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Revealing the determinants of shower water end use consumption: enabling better targeted urban water conservation strategies

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ABSTRACT

The purpose of this study was to explore the predominant determinants of shower end use consumption and to find an overarching research design for building a residential water end use demand forecasting model using aligned socio-demographic and natural science data sets collected from 200 households fitted with smart water meters in South-east Queensland, Australia. ANOVA as well as multiple regression analysis statistical techniques were utilised to reveal the determinants (e.g. household makeup, shower fixture efficiency, income, education, etc.) of household shower consumption. Results of a series of one-way independent ANOVA extended into linear multiple regression models revealed that females, children in general and teenagers in particular, and the showerhead efficiency level were statistically significant determinants of shower end use consumption. Eight-way independent factorial ANOVA extended into a three-tier hierarchical linear multiple regression model, was used to create a shower end use forecasting model, and indicated that household size and makeup, as well as the showerhead efficiency rating, are the most significant predictors of shower usage. The generated multiple regression model was deemed reliable, explaining 90.2% of the variation in household shower end use consumption. The paper concludes with a discussion on the significant shower end use determinants and how this statistical approach will be followed to predict other residential end uses, and overall household consumption. Moreover, the implications of the research to urban water conservation strategies and policy design, is discussed, along with future research directions.

1. Introduction

1.1. Urban water security

Water is one of the most vital resources on earth. Due to climate change consequences such as the increasing frequency and severity of droughts and the unpredictable changing rainfall patterns, water availability is becoming more variable. Drought, together with growing populations which results in an escalating urban water demand are making water a scarce resource in many regional and urban centres (Dvarioniene and Stasiskiene, 2007; Giurco et al., 2010; Hubacek et al., 2009; Willis et al., 2009a, 2010b). Scarcity of water is forcing many governments and public utilities to invest significantly in the development and the implementation of a range of water strategies (Correljé et al., 2007; Stewart et al., 2010), including dual supply schemes (Willis et al., 2011b), shower visual display monitors (Willis et al., 2010a) and the installation of rainwater tanks (Tam et al., 2010). These strategies aim at improving urban water security through a more sensible and sustainable water consumption to meet future demand (Mahgoub et al., 2010; Palme and Tillman, 2008). This scenario is common in Australia and to some extent the world (Commonwealth of Australia, 2011a; Giurco et al., 2010; Inman and Jeffrey, 2006).

South-East Queensland (SEQ), Australia has been suffering a long drought period, varying rainfall patterns, and a rapid increasing population. These factors together have lead to the enforcement of water demand management (WDM) strategies. Such strategies include water restrictions, rebate programmes for efficient fixtures, water efficiency labelling, and conservation awareness programs (Inman and Jeffrey, 2006; Mayer et al., 2004; Nieswaidomy, 1992). In spite of reductions in water consumption resulting from the implementation of such WDM strategies, government usually follows reactionary-based approaches rather

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than proactive-based approaches (Beal et al., 2010). Additionally, their effectiveness is dependent on differences in location, community attitudes and behaviours (Corral-Verdugo et al., 2003; Turner et al., 2005; Stewart et al., 2011). Further, estimations of water savings yielded from the implementation of such strategies and programs are often calculated based on limited evidence and with many assumptions due to the lack of appropriate data at the end use level, thereby deriving understated or grossly inaccurate values for water savings associated with them (Willis et al., 2009d). Therefore, the development of effective urban water conservation strategies, policies and forecasting models is essential to better manage our urban water resources.

1.2. Smart metering

The development of effective strategies and policies requires more detailed information on how and where residential water is consumed (e.g. shower, washing machine, dish washing, tap, bathtub, etc.) (Mayer and DeOreo, 1999; Willis et al., 2009a). This detailed knowledge of water consumption can provide a greater understanding on the key determinants of each and every water end use, and in return, will allow for the development of improved long-term forecasting models (Blokker et al., 2010; Stewart et al., 2010). The formulation of such models is paramount, especially when there is a distinct lack of micro-component level models that have been created from empirical water end use event data registries into forecasts for total urban residential connection demand as presented in the herein study.

The advent of advanced technology such as water smart metering, which encompasses high resolution data capturing, logging and wireless communication technologies has facilitated the collection, wireless transfer, storing and analysing of abundant detailed and useful water end use information (i.e. time and quantity of each and every end use) (Willis et al., 2009d). The alignment of such detailed and accurate water end use data with a range of socio-demographic, stock inventory, residential attitude and behavioural factors, will aid the development of models that are capable of revealing the determinants of each and every end use; thereby providing the foundations for more robust urban water demand forecasting models.

1.3. Water end use studies

Many residential water demand forecasting models have been developed based on historical billing data, existing statistical reports, or technical information from stock appliance manufacturers (Beal et al., 2010). Such models are not able to provide an accurate disaggregation of consumption into water end use categories. Therefore, long-term actual measurement and disaggregation of water end use data (i.e. micro-component analysis) using smart metering technology and computer software is considered the most robust and accurate foundation for the development of urban water demand forecasting models.

In general, there are few residential water end use studies that have been conducted using high resolution smart metering technologies. Internationally, a number of end use studies have been conducted in the United States of America (Mayer and DeOreo, 1999; Mayer et al., 2004) and more recently in New Zealand (Heinrich, 2007) and Sri-Lanka (Sivakumaran and Aramaki, 2010). Additionally, in South Africa, a conceptual end use model was developed by Jacobs (2004). Moreover, a number of water end use studies (also called water micro-component studies) have been conducted in the United Kingdom (Barthelemy, 2006; Creasey et al., 2007; Sim et al., 2007). In Australia, three major studies have been completed to date in Perth (Loh and Coghlan, 2003), Melbourne (Roberts, 2005) and most recently in Gold Coast City, Queensland (Willis et al., 2009a,b,c,d, 2010a,b, 2011a,b). Table 1 summarises established averages of total and indoor daily per capita water consumption volumes, as well as the indoor water end use breakdown percentages of previous studies conducted in Australia.

In 2010, a South-east Queensland Residential End Use Study (SEQREUS) was commissioned with the objective to gain a greater understanding on water end use consumption in this large urbanised region. This study was funded by the Urban Water Security Research Alliance (UWSRA), which is a partnership between the Queensland Government, CSIRO's Water for Healthy Country Flagship, Griffith University, and University of Queensland. The main aim of this alliance was to address SEQ's emerging urban water issues to inform the implementation of enhanced water strategy (Beal et al., 2010). The primary objective of the greater study was to quantify and characterise mains water end uses of single detached dwellings across four main regions (i.e. Sunshine Coast Regional Council, Brisbane City Council, Ipswich City Council, and Gold Coast City Council) in SEQ, Australia, as shown in Fig. 1 (Beal et al., 2011).

This herein described study utilises information collected in the SEQREUS July 2010 baseline data, where a Permanent Water Conservation Measures (PWCM) daily target of 200 L per person per day (L/p/d) was set by the State Government (Beal et al., 2011). Both the reported SEQREUS and Queensland Water Commission (QWC) water use averages of 145.3 L/p/d and 154 L/p/d, respectively, fell well below the government set target as shown in Fig. 2 (Beal et al., 2010; QWC, 2010). PWCM are not considered restrictions but mainly guidelines for the efficient use of potable water for irrigation purposes (e.g. irrigating lawns after 4 pm when less heat, etc.). Moreover, PCWM guidelines only provide very broad guidance on efficient indoor consumption. Thus in summary, there was not any restriction regime in place at the time of data collection related to this study that could have directly influenced householders' indoor consumption.

This paper describes a component of this greater SEQREUS study. The herein described research study seeks to formulate a bottom-up residential end use demand forecasting model, which includes a comprehensive listing of predictor variables.

1.4. Residential water demand influencing factors and forecasting models

There are several factors influencing water consumption that have been reported previously. Such factors are socio-demographic

Table 1
Previous residential water end use studies conducted in Australia (Beal et al., 2010).

Authors	Loh and Coghlan (2003)	Roberts (2005)	Willis et al. (2009a)
Study title	Domestic Water Use Study	REUMS	Gold Coast Watersaver End Use Study
Region	Perth	Melbourne	Gold Coast
Reporting year	1998–2001	2004	2009
Sample size (No. homes)	120	100	151
Average indoor consumption (L/p/d)	155	169	139
Average total consumption (L/p/d)	335	226	157
Bath/shower (%)	33	31	42
Washing machine (%)	28	26	22
Toilet (%)	22	18	15
Tap (%)	15	17	20
Leaks (%)	2	8	1

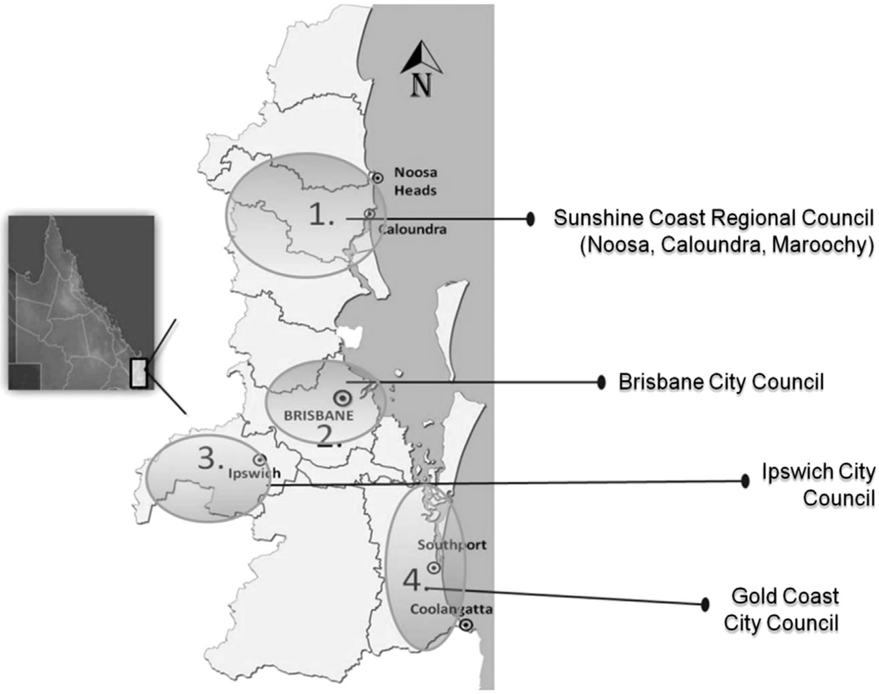


Fig. 1. Regions covered by SEQREUS (Beal et al., 2010).

and water stock efficiency related factors. Socio-demographic factors like household size and household income have been found to influence water consumption (Kim et al., 2007; Loh and Coghlan, 2003; Mayer and DeOreo, 1999; Renwick and Archibald, 1998; Turner et al., 2009). Additionally, other previous studies (Athuraliya et al., 2008; Heinrich, 2007; Mayer et al., 2004; Willis et al., 2009d, 2010a) have shown that the use of water efficient appliances and fixtures reduces water consumption.

As argued, smart metering and comprehensive end use studies provide immense opportunities to significantly improve current understanding on the determinants of residential water consumption, as well as the accuracy of demand forecasting models. A discussion on the relationship between a range of household descriptive characteristics, socio-demographic and stock efficiency characteristics and shower end use consumption is provided below.

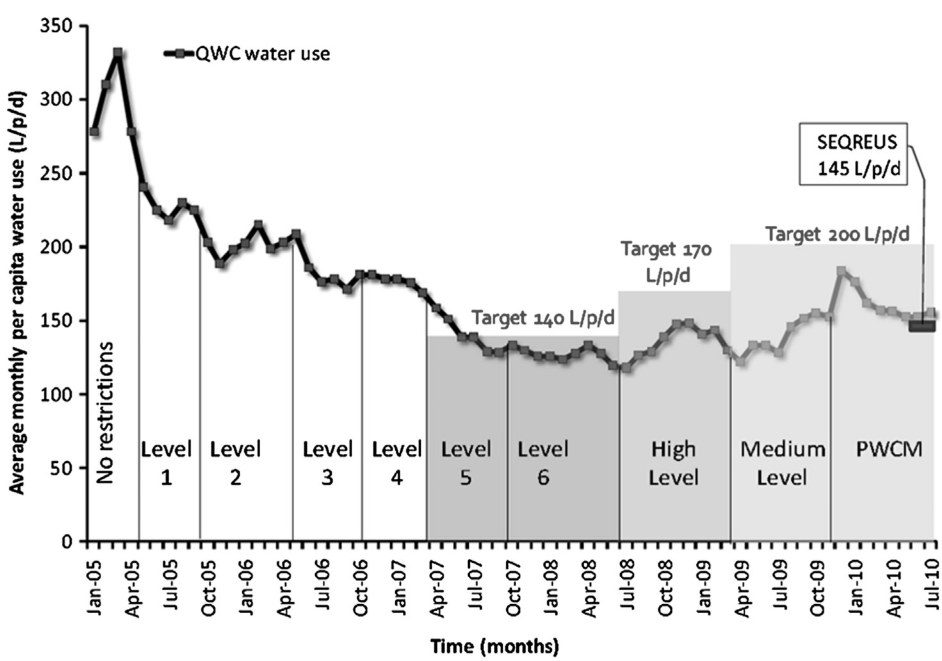


Fig. 2. Comparison between government and SEQREUS reported per capita consumption (Beal et al., 2010).

2. Determinants of shower end use consumption

While the greater SEQREUS has a repository of all residential water end use events, this study has been focussed on the shower end use category. The reason for this is that shower end use consumption, is often the highest indoor demand in residential households. Greater understanding on the primary determinants of shower end use consumption, will aid the preparation of strategic plans (e.g. showerhead rebate/replacement programs, social behavioural marketing, etc.) to reduce consumption during insecure water periods, thereby reducing overall shower consumption. Moreover, given that a high proportion of shower end use consumption is hot water, any conservation of shower water, has a flow-on energy and GHG conservation benefit, so these must also be considered.

There are a number of categories of determinants of shower end use consumption. Some are associated with the macro environment and cultural context of the region (e.g. governance of water, social marketing, restrictions, dam levels, etc.), individuals' attitudes (e.g. conservation attitudes), household makeup (e.g. one male adult and two female teenagers), socio-demographic characteristics (e.g. income, education, etc.), right down to the stock efficiency rating of the showerhead (e.g. three star/AAA, etc.). This particular study scope, focuses on three key categories of predictor variables for shower end use, including:

- Household size and characteristics (e.g. one male adult and two teenagers reside in household, etc.);
- Showerhead stock efficiency rating (i.e. Water Efficiency Labelling Standard (WELS) rating) (Commonwealth of Australia, 2011b); and
- Socio-demographic characteristics of household (e.g. household income, education, etc.).

Individual householder attitudes are obviously a key determinant category for shower end use consumption; however, it has not been covered in the scope of this study. Reasons include the difficulty in ascertaining attitude data reliably, privacy issues, feasibility of collection by water businesses for future residential forecasting, the likelihood that attitudes may be a latent variable of other household demographic characteristics, to name a few. Ideally, if predicting shower end use consumption for individual households, attitudes play a bigger part, than for regional predictions (i.e. region or suburb average household shower end use consumption).

There are a number of extensive studies that have explored the topic of residential water consumption and conservation. However, there are limited studies to date that have been able to align a comprehensive repository of water end use data (i.e. shower end use in this case), with socio-demographic data and household water stock audits, in order to statistically reveal the determinants of that end use. Below represents a discussion on literature addressing the above three predictor categories relationship with the overall water consumption of households, and where available, shower end use.

2.1. Household size and characteristics and shower end use consumption

The household size is one of the most influential characteristics responsible of residential total water consumption. At the household level, the higher the occupancy rates, the higher the water consumption (Beal et al., 2010, 2011; Jacobs and Haarhoff, 2004a,b; Turner et al., 2009; Willis et al., 2009a). Therefore, any reliable urban water demand forecasting model includes household size as a forecasting parameter (Mayer and DeOreo, 1999; Willis et al., 2010a; White and Turner, 2003; WSAA, 2008). Although previously reported shower end use forecasting models are rare, the household size or the occupancy rate is usually included as a forecasting parameter (Duncan and Mitchell, 2008; Gato, 2006).

Additionally, household water consumption has been found to be influenced by the age profile of residents (Mayer and DeOreo, 1999). Therefore, in the herein study, the household makeup factor is represented into its size and age characteristics (Table 2). Furthermore, in this study, gender (Table 2) was also considered as an influential factor of shower end use consumption; the notation that females might have higher volume showers than males could be explored. This deeper approach allows for household size, age and gender combination influences on shower end use to be investigated.

2.2. Showerhead stock efficiency rating and shower end use consumption

Residential water consumption has been found to be influenced by the use of efficient water appliances (DeOreo et al., 2001; Inman and Jeffrey, 2006; Mayer et al., 2004; Willis et al., 2009d). Previous studies indicated that the use of efficient showerhead fixtures can result in significant reductions in this shower end use consumption (Inman and Jeffrey, 2006; Loh and Coghlan, 2003; Roberts, 2005; Willis et al., 2009d). Therefore, in this study, the showerhead stock efficiency rating was considered as an important characteristic in describing shower end use consumption, and was categorised into five categories (Table 2) based on its flow rate (L/min) in accordance to the WELS rating standard (e.g. AAA, AA, A, etc.) (Commonwealth of Australia, 2011b). Such clustering of showerhead efficiency categories enabled relationships between showerhead stock efficiency and household shower consumption to be explored in detail.

2.3. Socio-demographic characteristics of household and shower end use consumption

Socio-demographic characteristics such as income, occupation and education should be considered as indicators of residential water consumption (Inman and Jeffrey, 2006; Mayer and DeOreo, 1999; Nieswaidomy and Molina, 1989; Renwick and Archibald, 1998; Willis et al., 2009d, 2011a). Thus, income ranges, occupation type and educational level clusters were developed (Table 2) in order to explore their individual and combined influences on shower consumption.

Thus, these above discussed three categories of factors with their associated predictor variables are the focus of the investigation process described below.

3. Theoretical framework

3.1. Research objectives

As shown in Table 1, previous studies have revealed that showering is a major end use component representing around one third of the indoor consumption, and a significant contributor to both residential energy demand and resulting GHG emissions. Furthermore, the shower is one of the discretionary end uses from which residential households have the greatest potential to conserve water (Bonnet et al., 2002; Stewart et al., in press; Willis et al., 2010a, 2011a). Therefore, a greater understanding of the contributors to this major indoor end use consumption category, will allow the development of better targeted conservation strategies, and can be the foundation of a more robust forecasting model. Hence, the key objectives of this study are:

Table 2
Shower end use determinant categories, characteristics and groups.

Factor	Type	Unit	Characteristic (IV's)	Symbol	Groups	Symbol
Household composition	Household size, age, gender and makeup	Number of people	Household size	HHS	One Person	1P
					Two Persons[a]	2P
					Three Persons or more	$3P^{+}$
			Adults	A	One Adult	1A
					Two Adults[a]	2A
					Three Adults or more	$3A^{+}$
			Children	C	No Children[a]	0C
					One Child or more	$1C^{+}$
			Males	M	No Males	0M
					One Male[a]	1M
					Two Males or more	$2M^{+}$
			Females	F	No Females	0F
					One Female[a]	1F
					Two Females or more	$2F^{+}$
			Teenagers	T	No Teenagers[a]	0T
					One Teenager or more	$1T^{+}$
			Children aged between 4 and 12 years	$C_{4\le Age\le 12y}$	No Children aged between 4 and 12 years[a]	$0C_{4\le Age\le 12y}$
					One Child aged between 4 and 12 years or more	$1C^{+}_{4\le Age\le 12y}$
			Children aged 3 years or less	$C_{Age\le 3y}$	No Children aged 3 years or less[a]	$0C_{Age\le 3y}$
					One or more Children aged 3 years or less	$1C^{+}_{Age\le 3y}$
Socio-demographic	Household income	AUD	Annual income range	I	Annual Income is less than \$30,000	$I < \$30{,}000$
					Annual Income is between \$30,000 and \$59,999[a]	$\$30{,}000 \le I \le \$59{,}999$
					Annual Income is between \$60,000 and \$89,999	$\$60{,}000 \le I \le \$89{,}999$
					Annual Income is more than \$90,000	$I \ge \$90{,}000$
	Occupation	Status	Predominant occupational status	O	Working[a]	O_W
					Retired	O_R
	Education	Level	Predominant educational level	E	Trade/TAFE or Lower[a]	E_T^-
					Tertiary Undergraduate	E_U
					Tertiary Postgraduate	E_P
Water stock inventory	Stock efficiency	Water flow rates intervals (L/min)	WELS showerheads efficiency rating (Commonwealth of Australia, 2011b)	S	AAA (Flow Rate < 9 L/min)	S_{AAA}
					AA (9 < Flow Rate <12 L/min)	S_{AA}
					A (12 < Flow Rate < 15 L/min)	S_A
					Standard (15 < Flow Rate < 21 L/min)	$S_{Standard}$
					Old (Flow Rate > 21 L/min) [a]	S_{Old}

[a] Control group.

- To explore the predominant determinants of shower end use consumption at the household level;
- To build a forecasting model for shower end use that is capable of predicting average daily per household consumption.

This study also served as a significant milestone, to developing the statistical method design for an overarching model for forecasting residential indoor demand. Such a model will be capable of building a bottom-up and evidence-based forecast of domestic demand through the summation of each end use category prediction.

3.2. Research propositions

To achieve the two stated study objectives listed above and based on the arguments on the shower end use influencing factors presented earlier (Section 2), a detailed list of household makeup, socio-demographic and stock inventory factors and their associated characteristics was developed (Table 2).

Firstly, to achieve the first objective of this study, shower end use consumption determinants categories and variables listed in Table 2 were examined with the view to identify the strongest predictors of shower end use consumption. The following propositions were formed, relating to this objective of the study:

Proposition 1a: A change in any of the household size and composition characteristics accounts for a significant change in the average daily household shower consumption.

Proposition 1b: A change in the efficiency rating of the showerhead used in a household accounts for a significant change in the average daily household shower consumption.

Proposition 1c: A change in the households' socio-demographic characteristics accounts for a significant change in average daily household shower consumption.

Secondly, to build a forecasting model that is capable of predicting average daily per household shower consumption, a multi-tiered statistical analysis approach was applied. As discussed earlier, previous studies have revealed that household size and stock efficiency factors are the major predictors of household shower consumption.

The multiplication of household size by average daily per capita shower consumption could be thought of as the simplest model available to obtain a prediction value for household average daily shower consumption. Also, from a physical and relational perspective, household size and stock efficiency factors have a strong direct relationship with shower consumption. Considering these known principles as the starting point for building the forecasting model, both factors should be considered as the foundation of any shower end use forecasting model. Nevertheless, household size and composition is still considered the primary predictor of shower consumption when compared to stock efficiency in terms of the amount of influenced change in shower consumption volumes. On the other hand, other more latent socio-demographic variables (e.g. income, education, occupation, etc.) may also play a secondary, but

Table 3
Criteria for sample selection of SEQREUS households (Beal et al., 2010).

Criteria	Comment/Justification for criteria
Residential single detached dwelling	Required to have a single residential water meter specific only to the property being metered in order to capture single household data.
No internally plumbed rainwater tank. Rainwater tank for external use permitted.	Toilet and/or laundry end uses would be sourced from the rain tank and thus could not be measured by mains water meter. All internal end uses needed to be measured in this study. Rainwater tanks used predominately for external use only (i.e. not plumbed in to household) were accepted.
Owner-occupied household	Due to consent reasons and that water bills are paid for by the home owner (i.e. landlord); only home owners have been included in the study. Rental households are typically transient and can move every 6–12 months, thus not providing a good sample for seasonal comparisons.

still important role, in shower end use prediction. Given that unguided multiple regression analysis often produces statistically optimum combinations of predictor variables that are not necessarily sensible or practical, a more structured approach guided by literature, common sense, and the above singular determinants, was followed for the purposes of this study. For these reasons, the forecasting model was built considering the following research propositions:

Proposition 2a: Household size which was represented by its makeup characteristics composite is the primary predictor of average daily household shower consumption. Thus, the most appropriate composite representing household makeup should be entered as the foundation or the first tier of the regression model, when building the shower end use forecasting model.
Proposition 2b: Showerhead stock efficiency was selected as the next most influential predictor of household average daily shower consumption. Thus, it should be used as the second tier to building the forecasting model.
Proposition 2c: Socio-demographic characteristics such as income, education, and occupation should be used as the third tier input variable when building the forecasting model, after household size and stock efficiency characteristics.

The subsequent sections detail the research design and method applied to achieve the stated research objectives and propositions.

4. Research design

To achieve such comprehensive study objectives, a mixed method research design has been applied using both quantitative and qualitative approaches to obtain and analyse water end use data. This complex design allows the use of multiple methods to address research objectives (Creswell and Plano Clark, 2007). This mixed approach is adopted in data collection through collecting quantitative natural science data in the form of end use water consumption data, quantitative stock inventory data, qualitative water behaviour data, and quantitative socio-demographic survey data. The data was collected from a sample of 200 residential households across four main regions (i.e. Sunshine Coast Regional Council, Brisbane City Council, Ipswich City Council, and Gold Coast City Council) in SEQ, Australia (see Fig. 1). As presented in Table 3, the data was collected from residential single detached dwellings, where owners (i.e. landlords) were occupiers of houses which also have no internally plumbed rainwater tank. Moreover, the average number of people per household was relatively consistent across all regions forming an average occupancy of 2.6 people per household as presented in Table 4 with other general household characteristics of the utilised sample in this study.

Houses were fitted with high resolution smart meters (i.e. 0.014 L/pulse). These smart meters were connected to wireless data loggers which log (i.e. 5 s record intervals) and store water flow data. Data loggers transfer water flow data to a central computer via e-mail. Water flow data was analysed and disaggregated into a registry of detailed end use events (e.g. shower, washing machine, tap, etc.) using Trace Wizard® software version 4.1 (Aquacraft, 2010) on a personal or laptop computer.

Self-reported water use diaries of each household were developed to collect qualitative water behaviour data in the form of behavioural records of water usage over 2-week sampling periods. In addition to the water diaries, quantitative data on appliance stock inventory (e.g. flow rate of fixtures, star ratings, etc.) was obtained using individual household audits. Both water use audits and diaries assisted and ensured the validity of the Trace Wizard analysis by developing a qualitative understanding of where and when people are undertaking a certain water consuming activity in their household.

Furthermore, questionnaire surveys were developed and distributed to each smart metered household to collect quantitative socio-demographic data. The collected data was entered into SPSS© for Windows, Release Version 18.0 using desktop computer, to enable results analysis, particularly the determination and clustering of the household makeup, stock efficiency and socio-demographic groups (Table 2). The detailed process for this mixed method water end use study is presented in Fig. 3.

Water flow data utilised for the herein study was collected over a 2-week period in the winter season (i.e. July 2010) in the subtropical regional area of SEQ, Australia. The winter season is relatively mild in this region (i.e. 10–20° Celsius range for winter and 17–32° Celsius for other seasons), and this mild temperature range will have minimal impact on indoor end use consumption. However, in order to verify the representativeness of the indoor end use data, a comparative study was conducted between the average daily per capita water end use consumption breakdown utilised in this study and averages reported by a range of other studies recently conducted across Australia and New Zealand (Fig. 4). Shower, washing machine and tap usage consistently place the greatest demand on residential

Table 4
General characteristics of monitored households in SEQREUS (Beal et al., 2010).

Household characteristics of sample[a]	Gold Coast	Brisbane	Ipswich	Sunshine Coast	Average
Household occupancy	2.6	2.6	2.7	2.5	2.6
% Households with $\leq$2 people	58	41	51	69	55
% Households pensioners/retired	36	16	32	45	32
% Households with children (aged $\leq$ 17 years)	34	30	21	25	28
Average age of children (years)	8.8	2.7	4.4	10	6.5

[a] Data presented are averages.

water supply. Indoor water use, with the exception of taps, is relatively homogenous across the regions; with the lowest per capita variance occurring in appliances with fixed water volumes (e.g. clothes washers, dishwashers and toilets). Data presented in Fig. 4 show that indoor consumption figures measured in the SEQREUS were well within the range reported elsewhere in Australia and New Zealand ensuring the representativeness of the herein utilised data set for predictive purposes.

5. Research method

For the purpose of this study, all factors presented in Table 2 were classified as categorical variables. In other words, each variable is composed of mutually exclusive categories. For instance, as shown in Table 2, the household size characteristic labelled number of adults (A) is composed of households with one adult (1A), two adults (2A) and three adults or more ($3A^+$). To achieve the objectives of this study, a series of one-way independent ANOVA extended into a set of multiple regression models was applied for all categorical variables (Table 2), being the Independent Variables (IV's), against daily average household shower end use consumption, being the Dependent Variable (DV). However, such categorical variables needed to be coded first prior to statistical power and significance testing (Pedhazur, 1997; Field, 2009; Hardy, 1993). As shown in Table 2, categorical variables are either dichotomous (e.g. occupation status: working and retired), or polytomous (e.g. number of adults: one adult, two adults, three adults or more) (Hardy, 1993). In this study, both types of variables with their associated categories are represented as dichotomous variables using dummy coding.

5.1. Dummy coding

Dummy coding, or sometimes called binary coding, is used to represent groups of categorical variables in (0,1) format (Pedhazur, 1997; Field, 2009; Hardy, 1993). For instance, households which are members of a particular categorical variable group that belongs to a socio-demographic characteristic are assigned a code of (1); and those which are not in this particular group receive a code of (0). The generated coded groups for a particular categorical variable are called dummy variables. In order to develop mutually exclusive and exhaustive dummy variables that represent a particular categorical variable with j groups, a set of $j - 1$ dummy variables are needed (Pedhazur, 1997; Field, 2009; Hardy, 1993). For instance, the number of adults in households has three groups (e.g. 1A, 2A, $3A^+$). Therefore, it needs two (i.e. $3 - 1 = 2$) dummy variables coded in (0,1) to be represented (see Table 5). It can be seen from Table 5 that the first dummy variable represents households with one adult by giving a code of (1) for a household that belongs to this group and a code of (0) for the rest. Similarly, the second dummy variable represents households with three adults or more and (0) for the rest.

This way, all groups of the categorical variable A are represented in a dichotomous format into two dummy variables, where the group 1A receive a code of (1,0), the group 2A received a code of (0,0), and the group $3A^+$ receive a code of (0,1). It should be noted that, the membership to the group of households with two adults was chosen to receive the code of (1), but rather it was coded by default with (0) while coding the other groups. Hence, it received the code of (0,0) to act as the control group or also called the reference group (Pedhazur, 1997; Field, 2009; Hardy, 1993). Although there is no rule for choosing control groups, they are

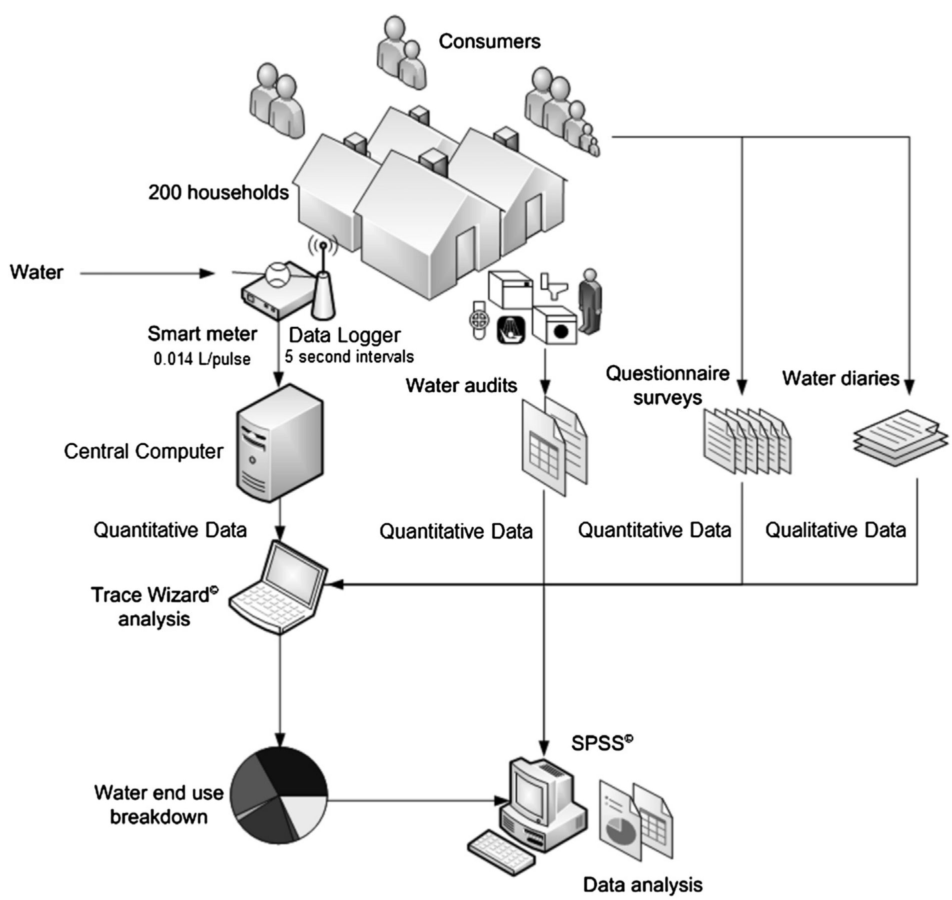


Fig. 3. Schematic illustrating water end use analysis process.

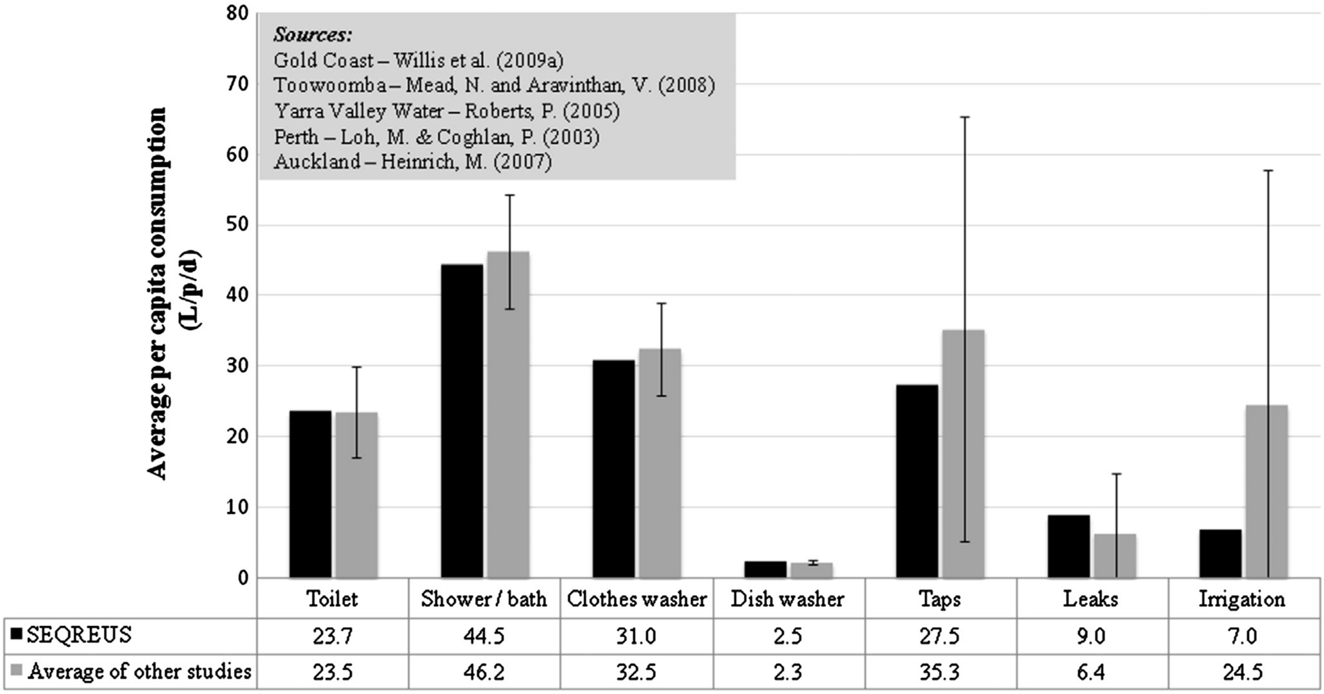


Fig. 4. Average daily per capita end uses consumption of SEQREUS versus previous end use studies (Beal et al., 2010, 2011).

usually determined based on either largest group sample size or a particular hypothesis of interest (Field, 2009). The control group 2A was chosen because it has the largest sample size. In other words, it is the most representative group in the sample of this study. Therefore, its mean is used as the reference for comparison with the other two groups' (i.e. 1A and 3A$^+$) means in ANOVA and multiple regression analysis to ensure robustness of the results. Furthermore, the control groups of all categorical variables shown in Table 2 were assigned consistently to ensure a balanced design. For instance, the group 2A is the control group for the characteristic A, therefore, *2 Persons* (2P) is the control group for the characteristic *Household Size* (HHS), and the group *No Teenagers* (0T) is the control group of the characteristic *Number of Teenagers* (T), and so on. Thus, when forming household makeup composites, there will not be overlapping control groups for each individual household makeup characteristic forming the composite.

The above dummy coding technique was applied to all household makeup, socio-demographic, and showerhead stock efficiency categorical variables shown in Table 2 to be represented in a dichotomous format and subsequently analysed using ANOVA and multiple regression statistical techniques.

5.2. ANOVA extended into regression

In order to test for the level of significance of differences between group means of a particular categorical variable in shower consumption, one-way independent ANOVA was used. In this case, the significance level of differences between the mean of a tested group and that of the control group was tested using the *t-statistic*

Table 5
Example of dummy coding.

Groups	Dummy Variable 1	Dummy Variable 2
1A	1	0
2A	0	0
3A$^+$	0	1

($p < 0.001$, $p < 0.01$, and $p < 0.05$). This analysis provided the significant difference between each of the categorical variable groups and their associated control group, when related to shower consumption (DV).

Commonly, regression analysis is used between one continuous DV versus one or more continuous IV's in order to measure the relationship between both types of variables and predict the DV from these IV's by fitting a statistical model in the form of a straight line represented by Equation (1) (Schroeder et al., 1986).

$$Y_i = b_0 + b_1 X_{i1} + \varepsilon_i \tag{1}$$

Where, Y_i is the outcome variable or DV for the ith case, b_0 is the intercept of the line, and b_1 is the rate of change that the IV X_{i1} makes in Y_i and it is the gradient of the line, and ε_i is the residual term that represents the difference between observed and predicted values.

However, in the case of this study, the DV is continuous (i.e. shower volume), whereas, the IV's or predictors are discrete (e.g. number of adults, etc.). Therefore, the use of dummy coding to represent such groups of categorical variables, and the use of ANOVA to test for significant differences between their means could be extended to a regression model (Cohen, 1968; Field, 2009; Hardy, 1993; Pedhazur, 1997) as shown in Equation (2).

$$Y_i = \beta_0 + \beta_1 X_{i1} + \ldots + \beta_n X_{in} + \varepsilon_i \tag{2}$$

Where, Y_i is the outcome variable or the DV, β_0 is the mean of the control group, and β_1 represents the significant difference between the mean of the first group of the ith categorical IV and the mean of the control group (i.e. β_1 = mean of the 1st group $-$ β_0) and so on, until the nth dummy variable. As such, all significant differences of the means between groups of a particular categorical variable and its associated control group are included in the model. Similar to Equation (1), ε_i is the residual term that represents the difference between observed and predicted values.

The importance of IV's was assessed by the *F-statistic* significance level ($p < 0.001$) generated for each model, and by checking the goodness of fit using parameters generated from each of the developed multiple regression models. Such parameters are the Coefficient of Determination (R^2), the Adjusted Coefficient of Determination ($AdjR^2$), the Standard Error (SE), and the Coefficient of Variation in the regression model ($CV_{Reg.}$).

Assumptions for ANOVA, such as normality and homogeneity of variance, were tested and met by ensuring sufficient groups sample size when clustering groups of each characteristic (i.e. all groups consisted of 30 or more cases unless there were not enough cases to represent mutually exclusive categories). Moreover, internal consistency was also achieved by removing outliers of shower consumption at the household level that may bias the statistical analysis due to extremely high or low consumptions (i.e. box plot with outliers outside $\pm 2\sigma$). In the case of testing the significance level of group mean differences for each of the factors presented in Table 2 using one-way independent ANOVA, outliers of each of the groups of a particular factor were not removed permanently from the study. This is because those households that appeared as outliers when testing a particular factor and its associated groups are not necessarily outliers for the other factors due to the fact that they also represent actual observed consumption patterns that are predominantly influenced by other factors. Thus, when testing each of the factors individual effect on shower consumption, the 200 households were considered each time and outliers of each of the groups which represent a particular factor were studied individually before their removal using appropriate statistical parameters (e.g. average leverage, Mahalanobis distance, DFBeta absolute values, and upper and lower limits of covariance ratio) that measure their effect size on the developed models (Field, 2009). This was deemed to be the most appropriate approach to reveal the genuine average difference in shower consumption between the bulk of households that belongs to a particular household makeup, stock efficiency, or socio-demographic group and the bulk of other households that belong to another group describing their characteristics for the same factor. Generally, outliers that appeared in the sample as a whole (i.e. $N = 200$) were often caused by one to two persons in a household that had extremely short or long showers (e.g. range of <5 L or >150 L per shower event). Given this study scope (i.e. studying shower consumption at the household level and not the personal level) did not include a factor to explain all householders' attitudes to water consumption, these outliers often distorted results. Further, the criterion used for dealing with missing data points when building all regression models in this study was to exclude any household that had at least one missing data point for one of the factors or its associated groups to ensure reliability of the generated R^2 values.

Moreover, a total of nine regression analysis assumptions of models generalisation (Berry, 1993) were met in order to be able to generalise the formulated findings beyond the sample of the study (i.e. $N = 200$). As reported by Field (2009), these assumptions are: type of DV and IV's included in the model being quantitative variables continuous or categorical with two groups and for the DV to be continuous and not bounded; having non-zero variance of predictors; having no perfect multicollinearity between IV's by checking the Average Variance Inflation Factor (*VIF*) being very close to the value of 1 indicating no multicollinearity (Bowerman and O'Connell, 1990; Myers, 1990); the assumption of no correlation between IV's and external variables which are not included in the model; homoscedasticity; having independent errors by checking the *Durbin–Watson* statistic being very close to a value of 2 indicating no dependency (Durbin and Watson, 1951); normally distributed errors; independence of DV values; and linearity of the relationship between DV and IV's.

To achieve the first objective of this study (i.e. to explore the predominant determinants of shower end use consumption), research propositions *1a*, *1b*, and *1c* presented in Section 3.2 were tested by applying the above described method to all of the household makeup, stock inventory, and socio-demographic factors shown in Table 2. Using SPSS (2009), all independent variables were clustered into appropriate groups; dummy coded and represented as dummy variables. Subsequently, they were analysed using one-way independent ANOVA extended into multiple regression models to test for differences between their group means, which in turn, resulted in an extraction of the significant determinants of household shower end use consumption.

To achieve the second objective of this study (i.e. to build a forecasting model for shower end use that is capable of predicting average daily per household consumption), research propositions *2a*, *2b*, and *2c* presented in Section 3.2 were applied to develop a multi-tier shower end use forecasting model based on the factorial independent ANOVA and extended into a multiple regression model following the method presented above. Hierarchical regression, which is often described as the Block-wise Entry regression (Field, 2009) method, was applied to build the multi-tier forecasting model. This method of regression allows the experimenter to build the model in an additive way; this in turn provides the flexibility of selecting which predictors to enter the model first according to their established priorities in the theory or by other previous researches (Field, 2009). In this way, a multiple regression model is developed in three blocks by entering the household makeup characteristics composite in the first block, the stock efficiency characteristic in the second block applying the Forced Entry Regression method (Field, 2009), and the socio-demographic factors in the third block. To explore the prediction priorities of factors in the third block, the Stepwise regression method was used in this block. As explained by Field (2009), Stepwise Regression will allow the computer to search and select the predictor that has the highest simple correlation with the outcome variable (i.e. shower consumption). In this study, the selection criterion of a predictor is based on the significance level of the *F-Statistic* generated for the model after the inclusion of the predictor with the highest simple correlation with shower end use consumption volumes. In this study, if the probability value is less than or equal to *0.05* the predictor will be added to the model; whereas, if the probability value is greater than *0.10* the predictor will be removed from the model.

Shower determinants and the generated forecasting model resulting from this described research method are presented in the subsequent sections.

6. Data analysis and results

Flow trace end use event disaggregation for the SEQREUS resulted in an average total indoor water consumption of 335.9 L per household per day (L/hh/d) for the sampled 200 houses over a 2-week data collection period and average occupancy of 2.6 persons per household. This represents an average per capita indoor consumption of 129.2 L/p/d. Fig. 5 illustrates that the shower end use category is the largest portion of indoor consumption with an average of 111 L/hh/d or 42.7 L/p/d representing 33% of the total indoor consumption (Beal et al., 2011). This per capita end use breakdown is similar to those reported in other recent end use studies in Australia (see Table 1).

6.1. Determinants of shower end use

To achieve the first objective of this study, all household makeup, stock inventory and socio-demographic factors and their associated variables were examined according to the three research propositions *1a*, *1b* and *1c*. To achieve this objective, a series of one-way independent ANOVA extended into multiple regression models was developed by linking each of the IV's in Table 2 against the DV being average daily shower consumption volumes (Figs. 6 and 7). Dummy variables and controls (shown in black in Figs. 6 and 7) were created for all groups using dummy coding in order to represent the membership of households.

6.1.1. Household makeup characteristics

As per Table 6, for the household makeup characteristic number of *Children* (C), the average daily shower consumption per household, for those households with one or more child at any age represented by the group ($1C^+$) was determined as 120.6 L/hh/d. This value is 71.8 L/hh/d more than the average consumption (i.e. 48.8 L/hh/d) of households with no children, which is represented by the control group (0C). Mean differences are statistically significant ($p < 0.001$). The generated multiple regression model presented in Table 6, shows that the IV, represented by the household makeup characteristic C, explained 58.6% of shower end use consumption.

Similarly, all of the household makeup characteristics variables (Fig. 6a–g) were examined individually. The statistical significance level of all group means and their differences from their associated control groups were tested and results are presented with their associated regression models in Table 6. Determinants shown in Table 6 have been ordered based on their power in explaining shower consumption (L/hh/d) with respect to the normal regression model parameters (i.e. R^2, $AdjR^2$ and *SE*). Results show that the household makeup characteristic C, is the most important determinant of shower consumption among all household makeup characteristics, followed by the number of *Females* in the household (F), which is capable of explaining 49.1% of shower consumption. Although F is a determinant of shower consumption, the difference between average shower consumption of households with no females (0F) and with those with one female (1F) is not statistically significant as shown in Table 6. This might be attributed to the small sample size of this 0F group ($n = 19$) as shown in Fig. 6b, and to the fact that average shower consumption of households where their members were all males which were usually adult males to the average consumption of households where their members were predominantly males with one female that was usually an adult female, where her solo consumption did not cause a significant difference in shower consumption at the household level. This insignificance does not imply that the factor F is not a significant determinant of shower consumption. It is worth mentioning that if the selected Control Group was not 1F as in this study but replaced with the group of households that had two females (2F), a significant difference between the group 0F and the new control group will be detected. However, besides that 1F was selected as the control group because it has the largest sample size ($n = 95$) being the most representative group of the sample for the factor F, it was also selected to achieve a balanced design by having compatible Control Groups for all factor categories in the study (Table 2), thereby allowing the combination of any of the factors together to form household makeup composites to be studied as discussed in Sections 5.1 and 6.2.

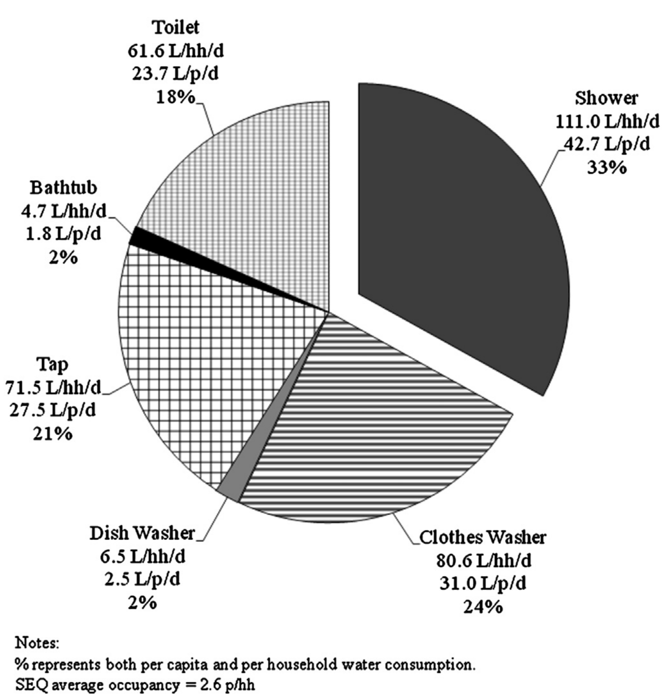


Fig. 5. Average indoor water end use breakdown for SEQREUS (adapted from Beal et al., 2011).

The number of *Teenagers* (T), *Males* (M), *Children aged 3 years or less* ($C_{Age \leq 3y}$), *Adults* (A), and *Children aged between 4 and 12 years* ($C_{4 \leq Age \leq 12y}$) were capable of explaining shower end use consumption by 41.7%, 40%, 36.6%, 26.1%, and 18.1%, respectively.

On one hand, it is evident when looking at the household size makeup composite from an age perspective and ignoring gender (i.e. A + C), that the number of children is more capable of explaining shower consumption than the number of adults. Furthermore, the household makeup characteristic addressing number of teenagers in the household is the most powerful variable of the three for explaining children (i.e. $C = T + C_{4 \leq Age \leq 12y} + C_{Age \leq 3y}$). Although the household makeup characteristic $C_{4 \leq Age \leq 12y}$ is a determinant of shower consumption, it was not determined as a strong predictor of shower consumption, probably because children within this age range may also be likely to use a bathtub than the shower. However, the household makeup characteristic variable $C_{Age \leq 3y}$ was determined as being more capable of explaining the shower consumption of a household than $C_{4 \leq Age \leq 12y}$ which was not expected. This result might be attributed to a latent reason that needs to be studied further, such as the parents of babies and toddlers taking more and longer showers for relaxation and hygiene.

On the other hand, looking at the household size makeup composite from the gender perspective and regardless of age (i.e. M + F), it can be seen that the number of females in households can explain shower consumption better than the number of males.

All household makeup characteristics are considered as shower determinants, as their generated models showed a statistically significant goodness of fit (assessed using *F-statistic*, $p < 0.001$) (Table 6). Additionally, generalisations of the developed models were also assessed by ensuring that the nine regression model assumptions discussed earlier (Section 5.2) are met. As shown in Table 6, the developed models showed acceptable values (Field, 2009) for the *Durbin-Watson* statistic and average *VIF* indicating relatively good levels of errors independency and lack of multicollinearity between predictors, especially when considering that all of the models are based on only one categorical IV. Hence, the above findings reveal that all household makeup characteristics are significant determinants of average daily shower consumption. Additionally, the findings provide empirical support for research proposition *1a* demonstrating that a change in each household makeup characteristic accounts for a significant change in shower consumption, with the exception of the non-significant difference in average shower consumption between households with no females and those with one female.

6.1.2. Stock efficiency

As shown in Fig. 7d, showerhead efficiency rating groups were clustered in accordance with the Water Efficiency Labelling

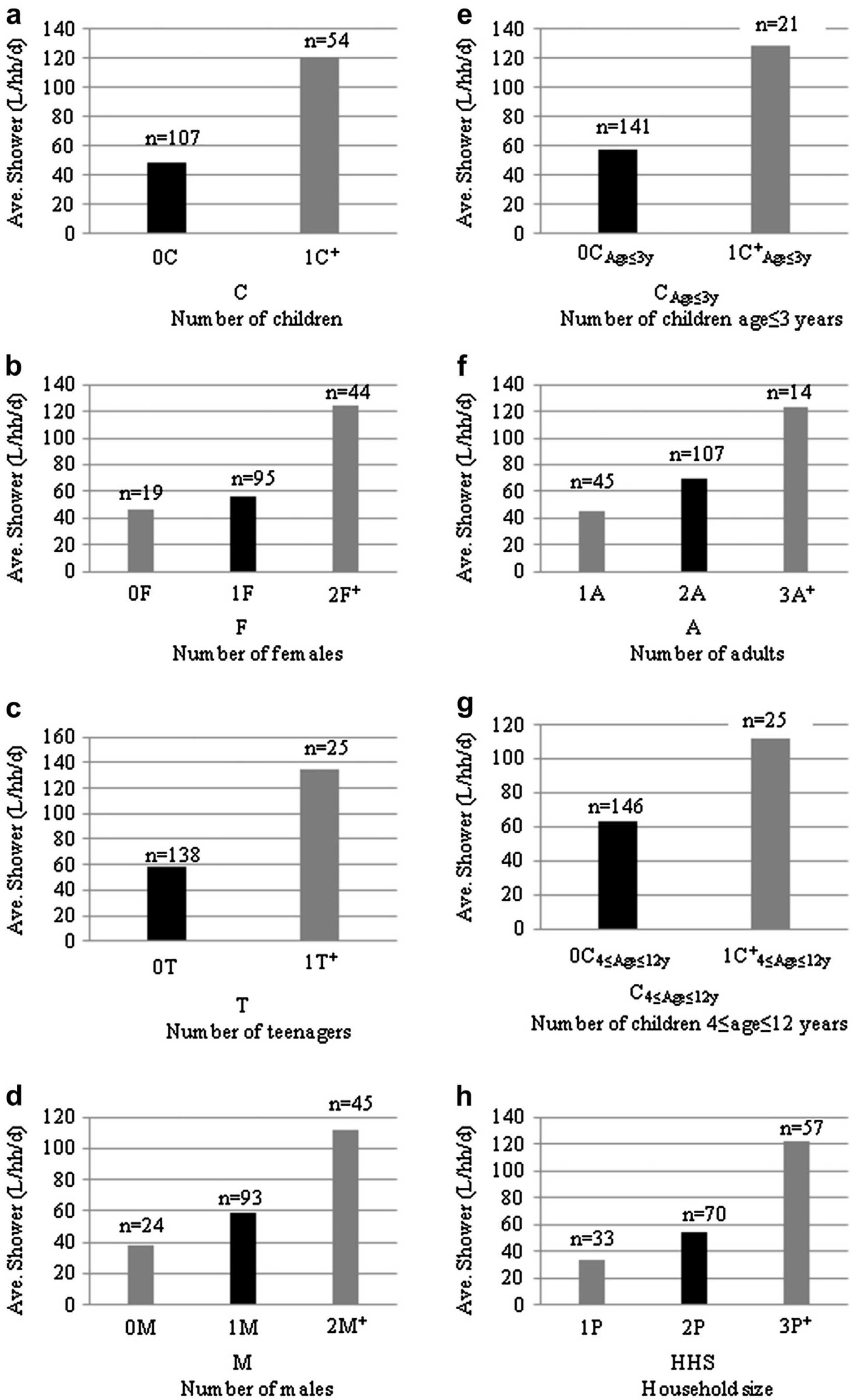


Fig. 6. Household makeup characteristic groups and average shower consumption.

standard (WELS) (Commonwealth of Australia, 2011b) (Table 2). Efficiency cluster group mean differences from the control group, which was represented by households using non-efficient or old showerhead (S_{old}) were tested. The results presented in Table 7, revealed that households using the most efficient shower appliance type, namely AAA rated (S_{AAA}) (i.e. flow rate <9 L/min), are on average consuming 77.0 L/hh/d less than households not using efficient fixtures with an average of 102.4 L/hh/d. The results also showed that households using the next efficient shower appliance types, namely, AA (S_{AA}) (i.e. 9 < flow rate < 12 L/min) and A (S_A) (i.e. 12 < flow rate < 15 L/min), are consuming 62.0 and 36.1 L/hh/d less than those not using efficient fixtures, respectively. Further, households using a standard shower appliance ($S_{Standard}$) (i.e. 15 < flow rate < 21 L/min) are

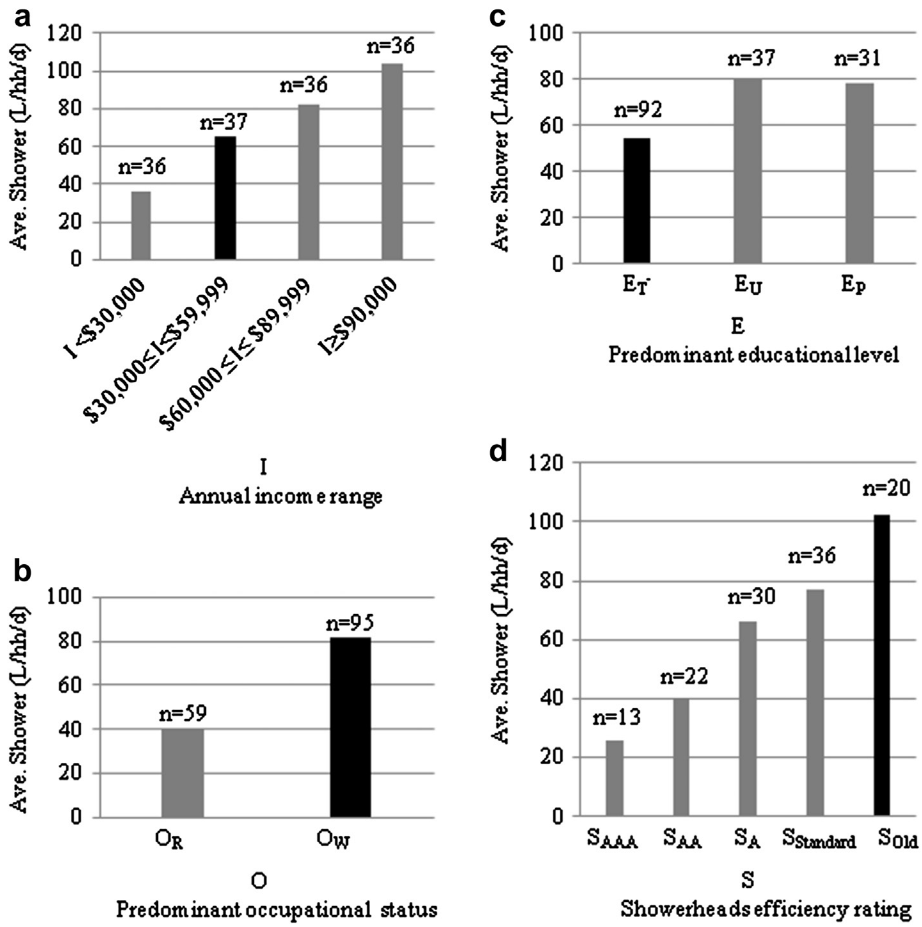


Fig. 7. Income, occupational status, education and stock efficiency groupings relationship with average daily household shower consumption.

consuming 25.6 L/hh/d less than those using old showerheads (S_{old}).

All group mean differences are statistically significant ($p < 0.001$) and the generated regression model shows that the stock efficiency factor (S) is capable of explaining 51.9% of the variation in average daily household shower end use consumption with a statistically significant ($p < 0.001$) goodness of fit assessed using the *F-statistic*, as well as, relatively acceptable errors independency and low multicollinearity levels between predictors (Table 7).

Hence, the above findings confirm that S is a significant determinant of average daily household shower end use consumption. Additionally, the findings provide empirical support for research proposition *1b*, that a change in showerhead efficiency accounts for a significant change in shower consumption.

Table 6
Household makeup characteristics' group mean differences and regression models.

IV	Model	Coefficient	*SE*	*df1*	*df2*	*F*	*Durbin-Watson*	*Ave. VIF*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
C	Constant	48.8***	28.7	1	159	224.613***	1.887	1.000	39.4	58.3	58.6
	$1C^+$	71.8***									
F	Constant	56.7***	32.0	2	155	74.779***	1.902	1.056	43.1	48.4	49.1
	0F	−10.2$^{n.s.}$									
	$2F^+$	67.4***									
T	Constant	58.6***	32.7	1	161	114.960***	1.857	1.000	46.6	41.3	41.7
	$1T^+$	76.3***									
M	Constant	59.3***	32.9	2	159	52.895***	2.020	1.072	46.5	39.2	40.0
	0M	−21.4**									
	$2M^+$	52.7***									
$C_{Age \le 3y}$	Constant	57.4***	31.9	1	160	92.509***	1.677	1.000	59.9	36.2	36.6
	$1C^+_{Age \le 3y}$	71.8***									
A	Constant	70.1***	34.2	2	163	28.795***	1.935	1.035	50.4	25.2	26.1
	1A	−25.1***									
	$3A^+$	53.2***									
$C_{4 \le Age \le 12y}$	Constant	62.9***	37.8	1	169	37.319***	1.889	1.000	53.8	17.6	18.1
	$1C^+_{4 \le Age \le 12y}$	49.9***									

Note: $^{n.s.}p > 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 7
Stock efficiency characteristics' group mean differences and regression model.

IV	Model	Coefficient	*SE*	*df1*	*df2*	*F*	*Durbin-Watson*	*Ave. VIF*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
S	Constant	102.4***	23.1	4	116	31.290***	1.875	1.760	34.8	50.2	51.9
	S_{AAA}	−77.0***									
	S_{AA}	−62.0***									
	S_{A}	−36.1***									
	$S_{Standard}$	−25.6***									

Note: ***$p < 0.001$.

6.1.3. Income, occupation, and education

As shown in Fig. 7a–c, annual income (I), predominant occupational status (O) and predominant educational level (E) groups were clustered and studied against shower end use consumption (L/hh/d). Table 8 shows that households with an annual income of less than \$30,000 are on average consuming 29.3 L/hh/d less than households with an annual income between \$30,000 and \$59,999 (i.e. 65.2 L/hh/d) which served as the control group. Furthermore, the results show that households with an annual income between \$60,000 and \$89,999, and those with an annual income greater than \$90,000 are on average consuming 16.7 and 39.2 L/hh/d more than households that belong to the control group, respectively.

The results also showed that, households that were classified as being of 'retired' occupational status (O_R) are on average consuming 40.8 L/hh/d less than households with a classified with a 'working' occupational status (O_W) (i.e. 81.5 L/hh/d).

Additionally, the results reveal that households with tertiary undergraduate (E_U) and postgraduate (E_P) educational levels are consuming 25.0 and 23.8 L/hh/d more than households with a trade/TAFE or lower predominant educational level ($E_{\bar{T}}$), respectively.

All group mean differences are statistically significant ($p < 0.001$, $p < 0.01$, and $p < 0.05$); and the generated regression models show that I, O and E are capable of explaining 36.2%, 30.3% and 11% of the variation in shower consumption, respectively (Table 8). Therefore, when considered separately, all three examined socio-demographic factors are considered as shower determinants as their generated models provided a statistically significant ($p < 0.001$) goodness of fit assessed using the *F-statistic*, as well as, relatively acceptable errors independency and low multicollinearity levels between predictors (Table 8). Although all these socio-demographic variables are determinants of shower consumption when considered individually, their power in explaining shower consumption is limited, especially the education level variable, when compared to the prior examined household makeup and showerhead efficiency factors. This finding provides some indications, that these socio-demographic variables may not be significant predictors of shower consumption in the later developed shower end use forecasting model.

Hence, the above findings underpin that I, O and E are significant determinants of shower consumption. Additionally, findings provide empirical support for research proposition *1c*, demonstrating that a change in the income, occupational status or the educational level characteristics in households accounts for a significant change in shower consumption.

Accordingly, all the household makeup, socio-demographic and stock inventory factors with their associated characteristics presented in Table 2, are significant determinants of residential shower end use consumption. However, each of these variables is not capable of providing an accurate prediction on their own. Prediction models applying such individual variables can only generate shower consumption predictions with a wide confidence interval as measured by the $CV_{Reg.}$ (see Tables 6, 7 and 8). Therefore, in order to go beyond understanding individual determinants of shower consumption towards an accurate and statistically robust forecasting model, the above findings have been applied in an independent factorial ANOVA extended into a three-tier hierarchical linear multiple regression model, as presented in the subsequent section.

6.2. Shower forecasting model

A domestic average daily per household shower end use forecasting model was built using eight-way independent factorial ANOVA and extended into a multiple regression model based on research propositions *2a*, *2b*, and *2c* presented earlier in Section 3.2. As discussed in Section 5.2, a hierarchical regression method is used to build the model in three blocks.

As discussed in Section 3.2 and based on research proposition *2a*, the household makeup characteristics composite should be used as the base or the first tier in building the forecasting model. However, based on household shower determinants presented into characteristics (Table 2), there are four possible household makeup composites that can be formed. The first composite considered to explain household makeup was represented by the number of people in a household (HHS) and its groups: one person (1P), two persons (2P) and three persons or more ($3P^+$) (see Fig. 6h). The second composite considered to explain household makeup was represented by age characteristics along with their

Table 8
Income, occupation and education characteristics' group mean differences and regression models.

IV	Model	Coefficient	*SE*	*df1*	*df2*	*F*	*Durbin-Watson*	*Ave. VIF*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
I	Constant	65.2***	33.6	3	141	26.630***	1.803	1.483	46.8	34.8	36.2
	I < \$30,000	−29.3***									
	\$60,000 ≤ I ≤ \$89,999	16.7*									
	I ≥ \$90,000	39.2***									
O	Constant	81.5***	30.3	1	152	66.096***	1.759	1.000	45.9	29.8	30.3
	O_R	−40.8***									
E	Constant	54.6***	34.7	2	157	9.724***	1.773	1.078	53.4	9.9	11.0
	E_U	25.0***									
	E_P	23.8**									

Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

associated groups in a household and ignoring gender (i.e. A + C). The third composite considered was a more detailed version of the second composite, and it was represented by age characteristics along with their associated groups with more detailed children characteristics (i.e. $A + T + C_{4 \leq Age \leq 12y} + C_{Age \leq 3y}$). The last composite considered was based on gender only and did not include age categories (i.e. M + F). Readers should note that considering both gender and detailed age characteristics diluted the clustered sample size too much for this composite to be possible.

The ability of the four household size makeup composites in explaining variation in the DV shower consumption was explored using ANOVA and extended into multiple regression models in order to select the best predictor of shower end use consumption (i.e. highest R^2 and lowest *SE*). Results presented in Table 9 show that the household makeup composite $A + T + C_{4 \leq Age \leq 12y} + C_{Age \leq 3y}$ with its associated groups can explain 74% of the variation in shower consumption with the relatively smallest *SE* of 23.5 L/hh/d and the narrowest prediction interval (i.e. $CV_{Reg.} = 0.329$) when compared to other composites. The examined composite possibilities A + C and HHS both explained 66.3% of variation in the DV, with 24.5 and 26.5 L/hh/d/ standard errors, respectively. Lastly, the gender based composite M + F can explain 57.7% of shower consumption, with the largest *SE* of 29.3 L/hh/d/, and the widest prediction interval (i.e. $CV_{Reg.} = 0.393$).

Thus, based on this combinations assessment, the household makeup composite represented by four variables $A + T + C_{4 \leq Age \leq 12y} + C_{Age \leq 3y}$ and their associated groups, was selected for representing the household size makeup when building the forecasting model. Therefore, it was entered in the first block of the model using the Forced Entry regression method as shown in Table 10. Subsequently, the S shower determinant represented by its associated groups was entered into the second block of the model as the fifth variable, also using the Forced Entry method. Finally, in the third block, the three socio-demographic shower determinants I, O and E were entered using the Stepwise Regression method to explore their priorities as discussed earlier in Section 5.2.

Results presented in Table 10 shown in the first block, reveals that all group mean differences from the control group (i.e. $2A + 0T + 0C_{4 \leq Age \leq 12y} + 0C_{Age \leq 3y}$), are significant ($p < 0.05$, $p < 0.01$, and $p < 0.001$). Further, the generated model using the household makeup composite alone is statistically significant ($p < 0.001$), and it accounts for 71.4% of the variation in shower L/hh/d consumption with a *SE* of 28.0 L/hh/d and a $CV_{Reg.}$ of 0.342.

The results presented in the second block of the model show that the addition of the stock efficiency factor with household size has increased the ability of explaining variation in shower consumption by 18.8%, and that this change is statistically significant (i.e. $F_{Change}(4,114) = 54.940$, $p < 0.001$). The generated model using both determinants is capable of explaining 90.2% of the variation in shower L/hh/d consumption with a relatively small *SE* of 16.68 L/hh/d and a narrow prediction interval (i.e. $CV_{Reg.} = 0.203$). The model has also a significant fit ($F(4,114) = 117.131$, $p < 0.001$) to the data, and if generalised beyond the sample of this study, it can explain 89.5% of the variation in shower consumption (i.e. $AdjR^2 = 0.895$).

The model shows that households with two adults that are not using efficient showerhead (i.e. control group) are consuming an average of 99.1 L/hh/d. Whereas, households with one adult are on average consuming 10.4 L/hh/d less than the control group. Further, households with three or more adults, one or more teenagers, one or more children aged between 4 and 12 years, and one or more children aged 3 years or less are consuming 76.2, 68.0, 16.3, and 42.0 L/hh/d more in shower end use consumption than the control group respectively. The model also shows that households using showerheads fixtures of the types AAA, AA, A, and Standard are on average consuming 67.3, 67.0, 44.1, and 27.8 L/hh/d less in the shower than the control group (i.e. Old), respectively.

In the third block of the model, income, occupation and education variables could not be entered into the model as they failed to meet the criteria of having an *F*-statistic probability value of less than or equal *0.05*. This indicates that they could not make a further significant contribution to the predictive power of the model in the second block (Field, 2009).

Hence, the generated model in the second block shows that household makeup (i.e. $A + T + C_{4 \leq Age \leq 12y} + C_{Age \leq 3y}$) and stock efficiency (i.e. S) are the most significant predictors of average daily shower end use consumption. Additionally, findings provide empirical support for research propositions *2a*, *2b* and *2c* demonstrating that shower end use forecasting models are better built when considering household makeup characteristics as the most important predictor of shower consumption, and then showerhead

Table 9
Household makeup composites' group mean differences and regression models.

Composite	Model	Coefficient	*SE*	*df1*	*df2*	*F*	*Durbin-Watson*	*Ave. VIF*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
$A + T + C_{4 \leq Age \leq 12y} + C_{Age \leq 3y}$	Constant	50.0***	23.5	5	146	82.893***	1.819	1.067	32.9	73.1	74.0
	1A	−15.8***									
	$3A^+$	48.8***									
	$1T^+$	89.7***									
	$1C^+_{4 \leq Age \leq 12y}$	34.6***									
	$1C^+_{Age \leq 3y}$	61.8***									
A + C	Constant	50.4***	24.5	3	150	98.276***	1.706	1.046	35.0	65.5	66.3
	1A	−17.0***									
	$3A^+$	49.0***									
	$1C^+$	62.1***									
HHS	Constant	53.6***	26.5	2	157	154.113***	1.733	1.168	35.8	65.8	66.3
	1P	−20.2***									
	$3P^+$	68.6***									
M + F	Constant	61.7***	29.3	4	155	52.762***	1.820	1.077	39.3	56.6	57.7
	0M	−36.9***									
	$2M^+$	40.1***									
	0F	−27.0***									
	$2F^+$	43.3***									

Note: ***$p < 0.001$.

Table 10
Average daily per household shower end use forecasting model.

Block	Description	IV's	Model	Coefficient	SE	df1	df2	F	F_{Change}	Durbin-Watson	Ave. VIF	$CV_{Reg.}$ (%)	Adj. R^2 (%)	R^2 (%)
Block 1 (Forced Entry)	Household makeup composite	$A + T + C_{4\leq Age\leq 12y} + C_{Age\leq 3y}$	Constant	60.1***	28.0	5	118	59.001***	59.001***	–	1.089	34.2	70.2	71.4
			1A	−19.9**										
			$3A^+$	78.7***										
			$1T^+$	79.0***										
			$1C^+_{4\leq Age\leq 12y}$	18.3*										
			$1C^+_{Age\leq 3y}$	48.9***										
Block 2 (Forced Entry)	Household makeup composite + Stock efficiency	$A + T + C_{4\leq Age\leq 12y} + C_{Age\leq 3y} + S$	Constant	99.1***	16.7	4	114	117.131***	54.940***	1.839	1.425	20.3	89.5	90.2
			1A	−10.4**										
			$3A^+$	76.2***										
			$1T^+$	68.0***										
			$1C^+_{4\leq Age\leq 12y}$	16.3***										
			$1C^+_{Age\leq 3y}$	42.0***										
			S_{AAA}	−67.3***										
			S_{AA}	−67.0***										
			S_A	−44.1***										
			$S_{Standard}$	−27.8***										
Block 3 (Stepwise)	Household makeup composite + Stock Efficiency + Socio-demographic factors		Socio-demographic (i.e. I, O, and E) variables could not enter the model											

Note: $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

efficiency rating as the second predictor, and then other socio-demographic factors.

Thus, the generated model in the second block which combines household makeup characteristic and showerhead efficiency rating predictors was considered the final forecasting model for Average Daily Household Shower Consumption (ADHSC) as presented in Equation (3).

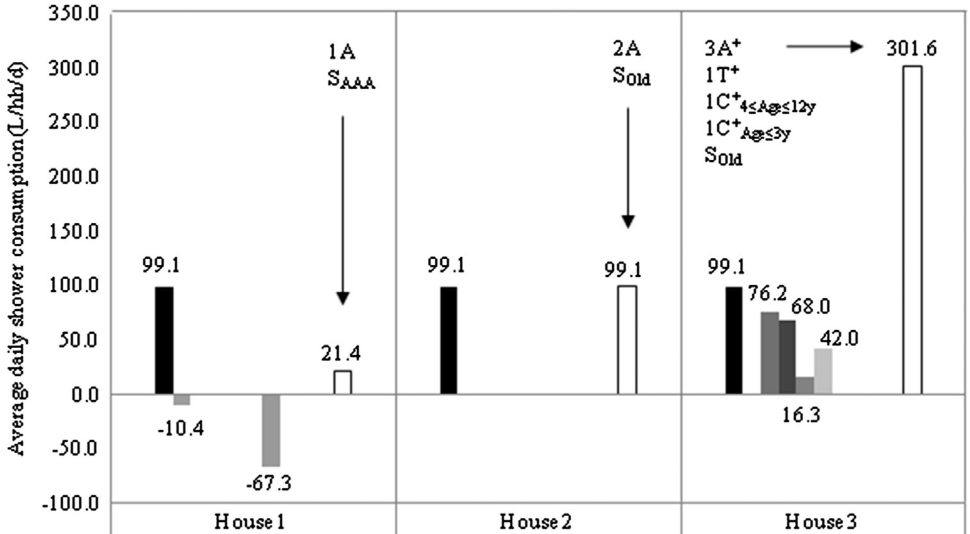
$$\begin{aligned} \text{ADHSC}\left(\text{L/hh/d}\right) = {} & 99.1 - 10.4(1A) + 76.2\left(3A^+\right) + 68.0\left(1T^+\right) \\ & + 16.3\left(1C^+_{4\leq Age\leq 12y}\right) + 42.0\left(1C^+_{Age\leq 3y}\right) \\ & - 67.3(S_{AAA}) - 67.0(S_{AA}) - 44.1(S_A) \\ & - 27.8(S_{\text{Standard}}) \pm 16.7 \end{aligned} \tag{3}$$

In order to obtain a prediction of ADHSC (L/hh/d) using the model presented in Equation (3), household makeup and showerhead stock efficiency characteristics should be determined by indicating the membership of the household using both factors groups (i.e. 0 or 1). In this way, values can be assigned to each variable, where a value of 1 refers to that household belonging to a particular characteristic group, and a value of 0 infers no belonging. To exemplify the calculation and possible variation in ADHSC, three household typology scenarios were developed and are presented in Fig. 8. The first scenario 'House 1' represents the lowest prediction figure that can be generated by the model. This house has only one adult resident who is using the most efficient showerhead fixture of the type AAA. By substituting a value of 1 in 1A and S_{AAA} and by a value of 0 in all other groups in Equation (3) (see Fig. 8), the predicted shower consumption was calculated to be 21.4 ± 16.7 L/hh/d (±16.7 represents the confidence interval of the developed regression model).

The second scenario represents the case of 'House 2' which has two adults that are using an old showerhead fixture (i.e. flow rate ≥ 21 L/min). This group is effectively the control group of the sample. As shown in Fig. 8, substituting a value of 0 in all groups yielded a predicted shower consumption volume that is equal to the constant, which is the average shower consumption of the control group. Therefore, the daily average shower consumption for House 2 was determined as 99.1 ± 16.7 L/hh/d.

The third scenario represents the highest prediction figure generated by the model. 'House 3'; is a large family that consisted of more than three adults, more than one teenager, more than one child aged between 4 and 12 years, and more than one child aged 3 years or less; who are all not using efficient showerhead fixtures. As shown in Fig. 8, when substituting all characteristics groups that this household belongs to by a value of 1and a value of 0 everywhere else, the predicted daily average shower consumption of House 3 is 301.6 ± 16.7 L/hh/d.

To validate the developed shower end use forecasting model, data collected from 30 households using the same sampling criteria followed in this study (see Table 3) were randomly retained before statistical model development. This independent data set was utilised to validate the developed model through comparing observed shower consumption (L/hh/d) to predicted average shower consumption (L/hh/d) calculated by Equation (3) as presented in Fig. 9. The comparison analysis showed that the average error of the developed model in predicting shower consumption of the 30 households was ±10.3 L/hh/d which is relatively lower than the standard error of the developed model of ±16.7 L/hh/d (see Table 10). Thus, the developed model was deemed a valid shower end use forecasting model.



	House 1	House 2	House 3
Control Group	99.1	99.1	99.1
1A	-10.4	0	0
3A+	0	0	76.2
1T+	0	0	68.0
$1C^{+}_{4\le Age\le 12y}$	0	0	16.3
$1C^{+}_{Age\le 3y}$	0	0	42.0
S_{AAA}	-67.3	0	0
S_{AA}	0	0	0
S_{A}	0	0	0
$S_{Standard}$	0	0	0
Ave. Shower	21.4	99.1	301.6

Fig. 8. Illustrative examples of shower consumption prediction.

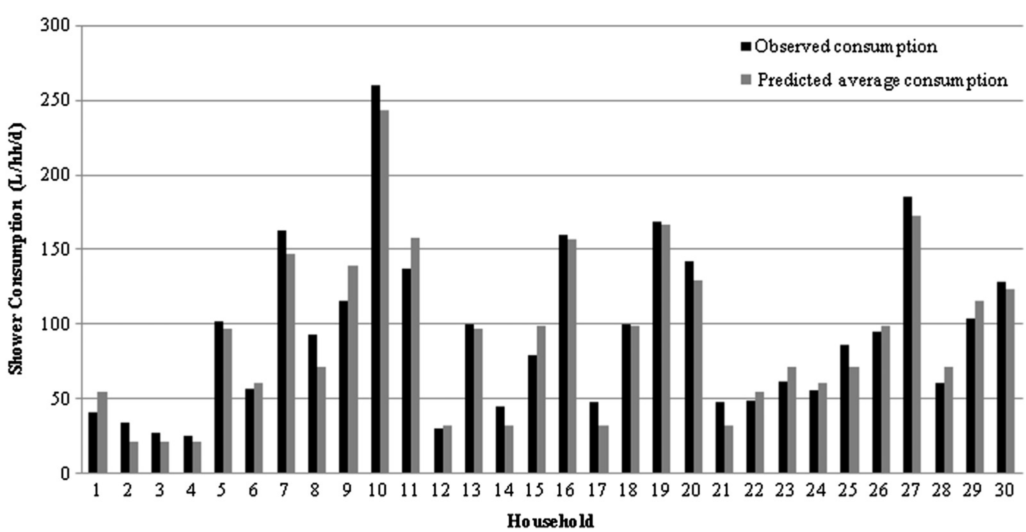


Fig. 9. Observed versus predicted average daily per household shower consumption.

7. Conclusion

A mixed method research design was applied to collect both quantitative and qualitative data from over 200 households in SEQ, Australia. This design required the implementation of a range of collection approaches, including smart metering technology, questionnaire surveys, diaries, and household water stock inventory audits. All such data collection requirements were essential in order to accurately disaggregate residential meter flow data into each and every water end use event. The disaggregation process revealed that shower end use was a major component of indoor consumption. Therefore, exploring the predominant determinants of its consumption and the development of a forecasting model that is capable of predicting this consumption were the key objectives of this study. This was achieved by aligning household makeup, socio-demographic and stock efficiency factors against the natural science data set being shower end use consumption. Dummy coding and ANOVA extended into multiple regression was firstly used to reveal significant determinants of shower consumption, followed by the development of a comprehensive forecasting model. Results of the study revealed that all examined variables, such as household makeup, income, education, occupation status, and showerhead efficiency level, are all significant determinants of shower consumption, when examined individually. Results also suggested that household makeup characteristics and the showerhead stock efficiency were the most important determinants of shower consumption, when compared to the other determinants. With respect to the household makeup characteristics, from an age perspective, results also revealed that the number of children and more specifically, the number of teenagers in a household are the most important household makeup characteristics in terms of influencing shower consumption. Moreover, from a gender perspective, results revealed that the number of females in a household is an important determinant of shower consumption.

Eight-way independent factorial ANOVA extended into three tiers of hierarchical linear multiple regression was applied to build a forecasting model for shower end use consumption, based on the significant determinants identified. The generated forecasting model shows that a household size makeup composite factor (i.e. $A + T + C_{4 \leq Age \leq 12y} + C_{Age \leq 3y}$) and a showerhead stock efficiency factor are the significant predictors of average daily shower consumption, explaining a healthy 90.2% of the variation in the DV. A shower end use forecasting model of this complexity and statistical significance has not been reported in the literature to date, thereby making it a worthwhile research contribution.

8. Study implications

Given that showering is often reported as the highest indoor consumption category, and that shower end use event volumes and frequency, are generally much higher than is required for sanitary purposes (i.e. showering is often considered as a leisure activity), this water end use category has the potential to be substantially reduced in drought periods. In such periods, or as a core long-term water conservation measure of the community, the herein described study findings can assist water businesses and government policy officers responsible with designing better targeted water conservation strategies and policies addressing shower end use. For instance, shower conservation awareness campaigns could be specifically designed to have greater appeal to females and teenagers, as these household groups were shown to have a greater influence on shower consumption. Additionally, this study has provided further empirical support to a growing existing body of knowledge highlighting that the replacement of low efficiency showerheads with higher ones, will result in a considerable reduction in average daily shower consumption in the household. Showerhead retrofit programs are confirmed herein as a least cost potable water savings measure that can be easily implemented by the water business or government. Finally, the formulated shower end use forecasting model will be invaluable for demand forecasting professionals based in urban water businesses when completing water balance or infrastructure planning exercises. However, as a note of caution to readers, the presented models should be considered in relation to the situational context of the research investigation (i.e. SEQ, Australia) and need to be adapted for use elsewhere. Nonetheless, it is believed that the herein identified determinants of shower consumption and their relative level of predictive power will hold true in other regions, both nationally (i.e. Australia) and in other developed nations.

9. Future work

The next stage of this investigation is to follow a similar research method to that described herein to reveal the significant determinants of all other indoor end use categories (e.g. toilet, tap, bathtub, clothes washing and dishwashing). Moreover, a modularised micro-component forecasting model will be built for each of these end uses combining significant predictors of that particular end use category. The summation of all end use predictions from such complex models can provide an evidence-based forecast of domestic household demand. Modules will also be developed 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. A web-based water end use demand forecasting tool will be developed. This 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.

10. Limitations and future research directions

Water end use studies using high resolution smart metering technology is 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; thereby enhancing the statistical power of the forecasting model. For instance, sample size constricted the number of dummy coded determinant categories and limited the level of detail that could be explored (i.e. female teenagers, male teenagers, female adults, male adults, etc.). Moreover, macro factors (i.e. government policy of region, environmental context, etc.), householder attitudinal data, and a range of other socio-demographic factors could be explored in future studies. Finally, the current model is static based on a snapshot of collected end use data. Over time, end use water consumption will change. Ideally, data is collected remotely and stored over longer time periods and automatically disaggregated into water end use events; 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.

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