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A worldwide review

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Investigating the characteristics of residential end uses of water: A worldwide review

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A B S T R A C T

A detailed characterization of residential water consumption is essential for ensuring urban water systems' capability to cope with changing water resources availability and water demands induced by growing population, urbanization, and climate change. Several studies have been conducted in the last decades to investigate the characteristics of residential water consumption with data at a sufficiently fine temporal resolution for grasping individual end uses of water. In this paper, we systematically review 114 studies to provide a comprehensive overview of the state-of-the-art research about water consumption at the end-use level. Specifically, we contribute with: (1) an in-depth discussion of the most relevant findings of each study, highlighting which water end-use characteristics were so far prioritized for investigation in different case studies and water demand modelling and management studies from around the world; and (2) a multi-level analysis to qualitatively and quantitatively compare the most common results available in the literature, i.e. daily per capita end-use water consumption, end-use parameter average values and statistical distributions, end-use daily profiles, end-use determinants, and considerations about efficiency and diffusion of water-saving end uses. Our findings can support water utilities, consumers, and researchers (1) in understanding which key aspects of water end uses were primarily investigated in the last decades; and (2) in exploring their main features considering different geographical, cultural, and socio-economic regions of the world.

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1. Introduction

The availability of water resources is of concern for many regions worldwide (McDonald et al., 2010; Suero et al., 2012). Growing population and urbanization have led to large areas under water stress, with population growth often coupled with variations in the per capita water consumption rates (Cosgrove and Loucks 2015). Population growth can stress local water resources even in areas with decreasing per capita water demands (Dieter et al., 2018). Moreover, water shortages – which currently affect more than 500 million people worldwide – are expected to be compounded as a consequence of climate change (Sønderlund et al., 2016) and feed back to changes in water demands across potentially conflicting sectors, such as drastic increases in the amount of water needed for irrigation and urban activities due to increasingly frequent and intense drought events (Evans and Sadler 2008). Effective planning and management of water systems are thus of great importance to cope with the grand challenges posed by population, climate, and water resources availability (Avni et al., 2015). However, the effectiveness of water supply operations and water demand management strategies to meet future demand under different scenarios depends on our knowledge on where, when, and how water is being used (Cardell-Oliver et al., 2016). This has motivated an increasing interest over time towards characterizing water consumption distribution across space and time in the water research literature (Sanchez et al., 2018).

In the last decades, many studies have been conducted to investigate water consumption characteristics at different spatio-temporal scales. In some cases (Danielson 1979; Tanverakul and Lee 2013), water consumption is explored by relying on monthly to yearly water data, typically read manually by water utility technicians for billing. However, as reported by Cominola et al. (2015), billed water data generally allow extracting information only to evaluate aggregate volumes of water consumption at a coarse spatiotemporal detail, i.e. entire-city or districts, and on a coarse temporal scale, i.e. monthly or seasonal. To overcome this limitation, more attention has recently been devoted to the investigation of water consumption at finer spatiotemporal resolutions, i.e. at the household or end use scale and with hourly to sub-minute temporal resolution. This finer-resolution monitoring was made possible by technological development and the diffusion of *smart* metering solutions (Gurung et al., 2015; Darby 2010), spanning from add-on data loggers – allowing water consumption data to be gathered in more detail than conventional meters – to digital meters capable of automatically processing and transmitting those data to the utility for monitoring and billing purposes. Smart meters and paired software (Bastidas Pacheco et al. 2020, 2021b) enable detailed analysis on heterogeneous water consumption behaviors and sub-daily patterns (Cubillo-González et al., 2008; Beal and Stewart, 2011; Horsburgh et al., 2017; Cominola et al., 2018b) and can be used to develop customized feedback and water conservation programs (Mayer et al., 2000; Willis et al., 2010b; Cominola et al., 2021a). When real-time information is available, smart metre data can also be exploited to provide real-time alerts for domestic leakages or anomalous water consumption patterns (Britton et al., 2013; Luciani et al., 2019; Mayer 2022), thus enabling prompt actions, with consequent water conservation or even life-saving (Salomons and Housh 2022). Furthermore, smart meters allow new, detailed information about water consumption to be obtained up to the level of individual end uses (i.e. domestic micro-components such as shower, taps, washing machine, etc.). This information includes daily volumes of water consumed, along with the daily water consumption profiles and routines at the end-use level and other parameters (e.g. duration, volume, flow rate, and frequency of use) of individual water uses.

With increasing frequency, greater focus has been given in the literature to the characterization of water consumption at the level of individual end use in the residential sector, mainly because residential consumers typically represent the highest number of water users in cities (Aksela and Aksela 2011). Residential end uses of water consumption had been scarcely explored before the introduction of smart metering technologies (not only digital meters but also – in a broader sense – the previously developed data-logging solutions and paired software for data processing) due to the effort required to obtain this information with previously available tools. Only few water consumption investigations at the end-use level were performed prior to the early 1990s. They were based on data-gathering campaigns developed using surveys, audits, and questionnaires to characterize the features of domestic appliances and people's habits, thus estimating water use (e.g. Butler 1991). Customer self-reported end-use water consumption studies have proved to be highly inaccurate as consumers typically have a poor understanding of their water use habits compared to norms and best practices (Beal et al., 2013).

Nowadays, residential water consumption data at the end-use level can be used for a variety of purposes, such as training and testing water demand models (e.g. Blokker et al., 2010) or the calibration and validation of water end-use disaggregation methods (Mayer et al., 1999; Nguyen et al., 2013a; Nguyen et al., 2018; Mazzoni et al., 2021). In addition, the availability of this information may support the development of technologies for water reuse and recycling (Dixon et al., 1999) or strategies aimed at increasing consciousness and awareness of water use (Beal et al., 2011b; Liu et al., 2016). Water utilities can rely on detailed water end-use information to review and improve their incentive and water pricing arrangement (Gleick et al., 2003), whereas users can receive helpful feedback and then change their water consumption behavior (Willis et al., 2010b; Stewart et al., 2018). Feedback targeted to specific consumer's water end-use consumption behaviors has great potential to conserve water during water scarcity periods (Fielding et al., 2013).

Yet, despite the advantages of end-use water consumption data, collecting and efficiently processing them is still challenging. On the one hand, the intrusive monitoring of each domestic appliance may be impractical, and householders are unlikely to provide permission to install this intrusive instrumentation (Cominola et al., 2015). On the other hand, when non-intrusive approaches are considered, automated techniques for the end-use disaggregation of the water consumption time series generally require information about end-use parameters that may be unavailable to the analysts (Mazzoni et al., 2021). In contrast, manual approaches typically involve considerable human effort and time due to the large amounts of data to analyse, along with potential bias and scarce reproducibility deriving from expert-based judgement (DeOreo et al., 1996).

While we acknowledge the above limitations related to the direct – or indirect – collection of end-use water consumption data, we believe that general analyses, water consumption models, and technological development may still be conducted by exploiting the ensemble of data and information already available, yet fragmented, in the literature. Indeed, the literature published in the past two decades includes numerous peer-reviewed journal publications or water utility reports exploring water consumption characteristics at the end-use level. Moreover, these studies consider different case studies, methodological approaches adopted to obtain end-use information, and end-use database features. Finally, there are considerable differences in the numerical end-use results shown. Thus, systematic reviews, comparisons, and elaborations of these fragmented data may promisingly lead to new applications in the field of water resources management.

In this context, some recent studies present the main characteristics of the major residential end-use studies available in the literature, such as location, sample size, and approach adopted to obtain end-use data (Nguyen et al., 2013a; Cominola et al., 2015). More specifically, in a review by Di Mauro et al. (2021), over one hundred studies on water consumption are clustered based on their spatiotemporal scale (i.e. ranging from urban to end-use level, and from daily to sub-minute resolution) and the level of accessibility of their related datasets. In addition, a recent study conducted by Abu-Bakar et al. (2021) provides a comprehensive overview of the current state of end-use disaggregation and classification techniques, along with a discussion of the results proposed by several studies about the determinants of water consumption, limited to the household level. At the end-use level, a summary comparison of the daily per capita water consumption values indicated in different studies is available in Mayer et al. (1999), Beal and Stewart (2011), Gurung et al. (2014), and Jordán-Cuebas et al. (2018). However, to the authors' knowledge, an extensive review about residential end uses of water – not only highlighting similarities and differences amongst the studies available in the literature but also systematically comparing all the numerical results about end-use water consumption globally – is still missing.

The current work aims to fill the abovementioned gap by providing a comprehensive review of the existing end-use studies conducted globally in the field of residential water consumption – along with an in-depth discussion of their scope, features, and results – to fully explore and quantify end-use characteristics in different contexts worldwide. Unlike other reviews available in the literature, this research is structured as a multi-level analysis, including: (1) a quantitative comparison of all the most common metrics about residential end-use water consumption (i.e. per capita daily end-use water consumption, end-use parameter average values, end-use parameter distributions, end-use daily profiles); and (2) a qualitative discussion about additional aspects of interest in the field of end-use water consumption (i.e. considerations about end-use determinants and water-saving efficiency). We believe that the findings of the current work may be applied to several contexts for which end-use water consumption data are needed (e.g. demand characterization, training and testing of demand models, development of technologies for water reuse and conservation, adoption of strategies to increase people's awareness, revision of water utility rate and billing system, water infrastructure planning and management). Ultimately, the results of this study may support water utilities and researchers in understanding which aspects were primarily explored in recent research and identifying the end-use databases and studies carried out in different geographical, cultural, and socio-economic regions of the world.

This review is organized as follows: Section 2 includes the methodological details of the literature review conducted to explore the state of the art of research about residential end-use water consumption, along with a preliminary overview of the main characteristics of the reviewed studies and datasets, and a presentation of the multi-level methodology adopted for end-use data analysis; Section 3 illustrates the quantitative and qualitative outcomes emerging from multi-level analysis conducted to compare the information included in the reviewed studies and datasets. Finally, the study's most relevant findings and implications are highlighted in Section 4, along with some considerations for future research directions.

2. Materials and methods

2.1. Literature review methods and search outcome

We carried out a systematic search of peer-reviewed journal papers, water utility reports, and other grey literature material (i.e. theses, research projects, presentations, etc.) to explore the current state of research on residential water consumption at the end-use level. The search was conducted between October 2020 and November 2022. Specifically, we searched for publications related to residential water consumption at the end-use level in the Elsevier's Scopus database (Elsevier 2021) as well as in some of the most accessed water journal editor databases, such as those of the International Water Association and the American Society of Civil Engineers. We initially searched for combinations of three keywords, i.e. "residential," "water," and "end uses", and limited the subject area to "engineering". This search led to an initial paper set of 271 publications, mostly (but not only) in English. We then manually checked the title and abstract of each publication and retained only those fitting the scope of our study. In greater detail, 40 publications were retained at this stage. Finally, we expanded the resulting set of papers by including other studies cited in the bibliography of the retained publications. The final paper set considered for the following analysis includes a total of 114 studies presenting – or making use of – residential water consumption data at the end-use level.

We reviewed these 114 studies, reported in Table 1 and hereinafter called *residential end-use studies* (REUS), to explore their contribution and implications to residential water consumption at the end-use level. A first analysis evaluated the objectives of each study, the primary of which was considered for classification (Fig. 1).

Fig. 1 reveals that, in most cases (42 studies, i.e. 37%), research was conducted to explore the characteristics of end-use water consumption in some specific geographical areas. However, end-use data were widely exploited also for other purposes, namely, to evaluate the potential for water conservation and recycling (17 studies, i.e. 15%), explore the determinants of water consumption (12 studies, i.e. 11%), develop or validate algorithms for water end-use disaggregation and classification (11 studies, i.e. 10%), and for water demand modelling (9 studies, i.e. 8%) or the retrieval of end-use information and evaluations about end-use data gathering and processing (9 studies, i.e. 8%). Other applications, albeit less common, include: investigation of strategies for wastewater management and/or the design of sewer systems; data exploitation to assess end-use peak demand or evaluate end-use probability of use; or end-use data analysis to quantify variations in users' perception and awareness. In addition, we investigated the following characteristics: (1) location; (2) period; (3) household sample size; (4) average duration of the monitoring period per household (if conducted); (5) temporal resolution of monitoring (if conducted); (6) approach adopted for end-use data gathering (i.e. end-use monitoring, interaction with householders, or end-use disaggregation method); and (7) dataset availability. All the above REUS characteristics are summarized in Table 1.

Our review reveals that the 114 REUS refer to 66 different databases, hereinafter called *end-use databases* (EUD). Specifically, some EUD are exploited in more than one REUS (see, e.g., the British EUD used by Butler (1991, 1993), or the Southeast Queensland EUD exploited by Beal et al. (2011a, 2011b, 2013) and other authors). In contrast, other EUD are used in only one REUS. It is also worth noting that some REUS have been conducted by exploiting only part of their related EUD (Willis et al., 2009c; Gato-Trinidad et al., 2011; Rathnayaka et al., 2015), whereas some other have exploited it entirely (Bennett and Linstedt, 1975; Mayer et al., 2000; Fontdecaba et al., 2013; Alharsha et al., 2022).

2.2. EUD clustering

We first clustered EUD based on the fields of investigation mentioned above (see Table 1). Overall, the fields of investigation selected for clustering are in line with those considered by Di Mauro et al. (2021). However, it is worth highlighting that the scope of our study extends the study by Di Mauro et al. (2021). Here, EUD clustering is conducted only to make an initial and qualitative discrimination amongst the EUD concerned, thus providing an organized dataset to achieve the key aim of the work, i.e. conducting a multi-level comparison (both qualitative and quantitative) of their end-use parameters and characteristics.

EUD were clustered manually and exclusively based on the information reported in their related REUS. This was done with the aim of standardizing the analysis in light of the fact that the majority of EUD are not publicly available (as detailed below). From an operational standpoint, we adopted the following criteria for clustering: (1) concerning the *study period*, we clustered EUD based on the first year of data collection; (2) concerning the *sample size*, the *average duration* of monitoring per household (if reported), and the *temporal data sampling resolution* (if reported), we clustered EUD based on the highest values inferred in the respective REUS. By way of example, in the case of EUD including water consumption data collected during two subsequent periods, the former conducted on a smaller sample and the latter

Table 1
Overview of the 114 reviewed Residential End-use Studies (REUS) and their related 66 End-use Databases (EUD). Columns L1 – L6 refer to the levels of analysis which can be carried out based on each EUD, as detailed in Section 2.3.

EUD	Location	REUS	Objective(s)	Study period	Household sample size	Household monitoring period (average)	Temporal data sampling resolution	End-use data gathering approach	EUD availability	L1	L2	L3	L4	L5	L6
1	Boulder, Colorado (USA)	Bennett and Linstedt, 1975	Wastewater study/ sewer system design	Unreported	5	40 days	Unreported	Direct monitoring, interaction with users	Unavailable	✓	✓	✓	✓	-	-
2	Unreported, Wisconsin (USA)	Siegrist et al., 1976	Wastewater study/ sewer system design	Unreported	11	40 days	Unreported	Direct monitoring, interaction with users	Unavailable	✓	✓	-	✓	-	-
3	Various (USA)	Brown and Caldwell Consulting Engineers, 1984	Water conservation/ recycling study	Unreported	210	2 weeks	Unreported	Direct monitoring, interaction with users	Unavailable	✓	✓	-	-	-	-
4	Unreported (UK)	Butler 1991	Wastewater study/ sewer system design	1987	28	1 week	-[a]	Interaction with users	Unavailable	-	✓	-	✓	-	-
		Butler 1993	Wastewater study/ sewer system design	1987	28	1 week	-	Interaction with users							
5	Tampa, Florida (USA)	Anderson et al., 1993	End-use water consumption study, water conservation/ recycling study	1992	25	2 months	Unreported	Direct monitoring	Unavailable	✓	✓	✓	-	-	✓
6	Unreported (UK)	Edwards and Martin 1995	End-use water consumption study, demand determinants study	1992–1993	100	1 year (pilot)	15 min	Direct monitoring	Unavailable	✓	-	-	-	-	-
7	Boulder, Colorado (USA)	DeOreo et al., 1996	End-use water consumption study	1994	16	3 weeks	10 s	Manual disaggregation	Unavailable	✓	✓	✓	-	-	-
8	Various (USA, Canada)	Mayer et al., 1999	End-use water consumption study	1996–1998	1188	4 weeks	10 s	Automated disaggregation (TraceWizard)	Restricted	✓	✓	✓	✓	-	✓
		Suero et al., 2012	Water conservation/ recycling study	1996–1998	Unreported	4 weeks	10 s	Automated disaggregation (TraceWizard)							
9	Bangkok (Thailand)	Darmody et al., 1999	End-use water consumption study, water conservation/ recycling study	Unreported	814	-[b]	-	Individual event observation, interaction with users	Unavailable	✓	-	-	-	-	✓
10	East Bay, California (USA)	Darmody et al., 1999	End-use water consumption study, water conservation/ recycling study	1994	657	-	-	Individual event observation, interaction with users	Unavailable	✓	-	-	-	-	✓
11	Seattle, Washington (USA)	Mayer et al., 2000	Water conservation/ recycling study	Unreported	37	8 weeks	10 s	Automated disaggregation (TraceWizard)	Unavailable	✓	✓	✓	-	-	✓
		Suero et al., 2012	Water conservation/ recycling study	Unreported	Unreported	8 weeks	10 s	Automated disaggregation (TraceWizard)							
12	Various (Netherlands)	Foekema and Engelsma 2001	End-use water consumption study, demand determinants study	2001	3200	1 week	-	Interaction with users	Unavailable	✓	✓	✓	-	✓	✓
		Blokker 2006	Demand modelling and forecasting	2001	3200	1 week	-	Interaction with users							
		Blokker 2010		2001	3200	1 week	-								

(continued on next page)

Table 1 (*continued*)

EUD	Location	REUS	Objective(s)	Study period	Household sample size	Household monitoring period (average)	Temporal data sampling resolution	End-use data gathering approach	EUD availability	L1	L2	L3	L4	L5	L6
			Demand modelling and forecasting					Interaction with users							
		Blokker et al., 2010	Demand modelling and forecasting	Unreported	3200	1 week	-	Interaction with users							
		Agudelo-Vera et al., 2014	End-use water consumption study	1992–2010	Unreported	1 week	-	Interaction with users							
13	San Francisco East Bay, California (USA)	Mayer et al., 2003	Water conservation/ recycling study	2001–2002	33	6 weeks	10 s	Automated disaggregation (TraceWizard)	Unavailable	✓	✓	✓	-	-	✓
		Suero et al., 2012	Water conservation/ recycling study	2001–2002	Unreported	6 weeks	10 s	Automated disaggregation (TraceWizard)							
14	Perth (Australia)	Loh and Coghlan 2003	End-use water consumption study, demand modelling and forecasting	1998–2001	244	14÷19 months	Unreported	Automated disaggregation (TraceWizard)	Unavailable	✓	✓	-	-	-	✓
15	Unreported (UK)	Kowalski and Marshallsay 2003	End-use disaggregation method development/ validation	2001	250	Unreported	Unreported	Automated disaggregation (Identiflow)	Unavailable	✓	-	✓	✓	-	-
		Kowalski and Marshallsay 2005	End-use water consumption study, water conservation/ recycling study	2001	500	Unreported	Unreported	Automated disaggregation (Identiflow)							
16	Unreported (UK)	Lauchlan and Dixon 2003	Wastewater study/ sewer system design	Unreported	Unreported	Unreported	Unreported	Unreported	Unavailable	-	✓	✓	-	-	-
17 [c]	Tampa, FL (USA)	Mayer et al., 2004	Water conservation/ recycling study	2002–2003	26	6 weeks	10 s	Automated disaggregation (TraceWizard)	Restricted	✓	-	-	-	-	-
18	Sydney (Australia)	White et al., 2004	End-use water consumption study, demand modelling and forecasting	1999	Unreported	-	-	Interaction with users	Unavailable	✓	-	-	-	-	✓
19	Yarra Valley (Australia)	Roberts 2005	End-use water consumption study, demand modelling and forecasting	2004	100	4 weeks	5 s	Automated disaggregation (TraceWizard)	Unavailable	✓	✓	✓	✓	✓	✓
		Gato-Trinidad et al., 2011	End-use water consumption study	2004	80÷93	6 weeks	5 s	Automated disaggregation (TraceWizard)							
20	Various (Netherlands)	Kanne 2005	End-use water consumption study, demand determinants study	2004	1684	1 week	-	Interaction with users	Unavailable	✓	✓	-	-	✓	✓
		Agudelo-Vera et al., 2014	End-use water consumption study	1992–2010	Unreported	Unreported	-	Interaction with users							
21	Palhoca (Brazil)	Ghisi and Oliveira, 2007	Water conservation/ recycling study	2004	2	4 weeks	-	Interaction with users	Unavailable	✓	✓	-	-	-	-
22	Various (South Africa)	Jacobs 2007	Demand modelling and forecasting	Unreported	123	2 years	1 month	Interaction with users	Unavailable	-	-	-	-	-	-
23	Kapiti Coast (New Zealand)	Heinrich 2007	End-use water consumption study,	2006–2007	12	8 months	10 s	Automated disaggregation (TraceWizard)	Unavailable	✓	✓	✓	-	✓	✓

(*continued on next page*)

Table 1 (*continued*)

EUD	Location	REUS	Objective(s)	Study period	Household sample size	Household monitoring period (average)	Temporal data sampling resolution	End-use data gathering approach	EUD availability	L1	L2	L3	L4	L5	L6
			data gathering and elaboration study												
24	Various (Korea)	Kim et al., 2007	End-use water consumption study, demand determinants study	2002–2006	145	3 years	1 h ÷ 1 day	Direct monitoring		-	-	-	-	-	-
25	Chiang Mai (Thailand)	Otaki et al., 2008	End-use water consumption study	Unreported	55÷63	2 months	Unreported	Direct monitoring	Unavailable	✓	-	-	-	-	-
26	Toowoomba, (Australia)	Mead 2008	End-use water consumption study	2008	10	138 days	10 s	Automated disaggregation (TraceWizard)	Unavailable	✓	✓	✓	✓	✓	✓
		Mead and Aravinthan 2009	End-use water consumption study	2008	10	138 days	10 s	Automated disaggregation (TraceWizard)							
27	Various (Netherlands)	Foekema et al., 2008	End-use water consumption study, demand determinants study	2007	2454	1 week	-	Interaction with users	Unavailable	✓	✓	-	-	✓	✓
		Agudelo-Vera et al., 2014	End-use water consumption study	1992–2010	Unreported	Unreported	-	Interaction with users							
28	Madrid (Spain)	Cubillo-González et al., 2008	End-use water consumption study	2002–2003	292	299 days	1 s	Manual disaggregation	Unavailable	✓	✓	✓	✓	✓	✓
		Ibáñez-Carranza et al., 2017	End-use disaggregation method development/ validation	2008-Uknown	300	2÷3 months	Unreported	Unreported							
29	Various, Gold Coast (Australia)	Willis et al., 2009a	Data gathering and elaboration study	2008	50	2 weeks	10 s	Unreported	Unavailable	✓	✓	✓	✓	✓	✓
		Willis et al., 2009b	End-use water consumption study	2008	151	2 weeks	10 s	Automated disaggregation (TraceWizard)							
		Willis et al., 2009c	End-use water consumption study, demand determinants study	2008	50	2 weeks	10 s	Unreported							
		Willis et al., 2010a	Water conservation/ recycling study	2208	151	Unreported	10 s	Automated disaggregation (TraceWizard)							
		Willis et al., 2010b	Water conservation/ recycling study	2008–2009	44÷151	4 weeks	10 s	Automated disaggregation (TraceWizard)							
		Willis et al., 2011a	Water conservation/ recycling study	2008	132	2 weeks	10 s	Automated disaggregation (TraceWizard)							
		Willis et al., 2011b	Water conservation/ recycling study	2008–2010	127÷134	Unreported	10 s	Automated disaggregation (TraceWizard)							
		Willis et al., 2013	End-use water consumption study, demand determinants study	2008	151	Unreported	10 s	Automated disaggregation (TraceWizard)							
30	Auckland (New Zealand)	Heinrich, 2010	End-use water consumption study	2008	51	9 weeks	10 s		Unavailable	✓	✓	✓	-	-	-

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Table 1 (*continued*)

EUD	Location	REUS	Objective(s)	Study period	Household sample size	Household monitoring period (average)	Temporal data sampling resolution	End-use data gathering approach	EUD availability	L1	L2	L3	L4	L5	L6
								Automated disaggregation (TraceWizard)							
31	Trincomalee (Sri Lanka)	Sivakumaran and Aramaki, 2010	End-use water consumption study	Unreported	106	-	-	Interaction with users	Unavailable	✓	-	-	-	-	-
32	Perth (Australia)	Water Corporation, 2010	End-use water consumption study	Unreported	Unreported	2 weeks	Unreported	Unreported	Unavailable	✓	✓	-	-	-	-
33	Khon Kaen (Thailand)	Otaki et al., 2011	End-use water consumption study	Unreported	59	1 month	Unreported	Direct monitoring	Unavailable	✓	-	-	-	-	-
34	Various (USA)	DeOreo et al., 2011	End-use water consumption study, water conservation/ recycling study	2006–2009	734	2 weeks	10 s	Automated disaggregation (TraceWizard)	Unavailable	✓	✓	✓	✓	-	-
35	Various (USA)	Aquacraft 2011	End-use water consumption study, water conservation/ recycling study	2006–2009	327	2 weeks	10 s	Automated disaggregation (TraceWizard)	Unavailable	✓	✓	✓	-	-	✓
		Cominola et al., 2018a	Demand modelling and forecasting	2007–2009	313	2 weeks	10 s	Automated disaggregation (TraceWizard)							
36	Various, SEQ (Australia)	Beal et al., 2011a	End-use water consumption study	2010	252	2 weeks	5 s	Automated disaggregation (TraceWizard)	Open access (SMIP 2011)	✓	✓	✓	✓	✓	✓
		Beal et al., 2011b	Study of users' perception and awareness	2010	222	2 weeks	5 s	Automated disaggregation (TraceWizard)							
		Beal and Stewart 2011	End-use water consumption study	2010–2012	83÷252	14 weeks	5 s	Automated disaggregation (TraceWizard)							
		Beal et al. 2012	Demand determinants study	2010–2011	252–110	6 weeks	5 s	Automated disaggregation (TraceWizard)							
		Beal et al., 2013	Study of users' perception and awareness	2010	222	2 weeks	5 s	Automated disaggregation (TraceWizard)							
		Makki et al., 2013	End-use water consumption study (shower)	2010	200	2 weeks	5 s	Automated disaggregation (TraceWizard)							
		Nguyen et al., 2013a	End-use disaggregation method development/ validation	2010–2011	110÷252	10 weeks	5 s	Automated disaggregation (TraceWizard)							
		Nguyen et al., 2013b	End-use disaggregation method development/ validation	2010–2011	110÷252	10 weeks	5 s	Automated disaggregation (TraceWizard)							
		Beal and Stewart 2014a	Peak demand study	2010–2011	110÷252	10 weeks	5 s	Automated disaggregation (TraceWizard)							
		Beal and Stewart 2014b	End-use water consumption study	2010–2012	53÷252	24 weeks	5 s	Automated disaggregation (TraceWizard, Autoflow)							
		Beal et al., 2014		2010–2013	69÷252	20 weeks	5 s								

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Table 1 (*continued*)

EUD	Location	REUS	Objective(s)	Study period	Household sample size	Household monitoring period (average)	Temporal data sampling resolution	End-use data gathering approach	EUD availability	L1	L2	L3	L4	L5	L6
			Study of users' perception and awareness					Automated disaggregation (TraceWizard)							
		Gurung et al., 2014	Peak demand study	2010–2012	44÷134	14 weeks	5 s	Automated disaggregation (TraceWizard)							
		Gurung et al., 2015	Peak demand study	2010–2012	44÷134	14 weeks	5 s	Automated disaggregation (TraceWizard)							
		Nguyen et al., 2015	End-use disaggregation method development/ validation	Unreported	Unreported	Unreported	5 s	Automated disaggregation (TraceWizard)							
		Yang et al., 2018	End-use disaggregation method development/ validation	Unreported	252	Unreported	5 s	Unreported							
		Nguyen et al., 2018	End-use disaggregation method development/ validation	2010–2012	Unreported	16 weeks	5 s	Automated disaggregation (TraceWizard)							
		Cominola et al., 2019	Data gathering and elaboration study	2010	252	Unreported	5 s	Automated disaggregation (Autoflow)							
		Meyer et al., 2021	End-use disaggregation method development/ validation (indoor-outdoor)	2010–2012	252	Unreported	5 s	Automated disaggregation (TraceWizard)							
37	Various (Netherlands)	Foekema and Van Thiel 2011	End-use water consumption study, demand determinants study	2010	1237	1 week	-	Interaction with users	Unavailable	✓	✓	-	-	✓	✓
		Agudelo-Vera et al., 2014	End-use water consumption study	1992–2010	Unreported	Unreported	-	Interaction with users							
38	Various (Korea)	Lee et al., 2012	End-use water consumption study	2002–2006	146	4 years	10 min	Direct monitoring	Unavailable	✓	-	-	-	✓	-
39	Hervey Bay (Australia)	Cole and Stewart 2013	Peak demand study	2008–2009	2884	1 year	1 h	Rough method (indoor + outdoor)	Unavailable	-	-	-	-	-	-
		Gurung et al., 2014	Peak demand study	2008–2009	2494	1 year	1 h	Rough method (indoor + outdoor)							
		Gurung et al., 2015	Peak demand study	2008–2009	2494	1 year	1h	Rough method (indoor + outdoor)							
40	Melbourne and Yarra Valley (Australia)	Redhead et al., 2013	End-use water consumption study	2010–2012	300	4 weeks	5÷10 s	Manual and automated disaggregation (TraceWizard)	Unavailable	✓	✓	✓	✓	✓	-
		Gan and Redhead 2013	End-use water consumption study	2010–2012	300	4 weeks	Unreported	Manual and automated disaggregation (TraceWizard)							
		Rathnayaka et al., 2015	End-use water consumption study	Unreported	117	Unreported	5 s	Automated disaggregation (TraceWizard)							
		Nguyen et al., 2015		Unreported	Unreported	Unreported	5 s								

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Table 1 (*continued*)

EUD	Location	REUS	Objective(s)	Study period	Household sample size	Household monitoring period (average)	Temporal data sampling resolution	End-use data gathering approach	EUD availability	L1	L2	L3	L4	L5	L6
			End-use disaggregation method development/ validation					Automated disaggregation (TraceWizard)							
		Siriwardene 2018	End-use water consumption study	2011–2012	100*	1 year	Unreported	Unreported							
41	Hanoi (Vietnam)	Otaki et al., 2013	End-use water consumption study	2011	56	2 months	Unreported	Direct monitoring	Unavailable	✓	✓	✓	-	✓	-
		Otaki et al., 2017	End-use water consumption study	2011	56	5 months	Unreported	Direct monitoring, interaction with users							
42	Various (USA, Canada)	DeOreo and Mayer 2013	End-use water consumption study	2012–2013	762	2 weeks	10 s	Automated disaggregation (TraceWizard)	Restricted	✓	✓	✓	✓	-	✓
		DeOreo et al., 2016	End-use water consumption study	2012–2013	737	2 weeks	10 s	Automated disaggregation (TraceWizard)							
		Buchberger et al., 2017	End-use probability study, peak demand study	1996–2011	1038	2 weeks	10 s	Automated disaggregation (TraceWizard)							
		Omaghomi et al., 2020	End-use probability study, peak demand study	1996–2011	1038	2 weeks	10 s	Automated disaggregation (TraceWizard)							
		Vitter and Webber 2018	End-use disaggregation method development/ validation	Unreported	94	Unreported	Unreported	Unreported							
43	Barcelona, Murcia (Spain)	Fontdecaba et al., 2013	End-use disaggregation method development/ validation	2009–2010	8	3 months	1÷5 s	Automated disaggregation (ad hoc method)	Unavailable	-	✓	✓	-	-	-
44	Davis, CA (USA)	Borg et al., 2013	End-use water consumption study, water conservation/ recycling study	Unreported	3	1 week	Unreported	Direct monitoring, interaction with users	Unavailable	✓	-	-	-	-	-
45	Various (Netherlands)	Van Thiel 2014	End-use water consumption study	2013	1349	1 week	-	Interaction with users	Unavailable	✓	✓	-	✓	✓	✓
		Blokker and Agudelo-Vera 2015	Demand modelling and forecasting	2013	1349	1 week	-	Interaction with users							
46	Various (Austria)	Neunteufel et al., 2014	End-use water consumption study	2012–2013	105	Unreported	10 s ÷ 1 day	Unreported	Unavailable	✓	✓	-	-	-	-
47	Adelaide (Australia)	Arbon et al., 2014	End-use water consumption study, demand determinants study	2013	140	2 weeks	10 s	Unreported	Restricted	✓	✓	-	✓	✓	✓
48	Unreported (Greece, Poland)	Shan et al., 2015	End-use water consumption study	Unreported	148	-	-	Interaction with users	Unavailable	-	✓	-	-	✓	-
49	Jaipur (India)	Sadr et al., 2015	End-use water consumption study	Unreported	90	-	-	Interaction with users	Unavailable	✓	-	-	-	✓	-
		Sadr et al., 2016	End-use water consumption study	Unreported	90	-	-	Interaction with users							
50	Duhok (Iraq)	Hussien et al., 2016	End-use water consumption study	Unreported	407	-	-	Interaction with users	Unavailable	✓	✓	-	-	✓	-
51	Unreported	Kozlovskiy et al., 2016	End-use water consumption study	2016	1	3 weeks	2 s	Unreported	Unavailable	-	-	-	-	-	-

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Table 1 (*continued*)

EUD	Location	REUS	Objective(s)	Study period	Household sample size	Household monitoring period (average)	Temporal data sampling resolution	End-use data gathering approach	EUD availability	L1	L2	L3	L4	L5	L6
52	Various (Netherlands)	Van Thiel 2017	End-use water consumption study, demand determinants study	2016	1617	1 week	-	Interaction with users	Unavailable	✓	✓	-	-	✓	✓
53	Sirte (Lybia)	Alharsha et al., 2018	End-use water consumption study	2017	230	-	-	Interaction with users	Unavailable	✓	✓	✓	✓	-	-
		Alharsha et al., 2022	End-use water consumption study	2017–2018	380	-	-	Interaction with users							
54	Unreported (USA)	Jordán-Cuebas et al., 2018	Demand determinants study, demand modelling and forecasting	2011–2013	2(30)	1 year	Unreported	Direct monitoring	Open access (Jordan-Cuébas et al., 2017)	✓	-	-	-	-	-
55	Melbourne (Australia)	Siriwardene 2018	End-use water consumption study	2017–2018	120	1 year	10 s	Automated disaggregation (Autoflow)	Unavailable	✓	✓	✓	✓	✓	-
56	Western Cape Province (South Africa)	Du Plessis et al. 2018	End-use water consumption study (indoor-outdoor)	2013–2015	371	Unreported	1 month	Water balance (urban scale)	Unavailable	✓[d]	-	-	-	-	-
57	Various (Greece and Poland)	Kofinas et al., 2018	Data gathering and elaboration study	2015–2016	16	13 months	30 s	Direct monitoring	Unavailable	-	-	-	-	-	-
58	Cape Town (South Africa)	Meyer and Jacobs 2019	End-use water consumption study (indoor-outdoor)	Unreported	10	11 days	2 min	Indirect monitoring (temperature sensors)	Restricted	-	✓[d]	✓[d]	-	-	-
		Meyer et al., 2021	End-use disaggregation method development/ validation (indoor-outdoor)	2016–2018	14	5 days	Unreported	Indirect monitoring (temperature sensors)							
59	Naples (Italy)	Di Mauro et al. 2020	Data gathering and elaboration study	2019	1	8 months	1 s	Direct monitoring	Open access (Venticinque et al. 2021)	-	✓	-	✓	-	-
		Di Mauro et al. 2022	Data gathering and elaboration study	2019–2020	1	20 months	1 s	Direct monitoring							
60	Illinois (USA)	Bethke 2020	End-use water consumption study	2018–2019	4	1 year	1 s	Automated disaggregation (ad hoc method)	Open access (Stillwell Research Group, 2021)	✓	✓	-	-	-	✓
		Bethke et al., 2021	End-use water consumption study	2018–2019	4	1 year	1 s	Automated disaggregation (ad hoc method)							
61	Madrid (Spain)	Díaz et al. 2021	End-use water consumption study	2021	3298	-	-	Interaction with users	Unavailable	-	✓	✓	-	-	-
62	Galle and Colombo (Sri Lanka)	Otaki et al., 2022	End-use water consumption study, water conservation/ recycling study	2017	127	3 weeks	1 week	Direct monitoring	Open access (Otaki et al., 2022)	✓	-	-	-	-	-
63	Various (Netherlands)	Mazzoni et al., 2022	End-use disaggregation method development/ validation	2019–2020	9	7 weeks	1 s	Manual and automated disaggregation, interaction with users	Restricted	✓	✓	✓	✓	-	-
		Mazzoni et al., 2023	End-use water consumption study	2019–2020	9	7 weeks	1 s	Manual and automated disaggregation,							

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Table 1 (*continued*)

EUD	Location	REUS	Objective(s)	Study period	Household sample size	Household monitoring period (average)	Temporal data sampling resolution	End-use data gathering approach	EUD availability	L1	L2	L3	L4	L5	L6
								interaction with users							
64	Unreported (Midwest USA)	Heydari et al., 2022	Data gathering and elaboration study	2021	1	4 weeks	1 s	Interaction with users	Open access (Stillwell Research Group 2022)	-	-	-	✓	-	-
65	Unreported	Arsene et al., 2022	End-use disaggregation method development/ validation, data gathering and elaboration study	Unreported	Unreported	Unreported	Unreported	Direct monitoring	Open access (Predescu 2022)	-	-	-	✓	-	-
66	Logan and Providence, Utah (USA)	Bastidas Pacheco et al. 2022	Data gathering and elaboration study	2022	2	2–3 weeks	1 s – 1 min	Manual disaggregation	Open access (Bastidas Pacheco et al. 2021a, Bastidas Pacheco and Horsburgh 2022)	✓	✓	✓	-	✓	✓
		Bastidas Pacheco et al. 2023	End-use water consumption study	2019–2021	31	4–23 weeks	4 s	Automated disaggregation (ad hoc method)							

Note: [a] Symbol – means that no data sampling was performed.
[b] Symbol – means that no monitoring was conducted.
[c] Study not available. Results were derived from Jordán-Cuebas et al. (2018) and Di Mauro et al. (2021).
[d] Only for outdoor use (irrigation).

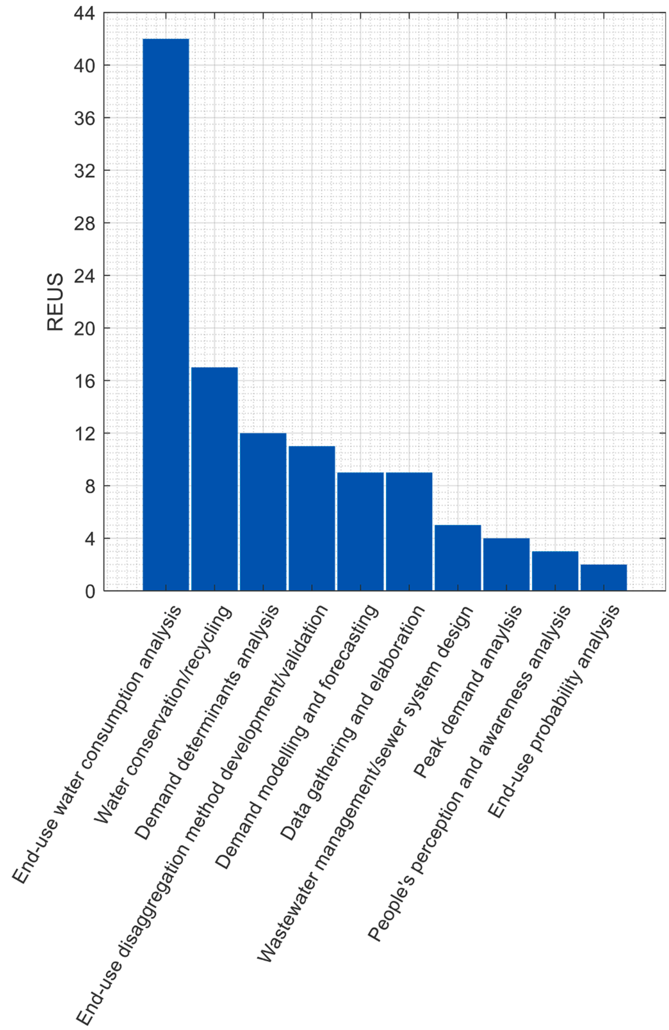

Fig. 1. Primary objective of the 114 REUS reviewed.

extended to a larger sample, the number of households making up the latter sample is considered for clustering. Similarly, when a measurement campaign is conducted in two (or more) stages, the first with a coarser and the second with a finer data sampling temporal resolution, the finest resolution is considered as a reference value for clustering. Finally, (3) concerning *dataset availability* – and similarly to Di Mauro et al. (2021) – we clustered EUD in three main categories of data accessibility: *open access* (if available in the literature and freely downloadable from the web), *restricted* (if not directly available, but details on how to obtain them are explicitly reported in the related REUS), and *unavailable* (if no information on how to access or purchase them is reported in the related REUS).

The results of the EUD clustering are shown in Fig. 2. The following findings emerge for each considered criterion:

- *Geographical area* (Fig. 2a). EUD include data collected across all the continents, but mainly in North America (18 databases), Europe (18 databases), and Oceania (13). A lower number of EUD include data collected in Asia (10), Africa (4), and South America (1). In general, a linkage between the level of digitalization of water utilities and the respective number of EUD is observed because their realization typically requires technologies and tools that may not be available in the most underdeveloped areas of the world. Moreover, a higher number of analyses – hence EUD – is observed for areas that have been strongly hit by water scarcity and drought conditions, such as the western coast of the United States or Australia (see, e.g., Mayer

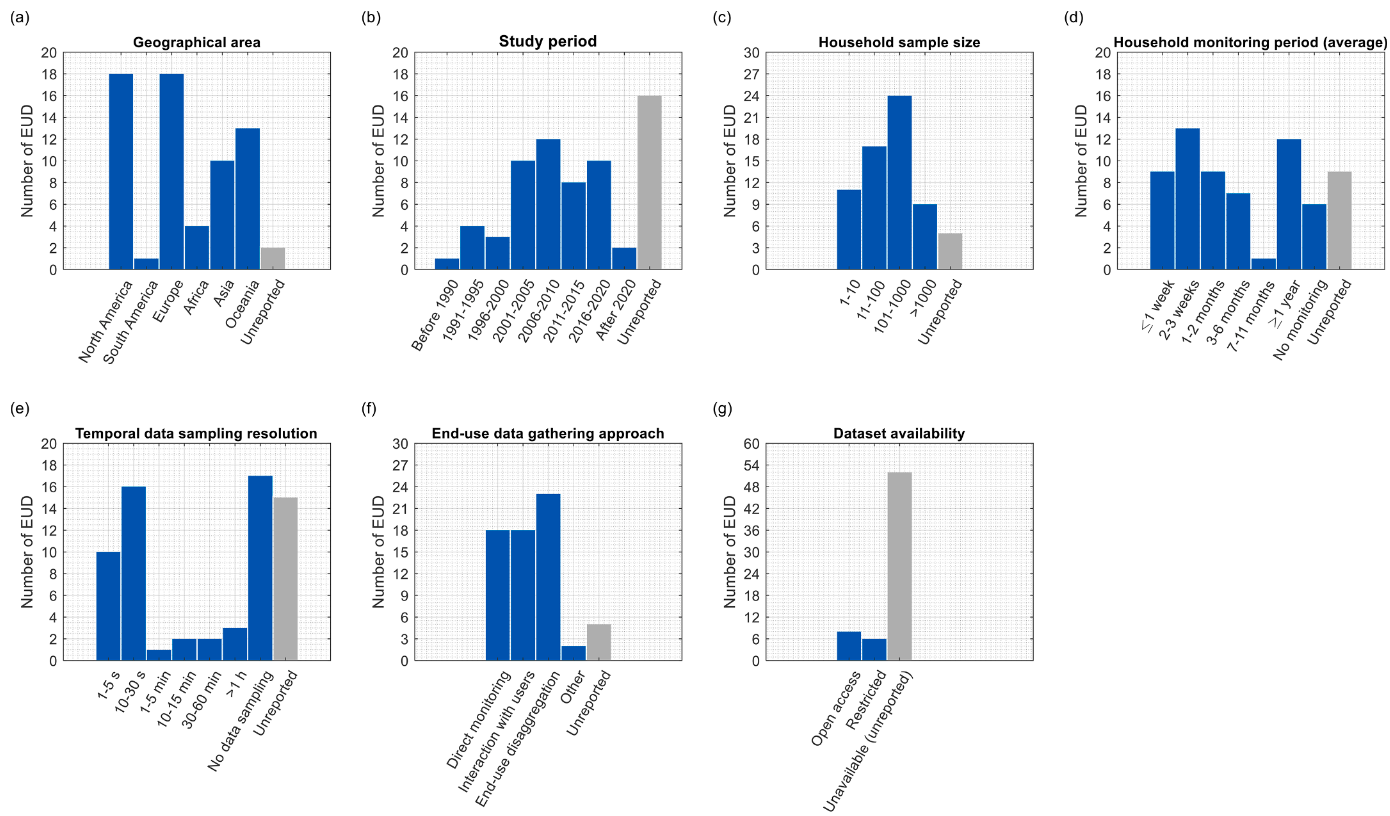

Fig. 2. EUD clustering results.

et al., 1999, Mayer et al., 2003, Beal and Stewart, 2011, and Beal et al., 2014).

- *Study period* (Fig. 2b). Although REUS have been conducted since the 1970s (Bennett and Lindstedt 1975, Siegrist et al., 1976), most EUD have been developed only after 2000. This finding is mainly due to the technological development in the late 1990s and, specifically, the advent of smart metering technologies, making available water consumption data at a fine spatial and/or temporal resolution, i.e. household or end-use level (Cominola et al., 2015; Gurung et al., 2015). This aspect also explains why these first REUS were generally conducted in developed countries. In contrast, developing countries such as Sri Lanka, Thailand, and Vietnam have undergone REUS only since the last decade (Sivakumaran and Aramaki, 2010, Otaki et al., 2011, Otaki et al., 2013). However, information on the first year of data collection is not available for a non-negligible group of 16 EUD (i.e. 24% of the total).
- *Household sample size* (Fig. 2c). The majority of the EUD include data collected for samples of households in a range between ten and a hundred (17 EUD, i.e. 26% of the total) or between hundred and a thousand (24 EUD, i.e. 36%). Only a limited number of EUD include data observed for samples smaller than ten households (11, i.e. 17%), or larger than a thousand (9, i.e. 14%). In general, household sample size (typically dependant on the scope of the research) is rather limited in the earliest studies, for which manual or laborious processes have been generally carried out to obtain water end-use data. For instance, in the EUD developed by DeOreo et al. (1996) – the first to be developed by relying on water consumption data at sub-minute resolution – 16 households were monitored. Their observed water consumption was manually disaggregated and classified into individual end uses based on the parameters of the water use events recorded at the household level. Considerable increases in the sample size were made possible by introducing automated methods for data processing and classification (Mayer et al., 1999; Kowalski and Marshallsay 2003; Beal et al., 2011a). As far as the relationship between household sample size and water consumption results is regarded, it is expected that increasing the household sample can lead to EUD that are more representative of end-use water consumption in a specific location. However, it is worth observing that, to date, no REUS primarily aiming to explore the effects of sample size on water consumption results – thus defining guidelines that can aid water utilities and researchers to identify an optimal sample size – have been conducted, making this research question still unsolved.
- *Household monitoring period (average)* (Fig. 2d). Regarding the EUD for which water consumption data have been obtained employing direct measurements, different monitoring durations per household are observed, ranging from a minimum of a few days (i.e. less than one week) to a maximum of more than one year. Although a marked correlation is not evident between the length of the monitoring period and the other clustering variables, an inverse relationship between the length of the monitoring period and temporal data sampling resolution is sometimes observed (regarding EUD with similar household sample size). This emerges, for example, when the EUD presented by Mayer et al. (1999) and DeOreo et al. (2011) is compared against the EUD reported by Cole and Stewart (2013). Indeed, in the former cases, about one thousand households were monitored for around two weeks at the 10-s sampling resolution. In contrast, the latter analysis exploits hourly-resolution data from approximately 3000 households. Lastly, for 14% of the EUD, data were not obtained by the monitoring but with different methods (e.g. interaction with users). As reported by Bastidas Pacheco et al. (2023), collecting water consumption data for short periods can lead to results that may not be representative of varying water consumption patterns, given that this also depends on seasonal factors. Although some EUD include data collected over different periods of the year in order to explore seasonal water consumption behaviors (e.g. those exploited by Mayer et al. (1999), Roberts (2005), Heinrich (2007), Beal and Stewart (2011), and Redhead et al. (2013)), it is worth noting that also the evaluation of the effects of data

monitoring periods on water consumption temporal variability is still an open issue.

- *Temporal data sampling resolution* (Fig. 2e). Several authors highlight that the introduction of smart metering technologies allows water consumption data to be collected not only at a fine spatial resolution but also at a fine temporal resolution, i.e. from several minutes up to a few seconds (Cominola et al., 2015, Clifford et al. 2018). In the case of the reviewed REUS, different monitoring temporal resolutions are observed, ranging from a minimum of 1 s to a maximum of less than one reading per month (which is in line with the traditional resolution of water metre readings for billing purposes). Moreover, the REUS review reveals that, in the case of coarse temporal resolution of monitoring, it is typically harder to identify all individual end uses of water, as also demonstrated by Cominola et al. (2018a), Bastidas Pacheco et al. (2022), and Heydari et al. (2022). By way of example, concerning the Hervey Bay (Australia) EUD, including aggregate water consumption data collected at hourly temporal resolution (Cole and Stewart 2013), only limited discriminations are made between indoor and outdoor water use. In contrast, Du Plessis et al. (2018) reveal that the same discrimination might be done also at the urban level by calculating a water balance, i.e. by relying on household water consumption data at a very coarse resolution (i.e. monthly) coupled with information obtained by monitoring wastewater flowing in sewer systems. However, it is worth noting that detailed information about individual end uses of water is typically obtainable only when data are available at sufficiently fine temporal resolution, i.e. more than one reading per minute. In fact, as reported by Cominola et al. (2018a) and Heydari et al. (2022) both on synthetic and real-world data, such a resolution generally allows end-use disaggregation and classification with acceptable accuracy, at least for the main end uses. This finding explains why most of the EUD reviewed include data with a temporal sampling resolution of at least one reading per minute (i.e. 26 of the 51 EUD for which this information is available).
- *End-use data gathering approach* (Fig. 2f). Although some EUD were obtained by directly monitoring each domestic end use (Anderson et al., 1993; Edwards and Martin 1995; Kim et al., 2007; Otaki et al., 2008), the economic, practical, and technological limitations related to this kind of approach have motivated the introduction of non-intrusive techniques, based on manual or automated processing of the data collected at the household level (i.e. at the domestic inlet point, in proximity to the water metre), to obtain end-use information (i.e. at the level of individual appliance/fixture). From an operational standpoint, this end-use level determination can be either achieved utilizing audits, reports, or questionnaires submitted to users (Butler 1991; Ghisi and Oliveira 2007; Shan et al., 2015; Alharsha et al., 2018, Díaz et al. 2021) or by applying manual, semi-automated, or automated methods for water end-use disaggregation and classification, such as those proposed by Mayer et al. (1999), Kowalski and Marshallsay (2003), Nguyen et al. (2013a), and Mazzoni et al. (2021). Some studies adopt hybrid approaches coupling different techniques, such as direct monitoring of only a limited subset of end uses coupled with interaction with the users to infer information on other water end uses (Bennett and Linstedt 1975, Siegrist et al., 1976, Brown and Caldwell Consulting Engineers, 1984, Otaki et al., 2017). In general, the earliest studies were typically carried out by exploiting analogue tools to record water consumption data (i.e. chart recorders driven by the water metre) and by manually processing the data collected. Conversely, in the case of larger or more recent EUD, end-use information is mainly achieved by automatically processing aggregate water consumption data collected at a very fine temporal resolution (Mayer et al., 1999; Cubillo-González et al., 2008; DeOreo and Mayer 2013). Overall, the application of methods for end-use disaggregation and classification of household-level data is the most commonly used technique to obtain information about the end uses of water (i.e. adopted in 23 of the EUD discovered, or 35%). However, it is worth observing that EUD obtained from data disaggregation and classification may be characterized by different levels of uncertainty based on the accuracy of the method considered – along with the inability of some of them to detect overlapping water-use events, or the a priori exclusion of overlapping events during data cleaning – two aspects which are hardly ever discussed in the related REUS (except those aimed at presenting new methods). Thus, due to the lack of sufficient information, EUD uncertainty in relation to disaggregation and classification performance will not be considered in the current study.
- *Dataset availability* (Fig. 2g). The vast majority of EUD is unavailable in the literature (52, i.e. 79%), whereas only a small group have open or restricted access (8 and 6, i.e. 12% and 9%, respectively). More specifically, most open-access EUD have been published in recent years (e.g. EUD exploited by Jordán-Cuebas et al. (2018), Di Mauro et al. (2020, 2022), Bethke et al. (2021), Otaki et al. (2022), Heydari et al. (2022), Arsene et al. (2022), and Bastidas Pacheco et al. (2023)). On the one hand, this is likely due to technological factors making digital data more available and shareable, as also highlighted by Di Mauro et al. (2021). On the other hand, this increasing trend in EUD accessibility may be fostered by the new policies typically adopted by scientific journals, encouraging authors to publicly share data for transparency and reproducibility purposes. In fact, the acknowledgement and awareness of the reproducibility challenge facing computational environmental modelling fields are currently growing (Choi et al., 2021). Conversely, only a few instances of open-access (or even simply restricted) EUD published in less recent years exist (i.e. EUD exploited by Mayer et al. (1999, 2004), Beal and Stewart (2011), and DeOreo and Mayer (2013)). Overall, it emerges that – despite the recent increase in open-access EUD – end-use data availability still represents a significant challenge in the spirit of open science and reproducible research. This motivates the current study of individual EUD characteristics and outcomes by relying only on the information reported in the REUS available in the literature (also due to the aim of standardizing the methodology for database analysis).

2.3. EUD processing

We systematically compared the EUD (based on results reported in the literature) by applying a six-level analysis (Fig. 3). This multi-level analysis aims to explore the characteristics of end-use water consumption from several points of view, revealing similarities and differences amongst the EUD concerning: (*Level 1*) daily per capita end-use water consumption; (*Level 2*) end-use parameter average values; (*Level 3*) end-use statistical parameter distributions; (*Level 4*) end-use daily profiles; (*Level 5*) end-use water consumption determinants; and (*Level 6*) efficiency and diffusion of water-saving end uses.

2.3.1. Level 1: daily per capita end-use water consumption

For each EUD including information about daily per capita water consumption at the end-use level, we considered the following categories of indoor water consumption: *dishwasher* (*D*), *washing machine* (*WM*), *shower* (*S*), *bathtub* (*B*), *toilet flusher* (F), *taps* (*T*), *leakages* (*L*), and *other* uses (*O*), this latter including all the indoor water uses which cannot be included in other categories (e.g. evaporative cooler, garbage disposal) or ambiguous water uses (e.g. *laundry* or *dishwashing*, if no information is available about the type of use, i.e. manual or automated). Specifically, for each EUD and end-use category, we processed data as follows:

- For REUS presenting daily per capita average values, we directly considered the reported values (once converted to *L/person/day*).
- For REUS presenting the end-use percent values of the daily per capita indoor water consumption, we turned these into daily per

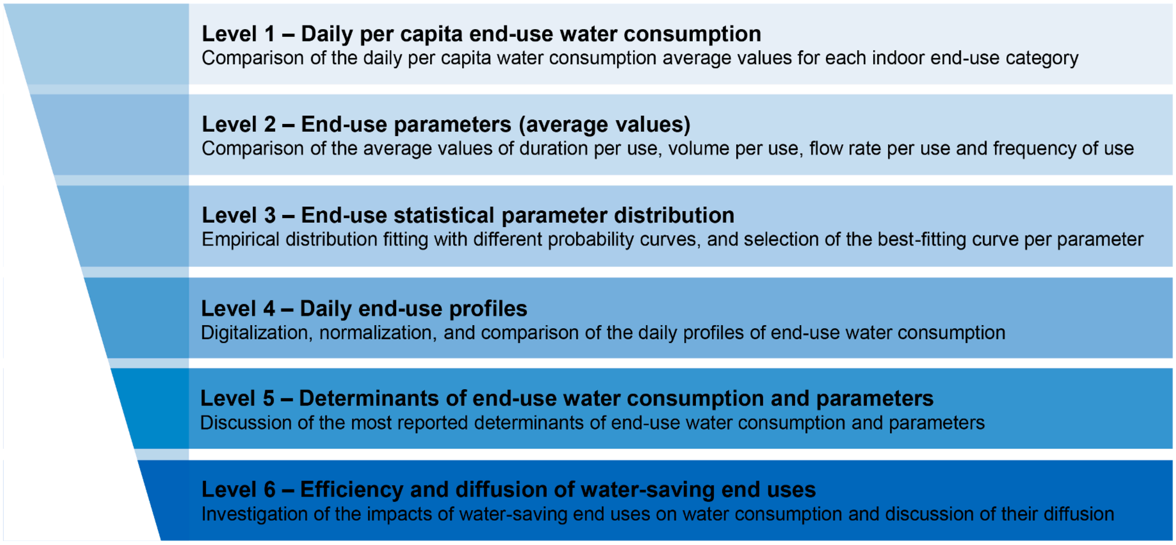

Fig. 3. Multi-level analysis layout.

capita values by exploiting the information about the average total daily per capita indoor water consumption reported.

- For REUS presenting values of end-use water consumption per family group per day, we turned these into daily per capita values by exploiting the information about the average occupancy rate of the households included in the study.
- For REUS presenting values specifically observed in different seasons (summer and winter), we averaged these to obtain values that could be representative of the overall EUD concerned (i.e. not affected by seasonal patterns) and, therefore, to be in line with those REUS describing the characteristics of water consumption only in relation to a single – sometimes already averaged – seasonal period (which are the majority).
- For REUS presenting multiple end-use water consumption values related to different subsets (regions, household types, etc.), we calculated a weighted average based on the size of each subset (i.e. the number of households monitored in each subset), to be in line with those REUS describing the characteristics of water consumption only in relation to the overall household sample (which are the majority).
- For REUS comparing baseline values against those observed after device retrofitting campaigns (e.g. low-flow toilet tank or tap aerator installations), we considered only pre-retrofitting data in order to explore the *status quo* of water consumption at the beginning of the study period, i.e. the conditions motivating the choice of installing new, more efficient fixtures.

2.3.2. Level 2: end-use parameters (average values)

To further explore the characteristics of water consumption at the end-use level, we computed four parameters describing the main features of different end uses: (1) *volume per use* (measured in *l/use*), defined as the volume of water consumed during an individual event of water use; (2) *duration per use* (measured in min/*use*), defined as the duration of an individual event of water use; (3) *flow rate per use* (measured in *l/* min), defined as the average flow rate characterizing an individual event of water use; and (4) *frequency of use* (measured in *uses/person/day*), defined as the number of times (per person per day) a water end-use occurs. Level 2 of analysis was conducted for all end-use categories introduced in Level 1, except for the *other* category, which was ignored due to the heterogeneity of water uses present. Moreover, the average values of the above four metrics were obtained for each study based on the assumptions made in Level 1 (see the related sub-section).

2.3.3. Level 3: end-use statistical parameter distributions

Level 3 of the analysis further explores the characteristics of end-use parameters defined in Level 2 by comparing their probability distributions. The motivation behind this analysis is that, in general, predictive or descriptive water demand models are calibrated based on predefined parameter distributions (i.e. the probability distribution of volume per use, duration per use, flow rate per use, and frequency of use for different end uses). However, to the authors' knowledge, the literature lacks a comprehensive database including and comparing this kind of information.

In most of the REUS including information about end-use parameter distributions, this information is shown in diagrams where the independent variable indicates the end-use parameter value (e.g. volume per shower use). Conversely, the dependant variable sometimes relates to the number of uses observed or to the relative frequency of occurrence. Therefore, given the tendency to include information in graphical form only – and in light of the high variability of the information available – we conducted Level 3 of analysis as follows:

1. We digitized the information originally in graphical form by means of the Web Plot Digitizer v4.3 software (Rohatgi 2021). Specifically, we processed the end-use parameter distributions shown in the studies for the five most common end-use categories (i.e. *dishwasher, washing machine, shower, toilet*, and *taps*) and the four parameters defined in Level 2 (i.e. *volume per use, duration per use, flow rate per use*, and *frequency of use*).
2. We processed the digitized information based on assumptions partially introduced in Level 1 and Level 2. Specifically: (i) we adapted the units of measurements to those selected for each end-use parameter in Level 2 (except tap duration that, given its limited average values, was assumed in *s/use*); (ii) in the case of REUS presenting end-use parameter distributions observed in specific seasons (summer and winter), we averaged these to obtain distributions not affected by seasonal patterns; (iii) in the case of REUS presenting multiple parameter distributions related to the type of end-use (e.g. *front* versus *top-load* washing machine) we calculated a weighted average based on the size of each subset; (iv) in the case of REUS comparing baseline distributions against those observed after device retrofitting, we considered pre-retrofitting distributions only.
3. We converted the distributions into empirical probability density function curves (i.e. empirical PDF).
4. We fitted the empirical PDF curves with MATLAB's R2019a® *fitdist* function. Specifically, five PDFs were assumed to fit each empirical

PDF: normal, lognormal, exponential, Weibull, and Gamma. We applied a one-sample Kolmogorov-Smirnov test to each fitted distribution type to evaluate its goodness-of-fit. Only the distribution types for which the Kolmogorov-Smirnov test was successful (i.e. provided the rejection of the null hypothesis at the 5% significance level) were then submitted to the Akaike's Information Criterion (AIC) test and compared (Akaike 1974). Finally, we selected the distribution type passing the Kolmogorov-Smirnov test and characterized by the minimum AIC parameter value as the best fitting PDF, with its related parameter values.

Overall, it is worth noting that uncertainties and potential errors may have arisen due to the reverse-engineering process adopted to obtain end-use statistical parameter distributions (e.g. digitization inaccuracy induced by low-resolution REUS histograms and, in turn, affecting curve fitting accuracy), the performance of which should be verified with actual end-use data distributions. However, given the scarce availability of most EUD (as demonstrated in Section 2.2) – motivating the characterization of end-use water consumption and parameters by relying only on the information reported in the REUS available in the literature – the above-mentioned approach resulted the most suitable method to uniformly process a large and heterogeneous amount of (graphical) end-use data.

2.3.4. Level 4: daily end-use profiles

Level 4 of the analysis focuses on the comparative analysis of the daily end-use profiles shown in the REUS. Overall, the most common end-use categories for which daily profiles are available are *dishwasher, washing machine, bathtub and shower, toilet, taps,* and *leakages*. As in the case of end-use parameter distributions, this information is typically provided exclusively in graphical form (i.e. by means of charts including the pattern of the average end-use water consumption over the 24 h of the day) and with different units of measurement. Therefore, as for Level 3 of the analysis, we first digitized the information on end-use daily profiles by means of the Web Plot Digitizer v4.3 software (Rohatgi 2021).

We then normalized (standardized) the digitized profiles for comparison and processed them based on the following assumptions: (1) in the case of REUS presenting the end-use daily profiles observed in specific seasons (summer and winter), we averaged these to obtain profiles not affected by seasonal patterns; (2) in the case of REUS presenting daily profiles related to multiple end uses of the same category (e.g. shower and bathtub, or kitchen sink and washbasin) we calculated a weighted-average profile based on the values of the daily per capita water consumption of each end use; and (3) in the REUS of studies comparing baseline profiles against those observed after device retrofitting, we considered only pre-retrofitting profiles.

2.3.5. Level 5: determinants of end-use consumption and parameters

Given the high heterogeneity in the determinants of the end uses of water presented in the REUS, Level 5 includes analyses aimed at quantifying the most reported categories. Following an approach similar to Cominola et al. (2021b), we adopted a *representation index* R^* (defined as the frequency of appearance of a determinant in the set of framework analysis studies) to quantify how popular a determinant is in the reviewed literature.

The frequency of appearance of a given determinant is evaluated with respect to (1) daily per capita end-use water consumption and (2) end-use parameters (i.e. volume per use, duration per use, flow rate per use, frequency of use). Moreover, we focused on *observable* and *external* end-use determinants (Cominola et al., 2021b), whereas we did not consider *latent* determinants (i.e. psychological drivers such as people's habits, perception, and awareness), which are typically less investigated at the end-use level. Specifically, we explored three categories:

- *Socio-demographic determinants*, i.e. occupancy rate, family type, householders' age, income, occupational status, educational level, and socio-economic region.
- *Property characteristics*, i.e. household type and lot size.
- *External determinants*, i.e. daily temperature and season.

2.3.6. Level 6: efficiency and diffusion of water-saving end uses

Level 6 of the analysis aims to explore the efficiency and the diffusion of water-saving end uses, along with their impact on water consumption. Specifically, due to the variety in the materials, methods, and implications of the REUS including considerations about end-use water-saving efficiency and diffusion, the analysis consists of a review of the main outcomes of the REUS focusing on these aspects, and their major implications. Although limited to a qualitative discussion, Level 6 of the analysis aims to be a reference point for those who intend to investigate the topic of efficiency and diffusion of water-saving end uses by providing a qualitative overview of the most relevant outcomes indicated in the literature.

3. Results and discussion

Given the differences in the content of the EUD and the heterogeneity of data presented in the REUS, we first assessed whether the information required to carry out the multi-level analysis for each EUD was included within the body of the corresponding REUS. Results are detailed in Table 1 and summarized in Fig. 4.

Daily per capita end-use water consumption data and the average values of end-use parameters are reported for at least one end-use category in the case of 52 and 44 of the 66 EUD (i.e. 79% and 67%, respectively). This means that these two aspects are the most explored in the literature. In contrast, considerations of end-use parameter distributions, daily end-use profiles, end-use determinants, or efficiency and diffusion of water-saving end uses can be outlined only in the case of 28, 21, 21, and 25 of the 66 EUD (i.e. 42%, 32%, 32%, and 38%, respectively). Thus, the results of the analysis show that attention is generally paid to the evaluation of daily per capita water consumption of different end uses or the average values of the end-use parameters (i.e. Level 1 and Level 2), while investigation of other aspects of the end-use water consumption such as parameter distributions (Level 3), daily profiles (Level 4), determinants (Level 5) or efficiency and diffusion (Level 6) is still rather limited. These outcomes are coherent with the findings of the literature reviews proposed in the framework of some REUS (Mayer et al., 1999; Beal and Stewart, 2011; Jordán-Cuebas et al., 2018), which include only the most relevant results accessible in the literature in terms of daily per capita end-use water consumption. Lastly, we observe a limited number of EUD with reported information that does not cover any level of the analysis (Jacobs 2007; Kim et al., 2007; Cole and Stewart 2013; Kozlovskiy et al., 2016; Kofinas et al., 2018). This is mainly because the related REUS exploit end-use data for a variety of applications (e.g. end-use demand model training/testing, end-use disaggregation and classification model calibration/validation, or considerations on data gathering at different sampling resolutions) without directly presenting the characteristics of the EUD concerned. Due to the lack of sufficient data, these EUD are cited in our study but not considered for further analyses.

3.1. Level 1: daily per capita end-use water consumption

Daily per capita water consumption data are available for at least one end-use category in the majority of EUD (52 out of 66, i.e. 79%). The average values of each study are shown in Table 2, which also features information on the average number of household occupants and the total indoor water consumption.

We observe that showers and toilets are typically the end-uses with the highest per capita daily water consumption (average of 44.1 and 38.0 L/person/day, respectively), followed by taps (32.9 L/person/day),

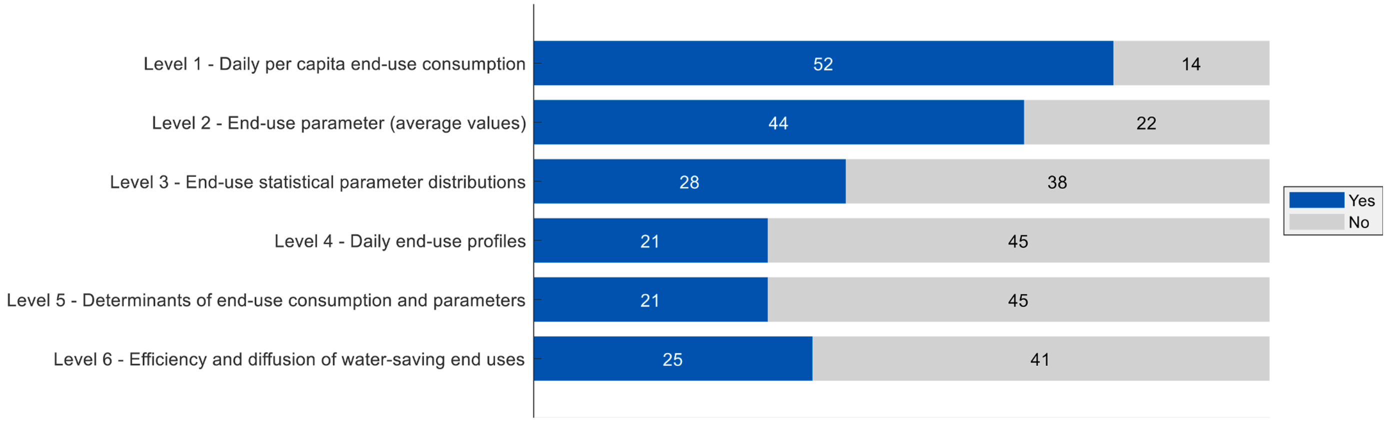

Fig. 4. Number of reviewed EUD addressing each aspect defined in Level 1 to 6 of the multi-level analysis.

washing machines (28.8 L/person/day), bathtubs (9.9 L/person/day), and dishwashers (3.0 L/person/day). The EUD reviewed also reveal non-negligible average values in the case of domestic leakages (16.6 L/person/day), including both permanent (e.g. pipe breaks) or temporary leakages (e.g. blockage of toilet float valve). First, the results obtained confirm that the majority of residential water consumption is primarily tied to the use of water for personal hygiene and flushing. Second, it emerges that some end uses have been drastically reduced due to behavioral change and the introduction of efficient devices, as substantiated in the following section. This reduction is mainly evident in the case of bathtubs, which have been almost entirely replaced by showers, but also applies to the case of tap use for dishwashing or laundry. However, although substantial water savings have generally been observed because of the diffusion of efficient devices like dishwashers (Agudelo-Vera et al., 2014), the tap component of water use is still non-negligible due to the high heterogeneity of uses associated with this end-use category (ranging from personal hygiene to cooking, drinking, or house cleaning).

The box-whisker plots of the distributions of the average daily per capita end-use consumption values are shown in Fig. 5. The figure reveals no substantial variations between the median of each distribution (white squares) and the aforementioned average values (red asterisks), with the exception of bathtub and leakages, whose median (about 4.5 and 10.3 L/person/day, respectively) is considerably below the average and reveals an asymmetry of the bathtub and leakage distribution also distinguishable from the position of quartiles. Considering value dispersion, the most scattered distributions of the average daily per capita water consumption are those related to toilets and washing machines (i.e. the end uses generally accounting for the largest portion of the total indoor water consumption along with showers). In contrast, less scattered values are observed for the other end uses (e.g. dishwasher, whose daily per capita consumption values are considerably in line). The high dispersion of toilet and washing machine values is more likely to be due to technological development rather than behavioral factors (i.e. changes in people's attitude towards water use), as demonstrated by the strongly decreasing volume-per-use trends (shown in Table 3 and discussed in the subsequent section) along with the absence of substantial variations in the daily frequency of use over years. However, it is worth noting that other factors may also contribute to this spread, e.g. inaccuracies in disaggregation and classification methods causing event misclassification.

Fig. 6 shows the trend of the daily per capita end-use water consumption over the last three decades, where dots represent the average values related to each EUD (colour and dimension are related to location and sample size, respectively). Specifically, the results are limited to those retrieved for the (developed) continents for which a sufficient number of EUD is available (i.e. Europe, North America, and Oceania).

Overall, Fig. 6 reveals considerable differences amongst EUD even in the case of studies conducted in similar locations and periods (see, e.g., the large spread of in the use of dishwasher in North America over the decade 1990–2000 shown in Fig. 6a, or the use of washing machine in Oceania over the 2000–2010 decade shown in Fig. 6b). However, as far as the trend of the daily per capita water consumption is regarded, a decrease between the 1990–2000 and the 2010–2020 decades emerges in most of the end uses shown in the figure. More specifically, some of the largest drops in water consumption are observed over time in the case of automated or fixed-volume end uses, such as washing machines (from 52.9 to 18.0 L/person/day, Fig. 6b) and toilets (from 62.3 to 35.7 L/person/day, Fig. 6e), confirming the large spread of values met in Level 1 of the analysis for these end uses. This drop is likely to be primarily due to technological development, which allowed an increase in the water-saving efficiency of these end uses. This is demonstrated by the decreasing trend of washing machine and toilet volume per use in Europe, North America, and Oceania from the 1990–2000 to the 2010–2020 decade, in spite of a constant or even slightly increasing frequency of use (observable in Table 3 of Section 3.2). Conversely, human-controlled end uses do not always show a decrease in their daily per capita average consumption. This emerges, for example, in the case of showers (Fig. 6c) – for which the 10-year average consumption slightly increases from the 1990–2000 decade (42.0 L/person/day) to the 2010–2020 decade (45.5 L/person/day) – whereas tap use drastically decreases over the same period (from 38.9 to 18.8 L/person/day, Fig. 6f). On the one hand, the increase in shower water consumption may be due to behavioral factors, such as the increase in the average frequency of use over decades (confirmed by the data reported in Table 3). On the other hand, the drastic decrease in tap water consumption may be related to the progressive replacement of manual water-consuming activities (i.e. laundry, dishwashing) with automated operations made by appliances, despite the lack of clear evidence in the trends of end-use parameters (such as volume per use and frequency of use). Lastly, we observe a decrease in the daily per capita consumption of dishwashers and bathtubs as well between the 1990–2000 and the 2010–2020 decades (Fig. 6a and 6d), reasonably due to the increase in dishwasher water-saving efficiency along with the reduction of bathtub use in favour of showers. Again, the above considerations are supported by the results included in Table 3, showing a negative trend of the dishwasher volume per load (in spite of a slightly increasing dishwasher frequency of use) over the last three decades, and a strong decrease in bathtub frequency. However, exceptionally high bathtub consumption emerges in the case of the British EUD reported by Kowalski and Marshallsay (2003) – along with a considerably low shower consumption of about 30 L/person/day – and the North American EUD by Jordán-Cuebas et al. (2018), characterized by a rather limited sample size.

Table 2
Summary of daily per capita end-use water consumption data.

EUD	REUS	Occupants per household (persons)	Daily Per Capita End-Use Water Consumption (l/person/day)[a] Total indoor	D	WM	S	B	F	T	L	Other
1	Bennett and Linstedt, 1975	3.7	168.4	4.2	43.9	32.9	[b]	55.6	28.8	-	3.0
2	Siegrist et al., 1976	4.5	161.0	-	-	37.9	[b]	34.8	-	-	88.3
3	Brown and Caldwell Consulting Engineers, 1984	2.7	250.6	5.3	47.7	45.0	26.5	75.7	34.1	16.3	-
5	Anderson et al., 1993 (pre-retrofitting)	2.9	191.9	-	-	39.7	-	50.3	-	-	101.9
	Anderson et al., 1993 (post-retrofitting)	2.9	162.0	-	-	26.1	-	27.3	-	-	108.6
6	Edwards and Martin 1995	-	140.8	1.5	30.4	5.8	18.9	47.9	36.3	-	-
7	DeOreo et al., 1996	2.9	220.6	7.1	53.9	37.9	3.8	56.7	34.1	27.2	-
8	Mayer et al., 1999	2.8	268.5	3.7	56.9	44.1	4.5	70.0	41.2	35.9	12.2
9	Darmody et al., 1999	4.0	190.0	4.0	-	66.0	2.0	27.0	-	21.0	70.0
10	Darmody et al., 1999	2.5	244.0	10.0	-	44.0	15.0	63.0	-	10.0	102.0
11	Mayer et al., 2000 (pre-retrofitting)	2.5	240.8	5.3	56.0	34.1	14.0	71.2	34.8	24.6	0.8
	Mayer et al., 2000 (post-retrofitting)	2.5	151.3	4.5	34.8	32.9	10.2	29.9	30.3	8.3	0.4
12	Foekema and Engelsma, 2001	-	126.2	2.4	22.8	42.0	3.7	34.8	20.4	-	-
13	Mayer et al., 2003 (pre-retrofitting)	2.6	325.9	3.8	52.6	45.4	11.4	75.3	39.7	97.3	0.4
	Mayer et al., 2003 (post-retrofitting)	2.5	199.8	3.4	33.3	40.5	10.6	37.1	39.7	33.7	1.5
14	Loh and Coghlan 2003 (average)	2.8	168.0	-	42.5	53.0	[b]	30.5	29.5	7.5	5.0
15	Kowalski and Marshallsay 2003	-	352.4	5.5	50.0	29.0	59.5	109.8	84.8	5.8	8.0
17[c]	Mayer et al., 2004 (post-retrofitting)	2.9	144.9	1.9	30.0	34.0	9.0	30.0	23.0	14.0	3.0
18	White et al., 2004	-	184.0	2.0	-	57.0	9.0	45.0	-	3.0	68.0
19	Roberts 2005	3.2	169.0	3.0	40.0	49.0	3.0	31.0	27.0	16.0	-
	Gato-Trinidad et al., 2011	3.2	165.0	-	39.8	47.4	-	29.1	-	12.0	36.7
20	Kanne 2005	2.49	123.6	3.0	18.0	43.7	2.8	35.8	20.3	-	-
21	Ghisi and Oliveira, 2007	2.5	153.7	-	11.0	59.2	-	41.4	-	-	42.1
23	Heinrich 2007 (average)	2.7	156.6	2.4	40.8	45.1	4.3	33.0	23.3	6.9	0.8
25	Otaki et al., 2008	4.4	77.0	-	-	-	25.0	15.0	-	-	37.0
26	Mead 2008; Mead and Aravinthan 2009	3.1	111.5	2.4	25.3	48.6	3.1	14.3	17.4	0.4	-
27	Foekema et al., 2008	2.5	127.5	3.0	15.5	49.8	2.5	37.1	19.6	-	-
28	Cubillo-González et al., 2008	3.8	95.5	0.6	9.6	25.7	-	19.2	37.1	3.3	-
29	Willis et al., 2009a; Willis et al., 2009b; Willis et al., 2009c; Willis et al., 2010b; Willis et al., 2013	-	138.6	2.2	30.0	49.7	6.5	21.1	27.0	2.1	0.0
30	Heinrich, 2010 (average)	2.7	160.7	2.3	42.4	48.9	2.5	32.7	25.0	6.0	0.9
31	Sivakumaran and Aramaki, 2010	4.7	110.0	-	-	37.0	[b]	19	-	-	54.0
32	Water Corporation, 2010	2.4	171.2	2.9	20.3	72.6	[b]	26.1	26.1	11.6	11.6
33	Otaki et al., 2011	4.7	63.3	-	-	-	23.7	9.8	-	-	29.8
34	DeOreo et al., 2011	3.0	222.9	1.9	39.2	43.9	4.7	47.7	41.7	39.3	4.6
35	Aquacraft 2011 (average)	2.9	180.6	2.6	36.4	39.8	4.5	35.2	32.6	25.8	3.7
36	Beal and Stewart 2011 (average, winter 2010)	2.7	126.5	2.0	28.9	40.3	1.5	24.3	23.9	5.6	-
	Beal and Stewart 2014b (average)	2.5	126.5	1.8	27.0	41.7	2.3	28.2	19.2	6.3	-
37	Foekema and Van Thiel 2011	3.1	120.1	3.0	14.3	48.6	2.8	33.7	17.7	-	-
38	Lee et al., 2012	-	151.3	-	-	-	24.7	38.5	-	-	88.1
40	Redhead et al., 2013 (average)	3.1	114.3	1.3	20.7	35.9	2.7	19.5	21.2	6.4	6.7
41	Otaki et al., 2013	-	60.9	-	-	10.4	[b]	18.6	-	-	31.9
	Otaki et al., 2017	-	60.9	-	-	14.1	[b]	21.7	-	-	25.1
42	DeOreo and Mayer 2013, DeOreo et al., 2016	2.6	195.3	2.2	32.3	39.9	5.1	46.9	37.3	24.2	7.4
44	Borg et al., 2013	5.0	130.3	-	16.0	70.3	-	24.4	19.5	-	-
45	Van Thiel 2014	2.9	118.9	2.0	14.3	51.4	1.8	33.8	15.6	-	-
46	Neunteufel et al., 2014	-	114.0	3.0	14.0	25.0	4.0	34.0	34.0	-	-
47	Arbon et al., 2014	2.5	144.9	1.7	24.8	48.3	3.0	27.8	28.8	10.5	-
49	Sadr et al., 2015	5.7	184.1	-	-	62.6	[b]	44.7	-	-	76.8
50	Hussien et al., 2016	7.0	251.2	-	-	36.8	0.5	26.2	-	-	187.7
52	Van Thiel 2017	2.7	107.0	2.5	14.1	44.2	1.6	34.6	10.0	-	-
53	Alharsha et al., 2018; Alharsha et al., 2022	6.6	255.0	0.7	13.4	41.0	13.0	50.7	133.1	-	3.1
54	Jordán-Cuebas et al., 2018	2.5	223.1	-	-	58.0	33.2	58.0	64.8	-	9.1
55	Siriwardene 2018	3.0	129.9	3.0	15.1	42.3	10.6	31.7	-	4.5	22.7
60	Bethke 2020; Bethke et al., 2021	4.0	126.7	1.9	4.0	59.4	-	11.1	40.5	-	9.8
62	Otaki et al., 2022	-	97.1	-	-	-	-	16.9	-	-	80.2
63	Mazzoni et al., 2023	3.9	121.6	3.6	17.0	46.2	[b]	32.8	14.6	-	7.3
66	Bastidas Pacheco et al. 2023	3.8	173.9	-	24.1	54.3	7.7	44.6	-	-	43.2
	Average	**3.4**	**163.4**	**3.0**	**28.8**	**44.1**	**9.9**	**38.0**	**32.9**	**16.6**	**34.9**

Note:.
[a] *D* = Dishwasher; WM = Washing machine; *S* = Shower; *B* = Bathtub; *F* = Flusher (toilet); *T* = Taps; *L* = Leakages.
[b] Together with shower.
[c] Study not available. Results were derived from Jordán-Cuebas et al., 2018.

3.2. Level 2: end-use parameters (average values)

Average values of end-use parameters such as volume per use, duration per use, flow rate per use, or frequency of use are reported in the literature for at least one end-use category in the case of 44 EUD (i.e. 67% of the total). Average end-use parameter values related to each EUD are shown in Table 3, along with the references to the respective REUS.

Overall, volume per use and daily frequency of use are the most frequently reported end-use parameters. In fact, these are available for at least one end-use category in the case of 41 and 39 EUD, respectively. For individual end uses, volume per use and the daily frequency of use have mainly been explored in the case of toilets (35 and 37 EUD, respectively), washing machines (29 and 32 EUD) and showers (27 and 32 EUD), whereas less relevance is given to dishwashers (20 and 25

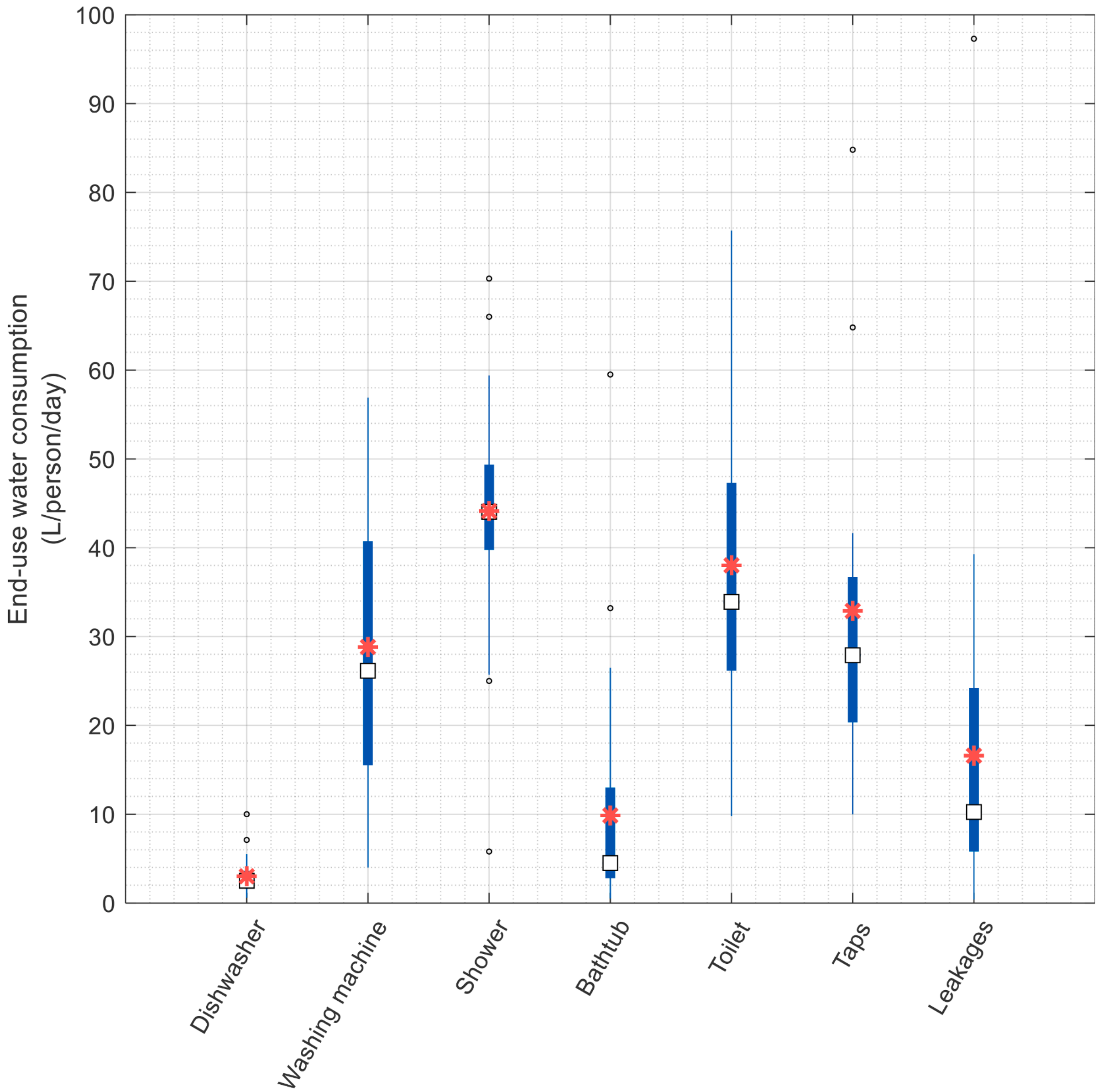

Fig. 5. Box-whisker plot of end-use water consumption (daily per capita average values) across all reviewed EUD. Median and average values are marked with white squares and red asterisks, respectively, whereas outliers are marked with grey dots.

EUD), bathtubs (19 and 21 EUD), and taps (11 and 20 EUD). These outcomes are most likely due to the major relevance that is typically given to toilets, washing machines, and showers because of their high daily per capita average water consumption values (see the results of Level 1 of the analysis), but it is also worth noting that the above-mentioned end-use events are typically amongst the most easily identifiable by automated disaggregation and classification methods, either because of their recognizable patterns, or high event volume and duration.

Conversely, duration per use and flow rate per use are less investigated. In fact, the average values of these parameters are available for at least one end-use category in the case of 34 and 32 EUD, respectively. It is worth noting that event duration is typically expressed in min/*use* in most of the cases, whereas, concerning taps, some studies (Mayer et al., 1999, 2000, 2003) evaluate it in terms of total duration of tap use per day. In addition, as far as the daily frequency of use is concerned (typically expressed in *uses/person/day*), some authors (e.g. Fontdecaba et al., 2013) reported this parameter in terms of uses/household/day without providing information about the average occupancy rate. Therefore, the above cases are not included in Table 3. For individual end uses, showers are the most explored (with 33 and 31 EUD showing average values of duration and flow rate per use, respectively), followed by taps (8 and 11 EUD, respectively). The other end-use categories are almost entirely excluded from the REUS: specifically, their average values of duration and flow rate per use are shown in at most three-four cases only.

The box-whisker plots of the end-use parameter average values provided in Table 3 are shown in Fig. 7, where we indicated only the sets of end-use parameter values appearing in at least five EUD. In greater detail, the following features emerge for different parameters:

- *Volume per use* (Fig. 7a). Bathtubs are the most consuming end use, with an average volume per use of about 105.5 L/use, followed by washing machines (92.2 L/load) and showers (63.1 L/use), whereas considerably lower volumes per use are related to dishwashers (17.6 L/load), toilets (9.0 L/flush) and taps (of about 2.3 L/use only). When the dispersion of the distributions is considered, it is worth noting that bathtubs and washing machines are also characterized by

Table 3
Summary of EUD parameters (average values).

EUD	REUS	Volume per use (l/use)[a]						Duration per use (min/use)[a]						Flow rate per use (l/min)[a]						Frequency of use (uses/person/day)[a]					
		D	WM	S	B	F	T	D	WM	S	B	F	T	D	WM	S	B	F	T	D	WM	S	B	F	T
1	Bennett and Linstedt, 1975	24.8	146.2	-	-	15.5	6.6	-	-	-	-	-	-	-	-	-	-	-	-	0.6	1.0	-	-	13.1	16.6
2	Siegrist et al., 1976	-	-	-	-	15.1		-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	2.3	-
3	Brown and Caldwell Consulting Engineers, 1984	-	-	-	-	19.7		-	-	-	-	-	-	-	-	10.4	-	-	-	0.2	0.3	0.7	0.4	4.0	-
4	Butler, 1991, 1993	-	-	36.0	74.0	8.8		-	-	-	-	-	-	-	-	-	-	-	-	-	0.2	0.3	0.2	3.7	5.3
5	Anderson et al., 1993 (pre-retrofitting)	-	-	55.6	-	13.6		-	-	6.3	-	-	-	-	-	9.5	-	-	-	-	-	-	-	3.8	-
	Anderson et al., 1993 (post-retrofitting)	-	-	33.7	-	6.1		-	-	6.0	-	-	-	-	-	5.7	-	-	-	-	-	-	-	4.5	-
7	DeOreo et al., 1996	-	-	59.1	-	15.6		-	-	-	-	-	-	-	-	-	-	-	-	0.2	0.3	0.7	-	3.8	-
8	Mayer et al., 1999	-	-	65.1	-	13.2		-	-	8.2	-	-	-	-	-	8.4	-	-	-	0.1	0.4	0.8	-	5.1	-
11	Mayer et al., 2000 (pre-retrofitting)	-	154.8	68.5	90.8	13.7		-	-	7.9	-	-	-	-	-	8.5	-	-	4.5	0.2	0.4	0.5	0.1	5.2	-
	Mayer et al., 2000 (post-retrofitting)	-	92.0	56.5	92.0	5.2		-	-	7.8	-	-	-	-	-	7.1	-	-	3.8	-	0.4	0.6	0.1	5.5	-
12	Foekema and Engelsma, 2001	20.0	80.3	-	113.5	8..1	-	-	-	7.6	-	-	-	-	-	7.7	-	-	-	0.2	0.3	0.7	0.1	6.0	14.7
	Blokker 2006; Blokker 2010; Blokker et al., 2010	14.0	50.0	-	120.0	6.0-9.0	-	1.4[b]	5.0[b]	8.5	10.0	2.4-3.6	0.25-0.80	10.0	10.0	8.5	12.0	2.5	2.5-7.5	0.3	0.3	0.7	0.0	6.0	16.7
13	Mayer et al., 2003 (pre-retrofitting)	33.7	154.1	69.7	-	14.7		-	-	8.9	-	-	-	-	-	7.6	-	-	4.5	0.1	0.4	0.7	0.1	5.1	-
	Mayer et al., 2003 (post-retrofitting)	-	103.0	57.9	-	6.2		-	-	8.2	-	-	-	-	-	6.8	-	-	3.5	-	0.3	0.7	0.1	5.6	-
14	Loh and Coghlan, 2003 (average)	-	33.0	59.5	-	7.8		-	-	7.0	-	-	-	-	-	8.6	-	-	-	-	-	0.8	-	3.6	-
16	Lauchlan and Dixon 2003 (average)	25.0	80.0	150.0	123.0	8.0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
19	Roberts 2005, Gato-Trinidad et al., 2011	23.9	143.0	-	123.0	7.6	1.3	-	-	7.1	-	-	-	-	-	9.5	-	-	3.3	0.2	0.3	0.9	-	4.2	20.0
20	Kanne, 2005	18.0	63.9	-	113.5	8.0	-	-	-	7.7	-	-	-	-	-	7.8	-	-	-	0.3	0.3	0.7	0.1	6.0	-
21	Ghisi and Oliveira, 2007	-	90.0	-	-	-	-	-	-	8.6	-	-	-	-	-	6.0	-	-	-	-	0.1	1.3	-	4.3	-
23	Heinrich, 2007 (average)	-	127.5	79.2	-	6.2	1.6	-	-	7.6	-	-	0.5	-	-	11.3	-	-	3.8	-	0.3	0.7	-	5.0	11.9
26	Mead, 2008; Mead and Aravinthan, 2009	17.7	106.9	61.2	75.5	5.4	1.0	-	-	7.2	-	-	0.4	-	-	8.8	-	-	2.1	0.1	0.2	0.9	0.1	2.6	16.4
27	Foekema et al., 2008	16.5	56.9	-	114.2	7.9	-	-	-	7.9	-	-	-	-	-	7.7	-	-	-	0.3	0.3	0.8	0.1	6.3	-
28	Cubillo-González et al., 2008	16.9	61.1	69.2	-	7.1	-	5.1[b]	9.3[b]	8.1	-	1.7	-	3.8	7.6	9.0	-	-	-	0.1	0.2	0.5	-	3.3	
29	Willis et al., 2010b (pre-retrofitting)	-	-	57.4	-	-	-	-	-	7.2	-	-	-	-	-	10.0	-	-	-	-	-	-	-	-	-
	Willis et al., 2010b (post-retrofitting)	-	-	42.0	-	-	-	-	-	5.9	-	-	-	-	-	9.0	-	-	-	-	-	-	-	-	-
30	Heinrich, 2010 (average)	-	122.5	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.4	-	-	-	-
32	Water Corporation, 2010	-	98.7	67.0	-	5.5	-	-	-	6.7	-	-	-	-	-	10.0	-	-	-	-	-	-	-	5.0	-
34	DeOreo et al., 2011	-	136.3	68.8	-	10.4	2.3	-	-	8.7	-	-	0.62	-	-	8.1	-	-	4.2	-	0.3	0.7	-	4.8	19.4
35	Aquacraft, 2011 (average)	-	121.5	60.2	-	7.9	-	-	-	-	-	-	-	-	-	7.5	-	-	4.2	-	0.3	0.7	-	4.4	-
36	Beal and Stewart, 2011	-	105.7	48.2	-	5.8	5.5	-	-	6.0	-	-	-	-	-	8.1	-	-	-	0.2	0.2	0.7	0.0	3.7	18.6
37	Foekema and Van Thiel, 2011	15.8	55.6	-	114.3	7.9	-	-	-	8.1	-	-	-	-	-	7.7	-	-	-	0.2	0.3	0.8	0.1	5.9	19.6
40	Redhead et al., 2013 (average)	15.1	90.5	47.2	130.1	5.9	1.4	-	-	6.6	-	-	0.38	-	-	7.2	-	-	2.8	0.2	0.2	0.8	0.1	3.9	19.7
41	Otaki et al., 2013	-	-	-	-	-	-	-	-	-	-	-	-	-	-	2.5	-	-	-	-	-	-	-	4.2	-
42	DeOreo and Mayer, 2013, DeOreo et al., 2016	-	-	70.0	-	9.8	1.9	-	-	7.8	-	-	0.50	-	-	-	-	-	-	0.1	0.3	0.7	0.1	5.0	19.6

(*continued on next page*)

Table 3 (*continued*)

EUD	REUS	Volume per use (l/use)[a]						Duration per use (min/use)[a]						Flow rate per use (l/min)[a]						Frequency of use (uses/person/day)[a]					
		D	WM	S	B	F	T	D	WM	S	B	F	T	D	WM	S	B	F	T	D	WM	S	B	F	T
43	Fontdecaba et al., 2013	10.2	38.1	36.4	-	5.6	-	-	-	5.3	0.7	-	-	-	-	-	-	-	-	-	-	-	-	-	-
45	Van Thiel, 2014	14.3	52.9	-	114.5	7.7	-	-	-	8.9	-	-	-	-	-	7.7	-	-	-	0.2	0.3	0.7	0.0	5.9	20.0
46	Neunteufel et al., 2014	16.3	44.0	36.0	76.0	5.9	1.7	-	-	-	-	-	-	-	-	-	-	-	-	0.2	0.4	0.7	0.0	6.1	21.0
47	Arbon et al., 2014	15.7	81.8	49.8	60.0	5.8	-	-	-	6.3	-	-	-	-	-	7.9	-	-	2.1	0.2	0.3	1.0	0.2	4.4	28.0
48	Shan et al., 2015 (average)	-	-	-	-	-	-	-	-	8.7	-	-	-	-	-	-	-	-	-	-	-	1.0	-	-	-
50	Hussien et al., 2016	-	-	77.9	132.0	5.5	-	-	-	8.6	-	-	-	-	-	9.0	-	-	-	-	-	0.5	0.0	4.7	-
52	Van Thiel, 2017	13.1	53.9	-	112.5	7.7	-	-	-	7.6	-	-	-	-	-	8.2	-	-	-	0.2	0.2	0.7	0.0	5.9	19.2
53	Alharsha et al., 2018; Alharsha et al., 2022	15.0	72.1	72.4	169.0	8.1	-	-	-	6.4	-	-	-	-	-	4.4	-	-	-	0.0	0.1	0.7	0.1	6.2	8.1
55	Siriwardene, 2018	13.7	104.0	48.9	71.6	5.4	1.2	-	-	6.4	-	-	0.40	-	-	8.1	12.7	-	2.7	0.3	0.2	0.9	0.4	6.4	16.8
59	Di Mauro et al. 2020	-	-	21.2	-	-	-	-	-	9.8	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
60	Bethke et al., 2021	-	-	112.0	-	6.8	-	-	-	14.3	-	1.3	-	4.2	16.5	7.9	-	5.8	-	-	-	-	-	-	-
61	Díaz et al. 2021	-	-	-	-	-	-	-	-	10.2	-	-	0.48	-	-	-	-	-	-	0.2	0.1	0.8	-	4.4	14.1
63	Mazzoni et al., 2023	11.4	62.9	63.6	[c]	6.8	1.2	4.2[b]	8.2[b]	8.0	[c]	0.8	0.20	2.8	7.0	7.9	[c]	8.3	4.8	0.3	0.3	0.8	[c]	4.2	13.8
66	Bastidas Pacheco et al., 2023	-	120.0	56.2	77.0	7.9	-	-	-	7.5	5.6	-	-	-	-	7.5	14.5	-	-	-	0.2	1.0	0.1	5.0	-

Note: [a] D = Dishwasher; WM = Washing machine; S = Shower; B = Bathtub; F = Flusher (toilet); T = Taps. [b] Duration related to water inflow only
[c] Together with shower.

the highest difference between the first and the last quantile, meaning that the average values available in the literature are generally more spread than those shown in the case of showers, dishwashers, and taps. We observe the smallest differences in the case of taps, with average values of the volume per use considerably in line with each other and in a range of only a few liters per use (or less). Overall, it is worth noting that a variety of values emerge when EUD from different geographical areas are compared. In particular, the average volumes per use observed in the North American EUD are typically higher than those reported in European and Oceanian EUD for all the end-use categories. In fact, the average appliance volume per load in the case of the American EUD is about 29.3 L/load (dishwashers) and 138.8 L/load (washing machines) as opposed to the European (16.0 and 58.3 L/load, respectively) and Oceanian (17.2 and 109.0 L/load) values. This is also evident in the case of human-controlled end uses such as showers and taps, being the American EUD average values (68.5 and 3.6 L/use, respectively) higher than the corresponding European (58.1 and 1.5 L/use) and Oceanian (57.6 and 2.0 L/use) values. However, it is worth observing that the average starting year of the American EUD is 2005, whereas those of the European and Oceanian EUD are 2009 and 2008, respectively. Therefore, differences in end-use parameter values might also be due to temporal offsets amongst the EUD of different areas.

- *Duration and flow rate per use* (Figs. 7b and 7c). Although a sufficient number of values is available only for showers and taps, our results reveal that shower use is typically characterized by much longer durations (on the order of several minutes and with an average of about 8.1 min/use) and higher flow rates (with an average of about 8.1 L/min) as opposed to taps. Moreover, tap uses typically last less than one minute (with an average of about 25 s/use and little dispersion of values) and have a limited flow rate (on average 3.5 L/min). The lack of sufficient information about the other end-use categories is mainly related to the fact that some other end uses are typically characterized by constant durations and flow rates per use (e.g. toilets), whereas some others are appliances and thus variations in the duration or flow rate per use are generally due to different programs selected. It also emerges that appliance load duration – which can be of several minutes up to some hours – is generally much longer than the total duration of water inflow, which is of a few minutes per load only (e.g. from 1.4 to 5.1 min in the case of dishwasher and from 5.0 to 9.3 min in the case of washing machine, based on the values reported by Cubillo-González et al. (2008), Blokker et al. (2010), and Mazzoni et al. (2023)). Furthermore – and similarly to the considerations set forth in the case of volume per use – different values emerge when the duration of the most reported end uses (i.e. showers and taps) is explored for different geographical areas. Overall, the analysis reveals that shower uses in the North American and European case studies are typically longer lasting (by about two minutes) than those related to Oceanian EUD (being the average duration of about 8.2–8.7 min/use in the former case and 6.8 min/use in the latter), although we do not observe large variations in the average flow rate per use. The American EUD reveal that, on average, also tap uses are longer lasting – and more intense – than Oceanian uses (i.e. 34 s/use and 4.4 L/min, versus 25 s/use and 2.8 L/min, respectively). However, as previously mentioned, these results might be affected by different study periods, being the year 2005 the average starting year of the American EUD and the years 2008–2009 those of Oceanian and European EUD, respectively. Lastly, we highlight that the comparison of end-use durations can also be affected by differences in data sampling resolutions adopted across EUD. Specifically, the sampling resolution in all the cases of EUD for which end-use parameter values are reported is equal to – or finer than – 10 s. As a consequence of different data sampling resolutions, uncertainties also arise in relation to end-use flow rate (i.e. the other time-dependant end-use

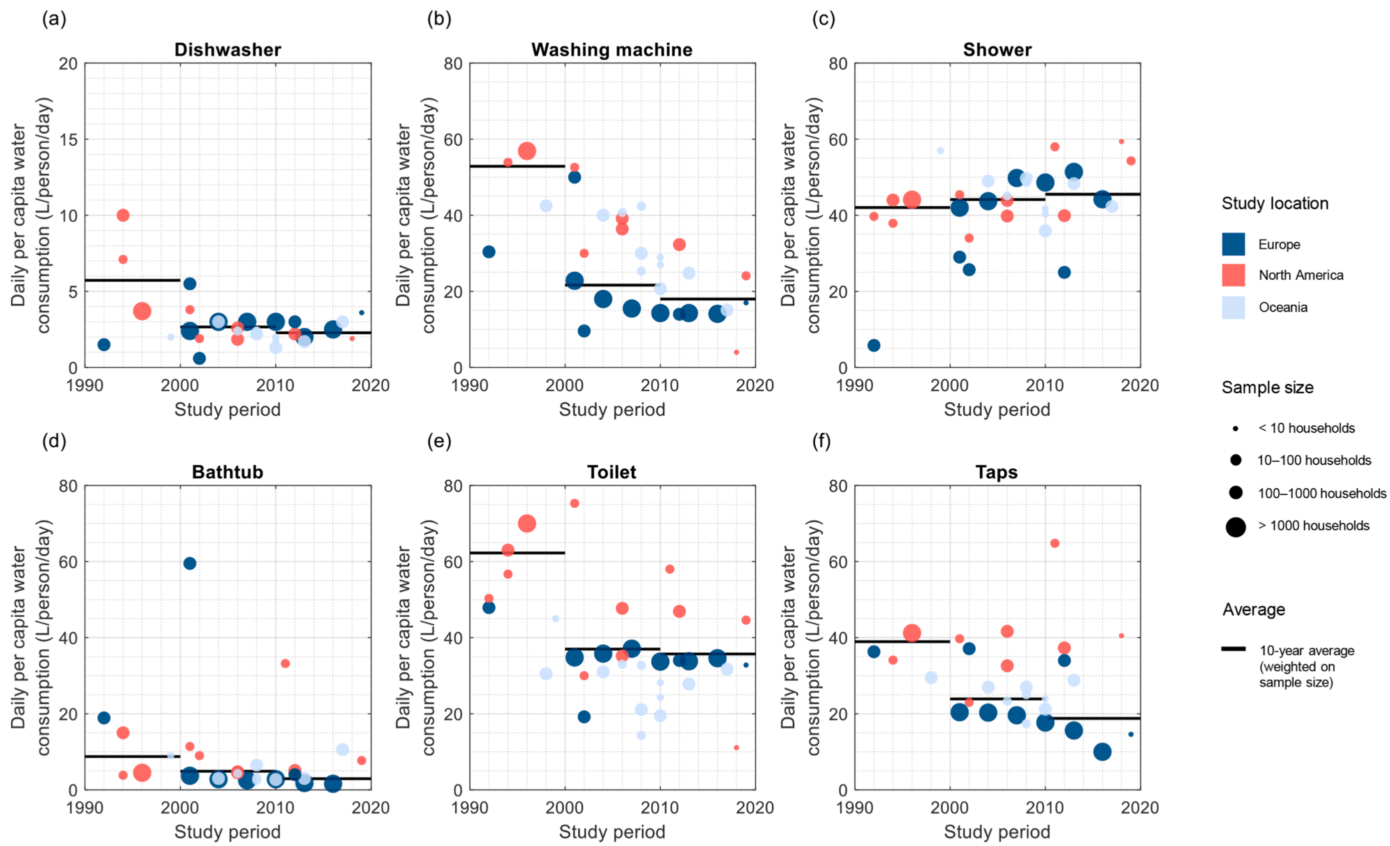

Fig. 6. End-use water consumption trends over the period 1990–2020. Filled dots are related to individual EUD, whereas their colour and dimension are related to study location and sample size, respectively.

parameter). However, unlike duration, the effects of different resolutions on flow-rate values cannot be directly assessed based on the information reported in the REUS concerned.

- *Frequency of use* (Fig. 7d). Different behaviors emerge when the daily frequencies of use of the end-use categories considered are compared. On the one hand, a frequent daily use of toilets and taps emerges, being the former used on average 4.95 times/person/day and the latter used on average 16.98 times/person/day. In particular, the toilet flusher is activated an average of 4.30 times/person/day in the case of the Oceanian EUD and 5.13–5.30 times/person/day in the case of North American and European EUD, whereas taps are opened between 16.05 (European EUD) and 18.52–18.78 times/person/day (Oceanian and North American EUD). These end uses are also characterized by the highest difference between the first and the last quantiles. On the other hand, less frequent use of shower, appliances, and bathtub is observed, with all these devices typically used less than once per person per day (i.e. 0.74 uses/person/day in the case of showers, 0.29 in the case of washing machines, 0.20 in the case of dishwashers, and 0.11 in the case of bathtubs). Specifically, shower frequency of use is slightly higher in the case of Oceanian EUD (0.84 times/person/day, as opposed to 0.69–0.70 times/person/day in the case of North American and European EUD), whereas washing machine frequency use is highest in North American EUD (0.38 loads/person/day versus 0.26 loads/person/day in the case of European and Oceanian EUD). Finally, as far as dishwasher use is considered, we observe no relevant differences in frequency of use amongst EUD from different continents. Overall, the main takeaways on end-use frequency of use are the following: (1) taps are generally the most frequently used devices – despite the limited duration of tap uses – due to their various utilization ranging from personal hygiene to cleaning, cooking, and washing; (2) toilets are typically flushed several times per person per day, although less frequently than taps; (3) showers are on average, used once per person per day or slightly less; (4) appliances are activated with daily (or higher) frequency only in case of households made up by three (or more) residents; (5) bathtubs are nowadays used only occasionally.

3.3. *Level 3: end-use statistical parameter distribution*

End-use parameter distributions are available – with regard to at least one end-use category and parameter – in the case of 28 EUD (i.e. 42% of the total), meaning that, in the literature, this kind of information is less explored than the respective average parameter values. In Fig. 8 we show a detailed overview of the most common end-use parameter distributions, where the heat map relates the distribution of each end use and parameter to its availability (bathtub is not included due to the insufficient amount of information in the literature about bathtub parameter distributions). Fig. 8 reveals that, on average, volume per use and frequency of use are the parameters for which distributions are mostly available in the literature, followed by duration per use and flow rate per use (typically investigated only in the case of showers and taps). In the case of individual end uses, most of the distributions are related to shower and toilet, whereas less relevance is given to taps and appliances. Overall, the results shown in Fig. 8 in relation to end-use statistical parameter distributions are consistent with the outcomes achieved by investigating the availability of information about the average values of end-use parameters (Level 2 of the analysis), which are indicated in Table 3.

The empirical distributions (i.e. empirical PDF curves) of end-use parameters, obtained by digitizing the information available in the REUS, are shown in Fig. S1 (see the Supplemental Data), whereas the respective probability distributions (i.e. statistical PDF curves) fitted by MATLAB's R2019a® *fitdist* function are shown in Fig. 9. The main characteristics of each best-fitting PDF curve (distribution type,

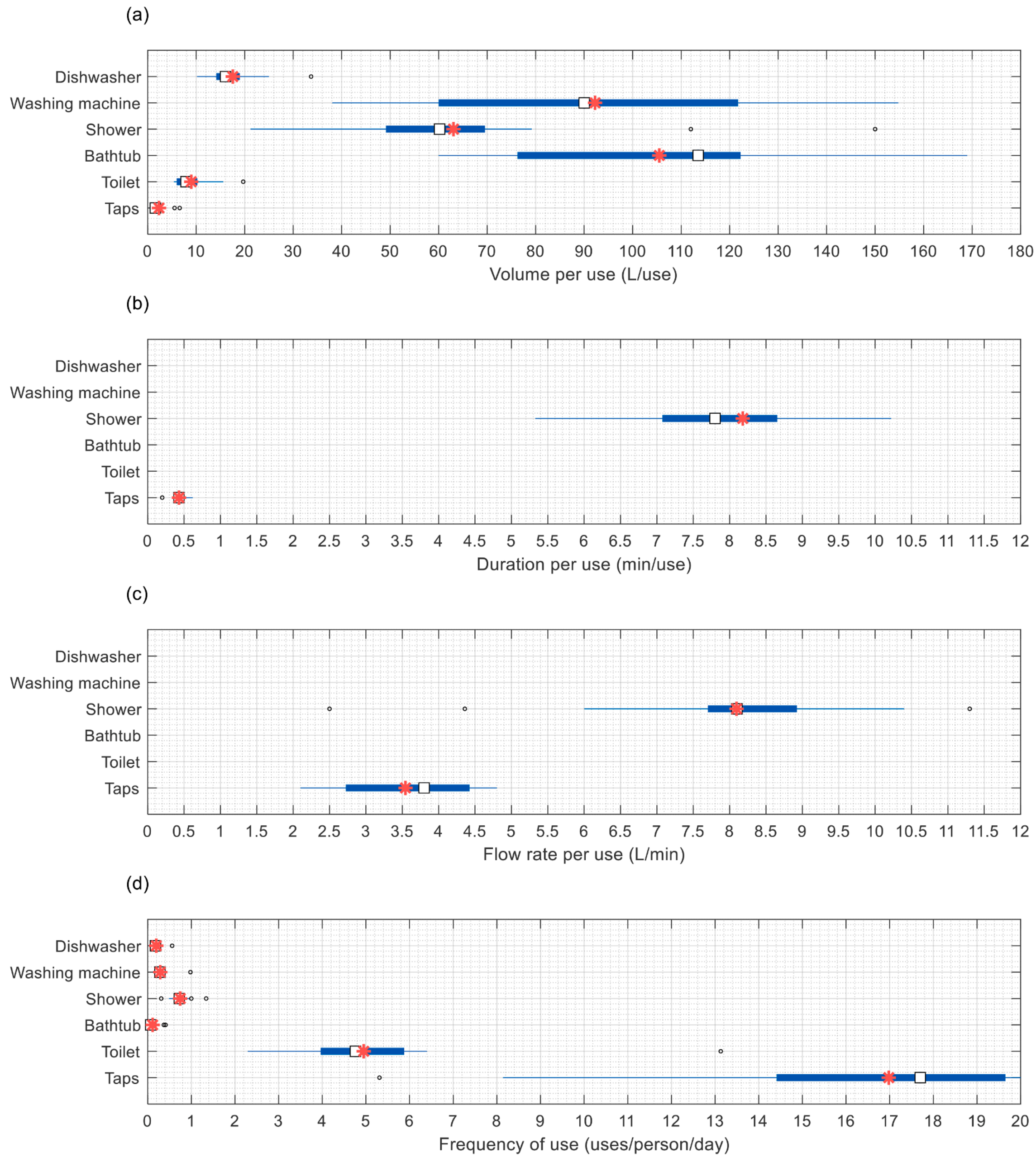

Fig. 7. Box-whisker plot of the end-use parameters (average values) of each EUD. White squares and red asterisks are Median and average values are marked with white squares and red asterisks, respectively, whereas outliers are marked with grey dots.

parameters) are also detailed in Table S1 (see Supplemental Data), along with the results of the preliminary Kolmogorov-Smirnov goodness-of-fit test.

The best-fitting PDF curves obtained from each distribution of end-use parameters allow the stochastic behavior of water consumption at the end-use level to be investigated more specifically. In particular, these findings show that:

- Volume-per-use distributions are fitted by different PDFs based on the end-use considered and the characteristics of the respective EUD. The obtained PDF curves are mostly consistent in the case of shower events (Fig. 9c), often assuming a slightly right-skewed shape characterized by an upper tail and described by lognormal or Gamma distributions. A similar behavior is observed for taps (Fig. 9e), although covering a range of much smaller volumes and with statistical curves also fitted by Weibull distribution (as in the case of the EUD used in Beal and Stewart (2011)). Conversely, differences amongst the distributions are clearly distinguishable for end uses not directly human-controlled, i.e. appliances (Figs. 9a and 9b) and toilet (Fig. 9d). These differences are mainly evident in the case of washing machine distributions (Fig. 9b), which include two clusters associated with peaks of about 50–80 and 130–150 L/load, respectively. In greater detail, the former cluster is tied to European or Oceanian REUS carried out after year 2008 (Cubillo-González et al., 2008; Beal and Stewart, 2011; Redhead et al., 2013; Siriwardene 2018), whereas the latter cluster is related to (mainly North American) REUS conducted before year 2011 (Bennett and Lindstedt 1975, Mayer et al., 1999, Roberts 2005, Heinrich, 2010, Aquacraft 2011, DeOreo et al., 2011). This difference is most likely due to a variety of temporal and geographical contexts (i.e. study period and location) amongst the EUD concerned, related to different levels of

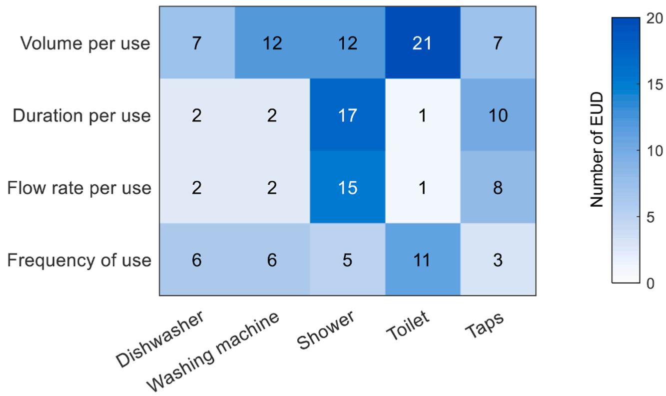

Fig. 8. Number of EUD including information about end-use parameter distributions.

technological development and thus differences in appliance makes and models.

- Duration-per-use distributions are fitted by Gamma or lognormal probability distributions in most of the cases, sometimes with right-skewed PDF curves. In the case of individual end uses, shower distributions result mainly in line with each other, showing peak durations of 5 to 9 min (Fig. 9h), whereas differences are observed between tap distributions (Fig. 9j) when the 20 s (or less) peak value indicated in Australian or New Zealand studies (Roberts 2005; Heinrich et al. 2007; Mead 2008; Redhead et al., 2013; Siriwardene 2018) is compared against the 30–40 s North American peak values reported by DeOreo et al. (2011) and DeOreo and Mayer (2013).
- Flow-rate-per-use distributions are generally fitted by nearly symmetrical shapes in the case of showers (Fig. 9m), whereas more skewed distributions emerge in the case of taps (Fig. 9o). Regarding taps – and similarly to the outcomes achieved in the case of tap duration distributions (Fig. 9j) – differences are observed when the 2 L/min peak value indicated in Australian or New Zealand studies (Roberts 2005; Heinrich et al. 2007; Mead 2008; Redhead et al., 2013; Siriwardene 2018) are compared against the North American and European peak values of about 4 L/min, reported by Cubillo-González et al. (2008), DeOreo and Mayer (2013), and Mazzoni et al. (2023).
- Small variations in shape and peak values are observed when the frequency-per-use distributions of different end uses are considered, with PDFs generally peaking at about 0.1–0.2 loads/person/day (dishwasher and washing machine), 0.7–1.0 uses/person/day (shower), and 3–5 flushes/person/day (toilet). As limited skewness characterizes the majority of these distributions, the above peak values are consistent with the average end-use parameter values shown with Level 2 of the analysis. Lastly, it is worth observing that the lack of a sufficient number of tap distributions does not allow observations about the frequency of use to be made regarding this end-use.

3.4. Level 4: daily end-use profiles

Information about daily end-use profiles is available in the case of 21 EUD (i.e. 32% of the total). Although the majority of REUS only show the average end-use daily profile, some others include several profiles per end use based on season (Roberts 2005; Kowalski and Marshallsay 2005; Redhead et al., 2013), day type (Siriwardene 2018), or layout of

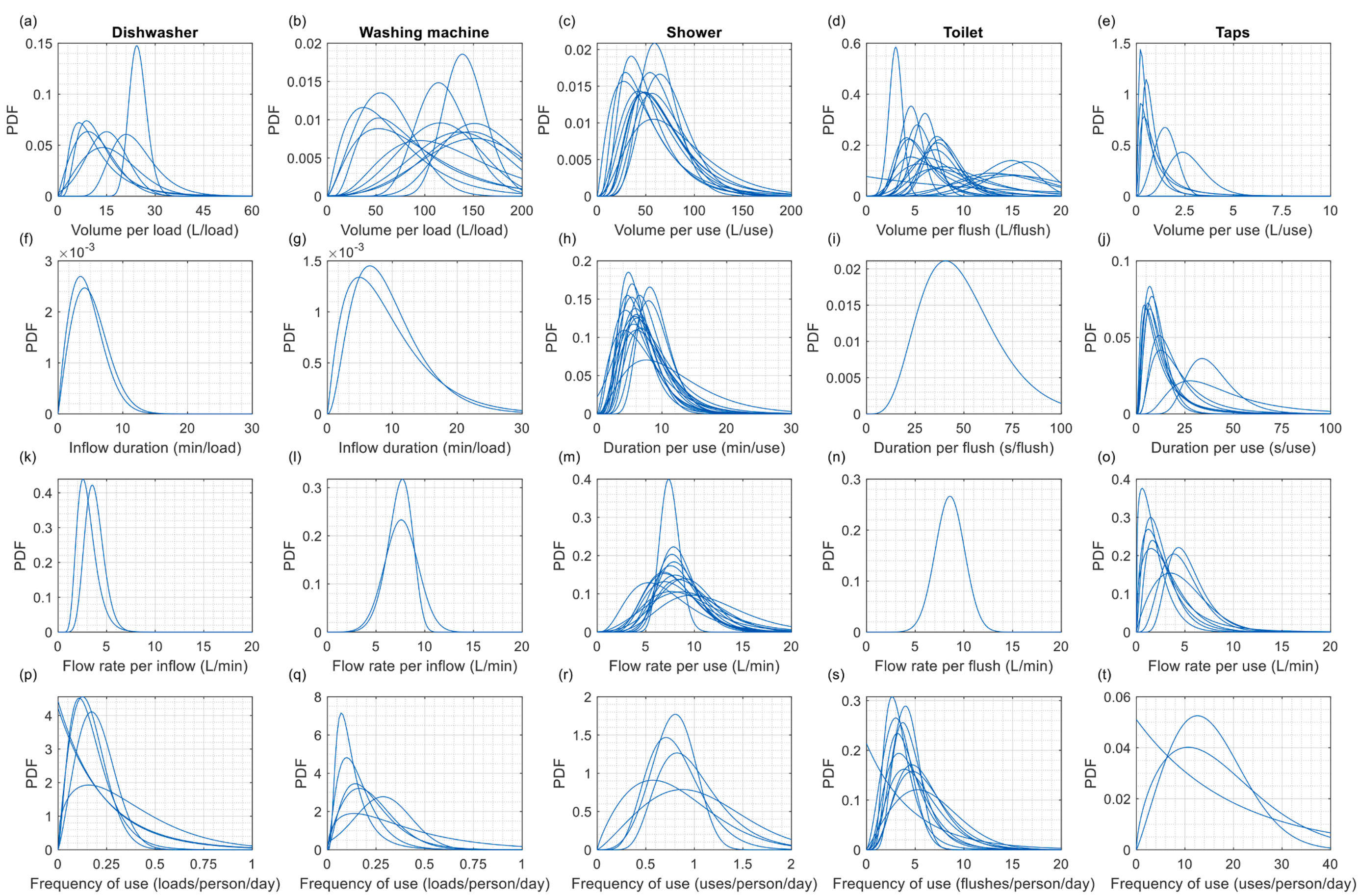

Fig. 9. PDF distributions of different end uses and parameters. Each line is related to an individual EUD.

water infrastructure supplying the monitored households (Willis et al., 2011b). In all the aforementioned cases, we calculated an average daily profile for each reported end use as also described in Sections 3.1 and 3.2 (Levels 1 and 2 of the analysis).

The results after data digitization and normalization are indicated in Fig. 10, where box-whisker plots of the average end-use daily profiles investigated in the reviewed REUS are shown. We observe peculiar shapes of the daily profiles based on the end use considered because of different water use behaviors, although the majority of profiles display minimum values at night and higher values during the day. Specifically, some end uses (i.e. toilet and taps) show a smooth profile over the 24 h (Figs. 10d and 10e), because people typically make use of these devices almost constantly during the day, whereas some others are characterized by marked fluctuations related to periods of increased use. This is particularly evident in the case of showers and bathtubs (Fig. 10c), which appear to be used mostly in the early morning (before leaving home for daily activities) and evening (when returning home), but also applies to the case of dishwasher – which is mostly activated after mealtimes (Fig. 10a) – and washing machine (Fig. 10b), whose profile is typically characterized by a single peak in the morning along with a decrease in water consumption during the afternoon.

In addition, the hourly (normalized) water consumption values available in the literature for each of the 24 h are characterized by quite similar values in the case of toilets and taps, meaning that the profiles are mostly close to each other independently of the case-study area. However, higher offsets – thus larger differences amongst the EUD – emerge for dishwasher, washing machine, shower, and bathtub profiles, as also observable from the differences between the quartiles of the distribution. The largest differences in the values reported in the literature are generally observable in early morning and evening values, i.e. when the largest volumes of water are typically consumed. This finding is most likely due to the variety in habits and lifestyles of populations across the globe. For instance, different peak times of end-use water consumption – but also different daily distributions – emerge from the comparison between North and South European EUD (the results of which are included in Fig. S2 (see Supplemental Data)). Different peak times and distributions are likely due to different traditions and climatic conditions (and, thus, different waking times, mealtimes, and working times). With specific reference to the United Kingdom and Spain – where the end-use profiles of water consumption have been evaluated by Kowalski and Marshallsay (2005) and Cubillo-González et al. (2008), respectively – the diversity in home return times affects the peak time of shower and bathtub use in the evening (between 18:00 and 19:00 in the case of the United Kingdom and at around 21:00 in the case of Spain). Similarly, a temporal offset of 2–3 h is observed when washing machine daily profiles are compared. Although the most relevant discrepancies between the two aforementioned case-study areas are mainly evident in the case of showers/bathtubs and washing machines, different peak times and distributions due to different habits also emerge in the case of toilets and taps. In fact, the analysis reveals that different waking times have effects on the morning peak time of these end uses (ranging from 8:00 in the case of the United Kingdom, to 10:00 – or even later – in the case of Spain).

Finally, the box-whisker plot of the leakage daily profiles reported in the literature is also shown (Fig. 10f). As expected, leakage profiles appear nearly constant throughout the day, because domestic leakages are typically permanent (e.g. those due to pipe breaks or leaking valves). However, a slight increase in leakage rate is observed in diurnal hours. This may be due to the fact that most of the REUS investigating leakage profiles (Roberts 2005; DeOreo et al., 2011; Willis et al., 2011b; Arbon et al., 2014; DeOreo et al., 2016; Siriwardene 2018) also consider temporary leakages (e.g. due to momentary valve blocks), which are more likely to occur when end uses are activated with higher frequency.

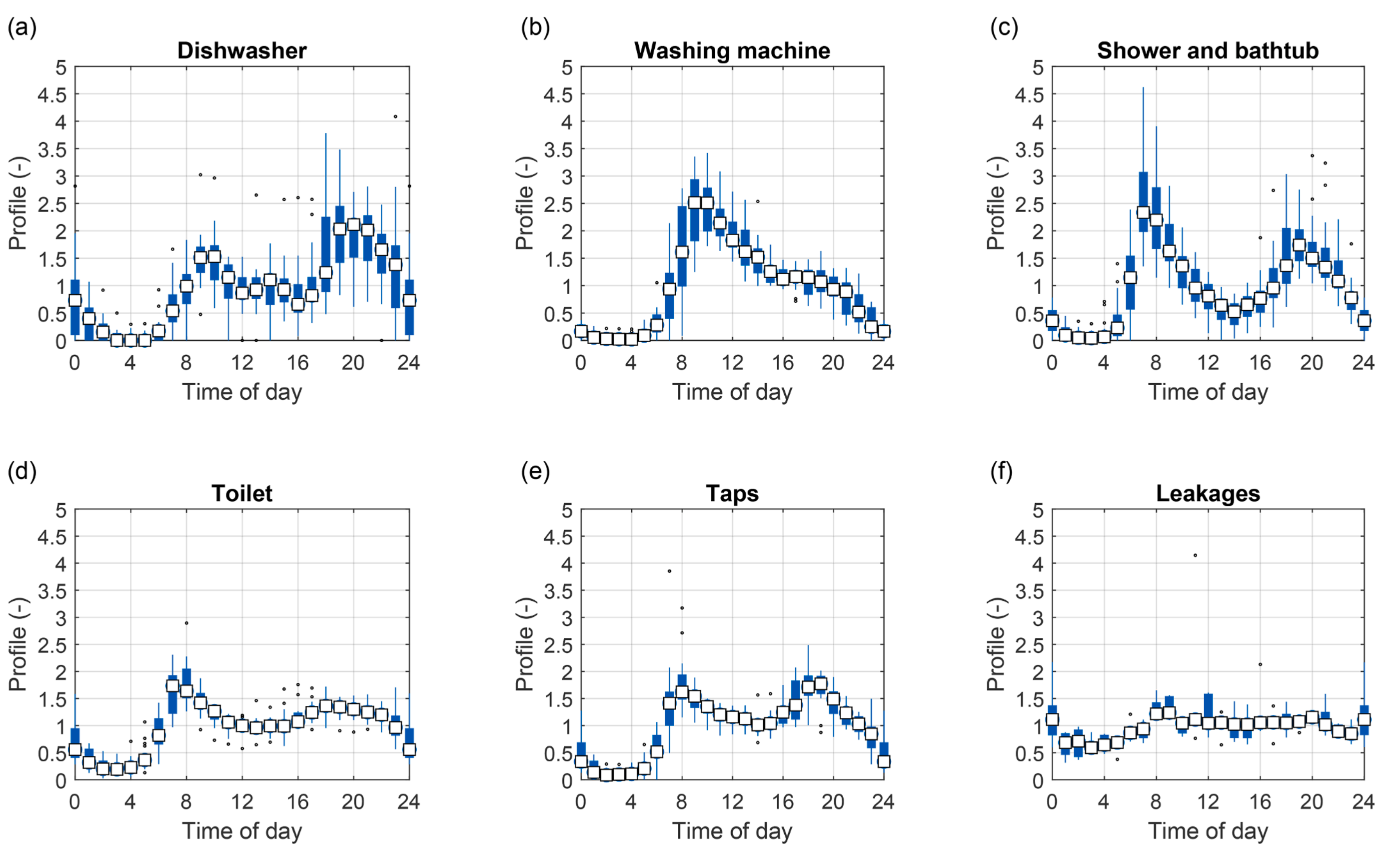

Fig. 10. Box-whisker plots of the normalized hourly end-use water consumption (i.e. daily profile) of each EUD. Median values are marked with white squares, whereas outliers are marked with grey dots.

3.5. Level 5: determinants of end-use consumption and parameters

Information about the determinants of end-use water consumption and parameters are available in the literature for only 21 EUD (i.e. 32% of the total). We computed the R* index for each possible combination of end uses, determinants, and parameters investigated in the REUS. The results are shown in Fig. 11.

The heat maps shown in Fig. 11 reveal that the majority of REUS available in the literature focus on the determinants of daily per capita end-use water consumption and frequency of use, whereas less relevance is given to the investigation of the determinants of end-use volume, duration, and flow rate per use. This is also consistent with the findings achieved in similar studies conducted with regard to the household level of detail (e.g. Cominola et al., 2021b).

Concerning daily per capita end-use water consumption, the most explored determinants are socio-demographic, specifically as regards occupancy rate and family income. In the case of occupancy rate, some studies simply report the daily per capita end-use water consumption average values related to different household family sizes, whereas others (e.g. Mead 2008) make use of optimization methods to obtain the parameter values of the function best approximating the data observed. In general, the studies agree that daily per capita water consumption is inversely correlated with the occupancy rate in the case of toilets (Cubillo-González et al., 2008; Beal and Stewart, 2011; Lee et al., 2012; Willis et al., 2013; Arbon et al., 2014) and reveal different behaviors – although characterized by a decrease in the per capita water consumption along with an increase in the occupancy rate – in the case of showers and taps (Roberts 2005; Cubillo-González et al., 2008, Beal et al., 2012, Makki et al., 2013, Willis et al., 2013, Redhead et al., 2013, Arbon et al., 2014, Siriwardene 2018). Moreover, discordant findings emerge when the impacts of family size on washing machine per capita water consumption are compared – in some cases characterized by a positive correlation with high occupancy rates (Willis et al., 2013), in some others by a negative correlation (Roberts 2005; Mead 2008; Arbon et al., 2014) or not correlated (Beal et al., 2012). Furthermore, no marked correlations are found in the case of dishwashers and bathtubs, with the daily per capita water consumption on the latter end use more affected by family type, e.g. number of children, as in Redhead et al. (2013) and Arbon et al. (2014). Arbon et al. (2014) show that also family type has an impact on water consumption, highlighting a higher daily per capita consumption of showers in households without children and even higher in families with teenagers. Concerning income, the studies available in the literature reveal, on the one hand, a positive correlation with daily per capita water consumption, specifically as regards showers (Makki et al., 2013; Arbon et al., 2014), but also bathtubs and taps (Hussien et al., 2016). These findings are also confirmed by a study by Bastidas Pacheco et al. (2023) relating the daily per capita water consumption of these end uses to the daily total per capita water consumption, which may be reasonably considered a rather good substitute indicator of determinants such as family type and income. On the other hand, a negative correlation sometimes emerges in the case of toilets (Arbon et al., 2014; Hussien et al., 2016; Siriwardene 2018). This finding is most likely because higher-income families can have newer and more efficient toilet cisterns, allowing water savings upon the activation of flushers. However, this negative correlation is not observed in the case of human-controlled end uses (i.e. showers, bathtubs, taps), whose duration of use – thus consumption – is at the discretion of householders and may be less moderate in the case of high-income residents. Moreover, as in the case of occupancy rate, different behaviors emerge from the analysis of the correlation between income and the per capita water consumption for washing machine: these parameters show a positive correlation in some cases (Beal and Stewart, 2011) and a negative

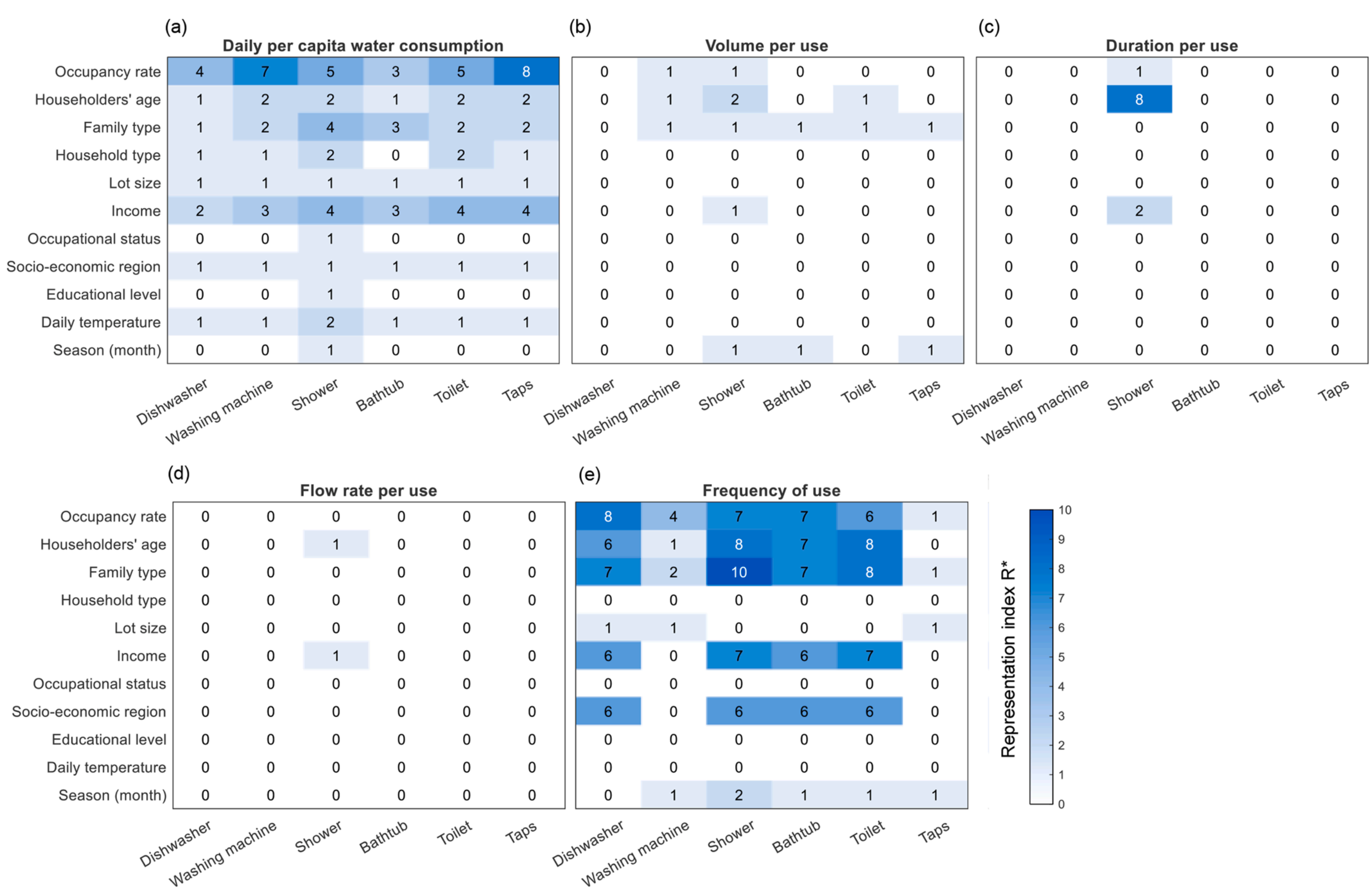

Fig. 11. Representation index (R*) of the EUD about end-use determinants available in the literature.

correlation in some others (Arbon et al., 2014; Siriwardene 2018).

As far as the determinants of end-use parameters are concerned, the literature lacks sufficient information about the drivers of end-use volume, duration, and flow rate per use, except shower duration, whose relationship with householders' age is explored in several studies reporting that teenagers and young adults typically have longer showers than older people (Foekema and Engelsma 2001; Kanne 2005; Foekema et al., 2008; Foekema and Van Thiel 2011; Arbon et al., 2014; Van Thiel 2014; Van Thiel 2017). Moreover, more attention is paid to the determinants of the daily per capita frequency of use. On the one hand, an inverse correlation between daily per capita frequency of shower use and the number of children is reported by some authors (Roberts 2005; Mead 2008), along with a negative correlation between daily per capita frequency of washing machine use and occupancy rate (Roberts 2005; Redhead et al., 2013; Arbon et al., 2014; Siriwardene 2018). On the other hand, the correlation between end-use frequency of use and occupancy rate, householders' age, family type, income, or socio-economic region is deeply explored in the series of Dutch studies conducted between 2001 and 2017 (Foekema and Engelsma 2001; Kanne 2005; Foekema et al., 2008, Foekema and Van Thiel 2014, Van Thiel 2014, Van Thiel 2017). Specifically, the studies show a positive correlation between householders' age and frequency of toilet use and also demonstrate that bathtubs are more frequently used in households with young children.

3.6. Level 6: efficiency and diffusion of water-saving end uses

Considerations about efficiency and diffusion of water-saving end uses are available in the literature with respect to 25 EUD (i.e. 38% of the total), mainly focused on American or Oceanian case-study areas, where the analyses about water conservation and end-use efficiency are motivated by the presence of areas generally affected by relevant water scarcity issues and drought conditions (Carrão et al., 2016). Specifically, different approaches are adopted to explore the topic, and therefore results are presented in different ways, making normalization and comparison impractical. Only the most relevant key points are discussed in the following, whereas the detailed findings of each study are shown in Table S2 (Supplemental Data).

First, it is worth noting that many studies presenting results about water-saving end-use efficiency and diffusion aim to promote water conservation. Different levels of water savings are achieved by adopting different strategies, ranging from the installation of alarm displays in proximity to some end uses for providing real-time feedback about water use (Willis et al., 2010b) to the retrofitting of some end uses with newer and more efficient ones, such as low-flow showerheads and toilets (Anderson et al., 1993) but also tap aerators and water-saving washing machines (Darmody et al., 1999; Mayer et al., 2000; Mayer et al., 2003; Roberts 2005; DeOreo and Mayer 2013). Willis et al. (2010b) observe that the average volume and duration per shower use decreases by 10% and 18%, respectively, after the installation of alarm displays in showers (see the related values in Table 3). Anderson et al. (1993), Mayer et al. (2000), Mayer et al. (2003), Roberts (2005), and DeOreo and Mayer (2013) observe a drop in the daily per capita water consumption of the end-use categories involved in retrofitting, along with a decrease in their volume per use (as shown in Table 2 and Table 3). Some studies also show a general increase in the daily frequency of some end uses after retrofitting, e.g. toilets (Anderson et al., 1993; Mayer et al., 2000; Mayer et al., 2003), along with an increase in the average duration of some others, e.g. showers (DeOreo and Mayer 2013). However, the effects of these increases in the duration and/or frequency of water use are balanced by the higher efficiency of water-saving devices, overall resulting in lower daily per capita water consumption values. Again in this context, Bastidas Pacheco et al. (2023) compare shower, toilet, and tap parameters obtained by monitoring against those defined by national standards to evaluate the efficiency level for the aforementioned end uses, demonstrating that there are conservation opportunities especially with reference to toilet and showerhead retrofitting. Finally, it is also worth noting that studies exploring the potential water conservation achievable by retrofitting highlight that this strategy can have considerable implications on peak consumption (Beal and Stewart, 2014b), with the most consistent savings obtainable by installing more efficient toilets and washing machines (Heinrich et al. 2007).

Other studies about efficiency of water-saving end uses (Mayer et al., 1999; Loh and Coghlan 2003; Roberts 2005; Mead 2008; Blokker 2010; Blokker et al., 2010, Aquacraft 2011, Beal and Stewart, 2011) compare the characteristics of different end-use makes, models and year of installation, along with the technologies already available in the monitored households – such as top- and front-load washing machines, standard and low-flow toilets, and normal and efficient showerheads – and their related effects on water consumption. The studies show different consumption patterns and lower per capita water consumption values in the case of low-flow end uses and front-load washing machines. However, as in the case of retrofitting studies, they reveal an increase in some characteristics of water use for efficient end uses, such as longer shower durations (Mead 2008; Arbon et al., 2014).

The third group of studies investigate the evolution of end-use water consumption over the last decades, along with the diffusion of water-saving fixtures on the market in replacement of the traditional ones (Foekema and Engelsma 2001; Loh and Coghlan 2003; White et al., 2004; Cubillo-González et al., 2008; Blokker 2010; Blokker et al., 2010, Aquacraft 2011, Agudelo-Vera et al., 2014). The studies show a general reduction of the per capita water consumption of different end uses, although with some exceptions. In fact, Loh and Coghlan (2003) observe an increase in the daily per capita water consumption of washing machines between the early 1980s and the late 1990s, whereas the Aquacraft 2011 study reports an increase in the shower water consumption – due to a higher shower duration and frequency of use – when the values observed in households built after the year 2000 are compared against those presented by Mayer et al. (1999). Similar observations are also made in the study conducted by DeOreo et al. (2016), showing an increase in toilet, tap, and dishwasher frequency of use. Moreover, Agudelo-Vera et al. (2014) observe a decrease in the water consumption and daily frequency of use of some end uses over time due to technological improvements and changes in people's habits (e.g. the reduction of baths in favour of showers). The study also indicates that the highest efficiency of water-saving end uses has been achieved in the case of washing machines, dishwashers, and toilets (with reductions in the average water consumption per use between 1992 and 2010 of about 40%, 30%, and 20%, respectively), whereas different diffusion rates have emerged based on the end use considered (ranging from almost 100% in the case of washing machines to 60% in the case of dishwashers, and 50–70% in the case of efficient toilets and showers). Similar results for toilet dual-flush systems are reported in the White et al. (2004) study, where a sample of over 2500,000 Australian users is considered, for which a progressive increase in the diffusion of dual-flush toilets is observed, ranging from 0% in 1980 to 74% in 2010. Moreover, the Foekema et al. (2001), Blokker (2010), and Blokker et al. (2010) studies report an increase in the diffusion of dishwashers in the Netherlands from 45% to 54% (years 2001–2007) along with a decrease in the diffusion of bathtubs. The above studies also report that the diffusion of dishwashers positively relates to household occupancy rate, whereas the diffusion of bathtub is nowadays mainly dependant on wealth class (income), coherently with some of the considerations made by Cubillo-González et al. (2008).

3.7. Summary of study findings

In light of the variety of outcomes presented and discussed in the study in relation to the characteristics of end-use water consumption from several points of view, the major findings that emerged at each level of the analysis can be summarized as follows:

- ***Daily per capita end-use water consumption* (Level 1)**. The highest daily per capita water consumption is typically tied to showers, toilets, and washing machines, whereas lower values are generally related to taps, dishwashers, and bathtubs (with these end uses almost entirely replaced by showers nowadays). Moreover, the analysis points out that the largest decrease in the end-use water consumption of developed countries over the last three decades is related to washing machine, toilet, and tap uses, whereas a slight increase has emerged in the case of showers.
- ***End-use parameter average values* (Level 2)**. Volume per use and frequency of use are generally the most explored end-use parameters, whereas duration and flow rate per use are typically investigated only in the case of specific end uses such as showers and taps. In general, the highest volumes per use are observed for bathtubs, followed by washing machines and showers. In addition, as far as the end-use frequency is concerned, the analysis reveals considerable differences amongst the end uses, ranging from a maximum of more than 10 times per person per day (taps) to a minimum of about 0.1 (bathtub).
- ***End-use statistical parameter distributions* (Level 3)**. While less common than the end-use parameter average values, a large variety of end-use parameter distributions are observed. As in the case of Level 2 of analysis, volume per use and frequency of use are mostly investigated, whereas duration and flow rate distributions are generally reported only for showers and taps. Focusing on volume per use, distributions are mostly in line in the case of human-controlled end uses (showers, taps), leading to greater differences in the case of appliances and toilets.
- ***Daily end-use profiles* (Level 4)**. The studies reviewed reveal different daily patterns based on the end uses. In general, smaller fluctuations throughout the day are observed for toilets and taps – which also relate to end uses with the smallest differences in the daily profiles available in the literature – whereas more heterogeneous patterns are observed in the case of appliances, bathtubs, and showers, because of different habits and lifestyles from around the world.
- ***Determinants* of *end-use water consumption and parameters* (Level 5)**. Only the determinants of daily per capita end-use water consumption (i.e. the socio-demographic ones such as family size and income), and end-use frequency of use are explored and discussed in a sufficient number of EUD. Concerning family size, most of the related REUS report an inverse correlation between the occupancy rate and the daily per capita water consumption of toilets, showers, and taps, with a variety of behaviors in the case of appliances. Moreover, regarding the effects of income on water use, it emerges that, although higher income households typically have more efficient devices, their end-use water consumption is generally higher.
- ***Efficiency and diffusion of water-saving end uses* (Level 6)**. Most of the REUS including considerations about water-saving efficiency and diffusion of the related EUD show that the strategies with the aim of water conservation, such as retrofitting programs, are generally helpful in reducing water consumption, although the installation of low-flow devices may result in longer durations per use or higher frequency of use. The general decrease in the end-use water consumption – sometimes related to an increase in the duration of use or frequency per use – is likewise reported by the studies making observations about the evolution of water consumption in the last decades, which also reveal an increasing diffusion of efficient water-saving end uses (dishwashers, low-flow showerheads, and toilet flushers, water-saving washing machines) along with the replacement of the most consuming ones.

4. Conclusions

In this review study, we provided a comprehensive overview of the state-of-the-art about research in the field of residential water consumption at the end-use level. Specifically, we reviewed 114 Residential End-Use Studies (REUS) available in the literature, and qualitatively and quantitatively investigated the information about the characteristics of 66 related End-Use Databases (EUD) by carrying out a multi-level analysis to evaluate the main perspectives from around the world in terms of water consumption. Based on the results available in the literature, our research revealed that most of the REUS mainly focus on the evaluation of the daily per capita end-use water consumption and the average values of end-use parameters (i.e. Levels 1–2 of the analysis), whereas, generally, less relevance is given to the investigation of end-use parameter distributions, daily profiles, determinants, and efficiency (i.e. Levels 3–6).

The findings of this study will likely be of interest to different actors involved in water resources management and water demand management. First, the findings of this work may be a reference for water utilities seeking information about the main characteristics of water consumption at the end-use level at both larger (i.e. worldwide) and smaller (i.e. regional) spatial scales. The availability of this information may allow water utilities to introduce or rethink strategies for more efficient management of water resources and infrastructure, e.g. revision of water tariffs and incentives, development of campaigns aimed to raise consumers' awareness, but also planning of additional measurement campaigns or end-use studies with the objective of obtaining more detailed end-use water consumption data. Second, the end-use data presented in the current work can support research involved in the field of water systems in developing and validating demand models, methods for water end-use disaggregation and classification, or technologies for water reuse, recycling, and conservation. In addition, the findings of the study may help understand which aspects have been mostly explored in recent research and, if needed, identify the REUS of interest based on their geographical and methodological details. Third, the study can help citizens gain knowledge about the main characteristics of residential end-use water consumption from different contexts across the globe and in their living areas. The data reported here would be a valid benchmark against which to compare consumer habits and behaviors, thus encouraging more conscious and sustainable use of water.

Beside the specific findings of this research, we highlight some general outcomes and outline recommendations for future research. Overall, data availability has been demonstrated to still be a substantial challenge, considerably limiting open science and reproducible research (Choi et al., 2021). Indeed, in light of the unavailability of the vast majority of EUD in the literature, the analyses conducted in this study were carried out by relying only on the information reported in the related REUS. This may have affected the results presented, since the amount of information obtainable from written publications is smaller than the information potentially obtainable by having access to the actual end-use data (i.e. the entire EUD). Uncertainties in the reported outcomes may have arisen due to the variety of methods (ranging from data averaging to digitization) adopted to standardize the variety of results reported in the literature. These results are also based on different data collection techniques, data resolutions, monitoring periods, and end-use data gathering approaches, which all limit the possibility to observe generalized behaviors and differences across studies. More specifically, the comparison of time-dependant end-use parameter values could be affected by the exploitation of data collected at different sampling resolutions. In fact, although all the data exploited in the analysis of end-use parameters are characterized by rather fine resolutions (e.g. 1–10 s), which have been demonstrated to be typically sufficient to grasp all different end uses of water (Heydari et al., 2022), the comparison of data collected at different resolutions may still affect the accuracy in quantifying residential end-use parameter values, especially in relation to short-duration events. This suggests new data sampling to be conducted at the highest possible resolution to allow end-use characterization – and additional comparisons – to be performed with reduced level of uncertainty, as also suggested by Cominola et al. (2018a) and Bastidas Pacheco et al. (2022). Again, we note that the majority of EUD were obtained through disaggregation and classification approaches, the performance of which can considerably vary across the methods. Therefore, errors in EUD may also be due to different method accuracies in disaggregating and classifying end-use events, along with the potential inability of some methods to successfully detect overlapping water uses, when these are not excluded from analysis a priori. However, this aspect could not be considered in our study due to the lack of sufficient information in the REUS concerned. Lastly, it is worth pointing out that, despite the relevant number of REUS and EUD reported and reviewed in the current research, some others could have been missed by the authors – and thus may be missing in this study – due to limited diffusion in the literature or because of publication in languages different from those known by the authors.

In conclusion, our results can be considered as a first step to present and classify a large amount of fragmented data, and to outline what is currently available in the literature. It is also a sound starting point from which future studies on residential end uses of water can be developed. There is still wide room for investigation on many relevant open issues that should be addressed in future research. On the one hand, although not yet possible based on the very limited number of currently available datasets, the realization of a fully open-access end-use database – including a comprehensive number of water events observed and collected in a variety of spatiotemporal contexts – would represent an important step forward allowing for detailed and wide analyses to be carried out, going beyond the limits currently affecting the literature on residential end uses of water. On the other hand, in-depth evaluations should be carried out in relation to aspects such as the identification of the required household sample size and monitoring period duration to properly determine statistically significant water consumption features. This would enable water utilities and researchers to successfully compensate for the differences in water consumption behaviors observable over too limited periods or household samples, while reducing monitoring efforts and the invested resources.

Author contributions

Conceptualization: F. M., S. A., M. B., S. B., A. Ca., A. Co., M-P. G., H. J., D. S., R. S., A. S., V. T., V-H. A. Y., M. F.; Data curation: F. M., S. A., M-P. G., M. B. A. Co.; Methodology: S. A., M. B., S. B., A. Ca., A. Co., H. J., D. S., R. S., A. S., V. T., V-H. A. Y., M. F.; Software: F. M., M-P. G.; Resources: F. M., S. A., M-P. G., M. B. A. Co.; Writing—original draft : F. M.; Writing—review & editing: F. M., S. A., M. B., S. B., A. Ca., A. Co., M-P. G., H. J., D. S., R. S., A. S., V. T., V-H. A. Y., M. F.; Supervision: S. A., M. B., S. B., A. Ca., A. Co., H. J., D. S., R. S., A. S., V. T., V-H. A. Y., M. F.; Project administration: S.A., M.F. All authors have read and agreed to the published version of the manuscript.

Data availability

All the data obtained from the analyses are included either in the paper or in the Supplemental Materials. The raw digitized data (i.e. input data for Level 3 and 4 of the analysis) and the MATLAB R2019a® code developed to conduct the multi-level analysis will be made available by the authors on request.

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Supplemental Materials

The following supporting information is provided: Fig. S1. Empirical PDF distributions of different end uses and parameters; Fig. S2. Comparison between North-European (e.g. Kowalski and Marshallsay, 2005) and South-European (e.g. Cubillo-González et al., 2008) daily end-use profiles. Median values are marked with white squares, whereas outliers are marked with dots.; Table S1. End-use statistical parameter distributions: curve fitting results; Table S2. Efficiency and diffusion of water-saving end uses: study characteristics and implications.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.watres.2022.119500.

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