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Analysis and characterization of residential and non-residential water consumption at different levels of spatio-temporal detail

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To my aunt,

Vittoria

Abstract

Population growth, urbanization, and climate changes are leading large areas under water stress. Within this framework, a detailed information on where, when, and how water is being used is an essential requirement for effective strategies aimed at meeting current and future demand. To pursue this, more attention has been recently devoted to the investigation of water consumption at fine levels of spatio-temporal detail (e.g. up to the level of individual end uses of water), the knowledge of which can aid demand modelling, technologies for water saving, or campaigns aimed at increasing people's awareness towards consumption. As a result, the recent literature includes numerous publications exploring the residential end uses of water, but systematic comparisons and elaborations of these fragmented data are missing. Moreover, collecting and processing end-use data may be challenging, since most of the developed methods to obtain end-use information from user-level data can exploit only data collected at temporal resolutions which may be unavailable to water utilities. Also, in some cases, non-residential users may consume a more relevant quantity of water, and with profiles different from those related to the residential uses of water. However, to date, research on non-residential consumption has been mostly carried out in relation to specific users, and typically at very coarse temporal resolutions. Nevertheless, it has scarcely focused on water consumption in the event of non-ordinary situations affecting people's habits or the operational conditions of water distribution systems, such as disasters or pandemics.

The aim of this thesis is to take a step forward in the characterization of residential and non-residential water consumption at different levels of spatio-temporal detail, and by considering different demand conditions. First, with reference to the residential sector, a comprehensive analysis of more than one hundred end-use studies conducted worldwide is carried out – along with an in-depth discussion of their scope, features, and results – to investigate the main perspectives from around the world and highlighting which aspects have been mostly explored. In addition, an automated method for residential end-use disaggregation and classification – exploiting user-level data collected at a sampling resolution which is close to that of the smart meters available to water utilities – is developed and validated with data from two different geographical areas. Second, the water consumption of some still unexplored non-residential contexts, or under non-ordinary demand conditions, is investigated: in greater detail, insight into the effects of seaside tourism on water consumption is provided by exploring the impacts of bathing facilities and holiday homes in coastal area subjected to high tourist fluctuations, whereas an overview of the effects of COVID-19 pandemic on water consumption is provided in relation to different urban contexts for which analyses are conducted up to the level of individual users.

Overall, the current thesis: (1) provides an extensive, worldwide database of residential end uses of water from which many future studies can be developed; (2) presents a generalized and robust method for end-use disaggregation and classification, widely applicable to several residential water consumption contexts; (3) demonstrates the effects of seaside tourism on water consumption and its profiles; and (4) quantifies the impacts of the lockdown imposed to limit the spread of COVID-19 on water consumption based on multiple temporal scales and in relation to different types of consumption. It is believed that the findings of this thesis can aid water utilities and their users in better understanding the major characteristics of water consumption in different contexts and scenarios, supporting the formers in efficiently managing water systems, and encouraging the latter to a more conscious use of water resources.

Sommario

Incremento demografico, urbanizzazione e cambiamenti climatici stanno esercitando una pressione sempre maggiore sulle risorse idriche. In questo contesto, conoscere le distribuzioni spazio-temporali delle richieste idriche con elevato grado di dettaglio risulta essenziale per lo sviluppo di strategie finalizzate a garantire le attuali e future condizioni di domanda, sviluppare tecnologie per il risparmio idrico e promuovere iniziative di sensibilizzazione a un utilizzo consapevole. Alla luce di ciò, la recente letteratura si è arricchita di numerosi studi finalizzati a investigare i consumi idrici, fino al livello di utilizzi finali dell'acqua (*end uses*) e con particolare riferimento al settore residenziale, mancando tuttavia di un'analisi dettagliata degli studi esistenti, inclusiva di un confronto sistematico e di un'elaborazione omnicomprensiva dei dati riportati. Inoltre, la maggior parte dei metodi recentemente sviluppati per ottenere dati di consumo idrico a livello di *end use* partendo dalle informazioni raccolte a livello di intera unità abitativa risulta generalmente in grado di elaborare solo dati a risoluzioni temporali difficilmente a disposizione dei gestori idrici. Nondimeno, ad oggi, solo un numero limitato di studi ha investigato i consumi idrici in contesti non residenziali o le variazioni di consumo a fronte di circostanze straordinarie quali catastrofi o pandemie.

La presente tesi si ripropone di contribuire alla caratterizzazione dei consumi idrici residenziali e non residenziali con elevato grado di dettaglio spazio-temporale e sotto diverse condizioni di domanda idrica. In primis, viene condotta un'analisi estensiva di più di cento pubblicazioni sui consumi idrici residenziali a livello end use, alla quale segue una discussione sistematica dei

relativi contenuti e risultati proposti, con al fine di approfondire le caratteristiche di consumo residenziale in diversi contesti del mondo ed evidenziarne gli aspetti maggiormente investigati. Si presenta, altresì, una metodologia per la disaggregazione di dati di consumo idrico monitorato a livello di unità abitativa e la relativa classificazione nei diversi *end use*. La metodologia, basata su dati a una risoluzione temporale simile a quella della maggior parte degli *smart meter* tipicamente a disposizione dei gestori idrici, viene validata con dati raccolti in due differenti aree geografiche. La seconda parte della tesi si focalizza invece sulla caratterizzazione dei consumi idrici in contesti non residenziali non ancora investigati o sotto particolari condizioni di domanda idrica. Più nel dettaglio, viene fornita una panoramica sugli effetti del turismo balneare sui consumi idrici – analizzando l'impatto di stabilimenti balneari e case-vacanza in una zona costiera soggetta a elevate fluttuazioni turistiche – e si valuta altresì l'effetto della pandemia da COVID-19 sui consumi idrici, con riferimento a due differenti contesti urbani e fino al livello di singola utenza.

I principali contributi della presente tesi risultano i seguenti: (1) viene fornito un ampio database a scala mondiale degli utilizzi finali dell'acqua a livello residenziale; (2) si presenta una metodologia robusta e versatile per la disaggregazione *end use* dei dati di consumo idrico, ampiamente trasferibile ad altri contesti residenziali; (3) si dimostra l'impatto del turismo balneare sui consumi idrici e sulle relative distribuzioni; (4) si quantificano gli impatti del lockdown da COVID-19 sui consumi idrici a diverse scale spazio-temporali e con riferimento a differenti tipologie di utilizzo dell'acqua. Nel complesso, si evidenzia come i risultati presentati nella corrente tesi possano essere di interesse ai gestori idrici e ai relativi utenti nel meglio comprendere le principali caratteristiche del consumo idrico in diversi contesti e scenari, supportando i primi nell'efficientamento della gestione dei sistemi idrici e indirizzando i secondi a un consumo più consapevole della risorsa idrica.

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Here I am, concluding the writing of a work which reflects my last four years in the Water Systems Group of the University of Ferrara. Four intense years, rich in projects, activities, experiences, but especially people I would like to thank and to whom I am sincerely grateful.

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Abbreviations, acronyms, and symbols

Abbreviations and acronyms

AIC	Akaike’s Information Criterion
A(A)	Automated disaggregation (with Autoflow® software)
A(I)	Automated disaggregation (with Identiflow® software)
A(O)	Automated disaggregation (with other method)
A(T)	Automated disaggregation (with Trace Wizard® software)
B	Bathtub
COVID-19	Coronavirus Disease 19
DAQ	Data acquisition
DD	Study on demand determinants
DGE	Study on data gathering and elaboration study

DM	End-use data gathering by direct monitoring
DMA	District Metered Area
DMF	Study on demand modelling and forecasting
DW	Dishwasher
EUD	End-Use Database
EUDM	Study on end-use disaggregation methods
EUP	Study on end-use probability
EUWC	Study on end-use water consumption
F	Toilet flush
GIS	Geographical Information System
H1–H13	Monitored households (Italian and Dutch dataset)
IO	Indoor-outdoor disaggregation
IU	End-use data gathering by interacting with users/householders
L	Leakages
LV1–LV6	Levels of the analysis of residential water consumption at the end-use level
M	End-use data gathering through manual disaggregation
NRMSE	Normalized Root-Mean-Square Error
O	Other/Unknown
PD	Study on peak demand
PDF	Probability-Density Function
resp.	Respectively
REUS	Residential End-Use Study

S	Shower
SCADA	Supervisory Control And Data Acquisition
T	Taps
UPS	Study on users' perception and awareness
WB	End-use data gathering through water balance
WCA	Water Contribution Accuracy
WCS	Study on water conservation and recycling
WM	Washing machine
WWSS	Study on wastewater or sewer system design

Symbols

acc = meter accuracy

CF = correction factor

C^{t_H} = hourly net inflow coefficients (DMA level) or hourly water consumption coefficient (users grouped together)

c^{t_H} = hourly water consumption coefficients (user level)

$C_1, C_2, \dots$ = closing manoeuvres

$D_{DW,avg}$ = average duration of dishwasher load

$D_{DW,max}$ = maximum duration of dishwasher load

$d_{DW,max}$ = maximum duration of dishwasher individual water withdrawals

$D_{DW,min}$ = minimum duration of dishwasher load

$d_{DW,min}$ = minimum duration of dishwasher individual water withdrawals

$D_{F,avg}$ = average duration of toilet use

$D_{F,max}$ = maximum duration of toilet use

$D_{F,min}$ = minimum duration of toilet use

$D_{S,avg}$ = average duration of shower use

$D_{S,max}$ = maximum duration of shower use

$D_{S,min}$ = minimum duration of shower use

$D_{T,avg}$ = average duration of tap use

$D_{T,max}$ = maximum duration of tap use

$D_{T,min}$ = minimum duration of tap use

$D_{WM,avg}$ = average duration of washing machine load

$D_{WM,max}$ = maximum duration of washing machine load

$d_{WM,max}$ = maximum duration of washing machine individual water withdrawals

$D_{WM,min}$ = minimum duration of washing machine load

$d_{WM,min}$ = minimum duration of washing machine individual water withdrawals

dp = meter pulse duration

E_A = appliance Euclidean distance

E_F = toilet-flush Euclidean distance

E_S = shower Euclidean distance

E_T = tap Euclidean distance

i = DMA or user index

j = day-type index (e.g. weekday, holiday, Monday, Tuesday, etc.)

k = end-use index

n = inlet-point index

N_{BF} = number of monitored bathing facilities (Touristic DMA)

N_{CU} = number of commercial users with available data (Commenda DMA)

N_{RU} = number of residential users with available data (Commenda DMA)

N_{TU} = total number of users with available data (Commenda DMA)

$n_{DW,max}$ = maximum number of dishwasher loads per household day

np = number of meter pulses

n_{Smax} = maximum number of showers per household day

$n_{WM,max}$ = maximum number of washing machine loads per household day

o = outlet-point index

$O_1, O_2, \ldots$ = opening manoeuvres

p = p-value

PC = partition class (cluster)

$pi_{DW,max}$ = maximum time distance from first to second dishwasher withdrawal

$pi_{DW,min}$ = minimum time distance from first to second dishwasher withdrawal

$pi_{WM,max}$ = maximum time distance from first to second washing machine withdrawal

$pi_{WM,min}$ = minimum time distance from first to second washing machine withdrawal

$pf_{DW,max}$ = maximum time distance between subsequent dishwasher withdrawals

$pf_{DW,min}$ = minimum time distance between subsequent dishwasher withdrawals

$pf_{WM,max}$ = maximum time distance between subsequent washing machine withdrawals

$pf_{WM,min}$ = minimum time distance between subsequent washing machine withdrawals

$p_{S,max}$ = maximum duration of flow interruption during a shower use

Q = observed DMA net inflow or water consumption of a group of users (general)

q = observed water consumption at the user level (general)

Qd = observed DMA net inflow or water consumption of a group of users (daily resolution)

qd = observed water consumption at the user level (daily resolution)

qe = observed water consumption at the end-use level (general)

$\widehat{qe}$ =disaggregated water consumption at end-use level (general)

Qh = observed DMA net inflow or water consumption of a group of users (hourly resolution)

qh = observed water consumption at the user level (hourly resolution)

Qin = observed DMA inflow

Qm = observed DMA net inflow or water consumption of a group of users (monthly resolution)

qm = observed water consumption at the user level (monthly resolution)

$Qout$ = observed DMA outflow

t = time index (general)

t_d = time index (day of a given period)

t_h = time index (hour of a given day)

t_j = time index (day of type j of a given period)

$t_{j,rain}$ = time index (rainy day of type j of a given period)

$t_{j,rainless}$ = time index (rainless day of type j of a given period)

t_m = time index (month of a given year)

t_s = time index (second of a given hour)

$V_{DW,avg}$ = average consumption of dishwasher load

$V_{DW,max}$ = maximum consumption of dishwasher load

$v_{DW,max}$ = maximum consumption of dishwasher individual water withdrawals

$V_{DW,min}$ = minimum consumption of dishwasher load

$v_{DW,min}$ = minimum consumption of dishwasher individual water withdrawals

$V_{F,avg}$ = average consumption of toilet use

$V_{F,max}$ = maximum consumption of toilet use

$V_{F,min}$ = minimum consumption of toilet use

$V_{S,avg}$ = average consumption of shower use

$V_{S,max}$ = maximum consumption of shower use

$V_{S,min}$ = minimum consumption of shower use

$V_{T,avg}$ = average consumption of tap use

$V_{T,max}$ = maximum consumption of tap use

$V_{T,min}$ = minimum consumption of tap use

$V_{WM,avg}$ = average consumption of washing machine load

$V_{WM,max}$ = maximum consumption of washing machine load

$v_{WM,max}$ = maximum consumption of washing machine individual water withdrawals

$V_{WM,min}$ = minimum consumption of washing machine load

$v_{WM,min}$ = minimum consumption of washing machine individual water withdrawals

$X_{DW,avg}$ = average number of water withdrawals per dishwasher load

$X_{DW,min}$ = minimum number of water withdrawals per dishwasher load

$X_{DW,max}$ = maximum number of water withdrawals per dishwasher load

$X_{WM,avg}$ = average number of water withdrawals per washing machine load

$X_{WM,min}$ = minimum number of water withdrawals per washing machine load

$X_{WM,max}$ = maximum number of water withdrawals per washing machine load

Δqd_i = difference between daily average water consumption of user i (Commenda DMA) during the lockdown period of the year 2020 and that of the corresponding period of 2019

$\Delta qh_i^{t_h}$ = difference between hourly average water consumption of user i (Commenda DMA) at the t_h-hour of the day during the lockdown period of the year 2020 and that of the corresponding period of 2019

ρ = degree of correlation

Chapter 1

Introduction

Water consumption is the main driver of water distribution systems, the primary function of which is to provide the required amount of drinking water to users. Efficient water distribution systems are those which can deliver water continuously, at sufficient quality, with adequate pressure head and avoiding excessive leakages, thus minimizing the energy consumption needed for water potabilization and distribution while aiming to the conservation of the available water resources.

The issue of water resource availability is nowadays of concern for many regions of the world (McDonald et al. 2010, Suero et al. 2012, Nguyen et al. 2015). On the one hand, the demographic growth –along with urbanization– has led to large areas under water stress, with increases in population often coupled with increases in the per capita water consumption rates (Cosgrove and Loucks 2015). In particular, it was demonstrated that the demographic growth can stress local water resources even in areas with decreasing per capita water consumption (Dieter et al. 2018). On the other hand, water shortages –currently involving more than 500 million people worldwide– are expected to be further compounded by the effects of climate change (Sønderlund et al. 2016), affecting water consumption in potentially conflicting sectors. By way of example, considerable increases in the amount of water needed for both irrigation and urban activities are expected in near future, due to the increase in the frequency and intensity of drought events (Evans and Sadler 2008).

In this era of rapid changes and relevant environmental issues, effective planning and management of water distribution systems are of great importance to cope with the challenges posed by increasing population, climate variability, and water resources availability (Aksela and Aksela 2011, Agudelo-Vera et al. 2013, Avni et al. 2015, Bolorinos et al. 2020). Effective planning and management of water distribution systems can be pursued through several strategies, such as new water-saving technologies, smarter water policies, regulations, incentives, proper water pricing, information, and education (Gleick et al. 2003). However, the effectiveness of these strategies in meeting current and future demand conditions under different scenarios is generally based on a detailed knowledge about where, when, and how water is being used, allowing the characterization of water consumption across space and time (Sanchez et al. 2018) and, therefore, its footprint on the energy sector (Chini and Stillwell 2019).

From an operational standpoint, the characterization of water consumption and its variations over space and time can be useful to the subjects involved in the water resources management –such as water utility companies– for optimizing the functioning of control devices within the water distribution network (Cardell-Oliver et al. 2016), thus ensuring an appropriate spatial and temporal allocation of water resources. That is why, in the last decades, many studies have been conducted to investigate water consumption at different spatio-temporal scales (Cominola et al. 2019).

Traditionally, water consumption characteristics have been mainly explored in relation to the residential sector (Aksela and Aksela 2011). This was mainly due to the fact that residential users typically account for the largest portion of water consumption users. In this context, a number of studies were conducted to evaluate and predict the residential water consumption at multiple levels of spatial aggregation, ranging from the entire-city or district scale (Billings and Day 1989, Gato-Trinidad et al. 2011) up to the user scale (Cole and Stewart 2013; Cardell-Oliver 2013a, 2013b). In greater detail, as far as the user level of detail is concerned, water consumption was originally explored by relying on monthly to yearly water data (Danielson 1979, Tanverakul and Lee 2013), which are typically read manually on water meters by utility technicians for billing. However, this kind of data generally allows extracting information only to evaluate the aggregate volumes of water consumption on a very large temporal scale, i.e. monthly or seasonal.

To overcome this limitation, more attention has been recently devoted to the investigation of user water consumption at finer temporal resolutions, i.e. with hourly to sub-minute monitoring. This was made possible by technological development and the diffusion of *smart* metering solutions (Gurung et al. 2015, Darby 2010), spacing 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 enable detailed analysis on heterogeneous water consumption behaviours and daily user patterns (*profiles*) (Cubillo-González et al. 2008, Beal and Stewart 2011, Cominola et al. 2018b) and can be used to develop customized feedback and water conservation programs (Mayer et al. 2000, Willis et al. 2010b, Sønderlund et al. 2016, Cominola et al. 2021a). Moreover, when real-time information is available, smart meter data can also be exploited to provide real-time alerts for network or post-meter leakages, or anomalous water consumption patterns (Britton et al. 2013, Luciani et al. 2019, Steffelbauer et al. 2022a, Mayer 2022), thus enabling prompt actions, with consequent water conservation or even life-saving (Salomons and Housh 2022). Lastly, smart meters allow new, detailed information about water consumption to be obtained up to the finer level of individual end uses of water (i.e. micro-components such as showers, taps, or washing machines). This information may include daily volumes of water consumed, along with the daily water consumption profiles and routines at the end-use level and other physical characteristics such as duration, volume, flow rate, and frequency of use of individual water uses.

Greater focus is nowadays being given in the literature to the characterization of water consumption at such a fine level of spatiotemporal detail in the residential sector. Indeed, this aspect 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. In fact, only few water consumption investigations at the end-use level were performed prior to the early 1990s. They were mainly 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). However, customer self-reported end-use water consumption studies have been proved to be rather inaccurate as consumers typically have a poor understanding of their water use habits compared to norms and best practices (Beal et al. 2013).

Water consumption data at the end-use level can be exploited for a variety of purposes. For example, these can be used for training and testing water demand models (e.g. Blokker et al. 2010, Xenochristou et al. 2021, Steffelbauer et al. 2022b). In addition, the availability of this information may support the development of technologies for water reuse and recycling (e.g. Dixon et al. 1999) or strategies aimed at increasing people's consciousness and awareness of water consumption (e.g. Beal et al. 2011b, Liu et al. 2016). Also, 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 behaviour (Willis et al. 2010b, Stewart et al. 2018). Feedback targeted to specific consumer's water end-use consumption behaviours has great potential to conserve water during water scarcity periods (Fielding et al. 2013).

Despite the advantages of end-use water consumption data, collecting and efficiently processing them is still challenging. From an operational standpoint, the intrusive monitoring of each domestic end use may be impractical, and householders are unlikely to provide permission to install this intrusive instrumentation (Cominola et al. 2015). Limits to directly collecting water consumption data at the domestic end uses has recently led to the development of several non-intrusive techniques, which show the advantage of allowing the decomposition (i.e. *disaggregation*) of data measured at the user level (i.e. aggregate water consumption) into the individual contribution of each end use (Cominola et al. 2017). It is worth noting that most of these approaches are currently automated. In fact, manual disaggregation and classification methods may be applied as well, but they 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.

Generally, automated end-use disaggregation and classification techniques are applied on flow data collected by reading the user water meter, but techniques also exploiting other data (e.g. pressure data) have been proposed as well (Kim et al. 2008; Froehlich et al. 2009, 2011; Srinivasan et al. 2011; Ellert et al. 2015; Vitter and Webber 2018). Focusing on techniques relying on flow data, it is worth observing that most of them can process data at very high temporal resolution only, such as 1–10 s (Mayer et al. 1999, Kowalski and Marshallsay 2003, Nguyen et al. 2013a, Fontdecaba et al. 2013, Bethke et al. 2021), which may not be at the disposal of water utilities. In fact, even though several commercial smart water meters with such a fine monitoring resolution exist, data logging is often limited to coarser resolutions – such as 1-min – to not saturate the device's memory and to increase the battery life. However, in this context, only a few machine learning methods or optimization algorithms have been developed for end-use disaggregation and classification (Piga et al. 2015, Cominola et al. 2017), mainly validated with synthetically generated water consumption data.

While acknowledging the above-mentioned limitations related to the direct – or indirect – collection of end-use water consumption data, it is believed 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 journal publications or water utility reports exploring residential 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. There are also 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.

Overall, the literature of the last decades mainly focused on the characterization of residential water consumption. However, residential users may consume a much smaller portion of the overall volume of water provided by water utilities in some areas, as a consequence of the presence of industries, commercial business, tertiary activities, and other services. In addition, the daily profiles of water consumption may be considerably different in the case of areas where non-residential activities are predominant. In the light of the above, analysis of water consumption at the non-residential level has recently gained more attention (Morales and Heaney 2014, Attallah et al. 2021). To date, research in the non-residential field has been mostly carried out in the case of peculiar districts (Toth et al. 2018) or specific users such as schools or campuses, office buildings, sport facilities, or hotels (Bonnet et al. 2002, Farina et al. 2013, Horsburgh et al. 2017, Clifford et al. 2018). Secondly, in most of the cases, water consumption of these non-residential users was typically explored at a very coarse temporal level of detail, i.e. by exploiting annual or monthly water consumption data (Hof and Schmitt 2011, Morote et al. 2018, Garcia et al. 2020). Therefore, there is still great potential in further – and more deeply – investigating the characteristics of non-residential water consumption, trying to fill the gap of unavailability of studies exploring some non-residential users, or by exploring the features of water consumption at a finer temporal resolution (weekly, daily, or sub-daily).

It is also worth highlighting that the past literature has mainly focused on the investigation of the characteristics of residential or non-residential water consumption under ordinary demand conditions, i.e. in the event that the users are having a typical attitude towards water consumption. Although even in standard situations water consumption and its profiles – reflecting users' habits and lifestyle – can be influenced by multiple factors from economic to climatic, sociodemographic, and geographic (Jorgensen et al. 2009, Hester and Larson 2016), water use may be considerably different in case of exceptional situations, i.e. conditions strongly affecting people's lifestyle or the operational conditions of water distribution systems, such as disasters or pandemics (Miyajima, 2013, Capponi et al. 2019, Hidayat et al. 2020). In this context, the recent SARS-CoV-2 (COVID-19) epidemic has represented a new, emergency situation for many countries throughout the world. After breaking out in the region of Hubei (China) in December 2019 (World Health Organization 2020), the epidemic spread rapidly around the globe, so that it was declared a pandemic by the World Health Organization on 11 March 2020 (McNeil 2020). In order to limit the spread of the pandemic, several national governments implemented a series of restrictive measures, such as home isolation, the suspension of all school and non-essential work activities, as well as the closure of all commercial establishments (except for those selling essential goods) and the ban on travel outside the municipality of residence, except for documented work-related needs, situations of absolute urgency or health reasons. These measures occurred in many European and non-European countries, such as, Spain, France, Great Britain, and China (British Broadcasting Corporation 2020a, 2020b), albeit with timing and modalities varying from case to case. Overall, such restrictions deeply affected the habits and lifestyle of most of the population and reflected also in water consumption. Clearly, due to the novelty of the circumstance, no studies evaluating the effects of pandemics on water consumption – and based on actual data – were available in the literature before the outbreak of the disease.

The current thesis aims to take a step forward in the field of user-level water consumption characterization in relation to residential and non-residential contexts, at different levels of spatio-temporal detail and under different conditions of water demand. In fact, in the light of the aforementioned research gaps, it is believed that significant research opportunities arise, in relation to four main research questions: (1) *How could the available, but fragmented, information on the residential end uses of water be exploited in order to extensively and systematically compare the characteristics of end-use water consumption globally (not only highlighting similarities and differences among the studies available in the literature, but also investigating end-use consumption distribution throughout the day, end-use consumption average parameter values, and their related statistical behaviour)?* (2) *How could detailed information on the residential end uses of water be effectively obtained by exploiting only water consumption data collected at the household level with a temporal resolution that is close to that of the most widespread commercial smart meters?* (3) *Which are the most relevant characteristics of non-residential water consumption with reference to those user types which have not been investigated in the scientific literature, but the presence and the impacts of which may be significant in several contexts (e.g. bathing facilities for the tourist sector)?* (4) *How large is the impact of non-ordinary demand conditions (e.g. those due to exceptional circumstances like pandemics or extreme events) on residential and non-residential water consumption*?

Overall, the motivation lying behind this thesis is based on two key-challenges: (*I*) further deepening the knowledge of residential water consumption up to level of individual end uses of water based on the fragmented information currently available in the literature, and developing new approaches enabling end-use water consumption to be characterized by exploiting the tools typically at disposal of water utilities; and (*II*) investigating aspects which have been explored only in a limited manner in the literature about water consumption to date, such as the characterization of water consumption at the user level in relation to some still unexplored non-residential contexts, or under specific non-ordinary conditions affecting water demand.

Each aforementioned research question is intended to be addressed through a specific research objective:

1. Providing a comprehensive analysis 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 (thus addressing the first research question). These analyses are intended to be carried out in order to fill the gap related to the lack of an extensive review about residential end uses of water – not only highlighting similarities and differences among the studies available in the literature but also systematically comparing all the numerical results about end-use water consumption globally.

2. Developing and testing a methodology enabling end-use disaggregation and classification of residential water consumption to be performed on data the resolution of which is close to that of the most widespread commercial smart meters and validating the method with actual smart-metered water consumption data collected in different geographical areas, thus making it potentially applicable and transferrable to several residential contexts (and addressing the second research question).

3. Investigating the characteristics of water consumption at some (still unexplored) non-residential users of interest for the tourist sector – such as bathing facilities and holiday homes, the diffusion of which in the European Mediterranean coastal areas is high – with high level of spatio-temporal detail. More specifically, the research is intended to explore the features and the profiles of water consumption of these users and provide insight into the effects of seaside tourism on water consumption (thus addressing the third research question). The motivation of the research is mainly supported by the fact that a wide spread of tourism –in particular, seaside tourism– was experienced in the European Mediterranean regions since the 1960s (Morote et al. 2016b) with considerable effects on economy, land use, urbanisation, and infrastructures.

4. Playing a part in the field of water consumption characterization under non-ordinary conditions of water demand by exploring the effects of the restrictions adopted to limit the spread of COVID-19 pandemic on residential and non-residential water consumption at the

user level. In greater detail, the analysis is intended to be carried out based on actual water consumption data collected in field before and during lockdown, and by considering different levels of temporal aggregation, up to the hourly scale (thus addressing the fourth research question).

Given the variety of research questions, key-challenges, and the main objectives of the research, the work – aiming at advancing user water consumption in different contexts and under different demand conditions – is ideally structured in two parts. *Part I* is devoted to the characterization of residential water consumption under ordinary conditions, in relation to which a step towards the end-use level of detail is made, given the current maturity of the literature about residential water consumption at the user level. *Part II* is focused on the characterization of user water consumption in relation to some still unexplored non-residential contexts and under non-ordinary conditions of water demand.

In greater detail, the current thesis is developed in seven chapters, as detailed below. The link between research questions, thesis objectives, chapters, and candidate's publications are summarized in Table 1.1, whereas the overall layout of the thesis is shown in Figure 1.1

- *Chapter 1* is devoted to the introduction of context, challenges and motivations lying behind the current research, and highlights the main objectives of the thesis.
- *Chapter 2* includes a review of the literature about residential and non-residential water consumption, contextualizing the topic of the current thesis. Specifically, studies contributing to the characterization of residential water consumption at multiple spatiotemporal levels of detail (i.e. user and end-use level) is presented, with the aim of highlighting the main research opportunities in residential sector. Similarly, a comprehensive number of studies about user water consumption in non-residential contexts or under non-ordinary conditions were systematically reviewed, in order to point out which scenarios that have been typically less investigated in past literature and draw the margins for new research contributions.
- *Chapter 3* includes a detailed analysis of the most relevant studies about residential water consumption at the end-use level, conducted with the primary aim of comprehensively investigating end-use characteristics in different contexts worldwide (thus addressing the first research question and the related objective of the current thesis). 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 such as considerations about end-use determinants and water-saving efficiency. The content of the chapter is adapted from Mazzoni et al. (2023a).

- *Chapter 4* presents a revised, automated method for the end-use disaggregation and classification of coarse-resolution water consumption data, i.e. data at one-minute resolution (addressing the second research question and the related objective of the current thesis). The methodology developed is based on deterministic rules relying on water use physical parameters (i.e. duration, flow rate, consumed volume) and is validated with real end-use water consumption data collected in considerably different geographical contexts, i.e. the city of Bologna (Italy) and some urban areas of the North Holland province (the Netherlands). Specifically, the method represents the first case in which disaggregation and classification performance on coarse-resolution water consumption time series is directly assessed through a comparison against data collected in field. The content of the chapter is adapted from Mazzoni et al. (2019), Mazzoni et al. (2021a), Mazzoni et al. (2022a), Mazzoni et al. (2022b), and Mazzoni et al. (2023b).
- *Chapter 5* provides insight into non-residential user water consumption and investigates the effects of seaside tourism on water use, in relation to the coastal area of Lidi Ferraresi (northern Italy) typically subjected to high tourist fluctuations throughout the year. In greater detail, the area concerned features a high number of bathing facilities, the water consumption of which is investigated trying to fill the gap of unavailability of studies exploring these non-residential users (addressing the third research question and the related objective of the current thesis). In particular, analyses at the user level of detail are conducted in relation to a group of nine bathing facilities, for which water consumption was monitored with hourly resolution over a period of three months during tourist season. Additionally, data collected at very high temporal resolution (i.e. 1-s) in a holiday home over nearly three weeks are considered to evaluate the characteristics of water consumption in this type of tourist accommodation.

Lastly, the results are compared against those of a nearby area not significantly affected by tourist flows and where water consumption is mainly tied to residential users. The content of the chapter is adapted from Mazzoni et al. (2022c).

- *Chapter 6* focuses on the characterization of water consumption under non-ordinary conditions, i.e., in the event of exceptional circumstances deviating water demand from the standard (addressing the fourth research question and the related objective of the current thesis). In greater detail, the chapter investigates the effects of the restrictions adopted to limit the first COVID-19 wave on water consumption with reference to more than 200 residential and non-residential users in the city of Rovigo (Italy), in which smart monitoring of hourly water consumption at the level of individual user has been ongoing since 2019. Greater focus is given to the evaluation of the effects of COVID-19 restrictions in contexts characterized by various levels of non-residential water consumption based on data collected in three areas of the water distribution network of Padua (Italy), featuring different characteristics and supplying a wide range of activities. The content of the chapter is adapted from Alvisi et al. (2021) and Mazzoni et al. (2021b).
- *Chapter 7* summarizes the major outcomes achieved with the research presented in the current thesis, outlines the conclusions, and provides ideas for future research.

Table 1.1. Link between research questions, thesis objectives, chapters, and candidate's publications.

Research question	**Thesis objective(s)**	**Thesis chapter**	**Candidate's publication(s)**
1. How could the available information on the residential end uses of water be exploited to compare the characteristics of end-use water consumption globally, extensively, and systematically?	Providing a comprehensive analysis of the existing end-use studies conducted globally in the field of residential water consumption to fully explore and quantify end-use characteristics in different contexts worldwide.	Chapter 3	Mazzoni et al. (2023a)
2. How could detailed information on the residential end uses of water be obtained by exploiting aggregate water consumption data collected at the household level with a temporal resolution that close to that of the most widespread commercial smart meters?	Developing and testing a methodology enabling end-use disaggregation and classification of residential water consumption to be performed on coarse-resolution data and validating the method with actual data collected in different geographical areas.	Chapter 4	Mazzoni et al. (2019) Mazzoni et al. (2021a) Mazzoni et al. (2022a) Mazzoni et al. (2022b) Mazzoni et al. (2023b)

Table 1.1 (Continued). Link between research questions, thesis objectives, chapters, and candidate's publications.

Research question	Thesis objective(s)	Thesis chapter	Candidate's publication(s)
3.Which are the most relevant characteristics of non-residential water consumption, with reference to those user types which have not been investigated in the scientific literature?	Investigating the characteristics of water consumption at some non-residential users of interest for the tourist sector (bathing facilities, holiday homes) with high level of spatial and temporal detail, thus providing insight into the effects of seaside tourism on water consumption.	Chapter 5	Mazzoni et al. (2022c)
4. How large is the impact of non-ordinary conditions on residential and non-residential water consumption?	Exploring the effects of the restrictions adopted to limit the spread of COVID-19 pandemic on residential and non-residential water consumption at the user level with high level of spatial and temporal detail.	Chapter 6	Alvisi et al. (2021) Mazzoni et al. (2021b)

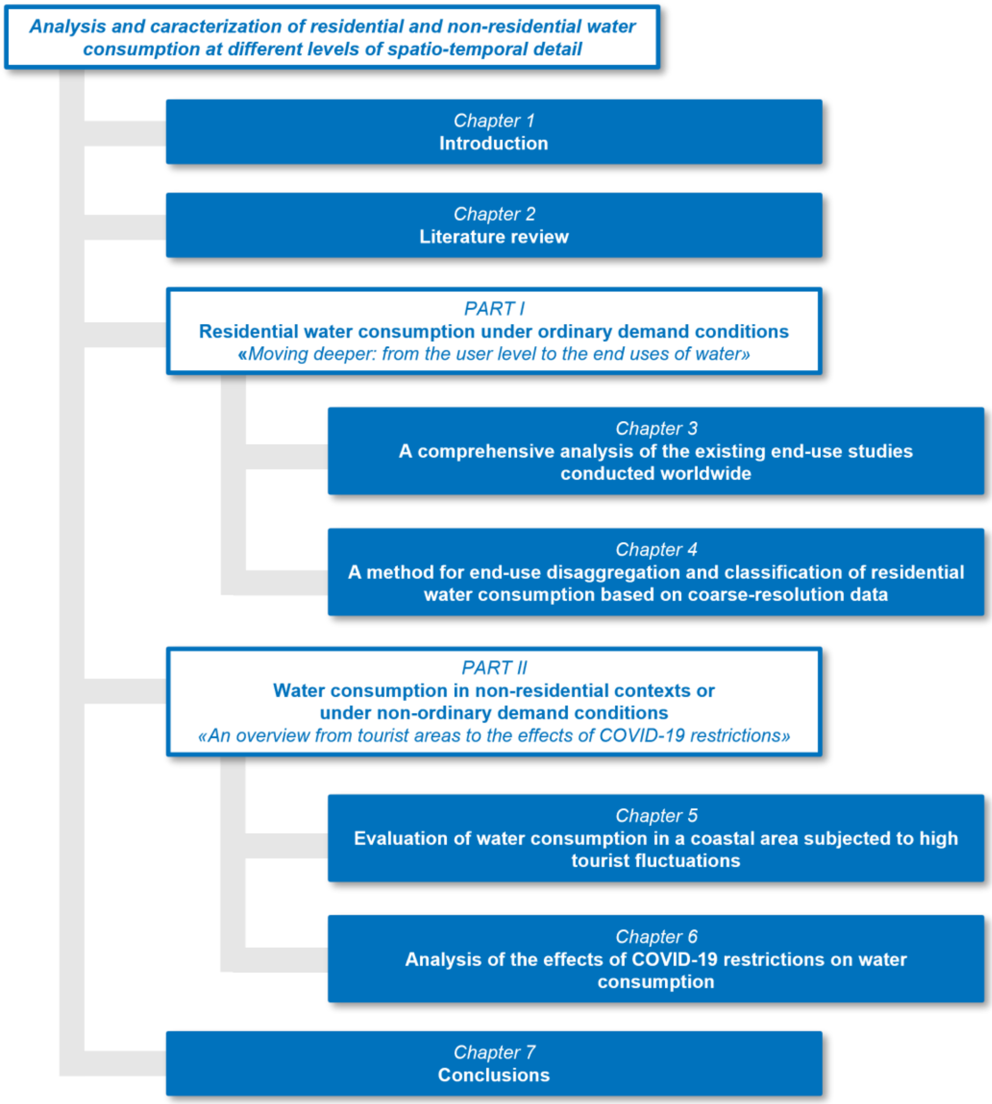

Figure 1.1. Thesis outline.

Chapter 2

Literature review

A detailed characterization of water consumption – the major driver of water distribution systems – has increasingly emerged as a key approach to integrate the traditional water supply operations (Di Mauro et al. 2021). In fact, the analysis of water consumption under multiple scenarios and conditions lays the basis for water demand modelling and forecasting, which is a challenging but essential task to meet the qualitative and quantitative standards required to ensure efficient which water distribution systems (House-Peters and Chang 2011). On the one hand, as far as water demand modelling is regarded, it is worth noting that this is typically allocated to the nodal elements of a water distribution model based on two approaches: *top-down* or *bottom-up* (Walski et al. 2003). The *top-down* approach relies on aggregate water consumption data typically observed on a large spatial scale (e.g. at the entire-city or district level) which are disaggregated and allocated to individual nodes based on the magnitude of all users adjacent to the node (e.g. based on water billing data typically collected on monthly to yearly basis, as in the study by Ansaloni et al. (2013)). By contrast, in the case of the *bottom-up* approach, nodal water consumption is obtained by aggregating the water consumption time series of individual users, which can be modelled based on different probabilistic techniques (e.g., Buchberger and Wu 1995, Alvisi et al. 2003, Blokker et al. 2010, Creaco et al. 2017, Steffelbauer et al. 2022b). On the other hand, as far as water demand forecasting is concerned, two main types of models were developed, depending on forecast horizon and frequency (Gagliardi et al. 2017, Pacchin et al. 2019): long-term models (providing monthly or yearly demand forecasts with a temporal horizon of one or many years), typically used for resource allocation, and short-term models (providing hourly or daily demand forecasts over time horizons of one day to one month), mainly used for water distribution system management. Therefore, it emerges that, in the case of water demand modelling, information on water consumption at different spatial scales is required based on the approach considered (Clifford et al. 2018), whereas water consumption data different temporal resolutions are needed based on the desired demand forecasting model.

In the light of the above, the state-of-the-art literature of the last decades has enriched in studies focused on water consumption analysis and characterization, based on which several methodologies for water demand modelling and forecasting have been developed, parametrized, and validated. Studies on water consumption monitoring, analysis and characterization have been conducted in relation to different levels of spatial and temporal detail (depending on data application purposes) and in different contexts of residential and non-residential water use.

The aim of this chapter is to offer a comprehensive overview about the state-of-the-art literature on the user-level water consumption. More specifically, a comprehensive state-of-the-art literature review is carried out for each of the four main objectives of this thesis introduced in *Chapter 1*. First, in the case of residential consumption, the analysis is indented to further deepen to the level of water end use – i.e. the finest level of spatial detail achievable – in the light of the current maturity of the literature on residential water consumption at the user level (as highlighted in the extensive review by Di Mauro et al. (2021)). Second, insight about the state-of-the-art literature on the methods for the obtainment of end-use information from water consumption data at the user-level is provided, with specific regard to automated techniques for water end-use disaggregation and classification . Third, the chapter is devoted to the review of the studies on the characterization of water consumption at the user-level in the non-residential sector, which has been typically less investigated due to the fact that residential users generally account for the largest portion of water consumption users (Aksela and Aksela 2011). Fourth, an overview of the studies focusing on residential and non-residential water consumption under non-ordinary conditions, i.e. extraordinary circumstances of water demand such as disasters or pandemics, is provided.

2.1. Residential water consumption: a step towards the end-use level

Studies exploiting indoor end-use water consumption data have been available since the Sixties. For example, in a pioneer study by Haney and Hamann (1965) focused on the topic of dual water systems, an estimate of domestic water consumption – based on an average four-person American family of the future – is presented. In greater detail, the values reported by authors are daily per capita and relate to different domestic indoor and outdoor activities. Consumption ranges from a minimum of less than 10 L/person/day for drinking and cooking to more than 90 L/person/day for toilet, with a total amount of over 220 L/person/day. These estimates were considered and applied in other studies, e.g. the subsequent study by Bailey et al. (1969) on residential wastewater treatment and flow reduction, conducted to assess the typical wastewater flow discharged in domestic sewer systems.

The very first examples of end-use data not resulting from raw estimates appeared in a series of American studies developed in the Seventies (e.g. Cohen and Wallman (1974), Bennett and Linstedt (1975), Siegrist et al. (1976)), mainly focused on wastewater flows and treatment characteristics. The values reported in these studies refer to limited household samples (from five to eleven dwellings) and were obtained in different ways, spacing from the use of water consumption recording sheets compiled by users (e.g. Bennett and Linstedt (1975)) to actual field observations (e.g. Siegrist et al. 1976). In particular, in the study by Siegrist et al. (1976), an analog chart recorder – driven by the domestic water meter – was used to plot the aggregate water consumption time series for nearly 40 days per household. The aggregate trace was then analyzed, and individual water end uses were manually identified with the support of preliminary questionnaires, user reports, and toilet-flush counters installed in bathrooms. Overall, the proposed daily per capita water consumption value ranges from about 10 L/person/day for water softening to nearly 40 L/person/day for laundry, with a total indoor water consumption of over 160 L/person/day. In the following years, similar approaches for the characterization of the end uses of water were applied in the water-conservation study by Brown and Caldwell (1984) – considering a much wider household sample of more than two hundred dwellings, monitored for about two weeks each – and the Butler (1991) study on the optimal design of domestic sewer systems.

Since the early Nineties, the technological advancement, along with the diffusion of data-acquisition (DAQ) systems on a large scale, allowed new methods for the collection of information about water end uses to be developed. Anderson et al. (1993) made use of an extensive group of electronic water meters (along with pressure transducers and event counters) wired into an onsite computerized DAQ system to collect and store water consumption data at both aggregate and end-use level, with major emphasis placed on shower and toilet. Data were then manually downloaded and analyzed to explore the variations in the water of water consumption due to the retrofitting of traditional fixtures with efficient devices (e.g. low-flow showerheads and toilets) in a sample of 25 households in Tampa, Florida (United States) subjected to two-month monitoring. Similarly, in the study by DeOreo et al. (1996), a sample of 16 households in Boulder, Colorado (United States) was monitored by water meters and data loggers installed externally to the dwellings. Metered data were automatically logged every 10 seconds, periodically downloaded to disk, and processed. The data fine resolution permitted the full (manual) identification of individual end-use water consumption from the household-level water consumption time series, allowing the quantification of water use variations at the end-use level, along with the effects of water conservation measures.

At the dawn of the new millennium, an important role was played by the study on residential end uses of water published by the American Water Works Association (Mayer et al. 1999). The study was conducted on a massive sample including nearly 1,200 households across the United States that agreed to participate in a detailed end use survey. Every household was monitored for two summer and two winter weeks, respectively, by using compact data loggers paired to the external water meters and storing data with resolution of 10 s. This fine resolution was sufficient to identify and classify each individual end use of water end use within the household. This was done by exploiting Trace Wizard®, the first PC-based software for trace analysis, capable of automatically disaggregating the recorded (household-level) water consumption time series into individual water use events and classifying them based on the input and the controls provided by the analyst. Overall, a sizable residential water use database containing nearly one million individual water use events was obtained, providing extensive answers to questions about how much and where water is used in the residential contexts, along with an estimate of the savings water savings due to various conservation measures. The study also enabled the development of predictive demand models incorporating the detailed end use information and household level socioeconomic data. Following the approach proposed by Mayer et al. (1999), several similar studies were conducted in the subsequent years, investigating the characteristics of water end uses in different locations and contexts based on fine-resolution readings of the external water consumption, data logging, and the use of software for end-use disaggregation and classification. By way of example, the same authors explored the impacts of water-saving fixtures (low-flow toilet flush, shower efficient showerheads, and tap aerators) in 37 single-family households in Seattle, Washington (United States) (Mayer et al. 2000). Studies were also conducted in relation to 33 households in the East Bay, California (Mayer et al. 2003) and 26 dwellings in Tampa, Florida (Mayer et al. 2004).

In the United States, a second group of extensive American end-use studies appeared after the year 2010. In greater detail, the research conducted by Aquacraft (2011) compares the results of the end-use analysis by Mayer et al. (1999) against those of nearly 300 households built after 2001 and 25 high-efficiency dwellings built according to water use efficiency specifications. DeOreo et al. (2011) processed fine-resolution data collected and logged in more than 730 households across California, evaluating the potential to water conservation for both indoor and outdoor activities. The DeOreo et al. (2011) end-use data were also exploited by Cominola et al. (2018a) for the development of a stochastic demand model generating synthetic water end-use time series at 10-s (or coarser) resolutions. Moreover, the end-use database initially provided by Mayer et al. (1999) was updated (DeOreo and Mayer (2013), DeOreo et al. (2016)), with data from about 760 households across the United States and Canada subjected to end-use analysis and an additional sample of more than 100 dwellings also equipped with meters on the feed lines to their water heater. This allowed changes in water consumption profiles over a 15-year period to be evaluated, and variations in the water volumes required by each end use to be identified.

As far as the developed countries are regarded, it results that, despite the pioneer studies including data collection at fine-resolution, logging, and automated processing were mainly developed in the United States, greater and increasing relevance was given in the early 2000s to the topic of end-use water consumption in Australia and New Zealand. For example, in 2003, Loh and Coghlan investigated the features of end-use consumption, profiles, and trends in Perth (Australia). Roberts (2005) exploited the 5-s resolution data externally collected 100 households in the Yarra Valley (Australia) to collect end-use parameters required for the formulation of an end-use model.

Heinrich (2007, 2010) focused on a sample of 12 to 51 households in the Kapiti Coast (New Zealand) with the goal of developing a robust method for the investigation of the end uses of water. Mead and Aravinthan (2009) made use of 10-s resolution data to identify the major components of the indoor water consumption, along with their diurnal profiles and influencing factors on a sample of 10 households in Toowoomba (Australia). In addition to the aforementioned studies, Willis et al. conducted a large number of studies on a sample of 50 to about 150 households in the Gold Coast region, monitoring water consumption at the 10-s resolution and making use of the Trace Wizard® disaggregation software. Research was conducted with several aims: developing a web-based system providing real-time end-use data to water utilities and consumers (Willis et al. 2009a); exploring the differences in the end-use consumption among socioeconomic regions (Willis et al. 2009b); investigating the determinants of end-use consumption (Willis et al. 2009c, 2013); estimating the volumes of wastewater that can be recycled through dual supply systems (Willis et al. 2010a, 2011b); evaluating the potential to water conservation through the influence of alarming visual display devices on end uses (Willis et al. 2010b); assessing people's attitude towards water conservation (Willis et al. 2011a). An extensive end-use study was also carried out in the South-East Queensland by Beal et al. (Beal and Stewart 2011, 2014b; Beal et al. 2011a), including the 5-s monitoring of household-level consumption in 80 to 250 households over two-week periods of different seasons. These data were also applied to study the relationship between people's perceptions of their water consumption and the actual water use (Beal et al. 2011b, 2013), the drivers of end-use water consumption (Beal et al. 2012, Makki et al. 2013), the end uses driving peak day consumption (Beal and Stewart 2014a), the rebound effect of water use behaviour in post-flood and post-drought periods (Beal et al. 2014), or to calibrate and validate new end-use disaggregation and classification models such as Autoflow® (Nguyen et al. 2013a, 2013b, 2015; Yang et al. 2018). Additional end-use studies were also performed by Gan and Redhead (2013), Redhead et al. (2013), Arbon et al. (2014) , Rathnayaka et al. (2015) and Siriwardene (2018) in the metropolitan areas of Melbourne and Adelaide, exploiting fine-resolution data collected at the household level by the local water utilities.

End-use water consumption in the residential sector was investigated by pairing water meters to data loggers (and data processing software) in a number of European studies as well. For instance, in the study by Edwards and Martin (1995), a sample of approximately one hundred dwellings in the United Kingdom were selected for special investigation. Water consumption was monitored by water meters and data loggers installed both externally and at every separate end use. Metered data (with 1-L resolution) were logged every 15 minutes, periodically downloaded by the water utility's technicians, and then processed. Also in the United Kingdom, Kowalski and Marshallsay (2003, 2005) yielded information on the end uses of water in domestic properties by exploiting the rule-based *Identiflow*® software for the automated disaggregation and classification of water end uses. In Madrid (Spain), about 300 households were subjected to a super-fine-resolution (i.e. 1 s) monitoring and data logging by Cubillo-González et al. (2008) and the end-uses characteristics, parameters, and profiles were evaluated through the manual disaggregation and classification of the household-level time series recorded. The end-use dataset obtained was also exploited by Ibáñez-Carranza et al. (2017), to test and validate a new method for end-use disaggregation and classification. In Barcelona and Murcia (Spain), Fontdecaba et al. (2013) installed a number of flow switches at different points of the domestic plumbing systems in eight households and exploited the information provided by these tools to obtain end-use data from the 5-and 1-s resolution time series collected at the domestic water inlet. These data were then used to develop, calibrate, and test the disaggregation and classification method proposed by the authors. In Kofinas et al. (2018), data collected and logged at the 30-s resolution by installing smart meters paired with loggers at some specific end uses (kitchen sinks, taps, electric appliances) in 16 households located in Skiatos (Greece) and Sosnowiec (Poland) were used to test a methodology for the generation of synthetic household water consumption data. Finally, Di Mauro et al. (2021) developed an Internet-of-Things-based end-use monitoring system capable of reading real-time end-use water consumption at the 1-s resolution and tested it in a pilot household over a period of nearly eight months.

It is worth noting that all the aforementioned studies about water end uses based on smart metering technologies were conducted in the developed areas of the globe. However, examples of studies based on automated data collection and logging have been carried out in developing areas as well. For instance. Kim et al. (2007), collected hourly to daily water consumption data at each domestic end use in a sample of 145 Korean households, while Otaki et al. (2008) directly measured the end uses of water in 55 to 63 households in Chiang Mai (Thailand) during both the dry and the rainy season. Analyses were repeated by the same authors also in Khon Kaen (Thailand) and Hanoi

(Vietnam), (Otaki et al. 2011, 2013, 2017). In addition, Sivakumaran and Aramaki (2010) exploited monthly tap readings to assess the residential end uses of water consumption in Trincomalee, in the dry zone of Sri Lanka. Other analysis about Korean end uses were performed by Lee et al. (2012) based on the nearly real-time monitoring of individual domestic fixtures in 146 households and with 10-min resolution.

Although the technological advancements of the last three decades enabled extensive research on the residential end uses of water to be carried out based on tools for data collection, logging, and processing at a fine temporal resolution, it is worth noting that end-use studies relying exclusively on information provided by users through surveys or questionnaires about water consumption (and sometimes paired to very coarse, i.e. monthly, meter readings) were still conducted as well. For example, in the Netherlands, extensive water consumption surveys have typically been submitted with three-year frequency since 2001 (Foekema and Engelsma 2001, Kanne 2005, Foekema et al. 2008, Foekema and Van Thiel 2011, Van Thiel 2014, Van Thiel 2017). These are generally sent to a large number of users, i.e. between 1,000 and 2,000 dwellings, with the aim of investigating the characteristics, the parameters, and the drivers of the end-use water consumption. The data reported in the aforementioned Dutch studies were also used for other purposes, such as developing residential demand models (Blokker et al. 2010, Steffelbauer et al. 2022b) or analysing the variations in the water consumption on a yearly temporal scale (Agudelo-Vera et al. 2014). In the South African study conducted by Jacobs (2007), the correlation between the estimated end-use water consumption (obtained through surveys) and the metered consumption for residential users is investigated, revealing people's subjectivity in replying to questionnaires, being the survey-based values of consumption not always in line with their corresponding measured values. Moreover, Ghisi and Oliveira (2007) evaluated the water-saving potential of rainwater and greywater in relation to two Brazilian case-study households. Specifically, end-use water consumption and parameters were obtained by pairing water bill data to the results of a report submitted to the residents, to be filled in every time they used any fixture. Similarly, Shan et al. (2015) developed a survey aimed at evaluating the features of water consumption at multiple scales (i.e. household and end-use level) along with its major drivers. The survey was submitted to more than one hundred households in Greece and Poland. A similar study by Sadr et al. (2015, 2016). allowed the characteristics of water end uses to be investigated in relation to a sample of about one hundred dwellings in Jaipur (India). Other examples of survey-based methods for end-use characterisation can be found in the study by Hussien et al. (2016) – focusing on more than four hundred intermittently supplied users in Duhok (Iraq) – and the Libyan case study proposed by Alharsha et al. (2018). Finally, recent research by Díaz et al. (2021) has aimed at gathering information to set up end-use demand models through an online survey collecting information about end-use consumption in households. The survey was submitted in Madrid (Spain) over the period of COVID-19 outbreak and received over 3,000 replies, the analysis of which outlined the peculiarities in the water consumption due to the COVID-19 lockdown and allowed to investigate the parameters of water end uses (mainly duration and frequency of use) with limited effort.

Overall, it is worth noting that the literature published in the past three decades includes numerous peer-reviewed journal publications or water utility reports exploring water consumption characteristics at the end-use level, considering different case studies and a variety of methodological approaches adopted to gather information on water end uses. There are also considerable differences in the numerical end-use results shown. In this context, some recent studies have reviewed the major studies on residential end uses of water available in the literature, with the aim of classifying them based on location, sample size, and approach adopted to obtain end-use data (Nguyen et al. 2013a, Cominola et al. 2015). Other studies also included a summary comparison of the daily per capita end-use water consumption values indicated in different studies (Mayer et al. 1999, Beal and Stewart 2011, Gurung et al. 2014, Jordán-Cuebas et al. 2018) or considerations about the accessibility of end-use data (Di Mauro et al. 2021). However, an extensive review about residential end uses of water – not only highlighting similarities and differences among the studies available in the literature but also systematically comparing all the numerical results about end-use water consumption globally – is currently missing.

2.2. Disaggregation and classification of the residential end uses of water

In the past decades, great relevance was given to the characterization of residential water consumption on a detailed spatial scale, i.e. up to the level of individual end uses of water. In some cases (e.g. Anderson et al. (1993), Edwards and Martin (1995), Otaki et al. (2008, 2011, 2013, 2017), Lee et al. (2012), Kofinas et al. (2018), Di Mauro et al. (2020)) information about water consumption at the end-use level was obtained through direct measurements via intrusive monitoring, i.e., by installing smart metering devices at all domestic end uses. However, this approach is often time-consuming and expensive. In addition, the installation of smart meters at end uses may sometimes be practically unfeasible, since some of these could have inaccessible inlet points (e.g., wall-mounted toilet tanks), and it could also be rejected by the householders because of the meter intrusiveness. The limitations in the monitoring of individual end uses, along with the general low accuracy of customer self-reported end-use water consumption studies (Beal et al. 2013), have led to the development of non-intrusive techniques allowing the segmentation (namely, *disaggregation*) of a signal – collected over time externally to households – into the contribution related to each individual water use event, and the subsequent labelling (namely, *classification*) of each event to the respective end-use category (Cominola et al. 2017). The application of these techniques allows the knowledge on where water is typically used within dwellings (and with which characteristics) in addition to how much water is globally consumed, thus enabling information about water consumption at the detailed level of individual end use to be obtained from data collected on a broader spatial scale, i.e. at the entire-household level.

It is worth noting that end-use disaggregation and classification have been primarily (and extensively) applied to the electricity sector. Coherently with the considerations set forth in the case of domestic water consumption, Zoha et al. (2012) pointed out that, although intrusive monitoring techniques are generally more accurate in quantifying the specific electricity consumption of each appliance, practical disadvantages may arise, including both high costs and complexity due to multiple sensor installation and configuration. This favoured the use of non-intrusive monitoring techniques especially in the case of large-scale applications. Examples of studies presenting end-use disaggregation and classification techniques are those by Baranski and Voss (2004), Kolter et al. 2010, Elhamifar and Sastry 2015, Piga et al. (2015, 2016), and Singh et al. (2016).

In the water consumption context, end-use disaggregation is feasible only if an adequate electro-mechanical system including at least one meter (e.g. volumetric meter, flow meter, or other) is installed at the inlet point of the domestic plumbing system and paired with a tool for data logging at a sufficiently fine resolution. Overall, disaggregation methods can be classified according to the nature of data collected. In fact, it is possible to distinguish between approaches relying only on flow (or volume); and (2) approaches making use of flow (or volume) data paired with other data; and (3) approaches exploiting other data.

Approaches using only flow (or volume) data collected at the household water inlet point have the advantage of not requiring multiple sensors, but a single meter (fully digital, or paired with data logging systems) which can be installed upstream the domestic plumbing system, e.g. in proximity to the water meter. As reported by Clifford et al. (2018), these techniques can be classified according to data temporal resolution, distinguishing between fine-resolution data (e.g. 1–10 s) and data at a coarser temporal resolution (e.g. on the order of a minute).

In the case of water consumption data at a fine temporal resolution (e.g., 1–10 s), two main approaches have been introduced (Cominola et al. (2015), Yang et al. (2018)): (1) decision-tree-based algorithms; and (2) machine learning algorithms and data mining methods. It is worth noting that detailed reviews of the current state of end-use disaggregation techniques, including discussions of the tools developed along with their potential applications, have been recently proposed by Cominola et al. (2015) and Abu-Bakar et al. (2021).

Decision-tree-based algorithms include rule-based tools such as Trace Wizard® and Identiflow®. Both tools disaggregate and classify end-use events based on their features (mainly flow rate, volume, and duration) and in the light of a given set of boundary conditions. Trace Wizard®, a tool developed by Aquacraft, Inc., was first presented in Mayer et al. (1999), and used in a variety of studies conducted in the last twenty years to obtain data at the end-use level of detail (e.g. Mayer et al. (2000, 2003), Loh and Coghlan (2003), Roberts (2005), Heinrich (2007, 2010), Willis et al. (2009a), DeOreo et al. (2011), Aquacraft (2011), Beal and Stewart (2011, 2014b), Redhead et al. (2013), DeOreo and Mayer (2013)). As reported by Cominola et al. (2015), the tool provides results with an average classification accuracy of 70%, but it is extremely resource intensive. In fact, analysts have to create specific templates that are required to successfully classify the disaggregated end-use events. This is typically done by exploiting information made available by surveys, weekly diaries of consumption, or water use samples preliminary collected at the desired households. It results that the performance of the tool is considerably dependent on the experience of the analyst. Moreover, the process can be quite time consuming: as highlighted by Mayer et al. (1999), when working for the first time with data from a household, approximately one hour per week of data is required to a trained analyst to complete flow trace analysis. The Identiflow® software was originally developed by the British Water Research Centre and subsequently applied in the studies by Kowalski and Marshallsay (2003, 2005). Similar to Trace Wizard®, this tool performs end-use disaggregation and classification based on decision-tree algorithms. Despite the slightly higher accuracy achieved as opposed to Trace Wizard®, i.e. about 75% (Nguyen et al. 2013b), the performance of the tool can be significantly affected by the values of end-use parameters to input (Yang et al. 2018). In addition, the tool is likely to poorly identify the most modern fixtures, due to significantly different characteristics (Cominola et al. 2015). Another decision-tree-based approach for end-use disaggregation and classification was proposed by Fontdecaba et al. (2013). Specifically, end-use events are labelled based on the comparison against the statistical parameter distribution of each end use (e.g., duration, volume, flow rate, number of uses). Assignment is made by applying a likelihood function and selecting the end-use type related to the maximum likelihood. The method was developed and validated with 5- and 1-s resolution data observed in eighteen households in Barcelona and Murcia (Spain) and showed an average identification accuracy of about 70%. Lastly, in the study recently conducted by Bethke et al. (2021), end-use disaggregation and classification have been conducted based on the analysis of derivative water consumption signal and k-means clustering, exploiting the information collected from the end uses. However, the method was applied only to the case study of a four-person household, where aggregate water consumption data were monitored at the resolution of 1 s. Also, the performance of the method was not validated with a significant database of end uses.

Machine learning and data mining methods include the Autoflow® software. A first version of the tool, performing end-use disaggregation and classification with 85% accuracy, was developed by Nguyen et al. (2013b) as a hybrid combination of the Hidden Markov Model and the Dynamic Time Warping algorithm. It was also integrated with a gradient vector filtering algorithm enabling combined end-use events to be detected (Nguyen et al. 2013a) and trained with the Australian end-use database made available by Beal and Stewart (2011, 2014b). To further increase the accuracy of the tool, a larger database including more than 80,000 end-use events from over 500 Australian households (derived by Beal and Stewart (2011, 2014b) and Gan and Redhead (2013)), was exploited to develop a new method employing a hybrid combination of the Hidden Markov Model, Artificial Neural Networks, and the Dynamic Time Warping algorithm. This allowed an increase in the average performance accuracy to about 96% (individual end-use events) and 90% (combined end-use events). The latest version of the software (i.e., Autoflow® v3.1) can currently perform end-use disaggregation and classification with an average accuracy of more than 94% (Yang et al. 2018). However, as highlighted by Cominola et al. (2015), despite the promising results achieved with these machine learning methods, it is worth noting that such data-driven tools still require human input – in addition to consistent training data sets – to effectively perform end-use disaggregation and classification with such a level of accuracy. Similar to the Autoflow® software, two machine-learning methods were developed by Ibáñez-Carranza et al. (2017) to identify residential end uses of water based on fine-resolution data collected at the household level. Both the methods rely on Support Vector Machines and Artificial Neural Networks and were trained with data sets extracted from the extensive sample of about 300 households in the Madrid region (Spain), including over 35 million water uses collected since 2008 and originally proposed by Cubillo-González et al. (2008). Moreover, a sensitivity analysis of model performance to data accuracy (i.e. 0.1 L/pulse versus 1 L/pulse) was carried out by the authors. Overall, the accuracy of the models in end-use disaggregation and classification resulted in line with that of the Autoflow® software, being of 85–90% in the case of data with 0.1 L/pulse accuracy (and of 70–80% in the case of data with 1 L/pulse accuracy).

Techniques using water consumption data collected at a medium temporal resolution (e.g. 1 min) can represent a more widely applicable tool than methods using fine-resolution data, since in practice a water utility may not be in possession of data collected with such level of detail. In fact, even though several commercial meters with a sampling frequency higher than 1 min (e.g. 15 s) exist – such as, by way of example, the Sensus® iPerl meters – data logging is often limited coarser frequencies so as not to saturate the device's memory and to increase the battery life. In this context (i.e. medium temporal resolution data), only a few machine learning methods or optimization algorithms have been developed to disaggregate and classify data into end uses. For example, the sparse optimization algorithm developed by Piga et al. (2015, 2016) – tested with 1-min power consumption readings of a single household located in the Vancouver region, British Columbia (Canada) – revealed a good accuracy in estimating the fraction of energy consumed by each appliance, but the performance of the method on water consumption data was not investigated. Cominola et al. (2017) developed a machine-leaming methodology for end-use disaggregation and classification based on the combination of Factorial Hidden Markov Models and Iterative Subsequence Dynamic Time Warping. The method was originally tested with the same energy consumption data exploited by Piga et al. (2015, 2016) and then applied to disaggregate the synthetically generated water consumption data of 500 dwellings at different temporal resolution, revealing an average accuracy of at least 89% (Cominola et al. 2018a). However the method was not applied to actual water consumption data collected in field. In conclusion, despite showing good performance with respect to the electricity field, none of the above-mentioned approaches for end-use disaggregation and classification of water consumption data at medium temporal resolution have been extensively tested in the water field to date.

As far as data collected with coarser temporal resolutions (e.g. from one hour to one day) are concerned, it is worth noting that – as demonstrated in the study by Cominola et al. (2018a) – a complete end-use disaggregation and classification cannot generally be performed efficiently. In fact, over the last decade, machine learning approaches (Cardell-Oliver 2013a, 2013b) and rule-based methods (Cole and Stewart 2013) were developed to explore the characteristics of water consumption at these resolutions, but a detailed identification of water end uses has not been performed. In greater detail, the approach proposed by Cardell-Oliver (2013a, 2013b) – and tested on hourly-resolution water consumption data collected by over 11,000 smart meters in Australia – only allows to derive some useful consumption patterns (i.e. peak days, continuous-flow days, etc.) without going deeper towards individual end uses, due to the coarse resolution of data. Similarly, the study presented by Cole and Stewart (2013) includes only a raw disaggregation between indoor and the outdoor component of water consumption in relation to nearly 3,000 users located in the Queensland region (Australia) based on hourly-resolution data.

End-use disaggregation and classification can also be performed by pairing water consumption data with data obtained from other sensors. Indeed, a number of techniques were developed, based on a variety of sensors, such as: vibration sensors applied externally to pipes (Kim et al. 2008), motion sensors installed in every room including fixtures (Srinivasan et al. 2011), or electricity meters (Ellert et al. 2015, Vitter and Webber 2018). Although in some cases an accurate performance is achieved, the need of several sensors to install in proximity to the domestic plumbing or electricity systems can lead to high costs. For example, the approach proposed by Vitter & Webber (2018) combines the data collected at some specific points of the plumbing system (i.e. irrigation, hot water) with water and electricity data observed at the household level, but few dwellings can actually include such dedicated metering systems. Moreover, some of these methods (e.g. Ellert et al. (2015)) are only able to disaggregate and classify specific end uses of water related to energy consumption as well (e.g. dishwasher and washing machine). Also, some of the above-mentioned methods (e.g. Kim et al. (2008)) can only evaluate the amount of water flowing in single pipes without performing an effective end-use classification.

Lastly, approaches for end-use analysis not exploiting water consumption data have been recently developed as well. For example, Fogarty et al. (2006) aimed to identify water end uses in a two-person household by analysing acoustic data from multiple microphones placed in strategic points of the domestic water plumbing system. The methodology developed led to promising results in terms of detected events, but it is currently not able to quantify the consumed volumes. In addition, Froehlich et al. (2009, 2011) developed HydroSense®, an alternative software based on pressure data collected at super-fine temporal resolution (i.e. 1 KHz). Specifically, since water use events produce pressure drops in the domestic plumbing system, fixture-valve opening and closure events can be identified by the software based on time instants with abrupt pressure variations (i.e. increase or decrease). Valve opening and closure events are then labelled to individual fixtures based on transient signatures and a template-based, hierarchical classifier. Overall, HydroSense® can detect water end uses with a considerably high accuracy (i.e. 90%) even in the case of a single pressure sensor installed, but an intrusive calibration phase requiring the use of multiple sensors is still needed initially to obtain the templates (Cominola et al. 2015). Moreover, the use of a single pressure sensor would not allow to discriminate between pressure drops caused by in-house and external end-use events.

To summarize, it is worth highlighting that almost all the above-mentioned methods for water end-use disaggregation and classification can process data at high (or very high) temporal resolution only – i.e. 1–10 s – which may not be at the disposal, or feasible, to water utilities. This considerably contrasts the transferability of most of these tools on a large scale. Therefore, there are wide margins to deepen the research on the development, the refinement, and the validation of methods capable of processing data the resolution of which is close to that of the most widespread commercial smart meters, thus making those tools potentially applicable to several contexts in the field of water consumption characterization.

2.3. Non-residential water consumption

All the above-mentioned studies about water consumption were conducted with specific regard to the residential sector. This was mainly due to the fact that residential users typically account for the largest portion of water consumption users. However, residential users may consume a much smaller portion of the overall volume of water provided by water utilities in some areas, as a consequence of the presence of industries, commercial activities, and other tertiary services (Aksela and Aksela 2011). In the light of the relevance that water consumption may have in the industrial, commercial, and tertiary sector, analysis of water consumption at the non-residential level has recently gained more attention. Therefore, descriptive and predictive models of non-residential water consumption are being developed (e.g. Blokker et al. (2011), Barua et al. (2013), Pieterse-Quirijns et al. (2013)), along with the conduction of an increasing number of studies investigating the characteristics of non-residential water consumption in relation to different contexts, user samples, and temporal resolutions.

Considering, first of all, the studies focusing on a sample of different and heterogeneous non-residential users, Morales and Heaney (2014) explored the monthly profiles of water consumption of over 4,600 commercial, industrial, and institutional users in Austin, Texas (United States), highlighting the variety of water consumption profiles among different activities. Also, in a recent study by Attallah et al. (2021) aimed at a non-intrusive characterization of non-residential consumption, four highly consuming industries and two assisted-care facilities in Logan, Utah (United states) have been monitored for nearly one year at fine temporal resolution (i.e. between 5-min and 5-s). Specifically, the 5-s temporal resolution of data allowed water consumption to be automatically disaggregated and classified in macro-categories (industrial, outdoor, humidifying, indoor shower, indoor toilet) based on the characteristics of disaggregated events. However, it is worth noting that the former study explored the features of water consumption only on a large temporal scale (by exploiting billing data), whereas the authors of the latter study acknowledged the need to expand data collection for more commercial and industrial sectors and facilities to better quantify end uses and identify water conservation opportunities.

Several studies on non-residential water consumption were carried out in the case of specific users, such as schools, campuses, office buildings, and sport facilities. As far as schools and campuses are concerned, Bonnet et al. (2002) explored the diversity of activities in the University of Bordeaux (France), and their related end uses of electricity and water. The analysis was based on manual meter readings, surveys, and the assessment of floor surface rations for each activity. With specific reference to water consumption, an estimation of the yearly water use per unit area is provided for a group of facilities including libraries, student houses, lecture halls, restaurants, cafés, laboratories, and educational institutions. Still relying on coarse-resolution data, Farina et al. (2013) integrated yearly and monthly readings with and historical data about users in buildings with the aim of quantifying the average consumption per student in different types of Italian kindergartens and schools. On a finer temporal scale, the study by Horsburgh et al. (2017) focused on the characterization of water end uses (taps, toilets) in two public restrooms at Utah State University (United States) and the effects of new, water-conserving fixtures. The analysis was conducted by exploiting and processing 4-s resolution data collected by monitoring each individual end use. Similarly, a medium- to fine-resolution (i.e. up to 1 s) monitoring system was implemented by Clifford et al. (2018) in two scholastic and academic facilities in Galway (Ireland) to investigate the effects of spatial and temporal data aggregation on water consumption analysis and possibilities. In the case of office buildings, Wu et al. (2017) relied on water meter readings and the use of ultrasonic flow meters installed at various floors of a six-story building in order to compare and validate the accuracy of different methods for water load calculation. Finally, examples of research on water consumption in sport facilities are available in relation to swimming pools, where water and energy consumption typically lead to significant operational costs. For instance, Lewis et al. (2015) focused on monthly water consumption at a fully operational facility in the United Kingdom, which was equipped with a number of inline flow meters (paired with data loggers) at the facility inlet and at some specific end uses such as pool, sanitation system, and garden. A finer-resolution analysis was conducted by Maglionico and Stojkov (2015) in relation to a small swimming pool located in Bologna (Italy) and subjected to water consumption monitoring at the water inlet with 15-min readings. The analysis allowed daily profiles of hot- and cold-water consumption to be investigated, along with a survey-based estimate of end uses of water in locker rooms.

In the context of non-residential water consumption, an important role is also played by tourism. Gössling et al. (2012) reported that tourism is dependent on water resources but is also an important driver of water consumption. In fact, tourists typically consume water for several purposes and activities and can have direct and indirect impact on water consumption (Hadjikakou et al. 2013). On the one hand, direct water consumption spaces from personal hygiene and laundry to recreational activities, such as the use of spas, saunas, and pools (Gössling and Peeters 2014, Morote et al. 2016a, Hof et al. 2018). On the other hand, an additional, indirect water consumption in tourist sector is related to food production, accommodation facility cleaning, garden irrigation, catering or shopping services, snowmaking, and sport course maintenance (Gopalakrishnan and Cox 2003, Rixen et al. 2011, Gössling and Peeters 2014). Clearly, direct and indirect tourist water consumption – which is expected to grow by up to 90% by year 2050 (Gössling and Peeters 2014) – leaves behind a significant footprint on water resource (Fernandes et al. 2020). In this context, some studies (e.g. Yang et al. (2011)) demonstrated that tourists can consume even more water than residents on a per capita basis, whereas some others (e.g. Lamei et al. (2009)) reported that serious environmental problems may arise in tourist areas as a consequence of freshwater production, due to high energy consumption and uncontrolled disposal of materials in the environment. These issues are particularly evident in the case of scarcely resilient water systems, such as intermittent networks (Reyes et al. 2017).

In the literature, a number of studies focused on the nexus between tourism and water consumption, specifically in relation to locations typically affected by water scarcity and where tourism can mostly affect water resource availability. Considering, for example, Mediterranean and Atlantic coastal areas, Hof and Schmitt (2011) combined water consumption data with land-use and demographic data to compare the per capita water consumption among different types of tourism (i.e. mass tourism, quality tourism, and tourism in residential urban areas) in Mallorca (Balearic Islands, Spain). The study shows that the highest (and raising) water consumption is produced by wealthy tourism on a per capita basis (with garden irrigation accounting for more than 70%) but even in the areas subjected to mass tourism it accounts for up to 30% of total water consumption in summer. Also, a considerably high additional average water consumption exceeding 20 L/person/day is shown to be related to private swimming pools. By contrast, the survey-based study by Rico et al. (2019) shows different trends in the water consumption on over one hundred mass-tourism hotels in the Benidorm seaside resort (Spain), with three-star hotels – the most common – observing a decrease of about 20% and higher-star hotels experiencing the opposite trend. The authors also highlight a conflict between water-conservation measures and the continuous expansion of water-related activities. Again in the context of hotels, Deyà-Tortella and Tirado (2011) developed a water consumption model for hotels and tested it with data collected in Mallorca. The authors also investigated the short-term effects of water tariff reforms on hotel water consumption, proving the inefficiency of such measurements as a means to reduce water use (Deyà-Tortella et al. 2019), and explored the drivers of water-saving measures in such facilities (Tirado et al. 2019). The effects of the implementation of water-saving technologies in hotels were also investigated by Ruiz-Rosa et al. (2017) in relation to a case-study hotel in Tenerife (Canary Islands, Spain). The authors highlight that almost the total of the investment can be recovered in short periods (i.e. five years) just through savings resulting from water conservation. Other research carried out in the aforementioned areas also focuses on the impacts of private swimming pools (Morote et al. 2016a, Hof et al. 2018) or cruise activity (Garcia et al. 2020). Finally, studies focusing on the nexus between tourism and water consumption in other areas have been conducted as well. For example, Gössling (2002) investigated the groundwater consumption in Zanzibar (Tanzania), where massive tourism has been experienced since the Nineties. Lamei et al. (2009) explored the water management practices in Sharm El Sheikh (Egypt), an area of extreme aridity undergoing rapid development and attracting about one million tourists annually; Ramazanova et al. (2021) analyzed the main drivers of hotel water consumption in the Shchuchinsk-Burabay resort area (Kazakhstan) highlighting that that facility surface, pool size, accommodation type, and water-saving measures are among the most impacting. Interestingly, the general outcomes of the study by Ramazanova et al. (2021) appeared in line with those reported in a previous, similar study by Bohdanowicz and Martinac (2007), despite the considerably different context of the latter, i.e. a sample of nearly 200 multinational-brand hotels in Europe.

As far as the spatial level of detail is concerned, it is worth noting that almost all the studies on the effects of tourism on water consumption have been conducted either by investigating specific types of user – as reported in the aforementioned studies by Bohdanowicsz and Martinac (2007), Deyà-Tortella and Tirado (2011), Hof et al. (2018), Deyà-Tortella et al. (2019), Rico et al. (2019), Ruiz-Rosa et al. (2019), Tirado et al. (2019), Garcia et al. (2020), Ramazanova et al. (2021) – or at the entire-city or regional scale, as, e.g., in the study by Toth et al. (2018), in which the nexus between tourism, climate and water consumption in a set of five Italian coastal municipalities is investigated and modelled by correlating the time series of monthly water inflow with those of monthly tourists' overnight stays, temperatures, and rainfall depths. Other models for the municipality-level water consumption as a function of climatic and tourist variables have been recently developed by Bich-Ngoc and Teller (2020) and Changklom et al. 2022, with reference to the city of Liege (Belgium) and the island of Phuket (Thailand). However, as better detailed in *Chapter 5* of the current thesis, there is still a wide margin of further contributing to the analysis of non-residential water consumption in the tourist sector by investigating several user types the characteristics of which have not been studied yet.

Lastly, as far as the temporal level of detail is regarded, most of the studies proposed investigate the effects of tourism on water consumption at the annual (e.g. Morote et al. (2018), Rico et al. (2019), Ramazanova et al. (2021)), seasonal (e.g. Hof et al. (2018), Garcia et al. (2020)), or monthly scale (e.g. Hof and Schmitt (2011), Toth et al. (2018)), without moving deeper at a weekly, daily, or sub-daily level. The only exception is represented by the study by Kara et al. (2016), which included the 5-min resolution monitoring of water consumption at 13 users of interest for tourism – a restaurant, a café, two hostels, a museum, a public toilet, etc. – in the city of Antalya (Turkey). In any case, these users were monitored for a very limited period (i.e. five days), and water consumption data were exploited only for modelling purposes. It is believed that analyses at such a fine level of temporal detail would allow new features of tourist water consumption to be better explored, e.g. the daily profiles of water consumption and the distributions of daily water consumption over the week. The latter aspect would be particularly of interest in the areas strongly affected by mid- and short-term tourist fluctuations.

2.4. Water consumption under non-ordinary conditions

In the literature, the majority of studies on residential and non-residential water consumption have been conducted under ordinary conditions, i.e. in the event of standard circumstances of water demand. Specifically, it has been widely demonstrated that, even under ordinary conditions, water consumption and its profiles – reflecting users' habits and lifestyles – vary on multiple spatial and temporal scales. For example, in relation to the residential context, it was observed that water consumption generally changes over the day, assuming the lowest values at night (Gargano et al.

2012). By contrast, on weekdays, water consumption is typically characterized by higher values in daylight hours, with a first peak in the morning and a second (lower) peak in the evening, corresponding to the periods in which people prepare to go to work and come back home, respectively (Gargano et al. 2012, Cheifetz et al. 2017). Additionally, water consumption may change over the weekend due to the presence of more people at home and more frequent use of appliances (Loureiro et al. 2015). With reference to the non-residential sector, a variability of water consumption was observed as well, based on day, time, and user characteristics (e.g. McKenna et al. 2014). Again under ordinary conditions, several authors focused on the variability of water consumption due to additional factors, demonstrating that ways and times in which water is consumed can also be influenced by multiple drivers, from economic to climatic, sociodemographic, and geographic (Jorgensen et al. 2009, Hester and Larson 2016, Steffelbauer et al. 2021). Considering economic drivers, the correlation between water consumption, water cost, and income was widely investigated. On the one hand, low-income people or people using taps as the primary source of drinking water are generally more responsive to price changes as they will likely decrease their consumption if the cost of water increases (Grafton et al. 2011, Zamenian et al. 2020). On the other hand, high-income users tend to be rather inelastic in respect to price, as bills are a small proportion of their income (Arbués et al. 2003). Additionally, a positive correlation between water consumption and income was demonstrated. In fact, a high income typically implies higher living standards and thus a higher water consumption (Corbella and Pujol 2009). Concerning climatic drivers, it has been demonstrated that variables such as temperature and rainfall can significantly impact water consumption. Water consumption is, in general, positively correlated with temperature and inversely correlated with rainfall, although with rather different behaviours based on location. Indeed, high temperatures generally imply high water consumption, whereas rainfall may reduce the amount of water consumed in external uses (Hoffmann et al. 2006, Chang et al. 2014, Xenochristou et al. 2020, Fiorillo et al. 2021). Water consumption can also be affected by sociodemographic factors. For instance, awareness-rising campaigns may have a positive effect on water consumption because users are encouraged to revise their attitude towards water consumption (Howarth and Butler 2004). The adoption of water conservation policies and measures may be useful especially in those areas where water resources are scarce (March and Saurì 2010, Maggioni 2015, Salvaggio et al. 2014).

However, it is worth noting that water consumption may not adhere to the preceding results in the case of non-ordinary situations, e.g. emergencies or disasters because of which, in worst cases, water distribution systems can even stop functioning. In this regard, Miyajima (2013) explored the damage to water supply pipelines during the earthquake of magnitude 9.0 – and the related tsunami – occurring in Japan on March 2011. Based on Geographical Information System (GIS) analysis, the author highlights severe damages to water supply and distribution systems due to strong ground motion and soil liquefaction (in some cases reaching a network failure rate of nearly two cases/km) and highlights that damages to pipelines can start occurring even at lower Mercalli seismic intensity, e.g. 6.0. Similarly, Capponi et al. (2019) point out that fractures and bursts on pipes (along with alterations in the water quality and in the flow regimes of some rivers and uptakes) were observed in Central Italy due to the 2016-2017 earthquakes of magnitude larger than 5.0, whereas the study by Hidayat et al. (2020) on the effects of the Indonesian 6.4-6.9 magnitude earthquake of August 2018 reveals a 19% decrease in the water demand in the case-study area of Lombok Island after the earthquake, along with variations in the amounts of drinking water extracted from different sources. However, apart the aforementioned case studies, it is worth noting that the literature is poor in other research focused on the effect of such extreme phenomena on water consumption and water distribution systems. Also, none of the above-mentioned studies deeply investigates the variations in water consumption at the level of individual users, i.e. due to changes in people's habits under those exceptional circumstances. Similar considerations also apply to the case of other non-ordinary conditions (e.g. droughts) and their effects on water consumption, the literature of which appears rather poor as well. By way of example, in the review by Manouseli et al. (2018) on the current empirical literature on the drivers of residential water consumption under both ordinary and drought conditions, the authors observe that little is known about users' response to drought, and there are only few studies which incorporate the available information into demand forecasting models of demand forecasting to support operational decisions and identify the most effective drought-management measures. Some of these few instances are the studies of Frick et al. (1990) and Tsiourtis and Kindler (1995) in which water supply is simulated under drought condition scenarios to determine the yield in the locations analyzed as case study (i.e. Fort Collins, Colorado, United States, and the island of Cyprus, respectively) as a function of different allocation layouts of water supply sources (Frick et al.

1990) or consumption points (Tsiourtis and Kindler 1995). Lastly, even less is known about non-residential water consumption under non-ordinary conditions. The only example is the recent study by Spearing et al. (2022) focusing on hourly water consumption changes during Winter Storm Uri, on February 2021 – the occurrence of which also coincided with COVID-19 pandemic – in four buildings at the University of Texas, Austin (United States). The authors observe completely different daily profiles compared to the ordinary conditions, as a consequence of people sheltering in some of those buildings while abandoning some others.

The recent SARS-CoV-2 disease (COVID-19) has represented an exceptional and emergency situation for many countries worldwide. After breaking out in the region of Hubei, China, between December 2019 and January 2020 (World Health Organization 2020), the epidemic spread rapidly around the globe, so that it was declared a pandemic by the World Health Organization on 11 March 2020 (McNeil 2020). To limit the spread of the virus, several national governments implemented a series of restrictions, including home isolation, the suspension of educational and non-essential work activities, as well as the closure of all commercial establishments (except for those selling essential goods) and the ban on travel outside the municipality of residence, except for documented work-related needs, situations of absolute urgency or health reasons. These measures occurred in many European and non-European countries, such as Italy, Spain, France, Great Britain, and China (British Broadcasting Corporation 2020a, 2020b), albeit with timing and modalities varying from case to case. As far as Italy is regarded, restrictive measures were implemented by the national government between 23 February and 11 March, 2020. These remained in force until 4 May 2020, when the restrictions started to be gradually lifted, and various businesses and facilities were reopened. Therefore, from 11 March to 3 May 2020, Italy underwent a period of lockdown with a halt to activities and movements (Governo Italiano 2020). Clearly, such restrictions affected habits and lifestyles of most of the population. This, in turn, was also reflected in water consumption.

In general, changes in water consumption can generally be an issue for water utilities, revealing vulnerabilities of water distribution networks. In greater detail, in the event of restrictions and/or activity stops (as in the case of the COVID-19 pandemic), water consumption drops for industrial and commercial activities can result in zones of water stagnation, with a consequent possible increase in water age, disinfectant decay, and microbial growth (Faust et al. 2021). Moreover, changes in water consumption may alter water flows to the point that new operational criteria are required for adequate management of the network, whereas social distancing policies and the obligation to work from home can limit water utility employees' inspections, thus decreasing maintenance actions and meter readings (Berglund et al. 2021).

Due to the novelty of the circumstance, no data-based studies evaluating the effects of pandemics on water consumption were available in the literature before the outbreak of the disease. The first, pioneer studies investigating the effects of COVID-19 on water consumption appeared in the second half of 2020. The study conducted by Cooley et al. (2020) by exploiting water data of nearly 40 American water utilities highlights different and heterogeneous trends, with increases or decreases in the water consumption based on the municipality concerned. Moreover, Balacco et al. (2020) showed the changes in the hourly water inflow before and after the lockdown restrictions with reference to five areas in Southern Italy, whereas Kalbusch et al. (2020) studied the evolution of daily water consumption for a set of around one thousand users in Joinville (southern Brazil). Both studies highlight a heavy drop in the water consumption for industrial and commercial activities along with increases in residential water consumption and changes in water use profiles due to confinement and teleworking.

It is worth noting that, until late 2020 – when most of the analyses described in *Chapter 6* of this thesis were carried out – no works in the scientific literature evaluating the effects of the COVID-19 pandemic on water consumption with high level of both spatial and temporal detail (i.e. based on hourly water consumption data collected at the user scale) were available. Since early 2021, many other studies about the relationship between COVID-19 and water consumption have been published, exploiting data collected at different spatial and temporal scales. Kazac et al. (2021) analyzed the monthly water inflow in over 20 District Metered Areas (DMA) in Wroclav (Poland) before and during lockdown, pointing out a 13% increase in residential consumption and a considerable decrease in the consumption of commercial and educational activities (–17% and –38%, respectively). A 4% increase in the water consumption was also observed by Cvetković et al. (2021) with reference to the city of Kraguievac (Serbia) when comparing the data with those of the previous year. Moreover, Lüdtke et al. (2021) focused on hourly data from the city of Hamburg (Germany), the analysis of which allowed to investigate the variations in the daily profiles of weekday and holiday water consumption with the advent of lockdown. Water consumption data at hourly resolution were mostly exploited in studies evaluating the effects of COVID-19 at the user (i.e. household or, more in general, property) level. For example, Dzimińska et al. (2021) analyzed the hourly water consumption in three multi-apartment buildings in Bydgoszcz (Poland); Kim et al. (2021) focused on nearly one thousand dwellings in Seongnam (Korea); Rizvi et al. (2021) considered about 7,000 residential smart meters in Dubai (Arab Emirates); and Menneer et al. (2021) monitored the water consumption in 22 households in Camborne and Redruth, Cornwall (United Kingdom) increasing the sampling frequency up to eight readings per hour. In addition, Cominato et al. (2022) evaluated the variations in the hourly water consumption due to COVID-19 in 14 households in Joinville (Brazil), whereas Evangelista et al. (2022) carried out hourly analyses on over 200 households in Naples (Italy). It is worth noting that studies focusing on hourly data with specific regard to hot water consumption were also conducted (e.g. Irwin et al. (2021)). Overall, most of the studies carried out on a sub-daily basis highlight an attenuation of the peak morning consumption, along with a delay of at least one hour, as a consequence of the changes in people's habits due to home isolation and, more in general, the restrictions imposed during lockdown. Finally, examples of survey-based studies aimed at assessing the changes in people's attitude towards water consumption induced by the pandemic are available as well. Campos et al. (2021) observed an increase in the daily frequency of some end uses (such as taps and showers) for nearly 150 respondents, along with an increase in their duration of use. An increase in the per capita water consumption is pointed out also in the study by Almulhim and Aina (2022), in which a questionnaire about residential water use was submitted to about 800 people. Online surveys about residential water consumption during lockdown were also developed by Díaz et al. (2021), the analysis of which enabled the assessment of the variations in end-use duration and frequency of use in the light of the restrictions imposed.

It is worth noting that detailed reviews of the state-of-the-art literature on the nexus between COVID-19 and water consumption is available in Cahill et al. (2021) and Jia et al. (2021).

2.5. Summary of the most relevant gaps in the scientific literature

In conclusion to this chapter, a summary of the most relevant key knowledge gaps affecting the scientific literature on residential and non-residential water consumption is provided (Table 2.1).

These gaps motivated the four research objectives defined in *Chapter 1*, and therefore laid the basis to the development of the current thesis. The reference to the chapter of the thesis in which each research objective is addressed is also reported.

Table 2.1. Summary of the most relevant gaps in the scientific literature on water consumption.

Scientific literature field	**Most relevant research gap(s)**	**Thesis objective(s) and chapter**
Residential water consumption at the end-use level of detail	● There is a large amount of information, yet fragmented, included in the numerous peer-reviewed journal publications on the topic or water utility reports. ● The available studies consider different contexts and a variety of methodological approaches to gather information on water end uses. The numerical end-use results are also reported in a variety of ways. ● An extensive review on the residential end uses of water is missing. Some previous review studies have focused only on the major characteristics of the studies available in the literature, without quantitatively comparing all the most common metrics about residential end-use water consumption and qualitatively discussing about additional aspects of interest in the field of end-use water consumption	Providing a comprehensive analysis of the existing end-use studies conducted globally in the field of residential water consumption to fully explore and quantify end-use characteristics in different contexts worldwide (*Chapter 3*).
Disaggregation and classification of the residential end uses of water	● The majority of methods for water end-use disaggregation and classification can process data at high temporal resolution only (e.g. 1–10 s), which may not be at the disposal to water utilities or feasibly collectable. This contrasts the transferability of these tools on a large scale. ● Only a small group of disaggregation and classification methods exploiting data collected with a coarser resolution (e.g. 1 min) exist, the validation of which has been performed only with synthetically generated water consumption data.	Developing and testing a methodology enabling end-use disaggregation and classification of residential water consumption to be performed on coarse-resolution data and validating the method with actual data collected in different geographical areas (*Chapter 4*).
Non-residential water consumption	● The majority of studies have been conducted either by investigating specific types of users, or at the entire-city or regional scale. There are numerous non-residential user types the water consumption of which has not been deeply investigated yet. ● Most of the studies consider coarse temporal scales, i.e. annual, seasonal, or monthly. Analyses at a finer scale (e.g. daily or hourly) allowing daily profiles of water consumption and the distributions of daily water consumption over the week to be investigated, are currently missing.	Investigating the characteristics of water consumption at some non-residential users of interest for the tourist sector (bathing facilities, holiday homes) with high level of spatial and temporal detail, thus providing insight into the effects of seaside tourism on water consumption (*Chapter 5*).
Water consumption under non-ordinary demand conditions	● The literature is generally poor in research on the effects of extreme conditions on water consumption, especially with reference to the level of individual users. ● Until late 2020 (when most of the analyses described in this thesis were carried out) no works evaluating the effects of the COVID-19 pandemic on water consumption with high level of both spatial and temporal detail were available.	Exploring the effects of the restrictions adopted to limit the spread of COVID-19 pandemic on residential and non-residential water consumption at the user level with high level of spatial and temporal detail (*Chapter 6*).

Part I
Residential water consumption under ordinary demand conditions

"Moving deeper: from the user level to the end uses of water"

Chapter 3

A comprehensive analysis of studies on the residential end uses of water

An extensive analysis of residential end uses of water – not only highlighting similarities and differences among the studies available in the literature but also systematically comparing all the numerical results about end-use water consumption globally – is currently missing. This chapter aims to fill the above-mentioned 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). The findings highlighted in the current chapter 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 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.

3.1. Literature review methods and search outcome

A systematic search of peer-reviewed journal papers, water utility reports, and other grey literature material (i.e. theses, research projects, presentations, etc.) was carried out to deeply explore the current state of research on residential water consumption at the end-use level. Specifically, publications related to residential water consumption at the end-use level were searched 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. The initial search was done in relation to the combination of three keywords, i.e. "residential," "water," and "end uses", and the subject area was limited to "engineering". This led to an initial paper set of 271 publications, mostly (but not only) in English. A manual check of the title and abstract of each publication was then conducted, and only those fitting the scope of the study were retained. In greater detail, 40 publications were retained at this stage. Finally, the resulting set of papers was expanded by including other studies cited in the bibliography of the retained publications. The final paper set considered for following analysis included a total of 104 studies presenting – or making use of – residential water consumption data at the end-use level. The above-mentioned 104 studies, reported in Table 3.1 and hereinafter called residential end-use studies (REUS), were extensively reviewed to explore their contribution and implications to residential water consumption at the end-use level.

Table 3.1. Overview of the 104 reviewed Residential End-use Studies (REUS) and their related 62 End-use Databases (EUD).

EUD	Location	REUS	Objective(s)	Study period	Household sample size	Household monitoring period (average)	Temporal data sampling resolution	End-use data gathering approach
1	Boulder, Colorado (United States)	Bennett and Linstedt 1975	WWSS	Unreported	5	40 days	Unreported	DM, IU
2	Unknown, Wisconsin (United States)	Siegrist et al. 1976	WWSS	Unreported	11	40 days	Unreported	DM, IU
3	Various (United States)	Brown and Caldwell 1984	WCR	Unreported	210	2 weeks	Unreported	DM, IU
4	Unknown (United Kingdom)	Butler 1991	WWSS	1987	28	1 week	-	IU
		Butler 1993	WWSS	1987	28	1 week	-	IU
5	Tampa, Florida (United States)	Anderson et al. 1993	EUWC, WCR	1992	25	2 months	Unreported	DM
6	Unknown (United Kingdom)	Edwards and Martin 1995	EUWC, DD	1992-1993	100	1 year (pilot)	15 min	DM
7	Boulder, Colorado (United States)	DeOreo et al. 1996	EUWC	1994	16	3 weeks	10 s	M
8	Various (United States, Canada)	Mayer et al. 1999	EUWC	1996-1998	1188	4 weeks	10 s	A (T)
		Suero et al. 2012	WCR	1996-1998	Unreported	4 weeks	10 s	A (T)
9	Bangkok (Thailand)	Darmody et al. 1999	EUWC, WCR	Unreported	814	-	-	DM, IU
10	East Bay, California (United States)	Darmody et al. 1999	EUWC, WCR	1994	657	-	-	DM, IU
11	Seattle, Washington (United States)	Mayer et al. 2000	WCR	Unreported	37	8 weeks	10 s	A (T)
		Suero et al. 2012	WCR	Unreported	Unreported	8 weeks	10 s	A (T)
12	Various (Netherlands)	Foekema and Engelsma 2001	EUWC, DD	2001	3200	1 week	-	IU
		Blokker 2006	DMF	2001	3200	1 week	-	IU
		Blokker 2010	DMF	2001	3200	1 week	-	IU
		Blokker et al. 2010	DMF	Unreported	3200	1 week	-	IU
		Agudelo-Vera et al. 2014	EUWC	1992-2010	Unreported	1 week	-	IU
13	East Bay, California (United States)	Mayer et al. 2003	WCR	2001-2002	33	6 weeks	10 s	A (T)
		Suero et al. 2012	WCR	2001-2002	Unreported	6 weeks	10 s	A (T)

Table 3.1 (Continued). Overview of the 104 reviewed Residential End-use Studies (REUS) and their related 62 End-use Databases (EUD).

EUD	Location	REUS	Objective(s)	Study period	Household sample size	Household monitoring period (average)	Temporal data sampling resolution	End-use data gathering approach
15	Unknown (United Kingdom)	Kowalski and Marshallsay 2003	EUDM	2001	250	Unreported	Unreported	A (I)
		Kowalski and Marshallsay 2005	EUWC, WCR	2001	500	Unreported	Unreported	A (I)
16	Unknown (United Kingdom)	Lauchlan and Dixon 2003	WWSS	Unreported	Unreported	Unreported	Unreported	Unreported
17[a]	Tampa, Florida (United States)	Mayer et al. 2004	WCR	2002-2003	26	6 weeks	10 s	A (T)
18	Sydney (Australia)	White et al. 2004	EUWC, DMF	1999	Unreported	-	-	IU
19	Yarra Valley (Australia)	Roberts 2005	EUWC, DMF	2004	100	4 weeks	5 s	A (T)
		Gato-Trinidad et al. 2011	EUWC	2004	80÷93	6 weeks	5 s	A (T)
20	Various (Netherlands)	Kanne 2005	EUWC, DD	2004	1684	1 week	-	IU
		Agudelo-Vera et al. 2014	EUWC	1992-2010	Unreported	Unreported	-	IU
21	Palhoca (Brazil)	Ghisi and Oliveira 2007	WCR	2004	2	4 weeks	-	IU
22	Various (South Africa)	Jacobs 2007	DMF	Unreported	123	2 years	1 month	IU
23	Kapiti Coast (New Zealand)	Heinrich 2007	EUWC, DGE	2006-2007	12	8 months	10 s	A (T)
24	Various (Korea)	Kim et al. 2007	EUWC, DD	2002-2006	145	3 years	1 h ÷ 1 day	DM
25	Chiang Mai (Thailand)	Otaki et al. 2008	EUWC	Unreported	55÷63	2 months	Unreported	DM
26	Toowoomba, (Australia)	Mead 2008	EUWC	2008	10	138 days	10 s	A (T)
		Mead and Aravinthan 2009	EUWC	2008	10	138 days	10 s	A (T)
27	Various (Netherlands)	Foekema et al. 2008	EUWC, DD	2007	2454	1 week	-	IU
		Agudelo-Vera et al. 2014	EUWC	1992-2010	Unreported	Unreported	-	IU
28	Madrid (Spain)	Cubillo-González et al. 2008	EUWC	2002-2003	292	299 days	1 s	M
		Ibáñez-Carranza et al. 2017	EUDM	2008-Uknown	300	2÷3 months	Unreported	Unreported

Table 3.1 (Continued). Overview of the 104 reviewed Residential End-use Studies (REUS) and their related 62 End-use Databases (EUD).

EUD	Location	REUS	Objective(s)	Study period	Household sample size	Household monitoring period (average)	Temporal data sampling resolution	End-use data gathering approach
29	Various, Gold Coast (Australia)	Willis et al. 2009a	DGE	2008	50	2 weeks	10 s	Unreported
		Willis et al. 2009b	EUWC	2008	151	2 weeks	10 s	A (T)
		Willis et al. 2009c	EUWC, DD	2008	50	2 weeks	10 s	Unreported
		Willis et al. 2010a	WCR	2208	151	Unreported	10 s	A (T)
		Willis et al. 2010b	WCR	2008-2009	44÷151	4 weeks	10 s	A (T)
		Willis et al. 2011a	WCR	2008	132	2 weeks	10 s	A (T)
		Willis et al. 2011b	WCR	2008-2010	127÷134	Unreported	10 s	A (T)
		Willis et al. 2013	EUWC, DD	2008	151	Unreported	10 s	A (T)
30	Auckland (New Zealand)	Heinrich et al. 2010	EUWC	2008	51	9 weeks	10 s	A (T)
31	Trincomalee (Sri Lanka)	Sivakumaran and Aramaki 2010	EUWC	Unreported	106	-	-	IU
32	Perth (Australia)	Water Corporation 2010	EUWC	Unreported	Unreported	2 weeks	Unreported	Unreported
33	Khon Kaen (Thailand)	Otaki et al. 2011	EUWC	Unreported	59	1 month	Unreported	DM
34	Various (United States)	DeOreo et al. 2011	EUWC, WCR	2006-2009	734	2 weeks	10 s	A (T)
35	Various (United States)	Aquacraft 2011	EUWC, WCR	2006-2009	327	2 weeks	10 s	A (T)
		Cominola et al. 2018a	DMF	2007-2009	313	2 weeks	10 s	A (T)
36	Various, South-East Queensland (Australia)	Beal et al. 2011a	EUWC	2010	252	2 weeks	5 s	A (T)
		Beal et al. 2011b	UPA	2010	222	2 weeks	5 s	A (T)
		Beal and Stewart 2011	EUWC	2010-2012	83÷252	14 weeks	5 s	A (T)
		Beal et al. 2012	DD	2010-2011	252-110	6 weeks	5 s	A (T)
		Beal et al. 2013	UPA	2010	222	2 weeks	5 s	A (T)
		Makki et al. 2013	EUWC	2010	200	2 weeks	5 s	A (T)
		Nguyen et al. 2013a	EUDM	2010-2011	110÷252	10 weeks	5 s	A (T)
		Nguyen et al. 2013b	EUDM	2010-2011	110÷252	10 weeks	5 s	A (T)
		Beal and Stewart 2014a	PD	2010-2011	110÷252	10 weeks	5 s	A (T)

Table 3.1 (Continued). Overview of the 104 reviewed Residential End-use Studies (REUS) and their related 62 End-use Databases (EUD).

EUD	Location	REUS	Objective(s)	Study period	Household sample size	Household monitoring period (average)	Temporal data sampling resolution	End-use data gathering approach
36	(Continued)	Beal and Stewart 2014b	EUWC	2010-2012	53÷252	24 weeks	5 s	A (T)(A)
		Beal et al. 2014	UPA	2010-2013	69÷252	20 weeks	5 s	A (T)
		Gurung et al. 2014	PD	2010-2012	44÷134	14 weeks	5 s	A (T)
		Gurung et al. 2015	PD	2010-2012	44÷134	14 weeks	5 s	A (T)
		Nguyen et al. 2015	EUDM	Unreported	Unreported	Unreported	5 s	A (T)
		Yang et al. 2018	EUDM	Unreported	252	Unreported	5 s	Unreported
		Nguyen et al. 2018	EUDM	2010-2012	Unreported	16 weeks	5 s	A (T)
37	Various (Netherlands)	Foekema and Van Thiel 2011	EUWC, DD	2010	1237	1 week	-	IU
		Agudelo-Vera et al. 2014	EUWC	1992-2010	Unreported	Unreported	-	IU
38	Various (Korea)	Lee et al. 2012	EUWC	2002-2006	146	4 years	10 min	DM
39	Hervey Bay (Australia)	Cole and Stewart 2013	PD	2008-2009	2884	1 year	1 h	IO
		Gurung et al. 2014	PD	2008-2009	2494	1 year	1 h	IO
		Gurung et al. 2015	PD	2008-2009	2494	1 year	1h	IO
40	Melbourne and Yarra Valley (Australia)	Redhead et al. 2013	EUWC	2010-2012	300	4 weeks	5÷10 s	M, A (T)
		Gan and Redhead 2013	EUWC	2010-2012	300	4 weeks	Unreported	M, A (T)
		Rathnayaka et al. 2015	EUWC	Unreported	117	Unreported	5 s	A (T)
		Nguyen et al. 2015	EUDM	Unreported	Unreported	Unreported	5 s	A (T)
		Siriwardene 2018	EUWC	2011-2012	100*	1 year	Unreported	Unreported
41	Hanoi (Vietnam)	Otaki et al. 2013	EUWC	2011	56	2 months	Unreported	DM
		Otaki et al. 2017	EUWC	2011	56	5 months	Unreported	DM, IU
42	Various (United States, Canada)	DeOreo and Mayer 2013	EUWC	2012-2013	762	2 weeks	10 s	A (T)
		DeOreo et al. 2016	EUWC	2012-2013	737	2 weeks	10 s	A (T)
		Buchberger et al. 2017	EUP, PD	1996-2011	1038	2 weeks	10 s	A (T)
		Omaghomi et al. 2020	EUP, PD	1996-2011	1038	2 weeks	10 s	A (T)
		Vitter and Webber 2018	EUDM	Unreported	94	Unreported	Unreported	Unreported

Table 3.1 (Continued). Overview of the 104 reviewed Residential End-use Studies (REUS) and their related 62 End-use Databases (EUD).

EUD	Location	REUS	Objective(s)	Study period	Household sample size	Household monitoring period (average)	Temporal data sampling resolution	End-use data gathering approach
43	Barcelona, Murcia (Spain)	Fontdecaba et al. 2013	EUDM	2009-2010	8	3 months	1÷5 s	A (O)
44	Davis, California (United States)	Borg et al. 2013	EUWC, WCR	Unreported	3	1 week	Unreported	DM, IU
45	Various (Netherlands)	Van Thiel 2014	EUWC	2013	1349	1 week	-	IU
		Blokker and Agudelo-Vera 2015	DMF	2013	1349	1 week	-	IU
46	Various (Austria)	Neunteufel et al. 2014	EUWC	2012-2013	105	Unreported	10 s ÷ 1 day	Unreported
47	Adelaide (Australia)	Arbon et al. 2014	EUWC, DD	2013	140	2 weeks	10 s	Unreported
48	Unknown (Greece, Poland)	Shan et al. 2015	EUWC	Unreported	148	-	-	IU
49	Jaipur (India)	Sadr et al. 2015	EUWC	Unreported	90	-	-	IU
		Sadr et al. 2016	EUWC	Unreported	90	-	-	IU
50	Duhok (Iraq)	Hussien et al. 2016	EUWC	Unreported	407	-	-	IU
51	Unknown	Kozlovskiy et al. 2016	EUWC	2016	1	3 weeks	2 s	Unreported
52	Various (Netherlands)	Van Thiel 2017	EUWC, DD	2016	1617	1 week	-	IU
53	Sirte (Lybia)	Alharsha et al. 2018	EUWC	Unreported	230	-	-	IU
54	Unknown (United States)	Jordan-Cuébas et al. 2018	DD, DMF	2011-2013	2(30)	1 year	Unreported	DM
55	Melbourne (Australia)	Siriwardene 2018	EUWC	2017-2018	120	1 year	10 s	A (A)
56	Western Cape Province (South Africa)	Duplessis et al. 2018	EUWC	2013-2015	371	Unreported	1 month	WB
57	Various (Greece and Poland)	Kofinas et al. 2019	DGE	2015-2016	16	13 months	30 s	DM
58	Naples (Italy)	Di Mauro et al. 2020	DGE	2019	1	8 months	1 s	DM
59	Illinois (United States)	Bethke 2020	EUWC	2018-2019	4	1 year	1 s	A (O)
		Bethke et al. 2021	EUWC	2018-2019	4	1 year	1 s	A (O)
60	Madrid (Spain)	Diaz et al. 2021	EUWC	2021	3298	-	-	IU

Table 3.1 (Continued). Overview of the 104 reviewed Residential End-use Studies (REUS) and their related 62 End-use Databases (EUD).

EUD	Location	REUS	Objective(s)	Study period	Household sample size	Household monitoring period (average)	Temporal data sampling resolution	End-use data gathering approach
61	Galle and Colombo (Sri Lanka)	Otaki et al. 2022	EUWC, WCR	2017	127	3 weeks	1 week	DM
62	Various (Netherlands)	Mazzoni et al. 2023b	EUWC	2019	9	7 weeks	1 s	M, A, IU

Note. Legend for REUS objectives: DD = study of demand determinants; DGE = data gathering and elaboration study; DMF = demand modelling and forecasting; EUDM = end-use disaggregation method; EUP = end-use probability study; EUWC = end-use water consumption study; PD = peak end-use demand study; UPA = study on users' perception and awareness; WCS = study on water conservation and recycling; WWSS = wastewater or sewer system design study. Legend for end-use data gathering approaches: A(A) = automated disaggregation (Autoflow); A(I) = automated disaggregation (Identiflow); A(O) = automated disaggregation (ad hoc method); A(T) = automated disaggregation (Trace Wizard); DM = direct monitoring; IO = rough indoor-outdoor disaggregation; IU = interaction with users; M = Manual disaggregation; WB = water balance. [a] Study not available. Results were derived from Jordan-Cuébas et al. (2018).

A first analysis evaluated the objectives of each study, the primary of which was considered for classification (Figure 3.1). The figure reveals that, in most cases (39 studies, i.e. 38%), 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. 16%), explore the determinants of water consumption (12 studies, i.e. 12%), develop or validate algorithms for water end-use disaggregation and classification (9 studies, i.e. 9%), and for water demand modelling (9 studies, i.e. 9%). Other applications, albeit less common, include: investigation of strategies for wastewater management and/or the design of sewer systems; retrieval of end-use information and evaluations about end-use data gathering and processing; data exploitation to assess end-use peak demand, evaluate end-use probability of use, or develop demand models; or end-use data analysis to quantify variations in users' perception and awareness. In addition, the following characteristics were investigated: i) location; ii) period; iii) household sample size; iv) average duration of the monitoring period per household (if reported); v) temporal resolution of monitoring (if reported); and vi) approach adopted for end-use data gathering (i.e. end-use monitoring, interaction with householders, or end-use disaggregation method). All the above-mentioned REUS characteristics are summarized in Table 3.1.

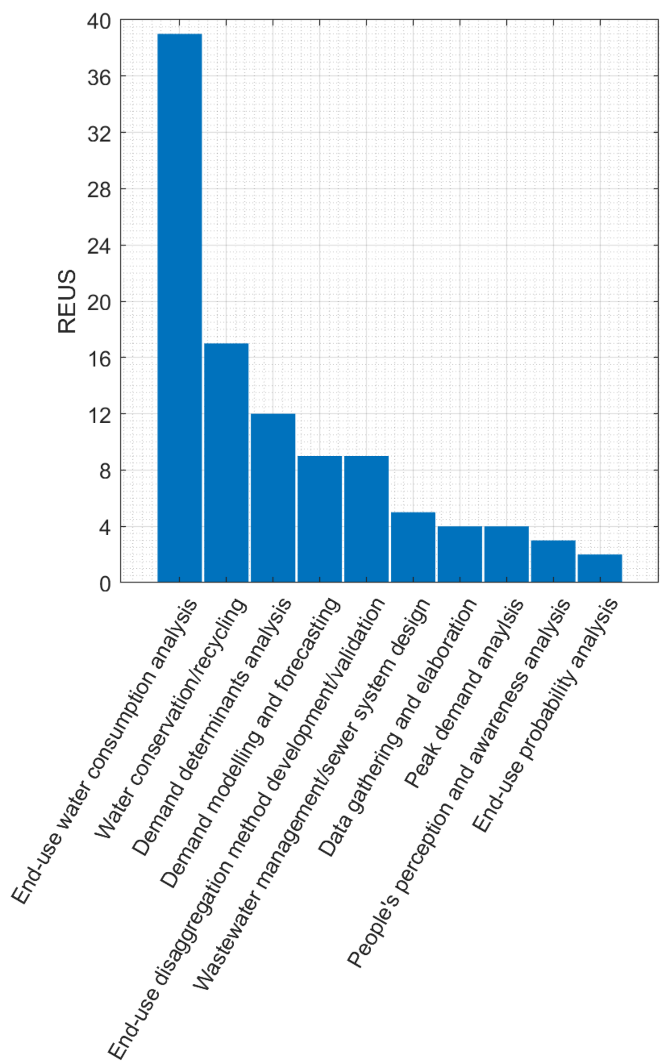

Figure 3.1. Primary objective of the 104 REUS reviewed.

The review revealed that the 104 REUS refer to 62 different databases, hereinafter called end-use databases (EUD). Specifically, some EUD have been 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 have been used in only one REUS. It is also worth noting that some REUS have been conducted by exploiting only part of their related EUD (e.g. Willis et al. 2009c, Gato-Trinidad et al. 2011, Rathnayaka et al. 2015), whereas some other have exploited it entirely (e.g. Bennett and Linstedt 1975, Mayer et al. 2000).

3.2. EUD clustering

The 62 EUD were clustered in reference to the fields of investigation mentioned above (see Table 3.1). Specifically, EUD clustering was conducted manually and exclusively based on the information available in the literature (i.e. provided by their related REUS) because the majority of EUD has restricted access, as reported in Di Mauro et al. (2021). From an operational standpoint, the following criteria were adopted for clustering: 1) concerning the study period, EUD were clustered 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), EUD were clustered 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 extended to a larger sample, the number of households making up the latter sample was considered for clustering. Similarly, when a measurement campaign was conducted in two (or more) stages, the first with a coarser and the second with a finer data sampling temporal resolution, the finest resolution was considered as a reference value for clustering.

The results of the EUD clustering are shown in Figure 3.2. The following findings emerge for each considered criterion:

- **Geographical area** (Figure 3.2 a). EUD include data collected across all the continents, but mainly in Europe (18 databases), North America (16 databases), and Oceania (13). A lower number of EUD include data collected in Asia (10), Africa (3), 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 et al. 1999, Mayer et al. 2003, Beal and Stewart 2011, and Beal et al. 2014).

- **Study period** (Figure 3.2 b). Although REUS have been conducted since the 1970s (e.g. Bennett and Linstedt 1975, Siegrist et al. 1976), most EUD have been developed 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 underwent REUS only in the last decade (Sivakumaran and Aramaki 2010, Otaki et al. 2011, Otaki et al. 2013). However, information on the first year of data collection was not available for a non-negligible group of 16 EUD (i.e., 26% of the total).
- **Household sample size** (Figure 3.2 c). The majority of the EUD include data collected for samples of households in a range between ten and a hundred (15 EUD, i.e. 24% of the total) or between hundred and a thousand (24 EUD, i.e. 39%). Only a limited number of EUD include data observed for samples smaller than ten households (10, i.e. 16%), or larger than a thousand (9, i.e. 15%). In general, household sample size (typically dependent on the scope of the research) is rather limited in the earliest studies, for which manual or laborious processes were 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 physical features 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).

- **Household monitoring period (average)** (Figure 3.2 d). Regarding the EUD for which water consumption data were 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 analyses exploited hourly-resolution data from approximately 3000 households. Lastly, for about 10% of the EUD, data were not obtained by the monitoring but with different methods (e.g. interaction with users).
- **Temporal data sampling resolution** (Figure 3.2 e). Several authors highlight that the introduction of smart metering technologies allowed 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 the traditional resolution of water meter 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). 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, Duplessis et al. (2018) revealed 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. 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. 24 of the 48 EUD for which this information is available).

- **End-use data gathering approach** (Figure 3.2 f). Although some EUD were obtained by directly monitoring each domestic end use (e.g. 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 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 meter), to obtain end-use information (i.e. at the level of individual appliance/fixture). From an operational standpoint, this end-use level determination was either achieved utilizing audits, reports, or questionnaires submitted to users (e.g. Butler 1991, Ghisi and Oliveira 2007, Shan et al. 2015, Alharsha et al. 2018, Diaz 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) and Nguyen et al. (2013a). Some studies adopted hybrid approaches coupling different techniques, such as direct monitoring of only a limited subset of end uses coupled with interaction with users to infer information on other water end uses (e.g. Bennett and Linstedt 1975, Siegrist et al. 1976, Brown and Caldwell 1984, Otaki et al. 2017). In general, the earliest studies were typically carried out by exploiting analog tools to record water consumption data (i.e. chart recorders driven by the water meter) and by manually processing the data collected. By contrast, in the case of larger or more recent EUD, end-use information was mainly achieved by automatically processing aggregate water consumption data collected at a very fine temporal resolution (e.g. 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 21 of the EUD discovered, or 34%).

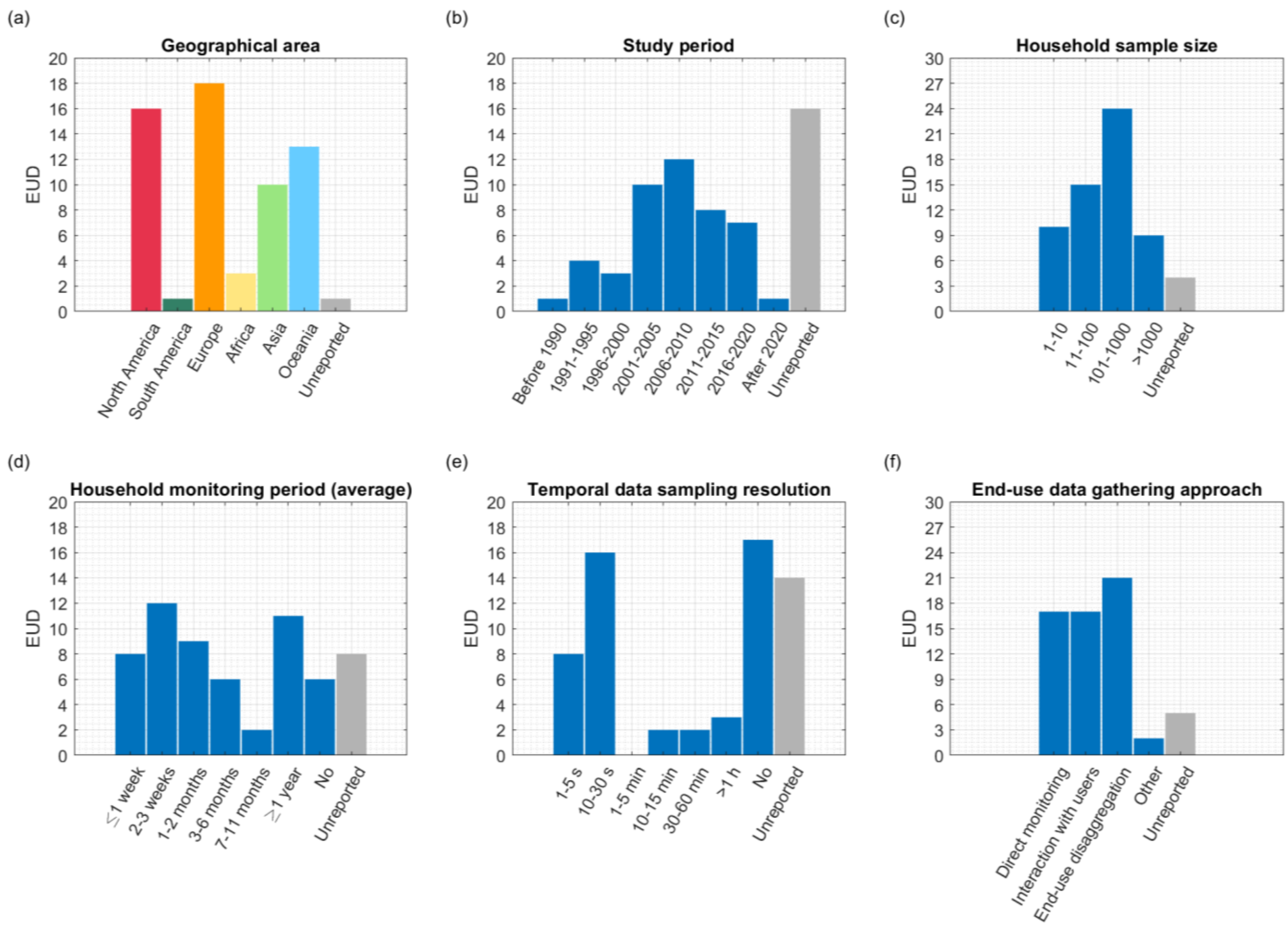

Figure 3.2. EUD clustering results.

3.3. EUD processing

The 62 EUD were systematically compared by applying a six-level analysis (Figure 3.3). This multi-level analysis aims to explore the characteristics of end-use water consumption from several points of view, revealing similarities and differences among the EUD concerning: (1) daily per capita end-use water consumption (*Level 1*); (2) end-use parameter average values (*Level 2*); (3) end-use statistical parameter distributions (*Level 3*); (4) end-use daily profiles (*Level 4*); (5) end-use water consumption determinants (*Level 5*); and (6) efficiency and diffusion of water-saving end uses (*Level 6*).

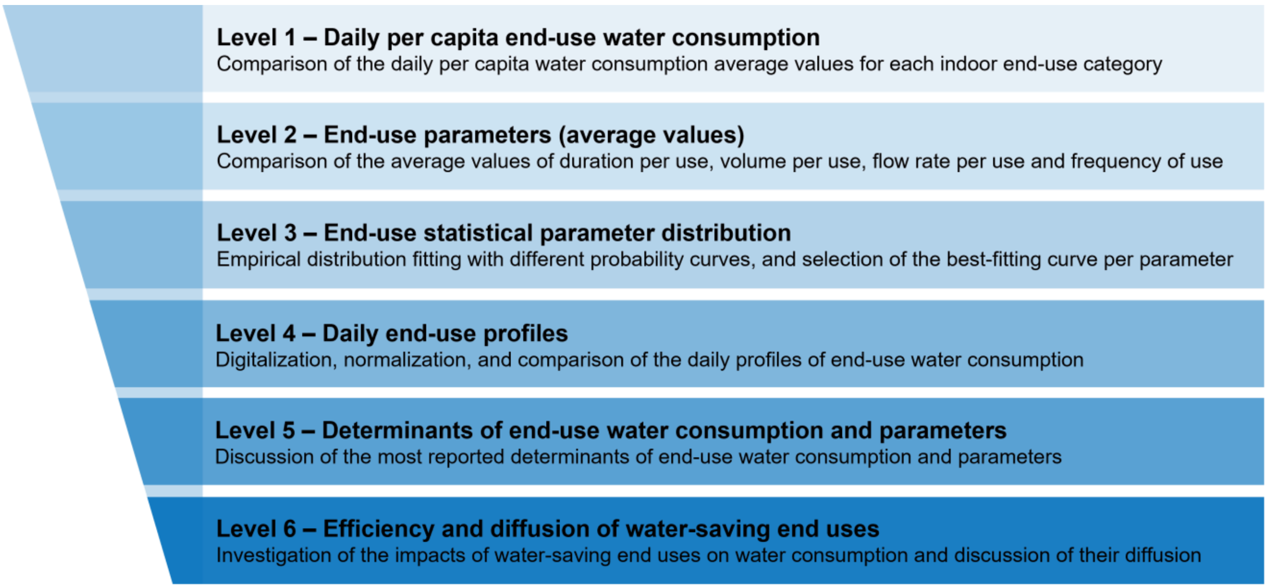

Figure 3.3. Multi-level analysis layout.

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

- For REUS presenting daily per capita average values, the reported values were directly considered (once converted to L/person/day).
- For REUS presenting the end-use percent values of the daily per capita indoor water consumption, these were turned into daily per 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, these were turned 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 multiple seasons (e.g. summer and winter), these were averaged to obtain values not affected by seasonal patterns.
- For REUS presenting multiple end-use water consumption values related to different subsets (e.g. regions, household types, etc.), a weighted average was calculated based on the size of each subset (i.e. the number of households monitored in each subset).
- For REUS comparing baseline values against those observed after device retrofitting campaigns (e.g. low-flow toilet tank or tap aerator installations), only pre-retrofitting data were considered.

3.3.2. Level 2. End-use parameters (average values)

To further explore the characteristics of water consumption at the end-use level, four metrics describing the main features of different end uses were computed: (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 four above-mentioned metrics were obtained for each study based on the assumptions made in Level 1 (see Paragraph 3.3.1).

3.3.3. 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 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). By contrast, the dependent 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 the light of the high variability of the information available – Level 3 of analysis was conducted as follows:

- The information originally in graphical form was digitalized by means of the Web Plot Digitizer v4.3 software (Rohatgi 2021). Specifically, 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) were processed.
- The digitalized information was processed based on assumptions introduced in Level 1 and Level 2. Specifically: (1) the units of measurements were adapted 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*); (2) in the case of REUS presenting end-use parameter distributions observed in specific seasons (e.g. summer and winter), these were averaged to obtain distributions not affected by seasonal patterns; (3) in the case of REUS presenting multiple parameter distributions related to the type of end-use (e.g. front versus top-load washing machine) a weighted average was calculated based on the size of each subset; (4) in the case of REUS comparing baseline distributions against those observed after device retrofitting, only pre-retrofitting distributions were considered.
- Distributions were converted into empirical probability density function curves (i.e. PDF).
- The empirical PDF curves were fitted with MATLAB's R2019a® *fitdist* function. Specifically, five PDFs were assumed to fit each empirical PDF: normal, lognormal, exponential, Weibull, and Gamma. A one-sample Kolmogorov-Smirnov test was applied 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, the distribution type passing the Kolmogorov-Smirnov test and characterized by the minimum AIC parameter value was selected as the best fitting PDF, with its related parameter values.

3.3.4. 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, and taps. 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 hours of the day) and with different units of measurement. Therefore, as for Level 3 of the analysis, the information on end-use daily profiles was first digitalized by means of the Web Plot Digitizer v4.3 software (Rohatgi 2021).

The digitalized profiles were then normalized (standardized) for comparison and processed based on the following assumptions: (1) in the case of REUS presenting the end-use daily profiles observed in specific seasons (e.g. summer and winter), these were averaged 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) a weighted-average profile was calculated 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, only pre-retrofitting profiles were considered.

3.3.5. 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 ones. Following an approach similar to Cominola et al. (2021b), a representation index R^* (defined as the frequency of appearance of a determinant in the set of framework analysis studies) was adopted to quantify how popular a determinant is in the reviewed literature.

Specifically, the frequency of appearance of a given determinant was 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, three categories of end-use determinants were explored:

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

3.3.6. Level 6. Efficiency and diffusion of water-saving end uses

Level 6 of the analysis aims to explore the efficiency and the diffusion 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.

3.4. Results and Discussion

Given the differences in the content of the EUD and the heterogeneity of data presented in the REUS, the availability of the information required to carry out the multi-level analysis was first evaluated. Results are detailed in Table 3.2 and summarized in Figure 3.4.

Table 3.2. Levels of the analysis addressed by each EUD.

EUD	Location	LV 1	LV 2	LV 3	LV 4	LV 5	LV 6
1	Boulder, Colorado (United States)	Yes	Yes	Yes	Yes	-	-
2	Unknown, Wisconsin (United States)	Yes	Yes	-	Yes	-	-
3	Various (United States)	Yes	Yes	-	-	-	-
4	Unknown (United Kingdom)	-	Yes	-	Yes	-	-
5	Tampa, Florida (United States)	Yes	Yes	Yes	-	-	Yes
6	Unknown (United Kingdom)	Yes	-	-	-	-	-
7	Boulder, Colorado (United States)	Yes	Yes	Yes	-	-	-
8	Various (United States, Canada)	Yes	Yes	Yes	Yes	-	Yes
9	Bangkok (Thailand)	Yes	-	-	-	-	Yes
10	East Bay, California (United States)	Yes	-	-	-	-	Yes
11	Seattle, Washington (United States)	Yes	Yes	Yes	-	-	Yes
12	Various (Netherlands)	Yes	Yes	Yes	-	Yes	Yes
13	East Bay, California (United States)	Yes	Yes	Yes	-	-	Yes
14	Perth (Australia)	Yes	Yes	-	-	-	Yes
15	Unknown (United Kingdom)	Yes	-	Yes	Yes	-	-
16	Unknown (United Kingdom)	-	Yes	Yes	-	-	-
17	Tampa, Florida (United States)	Yes	-	-	-	-	-
18	Sydney (Australia)	Yes	-	-	-	-	Yes
19	Yarra Valley (Australia)	Yes	Yes	Yes	Yes	Yes	Yes
20	Various (Netherlands)	Yes	Yes	-	-	Yes	Yes
21	Palhoca (Brazil)	Yes	Yes	-	-	-	-
22	Various (South Africa)	-	-	-	-	-	-
23	Kapiti Coast (New Zealand)	Yes	Yes	Yes	-	Yes	Yes
24	Various (Korea)	-	-	-	-	-	-
25	Chiang Mai (Thailand)	Yes	-	-	-	-	-
26	Toowoomba, (Australia)	Yes	Yes	Yes	Yes	Yes	Yes
27	Various (Netherlands)	Yes	Yes	-	-	Yes	Yes
28	Madrid (Spain)	Yes	Yes	Yes	Yes	Yes	Yes
29	Various, Gold Coast (Australia)	Yes	Yes	Yes	Yes	Yes	Yes
30	Auckland (New Zealand)	Yes	Yes	Yes	-	-	-
31	Trincomalee (Sri Lanka)	Yes	-	-	-	-	-
32	Perth (Australia)	Yes	Yes	-	-	-	-
33	Khon Kaen (Thailand)	Yes	-	-	-	-	-
34	Various (United States)	Yes	Yes	Yes	Yes	-	-

Table 3.2. (Continued). Levels of the analysis addressed by each EUD.

EUD	Location	LV 1	LV 2	LV 3	LV 4	LV 5	LV 6
35	Various (United States)	Yes	Yes	Yes	-	-	Yes
36	Various, South-East Queensland (Australia)	Yes	Yes	Yes	Yes	Yes	Yes
37	Various (Netherlands)	Yes	Yes	-	-	Yes	Yes
38	Various (Korea)	Yes	-	-	-	Yes	-
39	Hervey Bay (Australia)	-	-	-	-	-	-
40	Melbourne and Yarra Valley (Australia)	Yes	Yes	Yes	Yes	Yes	-
41	Hanoi (Vietnam)	Yes	Yes	Yes	-	Yes	-
42	Various (United States, Canada)	Yes	Yes	Yes	Yes	-	Yes
43	Barcelona, Murcia (Spain)	-	Yes	Yes	-	-	-
44	Davis, CA (United States)	Yes	-	-	-	-	-
45	Various (Netherlands)	Yes	Yes	-	Yes	Yes	Yes
46	Various (Austria)	Yes	Yes	-	-	-	-
47	Adelaide (Australia)	Yes	Yes	-	Yes	Yes	Yes
48	Unknown (Greece, Poland)	-	Yes	-	-	Yes	-
49	Jaipur (India)	Yes	-	-	-	Yes	-
50	Duhok (Iraq)	Yes	Yes	-	-	Yes	-
51	Unknown	-	-	-	-	-	-
52	Various (Netherlands)	Yes	Yes	-	-	Yes	Yes
53	Sirte (Lybia)	Yes	Yes	-	-	-	-
54	Unknown (United States)	Yes	-	-	-	-	-
55	Melbourne (Australia)	Yes	Yes	Yes	Yes	Yes	-
56	Western Cape Province (South Africa)	-	-	-	-	-	-
57	Various (Greece and Poland)	-	-	-	-	-	-
58	Naples (Italy)	-	Yes	-	Yes	-	-
59	Illinois (United States)	Yes	Yes	-	-	-	Yes
60	Madrid (Spain)	-	Yes	Yes	-	-	-
61	Galle and Colombo (Sri Lanka)	Yes	-	-	-	-	-
62	Various (Netherlands)	Yes	Yes	Yes	Yes	-	-

Note. Legend for EUD levels of analysis: LV 1 = Daily per-capita end-use water consumption; LV2 = End-use parameters (average values); LV 3 = End-use statistical parameter distributions; LV 4 = Daily end-use profiles; LV 5 = Determinants of end-use consumption and parameters; LV6 = Efficiency and diffusion of water-saving end uses.

Daily per capita end-use water consumption data and the average values of end-use parameters are available for at least one end-use category in the case of 50 and 42 of the 62 EUD (i.e. 81% and 68%, 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 25, 18, 20, and 24 of the 62 EUD (i.e. 40%, 29%, 32%, and 39% 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 (e.g. 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.

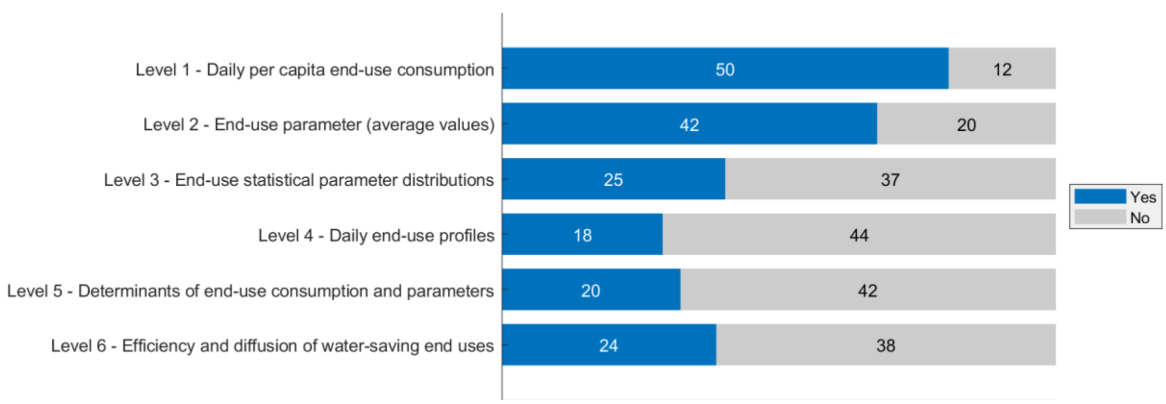

Figure 3.4. The proportion of reviewed EUD addressing the aspects defined by Level 1 to 6 of the analysis.

3.4.1. 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 (50 out of 62, i.e. 81%). The average values of each EUD are shown in Table

3.3, which also features information on the average number of household occupants and the total indoor water consumption.

Table 3.3. 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)								
			Total indoor	D	WM	S	B	F	T	L	O
1	Bennett and Linstedt 1975	3.7	168.4	4.2	43.9	32.9	[a]	55.6	28.8	-	3.0
2	Siegrist et al. 1976	4.5	161.0	-	-	37.9	[a]	34.8	-	-	88.4
3	Brown and Caldwell 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	-	-	-
	Anderson et al. 1993 (post-retrofitting)	2.9	162.0	-	-	26.1	-	27.3	-	-	-
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	262.3	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	2.8	168.0	-	42.5	53.0	[a]	30.5	29.5	7.5	5.0
15	Kowalski and Marshallsay 2003	-	354.8	5.5	50.0	29.0	59.5	109.8	84.8	5.8	8.0
17	Mayer et al. 2004 (post-retrofitting)	2.9	146.0	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	153.0	-	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 2006	2.5	153.7	-	11.0	59.2	-	41.4	-	-	42.1
23	Heinrich 2007 (average)	2.7	149.2	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

Table 3.3 (Continued). 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)								
			Total indoor	D	WM	S	B	F	T	L	O
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, 2009b, 2009c, 2010b, 2013	-	138.6	2.2	30.0	49.7	6.5	21.1	27.0	2.1	0.0
30	Heinrich et al. 2010	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	-	-	37.0	[a]	19	-	-	54.0
32	Water Corporation 2010	2.4	171.2	2.9	20.3	72.6	[a]	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(winter 2010)	2.7	126.5	2.0	28.9	40.3	1.5	24.3	23.9	5.6	-
	Beal and Stewart 2014b	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	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	[a]	18.6	-	-	31.9
	Otaki et al. 2017	-	60.9	-	-	14.1	[a]	21.7	-	-	51.3
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	6.8	339.8	-	38.9	38.9	14.2	38.9	-	-	208.9
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
59	Bethke 2020; Bethke et al. 2021	4.0	126.7	1.9	4.0	59.4	-	11.1	40.5	-	9.8
61	Otaki et al. 2022	-	97.1	-	-	-	-	16.9	-	-	80.2

Table 3.3 (Continued). 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)								
			Total indoor	D	WM	S	B	F	T	Le	O
62	Mazzoni et al. 2023b	3.9	121.6	3.6	17.0	46.2	[a]	32.8	14.6	-	7.3

Note: Legend for daily per capita end-use water consumption: D = dishwasher; WM = washing machine; S = shower; B = bathtub; F = flush (toilet); T = taps; L = leakages. [a] Together with shower.

Level 1 of the analysis reveals that showers and toilets are typically the end-uses with the highest per capita daily water consumption (43.8 and 37.7 L/person/day, respectively), followed by taps (30.0 L/person/day), washing machines (29.6 L/person/day), bathtub (9.9 L/person/day), and dishwashers (3.1 L/person/day). Non-negligible average water consumption values are also observed 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 largest part 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 behavioural change and the introduction of efficient devices. This change 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. Although substantial water savings were brought by 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 washing).

The box-whisker plots of the distributions of the average daily per capita end-use consumption values are shown in Figure 3.5. The figure reveals no substantial variations between the median of each distribution and the aforementioned average values, with the exception of bathtub and leakages, the median of which (about 4.5 and 10.3 L/person/day, respectively) is 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, the daily per capita consumption values of which are considerably in line).

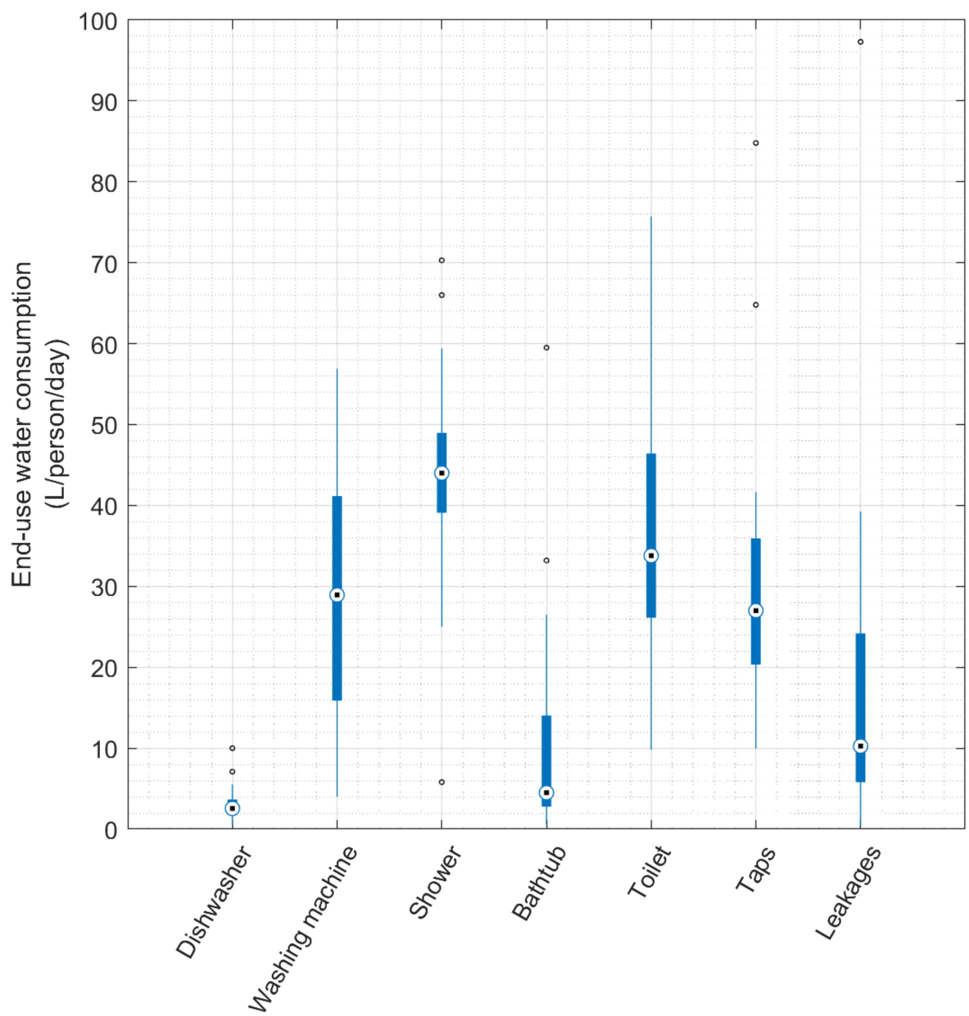

Figure 3.5. Box-whisker plot of end-use water consumption (daily per capita average values) across all reviewed EUD.

Figure 3.6 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).

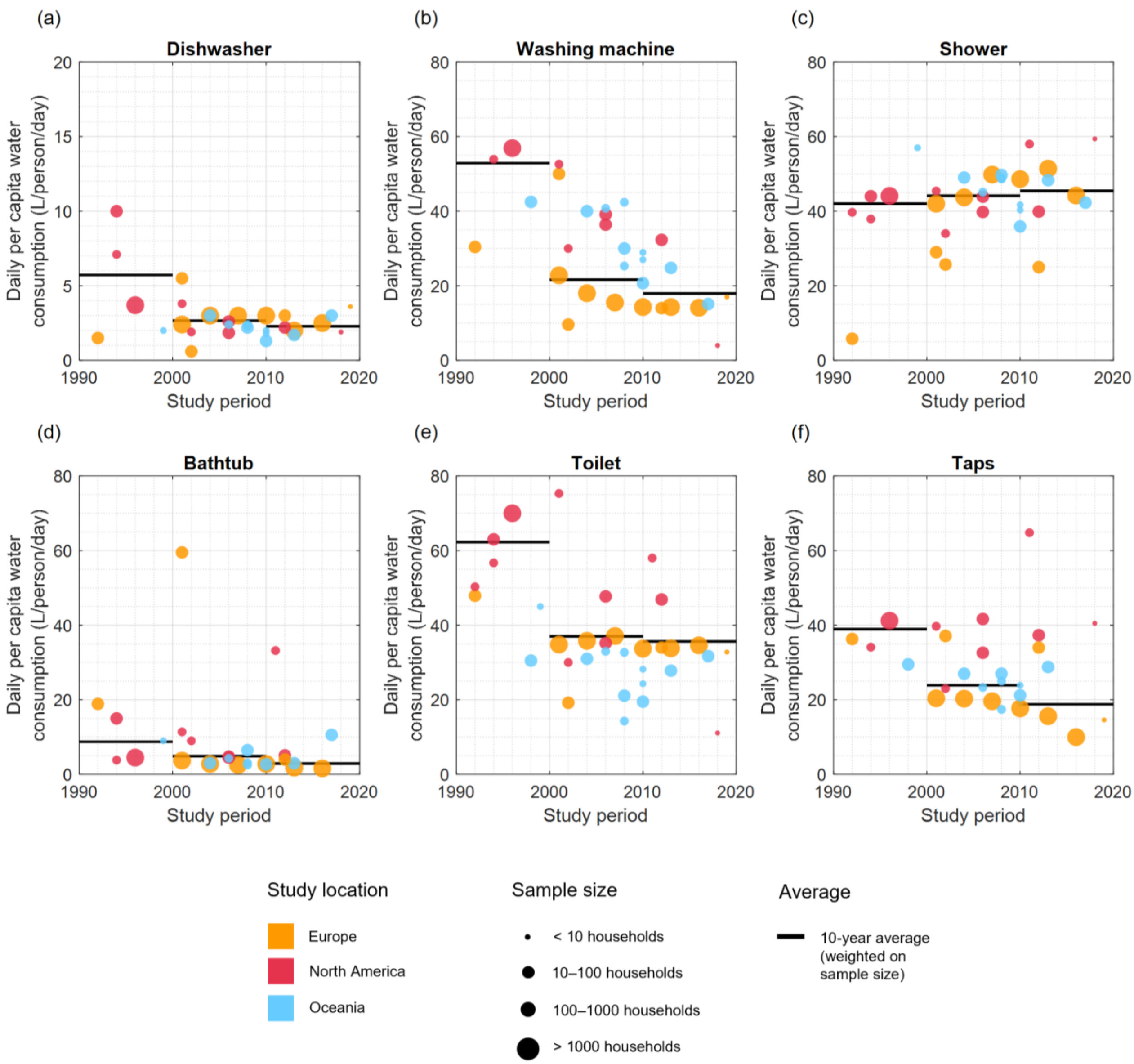

Figure 3.6. End-use water consumption trend over the period 1990-2020.

The results in Figure 3.6 are limited to those retrieved for the (developed) continents for which a sufficient number of EUD was available (i.e. Europe, North America, and Oceania). A decrease in the daily per capita water consumption between the 1990-2000 and the 2010-2020 decades emerges in most of the cases. This is likely to be primarily due to technological development, allowing an increase in the water-saving efficiency of end uses. In fact, 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 17.9 L/person/day) and toilets (from 62.3 to 35.6 L/person/day). By contrast, behavioural factors (e.g. changes in people's attitude towards water use) seem to affect end-use water consumption only in a limited manner since 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 – 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), reasonably because of the progressive replacement of manual water-consuming activities (i.e. laundry, dishwashing) with automated operations made by appliances. Lastly, decrease in the daily per capita consumption of dishwashers and bathtubs is observed as well between the 1990-2000 and the 2010-2020 decades. This is reasonably due to be related to the increase in dishwasher water-saving efficiency, along with the reduction of bathtub use in favour of showers. However, exceptionally high bathtub consumption values emerge 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 Jordan-Cuébas et al. (2018), characterized by a rather limited sample size.

Although the research is primarily focused on residential water consumption at the end-use level, it is worth noting that the availability of information about the daily per capita end-use water consumption – along with the one related to all the indoor end uses not included in the selected categories (excluding leakages) – also allowed further observations about the aggregate indoor water consumption. Specifically, Figure 3.7 shows the average daily per capita indoor water consumption of each EUD, where bar colours are related to different continents. Based on the results shown in the figure, it can be observed that – despite a possible bias related to the neglection of study period and the possible presence of intermittent systems – the lowest values of the aggregate indoor water consumption are typically met in the case of studies conducted in developing countries (e.g. Otaki et al. (2008, 2011, 2013)), whereas the highest values were generally found in the case of developed areas such as the United States, Canada, or the United Kingdom (e.g. Mayer et al. (1999, 2003), Kowalski and Marshallsay (2003)). Unexpectedly, some of the highest values are related to Iraq (Hussien et al. 2016) and Libya (Alharsha et al. 2018). This is most likely because, in those countries, the water tariff is low – or even null – despite pronounced water scarcity (United Nations 2013, Middle East Institute 2021).

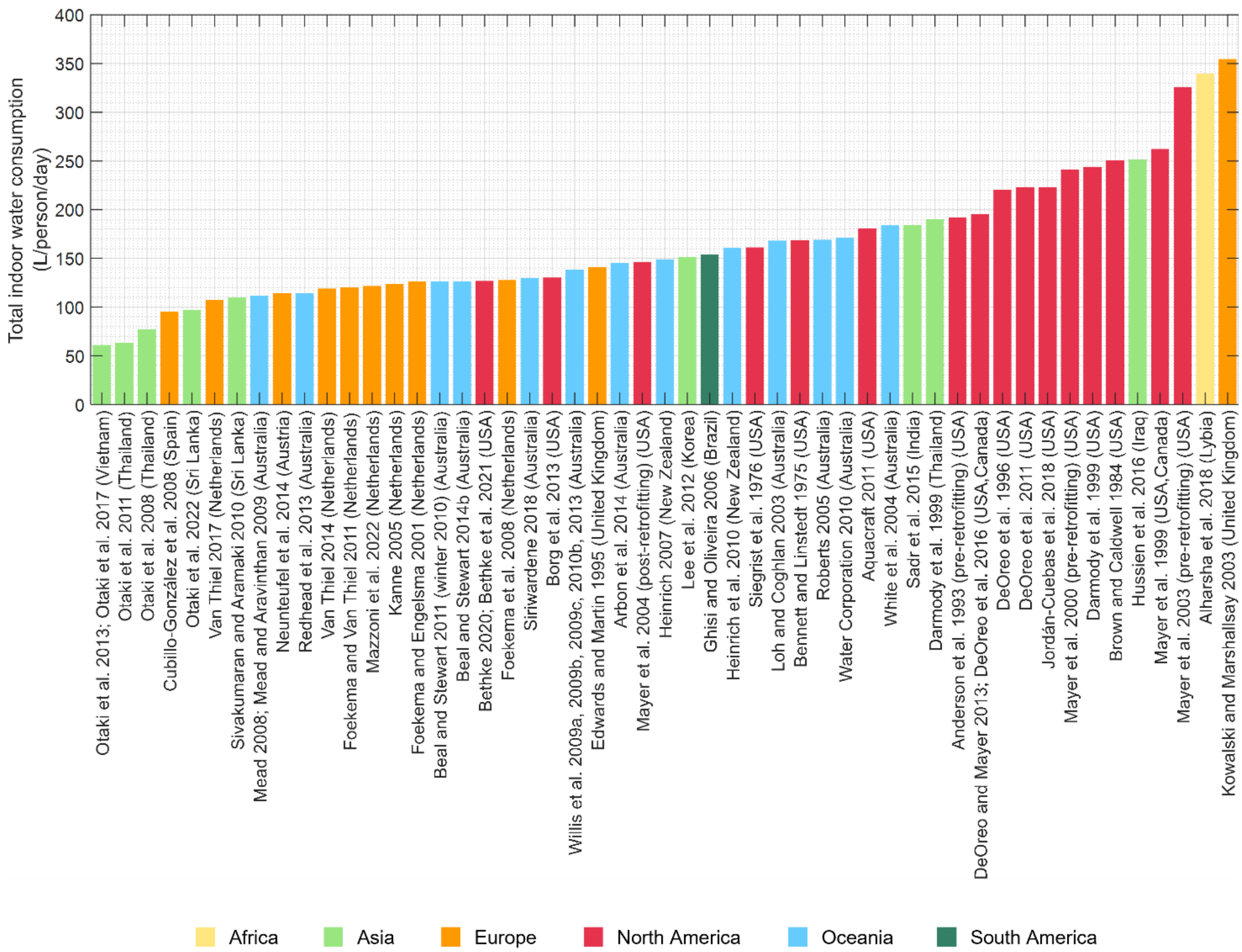

Figure 3.7. Aggregate indoor water consumption (daily per capita average values) of each EUD.

Finally, the scatter plot in Figure 3.8 relates the average per capita daily indoor water consumption with occupancy rate (in the case of EUD including information about both).

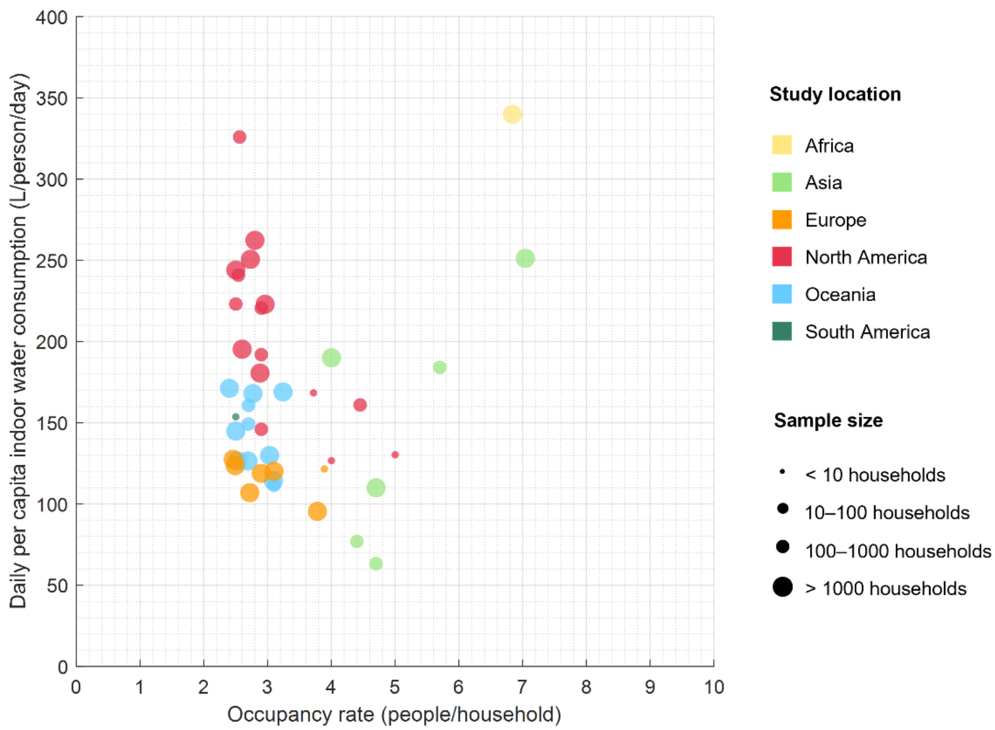

Figure 3.8. Scatter plot of the aggregate indoor water consumption (daily per capita average values) as a function of average occupancy rate and household sample size.

The figure reveals that, on the one hand, studies carried out in North America show higher indoor water consumption values as opposed to those observed in the case of Oceanian studies, although the average occupancy rate of the latter group is in line with the one of the former. Specifically, this difference in water consumption is of about 50 to 100 l/person/day. However, since several studies proved that both continents are subjected to drought risk (e.g. Carrão et al. (2016)), it can be reasonably assumed that this difference is mainly due to behavioural and socio-demographic factors. On the other hand, regarding the few Asian and African EUD for which information about occupancy rate was available, wide-ranging values of the daily per capita indoor water consumption emerged, mainly related to different water policies, geographical and climatic contexts, and level of development. However, higher occupancy rates were generally observed when those data are compared against those from other continents, being the daily per capita water consumption in the same range.

3.4.2. 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 available in the literature for at least one end-use category in the case of 42 EUD (i.e. 68% of the total). Average end-use parameter values related to each EUD are shown in Table 3.4 and Table 3.5, along with the references to the respective REUS.

Table 3.4. Summary of EUD parameters: volume per use and frequency of use.

EUD	REUS	Volume per use (l/use)						Frequency of use (uses/person/day)					
		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 1984	-	-	-	-	19.7		0.2	0.3	0.7	0.4	4.0	-
4	Butler 1991, Butler 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		-	-	-	-	3.8	-
	Anderson et al. 1993 (post-retrofitting)	-	-	33.7	-	6.1		-	-	-	-	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		0.1	0.4	0.8	-	5.1	-
11	Mayer et al. 2000 (pre-retrofitting)	-	154.8	68.5	90.8	13.7		0.2	0.4	0.5	0.1	5.2	-
	Mayer et al. 2000 (post-retrofitting)	-	92.0	56.5	92.0	5.2		-	0.4	0.6	0.1	5.5	-
12	Foekema and Engelsma 2001	20.0	80.3	-	113.5	8..1	-	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	-	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		0.1	0.4	0.7	0.1	5.1	-
	Mayer et al. 2003 (post-retrofitting)	-	103.0	57.9	-	6.2		-	0.3	0.7	0.1	5.6	-
14	Loh and Coghlan 2003	-	33.0	59.5	-	7.8		-	-	0.8	-	3.6	-

Table 3.4 (Continued). Summary of EUD parameters: volume per use and frequency of use.

EUD	REUS	Volume per use (l/use)						Frequency of use (uses/person/day)					
		D	**WM**	**S**	**B**	**F**	**T**	**D**	**WM**	**S**	**B**	**F**	**T**
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	0.2	0.3	0.9	-	4.2	20.0
20	Kanne 2005	18.0	63.9	-	113.5	8.0	-	0.3	0.3	0.7	0.1	6.0	-
21	Ghisi and Oliveira 2006	-	90.0	-	-	-	-	-	0.1	1.3	-	4.3	-
23	Heinrich 2007	-	127.5	79.2	-	6.2	1.6	-	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	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	-	0.3	0.3	0.8	0.1	6.3	-
28	Cubillo-González et al. 2008	16.9	61.1	69.2	-	7.1	-	0.1	0.2	0.5	-	3.3	
29	Willis et al. 2010b (pre-retrofitting)	-	-	57.4	-	-	-	-	-	-	-	-	-
	Willis et al. 2010b (post-retrofitting)	-	-	42.0	-	-	-	-	-	-	-	-	-
30	Heinrich et al. 2010	-	122.5	-	-	-	-	-	0.4	-	-	-	-
32	Water Corporation 2010	-	98.7	67.0	-	5.5	-	-	-	-	-	5.0	-
34	DeOreo et al. 2011	-	136.3	68.8	-	10.4	2.3	-	0.3	0.7	-	4.8	19.4
35	Aquacraft 2011	-	121.5	60.2	-	7.9	-	-	0.3	0.7	-	4.4	-
36	Beal and Stewart 2011	-	105.7	48.2	-	5.8	5.5	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	-	0.2	0.3	0.8	0.1	5.9	19.6
40	Redhead et al. 2013	15.1	90.5	47.2	130.1	5.9	1.4	0.2	0.2	0.8	0.1	3.9	19.7
41	Otaki et al. 2013	-	-	-	-	-	-	-	-	-	-	4.2	-
42	DeOreo and Mayer 2013, DeOreo et al.2016	-	-	70.0	-	9.8	1.9	0.1	0.3	0.7	0.1	5.0	19.6
43	Fontdecaba et al. 2013	10.2	38.1	36.4	-	5.6	-	-	-	-	-	-	-
45	Van Thiel 2014	14.3	52.9	-	114.5	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	-	0.2	0.3	1.0	0.2	4.4	28.0
48	Shan et al. 2015	-	-	-	-	-	-	-	-	1.0	-	-	-
50	Hussien et al. 2016	-	-	77.9	132.0	5.5	-	-	-	0.5	0.0	4.7	-
52	Van Thiel 2017	13.1	53.9	-	112.5	7.7	-	0.2	0.2	0.7	0.0	5.9	19.2
53	Alharsha et al. 2018	-	-	-	-	-	-	0.4	0.6	0.6	0.1	5.0	13.0
55	Siriwardene 2018	13.7	104.0	48.9	71.6	5.4	1.2	0.3	0.2	0.9	0.4	6.4	16.8
58	Di Mauro et al. 2020	-	-	21.2	-	-	-	-	-	-	-	-	-
59	Bethke et al. 2021	-	-	112.0	-	6.8	-	-	-	-	-	-	-
60	Diaz et al. 2021	-	-	-	-	-	-	0.2	0.1	0.8	-	4.4	14.1
62	Mazzoni et al. 2023b	11.4	62.9	63.6	[a]	6.8	1.2	0.3	0.3	0.8	[a]	4.2	13.8

Note: Legend for volume per use and frequency of use: D = dishwasher; WM = washing machine; S = shower; B = bathtub; F = flush (toilet); T = taps. [a] Together with shower.

Table 3.5. Summary of EUD parameters: duration and average flow rate per use.

EUD	REUS	Duration per use (min/use)						Flow rate per use (l/min)					
		D	**WM**	**S**	**B**	**F**	**T**	**D**	**WM**	**S**	**B**	**F**	**T**
3	Brown and Caldwell 1984	-	-	-	-	-	-	-	-	10.4	-	-	-
5	Anderson et al. 1993 (pre-retrofitting)	-	-	6.3	-	-	-	-	-	9.5	-	-	-
	Anderson et al. 1993 (post-retrofitting)	-	-	6.0	-	-	-	-	-	5.7	-	-	-
8	Mayer et al. 1999	-	-	8.2	-	-	-	-	-	8.4	-	-	-
11	Mayer et al. 2000 (pre-retrofitting)	-	-	7.9	-	-	-	-	-	8.5	-	-	4.5
	Mayer et al. 2000 (post-retrofitting)	-	-	7.8	-	-	-	-	-	7.1	-	-	3.8
12	Foekema and Engelsma 2001	-	-	7.6	-	-	-	-	-	7.7	-	-	-
	Blokker 2006; Blokker 2010; Blokker et al. 2010	1.4[a]	5.0[a]	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
13	Mayer et al. 2003 (pre-retrofitting)	-	-	8.9	-	-	-	-	-	7.6	-	-	4.5
	Mayer et al. 2003 (post-retrofitting)	-	-	8.2	-	-	-	-	-	6.8	-	-	3.5
14	Loh and Coghlan 2003	-	-	7.0	-	-	-	-	-	8.6	-	-	-
19	Roberts 2005, Gato-Trinidad et al. 2011	-	-	7.1	-	-	-	-	-	9.5	-	-	3.3
20	Kanne 2005	-	-	7.7	-	-	-	-	-	7.8	-	-	-
21	Ghisi and Oliveira 2006	-	-	8.6	-	-	-	-	-	6.0	-	-	-
23	Heinrich 2007	-	-	7.6	-	-	0.5	-	-	11.3	-	-	3.8
26	Mead 2008; Mead and Aravinthan 2009	-	-	7.2	-	-	0.4	-	-	8.8	-	-	2.1
27	Foekema et al. 2008	-	-	7.9	-	-	-	-	-	7.7	-	-	-
28	Cubillo-González et al. 2008	5.1[a]	9.3[a]	8.1	-	1.7	-	3.8	7.6	9.0	-	-	-
29	Willis et al. 2010b (pre-retrofitting)	-	-	7.2	-	-	-	-	-	10.0	-	-	-
	Willis et al. 2010b (post-retrofitting)	-	-	5.9	-	-	-	-	-	9.0	-	-	-
32	Water Corporation 2010	-	-	6.7	-	-	-	-	-	10.0	-	-	-
34	DeOreo et al. 2011	-	-	8.7	-	-	0.62	-	-	8.1	-	-	4.2
35	Aquacraft 2011	-	-	-	-	-	-	-	-	7.5	-	-	4.2
36	Beal and Stewart 2011	-	-	6.0	-	-	-	-	-	8.1	-	-	-
37	Foekema and Van Thiel 2011	-	-	8.1	-	-	-	-	-	7.7	-	-	-

Table 3.5 (Continued). Summary of EUD parameters: duration and average flow rate per use.

EUD	REUS	Duration per use (min/use)						Flow rate per use (l/min)					
		D	WM	S	B	F	T	D	WM	S	B	F	T
40	Redhead et al. 2013	-	-	6.6	-	-	0.38	-	-	7.2	-	-	2.8
41	Otaki et al. 2013	-	-	-	-	-	-	-	-	2.5	-	-	-
42	DeOreo and Mayer 2013, DeOreo et al.2016	-	-	7.8	-	-	0.50	-	-	-	-	-	-
43	Fontdecaba et al. 2013	-	-	5.3	0.7	-	-	-	-	-	-	-	-
45	Van Thiel 2014	-	-	8.9	-	-	-	-	-	7.7	-	-	-
47	Arbon et al. 2014	-	-	6.3	-	-	-	-	-	7.9	-	-	2.1
48	Shan et al. 2015	-	-	8.7	-	-	-	-	-	-	-	-	-
50	Hussien et al. 2016	-	-	8.6	-	-	-	-	-	9.0	-	-	-
52	Van Thiel 2017	-	-	7.6	-	-	-	-	-	8.2	-	-	-
55	Siriwardene 2018	-	-	6.4	-	-	0.40	-	-	8.1	12.7	-	2.7
58	Di Mauro et al. 2020	-	-	9.8	-	-	-	-	-	-	-	-	-
59	Bethke et al. 2021	-	-	14.3	-	1.3	-	4.2	16.5	7.9	-	5.8	-
60	Diaz et al. 2021	-	-	10.2	-	-	0.48	-	-	-	-	-	-
62	Mazzoni et al. 2023b	4.2[a]	8.2[a]	8.0	[b]	0.8	0.20	2.8	7.0	7.9	[b]	8.3	4.8

Note: Legend for volume per use and frequency of use: D = dishwasher; WM = washing machine; S = shower; B = bathtub; F = flush (toilet); T = taps. [a] Duration related to water inflow only; [b] Together with shower.

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 39 and 38 EUD, respectively (Table 3.4). For individual end uses, volume per use and the daily frequency of use have mainly been explored in the case of toilets (33 and 36 EUD, respectively), washing machines (27 and 31 EUD) and showers (25 and 31 EUD), whereas less relevance is given to dishwashers (19 and 25 EUD), bathtubs (17 and 20 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).

By contrast, duration per use and flow rate per use are less investigated since the average values of these parameters are available for at least one end-use category in the case of 32 and 30 EUD, respectively (Table 3.5). It is worth noting that event duration is typically expressed in *min/use* in most of the cases, whereas, concerning taps, some studies (e.g. 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-mentioned cases are not included in Table 3.5. For individual end uses, showers result the most explored (with 31 and 29 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: in fact, their average values of duration and flow rate per use is 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 Figure 3.9, where only the sets of end-use parameter values appearing in at least five EUD were indicated. In greater detail, the following features emerge for different parameters:

- *Volume per use* (see Figure 3.9 a). Bathtubs are the most consuming end use, with an average volume per use of about 103.4 l/use, followed by washing machines (92.0 l/load) and showers (63.0 l/use), whereas considerably lower volumes per use are related to dishwashers (17.7 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 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. The smallest differences are observed 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 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 142.6 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

(69.9 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, the average starting year of the American EUD is 2003, 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 among the EUD of different areas.

- *Duration and flow rate per use* (see Figure 3.9 b and Figure 3.9 c). Although a sufficient number of values is available only for showers and taps, results reveal that shower use is typically characterized by much longer durations (on the order of several minutes and with an average of about 7.9 min/use) and higher flow rates (with an average of about 8.2 l/min) as opposed to taps. Moreover, tap uses typically last less than one minute (with an average of about 24 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), and Blokker et al. (2010). 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 8.2–8.9 min/use in the former case and 6.8 min/use in the latter), although significant differences in the average flow rate per use are not observed. 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 also be affected by different study periods, being the year 2003 the average starting year of the American EUD and the years 2008-2009 those of Oceanian and European EUD, respectively.

- *Frequency of use* (see Figure 3.9 d). Different behaviours 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 4.92 times/person/day and the latter used on average 17.22 times/person/day. In particular, toilet flush is activated an average of 4.30 times/person/day in the case of the Oceanian EUD and 5.14–5.30 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, 0.31 in the case of washing machines, 0.21 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 0.67–0.69 times/person/day in the case of North American and European EUD), whereas washing machine frequency use is highest in North American EUD (0.40 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, no relevant differences in frequency of use among EUD from different continents are observed. 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 frequency only in case of households made up by three to five residents; (5) bathtubs are nowadays used only occasionally.

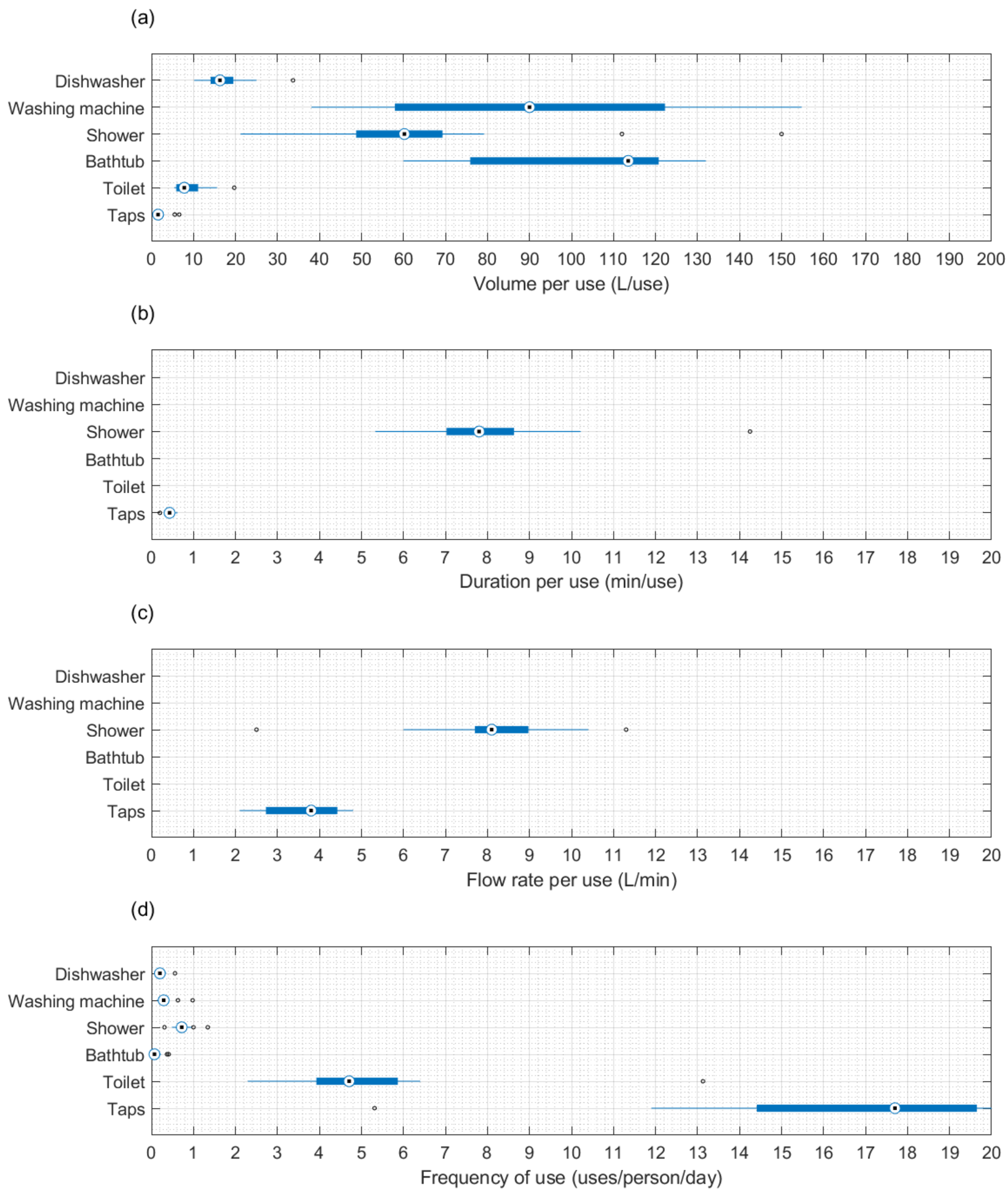

Figure 3.9. Box-whisker plot of the end-use parameters (average values) of each EUD: volume per use (a), duration per use (b), flow rate per use (c), and frequency of use (d).

3.4.3. Level 3. End-use statistical parameter distribution

End-use parameter distributions are available – with reference to at least one end-use category and parameter – in the case of 25 EUD (i.e. 40% of the total), meaning that, in the literature, this kind of information is less explored than the respective average parameter values. In Figure 3.10 a detailed overview of the most common end-use parameter distributions is provided, 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). The figure 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. This finding is coherent with the outcomes achieved by investigating the availability of information about the average values of end-use parameters (Level 2 of the analysis).

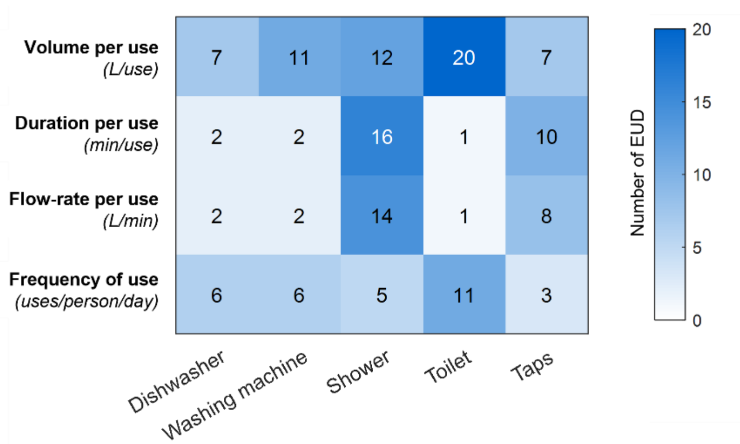

Figure 3.10. Number of EUD including information about end-use parameter distributions.

The empirical distributions (i.e. empirical PDF curves) of end-use parameters, obtained by digitalizing the information available in the REUS, are shown in Figure 3.11, whereas the respective probability distributions (i.e. statistical PDF curves) fitted by MATLAB's R2019a® *fitdist* function are shown in Figure 3.12. The main characteristics of each best-fitting PDF curve (distribution type, parameters) are also detailed in Table A.1 (Appendix A) along with the results of the preliminary Kolmogorov-Smirnov goodness-of-fit test.

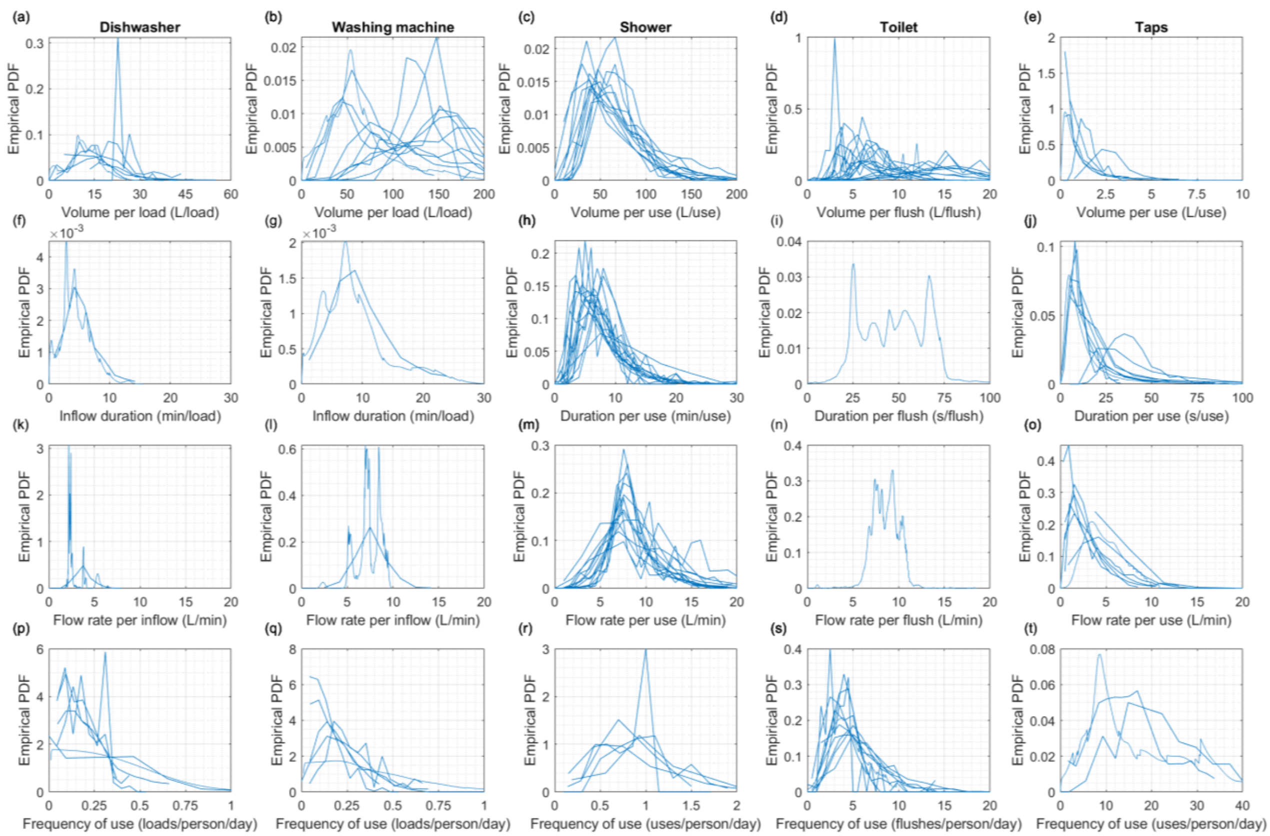

Figure 3.11. Empirical PDF distributions of different end uses and parameters.

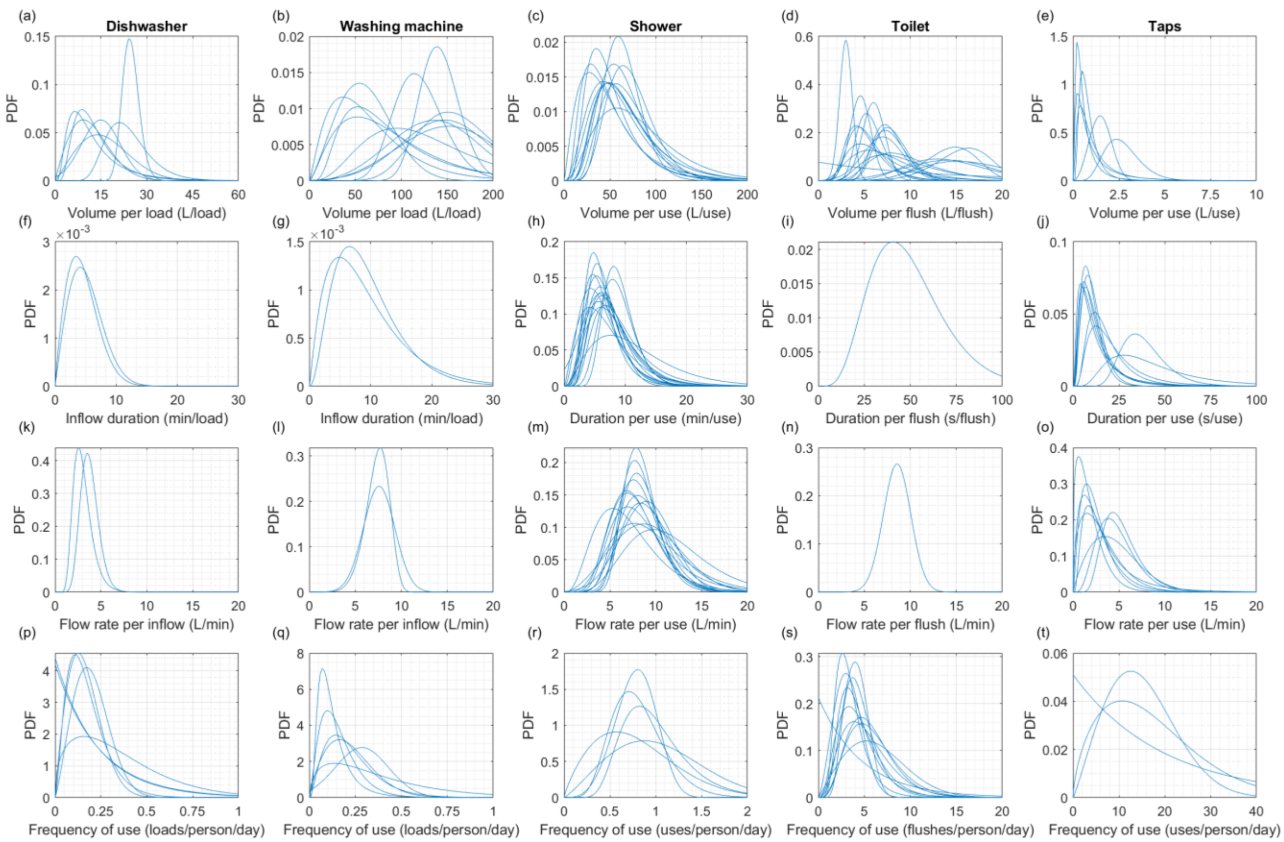

Figure 3.12. Statistical (i.e. fitted) PDF distributions of different end uses and parameters.

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

- Volume-per-use distributions is fitted by different PDF based on the end-use considered and the characteristics of the respective EUD. The obtained the PDF curves are mostly consistent in the case of shower events (Figure 3.12 c), often assuming a slightly right-skewed shape characterized by an upper tail and described by lognormal or Gamma distributions. A similar behaviour is observed for taps (Figure 3.12 e), 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)). By contrast, differences among the distributions are clearly distinguishable for end uses not directly human-controlled, i.e., appliances (Figure 3.12 a and Figure 3.12 b) and toilet (Figure 3.12 d). These differences are mainly evident in the case of washing machine distributions (Figure 3.12 b), 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 Linstedt 1975, Mayer et al. 1999, Roberts 2005, Heinrich et al. 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) among the EUD concerned, related to different levels of 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 (Figure 3.12 h), whereas differences are observed between tap distributions (Figure 3.12 j) 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 shower (Figure 3.12 m), whereas more skewed distributions emerge in the case of taps (Figure 3.12 o). Regarding taps – and similarly to the outcomes achieved in the case of tap duration distributions (Figure 3.12 j) – 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), and DeOreo and Mayer (2013).

- 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, Figure 3.12 p and Figure 3.12 q), 0.7-1.0 uses/person/day (shower, Figure 3.12 r), and 3-5 flushes/person/day (toilet, Figure 3.12 s). As limited skewness characterizes the majority of these distributions, the above-mentioned peak values are coherent 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.

3.4.4. Level 4. Daily end-use profiles

Information about daily end-use profiles is available in the case of 18 EUD (i.e. 29% 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 (e.g. Roberts (2005), Kowalski and Marshallsay (2005), Redhead et al. (2013)), day type (e.g. Siriwardene (2018)), or layout of water infrastructure supplying the monitored households (e.g. Willis et al. (2011b)).

The results after data digitization and normalization are indicated in Figure 3.13, where box-whisker plots of the average end-use daily profiles investigated in the reviewed REUS are shown. Peculiar shapes of the daily profiles are observed based on the end use considered because of different water use behaviours, 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 hours, 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, which appear to be used mostly in the morning (before going to work) and evening (when returning home), but also applies to the case of dishwasher – which is mostly activated after mealtimes – and washing machine, the profile of which is typically characterized by a single peak in the morning along with a decrease in water consumption during the afternoon.

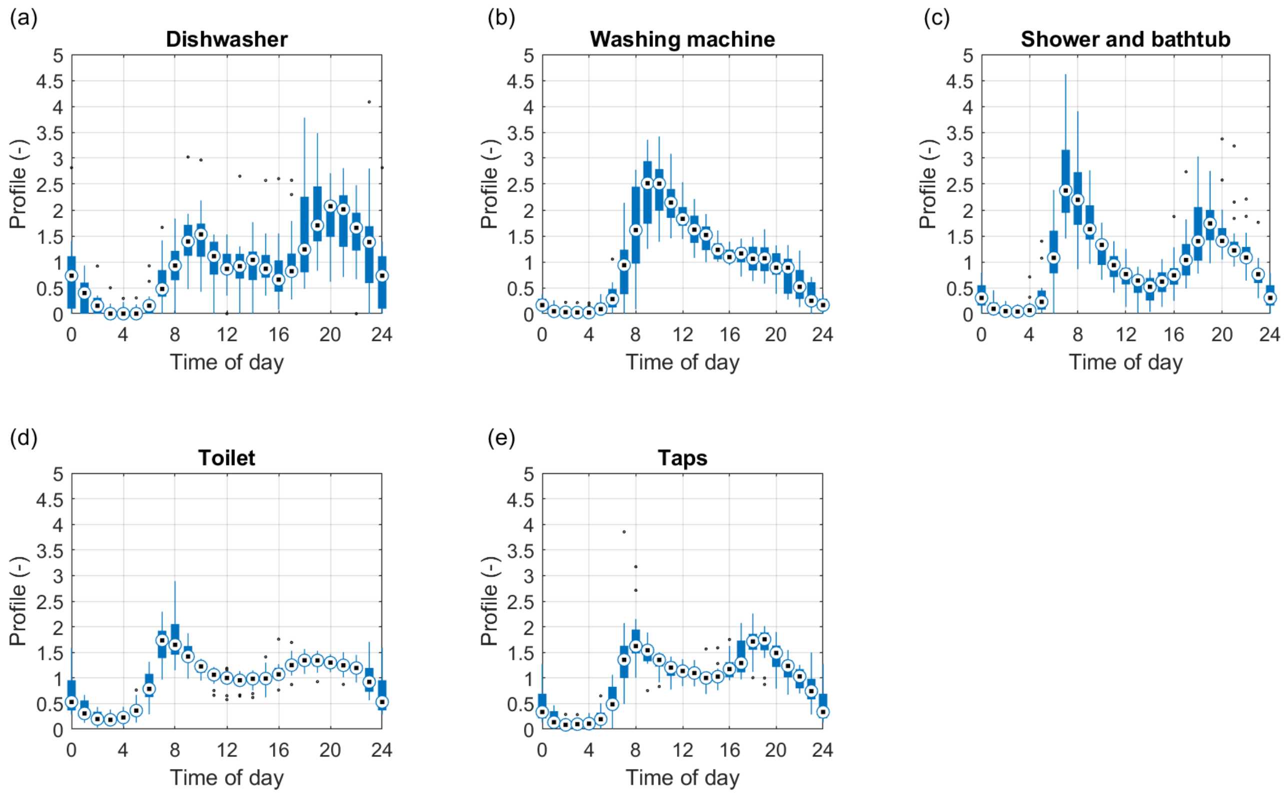

Figure 3.13. Box-whisker plots of the normalized hourly end-use water consumption (i.e. daily profile) of each EUD.

In addition, the hourly (normalized) water consumption values available in the literature for each of the 24 hours 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 among the studies – 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 available in the literature are generally observable in 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, the analysis reveals different peak times of end-use water consumption between North and South European countries, featuring 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 were evaluated by Butler (1991), Kowalski and Marshallsay (2005), and Cubillo-González et al. (2008), respectively – the diversity in home return times impacts 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). However, although the most relevant discrepancies between the two aforementioned case-study areas are evident in the case of showers and bathtubs, some minor temporal differences due to different habits also emerge in the case of toilet. In fact, the analysis reveals that different waking times have effects on the morning peak time of toilet use (ranging from 8:00 in the case of the United Kingdom to 10:00 in the case of Spain).

3.4.5. Level 5. Determinants of end-use consumption and parameters

Information about the determinants of end-use water consumption and parameters were available in the literature for only 20 EUD (i.e., 32% of the total). We computed the R^* index for each possible combination of end uses, determinants, and features investigated in the REUS. The results are shown in Figure 3.14. The heat maps shown in the figure 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 in relation to the household level of detail (e.g. Cominola et al. (2021b)).

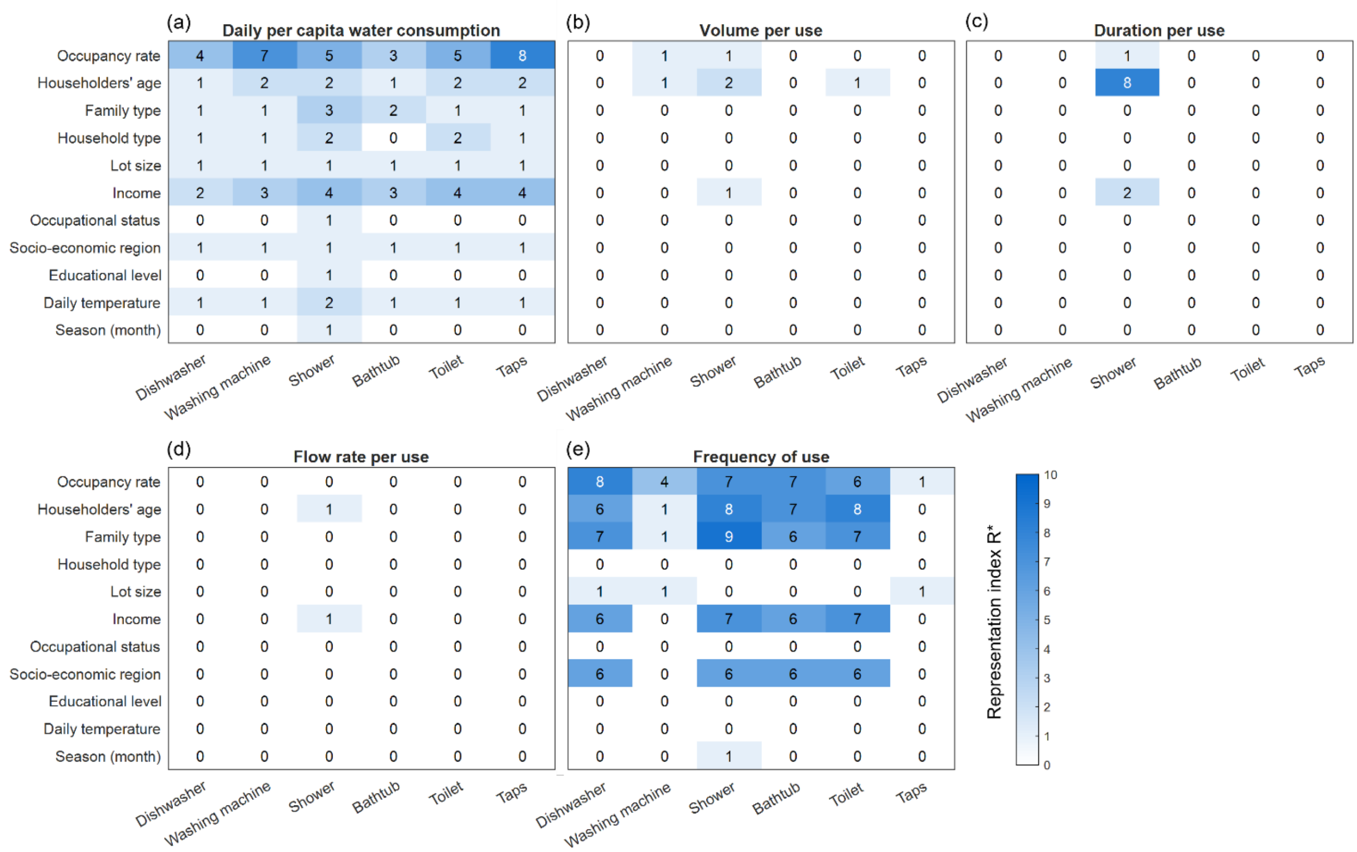

Figure 3.14. Representation index (R^*) of the EUD about end-use determinants available in the literature.

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 behaviours – 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) also show that 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). On the other hand, a negative correlation 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 typically have newer and more efficient toilet cisterns, allowing water savings upon flushing. However, this negative correlation is not observed in the case of human-controlled end uses (i.e. showers, bathtubs, taps), the duration-of-use of which – and 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 behaviours emerge in the light of the comparison of the impacts of income on washing machine per capita water consumption, which are positively correlated in some cases (e.g. Beal and Stewart (2011)) and negatively correlated 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, the relationship of which with householders' age is explored in several studies (e.g. 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)) reporting that teenagers and young adults typically have longer showers than older people. 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 explored in the series of Dutch studies conducted between 2001 and 2017 (i.e. 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)). Specifically, the studies show a positive correlation between householders' age and frequency of toilet use and also demonstrate that bathtub is more frequently used in households with young children.

3.4.6. 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 24 EUD (i.e. 39% 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 difficult. Only the most relevant key points are discussed below, whereas the detailed findings of each study are shown in Table B.1 (Appendix B).

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 decrease by 10% and 18%, respectively after the installation of alarm displays in showers (see the related values in Table 3.4 and Table 3.5). 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 3.3 and Table 3.4). 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. Finally, studies exploring the potential water conservation achievable by retrofitting also 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 (e.g. 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 end uses on the market in replacement of the traditional ones (e.g. 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 was 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 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 about 2,500,000 Australian users is considered, for which a progressive increase in the diffusion of dual-flush toilets was 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-mentioned studies also report that the diffusion of dishwashers positively relates to household occupancy rate, whereas the diffusion of bathtub is nowadays mainly dependent on wealth class (income), coherently with some of the considerations made by Cubillo-González et al. (2008).

3.5. Conclusions

In this chapter, an overview of the state-of-the-art about research in the field of residential water consumption at the end-use level was provided by reviewing 104 Residential End-Use Studies (REUS), and qualitatively and quantitatively investigating the information about the characteristics of the related 62 End-Use Databases (EUD). This was done by carrying out a multi-level method of analysis to evaluate the main perspectives from around the world in terms of water consumption. The major findings emerged at each level of 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 was observed for washing machines, toilets, and taps, whereas a slight increase 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 among 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 profiles 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 profiles 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 REUS. Concerning family size, most 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 behaviours 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 end-use water-saving efficiency and diffusion 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 reduced toilet cisterns, water-saving washing machines) along with the replacement of the most consuming ones.

In conclusion, beside the specific findings of this research, some general can be pointed out. First, data availability has been demonstrated to be a substantial challenge, considerably limiting open science and reproducible research. 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. Moreover, uncertainties in the reported outcomes may have arisen due to the variety of methods adopted to standardize the variety of results reported in the literature (based on different data collection techniques, data resolutions, monitoring periods, and end-use data gathering approaches) which all limit the possibility to observe generalized behaviours and differences across studies. Despite the aforementioned limitations, the results reported in this chapter 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.

Chapter 4

A method for end-use disaggregation and classification based on coarse-resolution data

Despite their interest in the field of water resources management, residential water consumption data at the end use level may not be directly collected in field due to the high costs of monitoring tools, practical difficulties in installing smart meters upon each end use, and inhabitants' rejection. These limitations have led to the development of several approaches allowing household-level data to be automatically or semi-automatically disaggregated and classified into individual end-use events, thus enabling a large amount of information about end-use water consumption to be gathered. However, most of the methods developed in the last two decades (Mayer et al. 1999, Kowalski and Marshallsay 2003, Nguyen et al. 2005, Bethke et al. 2021) can process only data at very fine temporal resolution, i.e. 1–10 s, which may not be at the disposal of water utilities, whereas only a small group of disaggregation and classification methods exist (Cominola et al. 2017, 2018a), the validation of which has been performed only with synthetically generated water consumption data.

In this chapter, a new, rule-based, automated disaggregation methodology is presented, allowing water consumption data collected at 1-min frequency at the household inlet point to be disaggregated and classified into the end uses of water. Like other rule-based tools, such as Trace Wizard (Mayer et al. 1999) and Identiflow (Kowalski and Marshallsay 2003), the methodology developed is based on deterministic rules relying on the characteristics of water uses (e.g. duration and consumed volume) to perform water end-use disaggregation and classification. However, accurate results are achieved with water consumption data the resolution of which is close to that of the most widespread commercial smart meters (i.e., 1 min instead of 1–10 s), thus making the method potentially applicable to several contexts in the field of residential water consumption. Moreover, unlike in the case of some of the aforementioned tools, the performance is not dependent on the experience of the analyst.

The methodology is applied to data from two different geographical contexts: a first validation and test was conducted with reference to a sample of four households in Bologna (Italy), whereas a further test of the method – aimed at evaluating its robustness – is carried out with end-use data collected at nine households located in the North Holland province (Netherlands), i.e. in a considerably different context with respect to that for which the method is initially implemented. Although the limited sample of monitored households, this represents the first case in which disaggregation performance is directly assessed through a comparison against actual water consumption data collected at each domestic end use with 1-min resolution.

4.1. Data collection and processing

In order to calibrate, validate, and subsequently test the robustness of the methodology for end-use disaggregation and classification with respect to a variety of contexts of residential water consumption, data were collected in two household samples in different locations and with different levels of detail. First, a group of four households located in the peripheral area of Bologna (Italy) – and hereinafter called *Italian dataset* – were monitored at a coarse resolution (i.e. 1 min) for nearly two months in early 2018, by installing mechanical water meters paired with data loggers at each domestic end use. Second, household-level data were collected over periods of varying lengths in a sample of nine households of the North Holland province (Netherlands) – hereinafter called *Dutch dataset* – at a very fine resolution (i.e. 1 s).

4.1.1. Italian dataset

A preliminary monitoring of water consumption was conducted in early 2018, in four households (denoted here as H1, H2, H3, and H4) located in the peripheral area of the city of Bologna, Italy. Although they represent a relatively small sample of water-use data, the selected households are different in terms of number of occupancy rates, daily per capita average consumption, and type of water end uses, as reported in Table 4.1.

Table 4.1. Main features of monitored households (Italian dataset).

Household	Location	Number of occupants (persons)	Children or teenagers (0-18)	Adults or Seniors (19+)	Monitoring start	Monitoring end	Monitoring period (days)	Daily per capita water consumption (L/person/day)
H1	Bologna	1	0	1	1 January 2018	25 February 2018	56	113
H2	Bologna	1	0	1	1 January 2018	25 February 2018	56	88
H3	Ozzano dell'Emilia	2	0	2	1 January 2018	25 February 2018	53[a]	129
H4	Ozzano dell'Emilia	3	0	3	1 January 2018	25 February 2018	42[a]	124

Note: [a] Restricted period due to a malfunctioning of the monitoring system.

From an operational standpoint, the intrusive monitoring was initiated by installing mechanical water meters (paired with data loggers) at the domestic water inlet point and at each end-use point. Specifically, All the mechanical Itron® water meters were equipped with an optical reader and a radio transmitter (EquaScan wMIU-RF, making use of the Wireless M-Bus communication protocol). Data collected were transmitted to a receiver kit, logged at the 1-min temporal resolution (as cumulative volume information) and sent to a digital platform with daily frequency by means of a domestic Wi-Fi connection. Based on the available technology, and in the light of the intrusiveness of the end-use monitoring system and users' readiness to cooperate, it was possible to record water use data for 8 weeks (i.e., 56 days, from 1 January to 25 February 2018) at 1-min resolution and with 1-L accuracy.

In addition, surveys and interviews were submitted to householders in order to collect information about the householders themselves and their habits (e.g. daily use frequency for each end use) and characteristics of the end uses (e.g. manufacturer and model). However, apart from data about the householders' age and number (Table 4.1), the information collected via surveys was intentionally omitted from consideration in the study, in order to develop a methodology that could be used even when such an information is not available. Although the households were different in terms of number and characteristics of the end uses, it was possible to identify five main categories of indoor end uses of water: *dishwasher*, *taps*, *washing machine*, *shower and bathtub*, and *toilet*. It is worth noting that some of the selected households also included outdoor end uses (e.g. irrigation systems or outdoor sinks), but the lack of use thereof during the monitored period did not enable them to be considered in the study.

A preliminary phase was aimed at detecting smart meter data gaps, i.e., periods of time when data were not recorded due to disturbances affecting the monitoring system (e.g. blackouts) or data transmission (e.g. Wi-Fi connection drops). All water consumption data for each of the four households were analyzed using a Microsoft Excel spreadsheet, in order to detect data gaps. Specifically, households H1 and H2 showed no data gaps across the monitoring period, whereas the other two revealed some gaps, due to which the total length of the monitoring period was reduced to 53 days (household H3) and 42 days (household H4) of available data. Moreover, the water consumption data collected were checked for consistency to avoid considering long periods without any water consumption in the analyzed households (e.g. due to users' absence). This was done considering a threshold time period of three days without any water use. The aggregate volume of water used was calculated for each day and for each household and no periods without water use longer than three days were observed in any household. Overall, the following aspects regarding the Italian dataset emerged: (1) the average daily per capita water consumption of each household is in line with the average domestic water consumption of the city of Bologna for the year 2018, i.e. 152.5 L/person/day (Comune di Bologna 2019); (2) households were not affected by leakages in the monitoring period, since the overall water consumption observed at the domestic inlet point equals the sum of domestic end-use volumes; and (3) Only 9.4% of the monitored water uses were combined uses (i.e. simultaneous water uses) and the majority of those (i.e. 6.1% out of 9.4%) were a combined use of a toilet and a tap.

4.1.2. Dutch dataset

The second water consumption measurement campaign started in 2019 in nine households located in the North Holland province, Netherlands (denoted here as H5–H13) and was fully conducted before the adoption of restrictive measures to limit the spread of the COVID-19. Due to privacy reason, these nine households were selected among those owned by water utility employees who had previously agreed to take part in the research. Specifically as in the case of the Italian dataset, households with different number of inhabitants and family types were considered, in order to include water consumption data from different socio-demographic contexts. The main features of each household subjected to water consumption monitoring are included in Table 4.2.

Table 4.2. Main features of monitored households (Dutch dataset).

Household	Location	Number of occupants (persons)	Children or teenagers (0-18)	Adults or Seniors (19+)	Monitoring start	Monitoring end	Monitoring period (days)	Daily per capita water consumption (L/person/day)
H5	Bevervijk	4	1	3	4 July 2019	4 October 2019	94[a]	152
H6	Alkmaar	4	2	2	8 November 2019	9 January 2020	63	125
H7	Heerhugowaard	4	0	4	8 November 2019	10 January 2020	64	121
H8	IJmuiden	4	2	2	8 November 2019	10 January 2020	64	110
H9	Assendelft	4	0	4	12 November 2019	11 January 2020	62	135
H10	Egmond aan Zee	4	2	2	10 January 2020	31 January 2020	22	108
H11	Purmerend	2	0	2	13 January 2020	25 February 2020	44	130

Table 4.2 (Continued). Main features of monitored households (Dutch dataset).

Household	**Location**	**Number of occupants (persons)**	**Children or teenagers (0-18)**	**Adults or Seniors (19+)**	**Monitoring start**	**Monitoring end**	**Monitoring period (days)**	**Daily per capita water consumption (L/person/day)**
H12	Alkmaar	4	2	2	16 January 2020	4 February 2020	20	70
H13	Noord Scharwoude	5	2	3	17 January 2020	28 January 2020	12	113

Note: [a] only 73 of 94 days are considered in the study, due to the occurrence of 21 days with no water consumption because of householders' absence.

From an operational standpoint, high-resolution monitoring systems made up of Itron® CENTRON R400 water meters with 0.1 L/pulse accuracy and IoTSensReader® devices for remote data logging were installed at each household water inlet point. It is worth noting that the number of pulses produced over time (and, specifically, over 1- or 2-s time intervals) by each water meter were collected, so a pre-processing of data was required to convert them in water consumption data (L/min). Overall, raw data were registered at the household-level over about 447 days, albeit with different periods based on the household concerned (ranging from a maximum of 94 days in the case of household H5, up to a minimum of 12 days in the case of household H13).

The raw data collected in the households considered (i.e. number of pulses over time) were converted to water consumption data according to Equation (4.1):

$$q_{i,t} = \frac{acc \cdot np_{i,t}}{dp_{i,t}} \cdot CF \tag{4.1}$$

where $q_{i,t}$ (L/min) is the average water consumption observed at the water inlet point of the i-th household ($i = 1, \dots, 9$) during the t-th time interval of the monitoring period ($t = 1, \dots, T_i$), $acc = 0.1$ L/pulse is the accuracy of the Itron® CENTRON R400 smart meter used for monitoring, $np_{i,t}$

is the number of pulses counted by the water meter installed at the water inlet point of the i-th household during the t-th time interval, $dp_{i,t}$ (s) is the length of the time interval (typically of 1 to 2 s), and $CF = 60$ is a conversion factor allowing data conversion of from L/s to L/min.

The application of Equation (4.1) led to the obtainment of high-resolution (i.e. 1 or 2 s) water consumption time series at the household level. These were first subjected to linear interpolation in order to obtain a homogeneous set of water consumption data at the 1-s temporal resolution for all the households. From an operational standpoint, interpolation was carried out by using the *interp1* function tool included in MATLAB R2019a® programming software.

As far as the obtained 1-s resolution time series are concerned, data were checked for consistency to avoid considering periods without water consumption, as in the case of the Italian dataset. On the one hand, this led to the removal of 21 days without any water use in household H5 (due to holidays) and therefore to the reduction of the length of household H5 dataset to 73 days. On the other hand, no anomalous periods were found in the case of the other households. Overall, as shown in Table 4.2, daily average per capita water consumption of 70 to 152 L/person/day emerged, that is in line with the value of 107 L/person/day reported in the most recent Dutch study on residential water consumption available in the literature (i.e. Van Thiel (2017)). In addition, all water use events (i.e. time periods characterized by a positive flow rate and isolated from other events by a time interval of at least 1 s with no consumption) of duration of only 1 s and volume of 0.1 L were removed. In fact, these events – characterized by individual water meter pulses and reasonably assumed to be due to pulse conversion or meter in-accuracies – are likely to be unrelated to any effective end-use event. A total of 36,297 water use events of duration longer than 1 s and volume larger than 0.1 L were observed in the water consumption time series of the Dutch dataset.

Because water consumption of the Dutch dataset was collected at the household level, data processing and analysis were required to obtain water consumption time series at the end-use level. Specifically, the 36,297 water use events observed were automatically segmented into individual events by means of a new, rule-based filtering algorithm, and then manually labelled by expert analysts based on engineering judgment and the responses of water use questionnaires submitted to household inhabitants (as detailed in Paragraph 4.1.2.1 and Paragraph 4.1.2.2). To the latter aim, surveys about the main features of residential end uses and inhabitants' behaviours in terms of water use were submitted to the inhabitants of households H5–H13. Specifically, the survey sent to each household was designed in order to gather information about:

- Family composition (i.e. number of inhabitants, age range, and employment).
- Presence, type, and characteristics of domestic end uses (i.e. dishwasher, washing machine, mixer or knob taps, dual-flush toilet, and bathtub).
- Dishwasher, washing machine shower, and bathtub average frequency of use.
- Outdoor or other special water uses (e.g. garden taps, active irrigation systems, etc.)

The analysis of the replies sent back revealed that: (1) the households were occupied by 2 to 5 people in the period concerned, spacing from children and teenagers to adults (part- and full-time workers) and elders (retirees); (2) all the households are equipped with a washing machine and a dishwasher (except household H9, for which no information about dishwasher presence was given); (3) only households H5, H7 and H10 are equipped with a bathtub, although only the inhabitants of the households H5 and H7 declared that it is used sometimes; (4) households H5, H7, H10 and H11 are equipped with garden taps, but only the inhabitants of household H10 declared that it was occasionally used during the monitoring period (mainly for washing bicycles and not for irrigating).

4.1.2.1. Automated event segmentation and clustering

The Itron® water meters installed during the monitoring period were placed at the water inlet point of each household of the Dutch database. Given this, the water consumption time series obtained are representative of the total amount of water entering the households each second, with no information about the number and type of devices producing water inflow. Therefore, both individual and combined water use events are included in the (raw) aggregate water consumption trace of households H1-H9.

In the light of the above, a new, rule-based, automated method for the segmentation of combined water uses into individual uses was developed and applied to each event detected in the aggregate water consumption time series. Automated segmentation was carried out with the aim of providing the analysts a database of individual water uses to label without the need to manually segment combined water uses into individual events. In greater detail, consistently with Buchberger et al. (2003), the method is based on the following assumption: (1) individual water uses are typically characterized by constant (or nearly constant) flow rate, so they can be described by a rectangular shape in the time-flow plane (the area of which indicates the volume of water consumed); and (2) combinations of individual uses (i.e. combined events) generally appear as composite rectangular shapes due to partial overlaps of individual uses.

The main structure of the automated method for individual event segmentation is the following (see also Figure 4.1):

- Each water use event (i.e. each portion of the raw aggregate water consumption time series with a positive flow rate) is considered in turn (Figure 4.1 a). A moving window of limited width (e.g. 3 s) is used to filter the raw time series based on a moving average technique. Specifically, if an abrupt flow rate variation is observed in the raw signal – i.e. if the absolute difference between the average flow rate obtained by means of the moving average techniques at time t (s) and that obtained at time $t-1$ (s) exceeds a threshold value (e.g. 1 L/min) – this is related to the occurrence of a new opening or closing manoeuvre.
- The raw time series is split into sub-periods with nearly constant flow rate (Figure 4.1 b**)** based on time instants related the occurrence of opening or closing manoeuvres.
- The raw time series is smoothed based on the average value of flow rates observed in each sub-period (Figure 4.1 c). Moreover, opening (O) and closing (C) manoeuvres are numbered and selected on the raw signal, and their magnitude (i.e. flow rate variation) is calculated. In the case of non-combined water uses, only two manoeuvres (i.e. an opening and a closing manoeuvre of the same magnitude) are detected by the algorithm, due to the presence of an individual end-use event. By contrast, in the case of combined (i.e. water uses composed of more than one individual event)water uses, more than two manoeuvres are detected.
- As far as combined water uses are concerned, a first group of individual events making up the water use is identified through the direct matching of opening and closing manoeuvres of similar magnitude (Figure 4.1 d): in turn, each opening manoeuvre is matched to the closing

manoeuvre associated to the most similar flow rate variation. Moreover, the portion of the combined event between the time instants of occurrence of the two matched manoeuvres is considered as an individual water use event (characterized by a flow rate equal to that of the two matched manoeuvres). The detected individual event is then removed from the smoothed time series.

- In the event that not all the manoeuvres are directly relatable (e.g. in the case of manoeuvres of different magnitude, or combined water uses for which a different number of opening and closing manoeuvres are identified), the residual portion of the smoothed time series is segmented through horizontal cuts (Figure 4.1 e). In this event, two (or more) closing manoeuvres are relatable to a single opening manoeuvre (or vice versa).
- All the (combined and non-combined) events are removed from the raw water consumption time series, and the related set of individual events detected are considered instead.

The effectiveness of the automated method for the segmentation of water consumption data observed in households H5–H13 into individual events was first checked by testing its performance with reference to about 50 combined uses – including from one to four individual end-use events – for which segmentation could be reasonably verified by the analysts. However, it is worth specifying that the lack of a dataset of (known) combined water use events to use as a benchmark precluded a full evaluation of the overall performance of the method in successfully segmenting the combined water uses. Also, different results may be obtained in the case of the application of the method with different threshold values (e.g. 5-s wide moving window, or minimum allowable flow rate variations of 2 L/min in the case of opening and closing manoeuvres). Overall, the application of the method for the segmentation of Dutch water consumption data led to an increase in the number of water uses from 36,297 (4,319 of which are combined, i.e. the 11.9%) to 44,115. In greater detail, it results that the 4,319 combined uses detected were automatically segmented into 12,137 individual events, indicating that, on average, each combined water use is composed of 2.81 individual end-use events.

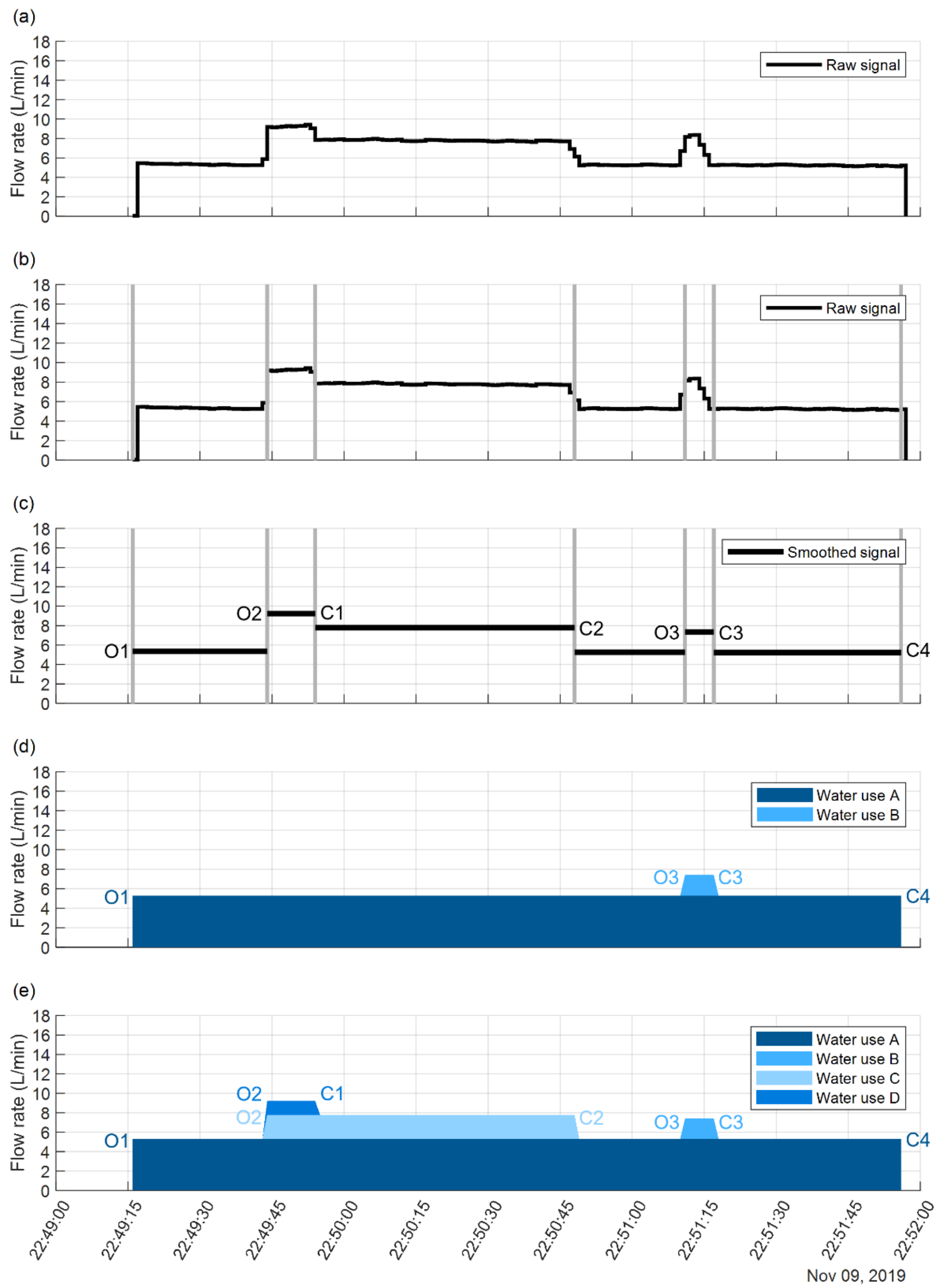

Figure 4.1. Example of application of the automated methodology for water use segmentation into individual events. The combined water use reported was observed in household H7.

In addition, once the set of 44,115 individual end-use events had been obtained, a clustering analysis was performed to provide the analyst with further information for event labelling. In greater detail, for each household, the frequency of occurrence of individual events was explored by locating each event in the duration-volume plane, i.e. by evaluating the number of events falling within each cell of a duration-volume mesh based on event duration and volume of water consumed (as shown in Figure 4.2).

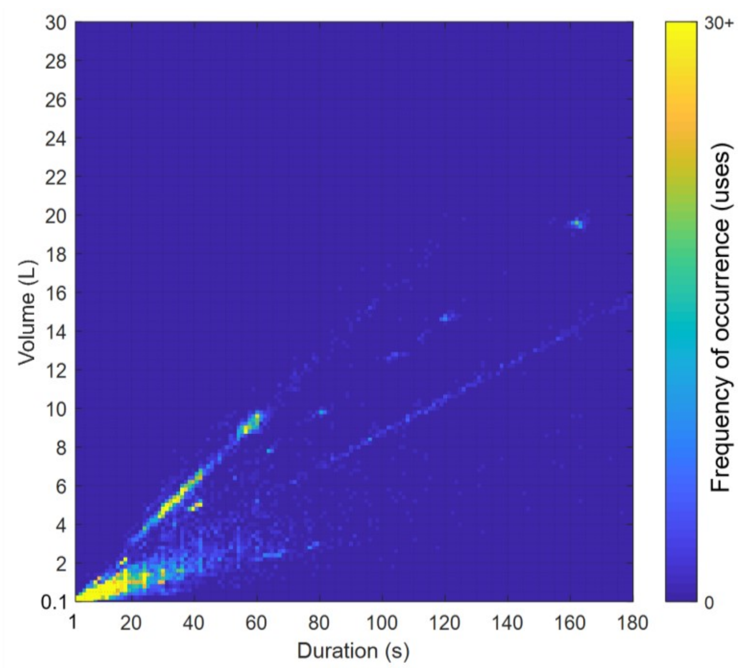

Figure 4.2. Individual water use clustering based on event duration and volume. Individual uses spread over lines are related to human-controlled end uses (e.g. taps, showers), whereas hotspots are related to fixed-volume or automated end uses (e.g. toilet, electric appliances). Water uses of household H7 are considered by way of example

The analysis revealed that, in general: (1) water use events are typically below a line the slope of which is equal to the maximum flow rate that can be provided by the domestic end uses of the household considered; (2) some events can be spread over lines and they are most likely related to human-controlled end uses (due to different durations and the constant flow rate); (3) some other events can be lumped into single hotspots and these are most likely related to fixed-volume or automated end-use events (e.g. toilet flushing or appliance uses). Specifically, the above-mentioned analysis allowed the obtainment of helpful information about the possible end-use category of individual events achieved. This information was considered – along with the information provided by the household inhabitants through surveys – when individual event labelling was conducted (as detailed in Paragraph 4.1.2.2).

4.1.2.2. Event manual labelling

All the individual uses resulting from the automated segmentation of the water consumption trace of the Dutch dataset were manually labelled, i.e. assigned to specific end-use categories. Event labelling was carried out with the aim of obtaining a water use database not only at high temporal level of detail but also at high spatial level (end-use level). From an operational standpoint, classification was conducted based on engineering judgment and relying both on the information obtained by clustering the events in the duration-volume mesh and those obtained from the replies of water use surveys submitted to the inhabitants. In greater detail, events were individually classified based on: (1) water use physical features (duration, volume, flow rate); (2) time of occurrence; (3) frequency of occurrence of events with similar characteristics; and (4) temporal distance from other events (with similar or dissimilar characteristics). In particular, as in the case of the Italian dataset, five categories were assumed: *dishwasher*, *taps*, *washing machine*, *shower and bathtub*, and *toilet*. Additionally, all the events the characteristics of which did not allow high confidence classification were labelled as *uncertain* uses. It is worth noting that shower and bathtub uses are considered together due to: (1) the similarity in duration and volume per use between these two categories, making the manual discrimination rather difficult in most of the cases; (2) the current tendency of people to mostly use the bathtub for having showers instead of baths, by basically activating the same tap; and (3) the limited use of the bathtub in the households concerned, as reported in the surveys.

Event labelling was conducted considering each individual event in turn (along with its characteristics and position in the aggregate water consumption time series). Classification was carried out by visualizing each event along with its features by means of MATLAB R2019a® programming software. Overall, given (1) the capability of labelling a maximum of 2,000 individual events per working day, and (2) an additional time of nearly two hours per household required to cluster individual events and process the information available in the water use surveys, a total of about 150 hours were required to perform manual labelling of all the 44,115 individual water use events resulting from the automated segmentation phase.

4.2. End-use data analysis

Subsequently to data collection and processing, the characteristics of end-use water consumption of the Italian and Dutch household samples were explored. Coherently with the research method adopted in *Chapter 3*, four of the six levels of the previously introduced end-use analysis (see Paragraph 3.3) were investigated, i.e.: (1) daily per capita end-use water consumption (Level 1); (2) end-use parameter average values (Level 2); (3) end-use statistical parameter distributions (Level 3); and (4) end-use daily profiles (Level 4). It is worth noting that, due to the lack of sufficient information, the evaluation of the determinants of end-use water consumption (i.e. Level 5) and the efficiency of water-saving end uses (i.e. Level 6) was not carried out at this stage.

From an operational standpoint, in order to compensate for the effects of individual water consumption behaviours observed in single households, the multi-level analysis carried out in relation to the overall group of monitored households Moreover, due to the coarser temporal resolution of the Italian dataset (i.e. 1 min), only Level 1 and Level 4 of the analysis were investigated, whereas the finer resolution of the Dutch dataset (i.e. 1 s) allowed a complete analysis on all the four levels. Lastly, as far as the Dutch dataset is concerned, a minimum temporal distance between two subsequent events of the same category was assumed for each end-use class, above which to consider them as separated water uses. Specifically, a minimum temporal distance of 5 s was considered in the case of taps and toilets, whereas a threshold of 2 min was assumed in the case of showers (given that people may be used to turn off the water several times – and also for some minutes – during the shower). In addition, as far as electric appliances are concerned, dishwasher and washing machine events occurring more than 90 min after their previous were considered to be related to separate loads.

4.2.1. Italian dataset

An (aggregate) average value of 115 L/person/day was observed in the households of the Italian dataset, the largest part of which is related to the use of taps (48 L/person/day, i.e. 42%) and toilets (34 L/person/day, i.e. 30%), as shown in Figure 4.3. Lower values are related to the use of washing machines (20 L/person/day, i.e. 17%), showers and bathtubs (9 L/person/day, i.e. 8%), and dishwashers (4 L/person/day, i.e. 3%). It is worth noting that, unexpectedly, daily per capita water consumption of showers and bathtubs is – on average – less than 10 L/person/day, as opposed to the results shown by other end-use studies carried out in similar contexts (see Table 3.3). However, this aspect was further investigated by checking on the replies of the surveys submitted to users, which confirmed that most of the householders have a tendency of showering at the sport facility (gym, swimming pool, etc.) rather than at home. Still with reference to the values reported in Table 3.3 for taps, considerably higher daily per capita values were met in the case of Italian database, which confirmed the most consuming end-use category.

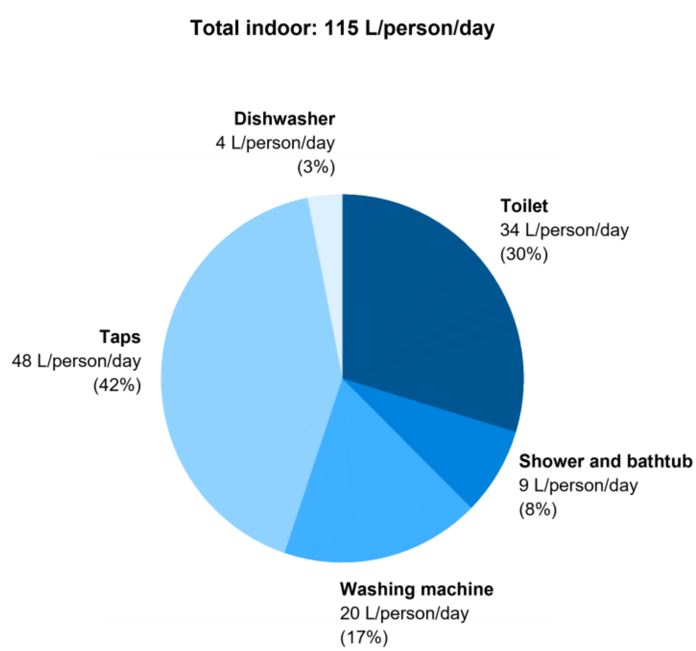

Figure 4.3. Daily per capita end-use water consumption (Italian dataset).

Despite the limited household sample making up the Italian dataset, the evaluation of the normalized (i.e. standardized) profiles of end-use water consumption highlights, on a daily basis, minimum consumption at night for all end uses, along with a variety of behaviours in diurnal hours based on the end use considered, as shown in Figure 4.4. In greater detail, a single (morning) peak in is observed for taps (Figure 4.4 b) and toilets (Figure 4.4 e), reasonably related to the routine morning activity of users (i.e. wakeup and preparation to go to work). However, the use of toilets and taps is rather constant throughout the day. By contrast, two peaks in washing machine use emerge (Figure 4.4 c) – suggesting that this kind of appliance is mostly used around midday and in the evening – whereas a more irregular profile is related to the use of showers-bathtubs and dishwashers (Figure 4.4 a and Figure 4.4 d). Regarding showers and bathtub, several peaks are observed at specific times of the day, most likely due to different habits, such as having showers before or after breakfast time, or when people come back home. Interestingly, regarding dishwashers, water uses are typically observed after mealtimes, i.e. in the afternoon or, mostly, at the early hours of the night.

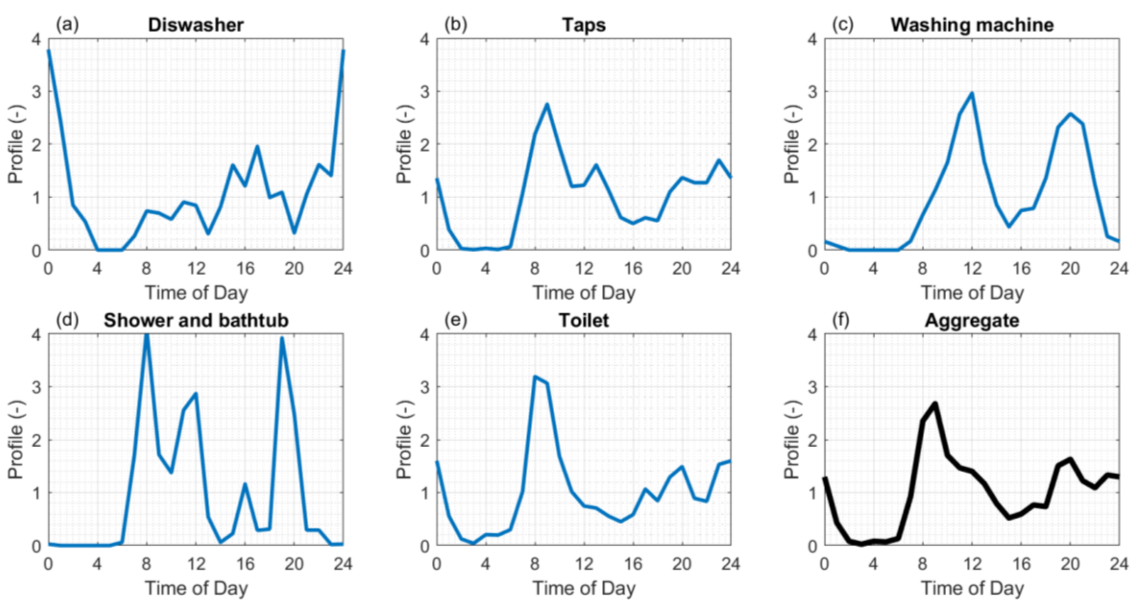

Figure 4.4. Daily end-use and aggregate profiles of water consumption (Italian dataset).

4.2.2. Dutch dataset

As far as the Dutch dataset is concerned, an (aggregate) average value of 121 L/person/day was observed, the majority of which is tied to the use of showers-bathtubs (46 L/person/day, i.e. 38%) and toilets (33 L/person/day, i.e. 27%), as indicated in Figure 4.5. By contrast, lower volumes are related to the use of washing machines (17 L/person/day, i.e. 14%), taps (15 L/person/day, i.e. 12%), and dishwashers (4 L/person/day, i.e. 3%), with a residual amount of 7 L/person/day (i.e. 6%) classified as uncertain use of water. Overall, the results obtained are in line with those reported by other end-use studies conducted with reference to similar geographical contexts (see Table 3.3) and confirm that, on average, the largest components of the daily residential water consumption are typically related to the use of showers/bathtubs and toilets, typically by washing machines and taps (the daily per capita water consumption values of which are generally rather close, as confirmed by the results shown in Figure 3.5).

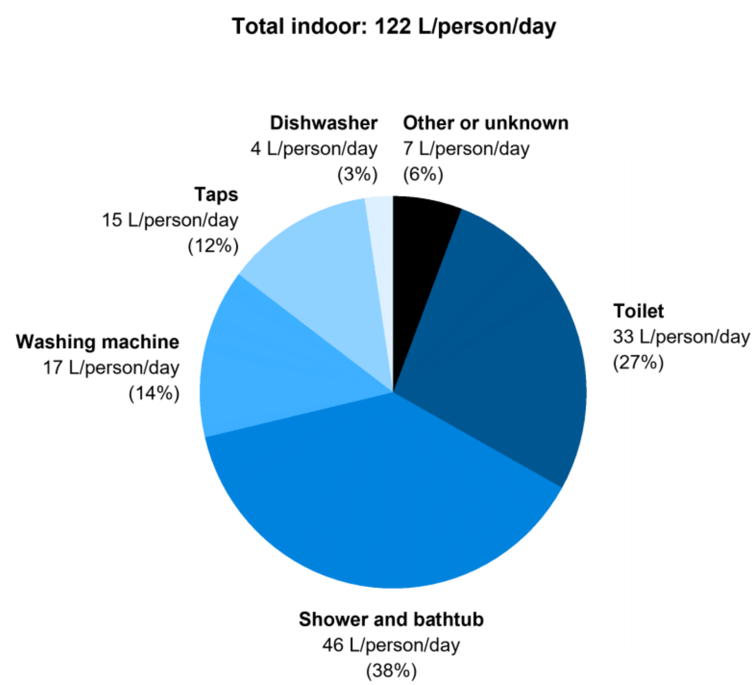

Figure 4.5. Daily per capita end-use water consumption (Dutch dataset).

The evaluation of the normalized (i.e. standardized) daily profiles of end-use water consumption reveals that, as expected, water consumption of toilets (Figure 4.6 e) and taps (Figure 4.6 b) is minimum at night and pretty constant in diurnal hours, confirming that the above-mentioned end uses are generally used in a constant manner throughout the day (although peaks in water consumption emerged in the morning and at dinner time, respectively, when people are most likely to be at home). On the other hand, a more lumped water consumption of showers-bathtubs (Figure 4.6 d) is met at specific times of the day, being these end-uses characterized by a higher peak of use in the morning (when people get up) along with a lower peak in the evening (when people come back home). In greater detail, two peaks of water consumption emerge in the morning, the former of which around 7:00 and the second of which around 9:00. These different behaviours in terms of water use are most likely due to different inhabitants' profiles (ranging from children to students, part- or full-time workers, and retirees) and also different habits, such as having showers before or after breakfast time. Furthermore, as far as appliance profiles are concerned, a single peak of water consumption is observed around midday in the case of washing machine (Figure 4.6 c), whereas a rather heterogeneous profile emerges in the case of dishwasher use (Figure 4.6 a), although it reveals that – as in the case of the Italian dataset – this appliance is typically used around breakfast/mealtime or during the night. Overall, the daily end-use profiles obtained are in line with those shown in the number of end-use studies including this kind of information (see, by way of comparison, Figure 3.13).

In addition, the high-resolution of the Dutch dataset allowed the investigation of end-use parameters (such as daily frequency of use, volume per use, duration per use, and flow rate per use) along with their probability distribution. This information was obtained by statistically analysing the characteristics of all the events included in each end-use category, in turn. As far as the duration per use is concerned, it results that only shower uses last several minutes (on average, 8.0 min/use), whereas toilet and tap use duration is only of some seconds (on average, about 50 s/use in the former case and 15 s/use in the latter). It can be also observed that, despite the considerably long duration of appliance loads (which may typically last up to 3 hours), the average total duration of washing machine and dishwasher inflow is only of about 8.2 and 4.3 min/load, respectively, revealing that appliances typically work without drawing water in for most of the duration of the load. In addition, considering volume per use, the analysis shows that showers-bathtubs and washing machines are the most consuming end uses, with about (on average) 63.6 L/use and 62.9 L/load respectively. These are followed by dishwashers (11.4 L/load), toilets (6.8 L/flush), and taps (1.2 L/use). When the flow rate per use is considered, the highest average values are observed in the case of toilets (8.3 L/min), showers (7.9 L/min), and washing machines (7.0 L/min), whereas lower values emerge in the case of taps (4.8 L/min) and dishwashers (2.8 L/min). At last, considering frequency of use, it emerges that, on average, taps are activated the most (about 13.8 times/person/day), followed by toilets (4.2 flushes/person/day). Besides, inhabitants are used to having a shower (or a bath) about three times every four days (i.e. 0.76 uses/person/day), whereas dishwashers and washing machines are typically loaded with daily frequency only in households with 3-4 inhabitants (i.e. 0.27 loads/person/day). This means that, although toilet and tap volumes per use are generally the smallest, the contribution of these end uses to the total indoor water consumption is significant because of their considerably high daily frequency of use.

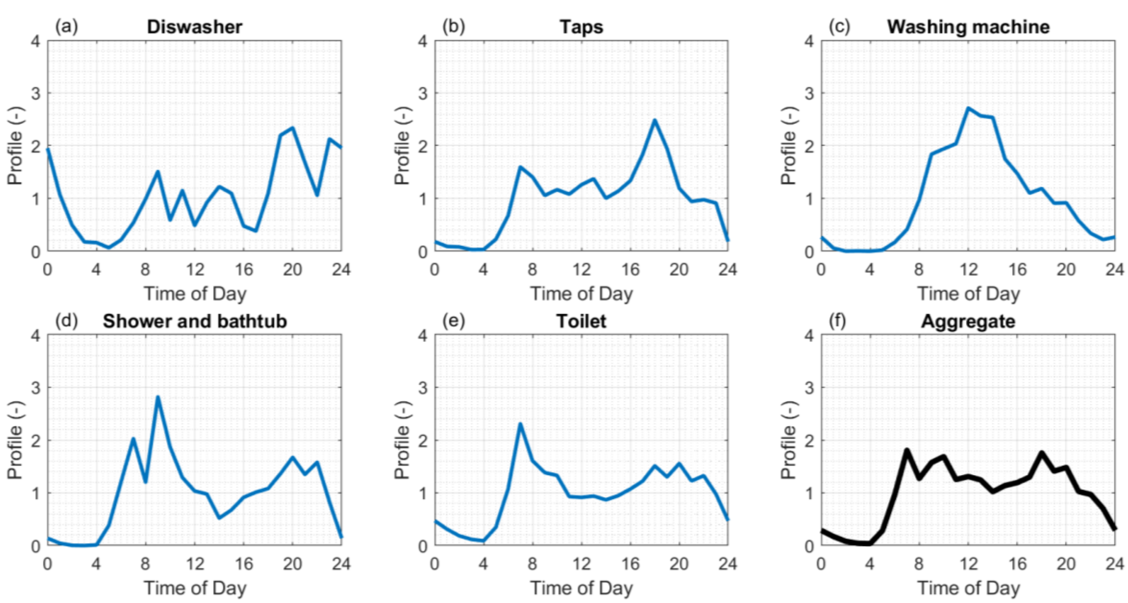

Figure 4.6. Daily end-use and aggregate profiles of water consumption (Dutch dataset).

In general, the average end-use parameter values obtained result in line with those of some previously conducted Dutch end-use studies (i.e. Kanne (2005), Foekema et al. (2008), Foekema and Van Thiel (2011), Van Thiel (2014), Van Thiel (2017)), although with some slight differences for some end uses and parameters. More details on the average end-use parameter values of the Dutch dataset and the corresponding values reported in other Dutch studies are available in Table C.1 and Table C.2 (Appendix C).

The findings met in the case of the end-use parameter average values are confirmed by the outcomes achieved with the analysis of their statistical distribution. The statistical distributions of the overall Dutch dataset are shown in Figure 4.7 (blue lines) along with details about distribution type and parameters. Statistical distributions are also compared against their respective empirical distributions (thick grey lines) obtained with respect to the overall Dutch dataset. Overall, right-skewed PDFs emerge in most of the cases, fitted by lognormal, Weibull, or Gamma distributions. However, some parameter distributions are fitted by normal or nearly normal curves (e.g. toilet duration, shower flow rate, and toilet flow rate), indicating that, in these cases, the end-use parameter values are distributed almost symmetrically around the average. By contrast, an exception is represented by washing machine flow rate values, which are successfully fitted by a slightly left-skewed Weibull PDF. As far as duration and volume distributions are concerned, empirical and statistical PDFs substantially fit in the case of some end uses (taps, washing machine, shower, and bathtub), while larger differences emerge for other uses (dishwasher, toilet). This deviation between empirical and statistical PDFs of dishwasher and toilet uses is partially due to the limited household sample of the Dutch dataset – making the empirical distribution of parameter values nearly multimodal – and partially due to the limited variability of appliance and toilet parameters in the same household, in the light of the fact that their volume and duration are generally fixed. In fact, parameter distributions of individual households result considerably narrower than the corresponding statistical distribution of the overall set of households. In general, differences between statistical and empirical PDFs are also observed in the case of end-use flow rates, which may differ from household to household based on: (i) location (i.e. pressure head available at the water inlet point); (ii) plumbing system layout and age; (iii) end-use type (i.e. make and model). The only exception is represented by tap flow rate, which is characterized by a smoothed distribution with the absence of multiple peaks. This is most likely due to the fact that

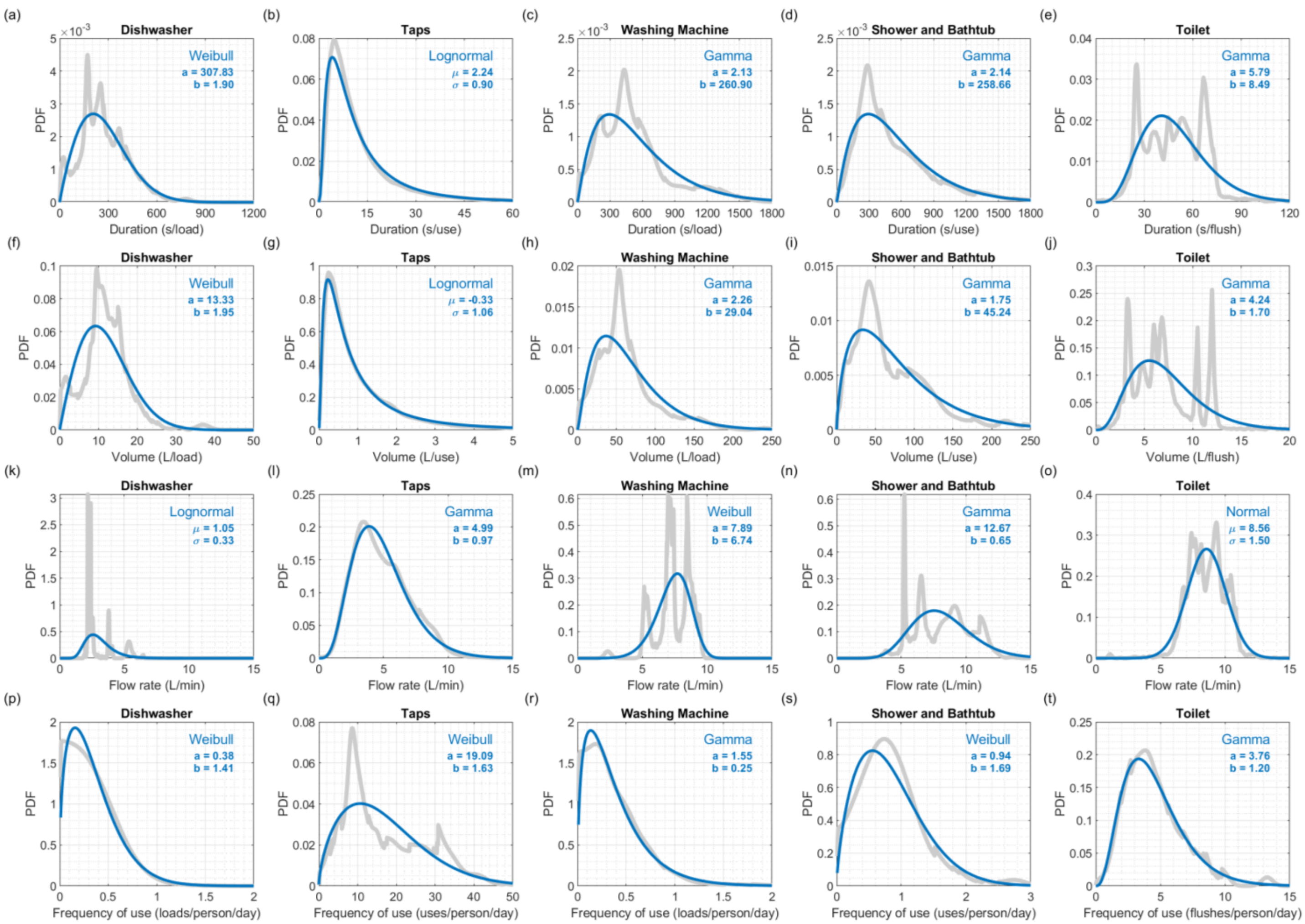

Figure 4.7. Statistical (blue) and empirical (grey) PDF curves of different end uses and parameters (Dutch dataset).

taps are typically used in a variety of ways (i.e. not only with different durations, but also by regulating the flow rate) even within the same household. Lastly, with reference to end-use daily frequency of use, most of the PDF obtained (i.e. nearly symmetrical or right-skewed Weibull or Gamma distributions) well approximate their respective empirical distributions. The highest differences are observed in the case of taps, where a multi-peak empirical distribution – fitted by a slightly right-skewed Weibull curve – is met, as a consequence of different behaviours in terms of tap use within households not only as far as end-use timing of use and modulation are concerned (see, by way of example, the statistical distribution of tap duration per use and flow rate), but also in terms of frequency of use. In the light of the aforementioned deviations between empirical and statistical PDFs of some end uses and parameters, only the empirical PDFs were considered to obtain the parameters required for automated end-use disaggregation and classification, as pointed out in Paragraph 4.4.

4.3. Automated methodology for end-use disaggregation and classification

The automated method for end-use disaggregation and classification presented in the current thesis is a revised version of the method originally proposed by Mazzoni et al. (2019), Mazzoni et al. (2021a) and Mazzoni et al. (2022b). This rule-methodology detects, disaggregates, and classifies individual water uses one end-use category at a time by means of a set of functions that are applied in a specific order, starting with the detection of automated water uses (i.e. appliance uses), and ending with the detection of human-controlled water uses (i.e. shower, toilet, and tap uses).

The main structure of the automated methodology is shown in Figure 4.8: first, the use of electric appliances is investigated through the *dishwasher function* and the *washing machine function*; then, shower uses are assessed through the *shower function*; lastly, toilet and tap uses (which are

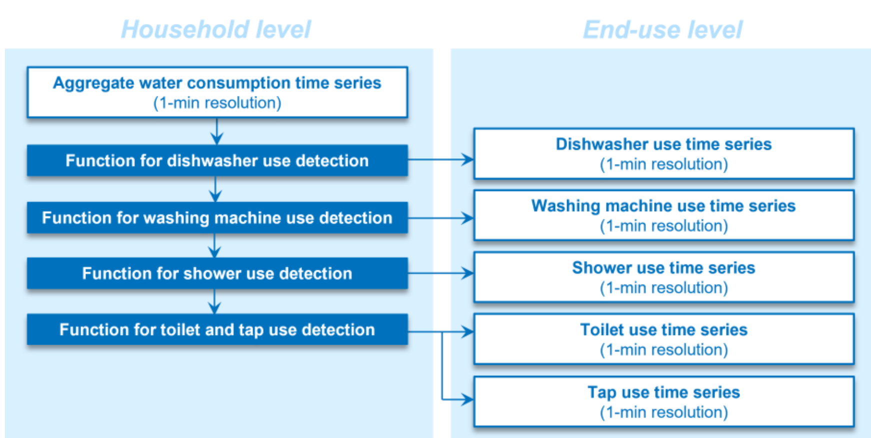

Figure 4.8. Structure of automated methodology for water end-use disaggregation.

generally less recognisable at 1-min resolution due to their limited duration) are detected and classified by means of the *toilet and tap function*. On completion of the process, the water use time series for each end-use category are available.

Both the original and the revised version of the method have been developed using MATLAB R2019a® programming software and consist of a main code – in which the Microsoft Excel® spreadsheet including the collected aggregate water use is loaded – and the functions for water-use disaggregation and classification, which are applied in turn, as described above. More specifically, the main improvements of the revised version of the method include:

- The adoption of a metric (i.e. Euclidean distance) allowing the assessment of how much water use events are similar to the most common events of each end-use category;
- The independence from temporal parameters (i.e. the search and the identification of all the events of a given end-use category is carried out throughout the whole day, and not only at specific times of the day);
- The possibility of identifying appliance operational programs (hereinafter called *loads*) made up of an arbitrary number of water inflows (hereinafter called *withdrawals*) defined by the analyst, and not only those made up of a fixed and predefined number.

Overall, in each function, end-use disaggregation and classification are performed based on: (1) the identification of all the water uses possibly related to that specific end-use category based on their characteristics (e.g. if volume and duration fall within a specific range related to that category); and (2) the selection of the events the characteristics of which are the most similar to the average water use characteristics of that category. Therefore (as detailed in Paragraph 4.4), to perform water use disaggregation and classification, the automated methodology requires the input of a set of parameters (related to householders' habits and end-use features) the value of which can be specifically defined for each household – based on knowledge about the householders' habits and the features of the end uses concerned – or by considering the average characteristics of water use, based on common-sense observations or relying on literature information.

The underlying ideas and the main characteristics of the functions for end-use disaggregation and classification are described below, whereas function flow charts are available in Appendix D (see Figure D.1, Figure D.2, and Figure D.3):

4.3.1. Appliance water use (dishwasher, washing machine)

Appliance loads typically include a number of relatively short inflow events (i.e. *withdrawals*) between longer periods of time during which the machine does not draw water in. Volume, duration, and time of occurrence of these water withdrawals are different based on manufacturer, model, and program. In the light of the above, the function for appliance use disaggregation and classification (Figure D.1) first identifies all the possible appliance withdrawals based on their physical features (i.e. duration d and volume v, the values of which have to fall within specific thresholds, i.e. $[d_{min}; d_{max}]$ and $[v_{min}; v_{max}]$, respectively). Then, a group of possible withdrawals is classified as a possible appliance load if their number X and temporal distance p from other possible withdrawals fall within the acceptance parameter thresholds (i.e. $[X_{min}; X_{max}]$, $[pi_{min}; pi_{max}]$, and $[pf_{min}; pf_{max}]$, respectively). In the case of time overlapping possible loads (or if the number n of daily possible loads is higher than a given threshold n_{max}) only the possible loads the characteristics of which are the closest to the average characteristics of appliance loads are selected. From an operational standpoint, the deviation of a possible appliance load from the average is evaluated through the Euclidean distance E_A, as shown in Equation (4.2):

$$E_A = \sqrt{\left(\frac{D - D_{avg}}{D_{max} - D_{min}}\right)^2 + \left(\frac{V - V_{avg}}{V_{max} - V_{min}}\right)^2 + \left(\frac{X - X_{avg}}{X_{max} - X_{min}}\right)^2} \qquad (4.2)$$

where: D, V, and X are the total duration of the possible load, its overall consumption, and the number of occurred water withdrawals, respectively; D_{avg}, V_{avg}, and X_{avg} are the average duration, consumption, and number of withdrawals of appliance loads in a selected household; and, finally, D_{min}, D_{max}, V_{min}, V_{max}, X_{min}, and X_{max} are the minimum and maximum values allowable for appliance loads in the household considered. It is worth noting that, based on Equation (4.2), a possible load event for which duration, consumption and number of withdrawals are equal to their respective average values of a given household would result in an error $E_A = 0$, whereas the largest is the deviation of one or many parameters from their average, the highest would be the error E_A. Overall, 18 parameters per appliance (i.e. dishwasher *versus* washing machine) are required to perform appliance use detection, disaggregation and classification, as detailed in Table 4.3 (Paragraph 4.4): minimum, average, and maximum load duration (i.e. D_{min}, D_{avg}, and D_{max}); minimum, average, and maximum load consumption (i.e. V_{min}, V_{avg}, and V_{max}); minimum, average, and maximum number of appliance withdrawal per load (i.e. X_{min}, X_{avg}, and X_{max}); minimum and maximum duration of individual withdrawals (i.e. d_{min} and d_{max}); minimum and maximum consumption of individual withdrawals (i.e. v_{min} and v_{max}); minimum and maximum time distance between the first two withdrawals of the load (i.e. pi_{min} and pi_{max}); minimum and maximum time distance between the subsequent withdrawals of the load (i.e. pf_{min} and pf_{max}); and maximum daily frequency for appliance use (i.e. n_{max}).

Lastly, it is worth noting that, although the function for appliance use detection is the same for dishwasher and washing machine, the parameter values to input are different based on the end-use to detect.

4.3.2. Shower water use

Shower uses are typically characterized by durations up to several minutes and considerable volumes of water used. However, these durations and volumes depend on the way in which people use showers: in fact, some people might be used to turning the water on and off, whereas some other may be used to having a shower with no water interruptions. The function for shower use detection (Figure D.2) analyses all the individual water uses in turn to first select all possible shower uses based on duration D, consumption V, and maximum duration p of water interruption during the use (the values of which have to fall within specific thresholds, i.e. $[D_{S,min}; D_{S,max}]$, $[V_{S,min}; V_{S,max}]$, and $[0; p_{S,max}]$ respectively. In the event that the number n of daily possible shower uses is higher than a given threshold $n_{S,max}$, only the uses the characteristics of which are the closest to the average characteristics of shower uses are selected. As in the case of appliance use detection, the deviation of a possible shower use from the average shower characteristics of a given household is evaluated through the Euclidean distance E_S, as shown in Equation (4.3):

$$E_S = \sqrt{\left(\frac{D - D_{S,avg}}{D_{S,max} - D_{S,min}}\right)^2 + \left(\frac{V - V_{S,avg}}{V_{S,max} - V_{S,min}}\right)^2} \tag{4.3}$$

where: D, and V are the total duration of the possible shower use and its overall consumption, respectively, whereas $D_{S,min}$, $D_{S,avg}$, $D_{S,max}$, $V_{S,min}$, $V_{S,avg}$, and $V_{S,max}$, are the minimum allowable, the average, and the maximum allowable values allowable for shower uses in the household considered. Therefore, 8 parameters are required to perform shower water use detection (see Table 4.3): minimum, average, and maximum shower duration (i.e. $D_{S,min}$, $D_{S,avg}$ and $D_{S,max}$); minimum, average, and maximum shower consumption (i.e. $V_{S,min}$, $V_{S,avg}$, and $V_{S,max}$); maximum duration of flow interruption during shower use (i.e. $p_{S,max}$); and maximum daily frequency for shower use (i.e. $n_{S,max}$).

4.3.3. Toilet and tap water use

As reported in *Chapter 3*, toilet water consumption per flush is generally constant in the case of the same fixture due to the characteristics of the current flushing systems, whereas tap water consumption can be considerably various based on householders' activity. However, as far as duration is concerned, both toilet and tap uses are typically characterized by minute or sub-minute durations, making these uses hard to detect at 1-min resolution.

In the light of the above, toilet and tap uses are detected by means of a function which is applied after appliance and shower use detection (the structure of which is shown in Figure D.3). As in the case of the other functions, each (still uncategorized) water use event is classified as toilet or tap use based on its physical features (i.e. duration D and consumed volume V): in greater detail, if the water use event is compatible with toilet characteristics (i.e. $D \in [D_{F,min}; D_{F,max}]$ and $V \in [V_{F,min}; V_{F,max}]$) but not with tap characteristics (i.e. $D \notin [D_{T,min}; D_{T,max}]$ or $V \notin [V_{T,min}; V_{T,max}]$), it is considered a toilet use. By contrast, if the event is compatible with tap characteristics but not with toilet characteristics, it is considered a tap use. Third, if the water use is compatible with both toilet and tap characteristics, the deviation between the average values of toilet and tap uses is evaluated and the Euclidean distance from them is calculated with respect to both categories (i.e. E_F and E_T), as shown in Equation (4.4) and Equation (4.5):

$$E_F = \sqrt{\left(\frac{D - D_{F,avg}}{D_{F,max} - D_{F,min}}\right)^2 + \left(\frac{V - V_{F,avg}}{V_{F,max} - V_{F,min}}\right)^2} \quad (4.4)$$

$$E_T = \sqrt{\left(\frac{D - D_{T,avg}}{D_{T,max} - D_{T,min}}\right)^2 + \left(\frac{V - V_{T,avg}}{V_{T,max} - V_{T,min}}\right)^2} \quad (4.5)$$

The event is then classified to the end-use category for which the Euclidean distance is the shorter (i.e. toilet, if $E_F \leq E_T$, and tap, if $E_F > E_T$). Finally, in the case that a residual water use event is not directly compatible with the characteristics of individual toilet or tap uses (i.e. $D \notin [D_{F,min}; D_{F,max}]$ and $V \notin [V_{F,min}; V_{F,max}]$, or $D \notin [D_{T,min}; D_{T,max}]$, and $V \notin [V_{T,min}; V_{T,max}]$), the event is split in two and assigned to both categories proportionally to the average volume per use of toilet and taps. Overall, a total of 12 parameters are required by the function to perform toilet and tap water use detection, as detailed in Table 4.3: minimum, average, and maximum toilet duration (i.e. $D_{F,min}$, $D_{F,avg}$, and $D_{F,max}$); minimum, average, and maximum toilet consumption . $V_{F,min}$, $V_{F,avg}$, and $V_{F,max}$); minimum, average, and maximum tap duration (i.e. $D_{T,min}$, $D_{T,avg}$, and $D_{T,max}$); and minimum, average, and maximum tap consumption (i.e. $V_{T,min}$, $V_{T,avg}$, and $V_{T,max}$).

4.3.4. Example of method application

An illustrative application of the methodology is shown in Figure 4.9 and discussed below, by way of example. In greater detail, the aggregate water consumption time series shown in the figure is taken from the water consumption time series of household H2 (Italian dataset). In addition, the parameters for end-use disaggregation and classification refer specifically to household H2 and were obtained by statistically analysing the end-use time series of this household for the calibration period, as detailed in Paragraph 4.4). The main steps of the automated methodology are as follows:

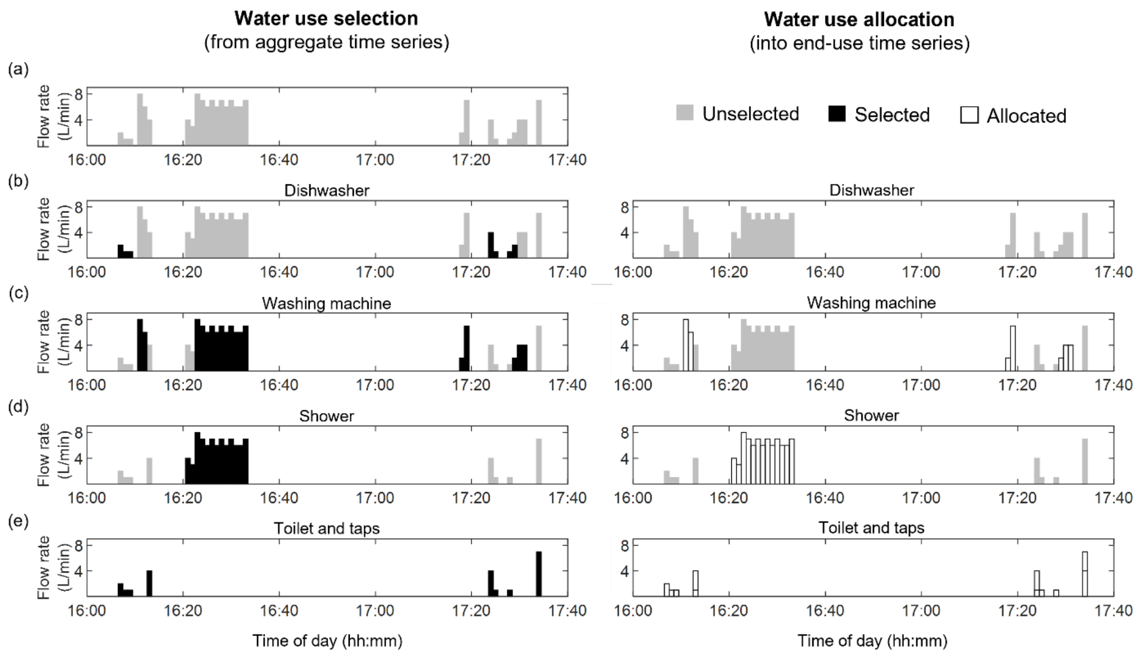

Figure 4.9. Example of application of automated methodology. Disaggregation parameters and the aggregate water consumption time series considered here refer to household H2 (Italian dataset).

1. Household parameters for end-use disaggregation and classification and the aggregate water consumption time series are considered (Figure 4.9 a).
2. The function for dishwasher use detection is applied (Figure 4.9 b). All possible daily dishwasher withdrawals are selected, i.e., water uses the duration d of which is in the range $[d_{DW,min}; d_{DW,max}]$ (e.g. $[1\ min; 2\ min]$) and the volume v of which is in the range $[v_{DW,min}; v_{DW,max}]$ (e.g. $[1\ L; 4\ L]$), without interruptions of flow. If some of these possible withdrawals are in a number $X \in [X_{DW,min}; X_{DW,max}]$ (e.g. $[1; 5]$) and time intervals p between the first two and the subsequent ones them are in the allowed ranges $[pi_{DW,min}; pi_{DW,max}]$ and $[pf_{DW,min}; pf_{DW,max}]$ (e.g. $[8\ min; 43\ min]$ and $[5\ min; 33\ min]$

respectively), such uses would be classified as a dishwasher load. In this example, owing to the lack of those conditions, no dishwasher load are found.

3. The function for washing machine use detection is applied (Figure 4.9 c). All possible daily dishwasher withdrawals are selected, i.e., water uses the duration d of which is in the range $[d_{WM,min}; d_{WM,max}]$ (e.g. $[1\ min; 3\ min]$) and the volume v of which is in the range $[v_{WM,min}; v_{WM,max}]$ (e.g. $[2\ L; 15\ L]$), without interruptions of flow. In this example, some of the selected possible withdrawals are in a number $X \in [X_{WM,min}; X_{WM,max}]$ (e.g. $[3; 7]$) and time intervals p between the first two and the subsequent ones them are in the allowed ranges $[pi_{WM,min}; pi_{WM,max}]$ and $[pf_{WM,min}; pf_{WM,max}]$ (e.g. $[2\ min; 84\ min]$ and $[6\ min; 86\ min]$ respectively). This group of withdrawals (i.e. possible washing machine load) also satisfies the following conditions: (i) the total duration D of the possible load is in the range $[D_{WM,min}; D_{WM,max}]$ (e.g. $[82\ min; 142\ min]$); (ii) the total consumption V of the possible load is in the range $[V_{WM,min}; V_{WM,max}]$ (e.g. $[54\ L; 62\ L]$); (iii) the possible load is not time overlapped with other loads; and (iv) the number n of daily possible loads is in the range $[0; n_{S,max}]$ (e.g. $[0; 1]$). Therefore, all the aforementioned water uses are classified as a washing machine load and removed from the aggregate time series.
4. The function for shower use detection is applied (Figure 4.9 d). All daily possible shower uses are selected, i.e. water uses the duration D of which is in the range $[D_{S,min}; D_{S,max}]$ (e.g. $[3\ min; 9\ min]$); and the consumption V of which is in the range $[V_{S,min}; V_{S,max}]$ (e.g. $[12\ L; 34\ L]$);,with a maximum flow interruption p of $p_{S,max}$ (e.g., 6 min). In this example, a single daily water use satisfying the above-mentioned conditions is found. Because it is in the range $[0; n_{S,max}]$ (e.g. $[0; 1]$), it is classified as a shower use and removed from the aggregate time series.
5. The function for toilet and tap use detection is applied (Figure 4.9 e). Residual water uses are analyzed in turn. If water use is compatible with toilet use – that is $D \in [D_{F,min}; D_{F,max}]$ (e.g. $[2\ min; 4\ min]$) and $V \in [V_{F,min}; V_{F,max}]$ (e.g. $[3\ L; 9\ L]$) – but not with tap use – that is $D \notin [D_{T,min}; D_{T,max}]$ (e.g. $[1\ min; 3\ min]$) or $[V_{T,min}; V_{T,max}]$ (e.g. $[1\ L; 8\ L]$) – the water use is classified as toilet use; (ii) if water use is compatible with tap use but not with toilet use, the water use is classified as tap use; (iii) if water use is compatible with both toilet and tap use,

the Euclidean distances E_F and E_T of the water use from the average toilet and tap uses – that is $\{D_{F,avg}; V_{F,avg}\}$ (e.g. $\{2\ min; 4\ L\}$), and $\{D_{T,avg}; V_{T,avg}\}$ (e.g. $\{1\ min; 2\ L\}$) – are calculated, and the water use is assigned to the end-use category related to the lowest Euclidean distance, i.e. $\text{argmin}\{E_F; E_T\}$; (iv) if water use is not compatible with toilet use and neither with and tap use, it is assigned to both toilet and tap by dividing its overall consumption proportionally to the average consumption of toilet and tap (i.e. $V_{F,avg} = 4\ L$ and $V_{T,avg} = 2\ L$). Each water use, once classified, is removed from the aggregate time series.

4.4. Disaggregation and classification parameters

To perform end-use disaggregation and classification of water consumption, the automated methodology requires the input of a set of household parameters – related to users' habits and end-use features – as shown in Table 4.3.

Table 4.3. Automated methodology parameters.

End use	**Feature**	**Parameter(s)**	**Unit**	**General values (Italian dataset)**			**General values (Dutch dataset)**		
				Min	**Avg**	**Max**	**Min**	**Avg**	**Max**
Dishwasher	Overall load duration	$D_{DW,min}$; $D_{DW,avg}$; $D_{DW,max}$	Min	36	77	96	25	73	118
	Overall load consumption	$V_{DW,min}$; $V_{DW,avg}$; $V_{DW,max}$	L	4	10	13	5	11	16
	Number of withdrawals per load	$X_{DW,min}$; $X_{DW,avg}$; $X_{DW,max}$	number/load	1	3	5	2	3	5
	Individual widthdrawal duration	$d_{DW,min}$; $d_{DW,max}$	Min	1	-	3	1	-	3
	Individual widthdrawal volume	$v_{DW,min}$; $v_{DW,max}$	L	1	-	5	1	-	5
	Time from first to second withdrawal	$pi_{DW,min}$; $pi_{DW,max}$	Min	14	-	34	8	-	54
	Time between subsequent withdrawal	$pf_{DW,min}$; $pf_{DW,max}$	Min	7	-	58	5	-	49
	Maximum number of loads per day	$n_{DW,max}$	uses/day	-	-	2	-	-	2
Washing machine	Overall load duration	$D_{WM,min}$; $D_{WM,avg}$; $D_{WM,max}$	Min	48	83	117	27	70	174
	Overall load consumption	$V_{WM,min}$; $V_{WM,avg}$; $V_{WM,max}$	L	31	42	60	29	54	98
	Number of withdrawals per load	$X_{WM,min}$; $X_{WM,avg}$; $X_{WM,max}$	number/load	3	4	6	2	4	9
	Individual withdrawal duration	$d_{WM,min}$; $d_{WM,max}$	Min	1	-	4	1	-	5
	Individual withdrawal volume	$v_{WM,min}$; $v_{WM,max}$	L	4	-	16	4	-	20
	Time from first to second withdrawal	$pi_{WM,min}$; $pi_{WM,max}$	Min	6	-	76	3	-	47

Table 4.3 (Continued). Automated methodology parameters.

End use	Feature	Parameter(s)	Unit	General values (Italian dataset)			General values (Dutch dataset)		
				Min	Avg	Max	Min	Avg	Max
Washing machine	Time between subsequent withdrawal	$pf_{WM,min}$; $pf_{WM,max}$	Min	3	-	47	4	-	47
	Maximum number of loads per day	$n_{WM,max}$	uses/day	-	-	2	-	-	2
Shower	Overall duration	$D_{S,min}$; $D_{S,avg}$; $D_{S,max}$	Min	4	8	15	5	9	15
	Overall consumption	$V_{S,min}$; $V_{S,avg}$; $V_{S,max}$	L	14	36	63	35	58	108
	Maximum duration of flow interruption	$p_{S,max}$	Min	-	-	3	-	-	1
	Maximum number of showers per day	$n_{S,max}$	uses/day	-	-	2	-	-	4
Toilet	Toilet flush duration	$D_{F,min}$; $D_{F,avg}$; $D_{F,max}$	Min	1	2	3	1	2	3
	Toilet flush consumption	$V_{F,min}$; $V_{F,avg}$; $V_{F,max}$	L	5	8	12	4	7	11
Faucets	Tap use duration	$D_{T,min}$; $D_{T,avg}$; $D_{T,max}$	Min	1	1	4	1	1	3
	Tap use consumption	$V_{T,min}$; $V_{T,avg}$; $V_{T,max}$	L	1	2	11	1	1	5

The values of each parameter vary among households because of different users' habits and end-use features. In the light of the above, the value for each parameter can be defined in a *specific* or a *general* way. On the one hand, specific parameter values relate to individual dwelling characteristics and can be obtained from the analysis of householders' habits and the features of the end uses concerned. However, the obtainment of such an information often requires direct, intrusive monitoring, single dwelling investigations, a detailed specification of appliance makes and models, and interaction with users (based, e.g., on surveys). On the other hand, general parameter values describe the average end-use features and the typical users' attitude towards water consumption. Such values can be obtained based on common-sense observations or by referring to information available in the literature, avoiding the need to conduct infeasible, expensive, and time-consuming operations for the assessment of the specific values.

The automated methodology for end-use disaggregation and classification was applied considering both specific and general parameter values. Parameter values were obtained as detailed below:

- The aggregate water consumption and the individual end-use time series of each household were split into (i) a *calibration* dataset (for the obtainment of household parameters) and (ii) a *validation* dataset (for testing the methodology). Only the calibration dataset was considered for the evaluation of disaggregation and classification parameters.

- Specific values were defined for each household through the empirical PDFs of the related end-use parameters. In greater detail, these were evaluated in relation to the calibration dataset and by considering water consumption time series at the 1-min temporal resolution (i.e. the resolution required by the model) for each household and end-use category, in turn. Specific values were assigned to each parameter based on the percentiles of the respective distribution: the 50th percentile of the distribution was assigned to average parameter values (e.g. $D_{DW,avg}$), whereas the 10th and the 90th percentile were assigned to the minimum and the maximum parameter values, respectively (e.g. $D_{DW,min}$ and $D_{DW,max}$). It is worth noting that the 10th and the 90th percentile were considered instead of the extreme values of each distribution to avoid assigning parameter values based on exceptional events (i.e. outlier uses) which are not really representative of the actual characteristics of water consumption.
- The values of the specific parameters obtained for all the households of a given dataset (i.e. Italian or Dutch) were then averaged to obtain the set of general parameter values, representative of the overall household sample. General parameter values for the two above-mentioned datasets are shown in Table 4.3.

On the one hand, far as the Italian dataset is considered, specific parameter values were defined by considering only households H1, H2, and H3 end-use time series over a monthly calibration period (i.e. using only the data collected from 1 to 31 January 2018). Specific values were then averaged to obtain the respective general values. By contrast, it is worth noting that household H4 was not considered for the calibration of the methodology, i.e. the end-use time series related to this household were not investigated to define specific and general parameter values. This was done in order to keep household H4 exclusively as a test sample for a further validation of the methodology and the demonstration of its effectiveness.

On the other hand, considering the Dutch dataset (for which end-use time series are first aggregated at the 1-min temporal resolution (according to the resolution required by the model), specific and general parameter values were obtained in relation to a calibration period covering the first half of the overall monitoring period of each household. The choice of considering calibration and validation datasets of different lengths – given the different duration of the monitoring periods among households, ranging from 10 to 92 days – was aimed at testing the method efficiency under different conditions, i.e. based on different-sized calibration datasets. It is also worth noting that only the water uses included in the five end-use categories denoted in Paragraph 4.3 (i.e. dishwasher, washing machine, shower, toilet, and taps) ware considered, whereas the events classified by the analysts as *uncertain* or *other* uses were neglected.

4.5. Evaluation of method performance

The performance of the automated methodology for end-use disaggregation and classification was assessed through a comparison against the observed end-use data. In greater detail, the aggregate water consumption time series (over the validation period) of each household was input in the model in turn – along with specific or general parameter values – whereas the data collected at the end-use level over the corresponding period were used as a benchmark against which to evaluate the performance of the method. To summarize, the following analyses were conducted:

- *Method original validation and test*, i.e. automated disaggregation and classification (with specific and general parameter values) of water consumption in households H1–H3 of the Italian dataset, and test of the performance (with the previously defined general parameter values) on household H4 water consumption data, the parameters of which have not been investigated;
- *Method application to data of a different geographical context*, i.e. automated disaggregation and classification (with specific and general parameter values) of water consumption in households H5–H13 of the Dutch dataset;

From an operational standpoint, following the approach adopted in the study by Cominola et al. (2018a), the evaluation of method performance was conducted by calculating the values of the following two metrics: (1) Water Contribution Accuracy (WCA), which indicates the efficiency of the performance at the level of overall end-use consumption; and (2) Normalized Root-Mean-Square Error ($NRMSE$), which quantifies the over- or underestimation of end-use time series. The formulation of the aforementioned metrics is shown in Equation (4.6) and (4.7):

$$WCA_i^k = 1 - \frac{\left|\sum_{t=1}^{T} qe_{i,t}^k - \sum_{t=1}^{T} \widehat{qe}_{i,t}^k\right|}{\sum_{t=1}^{T} q_{i,t}} \quad (4.6)$$

$$NRMSE_i^k = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(qe_{i,t}^k - \hat{q}e_{i,t}^k\right)^2}}{\max qe_{i,t}^k - \min qe_{i,t}^k} \quad (4.7)$$

where: subscripts i, k, and t are used to indicate household, end-use category, and time, respectively; T is the length of the dataset considered; $q_{i,t}$ is the aggregate water consumption of household i at time t; $qe_{i,t}^k$ is the observed water consumption of end-use category k in household i at time t; and $\widehat{qe}_{i,t}^k$ is the water consumption disaggregated and classified to end-use category k in household i at time t.

Given the nature of in Equation (4.6) and Equation (4.7)**,** the metric WCA_i^kcan assume a value between 0 and 1, with an accurate performance resulting in values close to 1. Given this fact, this metric will henceforth be expressed as a percentage. In contrast, the metric $NRMSE_i^k$can assume any positive value, and an accurate end-use disaggregation and classification would lead to values close to 0. It is worth noting that, although metrics WCA_i^k and $NRMSE_i^k$ are calculated for each end use k in household i, the overall performance of the methodology in successfully detecting different water end uses in relation to a group of dwellings can be assessed by averaging these metrics across all households (thus obtaining aggregate performance indicators for different end uses, i.e. WCA^k and $NRMSE^k$). In addition, aggregate indicators describing the average effectiveness of the method for a given set of households and end uses may be obtained by averaging metrics WCA^k and $NRMSE^k$ across all end uses (i.e. WCA and $NRMSE$).

Lastly, the choice of pairing WCA and $NRMSE$ is due to the fact according to which, as reported by Cominola et al. (2018a), care should be taken to use the WCA with unbalanced datasets, since – in the event that one or more end uses are activated only occasionally – a disaggregation algorithm might classify all estimated use as zero and achieve a WCA close to 100% even though it missed a few infrequent events for those end uses. Yet, a coupled analysis of WCA with other, less aggregated, metrics (such as $NRMSE$) can help better interpret results.

4.5.1. Original validation and test (Italian dataset)

The results obtained for the validation period in the case of households H1-H3 (Italian dataset) are shown in Figure 4.10, in which water consumption was disaggregated and classified based on the specific and general parameter values evaluated in the model calibration phase.

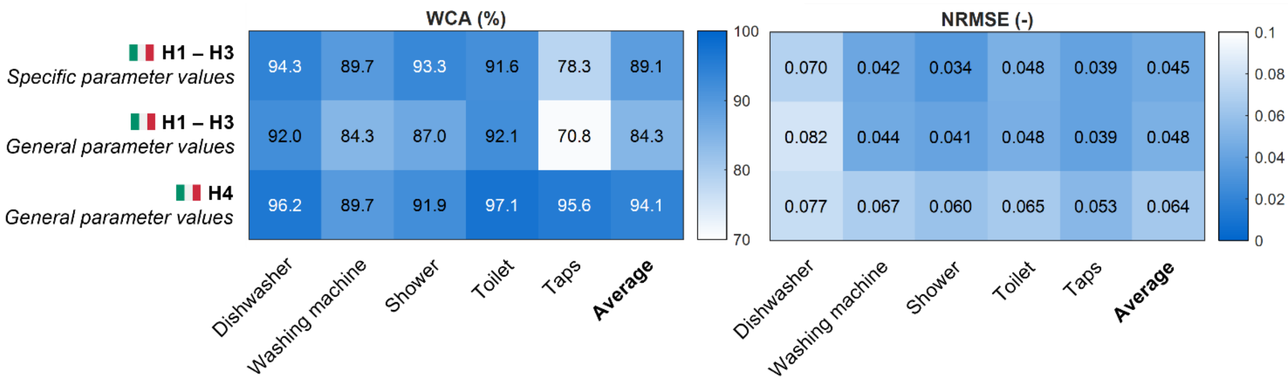

Figure 4.10. Disaggregation results in terms of Water Contribution Accuracy (WCA) and Normalized Root-Mean-Square Error (NRMSE): Italian dataset.

Overall, the automated methodology results in an average WCA between 80% and 90% by using both specific and general parameter values. More specifically, the most accurate case (average total WCA = 89.1%) is the one related to the use of specific parameter values, whereas a slightly lower accuracy (average total WCA = 84.3%) emerges by using general parameter values. The outcomes achieved in terms of WCA are coherent with the observations made by Mazzoni et al. (2021a), according to which specific parameter values are typically more representative of residential end-use features than the general ones, thus more accurate results are likely to be obtained when using specific values. However, the relatively small loss of accuracy resulting from the use of general rather than specific parameter values may be acceptable given the considerable time and effort needed to obtain specific parameter values for each household through, for example, surveys or intrusive monitoring. In addition, the WCA results achieved in the case of specific parameter values are in line with those reported by Cominola et al. (2018a) for the end-use disaggregation and classification of synthetically generated data at the 1-min temporal resolution (i.e. 89%), although less accurate of about 5% than the values presented in the study by

Mazzoni et al. (2021a) with respect to the original structure of the methodology for disaggregation and classification (i.e. 95.7% for specific parameter values and 90.4% for general parameter values, respectively). However, the slight decrease in the WCA values of households H1-H3 as opposed to the values reported in the Mazzoni et al. (2021a) study is most likely due to the generalization of the rules making up the disaggregation and classification method (e.g. comparison of water use characteristics against the average features of each end use based on the Euclidean distance, inclusion of additional parameters for appliances, etc.), in order to allow the applicability of the model to further household samples in different contexts.

When the performance of the method on individual end uses is considered, WCA is generally higher than 80% in both cases parameter values, with the only exception of tap uses, the accuracy of which decreases below this threshold (i.e. $WCA = 78.3\%$ and $WCA = 70.8\%$ for specific and general parameter values, respectively). In greater detail, the metric WCA is the generally the highest for dishwasher use (i.e. 94.3% in the case of specific parameter values and 92.0% in the case of general values), whereas a similar accuracy is met also for toilet use in the case of general values (i.e. 92.1%). Accurate results for dishwasher use are generally expected, due to the fact that the contribution of this kind of appliance to the total indoor water consumption is typically limited (i.e. less than 5%).

Most of the considerations set forth above are also confirmed by the results of the automated disaggregation and classification in terms of NRMSE. In fact, as expected, the lowest average NRMSE is observed in the case of specific parameter values (i.e. 0.045), whereas a slightly higher NRMSE emerges in the case of general parameter values (i.e. 0.048). This further proves the rather limited decrease in performance when general parameter values are used instead of specific values. In addition, the average NRMSE results are in line with those presented in the studies carried out by Cominola et al. (2018a), i.e. 0.040, and Mazzoni et al. (2021a), i.e. 0.036 and 0.045 for specific and general values, respectively. However, this increase in the error, related to a slightly greater tendency of the model in over- or underestimating end-use time series, is most likely due to the revision of some disaggregation and classification rules in order to make the method more general and transferrable. Lastly, regarding NRMSE for different end uses, the method resulted in the lowest errors for showers (0.034-0.041) and taps (0.039-0.039), whereas the highest errors are related to dishwasher uses (0.070-0.082). This is most likely due the limited range of dishwasher flow rates at the 1-min temporal resolution (i.e., 1-3 L/min) appearing in the denominator of Equation (4.7) and leading to a higher NRMSE than other end uses, as also observed in Mazzoni et al. (2021a).

Figure 4.10 also includes the results of the application of the methodology to test household H4 by using general parameter values. Specifically, results for this case are similar to those obtained for the automated disaggregation and classification of household H1, H2, and H3 water consumption with general values: the WCA ranges between 89.7% (washing machine) and 97.1% (toilet), with an average of 94.1%, whereas the $NRMSE$ is between 0.053 (taps) and 0.077 (dishwasher), with an average of 0.064. Thus, the results for this test are in line with – even though slightly less accurate than – the results of the other cases and those reported in the literature, despite the fact that household H4 end-use time series were not exploited to define the automated methodology parameters, i.e. disaggregation and classification were performed by using the set of general parameter values evaluated in relation to the other three households of the Italian dataset.

4.5.2. Application to data of a different geographical context (Dutch dataset)

The performance and the robustness of the automated disaggregation and classification method – originally validated and tested with reference to the limited household sample making up the Italian dataset – was evaluated also by using water consumption data collected in a different context with respect to that for which the method was initially implemented, i.e. the Dutch dataset. The results obtained for the validation period in the case of the nine households H5–H13 are shown in Figure 4.11, where a discrimination is made between the application of specific and general parameter values (as in the case of Figure 4.10).

On average, considering households H5–H13, the automated methodology resulted in an average WCA of 94.6% (specific parameter values) and 93.0% (general parameter values), that is even higher than the values obtained in the case of households H1–H3 of the Italian dataset (i.e. 89.1% and 84.3%, respectively) and in line with the average WCA values of 95.7% and 90.4% observed by Mazzoni et al. (2021a) by applying to the original version of the method on household H1–H3 data. This slight decrease in the WCA values when using general parameter values further confirms

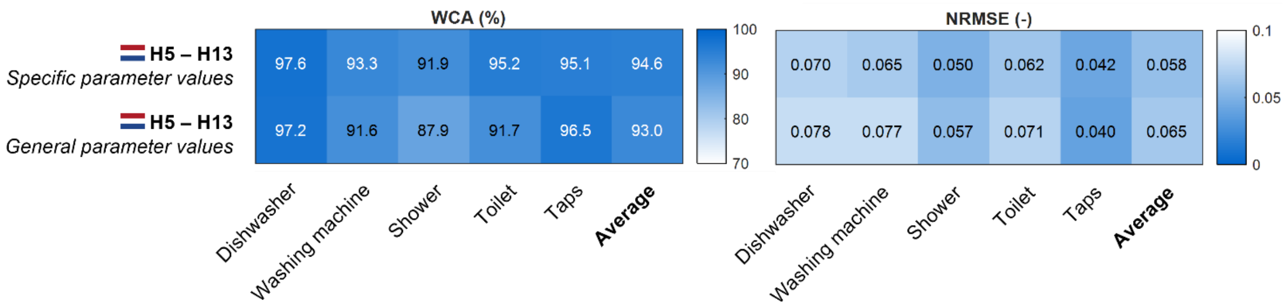

Figure 4.11. Disaggregation results in terms of Water Contribution Accuracy (WCA) and Normalized Root-Mean-Square Error (NRMSE): Dutch dataset.

that the method is able to provide accurate results at the level of aggregate end-use consumption despite the lack of a set of specific parameter values calibrated in relation to individual households. In greater detail, when the performance of the method in terms of end-use categories is considered, the most accurate case is that related to the use of dishwashers (WCA of 97.6% and 97.3%), followed by taps (WCA of 95.1% and 96.%), toilets (WCA of 95.2% and 91.7%), washing machines (WCA of 93.3% and 91.6%) and showers (WCA of 91.9% and 87.9%). As far as the results of the automated disaggregation and classification in terms of $NRMSE$ are concerned, limited NRMSE values are still observed for both cases of specific and general parameter values application (as shown in Figure 4.11). As expected, lower $NRMSE$ values are observed in the case of specific parameter values (i.e. 0.042–0.070, with an average of 0.058), as opposed to the case of general values (i.e. 0.040–0.078, with an average of 0.065). Despite slightly higher, the obtained $NRMSE$ results are still in line with those reported by Cominola et al. (2018a), i.e. 0.040, and Mazzoni et al. (2021a), i.e. 0.036–0.055. Lastly, in relation to $NRMSE$ values for individual end-use categories, the disaggregation and classification method results in the lowest errors for tap uses ($NRMSE$ of 0.042 and 0.040), whereas the highest errors are related to dishwasher uses ($NRMSE$ of 0.070 and 0.078).

Overall, the WCA and $NRMSE$ results obtained by performing end-use disaggregation and classification on water consumption data of the Dutch household sample confirm the potential to apply the method to broader contexts of residential water consumption, i.e. on data collected in different geographical and socio-demographic contest from those which were initially considered for model development and testing.

4.6. Conclusions

In this chapter, a revised version of the automated methodology for end-use disaggregation and classification of water consumption at 1-min resolution originally proposed by Mazzoni et al. (2019) and Mazzoni et al. (2021a) was presented. The methodology was initially calibrated and validated with reference to a sample of four households in Italy (i.e. Italian dataset) where 1-min resolution data were collected at the inlet point and at each end use over a period of 2 months, whereas its robustness was then evaluated by exploiting water consumption data collected at the inlet point of nine dwellings in the Netherlands (i.e. Dutch dataset), the high resolution of which (i.e. 1 s) allowed end-use time series to be obtained through automated segmentation and manual labelling. The performance of the method was evaluated using metrics already introduced in the literature (Cominola et al. 2018a) that quantify the success of detection by comparing disaggregated and observed water uses.

Based on the results obtained, the proposed methodology was able to effectively perform end-use disaggregation and classification of water consumption not only in relation to the Italian household sample that was initially considered for developing the method, but also with reference to the additional Dutch dataset. The effectiveness of the method on generalized contexts is evidenced in the obtained values of the metrics with reference to both datasets (i.e. average WCA of at least 84% and NRMSE typically lower than 0.07, also when using a set of general parameter values based on typical water use and its most common features). Moreover, the results are still consistent with those obtained in similar studies making use of synthetic data with 1-min resolution (i.e. Cominola et al. (2018a)).

In addition – and consistently with the aim of the study – the methodology as developed was able to perform endues disaggregation of water-use data collected at 1-min resolution, i.e., at a temporal resolution that is closer to the resolutions of commercial smart water meters than those used in most other existing methods. In fact, most approaches described in the literature make use of data collected at a higher resolution (e.g., 1 s or slightly lower), which may not be available or feasible to water utilities. Thus, the methodology proposed here might be extendable to broader and further contexts in the field of residential demand monitoring. The automated methodology is also transparent and easy to implement and use since it includes deterministic rules based on the analysis of physical features for each individual water use (i.e., duration and volume) and the comparison against the average characteristics of water end uses. No black box models, such as stochastic models or machine learning methods, were used here.

Part II
Water consumption in non-residential contexts or under non-ordinary demand conditions

"An overview from tourist areas to the effects of COVID-19 restrictions"

Chapter 5

Evaluation of water consumption in a coastal area subjected to high tourist fluctuations

In the European Mediterranean regions, a wide spread of tourism – in particular, seaside tourism – has been experienced since the Sixties (Morote et al. 2016b). Clearly, this is having considerable effects on economy, land use, urbanisation, and infrastructures in most countries of this area. Due to the high tourist pressure on the available resources in Mediterranean coastal areas, considerable seasonal fluctuations and peculiar water consumption may be observed in those regions which are typically subjected to high seaside tourist flows, leading to demanded volumes, daily profiles, and water use behaviours deviating from those typically characterizing the residential contexts.

Today's seaside tourists generally spend their days of vacation in accommodation facilities (e.g. hotels, guesthouses, resorts, holiday homes, campsites, etc) that are often located in proximity to beach resorts. During the day, tourists typically spend their time at the beach and, more specifically, several of them settle into the many bathing facilities available along the coast.

Bathing facilities are multifunctional establishments consisting of a leisure area on the beach with sun loungers and parasols, a restaurant and/or a café, and sanitary services including toilets and showers. Some facilities also include sport courts and pools. In addition, although most of the bathing facilities are typically open only in summer (when seaside tourism is high), it is worth noting that, in some cases, the restaurant can be active also over the winter period, when it is mainly attended by residents and locals. Bathing facilities are widespread in European Mediterranean coastal areas, specifically with reference to Greece, Spain, and Italy. In Italy, recent analyses have revealed the presence of a total of 11,000 bathing facilities over about 3,300 km of beach (Legambiente 2019), indicating, on average, about 3.3 bathing facilities per km of beach. However, to date, no studies have focused on water consumption in bathing facilities, despite their considerable diffusion.

The aim of this chapter is to contribute to the characterization of non-residential water consumption by providing insight into the effects of seaside tourism on water consumption, with reference to a coastal area in northern Italy typically subjected to high seaside tourist fluctuations throughout the year. More specifically, the area concerned features a high number of bathing facilities, in which water consumption is investigated trying to fill the gap of unavailability of studies exploring these non-residential users. Secondly, analyses shown in this chapter aim to investigate the impacts of climatic variables – such as temperatures and rainfalls – on local water consumption over the tourist season.

Unlike other cases, the study is carried out at different levels of spatial and temporal detail (i.e. from urban to user scale, and from daily to hourly scale, respectively). In particular, analyses at the user scale are conducted with reference to a group of nine bathing facilities – for which hourly-resolution water consumption data are available over a period of three months during the tourist season – in order to explore the characteristics of water consumption of this type of user. Additionally, all the results obtained are compared against those of a nearby area not significantly affected by tourist flows and where water consumption is mainly tied to residential users.

5.1. Case study and data collection

The study focused on the analysis of water consumption in a northern Italy region, close to the Adriatic Sea (Figure 5.1 a), featuring a District Metered Area (DMA) on the Adriatic coast (Figure 5.1 b) and an additional, inland and mainly residential DMA (Figure 5.1 c), considered as a baseline.

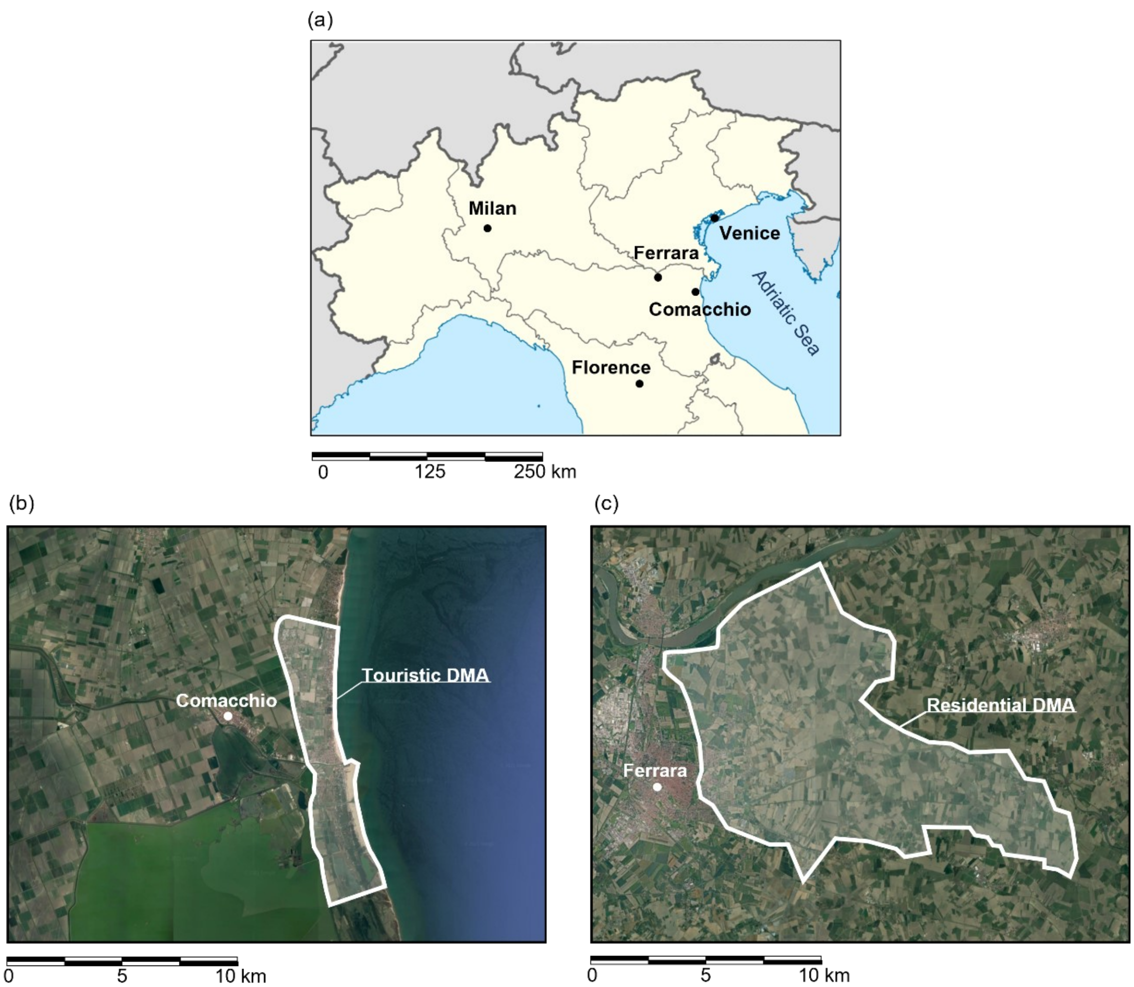

Figure 5.1. Overview of the northern Italy region (a) featuring the case study DMA on the Adriatic coastline, i.e. Touristic DMA (b) and an additional, inland DMA, i.e. Residential DMA (c) considered as a baseline.

The first DMA (hereinafter denoted as *Touristic DMA*) supplies five seaside resorts (Lido di Pomposa, Lido degli Scacchi, Porto Garibaldi, Lido degli Estensi, and Lido di Spina) in the municipality of Comacchio (Province of Ferrara), with a resident population of around 8,000 inhabitants according to the municipal statistics provided for the year 2014 (which coincides to the year of data collection, as detailed below). The area is primarily of interest for seaside tourism, which is the major economic source during summer period. As in most seaside resorts, the area is characterized by strong population fluctuations and, consequently, a considerable variability in the number of users over the year. Specifically, the total resident population of the municipality of Comacchio (where the Touristic DMA is located) was of about 23,000 inhabitants in the year 2014 (Regione Emilia-Romagna 2021), meaning that, at the height of the tourist season, the ratio between floating and resident population was of about 3.5, as shown in Figure 5.2 a. Similar results – even though with small differences – are also observed in the subsequent prior to the diffusion of COVID-19, i.e. from 2014 to 2019.

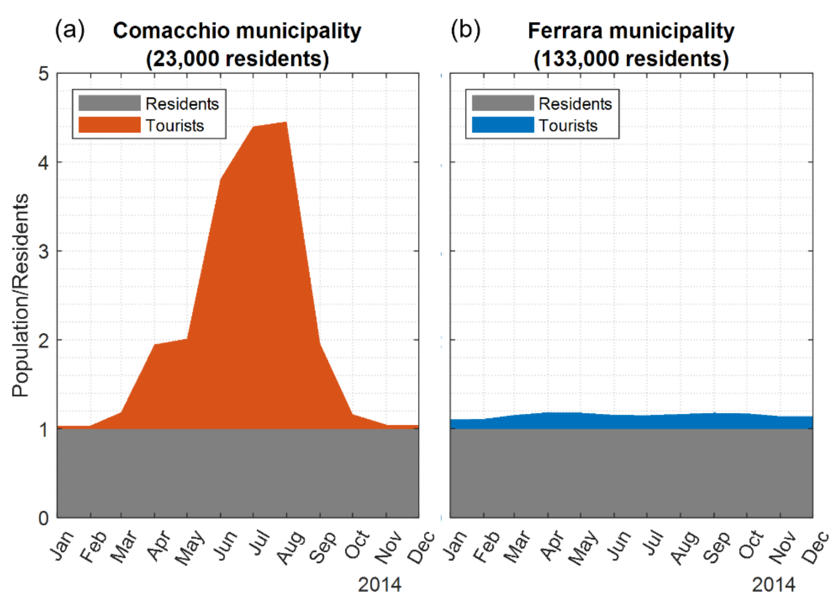

Figure 5.2. Monthly profiles of resident and floating population in the Comacchio and Ferrara municipalities, where the two DMAs considered in the case study are located.

The touristic nature of the area is detailed in Table 5.1, which shows the tourist accommodation capacity with respect to different facility types. In particular, it is worth noting that: (1) the municipality of Comacchio could potentially host a number of tourists which is about six times the number of residents; and (2) the vast majority of facilities is represented by accommodations in holiday homes/rentals (i.e. 82.5%), whereas the capacity of hotels and camping sites is much more limited (i.e. 2.5% and 15.0%, respectively). Therefore, the tourism of the area could be defined as *residential tourism*. In greater detail, the residential tourism of the area includes both local people residing in accommodation facilities or reaching their second homes only at the weekend (i.e. short-term tourists) and weekly or longer-period visitors (i.e. long-term tourists).

Table 5.1. Touristic DMA capacity with respect to different accommodation facilities.

Accommodation facility	Capacity (number of tourists)	Capacity (%)
Hotels	3,441	2.5%
Camping sites	20,372	15.0%
Holiday homes/rentals	111,737	82.5%
Total	**135,550**	**100.0%**

A second DMA (hereinafter denoted as *Residential DMA* given its mostly residential nature) is considered as a baseline to compare the results of the analysis of the impacts of tourism on water consumption achieved in the case of the Touristic DMA. The Residential DMA is about 55 km west from the area on the Adriatic coast where the Touristic DMA is located and covers part of the suburb of the city of Ferrara and its province, with a resident population of about 20,000 inhabitants. It is worth noting that the total floating population (i.e. tourists) of the municipality of Ferrara is generally constant throughout the year and represents only a small fraction of the overall population, including about 133,00 residents in the year 2014 (as shown in Figure 5.2 b).

In greater detail, data about resident and floating population shown in Figure 5.2 refer to the whole municipalities of Comacchio and Ferrara, since they are the result of demographic analyses conducted at the municipality level at the end of 2014 (Regione Emilia-Romagna 2021). However, as regards the impacts of tourism in the two DMAs concerned (which are only a part of these municipalities), it should be considered that: (1) the tourist component of the Touristic DMA is likely to be even higher than the value related to the case of the whole Comacchio municipality, since this municipality is of interest primarily for seaside tourism, which is typically concentrated in the proximity of beach resorts (i.e. in the Touristic DMA); and (2) the tourist component of the Residential DMA is likely to be even lower than the value reported in the case of the whole Ferrara municipality, since the city is of interest especially for cultural tourism, which is generally concentrated in proximity to the city centre (not included in the Residential DMA).

From an operational standpoint, HERA S.p.A. and C.A.D.F. S.p.A., i.e. the water utilities responsible for water distribution in the two DMAs concerned, made available:

- Hourly-resolution flow data (in *L/s*) observed at each inlet and outlet point of both DMAs over year 2014. These data were automatically collected, logged, and transmitted by means of the Supervisory Control and Data Acquisition (SCADA) system available to the above-mentioned water utilities.
- Hourly-resolution water consumption data collected in a sample of nine bathing facilities located in the Touristic DMA from 19 June 2014 to 15 September 2014 (i.e. over a period which nearly coincides with the tourist season in the DMA). Specifically, these data were collected by pairing Maddalena® mechanical water meters to data logging systems including Reed Switch® pulse counters (with accuracy of 10 *L/pulse*) and battery-powered loggers, and periodically downloaded by water utility operators. Overall, the monitored bathing facilities represent a significant sample – i.e. nearly 10% – of the total number of 103 facilities located in the Touristic DMA.

In addition, given the prevalent number of holiday home accommodations in the Touristic DMA, water consumption monitoring in a holiday home occupied by a family of tourists was conducted at very high temporal resolution (i.e. 1 s) for a period of nearly three weeks. It is worth highlighting that, although such data refer to an individual dwelling, monitoring was performed with the aim of qualitatively exploring the patterns of water consumption with reference to one sample of the most widespread type of tourist accommodation facilities in the DMA.

5.2. Data analysis

Water inflow data of the two DMAs concerned and water consumption observed at the monitored non-residential users of the Touristic DMA (i.e. bathing facilities and the holiday home) were first analysed with different spatio-temporal levels of detail. Secondly, qualitative and quantitative analyses were conducted to evaluate the impacts of climatic variables on water use – such as daily cumulative rainfall depth and daily average temperature – at both DMA level and user level.

5.2.1. DMA level

At the DMA level, the hourly-resolution time series of the net inflow was first obtained by applying water balance, as shown in Equation (5.1):

$$Q_i^t = \sum_{n=1}^{N_i} Qin_{i,n}^t - \sum_{o=1}^{O_i} Qout_{i,o}^t \tag{5.1}$$

where: Q_i^t is the hourly average net inflow of the DMA i at time t (i.e. at the t-th hour of the period between 1 January and 31 December, 2014; $j = 1, \dots ,8760$), $Qin_{i,n}^t$ is the hourly average inflow through the n-th inflow point of DMA i ($n = 1, \dots , N_i$ given the number N_i of inflow points of DMA i) and $Qout_{i,o}^t$ is the hourly average outflow through the o-th outflow point ($o = 1, \dots , O_i$ given the number O_i of outflow points of DMA i).

Analyses were then carried out considering three different temporal levels of detail:

- On the yearly scale, the average monthly net inflow $Qm_i^{t_m}$ over the t_m-th month of the year 2014 was calculated in the case of each DMA i by aggregating the hourly average net inflow time series Q_i^t, with t ranging from the first to the last hour of the t_m-th month of 2014 ($t_m = 1, \dots ,12$).

- On the seasonal scale, the average daily net inflow $Qd_i^{t_d}$ over the t_d-th day of the period between 19 June and 15 September 2014 (for which bathing facility water consumption data are also available) was calculated in the case of each DMA i by aggregating the hourly average net inflow time series Q_i^t, with t ranging from the first to the last hour of the t_d-th day of the period ($t_d = 1, \ldots, 89$).
- On the daily scale, two analyses were carried out. First, the daily profile of the net inflow of each DMA i (i.e. a set of 24 hourly inflow coefficients $C_i^{t_h}$) was calculated with reference to weekdays and weekend days/holidays of the period between 19 June and 15 September 2014, as shown in Equation (5.2):

$$C_i^{t_h} = \frac{\frac{1}{J}\sum_{j=1}^{J} Q_{i,j}^{t_h}}{\frac{1}{24}\frac{1}{J}\sum_{t_h=1}^{24}\sum_{j=1}^{J} Q_{i,j}^{t_h}} \tag{5.2}$$

where $Q_{i,j}^{t_h}$ is the hourly net inflow at hour t_h ($t_h = 1, \ldots, 24$) of the weekday or weekend day j ($j = 1, \ldots J$) and J is the number of weekdays or weekends/holidays occurring in the period. Therefore, the numerator indicates the average net inflow of DMA i at hour t_h on weekdays or weekend days/holidays, whereas the denominator represents the average hourly net inflow on weekdays or weekend days/holidays.

In addition, cluster analysis was conducted with the aim of exploring the relationship between the daily profiles of the net inflow and day types (i.e. weekdays and weekend days/holidays). Specifically, clustering is conducted by applying the K-means algorithm (Lloyd 1982). From an operational standpoint, daily profiles were partitioned into a number K of classes based on the K-value leading to the highest average value of the silhouette parameter (Rousseeuw 1987) and correlation was assessed by cross-checking the cluster associated with each daily profile and its corresponding day type.

5.2.2. User level (bathing facilities, holiday home)

In the case of the $N_{BF} = 9$ monitored bathing facilities of the Touristic DMA, analyses of water consumption data collected over the period between 19 June and 15 September 2014 were conducted at two temporal scales:

- On the seasonal scale, the hourly water consumption of all the N_{BF} bathing facilities was aggregated at the daily temporal resolution, as shown in Equation (5.3):

$$Qd^{t_d} = \frac{1}{24}\sum_{t_h=1}^{24}\sum_{i=1}^{N_{BF}} {q_i}^{t_h,t_d} \tag{5.3}$$

  where Qd^{t_d} is the daily average consumption of all the N_{BF} bathing facilities monitored in the Touristic DMA over the t_d-th day of the period considered, and ${q_i}^{t_h,t_d}$ is the hourly water consumption observed in the i-th bathing facility ($i = 1, \dots, N_{BF}$) at time t_h of the t_d-th day (i.e. at the t_h-th hour of the t_d-th day of the period considered). In addition, the correlation between the daily water consumption of all the bathing facilities monitored and the daily net inflow in the Touristic DMA was investigated for each day of the period concerned.
- On the daily scale, the daily profile of the water consumption of all the N_{BF} bathing facilities (i.e. a set of 24 hourly consumption coefficients c^{t_h}) was calculated with reference to weekdays and weekend days/holidays, as shown in Equation (5.4):

$$c^{t_h} = \frac{\frac{1}{J}\sum_{j=1}^{J}\sum_{i=1}^{N_{BF}} q_{i,j}^{t_h}}{\frac{1}{24}\frac{1}{J}\sum_{t_h=1}^{24}\sum_{j=1}^{J}\sum_{i=1}^{N_{BF}} q_{i,j}^{t_h}} \tag{5.4}$$

  where $q_{i,j}^{t_h}$ is the hourly water consumption in the i-th bathing facility at hour t_h ($t_h = 1, \dots, 24$) of the weekday or weekend day j ($j = 1, \dots J$) and J is the number of weekdays or weekends/holidays occurring in the period.

Furthermore, with reference to the holiday home in which water consumption was monitored at the water inlet point over a period of nearly three weeks (i.e. 18 days) at the height of the tourist season (i.e. between late July and late August), high resolution data were exploited – along with the reports compiled by users – to identify individual water uses and their related characteristics, thus allowing end-use water consumption and parameters to be evaluated. Moreover, data were aggregated and averaged at the hourly temporal resolution as shown in Equation (5.5):

$$qh^{t_h} = \frac{1}{3600}\sum_{t_s=1}^{3600} q^{t_s,t_h} \tag{5.5}$$

where qh^{t_h} is the hourly average water consumption over the t_h-th hour of the 18-day monitoring period considered ($t_h = 1, \dots, 24 \cdot 18$) and q^{t_s,t_h} is the water consumption recorded at t_s-th second of the t_h-th hour of the monitoring period considered ($t_s = 1, \dots, 3600$). In addition, the daily profile of holiday home water consumption is calculated as shown in Equation (5.4).

5.2.3. Impact of climatic variables on water consumption

Given the peculiar characteristics of seaside tourism in the area (i.e. presence of short-term tourists in addition to long-term tourists) the impacts of climatic variables on water consumption were also evaluated. This is motivated by the fact that different profiles of seaside tourists are expected to react differently to adverse weather conditions. In greater detail, the link between water use and climate was investigated at the DMA and user level (i.e. with respect to the two DMAs concerned and the set of all the N_{BF} bathing facilities monitored) by exploiting data related to cumulative rainfall depths and average temperatures. These data were collected daily, over the tourist period of the year 2014, at the two meteorological stations located in the Residential and Touristic DMA, respectively.

First, a qualitative analysis was performed by visually comparing the trend of the daily net inflow in the two DMAs concerned – and that of the daily water consumption of bathing facilities – against the trends of the daily rainfall depth and average temperature, with the aim of preliminary exploring the effects of rainfall and temperature variations on water consumption. Second, a quantitative analysis was conducted by evaluating the weekly distribution of the daily average net inflow in the two DMAs concerned – and the daily water consumption of the bathing facilities – in the case of: (1) rainy days; (2) rainless days; and (3) all the days of the period between 19 June and 15 September 2014. The weekly distributions were calculated as shown in Equation (5.6), (5.7) and (5.8), respectively:

$$Qd_i^{j,rain} = \frac{1}{T_{j,rain}} \sum_{t_{j,rain}=1}^{T_{j,rain}} Qd_i^{t_{j,rain}} \tag{5.6}$$

$$Qd_i^{j,rainless} = \frac{1}{T_{j,rainless}} \sum_{t_{j,rainless}=1}^{T_{j,rainless}} Qd_i^{t_{j,rainless}} \tag{5.7}$$

$$Qd_i^{j} = \frac{1}{T_j} \sum_{t_j=1}^{T_j} Qd_i^{t_j} \tag{5.8}$$

In the preceding equations, $Qd_i^{j,rain}$ is the daily average net inflow of DMA i (resp. the daily average water consumption of all N_{BF} bathing facilities) with reference to the all the $T_{j,rain}$ rainy days of type j (i.e. Mondays, Tuesdays, etc.) of the period; $Qd_i^{t_{j,rain}}$ is the daily average net inflow of DMA i (resp. the daily average water consumption of all N_{BF} bathing facilities) with reference to the $t_{j,rain}$-th rainy day of type j of the period ($t_{j,rain} = 1, \dots, T_{j,rain}$); $Qd_i^{j,rainless}$ is the daily average net inflow of DMA i (resp. bathing facilities water consumption) with reference to the all the $T_{j,rainless}$ rainless days of type j of the period; $Qd_i^{t_{j,rainless}}$ is the daily average net inflow of DMA i with reference to the $t_{rainless,j}$-th rainless day of type j of the period ($t_{rainless,j} = 1, \dots, T_{rainless,j}$); Qd_i^j is the daily average net inflow of DMA i (resp. the daily average water consumption of all N_{BF} bathing facilities) with reference to the all the T_j days of type j of the period; $Qd_i^{t_j}$ is the daily average net inflow of DMA i (resp. the daily average water consumption of all N_{BF} bathing facilities) with reference to the t_j-th day of type j of the period ($t_j = 1, \dots, T_j$).

5.3. Results and discussion

5.3.1. DMA level

The trend of the monthly average net inflow Qm of the Touristic DMA over the year 2014 is shown in Figure 5.3 a, where it is also compared against that of the Residential DMA (Figure 5.3 b). On the one hand, considerable variations in the monthly net inflow are observed in the Touristic DMA, where the ratio between the maximum and minimum monthly average inflow is of about 15.7 (being the extreme monthly average inflow values of about 14 and 218 L/s). On the other hand, less significant variations emerge in the case of the Residential DMA, where the ratio is of about 1.1.

Firstly, it is worth noting that the trend of monthly discharge inflow in the Touristic DMA (shown in Figure 5.3 a) nearly reflects the trend of the ratio between tourists and residents shown in Figure 5.2. In fact, both the highest net inflow and the highest tourist flow are observed between June and August 2014, that coincides with the height of the tourist season. To further explore the impact of tourism in the Touristic DMA, the tourist and residential contribution of water inflow are individually evaluated by assuming that: (1) the seasonal behaviour of resident population is comparable to that of the Residential DMA; and (2) water inflow in the Touristic DMA can be entirely related to leakages and the activity of resident population during the periods when the number of tourists is negligible, i.e. from October to March (as shown in Figure 5.2). In the light of the above-mentioned assumptions, the analysis reveals that the highest ratio between the tourist and the residential component of water inflow in the Touristic DMA (shown in Figure 5.3 a) is of about 4.2: in fact, at the height of the tourist season (i.e., August 2014, when also tourist flows are the highest), the residential component of water inflow in the DMA is of about 42 L/s, whereas the tourist component is of 176 L/s. This result is in line with the findings achieved when the highest ratio between tourists and residents in the Touristic DMA was investigated (Figure 5.2 a), being, in that case, equal to about 3.5. Therefore, it emerges that the increase in water inflow due to tourism is more than proportional to the increase in the total population – in agreement with the observations made by Toth et al (2018) – and confirms that the per capita water consumption related to tourism can be much higher than residential water consumption, even in the same area. This is likely to be due to the high water consumption of tourist-related activities (e.g. garden irrigation, pools, wellness facilities) but may also due to the less-aware consumption of tourists.

As far as the Residential DMA is concerned (Figure 5.3 b), the highest net inflow over the year 2014 is observed in the month of June, although the highest number of tourists is observed over in-between seasons (Figure 5.2 b**)**. This is likely to be due to the limited contribution of tourism in the Residential DMA, being the maximum ratio between tourists and residents of only 0.2 (as opposed to the value of about 3.5 observed for the Touristic DMA), thus being its effects negligible compared to those of seasonal factors. Hence, the above-mentioned considerations confirm that the effect of tourism flows on water use is evident especially in the cases where the number of tourists is not negligible compared to the number of residents.

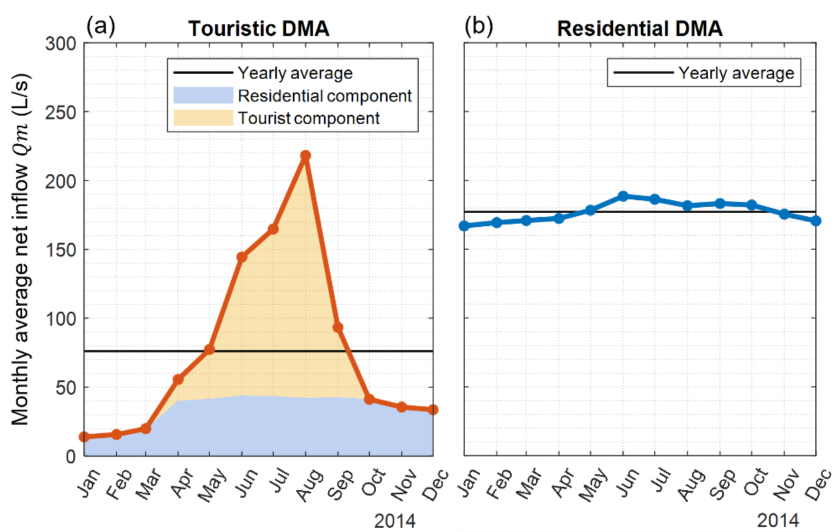

Figure 5.3. Monthly average net discharge in the Touristic DMA (a) and Residential DM (b). The estimate of the net inflow components of the Touristic DMA is shown in panel (a).

The trend of the daily average net discharge inflow Qd of the Touristic DMA over the period between 19 June and 15 September 2014 is shown in Figure 5.4, where it is also compared against that of the Residential DMA over the same period. On the one hand, considerable differences between weekday and the weekend/holiday net inflow emerge in the case of the Touristic DMA, being values typically higher in the latter case. In fact, the daily average net inflow over the selected period is of about 120.88 L/s (weekdays) and 145.09 L/s (weekend days and holidays). This is likely to be due to local people residing in accommodation facilities or reaching their second homes only at the weekend (i.e. short-term tourists). At a larger scale, a significant increase in the average net inflow due to long-term tourism is observed in mid-August and especially around 15 August (National Holiday), which typically coincides with the height of the summer season in Italy. On the other hand, no significant variations in the daily average net inflow are observed in the case of the Residential DMA, being the weekday average net inflow (i.e. 183.48 L/s) in line with that observed on weekends (i.e. 185.80 L/s). Moreover, a slight decrease is observed around 15 August, as opposed to the case of the Touristic DMA. This is most likely due to the high number of residents leaving their homes for summer holidays.

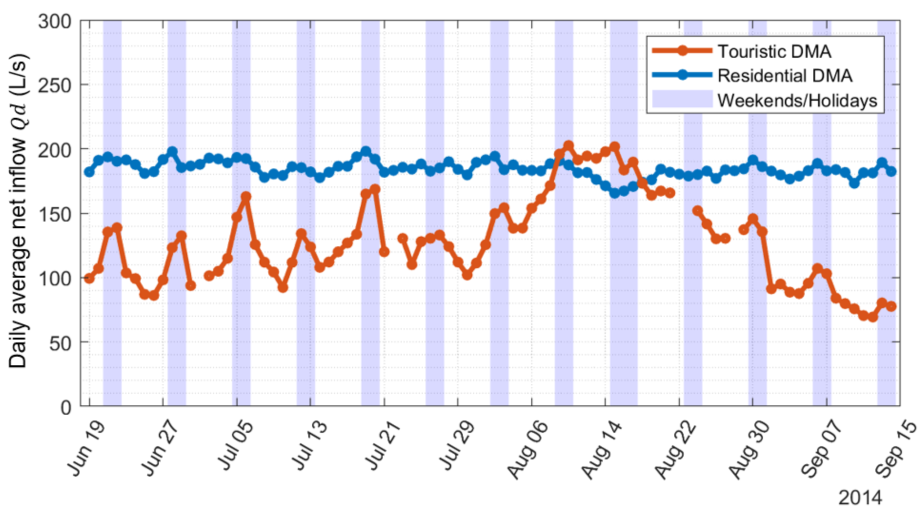

Figure 5.4. Daily average net inflow in the Touristic and Residential DMAs over the summer period of the year 2014.

On a daily scale, the average inflow profiles obtained in the case of the Touristic DMA (i.e. hourly inflow coefficients C^{t_h} shown in Figure 5.5 a) do not reveal any substantial difference between weekdays and weekend days/holidays, confirming that, despite the increase in the water use at the weekend due to local tourism, people tend to consume water in the same manner during the day, independently of day type. In greater detail, both the inflow profiles of the Touristic DMA show three distinct peaks (in the morning, around midday and in the eventing, respectively) being the evening peak the highest probably because of tourists returning to their accommodations after the day spent to the beach and showering, preparing themselves to go out, or preparing the dinner. By contrast, the profiles of the Residential DMA are mainly characterized by two major peaks occurring in the morning and in the eventing (as typically observed in residential areas) with a lower – almost undetectable – midday-peak. However, despite the small variations in the daily inflow of the Residential DMA between weekdays and weekends/holidays, considerable differences in the inflow profiles are observed (Figure 5.5 b), being the evening peak higher on weekdays and the inflow more distributed throughout the morning at the weekend. This confirms the changes in most of the residents' habits at the weekend, when they typically stop working.

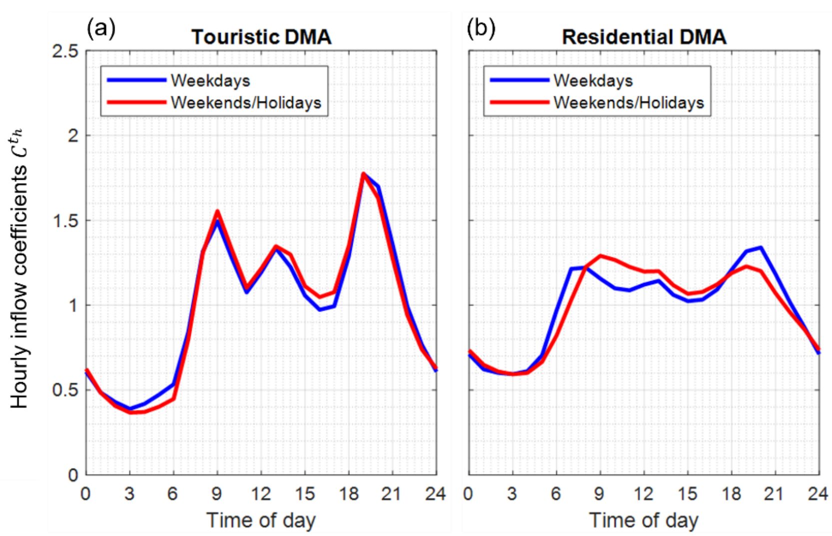

Figure 5.5. Average hourly inflow coefficients of the two DMAs concerned on weekdays and weekend day/holidays over the period between 19 June and 15 September 2014.

The above-mentioned considerations are further supported by the results of cluster analysis aimed at investigating the relationship between daily inflow profiles and day types. First, the application of the silhouette curve analysis shows that, in the case of both the Touristic and the Residential DMA, the average silhouette is the highest for $PC = 2$, thus revealing two main clusters in the daily inflow profiles. Second, the application of the K-means algorithm to cluster these profiles into $PC = 2$ partition classes and the comparison of the clustered profiles against their respective day type (i.e. weekday, weekend day/holiday, as shown in Table 5.2) reveals that:

- In the case of the Residential DMA, the degree of correlation between the clustered profiles and day types is of 100.0%. In fact, all weekday profiles (i.e. 69.3% of the total) were assigned to the first cluster, whereas all weekend/holiday profiles (i.e. the remaining 30.7%) were related to the second cluster.
- In the case of Touristic DMA, the degree of correlation between clustered profiles and day types is of 53.0% only. In fact, only half of the weekday profiles (i.e. the 38.9% over the 69.3%) were correctly associated with the first cluster, whereas only half of the weekend profiles (i.e. the 14.4% over the 30.7%) were correctly related to the second cluster.

Therefore, the results shown in Table 5.2 confirm that, on average during the tourist season, no substantial differences in the daily profiles of the net inflow occur between weekdays and weekends in the Touristic DMA, unlike the Residential DMA (where people tend to change substantially their water use habits at the weekend).

Table 5.2. Percentages of (normalized) daily inflow profiles associated with each of the two clusters in the Touristic and Residential DMA.

	Touristic DMA		**Residential DMA**	
	Cluster 1 (PC_1)	**Cluster 2 (PC_2)**	**Cluster 1 (PC_1)**	**Cluster 2 (PC_2)**
Weekdays	**38.9%**	16.6%	**69.3%**	0.0%
Weekends/holidays	30.4%	**14.1%**	0.0%	**30.7%**

Note: PC = partition class.

5.3.2. User level (bathing facilities, holiday home)

As far as the $N_{BF} = 9$ bathing facilities monitored in the Touristic DMA over the period between 19 June and 15 September 2014 are concerned, the trend of the daily water consumption of all the establishments is shown in Figure 5.6.

Consistent daily fluctuations are observed on the trend shown in the figure, with the water consumption of the monitored bathing facilities typically higher on weekend days or holidays because of short-term tourism. In greater detail, the average water consumption observed on weekdays in all the $N_{BF} = 9$ monitored bathing facilities is of about 0.18 L/s, whereas it increases up to 0.29 L/s (i.e. +60%) on weekend days and holidays. These results can be also projected by considering the total number of 103 bathing facilities located the Touristic. This leads to an expected total water consumption of about 2.02 L/s in the case of weekdays and 3.29 L/s in the case of weekends and holidays, i.e. the 1.67% and the 2.27% of the total net inflow of the Touristic DMA. It therefore emerges that the water consumption in bathing facilities affects the water balance of the Touristic DMA only on a limited basis.

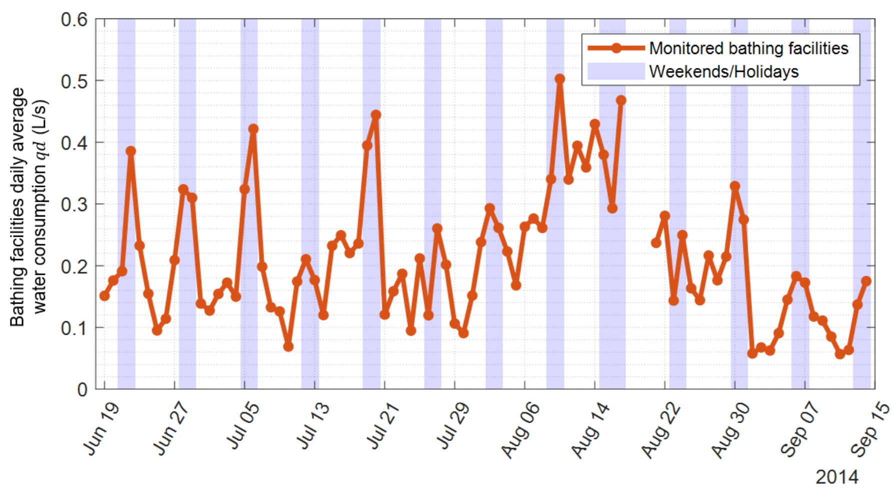

Figure 5.6. Daily average water consumption of all the monitored bathing facilities over the summer period of the year 2014.

In addition, the results of the analysis of correlation between the daily average net inflow in the Touristic DMA and the daily average water consumption of all the monitored bathing facilities over the summer period are shown Figure 5.7, where each dot relates to a day of the period.

Specifically, a high and statistically significant correlation (i.e. with degree $\rho = 0.860$ and p-value < 0.001) emerges from the analysis, meaning that, on average, water consumption of bathing facilities is the highest on days when the net inflow in the Touristic DMA is the highest too (despite the little contribution of bathing facilities in the water balance of the DMA). This is likely to be due to the fact that short- and long-term tourists consume water not only when they are at the beach (i.e. when they stay at the bathing facilities), but also when they return to their accommodation facilities or second houses to have showers, use toilets, prepare meals, etc.

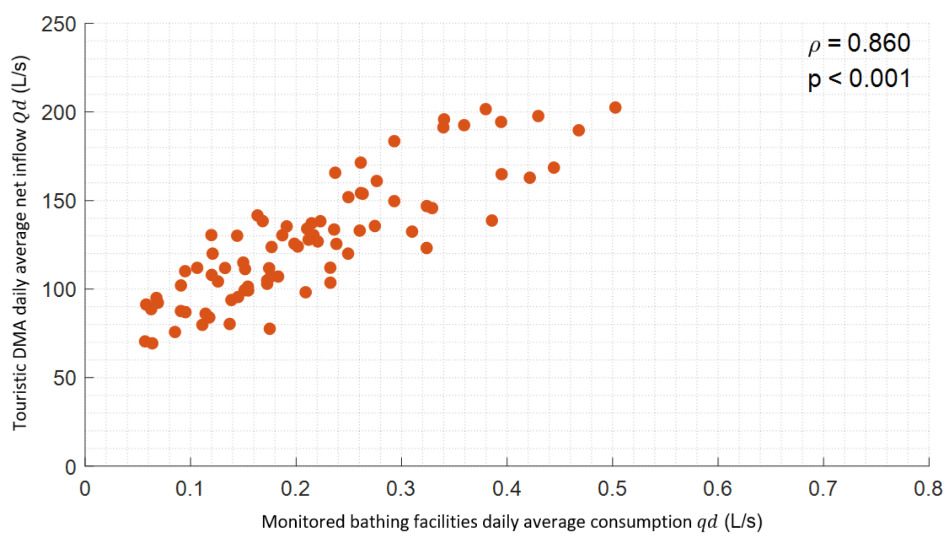

Figure 5.7. Results of the analysis of correlation between the daily net inflow of the Touristic DMA and the daily water consumption of all the monitored bathing facilities.

On a daily scale, the daily profiles of water consumption of all the monitored bathing facilities (i.e., hourly coefficients c^{t_h}) on weekdays and weekend days/holidays were calculated by applying Equation (5.4). Bathing facility profiles are shown in Figure 5.8. Specifically, despite the considerable variations in the water consumption of bathing facilities between weekdays and weekend days (Figure 5.6), no substantial differences emerge in the two average profiles, with the only exception of midday and the early afternoon. In greater detail, both profiles shown in Figure 5.8 reveal a first peak in late morning (between 10 and 11 a.m.) and a second peak in the afternoon (between 3 and 4 p.m.). The former peak is reasonably assumed to be due to the arrival of people to the bathing facility and the simultaneous start of cooking activities within the bathing facility restaurant (if present), whereas the second peak is likely to be related to the frequent use of water for showering during the hottest hours of the day, along with the use of water to cool down the sandy substrate of volley, tennis, and soccer courts. However, the weekend profile appears slightly higher in the central hours of the day. This is most likely to be due to the fact that, on Saturday and Sunday, more people (and, in particular, short-term tourists) have lunch at the bathing facility restaurants and stay at the beach all day long, whereas, on weekdays, long-term tourists often return at their accommodation facilities for lunch.

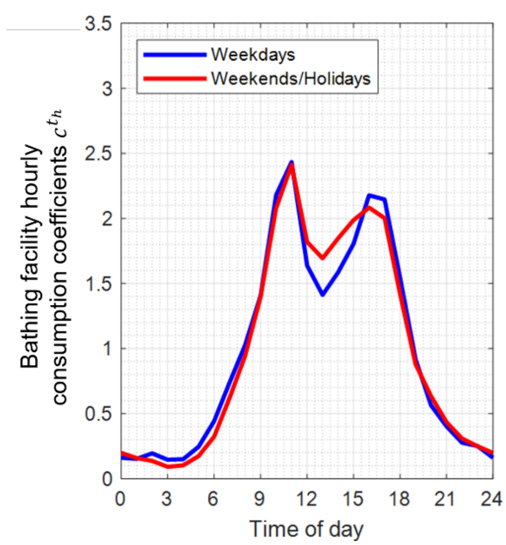

Figure 5.8. Average hourly consumption coefficients of all the monitored bathing facilities on weekdays and weekend day/holidays over the period between 19 June and 15 September 2014.

The hourly water consumption profile of the monitored holiday home is shown in Figure 5.9, where it is also compared against the hourly water consumption profile of all the monitored bathing facilities and the hourly net inflow profile observed in the Touristic DMA, with no distinction between weekdays and weekends/holidays.

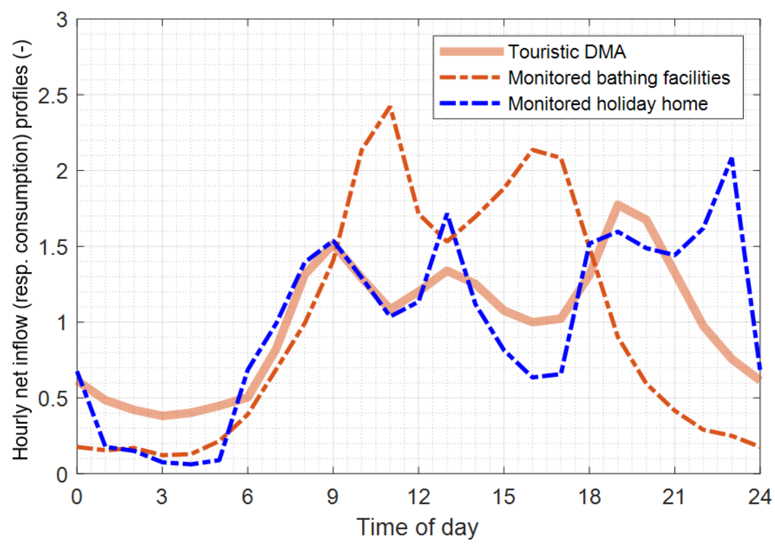

Figure 5.9. Comparison between the hourly net inflow profile of the Touristic DMA (orange continuous line) and the hourly consumption profiles of all the monitored bathing facilities (orange broken line) and the holiday home (blue broken line).

On the one hand, it is worth noting that the hourly water consumption profile of the holiday home is rather different from those typically reported in other studies exploring the daily profiles of water consumption at the household level (e.g. Mayer et al. (1999), DeOreo et al. (2011), Beal and Stewart (2011)) and those obtained with reference to the Italian and the Dutch household samples (see Paragraph 4.2) which were generally characterized by two peaks in the morning and at dinner time respectively. This is reasonably assumed to be related to different people's habits and behaviours during vacation periods, when they can wake up later, stay at home for lunch, and go to bed later. On the other hand, peak times of water consumption in the bathing facilities differ from peak times of the Touristic DMA net inflow (further confirming that, on average, the water consumption activity at the bathing facilities does not significantly affect the water balance of the DMA). Specifically, peak times at the bathing facilities are mainly observed when the DMA net inflow is relatively low, and vice versa. The complementarity between the profiles of these two user types suggest that the peaks observed in the hourly profile of the Touristic DMA net inflow are mainly due to the activity of short- and long-term tourists at their accommodation facilities rather than tourist water use at the bathing facilities. These findings are also confirmed by the trend of the hourly water consumption profile observed at the monitored holiday home, which is substantially in line with that of the DMA net inflow, and further suggests the greater impact of water use in the accommodation facilities on the Touristic DMA water balance.

5.3.3. Impact of climatic variables on water consumption

The impact of climatic variables on water use was first explored qualitatively by comparing the trend of the daily water inflow observed in the Touristic and the Residential DMAs over the tourist season – along with the trend of the daily water consumption of all the monitored bathing facilities – against: (1) the trend of the daily cumulative rainfall depth (mm/day); and (2) the trend of the daily average temperature (°C). The results of the analysis are shown in Figure 5.10.

The figure reveals a considerable sensitivity of the net inflow to both rainfall and temperature in the case of the Touristic DMA, where drops are observed during rainy or cooler days. By way of example, with reference to the sixth weekend of the period considered (i.e. 26–27 July 2014), a daily cumulative rainfall depth of about 30mm is observed. In parallel, the DMA daily average net inflow results smaller (of about 50–60 L/s) than the average value observed during the previous weekend, when no rainfall was registered (thus leading to a reduction in the daily average net inflow of about 30%). Also, a reduction of about 0.2 L/s (i.e. 50%) is observed during the same weekend. Similar observations can also be made in the case of other rainy weekends (see, by way of example, weekends including: 28–29 June; 12–13 July; and 2–3 August 2014).

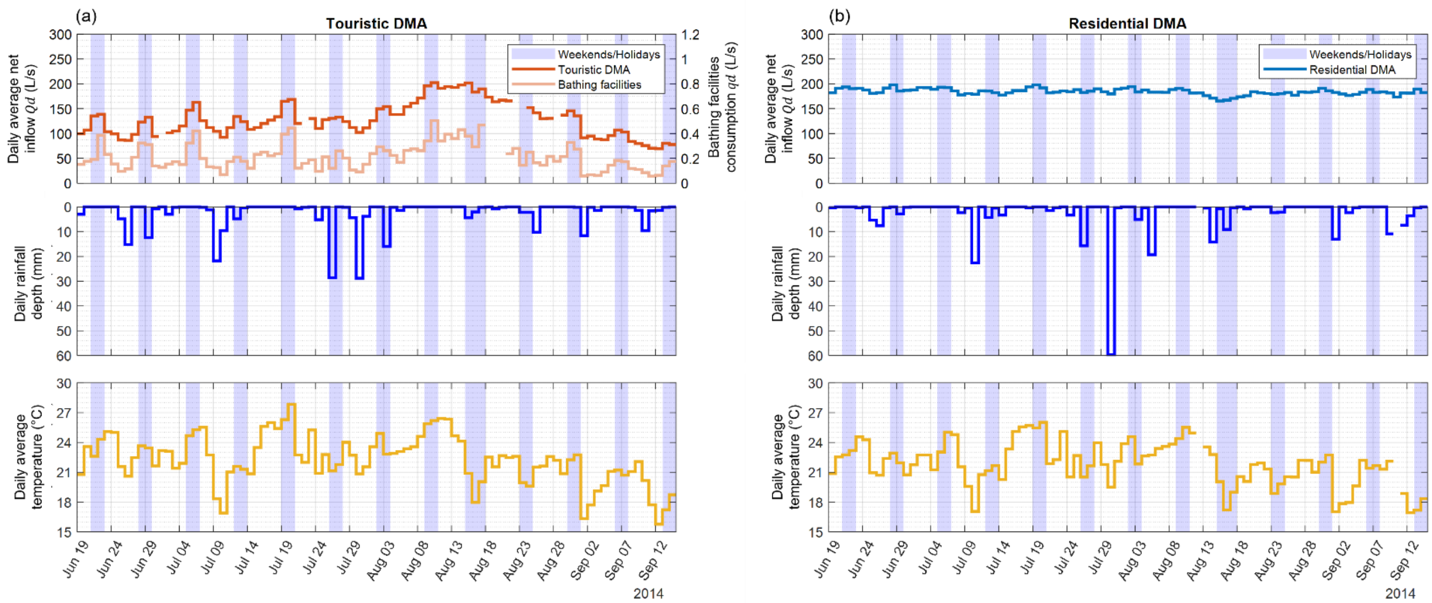

Figure 5.10. Comparison between the daily net inflow observed in the two case study DMAs (resp. the daily water consumption in the monitored bathing facilities) and climatic variables (i.e. daily cumulative rainfall depth and daily temperature) over summer period.

Drops in water consumption due to adverse weather conditions are particularly evident in the case of bathing facilities and are most likely due to the fact that people typically do not stay at the beach when the weather is bad, thus only small volumes of water are generally consumed at the bathing facilities in those days. Moreover, since short-term tourists usually move to the coast only in case of good weather, and long-term tourist tend to do alternative activities when the weather does not allow them staying at the beach (e.g. sightseeing in nearby cities), the impact of rainfalls and temperature drops reflects also in the water inflow of the overall Touristic DMA, as observable in Figure 5.10 a. It is also worth noting that, in the light of the aforementioned behaviours of tourists in case of adverse weather – and also considering the rapid reaction of short-term tourists with respect to bad weather conditions – no lagged effects between rainfall and changes in the water use are observed.

By contrast, no substantial variations in the net inflow of the Residential DMA are observed in the case of bad weather during the period considered (Figure 5.10 b). This is reasonably assumed to be related to the mainly residential nature of the DMA, in which the indoor water consumption is not generally affected by rainfalls or anomalous temperature values, and where the outdoor water consumption (e.g. garden irrigation) is likely to impact on the water balance of the overall DMA only modestly.

These considerations are further supported by the results of the quantitative analysis conducted to evaluate the weekly distribution of the average daily water inflow in the two DMAs concerned (along with the average daily water consumption of all the monitored bathing facilities) with reference to: (1) rainy days; (2) rainless days; and (3) all the days of the summer period considered. These distributions – calculated by applying Equation (5.6), (5.7), and (5.8)– are shown in Figure 5.11.

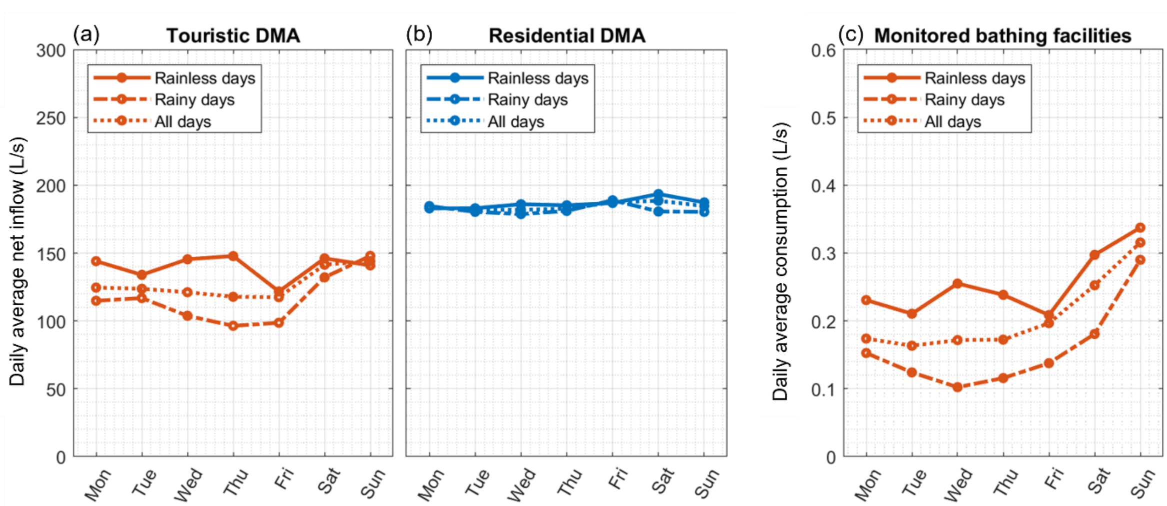

Figure 5.11. Weekly distribution of the daily average water inflow in the two DMAs concerned (resp. water consumption of all the monitored bathing facilities) for rainy days, rainless days and all the days of summer period.

In greater detail, the daily net inflow of the Touristic DMA shows a considerable sensitivity to rainfall (Figure 5.11 a). This is characterized by average values over the tourist season of 140.0 L/s in the case of rainless days and 115.8 L/s in the case of rainy days, thus revealing a 17.3% decrease in the case of bad weather. On the other hand, the daily average net inflow of the Residential DMA (Figure 5.11 b) is nearly unaffected by rainfall, ranging from 186.4 L/s in the case of rainless days to 182.1 L/s in the case of rainy days (i.e. 2.3% decrease). The higher sensitivity of the Touristic DMA to rainfall is also confirmed by analyzing the daily average water consumption of all the bathing facilities (Figure 5.11 c), which ranges between 0.254 L/s (rainless days) and 0.158 L/s (rainy days) and thus reveals a decrease of about 37.9% due to rain.

5.4. Limitations of the analysis

The main limitation of the analysis presented in this chapter is related to the fact according to which the unavailability of more recent data did not allow the study to be extended to periods after the year 2014 and, in particular, to the period when COVID-19 restrictions were implemented. However, no considerable differences in the results would be expected in relation to more recent periods, given the low variability in tourist flows in the Touristic DMA over the years of the last decade (Regione Emilia-Romagna 2021). Also, as shown in Figure 5.12, tourist flows in the Comacchio municipality (including the Touristic DM) were not significantly affected by COVID-19 restrictions. The reason lying behind is that – although some recent studies on COVID-19 (see the related literature review in Paragraph 2.4) have revealed considerable drops in the water consumption due to the stop of tourism in the first months of the year 2020 – the majority of the restrictive measurements were gradually lifted in late spring in most of the European countries (including Italy) and then re-implemented only over the next autumn, i.e at the end of the seaside tourist period. Therefore, it is believed that the impacts of COVID-19 restrictions on tourism – and, consequently, on water consumption – have been rather limited in the Tourist DMA (as opposed to the Ferrara municipality, in which the Residential DMA is located, and where tourism is mainly cultural).

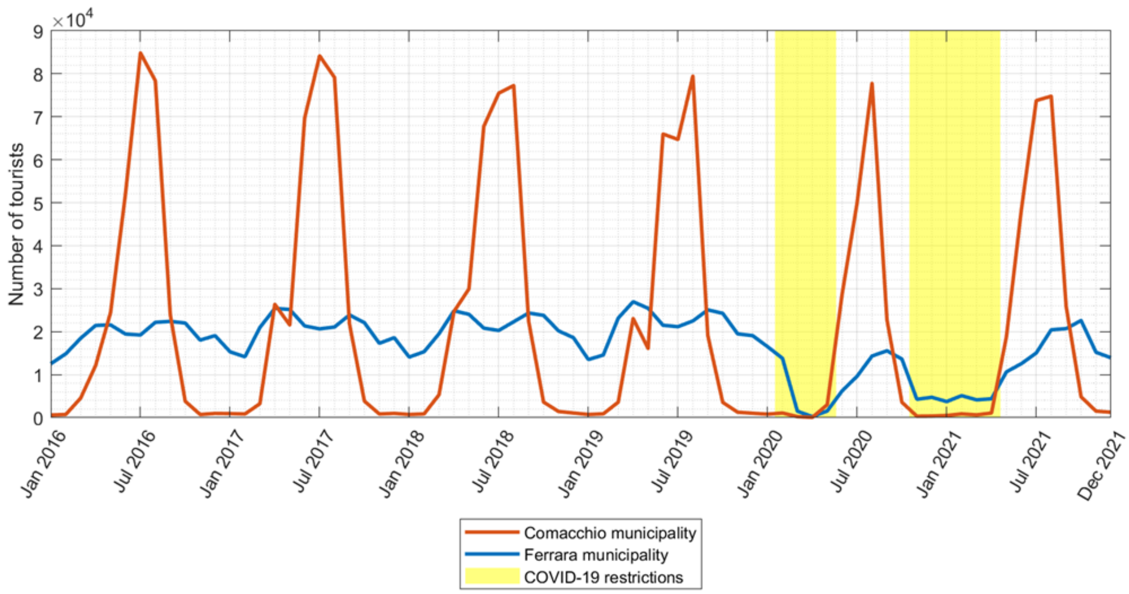

Figure 5.12. Monthly tourists in the Comacchio and Ferrara municipalities (where the two case study DMAs are located) over the period 2016–2021.

In addition, all the DMA-level analyses (the results of which are reported in Paragraphs 5.3.1 and 5.3.3) were conducted based on the DMA net-inflow time series, i.e. based on the time series of flow-rate at each inlet and outlet point of the two DMAs concerned. In the light of the above, water inflow variations were considered as an indicator of water consumption variations, although results can be affected by the presence of background leakages or changes in network controls (e.g. valve opening or closure). Therefore, although the water utilities responsible for water distribution in the two DMAs did not report any anomalous event in the period concerned (e.g. burst, leakage repair or variations in the status of network elements), results may be partially affected by undetected leakage evolution or minor unreported changes in network controls.

5.5. Conclusions

In this chapter, the characteristics of water consumption in a coastal area on the Adriatic Sea (northern Italy) – where tourism has a considerable impact during summer period – were explored.

From an operational standpoint, water consumption data were analysed at different levels of spatiotemporal detail, from the DMA to the user level – and compared against those of a nearby residential area not significantly affected by tourism.

The following key findings were achieved:

- At the DMA level, variations in the number of monthly tourists can be related to variations in the monthly water inflow. In the case of the Touristic DMA concerned, the average monthly water inflow ranges between 14 L/s 218 L/s based on tourist flows in the year considered. Specifically, at the height of tourist season, the tourist component of water inflow in the area is considerably higher than the residential component (i.e., 176 L/s versus 42 L/s).
- Over the tourist season, large weekly fluctuations in the daily water inflow (with a significant increase on weekend days and holidays) are observed in the Touristic DMA, as an effect of the number of short-term tourists reaching beach resorts only at the weekend. Weekly fluctuations are not observed in the case of the Residential DMA.
- No differences between weekday and weekend hourly profiles of net inflow are observed in the touristic DMA, meaning that tourists typically consume water in the same manner on weekdays and at the weekend. In contrast, significant variations in the hourly profiles are observed in the case of the Residential DMA.
- At the user level, water consumption in bathing facilities does not represent a significant component of the total water consumption of the Touristic DMA, being less than 3% of the daily net inflow. However, significant variations in the daily water consumption are observed in bathing facilities among different day types, because of the increase in tourist flows at the weekend.
- The hourly profiles of bathing facility water consumption differ from those of the Touristic DMA water inflow. Specifically, peak consumption times in the bathing facilities typically occur when the DMA inflow is low, and vice versa.
- Similarities between the hourly profile of the Touristic DMA water inflow and that of water consumption at the monitored holiday home are observed, revealing that tourists are most likely to consume water within their accommodation facilities rather than at bathing facilities.

- Climatic variables significantly impact on water consumption in the case of the Touristic DMA, due to the fact that tourists typically reach beach resorts only in case of good weather. Specifically, in the tourist season, a 17% decrease in the touristic DMA water discharge inflow is observed on rainy days, along with a drop of about 38% in the water consumption of bathing facilities. In contrast, the Residential DMA does not show high sensibility to climatic variables, being the average decrease in the case of rain of about 2% only.

Due to the nature of the case study analyzed, the results obtained may be applied to other contexts of seaside areas where short-term tourism is present, whereas they may not apply to the case of sites only – or mostly – characterized by long-term tourism. In fact, since long-term tourists typically stay for the overall holiday period despite the weather, a lower sensitivity of water consumption to climatic variables would be expected in those areas, at least at the DMA level. Conversely, changes in the water consumption of some individual users – not only bathing facilities, but also pools, golf courts, wellness areas, etc. – could be observed because of the alternative activities tourists generally do in case of bad weather.

In conclusion, the results reported in this chapter allow better understanding the characteristics and the drivers of water consumption in coastal areas subjected by high tourist fluctuations, and can be exploited by water utilities for a variety of purposes aimed at moving towards a more efficient management of their water systems. In fact, based on the knowledge of which users have the highest impact on water balance – and their sensitivity to factors such as period, day of week, and weather – the water utility can predict water demands more accurately and therefore adopt strategies for optimizing network controls and layout (e.g. pump scheduling, valve closures, tank filling). Moreover, specific awareness-rising campaigns can be conducted in relation to the most consuming users, along with other approaches for reducing water consumption and preventing water wastes (e.g. installation of low-flow devices and visual alarm systems on end uses, or systematic changes in the water tariff).

Chapter 6

Analysis of the effects of COVID-19 restrictions on water consumption

The recent COVID-19 pandemic has represented an emergency situation for many countries of the world. Over the spring of the year 2020, many governments implemented a series of restrictive measures to stop the diffusion of the virus, including home isolation, the obligation to practice teleworking and telematic educational activities, the suspension of non-essential businesses, the closure of all commercial establishments except for those selling essential goods, and the ban on travel outside the municipality of residence except for situations of absolute urgency. Clearly, the measurements implemented in this period strongly impacted on people's habits and lifestyles and reflected also in water consumption.

In this chapter, the effects of the first Italian COVID-19 lockdown (11 March – 3 May 2020) on water consumption are investigated with reference to district metered areas (DMA) in the cities of Padua and Rovigo (northern Italy). In greater detail, three DMAs featuring different characteristics and supplying residential, commercial and tourist areas are considered in Padua, in order to investigate the impact of COVID-19 restrictive measures on a variety of contexts featuring different rates of residential and non-residential water consumption. By contrast, as far as the case study of Rovigo is concerned, the analysis focused on a mainly residential DMA in which smart monitoring of water consumption at the individual user level has been ongoing since April 2019. In greater detail, all the analyses were conducted at different levels of temporal and spatial aggregation, up to the level of hourly water consumption profiles for individual users.

It is worth remarking that the study presented in this chapter was conducted between May and July of the year 2020, i.e. a few weeks after the gradual lift of the restrictions imposed and the suspension of the first lockdown in Italy. At that time, no other studies evaluating the effects of the COVID-19 pandemic on water consumption relating the variations to the predominant nature of the area, nor analyses carried out with such a fine level of spatiotemporal detail (i.e. up to hourly water consumption data collected at the user scale) were available in the scientific literature. Indeed, as better pointed out in Paragraph 2.4 other examples of studies focusing this topic with a similar level of detail have appeared only since late 2020.

6.1. Case study and data collection

6.1.1. DMA-level analysis: the Padua case study

The city of Padua (Figure 6.1 a), with around 210,000 inhabitants, is chief town of the homonymous province, and the third centre of the Veneto Region by population. The city is of interest for tourism, commercial activities, industries, and the presence of natural thermal site nearby (Abano Terme). Padua is supplied by a system of wells located about 60 km north-west of the city and its water distribution network is subdivided into ten major DMAs with different extension. The management of the network is entrusted to AcegasApsAmga S.p.A. water utility, which developed and installed a SCADA system including over two hundred pressure and flow meters located in the most relevant points of the network and at each DMA inflow/outflow point. All data are typically collected in real-time at hourly temporal resolution.

To evaluate the effects of COVID-19 restrictions on water consumption, three DMAs are considered, different in terms of number of users, types of water consumption, and percent value of the non-residential water consumption: (1) the *Montà-Arcella* DMA (of about 18,000 users), including a mainly residential area, where only 21.9% of consumption is non-residential; (2) the *Centro* DMA (of about 19,000 users), including the old town with commercial activities, restaurants, offices, and tourist facilities, and where 44.7% of consumption is non-residential users; and (3) the *Abano Terme* DMA (of about 10,000 users), supplying the homonymous thermal site including hotels, pools, restaurants, and tourist facilities, and where 58.0% of consumption is non-residential. It is worth noting that the information about the number of users per DMA and the percent values of residential and non-residential water consumption were directly provided by the AcegasApsAmga S.p.A. water utility based on the billing data of the year 2018 – i.e. the most recent year for which data were made available – and the details related to each water meter (e.g. holder, type of user, etc.).

The main characteristics of each DMA selected are indicated in Table 6.1, whereas their layout and location in the Padua water distribution network is shown in Figure 6.1 b.

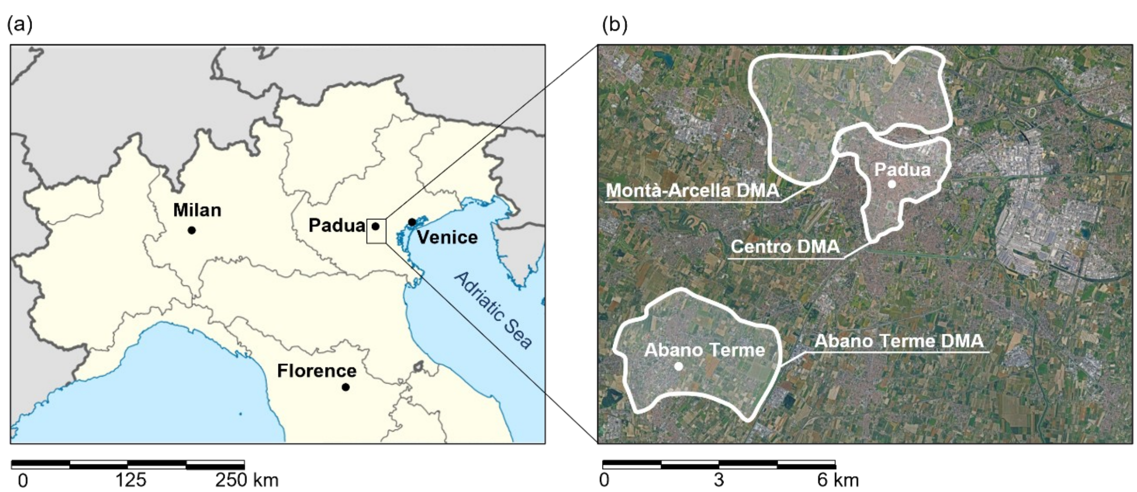

Figure 6.1. Overview of the northern Italy region featuring the city of Padua (a) and the three DMAs concerned, i.e. the Montà-Arcella DMA, the Centro DMA, and the Abano Terme DMA (b).

Table 6.1. Characteristics of the three DMAs concerned in the city of Padua.

Area	Characteristics	Number of users	Non-residential consumption
Montà-Arcella DMA	Mainly residential area	18,000	21.9%
Centro DMA	City centre	19,000	44.7%
Abano Terme DMA	Natural thermal area	10,000	58.0%
Padua (entire city)	**-**	**114,000**	**36.9%**

From an operational standpoint, the hourly-resolution time series of the net inflow Q_i^t of each DMA i concerned – along with that of the entire city – were obtained by applying water balance, as shown in Equation (5.1). In greater detail, the equation was applied to the flow data collected over the three following periods: (1) 11 March–3 May 2020 (lockdown period); (2) 1 February–10 March 2020 (pre-lockdown period); (3) 1 February–3 May 2019 (corresponding period of previous year).

A preliminary study was first carried out to ensure that – in the event that water inflow variations were observed in one or many DMAs during the lockdown period – these were not due to sociodemographic or climatic factors. On the one hand, regarding sociodemographic factors, analyses of the water utility database – along with the information directly provided by the water utility staff and technicians – revealed that: (1) no substantial changes in the DMA number of users between 2019 and 2020 have occurred; (2) the perimeter of each DMA has remained the same; (3) the cost of water has not subjected to changes; and (3) no awareness-rising campaigns have been carried out. On the other hand, regarding climatic factors, temperature and rainfall data were considered. First, it was checked whether the monthly temperatures and rainfall recorded with reference to the years 2019 and 2020 were consistent with the values observed over the previous decade (i.e., years 2010–2018) and whether they were characterized by anomalous/outlier values or not. Second, the possible existence of a correlation between the DMA net inflow and climatic factors during the lockdown period was investigated. In greater detail, a significance test was conducted by assuming a 95% significance level. For both climatic factors, the correlation with the water inflow of each DMA did not result statistically significant (i.e. had a p-value greater than 0.05), that is to say that water inflow changes over the selected period were not attributable to them.

Based on the available net inflow time series, the following analyses were then conducted:

- On the seasonal scale, the time series of the average daily net inflow $Qd_i^{t_d}$ was calculated in the case of each DMA i with reference to the pre-lockdown period and the lockdown period of the year 2020 – along with the corresponding period of the year 2019 – by aggregating the hourly average net inflow time series Q_i^t (with t ranging from the first to the last hour of the t_d-th day of the period concerned).

- On the daily scale, the daily profile of the net inflow of each DMA i (i.e. a set of 24 hourly inflow coefficients $C_i^{t_h}$) was calculated with reference to weekdays and weekend days/holidays of the lockdown period of the year 2020, as shown in Equation (5.2). In addition, the relationship between the daily profiles of the net inflow and day types (i.e. weekdays and weekend days/holidays) was investigated through clustering. In greater detail, the K-means algorithm was applied as detailed in *Chapter 5*, and daily profiles are partitioned into a number PC of classes based on the PC-value leading to the highest average value of the silhouette parameter. Finally, a degree of correlation was calculated by cross-checking the cluster associated with each daily profile and its corresponding day type.

6.1.2. User-level analysis: the Rovigo case study

User-level analyses were carried out in relation to the case study of Rovigo (Figure 6.2 a), a provincial city in the Veneto region (northern Italy), the number of inhabitants of which is about 51,000. Management of the integrated water distribution service in the city is entrusted to Acquevenete S.p.A., which overall serves over one hundred municipalities in northern Italy. Specifically, the study was conducted in the *Commenda* DMA, situated in the immediate outskirt of Rovigo (Figure 6.2 b).

The Commenda DMA supplies a mainly residential area including 301 users, 288 of which are residential users, and 13 are commercial establishments (e.g., a pharmacy, a hardware store, a homeopathic and wellness center, and a hairdresser), i.e. non-residential. In greater detail, this mainly residential DMA is populated with a medium-income community, ranging from single residents to couples and families with one or more children. Specifically, the average number of inhabitants per user is about 3. Around 60% of the residential users are detached or semidetached houses, whereas around 40% are flats. In the light of the above, the Commenda DMA can be assumed as representative of many residential areas in Italian and European medium-sized cities not significantly affected by urban commuting phenomena.

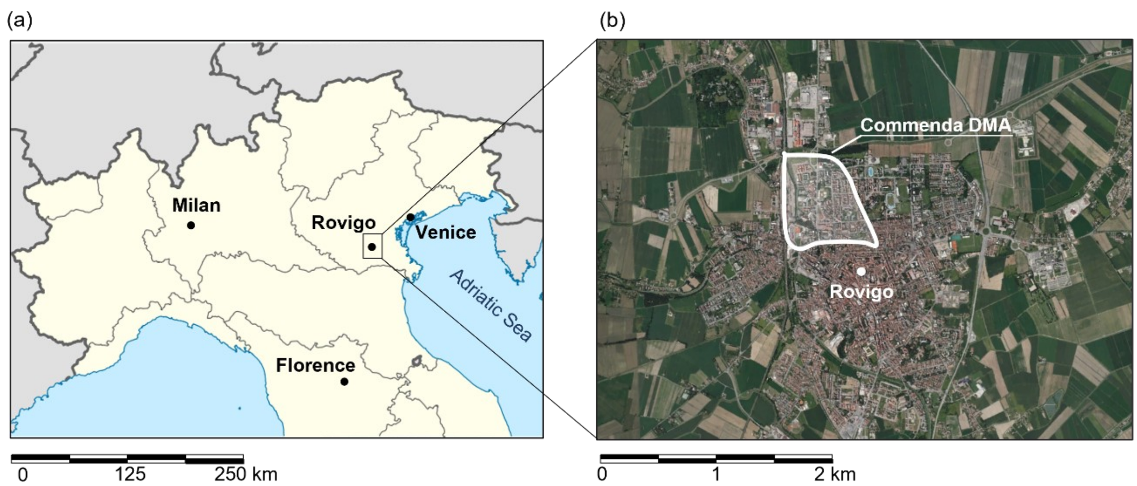

Figure 6.2. Overview of the northern Italy region featuring the city of Rovigo (a) and the Commenda DMA (b).

Starting from late 2018, the Commenda DMA underwent a complete renovation, including the installation of new connections to users and the replacement of the traditional (mechanical) water meters with Sensus iPerl® smart meters, new generation electromagnetic meters capable of logging data with hourly temporal resolution. Specifically, the meters were equipped with a radio transmitter making use of the wireless M-Bus communication protocol. The logged water consumption data are periodically collected onsite by the water utility technicians with the walk-by mode through a radio receiver kit. Therefore, since April 2019, water consumption has been smart metered, and this has resulted in the availability of hourly water consumption time series for each of the 301 users. In greater detail, the available water consumption time series relate to the period between 4 April 2019 and 3 May 2020.

Data collected in the period concerned allowed the following: (1) the analysis of residential and commercial water consumption (and profiles) throughout the period in which increasingly strict restrictions were applied to the complete lockdown due to the COVID-19 pandemic (i.e. pre-lockdown and lockdown period of the year 2020); and (2) the comparison of user water consumption during the lockdown period with that of the corresponding consumption of the previous year.

First – as in the case of the Padua dataset – a preliminary study was carried out to ensure that – in the event that water consumption variations were observed during the lockdown period – these were not due to sociodemographic or climatic factors. Second, the Rovigo dataset was subjected to a preliminary cleaning. From an operational standpoint, the cleaning process was developed in the phases described below: (1) removal of the users with a closed meter or subjected to a contract transfer; (2) removal of the users with no water consumption due to householders' absence; (3) removal of the users including missing or incorrect data, due to a malfunctioning in the meter; and (4) removal of the users affected by internal leakages. In particular, set (1) of the users to remove was identified by using the Acquevenete S.p.A. water utility database and searching for the users with contract closures or transfers. Set (2) was identified by looking for users including no water consumption for at least two weeks. Set (3) was identified by looking for users characterized by a negative consumption data or with at least two days of missing data. Lastly, set (4) was identified by looking for the users affected by internal leakages equal to or greater than $1\ L/h$ (detected, in turn, through the algorithm proposed by Luciani et al. (2019)). Overall, after the cleaning process, the hourly water consumption time series of a total of $N_{TU} = 216$ users ($N_{RU} = 208$ residential and $N_{CU} = 16$ commercial users) were selected for the study.

Water consumption data were then analyzed at different levels of temporal aggregation (i.e. seasonal scale *versus* daily scale). Analyses on the seasonal scale were first carried out by considering all the users together (i.e. at the level of a whole Commenda dataset). These were followed by a more detailed examination of the daily water consumption of each individual user i ($i = 1, \dots, N_{TU}$). Concerning the daily scale, the analysis of residential water consumption was conducted by considering both all the N_{RU}-residential users grouped together and each individual residential user i ($i = 1, \dots, N_{RU}$). However, given the limited sample of available commercial water consumption data and the very different nature of each commercial user), these were analyzed only at the level of individual user i ($i = 1, \dots, N_{CU}$).

- On the seasonal scale, the time series of the average daily water consumption of all the N_{TU} users of the Commenda DMA, i.e. Qd^{t_d}, was first calculated with reference to the pre-lockdown period and the lockdown period of the year 2020 [as shown in Equation (5.3)] by aggregating the hourly water consumption time series of each user $q_i{}^{t_h,t_d}$ (with $i = 1, \dots, N_{TU}$, and t_h ranging from the first to the last hour of the t_d-th day of the period concerned). In addition, considering individual users, the difference Δqd_i between the daily average water consumption of each user i ($i = 1, \dots, N_{TU}$) during the lockdown period and that of the corresponding period of the year 2019 was calculated as shown in Equation (6.1):

$$\Delta qd_i = \left(\frac{1}{T_d}\sum_{t_d=1}^{T_d}\sum_{t_h=1}^{24} q_i{}^{t_h,t_d}\right)_{2020} - \left(\frac{1}{T_d}\sum_{t_d=1}^{T_d}\sum_{t_h=1}^{24} q_i{}^{t_h,t_d}\right)_{2019} \tag{6.1}$$

  where $(\dots)_{2020}$ and $(\dots)_{2019}$ mean that all the variables within the brackets refer to data pertaining to the lockdown period for which user-level data are available and to its corresponding period of 2019, respectively (i.e. 3 April – 3 May 2020, and 3 April – 3 May 2019); $t_h = 1, \dots, 24$ is the t_h-hour of the t_d-h day of the period concerned; and T_d is the length (days) of the period.

- On the daily scale, the daily profile of water consumption of all the N_{RU}-residential users grouped together (i.e. a set of 24 hourly consumption coefficients C^{t_h}) was first calculated with reference to weekdays and weekend days/holidays of the lockdown period for which user-level data are available (i.e. 3 April – 3 May 2020) and the corresponding period of 2019, as shown in Equation (5.2). In this case, the numerator of the above equation defines the average water consumption of all the N_{RU}-residential users at hour t_h during weekdays or weekend days and holidays, whereas the denominator represents the average – over the day – of the hourly water consumption of all the N_{RU}-residential users during weekdays, or weekend days and holidays (i.e. Saturdays, Sundays, Easter Monday, the Anniversary of Italy's Liberation (25 April), and the International Workers' Day (1 May)).

Considering individual users, the difference $\Delta qh_i^{t_h}$ between the average water consumption of each residential user i ($i = 1, \dots, N_{RU}$) at the t_h-hour of the day ($t_h = 1, \dots, 24$) during the lockdown period and that of the corresponding period of the year 2019 was calculated as shown in Equation (6.2):

$$\Delta qh_i^{t_h} = \left(\frac{1}{T_d}\sum_{t_d=1}^{T_d} q_i{}^{t_h,t_d}\right)_{2020} - \left(\frac{1}{T_d}\sum_{t_d=1}^{T_d} q_i{}^{t_h,t_d}\right)_{2019} \tag{6.2}$$

where $(\dots)_{2020}$ and $(\dots)_{2019}$ mean that all the variables within the brackets refer to data pertaining to the lockdown period for which user-level data are available and to its corresponding period of 2019, respectively (i.e. 3 April – 3 May 2020, and 3 April – 3 May 2019); and T_d is the length (days) of the period concerned.

In addition, N_{RU}-average daily profiles of water consumption over weekdays (i.e. N_{RU}-sets of 24 hourly consumption coefficients $c_i^{t_h}$) were calculated for each residential user and with reference to the two above periods concerned. The K-means algorithm was then applied to cluster the set of hourly weekday profiles related to each residential user i ($i = 1, \dots, N_{RU}$). In greater detail, $2N_{RU} = 416$ profiles were clustered (i.e. N_{RU}-water consumption profiles for the period between 3 April and 3 May 2019 and N_{RU}-profiles for the corresponding 2019 period). These objects were partitioned into PC-classes based on the highest average silhouette-parameter value resulting from a preliminary silhouette curve analysis (see also Paragraph 6.1.1). Finally, percent changes in residential user profiles between 2019 and 2020 were quantified by cross-checking the partition class related to each user in the year 2019 and in the year 2020.

6.2. Results and discussion

6.2.1. DMA-level analysis: the Padua case study

As far as the Padua case study is regarded, different variations in the net inflow due to lockdown are observed on the seasonal scale (i.e. daily temporal resolution), based on the characteristics of the DMA concerned (Figure 6.3). Indeed, on the one hand, a 10.6% increase in the net inflow is observed in the Montà-Arcella DMA – where water consumption is mainly tied to residential users and domestic activities – during the lockdown period of 2020 (i.e. an average of $8983\ m^3/d$ between 11 March and 3 May 2020) when compared with the value of the corresponding period of year 2019 (i.e. $8122\ m^3/d$ observed between 11 March and 3 May 2019). Moreover, an increase of about 4.7% is observed when comparing the net inflow of the lockdown period against that of the period preceding the lockdown (i.e. an average of $8579\ m^3/d$ observed between 1 February and 10 March 2020). The aforementioned increase in the net inflow of the Montà-Arcella DMA – mainly ascribable to an increase in the residential water consumption of the area – is in line with the outcomes of the study by Kalbusch et al. (2020), i.e. one of the few studies to be published before the research proposed in this chapter. On the other hand, reductions in the net inflow are observed in the case of the other DMAs concerned (i.e. the Centro DMA and the Abano Terme DMA), in which the non-residential component is non-negligible and where the stop of non-essential activities during the lockdown period had the greatest impact. In greater detail, as far as the Centro DMA is regarded, decreases of 13.1% and 15.2% emerge when the average net inflow of lockdown period ($10558\ m^3/d$) s compared against that of the corresponding 2019 period ($12154\ m^3/d$) and that of the period preceding the lockdown ($12448\ m^3/d$), respectively. Moreover, in the case of the Centro DMA (where weekday net inflow before lockdown is typically higher at the weekend) a consistent variation in the weekly distribution of the net inflow emerged due to lockdown, being the weekday inflow in these circumstances in line with the values previously observed only during weekends/holidays. This is most likely due to be related to the imposed closure of the many commercial, institutional, and administrative activities located in the city centre (along with the obligation to work from home and the consequent reduction of urban commuting phenomena from the areas nearby), leading to a scenario which is rather close to that of weekends and holidays under ordinary demand conditions.

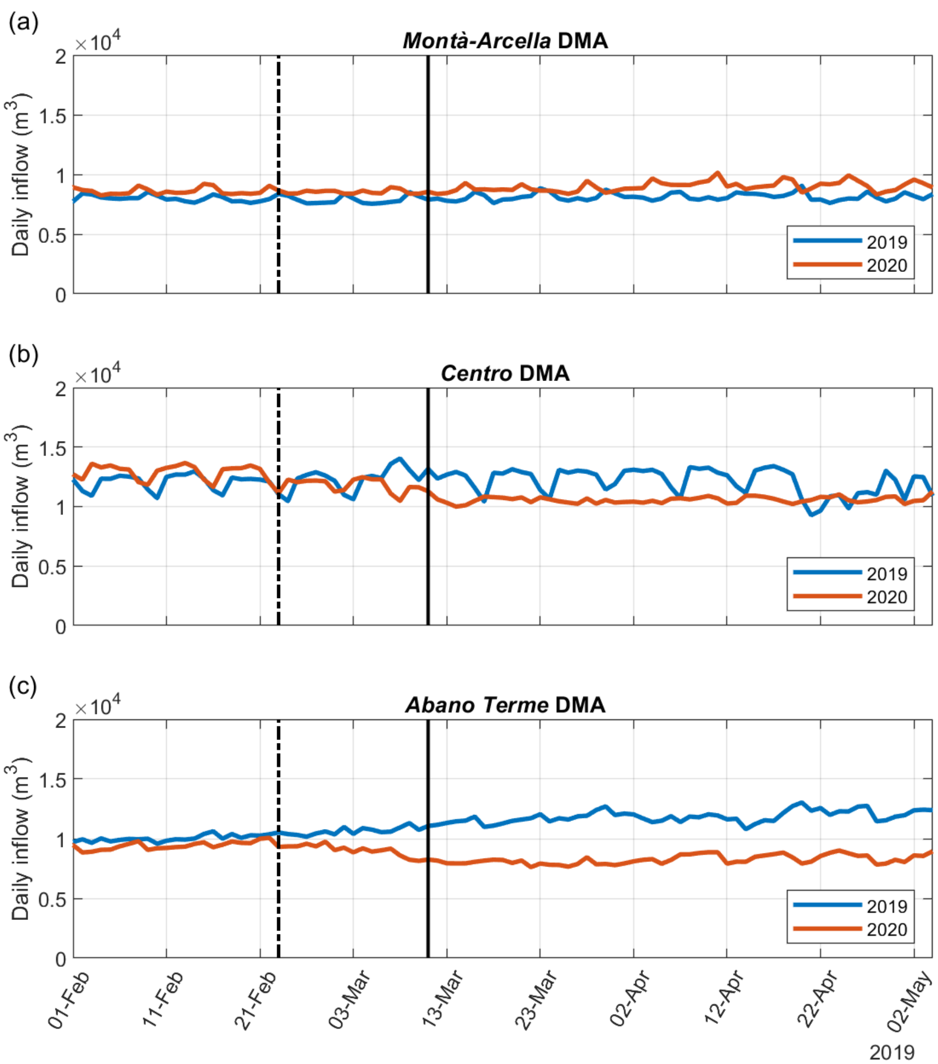

Figure 6.3. Daily average net inflow in the Montà-Arcella DMA (a), the Centro DMA (b), and the Abano Terme DMA (c) of the Padua water distribution network over the lockdown periods of 2020 (orange line) and the corresponding period of the year 2019 (blue line).The black broken line identifies the day when educational and non-essential activities were suspended in Italy (i.e. 23 February 2020), whereas the black continuous line is related to the first day of lockdown (i.e. 11 March 2020).

As far as the Abano Terme DMA is regarded, even higher drops in the net inflow emerged due to lockdown, i.e. 30.3% (when comparing the observed $8237 m^3/d$ against the $11826\ m^3/d$ of the corresponding 2019 period) and 11.2% (when comparing the value related to lockdown against the $9276 m^3/d$ observed before lockdown). These reductions are likely to be mainly related to a reduction in the non-residential water consumption, being the consequence of the stop of tourism and the closure of all thermal, wellness, catering, and accommodation facilities in the area. Lastly, with reference to the entire Padua water distribution network, it is worth noting a 9.6% reduction when comparing the net inflow observed during lockdown against the value of the corresponding 2019 period (along with a 6.6% reduction between the period preceding lockdown and the period of lockdown). This reveals that, overall, the COVID-19 restrictions had the effect of decreasing water consumption in the Padua water distribution network, where non-residential activities impact on water consumption for around 37%.

On the daily scale (i.e. hourly temporal resolution), the hourly average inflow coefficients of each DMA are shown in Figure 6.4 with reference to weekdays and weekends/holidays of the lockdown period of 2020 and the corresponding 2019 period. The figure reveals a general delay in the peak morning net inflow in each DMA during lockdown, when compared to the corresponding period of 2019. This is particularly evident in mainly residential areas over weekdays (e.g. the Montà-Arcella DMA, as shown in Figure 6.4 a) and confirms the tendency of people to change their water consumption habits as a consequence of the restrictions imposed. In fact, due to the obligation to work from home, most of the users did not have to wake up earlier to reach workplaces, thus consuming water in a more distributed manner throughout the morning over working days. This delay in the morning inflow, albeit less evident, is observable also in the case of the other DMAs and with reference to weekdays and holidays (see Figure 6.4 b, Figure 6.4 d, Figure 6.4 e, Figure 6.4 g, and Figure 6.4 h). By contrast, no substantial variations between 2019 and 2020 evening inflow profiles emerged, highlighting no relevant changes in the water consumption from late afternoon to the night.

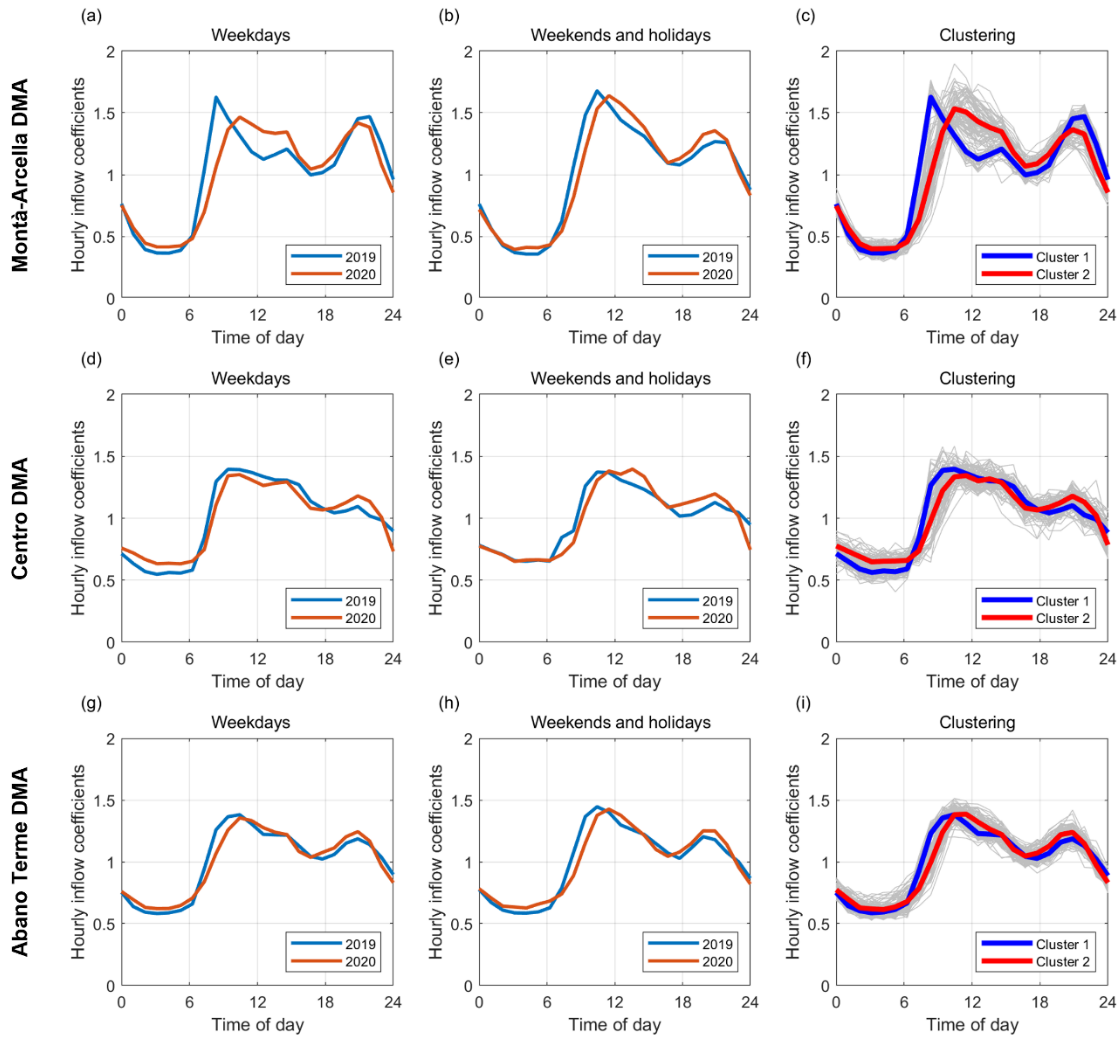

Figure 6.4. Average hourly inflow coefficients of the three Padua DMAs concerned on weekdays and weekend day/holidays over the lockdown period of 2020 and the corresponding 2019 period (panels a–b, d–e, and g–h). Results of cluster analysis are also reported (panels c, f, and i).

Figure 6.4 also shows the results of cluster analysis applied to divide all the daily net inflow profiles observed during lockdown and in the corresponding 2019 period in a number PC of partition classes. In this regard, the K-means clustering algorithm was applied to daily water use profiles by ranging the number of clusters (i.e. PC-value) from 2 to 10 and calculating the average silhouette value in turn. The highest silhouette value was observed for a number PC of partition classes equal to 2 in the case of each DMA, thus highlighting that the net inflow profiles of each DMA tend to assume two different shapes throughout the week. Therefore, the K-means algorithm was re-applied by assuming $PC = 2$. The two clusters obtained for each DMA are shown in Figure 6.4 c, Figure 6.4 f, and Figure 6.4 i, along with the profiles observed in each day of the lockdown period and the corresponding 2019 period (thin grey lines). Moreover, cross-correlation was made by comparing the cluster related to each daily profile and its corresponding day type based on the Italian calendar. The results of the analysis are indicated in Table 6.2 (Montà-Arcella DMA), Table 6.3 (Centro DMA), and Table 6.4 (Abano Terme DMA).

Table 6.2. Percentages of (normalized) daily inflow profiles associated with each of the two clusters in the Montà-Arcella DMA over the 2020 lockdown period and the corresponding 2019 period.

	11 March – 3 May 2019		**11 March – 3 May 2020**	
	Cluster 1 (PC_1)	**Cluster 2 (PC_2)**	**Cluster 1 (PC_1)**	**Cluster 2 (PC_2)**
Weekdays	**68.5%**	0.0%	**0.0%**	66.7%
Weekends/holidays	0.0%	**31.5%**	0.0%	**33.3%**

Note: PC = partition class.

Table 6.3. Percentages of (normalized) daily inflow profiles associated with each of the two clusters in the Centro DMA over the lockdown period and the corresponding 2019 period.

	11 March – 3 May 2019		**11 March – 3 May 2020**	
	Cluster 1 (PC_1)	**Cluster 2 (PC_2)**	**Cluster 1 (PC_1)**	**Cluster 2 (PC_2)**
Weekdays	**65.3%**	0.0%	**7.8%**	56.9%
Weekends/holidays	8.2%	**26.5%**	0.0%	**35.3%**

Note: PC = partition class.

Table 6.4. Percentages of (normalized) daily inflow profiles associated with each of the two clusters in the Abano Terme DMA over the lockdown period and the corresponding 2019 period.

	11 March – 3 May 2019		**11 March – 3 May 2020**	
	Cluster 1	**Cluster 2**	**Cluster 1**	**Cluster 2**
	$(\boldsymbol{PC_1})$	$(\boldsymbol{PC_2})$	$(\boldsymbol{PC_1})$	$(\boldsymbol{PC_2})$
Weekdays	**68.5%**	0.0%	**11.1%**	55.6%
Weekends/holidays	13.0%	**18.5%**	0.0%	**33.3%**

Note: PC = partition class.

On the one hand, with reference to the period between 11 March and 3 May 2019, the comparison of day types with their corresponding inflow cluster profiles reveals a strong correlation between them, further confirming that – under ordinary conditions – the water inflow typically tends to assume a different profile depending on whether the day is a weekday or a holiday. Indeed, a 92.9% average degree of correlation between Cluster 1 (resp. Cluster 2) and weekdays (resp. holidays) is observed, ranging from 100.0% in the case of the Montà-Arcella DMA to 91.8% in the case of the Centro DMA and 87.0% in the case of the Abano Terme DMA (thus slightly decreasing with the increase in the non-residential water consumption). On the other hand, with reference to the lockdown period (i.e. 11 March–3 May 2020), the degree of correlation between Cluster 1 (resp. Cluster 2) and weekdays (resp. holidays) decreases to the average value of 40.2%, ranging from 33.3% in the case of the Montà-Arcella DMA to 43.1% in the case of the Centro DMA and 44.4% in the case of the Abano Terme DMA (thus slightly increasing with the non-residential water consumption). This means that – in the light of the restrictions imposed and under non-ordinary conditions – water inflow profiles are not characterized anymore by a profile related to day type. In greater detail, it results that nearly all inflow profiles (i.e. an average of 93.7%, ranging from 100.0% in the case of the Montà-Arcella DMA, to 92.2% in the case of the Centro DMA and 88.9% in the case of the Abano Terme DMA) are associated with Cluster 2, i.e. the cluster originally related to weekends and holidays under ordinary conditions – despite day type, thus confirming the substantial change in people's lifestyle due to restrictions.

6.2.2. User-level analysis: the Rovigo case study

As far as the Rovigo case study is regarded, a positive trend over time in the water consumption Qd^{t_d} of all the aggregate N_{TU}-users is observed on the seasonal scale (i.e. daily resolution) in the period between 1 February and 3 May 2020 (Figure 6.5). Specifically, Qd^{t_d} rises from about $61.4\ m^3/d$ in the period preceding school closures (1–23 February 2020) to about $64.5\ m^3/d$ in the period of transition toward the complete lockdown (24 February–10 March 2020), and ultimately to $70.2\ m^3/d$ during the actual lockdown period (11 March–3 May 2020).

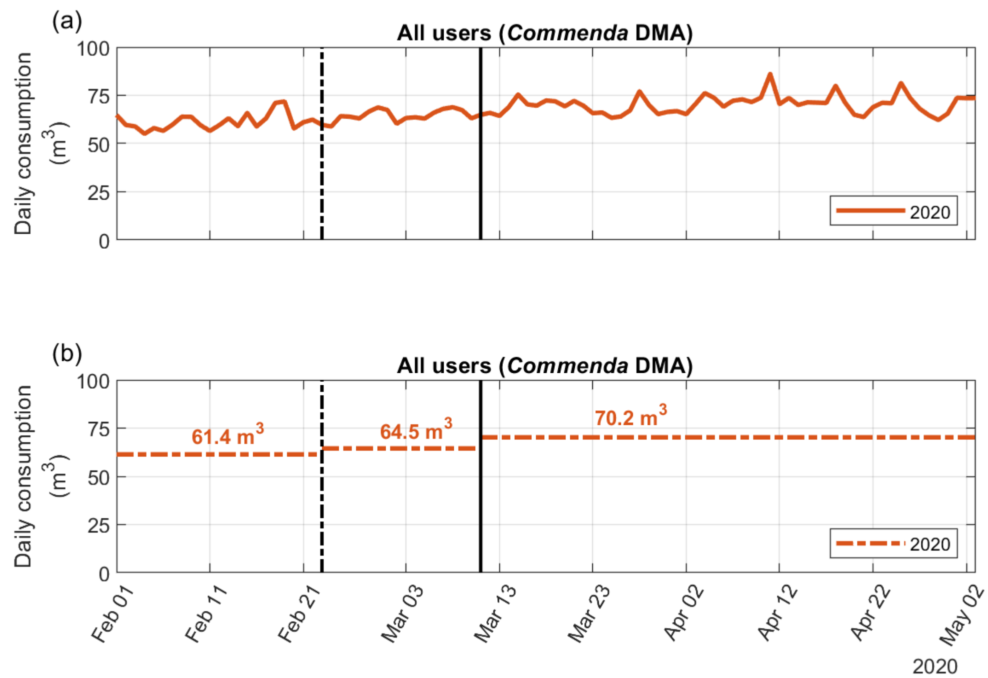

Figure 6.5. Daily water consumption trend (a) and average values (b) of all the N_{TU}-users of the Commenda DMA (Rovigo) over the pre-lockdown and lockdown periods of 2020 (i.e. 1 February – 3 May 2020).The black broken line identifies the day when educational and non-essential activities were suspended in Italy (i.e. 23 February 2020), whereas the black continuous line is related to the first day of lockdown (i.e. 11 March 2020).

The comparison between the daily average water consumption observed in the month of April 2020 (i.e. 4 April–3 May) and the water consumption in the same period of 2019 (Table 6.5) reveals that the increase – not ascribable to sociodemographic factors or anomalous climatic conditions but mainly due to the restrictions and lockdown imposed – is of approximately 18.3%. Specifically, it emerges that the increase in the overall consumption was mainly tied to residential users, as observed by Kalbusch et al. (2020). This increase is also in line with the 10.6% increase in the water inflow observed with reference to the Montà-Arcella DMA, i.e. the mainly residential Padua DMA analyzed in Paragraph 6.2.1. More specifically, residential users – including over 96% of the users of the Commenda DMA – show an overall increase of 19.2% in the daily average consumption (rising from 59.4 m^3/d in April 2019 to 70.8 m^3/d in April 2020) because of social distancing, which forced residents to stay at home. In contrast, in the case of commercial activities – representing a modest number of users in the DMA concerned – a 25.0% reduction in the daily average consumption is observed during the lockdown compared to the same period of the previous year. This is mainly ascribable to few commercial users the consumption of which fell to zero due to the forced closure of businesses imposed by the Italian government.

Table 6.5. Comparison between the daily average water consumption Qd (m^3/d) of the Commenda DMA (Rovigo) users in April 2019 versus April 2020.

Users	**Number**	**Daily average consumption Qd (m^3/d)**		**Variation**
		April 2019	**April 2020**	
Residential	208	59.4	70.8	19.2%
Commercial	8	1.2	0.9	–25.0%
All	216	60.6	71.7	18.3%

In addition, considering the daily consumption of each individual user i ($i = 1, \dots, N_{TU}$) (L/d), it emerges that the majority of users (around 75%) increased their daily average consumption during the month of April 2020 versus the month of April 2019, as shown in Figure 6.6. In over 50% of the cases, the increase is in the range of 0 to 100 L/d, whereas smaller percentages of users show increases exceeding $200\ L/d$ (i.e. nearly 25%) or a decrease (i.e. nearly 20%). As mentioned above, the increase is mainly tied to residential users, representing almost the totality of the set, whereas the majority of commercial users registered no changes or a decrease in the daily average water consumption due to the closure imposed on some of them. Considering all the N_{TU}-users grouped together, the mean increase is of $51.5\ L/d$ with a standard deviation of $107.5\ L/d$.

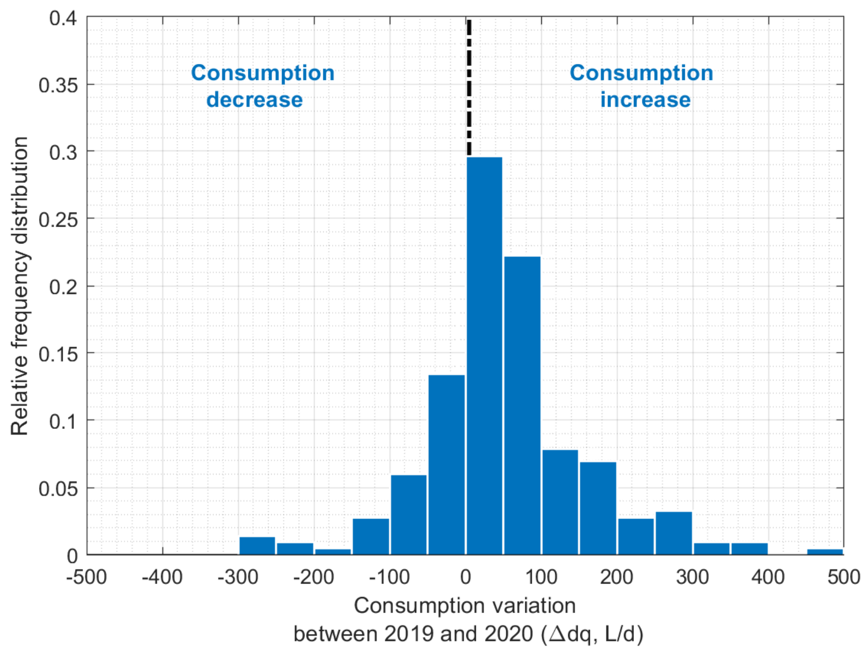

Figure 6.6. Relative frequency distribution of the variation Δqd_i (L/d) in the daily average consumption of each user i between the months of April 2019 and April 2020.

On the daily scale (i.e. hourly resolution) and focusing only on the N_{RU}-residential users (grouped together), the average water consumption profiles, i.e. hourly consumption coefficients C^{t_h}, were calculated by applying Equation (5.2). These are shown in Figure 6.7. It is worth noting that the choice of discriminating water consumption profiles between weekday and holiday profiles was motivated by the results of a preliminary cluster analysis. In greater detail, the K-means clustering algorithm was applied to all daily water consumption profiles observed in 2019 (i.e. under ordinary conditions) by ranging the PC-value from 2 to 10 and calculating the average silhouette value, in turn, as in the analyses carried out in Paragraph 6.2.1. Similarly to the three case study DMAs in Padua water distribution network, the highest average value was observed for $PC = 2$, highlighting that even the residential users of the Commenda DMA tend to consume water in two different ways throughout the week. Based on the Italian calendar, it can be demonstrated that the two clusters obtained correspond to weekdays and weekends/holidays, respectively.

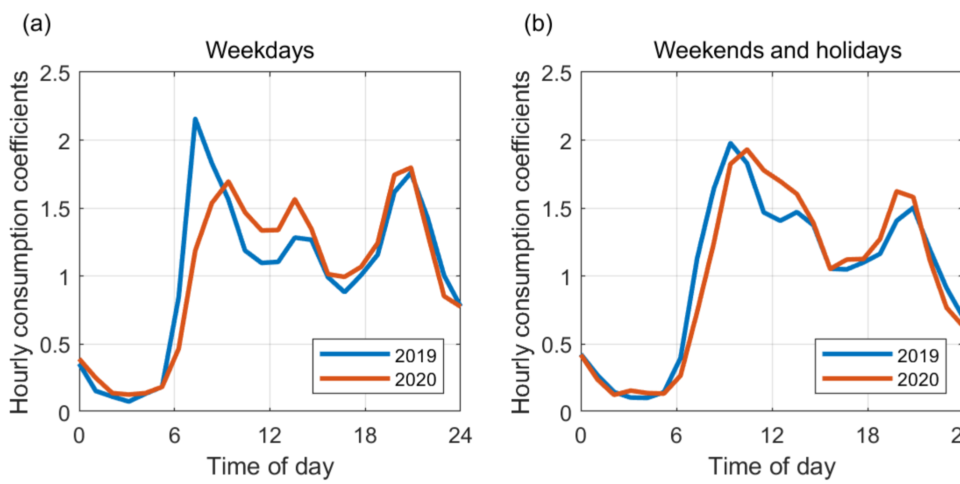

Figure 6.7. Average hourly consumption coefficients of all the N_{RU}-residential users of the Commenda DMA (Rovigo) on weekdays (a) and weekend day/holidays (b) over the months of April 2020 (i.e. lockdown) and April 2019.

Figure 6.7 a reveals that, in the case of weekdays, the peak morning consumption in April 2019 occurred between 7:00 a.m. and 8:00 a.m. ($C^{t_h} = 2.13$), whereas, during the lockdown, a significant reduction in its entity, as well as a delay of about 2 h (equivalent to a C^{t_h} of about 1.70 between 9:00 a.m. and 10:00 a.m.) was observed. This delay, also pointed out in the case study of Padua and in the analyses reported by Balacco et al. (2020), is ascribable to the fact that, on weekdays during the lockdown period, users tended to get up later than in the month of April 2019. With reference to diurnal hours, a general increase in C^{t_h} values is observed during the lockdown.

This new profile suggests the presence of a larger number of users confined to their respective homes as a result of the forced closure of schools and workplaces. Similar considerations partially apply also to the weekends/holidays water use profile (Figure 6.7 b). In fact, during the lockdown period, a slight delay in the morning peak occurred, as the highest value of C^{t_h} is shifted forward by 1 h, and a general increase in water consumption is observed during diurnal hours.

In greater detail, as far as weekdays are concerned, the differences $\Delta qh_i^{t_h}$ between the average water consumption of each residential user i over April 2020 and 2019 were calculated as shown in Equation (6.2). The box plots are shown in Figure 6.8.

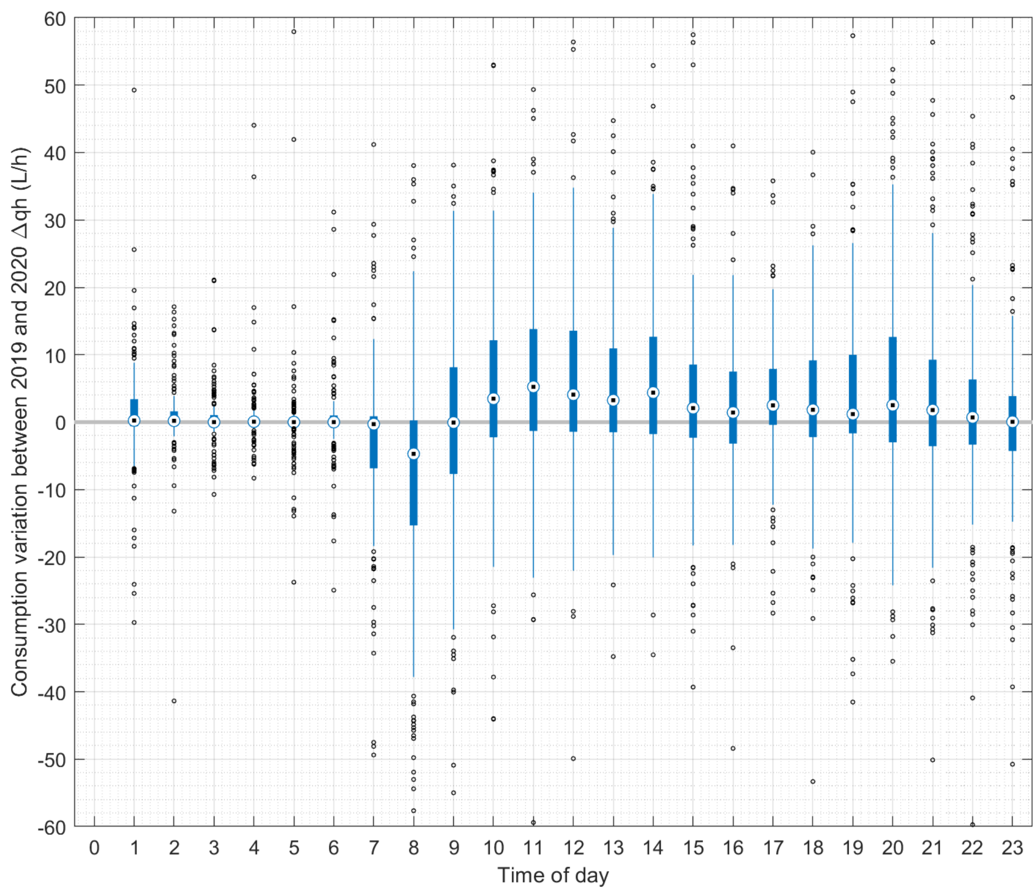

Figure 6.8. Box plots of the differences $\Delta qh_i^{t_h}$ between the average water consumption of April 2020 and 2019 (residential users, weekdays only).

The boxes shown in Figure 6.8 are characterized by values tightly packed around zero between 2:00 and 5:00, meaning that, on average, there was no substantial difference in residential water consumption from 2019 to 2020 during the night-time. In contrast, variations are more evident after 6:00. Specifically, between 6:00 and 8:00, nearly 75% of the residential users show a reduction in the average water consumption during the lockdown compared to 2019. By contrast, in the diurnal hours after 9:00, 75% of the users show an increase in the average water consumption during the lockdown compared to 2019. Analogous results, even though less marked, can be obtained for weekends and holidays.

Most of the preceding considerations about residential water consumption profiles on weekdays are further supported by the results of cluster analysis conducted with reference to the average weekday profiles observed in April 2019 at each residential user, and those observed in April 2020. Unlike the cases when clustering was applied on the daily inflow profiles of DMAs (Paragraph 5.3.1 and Paragraph 6.2.1) – or daily water consumption profiles of an aggregate sample of users (Paragraph 6.2.2) – the preliminary silhouette curve analysis conducted here to identify the optimal number of partitioning classes (i.e., optimal PC-value) showed the highest average silhouette for $PC = 4$, meaning that, on average, weekday profiles are most likely to assume four different shapes based on the residential user considered. The clusters emerged from the K-means analysis (Figure 6.9) are different in terms of water consumption distribution throughout the day and peak consumption time of occurrence. In greater detail, the following clusters were obtained: (1) profile with limited consumption during the day and a significant peak in the morning (PC_1); (2) profile with moderate consumption during the day and a peak in the morning (PC_2); (3) profile with limited consumption during the day and a significant peak in the evening (PC_3); and (4) profile with moderate consumption during the day and a peak in the evening (PC_4).

Table 6.6 shows the percentages of residential users related to each cluster in April 2019 and in April 2020. Overall, it is revealed that nearly 45% of users changed their partition class with the advent of the lockdown. Indeed, a high percentage of users (i.e. 16.3%) switched from PC_1 to the other clusters, whereas the vice versa is valid only for a small part (i.e. 1.9%). Therefore, the re-

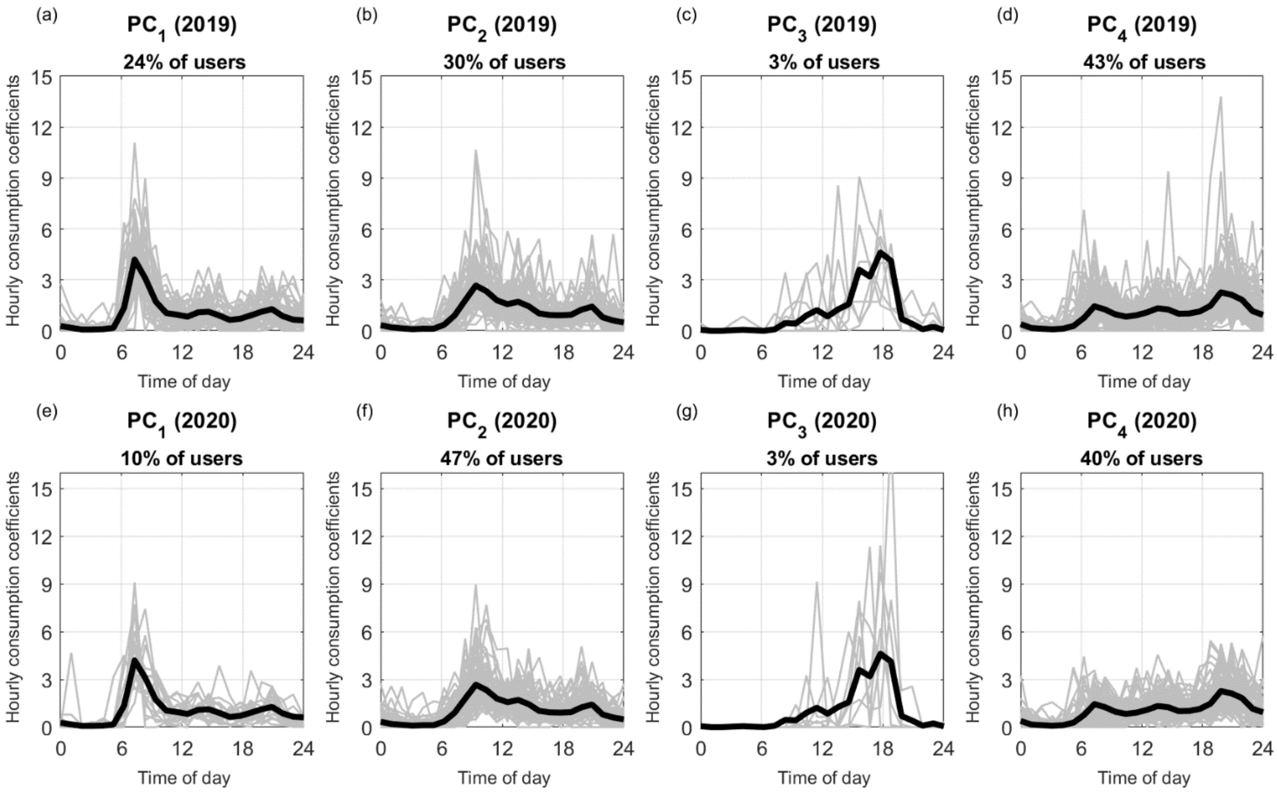

Figure 6.9. K-means algorithm results. Every panel includes the average 2019 and 2020 weekday water use profiles (i.e. c^{t_h}, thin grey lines) of individual residential users related to each of the PC-partition classes and the cluster (thick black line) associated with each partition class.

Table 6.6. Percentages of residential users assigned to each of the four partition classes in April 2019 (pre-lockdown period) and in April 2020 (lockdown period).

April 2019	April 2020				
	Cluster 1 (PC_1)	Cluster 2 (PC_2)	Cluster 3 (PC_3)	Cluster 4 (PC_4)	Total
Cluster 1 (PC_1)	7.7%	9.1%	0.0%	7.2%	**24.0%**
Cluster 2 (PC_2)	0.5%	22.1%	1.4%	5.8%	**29.8%**
Cluster 3 (PC_3)	0.0%	0.5%	0.6%	2.4%	**3.5%**
Cluster 4 (PC_4)	1.4%	14.9%	1.4%	25.0%	**42.7%**
Total	**9.6%**	**46.6%**	**3.4%**	**40.4%**	–

sults of the K-means algorithm application confirm a general change in the weekday behavior of residential users during the lockdown period due to social distancing and the obligation of working from home. There was a greater tendency to use water in a more evenly distributed manner during the day, with attenuation in the morning peak of consumption.

Lastly, in relation to the four commercial users of the Commenda DMA (Figure 6.10), it emerged that, during the lockdown, those providing essential goods (e.g. pharmacies and hardware stores) did not substantially change their water consumption behaviour compared to the same period of the previous year. In contrast, other commercial users (e.g. wellness centres and hairdressers) have

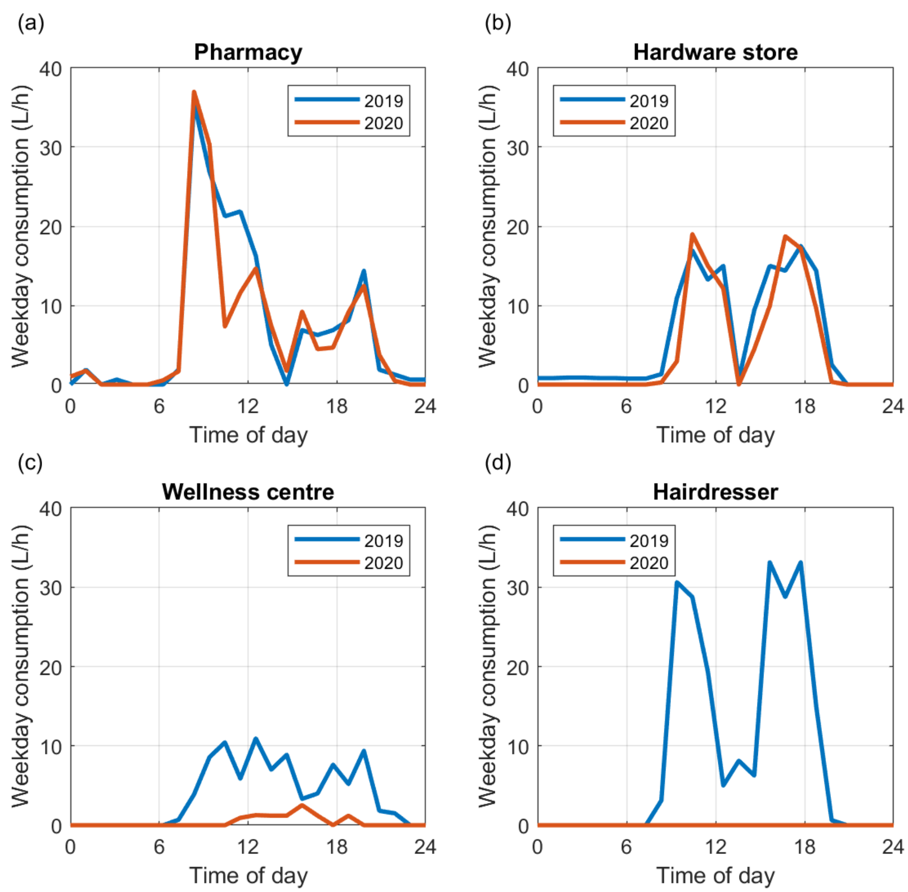

Figure 6.10. Weekday hourly average water consumption (L/h) in the months of April 2019 and 2020 of: a pharmacy (a); a hardware store (b); a wellness center (c); and a hairdresser (d).

completely changed their consumption profile, not consuming water at all during the period of forced closure of their businesses. It is also worth noting that this tendency to reduce or stop water consumption during the lockdown period is in line with the outcomes emerged with reference to the Padua DMAs in which the non-residential component of water consumption is non-negligible (i.e. Centro DMA and Abano Terme DMA). Indeed, although acknowledging that changes in the net inflow can generally be due to other factors beyond water consumption (e.g. leakage formation/repair and valve settings), no leak events – and neither changes in operational controls – were reported by the AcegasApsAmga S.p.A. water utility over the two 2019 and 2020 periods concerned. Therefore, as highlighted in Paragraph 6.2.1, it is reasonable to assume that the net inflow reductions in the two aforementioned Padua DMAs was mainly due to the closure of commercial and activities and the interruption of tourist services, coherently with the outcomes reported in the case of Rovigo.

6.3. Conclusions

This chapter aimed at investigating the effects of the restrictions imposted during the first COVID-19 lockdown in Italy (11 March – 3 May 2020) on residential and non-residential water consumption. Analysis were conducted at multiple levels of spatial scales (i.e. from the DMA to the individual user level) and temporal scales (from the daily to the hourly resolution) by exploiting water inflow and water consumption data collected in Padua and Rovigo (northern Italy). The study revealed that:

- The lockdown imposed to limit the spread of COVID-19 had the effect of decreasing the net inflow in the city of Padua by about 10% compared to the same period of year 2019.
- Different variations in the net inflow are observed based on the characteristics of the Padua DMAs considered, typically with increasing inflow in the case of mainly residential areas (Montà–Arcella) and decreasing in those areas where the non-residential component of water consumption is more consistent (Centro, Abano Terme). Similarly, in the concerned Rovigo DMA (Commenda), a 18% increase in the water consumption – mainly ascribable to residential users – is observed.

- Changes in the inflow daily profiles are observed in all the Padua DMAs considered, as well as a delay in the morning peak of 1 to 2 h. A clear delay in the morning peak consumption of the residential users– along with a general increase in water consumption during diurnal hours – is also observed in the Rovigo case study on weekdays, which is understandable given the fact that the suspension of school and job activities and the incentivization of homeworking induced people to consume water in a more distributed manner during the day
- Moreover, as opposed to the periods preceding lockdown (when the net inflow of each DMA typically assumed a different profile based on day type, i.e. weekdays versus holidays), about 94% of the daily profiles observed in the Padua DMAs during lockdown tended to fit the holiday typical profile independently of day type. Similar considerations also apply to the case of the Rovigo residential users, a considerable group of which (i.e. nearly 45%) changed their water consumption profile during lockdown.
- With reference to the few commercial users belonging to the Rovigo dataset, considerable changes in water consumption are observed in the case of activities for which a forced closure was imposed during lockdown.

Overall, it is worth noting that only net inflow analyses were carried out in the case of Padua. Therefore, even though no considerable anomalies were reported by the AcegasApsAmga S.p.A – the water utility responsible for water management in Padua – results may be partially affected by leakage evolution or minor unreported changes in network controls. Moreover, in the case of the users of the Rovigo dataset, it was not possible to investigate the correlation between water consumption changes and sociodemographic factors such as family size, family income, or household characteristics. Also, because user monitoring has been ongoing since April 2019, a comparison between the year 2020 water consumption and the years prior to 2019 was not possible. Lastly, it is worth highlighting that the unavailability of water consumption data collected over the first COVID-19 lockdown period at finer levels of spatial detail did not allow to investigate the effects of the pandemic on the end uses of water, limiting the analysis to coarser spatial resolutions (i.e. urban and user scale). Therefore, the investigation of the impacts of COVID-19 on water consumption at the end-use level still remains an open issue.

In conclusion – and despite the above-mentioned limitations – this study demonstrated that the adoption of restrictive measures to contain the COVID-19 pandemic largely influenced people's water consumption habits in the areas analyzed. It is believed that the results of the analyses could be transferred to additional similar contexts (i.e., DMAs of medium-sized cities – including not only residential areas but also districts of touristic or commercial interest – characterized by a variety of activities and different and heterogeneous types of water consumption) and used to improve the understanding of the network under non-ordinary demand conditions and to validate water distribution system models better, as also reported by Berglund et al. (2021). In fact, when transferred to similar contexts, the results reported in this chapter can aid water utilities in better forecasting the response of water distribution networks in case of future restrictions and adapting the network operational criteria to new conditions. Also, the outcomes demonstrate the significant advantages brought by smart meters for automated monitoring and remote data transmission, which made water consumption data collection possible in full compliance with social distancing and the other restrictive measurements in force during lockdown.

Chapter 7
Conclusions

Characterizing residential and non-residential water consumption with a high level of spatiotemporal detail undoubtedly enhances the effective planning and management of water systems and is becoming essential to compensate for the issues of population growth, water scarcity, and a changing climate regime. In the last few decades, the advancements in technology with the introduction of smart metering solutions enabled the collection of water consumption data with unprecedented fine spatial and temporal resolution. Since the early stages of smart metering technologies, the literature has witnessed an increase of studies using various technologies, methods, and techniques, presenting the characteristics of water consumption, with main regard to residential sector and under ordinary demand conditions. Large – yet fragmented – amounts of information on residential water consumption are nowadays available; however, there is still great potential in the investigation of the characteristics of water consumption in non-residential contexts or under non-ordinary demand conditions, i.e. in under the influence of events that deviate the typical attitude of people towards water consumption. In the light of the above, this thesis was developed with the aim of taking a step forward in the field of water consumption characterization at different levels of spatio-temporal detail (i.e. up to the end-use scale at sub-minute resolution), in different contexts (i.e. residential *versus* non-residential), and under different conditions of water demand (i.e. ordinary *versus* non-ordinary).

7.1. Summary of key findings and scientific contributions

The research presented in the current thesis – providing insight into residential and non-residential water consumption at different levels of spatio-temporal detail and by considering different conditions of water demand – was carried out with the aim of addressing four main research questions. The key findings and scientific emerged in relation to each research question are summarized, along with the related scientific contributions, in the following.

(1) "*How could the available, but fragmented, information on the residential end uses of water be exploited in order to extensively and systematically compare the characteristics of end-use water consumption globally (not only highlighting similarities and differences among the studies available in the literature, but also investigating end-use consumption distribution throughout the day, end-use consumption average parameter values, and their related statistical behaviour)?*"

To answer this question, a comprehensive overview of the state-of-the-art about research in the field of residential water consumption at the end-use level was provided. Over one hundred studies on residential end uses of water available in the literature were qualitatively and quantitatively reviewed by carrying out a multi-level method of analysis to evaluate the main perspectives from around the world in terms of residential end-use water consumption. Based on the results available in the literature, it emerged that most of the studies mainly focus on the evaluation of aspects such as the daily per capita end-use water consumption and the average values of end-use parameters, whereas, generally, less relevance is given to the investigation of end-use parameter distributions, daily profiles, determinants, and efficiency.

The findings of the study presented in *Chapter 3* will likely be of interest to the actors involved in water resources management and water demand management. In fact, the findings achieved 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. In addition, the end-use data presented in this thesis 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. Furthermore, the findings achieved may help understand which aspects have been mostly explored in recent research and, if needed, identifying the studies of interest based on their geographical and methodological details. Lastly, the outcomes 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, since the data reported would be a valid benchmark against which to compare consumer habits and behaviours, thus encouraging more conscious and sustainable use of water.

However, 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 behaviours observable over too limited periods or household samples, while reducing monitoring efforts and the invested resources.

(2) "*How could detailed information on the residential end uses of water be effectively obtained by exploiting only water consumption data collected at the household level with a temporal resolution that is close to that of the most widespread commercial smart meters?*"

In the light of the relevance of information on residential water consumption up to the level of water end uses, attention was then paid to methods for automated end-use disaggregation and classification of data collected at the household level, i.e. in proximity to the water meter. Specifically, to address the second research question, a methodology for end-use disaggregation and classification based on coarse-resolution (i.e. 1 min) data was presented in *Chapter 4* and validated with water consumption data collected in households featuring a variety of end uses and in considerably different geographical contexts, i.e. Italy and the Netherlands.

The results obtained confirm the potential of the method in disaggregating and classifying water end-use events effectively, i.e. with an average total accuracy equal to (or higher than) 84% even if general values of end-use disaggregation and classification parameters are input in the model instead of specific values. This proved that the method is able to perform an effective end-use disaggregation and classification independently of the availability of detailed information about end-use features and users' habits (i.e. specific parameter values), thus potentially allowing large amounts of aggregate water consumption data to be processed without the need to investigate the characteristics of water consumption in each individual household. In addition, the results – which demonstrated the robustness and the applicability of the method to broad contexts in the field of residential water consumption – proved that an accurate end-use disaggregation and classification is possible despite the 1-min resolution of data, in contrast with most of the approaches described in the literature and making use of data collected at a higher resolution (i.e. 5 or 10-s). This allows the method to be potentially applied to massive amounts of water consumption data, since the 1-min resolution is closer to the resolutions of commercial smart water meters and, therefore, these data may be more easily available to water utilities.

(3) *"Which are the most relevant characteristics of non-residential water consumption with reference to those user types which have not been investigated in the scientific literature, but the presence and the impacts of which may be significant in several contexts (e.g. bathing facilities for the tourist sector)?"*

As far as non-residential water consumption is regarded, a first analysis was conducted with the aim of answering the third research question, thus providing insight into the effects of seaside tourism on water consumption in a case study coastal area in northern Italy that is typically subjected to high tourist fluctuations throughout the year, and where the resident population is rather low compared to the tourist population during the summer period. The analysis was carried out at multiple spatiotemporal scales – from urban to user level, and from yearly to daily scale – by exploiting hourly flow data collected at the inflow points of the area and at some touristic users (i.e. nine bathing facilities and a holiday home). In addition, the impact of weather – temperature and rainfall – on water consumption was explored.

Overall, the study demonstrated that seasonal tourism and climatic variables largely influence water consumption in the coastal area concerned. It is believed that the results of the analyses – describing the behaviour of the DMA considered in face of changes in tourist or climatic conditions – can aid the water utility responsible for water distribution in this coastal area in better understanding the characteristics of water consumption and its main components, thus moving towards a more efficient management of the water system. In fact, especially in relation to tourist areas in coastal regions with limited availability of drinking water, a careful management of water systems is essential to satisfy users' needs without depleting excessive amounts of water or energy. This typically includes the adoption of strategies aimed at an optimal management of the network (e.g. by controlling tank filling, pump scheduling, or valve activation/closure), the efficiency of which can be evaluated also based on the findings of the study presented in *Chapter 5*. Furthermore, since the analysis of water consumption up to the level of individual users allowed understanding which types of users are mostly impacting on water balance – and revealed that most of the water used in the touristic DMA considered is tied to accommodation facilities – the outcomes may also support the water utility in preventing the waste of water at those users. This could be achieved, for example, by incentivizing the installation of low-flow devices, providing feedback to customers, developing awareness-rising campaigns, or evaluating whether systematic changes in the water tariff could lead to benefits in terms of water conservation.

(4) "*How large is the impact of non-ordinary demand conditions (e.g. those due to exceptional circumstances like pandemics or extreme events) on residential and non-residential water consumption?*"

Lastly, to answer the fourth research question, a part was played in the field of water consumption characterization under non-ordinary conditions of water demand by investigating the effects of the limitations imposed to contain the spread of COVID-19 pandemic on residential and non-residential water consumption at the DMA and user level. In particular, to support water utilities in understanding the impacts of the COVID-19 pandemic on water consumption and improving water distribution system resilience, the effects of the first Italian lockdown (11 March – 3 May 2020) were investigated with to regard to DMAs in the city of Padua (northern Italy) featuring different rates of residential and non-residential water consumption. Moreover, the water consumption recorded during the lockdown period in over two hundred users located in Rovigo (northern Italy) was analyzed at different levels of temporal and spatial aggregation and compared with the consumption recorded in the same period of the previous year. The results show that, during the lockdown period, the overall water inflow (or, respectively, water consumption) in mainly residential areas increased by 10% to 18%, whereas it decreased by 13% to 30% in those areas where the non-residential component of water consumption is non-negligible. Moreover, water consumption was observed to be more spread out over the day, with a decrease (and a delay) in peak morning consumption, which was particularly evident on weekdays.

Overall, the results of the study can be scaled to other contexts of medium-sized cities featuring a variety of activities and water uses, thus aiding water utilities in better predicting the response of water distribution networks under non-ordinary conditions (e.g. in case of future restrictions). Nevertheless, the outcomes of the analyses performed can hint at some considerations of interest for water utilities and system management. Indeed, on the one hand, it is worth recalling that changes in water consumption generally result in the need to rethink water distribution network operational criteria with the aim of adapting them to new conditions. This was confirmed by the water utilities responsible for water supply in the case study considered, which adopted new management strategies during the lockdown (e.g., modifications in the pump operation) to adapt the system to water consumption changes, providing larger volumes but with reduced peak discharge in the residential districts and lower volumes in the commercial districts. Furthermore, it is worth highlighting the considerable advantages brought to the water utility by smart meters for water consumption monitoring. Indeed, thanks to the monitoring systems, water consumption data could be collected despite the emergency condition and with respect to social distancing.

7.2. Future work recommendations

In the light of the most relevant outcomes reported in this thesis, follow-up research should focus on the following aspects:

- Realization of a fully open-access end-use database – featuring a comprehensive number of water-use events observed and collected in a variety of spatio-temporal contexts. Although not yet possible based on the limited number of datasets currently available in the literature, it would allow detailed analyses to be carried out, going beyond the limits currently affecting the literature on residential end uses of water.
- Smart metering the water consumption in additional residential samples to investigate the characteristics of water end uses for a larger and statistically significant number of households. This would make the obtainment of a more representative set of disaggregation parameters values possible, allowing the automated disaggregation and classification of massive water consumption data. Nevertheless, it would also allow in-depth evaluations to 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.
- Understanding whether the 1-min temporal resolution of water consumption data also allows disaggregating and classifying all the possible combinations of water end uses (e.g. shower and toilet used simultaneously) and, if so, adapting the disaggregation method accordingly.
- Expanding the statistical knowledge on non-residential water consumption and per user type such as schools, hospitals, catering activities, and sport facilities, in order to obtain information supporting water utilities in better validating water distribution system models (e.g. expected volumes, peak times, and profiles of water consumption).
- Evaluating the characteristics of residential water consumption under non-ordinary demand conditions – e.g. in the event of pandemics or other adverse phenomena strongly affecting people's lifestyle – up to the level of end uses, in order to understand which of them could be mostly impacted and for which parameters.

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Appendix A

End-use statistical parameter distributions: curve fitting results

Table A.1. End-use Statistical Parameter Distributions: Curve Fitting Results.

End Use	Parameter	Unit	REUS	Kolmogorov-Smirnov Test Results					Best-fitting distribution	Parameter 1[a]	Parameter 2[a]
				NRM	EXP	LOG	WBL	GAM			
D	Volume per use	L/load	Beal and Stewart 2011	0	1	1	0	0	LOG	2.46	0.53
D	Volume per use	L/load	Bennett and Linstedt 1975	1	1	1	1	1	LOG	3.20	0.11
D	Volume per use	L/load	Roberts 2005	1	1	1	1	1	LOG	3.14	0.30
D	Volume per use	L/load	Redhead et al. 2013	1	1	0	0	0	NRM	14.98	6.31
D	Volume per use	L/load	Siriwardene 2018	1	1	1	1	1	LOG	2.33	0.68
D	Volume per use	L/load	Cubillo-González et al. 2008	1	1	1	1	1	WBL	18.70	2.12
D	Volume per use	L/load	Mazzoni et al. 2023b	1	1	1	1	1	WBL	13.33	1.95
D	Duration per use[b]	s/load	Cubillo-González et al. 2008	1	1	1	1	1	WBL	347.69	2.00
D	Duration per use[b]	s/load	Mazzoni et al. 2023b	1	1	1	1	1	WBL	307.89	1.90
D	Flow rate per use	L/min	Cubillo-González et al. 2008	1	1	1	1	1	GAM	15.04	0.25
D	Flow rate per use	L/min	Mazzoni et al. 2023b	1	1	1	1	1	LOG	1.05	0.33
D	Frequency of use	loads/person/day	Mazzoni et al. 2023b	1	1	1	1	1	WBL	0.38	1.41
D	Frequency of use	loads/person/day	Diaz et al. 2021	1	1	1	1	1	WBL	0.23	2.23

Table A.1 (Continued). End-use Statistical Parameter Distributions: Curve Fitting Results.

End Use	Parameter	Unit	REUS	Kolmogorov-Smirnov Test Results					Best-fitting distribution	Parameter 1[a]	Parameter 2[a]
				NRM	EXP	LOG	WBL	GAM			
D	Frequency of use	loads/person/day	Redhead et al. 2013	1	1	1	1	0	WBL	0.18	1.93
D	Frequency of use	loads/person/day	Roberts 2005	1	1	1	1	1	GAM	2.68	0.06
D	Frequency of use	loads/person/day	Siriwardene 2018	1	1	0	0	0	EXP	0.23	-
D	Frequency of use	loads/person/day	Beal and Stewart 2011	1	1	1	1	1	EXP	0.24	-
WM	Volume per use	L/load	Bennett and Linstedt 1975	1	1	1	1	1	GAM	42.82	3.32
WM	Volume per use	L/load	Heinrich et al. 2010	0	1	1	0	1	GAM	19.19	6.27
WM	Volume per use	L/load	Beal and Stewart 2011	1	1	0	1	1	GAM	4.17	29.96
WM	Volume per use	L/load	Cubillo-González et al. 2008	1	1	1	1	1	WBL	69.89	2.29
WM	Volume per use	L/load	Siriwardene 2018	1	1	1	1	1	LOG	4.34	0.61
WM	Volume per use	L/load	Redhead et al. 2013	1	1	1	1	1	GAM	2.50	34.88
WM	Volume per use	L/load	Aquacraft 2011	1	1	1	1	1	WBL	151.75	3.28
WM	Volume per use	L/load	DeOreo et al. 2011	1	1	1	1	1	NRM	147.03	47.36
WM	Volume per use	L/load	Roberts 2005	1	1	1	1	1	WBL	168.83	3.29
WM	Volume per use	L/load	Mayer et al. 1999	1	1	1	1	1	GAM	14.12	11.50
WM	Volume per use	L/load	Mazzoni et al. 2023b	1	1	1	1	1	GAM	2.30	28.35
WM	Duration per use[b]	s/load	Cubillo-González et al. 2008	1	1	1	0	1	GAM	3.20	178.68
WM	Duration per use[b]	s/load	Mazzoni et al. 2023b	1	1	1	1	1	GAM	2.12	261.27
WM	Flow rate per use	L/min	Cubillo-González et al. 2008	1	1	1	1	1	NRM	7.59	1.71
WM	Flow rate per use	L/min	Mazzoni et al. 2023b	1	1	1	1	1	WBL	7.89	6.74
WM	Frequency of use	loads/person/day	Mazzoni et al. 2023b	1	1	1	1	1	GAM	1.55	0.25
WM	Frequency of use	loads/person/day	Diaz et al. 2021	1	1	1	1	1	LOG	-2.23	0.63
WM	Frequency of use	loads/person/day	Redhead et al. 2013	1	1	1	1	1	GAM	2.68	0.08

Table A.1 (Continued). End-use Statistical Parameter Distributions: Curve Fitting Results.

End Use	Parameter	Unit	REUS	Kolmogorov-Smirnov Test Results					Best-fitting distribution	Parameter 1[a]	Parameter 2[a]
				NRM	EXP	LOG	WBL	GAM			
WM	Frequency of use	loads/person/day	Siriwardene 2018	1	1	1	1	1	GAM	2.58	0.06
WM	Frequency of use	loads/person/day	Beal and Stewart 2011	1	1	1	1	1	WBL	0.25	1.82
WM	Frequency of use	loads/person/day	Roberts 2005	1	1	0	0	0	NRM	0.29	0.14
S	Volume per use	L/use	Mead 2008	1	1	1	1	1	GAM	3.53	16.91
S	Volume per use	L/use	Lauchlan and Dixon 2003	1	1	1	1	1	GAM	3.97	15.97
S	Volume per use	L/use	DeOreo et al. 1996	1	1	1	1	1	LOG	3.80	0.66
S	Volume per use	L/use	Aquacraft 2011	1	1	1	1	1	GAM	10.67	6.09
S	Volume per use	L/use	Willis et al. 2010b (pre-retrofitting)	1	1	1	1	1	LOG	3.83	0.52
S	Volume per use	L/use	DeOreo and Mayer 2013	1	1	1	1	1	GAM	6.43	9.99
S	Volume per use	L/use	DeOreo et al. 2011	1	1	1	1	1	GAM	8.36	8.74
S	Volume per use	L/use	Mayer et al. 2000 (pre-retrofitting)	1	1	1	1	1	LOG	4.24	0.45
S	Volume per use	L/use	Heinrich 2007	1	1	1	1	1	GAM	3.46	23.41
S	Volume per use	L/use	Mayer et al. 2003 (pre-retrofitting)	1	1	1	1	1	LOG	4.14	0.52
S	Volume per use	L/use	Mayer et al. 1999	1	1	1	1	1	LOG	4.15	0.50
S	Volume per use	L/use	Siriwardene 2018	1	1	1	1	1	GAM	2.30	21.00
S	Duration per use	min/use	Beal and Stewart 2011	0	1	1	0	0	LOG	1.85	0.40
S	Duration per use	min/use	Siriwardene 2018	1	1	0	0	0	NRM	5.84	3.13
S	Duration per use	min/use	Diaz et al. 2021	1	1	1	1	1	GAM	2.96	3.88
S	Duration per use	min/use	Anderson et al. 1993	1	1	1	1	1	LOG	1.74	0.41
S	Duration per use	min/use	Mead 2008	1	1	1	1	1	GAM	5.27	1.24
S	Duration per use	min/use	Aquacraft 2011	1	1	1	1	1	LOG	2.17	0.28
S	Duration per use	min/use	Willis et al. 2010b (pre-retrofitting)	1	1	1	1	1	LOG	1.78	0.49

Table A.1 (Continued). End-use Statistical Parameter Distributions: Curve Fitting Results.

End Use	Parameter	Unit	REUS	Kolmogorov-Smirnov Test Results					Best-fitting distribution	Parameter 1[a]	Parameter 2[a]
				NRM	EXP	LOG	WBL	GAM			
S	Duration per use	min/use	DeOreo and Mayer 2013	1	1	1	1	1	GAM	9.80	0.90
S	Duration per use	min/use	Roberts 2005	1	1	1	1	1	GAM	5.29	1.37
S	Duration per use	min/use	Redhead et al. 2013	1	1	1	1	1	GAM	3.36	1.85
S	Duration per use	min/use	Heinrich 2007	1	1	1	1	1	GAM	3.90	1.94
S	Duration per use	min/use	Mayer et al. 2003 (pre-retrofitting)	1	1	1	1	1	LOG	2.13	0.47
S	Duration per use	min/use	Mayer et al. 2000 (pre-retrofitting)	1	1	1	1	1	LOG	2.01	0.46
S	Duration per use	min/use	Mayer et al. 1999	1	1	1	1	1	LOG	2.03	0.46
S	Duration per use	min/use	Cubillo-González et al. 2008	1	1	1	1	1	GAM	2.47	2.84
S	Duration per use	min/use	Blokker 2010	1	1	1	1	1	GAM	3.94	2.07
S	Flow rate per use	L/min	Beal and Stewart 2011	1	1	1	1	1	GAM	11.97	0.69
S	Flow rate per use	L/min	Anderson et al. 1993	1	1	1	1	1	WBL	10.26	2.72
S	Flow rate per use	L/min	Aquacraft 2011	1	1	1	1	1	LOG	2.11	0.22
S	Flow rate per use	L/min	DeOreo et al. 2011	1	1	1	1	1	LOG	2.10	0.25
S	Flow rate per use	L/min	DeOreo and Mayer 2013	1	1	1	1	1	LOG	2.14	0.27
S	Flow rate per use	L/min	Siriwardene 2018	1	1	1	1	1	GAM	8.20	0.96
S	Flow rate per use	L/min	Mayer et al. 2000 (pre-retrofitting)	1	1	1	1	1	NRM	8.96	2.85
S	Flow rate per use	L/min	Redhead et al. 2013	1	1	1	1	1	GAM	4.09	1.71
S	Flow rate per use	L/min	Willis et al. 2010b (pre-retrofitting)	1	1	1	1	1	LOG	2.23	0.33
S	Flow rate per use	L/min	Roberts 2005	1	1	1	1	1	GAM	5.29	1.78
S	Flow rate per use	L/min	Heinrich 2007	1	1	1	1	1	GAM	6.74	1.70
S	Flow rate per use	L/min	Mayer et al. 2003 (pre-retrofitting)	1	1	1	1	1	GAM	8.42	0.92
S	Flow rate per use	L/min	Mayer et al. 1999	1	1	1	1	1	LOG	2.10	0.40

Table A.1 (Continued). End-use Statistical Parameter Distributions: Curve Fitting Results.

End Use	Parameter	Unit	REUS	Kolmogorov-Smirnov Test Results					Best-fitting distribution	Parameter 1[a]	Parameter 2[a]
				NRM	EXP	LOG	WBL	GAM			
S	Flow rate per use	L/min	Cubillo-González et al. 2008	1	1	1	1	1	GAM	10.16	0.88
S	Frequency of use	uses/person/day	Diaz et al. 2021	1	1	1	1	1	WBL	0.86	4.02
S	Frequency of use	uses/person/day	Roberts 2005	1	1	1	1	1	GAM	7.96	0.10
S	Frequency of use	uses/person/day	Siriwardene 2018	1	1	1	1	0	LOG	-0.07	0.36
S	Frequency of use	uses/person/day	Redhead et al. 2013	1	1	1	1	1	WBL	0.89	1.81
S	Frequency of use	uses/person/day	Beal and Stewart 2011	1	1	1	1	1	WBL	1.16	2.19
F	Volume per use	L/flush	Otaki et al. 2013 (half flush)	1	1	1	1	1	NRM	3.00	0.68
F	Volume per use	L/flush	Anderson et al. 1993	0	1	0	0	0	EXP	12.91	-
F	Volume per use	L/flush	Beal and Stewart 2011	1	1	1	1	1	NRM	4.58	1.13
F	Volume per use	L/flush	Otaki et al. 2013 (half flush)	1	1	1	0	1	NRM	6.01	1.23
F	Volume per use	L/flush	Beal and Stewart 2011	1	1	1	1	1	LOG	2.03	0.23
F	Volume per use	L/flush	Siriwardene 2018	1	1	1	1	1	LOG	1.57	0.39
F	Volume per use	L/flush	Redhead et al. 2013	1	1	1	1	1	LOG	1.72	0.26
F	Volume per use	L/flush	Roberts 2005	1	1	1	1	1	GAM	15.79	0.49
F	Volume per use	L/flush	Aquacraft 2011	1	1	1	1	1	LOG	2.07	0.23
F	Volume per use	L/flush	Cubillo-González et al. 2008	1	1	1	1	1	NRM	7.02	2.19
F	Volume per use	L/flush	Bennett and Linstedt 1975	1	1	1	1	1	WBL	16.85	6.12
F	Volume per use	L/flush	Heinrich 2007	1	1	1	1	1	LOG	1.77	0.50
F	Volume per use	L/flush	DeOreo and Mayer 2013	1	1	1	1	1	LOG	2.23	0.40
F	Volume per use	L/flush	DeOreo et al. 2011	1	1	1	1	1	LOG	2.18	0.47
F	Volume per use	L/flush	Mayer et al. 2000 (pre-retrofitting)	1	1	1	1	1	GAM	9.80	1.47
F	Volume per use	L/flush	Mayer et al. 2003 (pre-retrofitting)	1	1	1	1	1	GAM	10.63	1.57

Table A.1 (Continued). End-use Statistical Parameter Distributions: Curve Fitting Results.

End Use	Parameter	Unit	REUS	Kolmogorov-Smirnov Test Results					Best-fitting distribution	Parameter 1[a]	Parameter 2[a]
				NRM	EXP	LOG	WBL	GAM			
F	Volume per use	L/flush	DeOreo et al. 1996	1	1	1	1	1	WBL	15.40	5.77
F	Volume per use	L/flush	Mead 2008	1	1	1	1	1	LOG	1.62	0.38
F	Volume per use	L/flush	Mayer et al. 1999	1	1	1	1	1	WBL	15.65	3.48
F	Volume per use	L/flush	Mazzoni et al. 2023b	1	1	1	1	1	GAM	4.24	1.70
F	Duration per use	s/flush	Mazzoni et al. 2023b	1	1	1	1	1	GAM	5.79	8.49
F	Flow rate per use	L/min	Mazzoni et al. 2023b	1	1	1	1	1	NRM	8.56	1.50
F	Frequency of use	flushes/person/day	Roberts 2005	1	1	1	1	1	WBL	4.45	3.33
F	Frequency of use	flushes/person/day	Redhead et al. 2013	1	1	1	1	1	WBL	3.73	2.43
F	Frequency of use	flushes/person/day	Otaki et al. 2013 (half flush)	1	1	1	1	1	LOG	1.46	0.39
F	Frequency of use	flushes/person/day	Diaz et al. 2021	1	1	1	1	0	LOG	1.38	0.48
F	Frequency of use	flushes/person/day	Siriwardene 2018	0	1	0	0	0	EXP	4.68	-
F	Frequency of use	flushes/person/day	Anderson et al. 1993	1	1	1	1	1	LOG	1.17	0.45
F	Frequency of use	flushes/person/day	Beal and Stewart 2011	1	1	1	1	1	WBL	7.24	2.06
F	Frequency of use	flushes/person/day	Mayer et al. 2003 (pre-retrofitting)	1	1	1	1	1	GAM	5.12	1.13
F	Frequency of use	flushes/person/day	Blokker 2010	1	1	1	1	1	GAM	4.62	1.30
F	Frequency of use	flushes/person/day	Mayer et al. 2000 (pre-retrofitting)	1	1	1	1	1	GAM	3.64	1.47
F	Frequency of use	flushes/person/day	Mazzoni et al. 2023b	1	1	1	1	1	GAM	3.77	1.20
T	Volume per use	L/use	Mead 2008	1	1	1	1	1	LOG	-0.77	0.86
T	Volume per use	L/use	Beal and Stewart 2011	1	1	0	1	0	WBL	1.70	2.93
T	Volume per use	L/use	Siriwardene 2018	1	1	1	1	1	LOG	-0.35	0.59
T	Volume per use	L/use	Heinrich 2007	1	1	1	1	1	LOG	-0.16	0.89
T	Volume per use	L/use	DeOreo et al. 2011	1	1	1	1	1	GAM	7.74	0.35

Table A.1 (Continued). End-use Statistical Parameter Distributions: Curve Fitting Results.

End Use	Parameter	Unit	REUS	Kolmogorov-Smirnov Test Results					Best-fitting distribution	Parameter 1[a]	Parameter 2[a]
				NRM	EXP	LOG	WBL	GAM			
T	Volume per use	L/use	DeOreo and Mayer 2013	1	1	1	1	1	LOG	3.63	0.03
T	Volume per use	L/use	Mazzoni et al. 2023b	1	1	1	1	1	LOG	-0.33	1.06
T	Duration per use	s/use	Mayer et al. 2000 (pre-retrofitting)	1	1	1	1	1	GAM	3.20	3.11
T	Duration per use	s/use	Mayer et al. 2003 (pre-retrofitting)	1	1	1	1	1	GAM	3.52	3.17
T	Duration per use	s/use	Roberts 2005	1	1	1	1	1	LOG	2.38	0.67
T	Duration per use	s/use	Siriwardene 2018	1	1	1	1	1	LOG	2.30	0.71
T	Duration per use	s/use	Redhead et al. 2013	1	1	1	1	1	LOG	2.30	0.81
T	Duration per use	s/use	Mead 2008	1	1	1	1	1	LOG	2.78	0.57
T	Duration per use	s/use	Heinrich 2007	1	1	1	1	1	LOG	2.92	0.63
T	Duration per use	s/use	DeOreo et al. 2011	1	1	1	1	1	LOG	3.62	0.31
T	Duration per use	s/use	DeOreo and Mayer 2013	1	1	1	1	1	LOG	3.64	0.57
T	Duration per use	s/use	Mazzoni et al. 2023b	1	1	1	1	1	LOG	2.24	0.90
T	Flow rate per use	L/min	Mead 2008	1	1	1	1	0	WBL	1.96	1.28
T	Flow rate per use	L/min	Siriwardene 2018	1	1	1	1	1	GAM	2.38	1.07
T	Flow rate per use	L/min	Redhead et al. 2013	1	1	1	1	1	GAM	1.83	1.48
T	Flow rate per use	L/min	Roberts 2005	1	1	1	1	1	WBL	3.38	1.45
T	Flow rate per use	L/min	Heinrich 2007	1	1	1	1	1	LOG	1.07	0.76
T	Flow rate per use	L/min	Cubillo-González et al. 2008	1	1	1	1	1	WBL	5.30	1.85
T	Flow rate per use	L/min	DeOreo and Mayer 2013	1	1	1	1	1	LOG	1.62	0.39
T	Flow rate per use	L/min	Mazzoni et al. 2023b	1	1	1	1	1	GAM	5.07	0.95
T	Frequency of use	uses/person/day	Beal and Stewart 2011	0	1	0	0	0	EXP	19.59	-
T	Frequency of use	uses/person/day	DeOreo et al. 2011	1	1	1	1	1	WBL	16.99	2.12

Table A.1 (Continued). End-use Statistical Parameter Distributions: Curve Fitting Results.

End Use	Parameter	Unit	REUS	Kolmogorov-Smirnov Test Results					Best-fitting distribution	Parameter 1[a]	Parameter 2[a]
				NRM	EXP	LOG	WBL	GAM			
T	Frequency of use	uses/person/day	Mazzoni et al. 2023b	1	1	1	1	1	WBL	19.09	1.63

Note: [a] Parameter 1 and Parameter 2 are, respectively, the mean and the standard deviation of the Normal (or Lognormal) distribution, the scale and the shape parameter of the Weibull distribution, the shape and the scale parameter of the Gamma distribution. In the case of Exponential distribution, Parameter 1 is the mean. [b] Duration related to water inflow only. Legend for end-use: D = dishwasher; WM = washing machine; S = shower; F = toilet flush; T = taps. Legend for fitting distributions: NRM = normal; EXP = exponential; LOG = lognormal; WBL = Weibull; GAM = Gamma. Legend for Kolmogorov-Smirnov Test Results: 0 = failed; 1 = passed;

Appendix B

Characteristics and implications of REUS on efficiency and diffusion of water-saving end uses

Table B.1. Characteristics and implications of REUS on efficiency and diffusion of water-saving end uses.

EUD	REUS	Study Characteristics	Implications
5	Anderson et al. 1993	Fixture retrofitting with low-flow toilets and efficient showerheads.	Despite the decrease in the volume per use, an increase in the frequency of use was observed.
8	Mayer et al. 1999	Water use analysis for a group of users including low-flow toilets and efficient showerheads.	More frequent toilet flushing and longer showers were observed in the group of users including efficient fixtures.
9	Darmody et al. 1999	End-use study relying on the information obtained by interacting with users (i.e. surveys) and through field flow-rate measurements. Also, pilot fixture retrofitting including the installation of ultra-low-flow toilets (6 L) to replace the high-volume models (14 L), but also tap aerators and efficient showerheads.	The study does not show the post-retrofitting results. However, it is pointed out that, before retrofitting, 78% of toilets in the case-study area concerned are pour-flush toilets, whereas 22% of toilets are tank-flush toilets.
10	Darmody et al. 1999	End-use study relying on the information obtained by interacting with users (i.e. surveys) and through field flow-rate measurements.	The study points out that 100% of toilets of the case-study area concerned are tank-flush toilets.
11	Mayer et al. 2000	Fixture retrofitting with low-flow toilets, efficient showerheads, tap aerators, and efficient washing machines. Leak repairs.	Despite the decrease in the volume per use, an increase in the frequency of toilet and washing machine use is observed, along with the increase in the total daily duration of tap use. A decrease in shower duration is also observed.
12	Blokker 2006, Blokker 2010, Blokker et al. 2010	Discussion about the relationship between end-use make, model and year of installation and end-use parameter values (volume, duration, flow rate per use). Moreover, diffusion over time were evaluated.	Front-load washing machines (mainly used in Europe) have a considerably smaller total volume per use than top load machines (mainly used in the USA). Moreover, the diffusion of dishwasher has increased, whereas that of bathtub has decreased.
12, 20, 27, 37	Agudelo-Vera et al. 2014	Discussion about the evolution of end-use water consumption, parameters, efficiency, and diffusion in the Netherlands between 1900 and 2010, with specific reference to the period after 1992.	When considering the trend of the daily per capita end-use water consumption, a drastic reduction in the bathtubs use is observed. On the other hand, manual dishwashing, showers, toilets, and kitchen sinks (which have constantly increased

Table B.1 (Continued). Characteristics and implications of REUS on efficiency and diffusion of water-saving end uses.

EUD	REUS	Study Characteristics	Implications
12, 20, 27, 37	Agudelo-Vera et al. 2014 (Continued)		during the period) have reduced between 2007 and 2010. Moreover, a general increase of end-use diffusion is observed (although with specific behaviours based on the end-use), along with a decrease in the frequency of bathtub use and an increase in the frequency of shower. No considerable variations in the frequency of washing machine and dishwasher use are observed. Furthermore, the highest increase in end-use efficiency between 1992 and 2010 are observed for washing machines (40%), followed by dishwashers (30%) and toilets (20%).
12, 20, 27, 37, 45, 52	Foekema and Engelsma 2001, Kanne 2005, Foekema et al. 2008, Foekema and Van Thiel 2011, Van Thiel 2014, Van Thiel 2017	All studies looked at the effects of age, household size, socio-economic class, and Dutch region on end-use diffusion and end-use parameter values. Moreover, appliance makes and models and their relationships with end-use parameters are evaluated.	Volume and flow rate per use are strongly dependent on technological development and the year of installation. Moreover, in the case of fixed-volume end-uses (i.e. toilet flush), a reduction in the duration per use is also observed.
13	Mayer et al. 2003	Fixture retrofitting with low-flow toilets, efficient showerheads, tap aerators, and efficient washing machines. Leak repairs.	Despite the decrease in the volume per use, an increase in the frequency of toilet and shower uses is observed, along with the increase in the total daily duration of tap use. A decrease in shower duration and washing machine frequency of use is also observed.
14	Loh and Coghlan 2003	Analysis of the daily per capita end-use water consumption trends between 1981/1982 and 1998/2000. Comparison between normal and efficient showerheads and front- and top-load washing machines.	An increase in the daily per capita end-use water consumption is observed for washing machines, along with a slight increase for showers. Besides, a decrease is observed for bathtubs and toilets, whereas tap use has not changed. Moreover, no significant differences in duration are observed between normal and efficient showerheads. Higher volumes per load and daily per capita consumption are observed for top-load washing machines.
18	White et al. 2004	Ownership stock analysis aimed at the creation of a stock-ownership model to obtain information about water consumption at the end-use level.	With reference to a sample of about 2,500,000 Australian users, a progressive increase in the diffusion of dual-flush toilets is observed, ranging from 0% in 1980 to 56% in 2000. The dual-flush diffusion to year 2010 is estimated to 74%.
19	Roberts 2005	Comparison between normal and low-flow showerheads, different toilet types, and front- and top-loader washing machines. Fixture retrofitting with low-flow toilets in a subset of 21 households.	Inverse correlation between daily per capita toilet water consumption and flush efficiency. Higher volumes per load are also observed for top-load washing machines. When installing low-flow toilets in the selected households, a 26% reduction in the daily per capita toilet water consumption is observed.
23	Heinrich 2007	Discussion about the potential savings achievable by retrofitting devices with more efficient ones.	The most consistent savings can be obtained with low-flow toilets and efficient washing machines. Showers would not change the results as efficient showerheads have already been widely installed in the case-study area, while taps would not change the results as they are typically used with low flows.
26	Mead 2008	Investigation of end-use water consumption for different appliance characteristics.	Front-load washing machines are more efficient (i.e., have lower volumes per use) than top-load. Moreover, a positive correlation is observed between the average duration of shower use and shower efficiency.
28	Cubillo-González et al. 2008	Investigation of end-use water consumption with reference to the case-study area of Madrid (Spain). Analysis of the diffusion of dishwashers and washing machine in replacement of manual	Dishwashers and washing machines are generally less installed in the case of lower-income households, whereas the diffusion of dishwashers is considerably affected by household occupancy rate. In addition, washing machines have been

Table B.1 (Continued). Characteristics and implications of REUS on efficiency and diffusion of water-saving end uses.

EUD	REUS	Study Characteristics	Implications
28	Cubillo-González et al. 2008 (Continued)	laundry and dishwashing activities.	almost-entirely diffused in the contexts analysed, regardless of family size.
29	Willis et al. 2010b	Installation of alarm displays in shower to increase householders' perception of water use.	A decrease in the average shower duration and flow rate is observed after the installation of alarm displays.
	Willis et al. 2013	Evaluation of the effects of socio-demographic determinants and fixture efficiency on water consumption. Showers and washing machines were clustered based on efficiency.	A positive correlation is observed between water savings and the efficiency of showers and washing machines.
35	Aquacraft 2011	Comparison between end-use water consumption results for 302 houses built after the year 2000 (plus 25 new high-efficiency households) against the ones reported in the Mayer et al. (1999) database. Additional study of efficient end-use diffusion.	The daily per capita end-use water consumption is the highest in the Mayer et al. (1999) households and the lowest for the 25 new high-efficiency houses, with the exception of showers (which have the highest consumption in the new high-efficiency households). Besides, all the end uses of the new high-efficiency houses have lower end-use parameters than those of the households built after 2000, with the exception of showers (the frequency and duration of which are higher). Moreover, more than 95% of houses built after 2000 have already included efficient devices.
36	Beal and Stewart 2011	Analysis of fixture efficiency (i.e., number of stars) influence on water consumption and peak demand.	A positive correlation is observed between water savings and the fixture number of stars. It also emerges that front-load washing machines are more efficient than top-load and that water saving benefits related to the installation of efficient dishwasher are not clearly distinguishable due to the little dishwasher volumes per use. Moreover, significant reductions in the peak demand are observed when comparing 3- star houses against 3+ star households or when comparing the 50 most efficient households against the 50 least efficient ones.
	Beal et al. 2012	Analysis of fixture efficiency (i.e., number of stars) influence on water consumption and peak demand.	Some implications from the study by Beal and Stewart (2011) are reported.
	Makki et al. 2013	Analysis of shower efficiency (i.e., old fixtures, standard, A, AA, AAA, etc.) influence on water consumption.	A positive correlation is observed between water savings and shower efficiency.
	Beal and Stewart 2014b	Estimation of the potential reduction in water consumption daily profiles achievable by retrofitting fixtures with new and more efficient ones.	The installation of efficient devices (along with the adoption of strategies to encourage water use behavioural shifts away from peak times) could determine a shift downward of the daily water use profile and potential savings between 24 and 30%.
42	DeOreo and Mayer 2013	Comparison between the water use observed in the households of the Mayer et al. (1999) EUD and the one of the households included in the current EUD (DeOreo and Mayer 2013). Additional device retrofitting in a subset of 247 houses and evaluation of water savings achievable with respect to the DeOreo and Mayer (2013) EUD. Discussion of whether the values achieved meet the Environmental Protection Agency (EPA) standards.	When comparing the results of the study by DeOreo and Mayer (2013) against those of the Mayer et al. (1999) study, a decrease in the daily per capita water consumption and volume per use is observed for toilets, showers, taps, washing machines, and dishwashers. An increase in the frequency of use is observed for toilets, taps and dishwashers. Results do not significantly change in the case of shower duration of use, shower frequency of use, washing machine frequency of use, and tap daily total duration of use. Results do not significantly change also in the case of bathtub use. When comparing the results of the houses selected for retrofitting against those of the DeOreo and Mayer (2013) EUD, a decrease in the daily per capita water consumption is observed for all the end uses, except bathtubs and dishwashers. Moreover, an increase in the frequency of use

Table B.1 (Continued). Characteristics and implications of REUS on efficiency and diffusion of water-saving end uses.

EUD	REUS	Study Characteristics	Implications
42	DeOreo and Mayer 2013 (Continued)		is observed for all the end-uses, except taps. A decrease in the volume per use is observed for washing machines, showers, and toilets. Considering the shower, a reduction of flow rate is observed along with an increase in the duration.
	DeOreo et al. 2016	See DeOreo and Mayer (2013). Further discussion about the diffusion of efficient fixtures in the period 1999-2016.	The findings of DeOreo and Mayer (2013) are reported, along with additional information about ultra-efficiency standards. It is also observed that the diffusion of efficient washing machines, showers, and toilets has increased from 1999 to 2016.
47	Arbon et al. 2014	Discussion about the impacts of efficient end uses on water consumption; comparison between efficient and non-efficient households; and analysis of the correlation between diffusion of efficient end uses and income class.	When comparing the end-use parameters of efficient households against the ones of non-efficient households, lower per capita daily water consumption and flow rate are observed for showers, along with an increase in the duration and no changes in the frequency of use. Besides, lower per capita daily water consumption, volume per use, and frequency of use are observed for toilets. Also, washing machine daily per capita consumption and volume per load are lower for front-load appliances, while no variations in the frequency of use are observed between front- and top-load.
59	Bethke 2020, Bethke et al. 2021	End-use water consumption analysis in a single-family household. Discussion about the correlation between the end-use parameters obtained and the information provided by manufacturers	Electronic appliance volume per use are in line with (or slightly lower than) the values reported on the manuals. Besides, for a toilet of the case-study households, the observed volume per flush is higher than the corresponding value reported in the end-use specifications.

Appendix C

End-use parameters (Dutch database) and comparison against the values reported in other Dutch studies

Table C.1. End-use parameters (Dutch database) and comparison against the values reported in other Dutch studies: volume per use and frequency of use.

REUS	Volume per use (L/use)						Frequency of use (uses/person/day)					
	D	**WM**	**S**	**B**	**F**	**T**	**D**	**WM**	**S**	**B**	**F**	**T**
Kanne 2005	18.0	63.9	-	113.5	8.0	-	0.25	0.28	0.73	0.05	5.96	-
Foekema et al. 2008	16.5	56.9	-	114.2	7.9	-	0.25	0.28	0.80	0.05	6.27	-
Foekema and Van Thiel 2011	15.8	55.6	-	114.3	7.9	-	0.23	0.26	0.75	0.05	5.86	19.59
Van Thiel 2014	14.3	52.9	-	114.5	7.7	-	0.17	0.28	0.72	0.04	5.90	20.01
Van Thiel 2017	13.1	53.9	-	112.5	7.7	-	0.17	0.24	0.69	0.03	5.87	19.21
Current Study	**11.4**	**62.9**	**63.6[a]**	**-**	**6.8**	**1.2**	**0.27**	**0.27**	**0.76[a]**	**-**	**4.22**	**13.83**

Note: Legend for volume per use and frequency of use: D = dishwasher; WM = washing machine; S = shower; B = bathtub; F = toilet flush; T = taps. [a] Together with shower; [d] Total duration of water inflow during appliance load.

Table C.2. End-use parameters (Dutch database) and comparison against the values reported in other Dutch studies: duration and flow rate per use.

REUS	Duration per use (min/use)						Flow rate per use (L/min)					
	D	**WM**	**S**	**B**	**F**	**T**	**D**	**WM**	**S**	**B**	**F**	**T**
Kanne 2005	-	-	7.7	-	-	-	-	-	7.8	-	-	-
Foekema et al. 2008	-	-	7.9	-	-	-	-	-	7.7	-	-	-
Foekema and Van Thiel 2011	-	-	8.1	-	-	-	-	-	7.7	-	-	-
Van Thiel 2014	-	-	8.9	-	-	-	-	-	7.7	-	-	-
Van Thiel 2017	-	-	7.6	-	-	-	-	-	8.2	-	-	-
Current Study	**4.3**[a]	**8.2**[a]	**8.0**[b]	**-**	**0.8**	**0.2**	**2.8**	**7.0**	**7.9**[b]	**-**	**8.3**	**4.8**

Note: Legend for duration and flow rate per use: D = dishwasher; WM = washing machine; S = shower; B = bathtub; F = toilet flush; T = taps. [a] Total duration of water inflow during appliance load. [b] Together with shower.

Appendix D

Automated end-use disaggregation and classification method: function flow charts

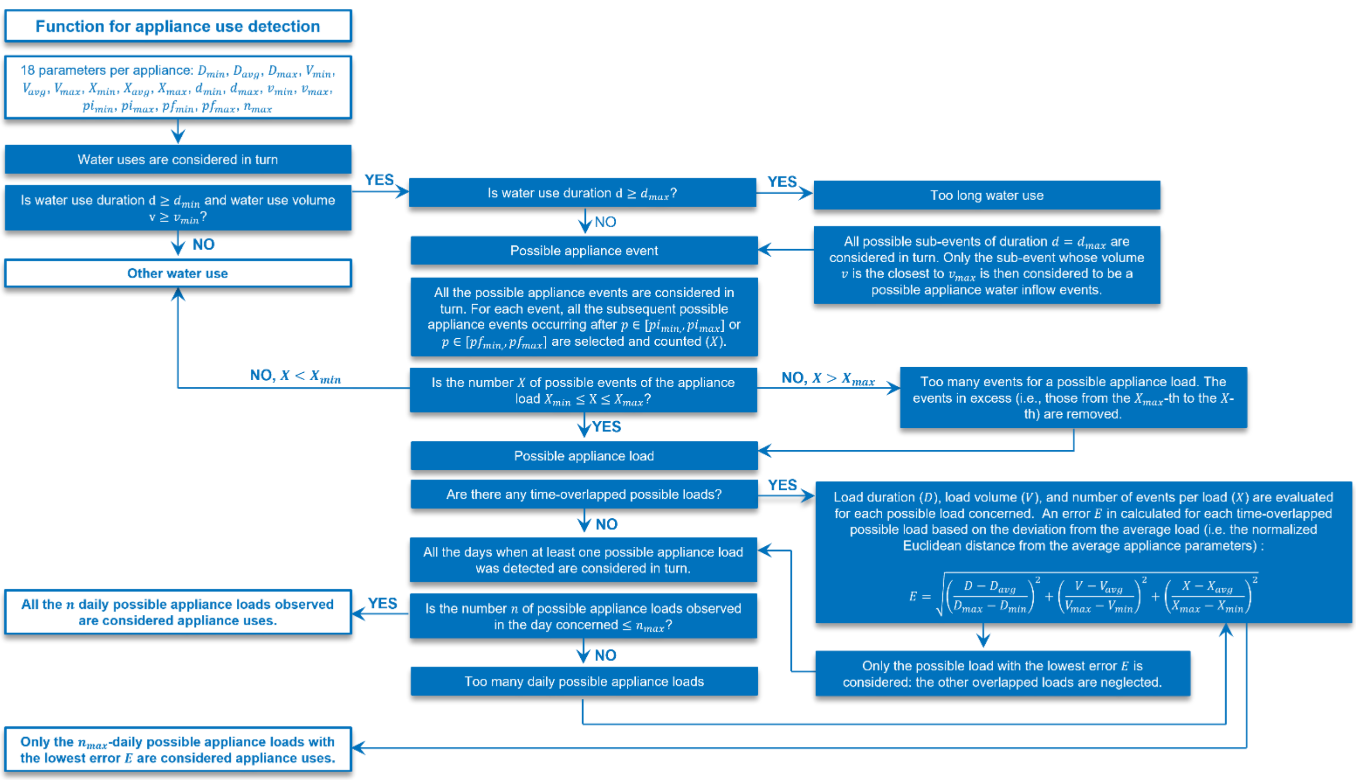

Figure D.1. Function for appliance (i.e. dishwasher, washing machine) use detection.

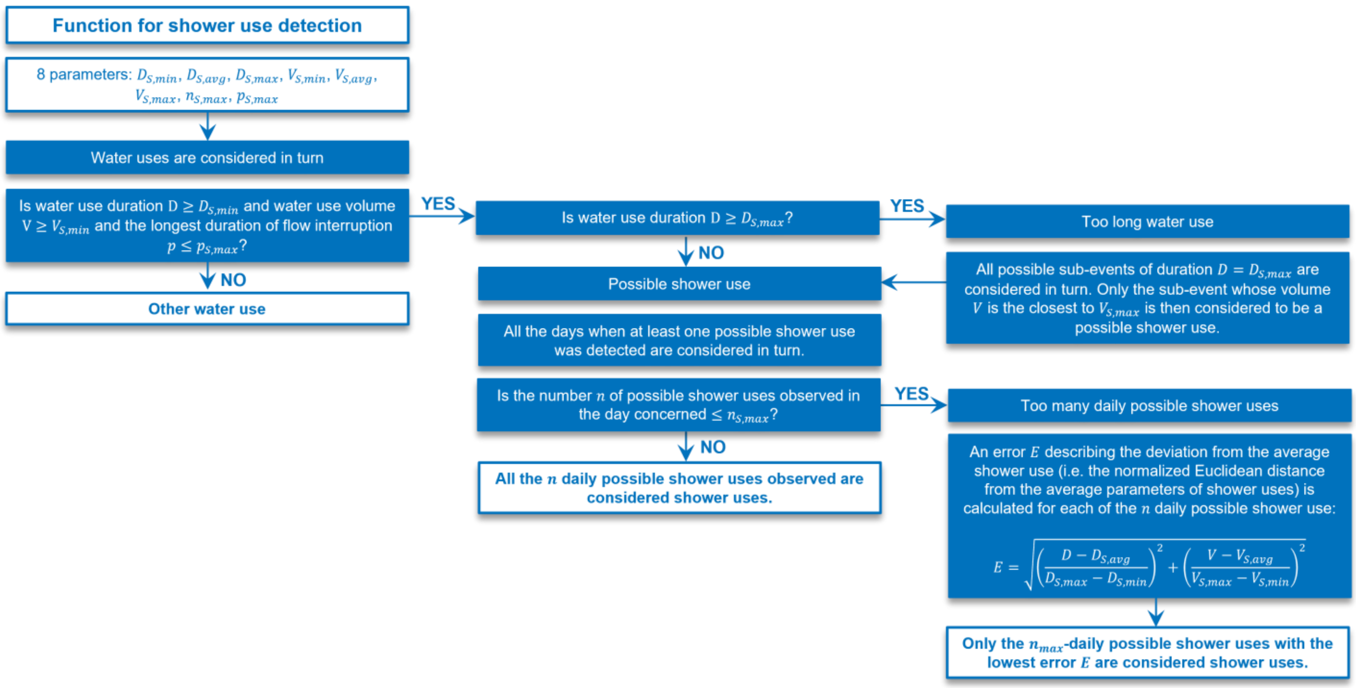

Figure D.2. Function for shower use detection.

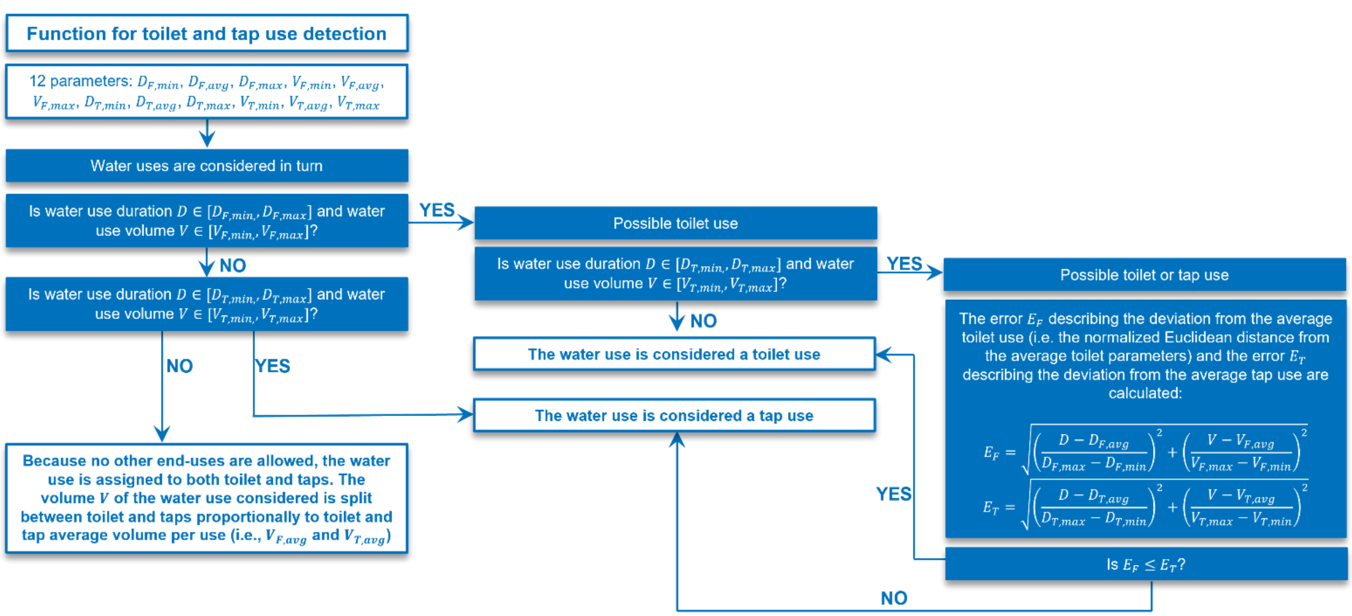

Figure D.3. Function for shower use detection

List of publications

I. Publications in Scientific Journals

Mazzoni, F., Alvisi, S., Franchini, M., Ferraris, M., and Kapelan, Z. **2021**. "Automated Household End-Use Disaggregation through Rule-Based Methodology." *Journal of Water Resources Planning and Management*, 147(6): 4021024. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001379.

Alvisi, S., Franchini, M., Luciani, C., Marzola, I., and Mazzoni, F. **2021**. "Effects of the COVID-19 Lockdown on Water Consumptions: Northern Italy Case Study." *Journal of Water Resources Planning and Management*, 147(11): 5021021. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001481.

Marzola, I., Mazzoni, F., Alvisi, S., and Franchini, M. **2022**. "Leakage Detection and Localization in a Water Distribution Network through Comparison of Observed and Simulated Pressure Data." *Journal of Water Resources Planning and Management*, 148(1): 4021096. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001503.

Mazzoni, F., Marsili, V., Alvisi, S., and Franchini, M. **2022**. "Exploring the Impacts of Tourism and Weather on Water Consumption at Different Spatiotemporal Scales: Evidence from a Coastal Area on the Adriatic Sea (Northern Italy)." *Environmental Research: Infrastructure and Sustainability*, 2(2): 25005. https://doi.org/10.1088/2634-4505/ac611f.

Mazzoni, F., Alvisi, S., Franchini, M., and Blokker, E. J. M. **2023**. "Exploiting high-resolution data to investigate the characteristics of residential water consumption at the end-use level: A Dutch case study." *Water Resources and Industry*, 29(Jun): 100198. https://doi.org/10.1016/j.wri.2022.100198

Mazzoni, F., Alvisi, S., Blokker, E. J. M., Buchberger, S. G., Castelletti, A., Cominola, A., Gross, M. P., Jacobs, H. E., Mayer, P., Steffelbauer, D. B., Stewart, R. A., Stillwell, A. S., Tzatchkov, V., Alcocer-Yamanaka, V. H., and Franchini, M. **2023**. "Investigating the characteristics of residential end uses of water: A worldwide review." *Water Research*, 230(Feb): 119500. https://doi.org/10.1016/j.watres.2022.119500.

II. Conference Publications

Mazzoni, F., Alvisi, S., Franchini, M., Ferraris, M., and Kapelan, Z. **2019**. “Disaggregation of Household Water Use by Means of a Rule-based, Automated Methodology.” In *Proceedings of the 17th International Conference on Computing and Control in the Water Industry*. Exeter, United Kingdom: University of Exeter.

Marzola, I., Mazzoni, F., Alvisi, S., and Franchini, M. **2020**. “A Pragmatic Approach for Leakage Detection Based on the Analysis of Observed Data and Hydraulic Simulations.” In *Battle of the Leakage Detection and Isolation Methods 2020*, Zenodo.

Mazzoni F, Alvisi, S., Odorisio, C., Tirello, L., Rubin, A., and Franchini, M. **2021**. “Effects of COVID 19 Restrictions on Water Consumption in the Padua Water Distribution Network (Italy).” In *Proceedings of the Aqua≈360: Water for All. Emerging Issues & Innovation Conference*. Exeter, United Kingdom: University of Exeter.

Mazzoni, F., Blokker, E. J. M., Alvisi, S., and Franchini, M. **2022**. “Evaluating Residential Water Consumption at High Spatio-Temporal Level of Detail: a Dutch case study.” In *Proceedings of EGU General Assembly 2022*. Vienna, Austria: European Geosciences Union.

Mazzoni, F., Blokker, E. J. M., Alvisi, S., and Franchini, M. **2022**. “Using High-Resolution Data to Test the Robustness of an Automated Method for Water End-Use Disaggregation and Classification.” In *Proceedings of the 2nd International Joint Conference on Water Distribution Systems Analysis & Computing and Control in the Water Industry*. Valencia, Spain: Universitat Politècnica de València.

Marsili, V., Mazzoni, F., Alvisi, S., Maietta, F., Meniconi, S., Capponi, C., Brunone, B., and Franchini, M. **2022**. “Monitoring a real service line under user activity.”, In *Proceedings of the 39th International Association for Hydro-Environment Engineering and Research World Congress*. Madrid, Spain: Spain Water.

Marzola, I., Marsili, V., Mazzoni, F., Alvisi, S., and Franchini, M. **2022**. “Rehabiliting Intermittent Water Supply Systems through a Multi-Objective Optimization Method Based on Hydraulic Simulations.” In *Proceedings of the 2nd International Joint Conference on Water Distribution Systems Analysis & Computing and Control in the Water Industry*. Valencia, Spain: Universitat Politècnica de València.