stewart R, Huang T, Rey E. SEQ residential end use study. J Aust Water Assoc 2011b;38:80–4.

Beal C, Stewart RA. South East Queensland residential end use study: final report. Urban Water Security Research Alliance. Technical Report No. 47; 2011 http://www.urbanwateralliance.org.au/publications/UWSRA-tr47.pdf

Beal CD, Sharma A, Gardner T, Chong M. A desktop analysis of potable water savings from internally plumbed rainwater tanks in South-East Queensland, Australia. Water Resour Manage 2012c;26(6):1577–90.

Beal CD, Stewart RA. Identifying residential water end-uses underpinning peak day and peak hour demand. J Water Resour Plan Manage 2013., http://dx.doi.org/10.1061/(ASCE)WR, 1943–5452.0000357.

Beal CD, Stewart RA, Gardner J, Fielding K, Spinks A, McCrae R. Mind or machine? Examining the drivers of residential water end-use efficiency. J Aust Water Assoc 2013;40(3):66–70.

Bennett C, Stewart RA, Beal CD. ANN-based residential water end-use demand forecasting model. Expert Syst Appl 2012;40:1014–23.

Berry WD. Understanding regression assumptions. Sage University paper series on quantitative applications in social sciences, 07-092. Newbury Park, CA: Sage; 1993.

Bertone E, Beal CD, Stewart RA. Using evidenced-based data to optimise water-energy-GHG nexus efficiency programs for residential developments in Queensland, Australia, IWA 2012. International Water Association; 2012.

Billings RB, Jones CV. Forecasting urban water demand. 2nd ed. Denver: American Water Works Association; 2008.

Blokker E, Vreeburg J, van Dijk J. Simulating residential water demand with a stochastic end-use model. J Water Resour Plan Manage 2010;136:19–26.

Britton T, Stewart RA, O'Halloran K. Smart metering: providing the foundation for post meter leakage management. In: 5th IWA specialist conference on efficient use and management of urban water. Australian Water Association; 2009.

Britton T, Stewart RA, O'Halloran K. Smart metering: enabler for rapid and effective post meter leakage identification and water loss management. J Clean Prod 2013;54:166–76.

Chen Z, Ngo HH, Guo W, Wang XC, Miechel C, Corby N, et al. Analysis of social attitude to the new end use of recycled water for household laundry in Australia by the regression models. J Environ Manage 2013;126:79–84.

Cole G, Stewart RA. Smart meter enabled disaggregation of urban peak water demand: precursor to effective urban water planning. Urban Water J 2012;10(3):174–94.

Commonwealth-of-Australia. Climate data online. Australian Government, Bureau of Meteorology; 2013a http://www.bom.gov.au/climate/data/index.shtml

Commonwealth-of-Australia. Drought. Australian Government, Bureau of Meteorology; 2013b http://www.bom.gov.au/lam/climate/levelthree/c20thc/drought.htm

Commonwealth-of-Australia. Living with drought. Australian Government, Bureau of Meteorology; 2013c http://www.bom.gov.au/climate/drought/livedrought.shtml

Commonwealth-of-Australia. Water Efficiency Labelling and Standards (WELS) scheme; 2011 http://www.waterrating.gov.au/

Cooley H, Christian-Smith J, Gleick PH, Cohen MJ, Heberger M, Ross N, et al. California's next million acre-feet: saving water, energy, and money. Oakland, September: Pacific Institute; 2010.

Corral-Verdugo Vc, Bechtel RB, Fraijo-Sing B. Environmental beliefs and water conservation: an empirical study. J Environ Psychol 2003;23:247–57.

Correljé A, François D, Verbeke T. Integrating water management and principles of policy: towards an EU framework? J Clean Prod 2007;15:1499–506.

Coultas E, Maheepala S, Neumann L, Beal C, Stewart RA, Chong M, et al. Towards the quantification of rainwater tank yield in South East Queensland by considering the spatial variability of tanks, Building Linkages, Collaboration and Science Quality. Urban Water Secur Res Alliance 2012:108–13.

Creasey J, Glennie E, Waylen C. Microcomponent-based forecasting for the AMP5 WRP: final report (August 2007). UK: Severn Trent Water, WRc plc; 2007 http://www.stwater.co.uk/upload/pdf/C5_WRc_report_UC7353_Microcomponents_for_AMP5_WRP_-_Revis_Au.pdf, UK.

Creswell JW, Clark VLP. Designing and conducting mixed methods research. USA: Sage Publications, Inc; 2007.

Davis LW. Durable goods and residential demand for energy and water: evidence from a field trial. RAND J Econ 2008;39:530–46.

DeOreo WB, Heaney JP, Mayer PW. Flow trace analysis to assess water use. J Am Water Works Assoc 1996;88:79–90.

Donkor EA, Mazzuchi TA, Soyer R, Roberson JA. Urban water demand forecasting: a review of methods and models. J Water Resour Plan Manage 2014;140(2):146–59.

Fielding KS, Russell S, Spinks A, Mankad A. Determinants of household water conservation: the role of demographic, infrastructure, behavior, and psychosocial variables. Water Resour Res 2012;48(10):1–12, http://dx.doi.org/10.1029/2012WR012398, W10510.

Fyfe J, May D, Turner A, White S. Complementary analytical techniques for urban water forecasting in IRP. In: Integrated resource planning for urban water—resource papers, Waterlines report. Canberra: National Water Commission; 2010.

Galán JM, López-Paredes A, Del Olmo R. An agent-based model for domestic water management in Valladolid metropolitan area. Water Resour Res 2009;45(5):1–17, http://dx.doi.org/10.1029/2007WR006536, W05401.

Gato-Trinidad S, Jayasuriya N, Roberts P. Understanding urban residential end uses of water. Water Sci Technol 2011;64:36–42.

Gato S. Forecasting urban residential water demand [PhD Thesis]. School of Civil, Environmental and Chemical Engineering. RMIT University; 2006.

Gleick PH. The world's water volume 7: the biennial report on freshwater resources. USA: Island Press; 2011.

Hanif HM, Rasmani KA, Ramli NM. Challenges in determining attributes to generate models for estimation of residential water consumption based on consumer data. In: AIP conference proceedings. Putrajaya, Malaysia: AIP Publishing LLC; 2013. p. 1306–11.

Heinrich M. Water end use and efficiency project (WEEP) – final report. BRANZ Study Report 159. New Zealand: Branz, Judgeford; 2007.

Heinrich M. Auckland water use study – monitoring of water end uses. SB10 New Zealand; 2009 http://www.branz.co.nz/cms_show_download.php?id=fd1b4c6fd498564cefe2084a7e99c7b0265b4607

House-Peters LA, Chang H. Urban water demand modeling: review of concepts, methods, and organizing principles. Water Resour Res 2011;47(5):1–15, http://dx.doi.org/10.1029/2010WR009624, W05401.

Howe CW, Linaweaver FP. The impact of price on residential water demand and its relation to system design and price structure. Water Resour Res 1967;3:13–32.

IBM_Corp. . IBM SPSS statistics for windows, version 21.0. Armonk, NY: IBM Corp; 2012.

Inman D, Jeffrey P. A review of residential water conservation tool performance and influences on implementation effectiveness. Urban Water J 2006;3:127–43.

Jacobs H, Haarhoff J. Application of a residential end-use model for estimating cold and hot water demand, wastewater flow and salinity. Water S A 2004a;30:305–16.

Jacobs H, Haarhoff J. Structure and data requirements of an end-use model for residential water demand and return flow. Water S A 2004b;30:293–304.

Jiang Y. China's water scarcity. J Environ Manage 2009;90(11):3185–96.

Jorgensen B, Graymore M, O'Toole K. Household water use behavior: an integrated model. J Environ Manage 2009;91:227–36.

Jorgensen BS, Martin JF, Pearce M, Willis E. Some difficulties and inconsistencies when using habit strength and reasoned action variables in models of metered household water conservation. J Environ Manage 2013a;115:124–35.

Jorgensen BS, Martin JF, Pearce MW, Willis EM. Predicting household water consumption with individual-level variables. Environ Behav 2013b:1–26, http://dx.doi.org/10.1177/0013916513482462.

Kenney DS, Goemans C, Klein R, Lowrey J, Reidy K. Residential water demand management: lessons from Aurora, Colorado1. J Am Water Resour Assoc 2008;44:192–207.

Kim S, Choi S, Koo J, Hyun I. Trend analysis of domestic water consumption depending upon social, cultural, economic parameters. Water Sci Technol: Water Supply 2007;7:61–8.

Kowalski M, Marshallsay D. Using measured microcomponent data to model the impact of water conservation strategies on the diurnal consumption profile. Water Sci Technol: Water Supply 2005;5(3–4):145–50.

Lee M, Tansel B. Life cycle based analysis of demands and emissions for residential water-using appliances. J Environ Manage 2012;101:75–81.

Lee M, Tansel B, Balbin M. Influence of residential water use efficiency measures on household water demand: a four year longitudinal study. Resour Conserv Recycl 2011;56:1–6.

Loh M, Coghlan P. Domestic water use study: in Perth, Western Australia, 1998–2001. Western Australia: Water Corporation; 2003.

Loh M, Coghlan P, Australia, W. . Domestic water use study: in Perth, Western Australia, 1998–2001. Water Corporation; 2003.

Makki AA, Stewart RA, Panuwatwanich K, Beal C. Development of a domestic water end use consumption forecasting model for South-East Queensland, Australia. In: The 6th IWA specialist conference on efficient use and management of water. International Water Association; 2011.

Makki AA, Stewart RA, Panuwatwanich K, Beal C. Revealing the determinants of shower water end use consumption: enabling better targeted urban water conservation strategies. J Clean Prod 2013;60:129–46.

Matos C, Teixeira CA, Bento R, Varajão J, Bentes I. An exploratory study on the influence of socio-demographic characteristics on water end uses inside buildings. Sci Total Environ 2014;466:467–74.

Mayer PW, DeOreo WB. Residential end uses of water. American Water Works Association; 1999.

Mayer PW, DeOreo WB, Towler E, Martien L, Lewis D. Tampa water department residential water conservation study: the impacts of high efficiency plumbing fixture retrofits in single-family homes. A report prepared for Tampa Water Department and the United States Environmental Protection Agency; 2004.

Mead N. Investigation of domestic water end use, Faculty of Engineering & Surveying. University of Southern Queensland. Research Project; 2008 http://eprints.usq.edu.au/5783/

Mitchell VG. Applying integrated urban water management concepts: a review of Australian experience. Environ Manage 2006;37:589–605.

Mourad KA, Berndtsson JC, Berndtsson R. Potential fresh water saving using greywater in toilet flushing in Syria. J Environ Manage 2011;92(10):2447–53.

Nguyen KA, Stewart RA, Zhang H. An autonomous and intelligent expert system for residential water end-use classification. Expert Syst Appl 2014;41(2):342–56.

Nguyen KA, Stewart RA, Zhang H. An intelligent pattern recognition model to automate the categorisation of residential water end-use events. Environ Model Softw 2013a;47:108–27.

Nguyen KA, Zhang H, Stewart RA. Development of an intelligent model to categorise residential water end use events. J Hydro-Environ Res 2013b;7(3):182–201.

Nieswiadomy ML. Estimating urban residential water demand: effects of price structure, conservation, and education. Water Resour Res 1992;28:609–15.

Parker JM, Wilby RL. Quantifying household water demand: a review of theory and practice in the UK. Water Resour Manage 2013;27:981–1011, http://dx.doi.org/10.1007/s11269-012-0190-2.

Price JI, Chermak JM, Felardo J. Low-flow appliances and household water demand: an evaluation of demand-side management policy in Albuquerque, New Mexico. J Environ Manage 2014;133:37–44.

Qi C, Chang NB. System dynamics modeling for municipal water demand estimation in an urban region under uncertain economic impacts. J Environ Manage 2011;92(6):1628–41.

QWC. Queensland water commission website media release for 25th June 2010. The State of Queensland 1995–2013. Queensland Government; 2010 http://www.qwc.qld.gov.au/tiki-read_article.php?articleId=410

Rathnayaka K, Malano H, Maheepala S, Nawarathna B, George B, Arora M. Review of residential urban water end-use modelling. In: 19th international congress on modelling and simulation. Perth, Australia: Modelling and Simulation Society of Australia and New Zealand; 2011.

Renwick ME, Archibald SO. Demand side management policies for residential water use: who bears the conservation burden? Land Econ 1998;74(3):343–59.

Roberts P. Yarra Valley Water 2004 residential end use measurement study. Final report, June 2005; 2005 http://www.yvw.com.au/yvw/groups/public/documents/document/yvw1001680.pdf

Russell S, Fielding K. Water demand management research: a psychological perspective. Water Resour Res 2010;46(5):1–12, W05302, doi:05310.01029/02009WR008408.

Sadalla E, Berlin A, Neel R, Ledlow S. Priorities in residential water use: a trade-off analysis. Environ Behav 2012:1–26, http://dx.doi.org/10.1177/0013916512456286.

Sim P, McDonald A, Parsons J, Rees P. WaND briefing note 28 revised options for UK domestic water reduction: a review, working paper 07/04. Leeds LS2 9JT, UK: School of Geography, University of Leeds; 2007. p. 1–50, http://eprints.whiterose.ac.uk/4978/.

Sivakumaran S, Aramaki T. Estimation of household water end use in Trincomalee Sri Lanka. Water Int 2010;35:94–9.

Stewart RA, Willis RM, Giurco D, Panuwatwanich K, Capati G. Web-based knowledge management system: linking smart metering to the future of urban water planning. Aust Plan 2010;47:66–74.

Stewart RA, Willis RM, Panuwatwanich K, Sahin O. Showering behavioural response to alarming visual display monitors: longitudinal mixed method study. Behav Inform Technol 2011:1–17.

Turner A, Fyfe J, Retamai M, White S, Coates A. SEQ's One To One Water Savings Program-Unpacking residential high water usage. Water (Melbourne, Artarmon) 2010;37(1):82–91.

Turner A, Fyfe J, Retamal M, White S, Coates A. The one to one water savings program unpacking residential high water usage. In: IWA efficient 09 conference; 2009.

Turner A, Hausler G, Carrard N, Kazaglis A, White S, Hughes A, et al. Review of water supply-demand options for South East Queensland. Sydney and Cardno, Brisbane: Institute for Sustainable Futures; 2007.

Turner A, White S, Beatty K, Gregory A, Cubillo F. Results of the largest residential demand management program in Australia. Water Sci Technol: Water Supply 2005;5:249–56.

UWSRA, Urban Water Security Research Alliance. http://www.urbanwateralliance.org.au/index.html

Walton C, Holmes K. How much water efficiency does $321 million buy? In: International Water Association (IWA), Australian Water Association, Sydney, Australia, editors. Proceedings of the 5th IWA specialist conference, efficient 2009; 2009.

Water Corporation. Perth residential water use study 2008/2009. Western Australia: Water Forever, Water Corporation; 2011 http://www.water.wa.gov.au/PublicationStore/first/98576.pdf

Willis RM. Domestic water end use study: an investigation of the water savings attributed to demand management strategies and dual reticulated recycled water systems [PhD Thesis]. School of Engineering. Griffith University; 2011.

Willis RM, Stewart RA, Capati B. Closing the loop on water planning: an integrated smart metering and web-based knowledge management system approach, ICA 2009. In: 10th IWA international conference on instrumentation control and automation; 2009a.

Willis RM, Stewart RA, Chen L, Rutherford L. Water end use consumption analysis study into Gold Coast dual reticulated households: pilot study, OzWater'09-From Challenges to Solutions. Australian Water Association (AWA); 2009b.

Willis RM, Stewart RA, Emmonds S. Pimpama-Coomera dual reticulation end use study: pre-commission baseline context and post-commission end use prediction. Water Sci Technol: Water Supply 2010a;10:302–14.

Willis RM, Stewart RA, Giurco DP, Talebpour MR, Mousavinejad A. End use water consumption in households: impact of socio-demographic factors and efficient devices. J Clean Prod 2013;60:107–15.

Willis RM, Stewart RA, Panuwatwanich K, Capati B, Giurco D. Gold Coast domestic water end use study. J Aust Water Assoc 2009c;36:79–95.

Willis RM, Stewart RA, Panuwatwanich K, Jones S, Kyriakides A. Alarming visual display monitors affecting shower end use water and energy conservation in Australian residential households. Resour Conserv Recycl 2010b;54:1117–27.

Willis RM, Stewart RA, Panuwatwanich K, Williams PR. Influence of household socioeconomic region and resident type on end use water consumption levels. In: 2nd international conference on water economics, statistics, and finance. International Water Association; 2009d.

Willis RM, Stewart RA, Panuwatwanich K, Williams PR, Hollingsworth AL. Quantifying the influence of environmental and water conservation attitudes on household end use water consumption. J Environ Manage 2011a;92:1996–2009.

Willis RM, Stewart RA, Talebpour MR, Mousavinejad A, Jones S, Giurco D. Revealing the impact of socio-demographic factors and efficient devices on end use water consumption: case of Gold Coast, Australia. International Water Association (IWA) Efficient 2009; 2009e.

Willis RM, Stewart RA, Williams P, Hacker C, Emmonds S, Capati G. Residential potable and recycled water end uses in a dual reticulated supply system. Desalination 2011b;272:201–11.

Yurdusev AN. 'Level of analysis' and 'unit of analysis': a case for distinction. Millenn – J Int Stud 1993;22:77–88.

Zhou Y, Zhang B, Wang H, Bi J. Drops of energy: conserving urban water to reduce greenhouse gas emissions. Environ Sci Technol 2013;47(19):10753–61, http://dx.doi.org/10.1021/es304816h.