AQUA

Water Infrastructure, Ecosystems and Society

 AQUA — Water Infrastructure, Ecosystems and Society Vol 70 No 8, 1248 doi: 10.2166/aqua.2021.088

Impact of COVID-19 emergency on residential water end-use consumption measured with a high-resolution IoT system

A. Di Mauro *, G. F. Santonastaso, S. Venticinque and A. Di Nardo

Università degli Studi della Campania Luigi Vanvitelli, via Roma 29, 81031 Aversa, Italy

*Corresponding author. E-mail: anna.dimauro@unicampania.it

ADM, 0000-0002-5397-3741; SV, 0000-0001-5042-3384; ADN, 0000-0002-8462-2258

ABSTRACT

In the era of Smart Cities, in which the paradigms of smart water and smart grid are keywords of technological progress, advancements in metering systems allow for water consumption data collection at the end-use level, which is necessary to profile users' behaviors and to promote sustainable use of water resources. In this paper, a real case study of residential water end-use consumption monitoring shows how data collected at a high-resolution rate allow for the evaluation of consumption profiles. The analysis was carried out by calculating consumption statistics, hourly consumption patterns, daily use frequency, and weekly use frequency. Then, the comparison of two consumption profiles, computed before and after the COVID-19 lockdown, allows us to understand how a change in social and economic factors can affect users' behavior. Finally, new perspectives for water demand modeling and management, based on data with high temporal frequency, are presented.

Key words: smart meters, user behaviors, user profiling, water end-use consumption, water management

HIGHLIGHTS

- Real water consumption data gathered at the fixture level contribute to understand users' behaviors and identify their impact on demand peak.
- Statistical evaluations used to analyze data sampled with a high temporal frequency show how disaggregated data facilitate the identification of water consumption patterns.
- The COVID-19 pandemic was used to explore how water end-use data allow for understanding changes of user's behavior.
- Data collected at the end-use level are possibly eligible as numerical benchmarks to investigate disaggregation algorithms.

INTRODUCTION

In recent times, the use of fresh water has increased significantly. As reported in the United Nations (UN) World Water Development Report (WWDR) (2018), the annual water consumption is estimated around 4,600 km^3, three times more than 50 years ago. Although agriculture and industry require, respectively, about 70 and 19% of worldwide freshwater, socio-economic development and demographic growth have led to an increased use of water at the household level by 600% from 1960 to 2014.[1] Moreover, world's urban population is expected to rise in the next 30 years (Gerland *et al.* 2014) boosting the residential water demand. As a consequence, an increasing number of countries will face the risk of water stress.

Despite the great interest in water savings that emerged in the last decades, a great amount of water continues to be wasted, the estimated volume of water losses in distribution systems all over the world is about 48 billion cubic meters per year (Ociepa *et al.* 2019). In this context, traditional water management systems need to be replaced with innovative solutions that focus on improving users' awareness, promoting sustainable behaviors and water conservation attitudes, and strengthening management policy and planning activities (Cary 2008; Beal *et al.* 2013).

[1] https://www.wri.org/insights/domestic-water-use-grew-600-over-past-50-years.

Recently, ubiquitous networks and the Internet of Things (IoT) have made available low-cost technologies for the widespread installation of smart meters in many application domains. High-resolution measures can be collected and transmitted in real time by either Advanced Metering Systems. The rapid spread of these technologies also in water systems allows the implementation of new strategies based on big data and machine learning algorithms which encourage the needed change of the traditional management paradigm focused only on supply water (Nguyen *et al.* 2013).

The possibility to record water consumption at different spatial and temporal scales, through smart water meters (SWMs), plays a key role in the smart management of water distribution networks (Swan & Ugursal 2009). High-resolution water data can support water utilities in decision-making processes with innovative involvement in demand forecasting, leak detection, water network modeling, users' awareness, etc. (Di Mauro *et al.* 2021b). Furthermore, the availability of high-resolution household data provides the opportunity to adopt the technique of user profiling, which is largely applied in other domains such as artificial intelligence, data science, and information science (Eke *et al.* 2019).

A user profile can be defined as 'the summary of the user's interests, characteristics, behaviors, and preferences, while user profiling is the system of collecting, organizing and inferring the user profile information' (Eke *et al.* 2019).

Through user profiling, customers are featured via a set of rules, settings, needs, interests, behaviors, and preferences (Cufoglu 2014), then the collected data can be applied to infer information and improve service personalization.

In the last decade, several studies in the urban water field, such as Beal & Stewart (2013) and Willis *et al.* (2013), and Fu & Wu (2014), highlighted the importance of end-use and profile data for several purposes such as: (1) understanding the average and peak end-use water consumption volumes of different fixtures (shower, toilet, etc.) at hourly, daily, and monthly levels of resolution to improve the planning process; (2) evaluating daily water end-use patterns to identify trends and peaks in water consumption throughout time; providing updated information on demand per capita, which, however, cannot be evaluated with traditional methods that do not take into account social changes over time; (3) examining peak day demand to understand the types of household practices that drive peak usage; (4) evaluating the seasonal impact of water usage. Moreover, since there is a strong relationship between highly personalized services and effects on water-saving, user profiling represents a fundamental strategy for promoting water-saving (Rahim *et al.* 2021).

However, aggregated domestic water consumption measurements do not provide detailed information to build profiling because they needed to be disaggregated to get single end-use categories. Machine learning techniques, i.e. disaggregation, require high-resolution data generally generated synthetically due to the lack of low-cost and non-intrusive sensing infrastructure able to be installed on water fixtures (shower, toilet, tap, etc.). Although user profiling is a widespread practice in many fields, its application in the water sector represents a challenge. Water appliance traces are strongly affected by different aspects, i.e. dependency on the piping infrastructure pressure, the degree of sink opening, etc., while in other fields (i.e. energy sector) they are less influenced by users' behaviors.

Nowadays, the importance of user profiling is stressed by the occurrence of the COVID-19 pandemic that has changed the lifestyle of a whole population and, consequently, modified by the typical water consumption and behaviors. Recent studies about the impact of COVID-19, based on aggregate demand data, have highlighted a significant shift of demand peak as well as an increase in peak daily consumption (Baker *et al.* 2020; Kalbusch *et al.* 2020). Although the different water usages are attributable to the pandemic condition because people are forced to remain at home, it represents a challenge for a water utility to understand features of increased water demand, adopt a novel model for demand forecasting, and improve the provided service in case of the modification of socio-economic parameters (Abu-Bakar *et al.* 2021).

In this study, a comparison between water demand before and after the impact of COVID-19, based on water end-use consumption of a residential apartment, is presented. Even if the case study deals with one customer, the modified behaviors of householder during the lockdown represents an opportunity to show how socio-economic factors, for instance, remote working, can affect water consumption. This paper, starting from the authors' previous work (Di Mauro *et al.* 2020), represents an advance of this study with a particular focus on the relevance of high-resolution data for user profiling.

MATERIALS AND METHODS

Customer profiling based on end-use water consumption data collected through SWMs facilitates identifying the water consumption patterns and habits of customers (Rahim *et al.* 2021). The approach proposed in this study aims to identify how high-resolution data at the end-use level are able to understand water use behaviors in a domestic environment.

To this scope, water data collected in a real case study have been used to highlight the change in users' behaviors caused by COVID-19.

Case study and data collection

The case study was carried out from 2019 to 2021 and was based on water consumption data gathered in a residential apartment sited in Naples, Italy. The apartment has one inhabitant and has seven fixtures: kitchen faucet, toilet, shower, washbasin, bidet, washing machine, and dishwasher. An IoT system developed combining a flow sensor, a micro-controller, and a content management system was installed on all the fixtures in the apartment except on the toilet and dishwasher due to positional constraints. To detect water consumption from flush toilet and dishwasher, an open-source app based on HTTP hyperlinks was configured (Di Mauro *et al.* 2019). Moreover, high-resolution data were also collected at the household level using an ultrasonic water meter based on Long-Range (LoRA) transmission. LoRA is a network technology that allows battery-operated devices to communicate across long-range connectivity. The metering systems collected water end-use consumption data at household and end-use levels, respectively, with 10 and 1 s resolutions. Data gathering started on 1st March 2019 and is still ongoing. The dataset includes 8 months of end-use measurements, from March to October 2019, plus 9 months of household and end-use data spanning from July 2020 to May 2021.

The dataset coupled with data analytic tools, respectively, obtained and developed from the case study has been named WEUSED-TO (Water End USE Dataset and Tools), and it is publicly available in an open GitHub repository[2] (Di Mauro *et al.* 2021a).

Data analysis

Statistical modeling has been carried out to obtain consumption patterns, relevant fixture use statistics, behavioral regularities, and temporal characteristics able to investigate which water end-use habit can be identified by data sampled with a high temporal frequency.

Despite the case study used in this paper referring to one house with one inhabitant, the pandemic forced an alteration of the user routine with a direct impact on daily water use.

The introduction of remote working allowed to compare two different profiles of the user: worker user and smart worker user.

To obtain this comparison, 4 months (from July to October) of the dataset WEUSED-TO have been selected in two years 2019 and 2020 (pre and during COVID-19). The choice of these two periods is related to the characteristics of the dataset that did not cover all the months of the years.

Statistical evaluation and summary measures are used to analyze the time series of water use gathered for different fixtures of the residential apartment belonging to the pilot site.

The authors decided to focus the attention on the four fixtures with a greater impact on behavioral routine and use pattern: bidet, washbasin, kitchen faucet, and shower.

Water use distribution during the two periods selected is evaluated. Each time series has been processed to identify the single usage of the related fixture. The usage, as a single event, has been characterized by the amount of water consumed, the duration of use, and by the hour and the day of the week on which that event occurred.

For each monitoring period, water use statistics were calculated as:

- *Consumption statistics*: Minimum, mean, and maximum volume (l), duration (s), and flow (ml/s) related to each single fixture (Table 1).
- *Hourly consumption patterns*: The volume of water used during each hour of the day was summed up to develop the hourly water demand pattern (Figure 2).
- *Daily frequency of use*: The frequency of water use during the hours of the day has been evaluated during the monitoring period. For each fixture, the number of events that occurred for each day was summed up (Figure 3).
- *Weekly frequency of use*: The frequency of water use during the days of the week has been evaluated during the monitoring period. It expresses how often the event occurs on a particular day. For each fixture, the number of events that occurred for each day was summed up (Figure 4).

[2] https://github.com/Water-End-Use-Dataset-Tools/WEUSEDTO.

Table 1 | Statistics of water consumption usage for fixture among 4 months (July–October) over 2 years (2019–2020)

	Shower		Bidet		Washbasin		Kitchen	
Year	**2019**	**2020**	**2019**	**2020**	**2019**	**2020**	**2019**	**2020**
No. of usages	130	141	228	315	549	711	409	841
Duration (s)								
Maximum	628	638	183	233	327	226	238	241
Mean	192.15	233.88	36.52	28.72	33.91	31.07	34.01	32.45
Minimum	15.00	15.00	10.00	10.00	10.00	10.00	10.00	10.00
Flow Q (ml/s)								
Maximum	150	371	137.00	162.00	166	162	184	227
Mean	78.84	87.87	49.44	46.66	39.85	43.72	55.67	56.62
Minimum	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00
Volume (l)								
Maximum	52.49	88.77	30.47	11.15	16.86	12.50	16.41	22.28
Mean	15.55	21.53	1.65	1.30	1.40	1.39	1.77	1.81
Minimum	5.03	5.09	0.30	0.29	0.24	0.25	0.26	0.27

RESULTS AND DISCUSSION

The analysis of household demand has highlighted different usages both in the total consumed volume and in a shift of demand peaks between the period before and after COVID-19 lockdown. The average water consumption in the 2020 period has increased by 30% compared with the 2019 period. As reported in Table 1, the number of usages in the 2020 period is greater than that of the 2019 period as well as the mean flow (Q), and mean volume (V), except the bidet that shows a reduction of statistical indices during the 2020 period, despite the number of usages is higher than 2019. As expected, the growth of water consumption is strictly connected to the large time spent at home after COVID-19 lockdown because the householder has continued to work remotely in their apartment.

The statistics show for all four fixtures the same flow minimum value equals to 6.00 ml/s. It corresponds to the minimum value of the flow registered by the sensor, which is detected as flow and not as leakage.

In Figure 1, the statistical distribution of shower water volume is reported. Box plots provide quick information about statistics of the considered sample: the bottom and top of each box are the 25th and 75th percentiles of the data, respectively; the red line is the median sample; the length of whiskers represents the variability outside the 25th and 75th percentiles and measures beyond the whisker length are marked as outliers (red crosses). The comparison between Figure 1(a) and 1(b) remarks the increasing water usage during 2020; in July, the shower usage is quite similar for 2019 and 2020, while the remaining months show a positive trend: the monthly consumption arises from August to October for both periods 2020 and 2019. Anyway, the larger usages of 2020 (as proved by the dimensions of boxes in 2020 which are about 40% greater than boxes of 2019) demonstrate a change of users' behavior: as consequences of remote working, householder spends more time in his apartment, then he takes more time for activities (in this case shower) that before lockdown required less time. This is confirmed by the volume distribution (see Figure 1) and the duration (see Table 1) per usage that, on the average, is higher.

The results of Figure 2 reveal two distinct hourly consumption patterns characterized by the shift of peak demand. The data reported in Figure 2 refer to the pattern of 4 months, because the monthly patterns show a similar consumption trend. In 2019, pre-lockdown, the peak demand occurs at 8:00 (early morning); while in 2020, after-lockdown, the pattern shows two peaks at 8:00, characterized by a consumption equal to the value in 2019, and at 17:00 (evening) with a remarkable increase of demand compared with 2019 (about 50%). Although from 1:00 to 7:00 there are no significant changes between two patterns, pre-lockdown, during the morning the demand decreases after 8:00 for 2019, while, after-lockdown, the value is quite constant for 2020. Likewise, in the evening, the demand is slightly variable in 2019, while it strongly goes down in 2020.

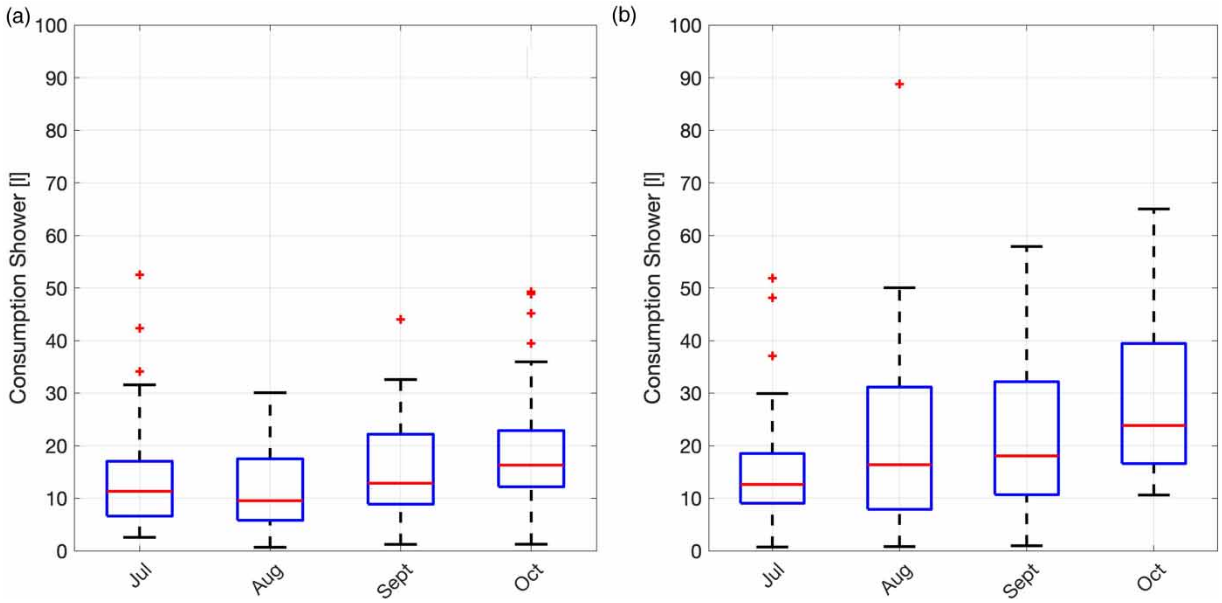

Figure 1 | The figure shows for one of the fixtures (Shower). The water consumption evaluated from July to October in both 2019 (a) and 2020 (b). Please refer to the online version of this paper to see this figure in colour: http://dx.doi.10.2166/aqua.2021.088.

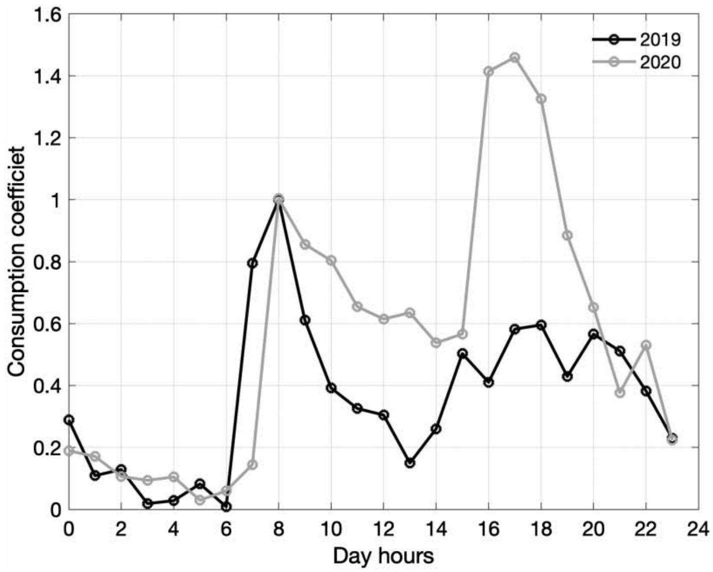

Figure 2 | Average water demand pattern among the same 4 months (July–October) over 2 years (2019 and 2020).

Even in this case, the change in the consumption pattern is caused by a forced modification of habits. Although the results of Figure 2 are based on water consumption of a single residential user, the shift of demand peaks occurs even at a large scale, e.g. at the water distribution scale, as reported by Abu-Bakar *et al.* (2021) who has analyzed the water consumption data of about 11,528 smart-metered households, from January to May 2020. Then, it is worth noting that it was not possible to consider the spatial variations in consumption patterns because the pandemic condition severely restricted the movement of persons.

Although, the growth of demand and the shift of peaks are related to the pandemic condition, to better understand the characteristics of these modifications, the consumptions of household fixtures are analyzed in detail. To this aim, the hourly usages of Figure 3 are evaluated to investigate the changes in consumption patterns between the years 2019 and

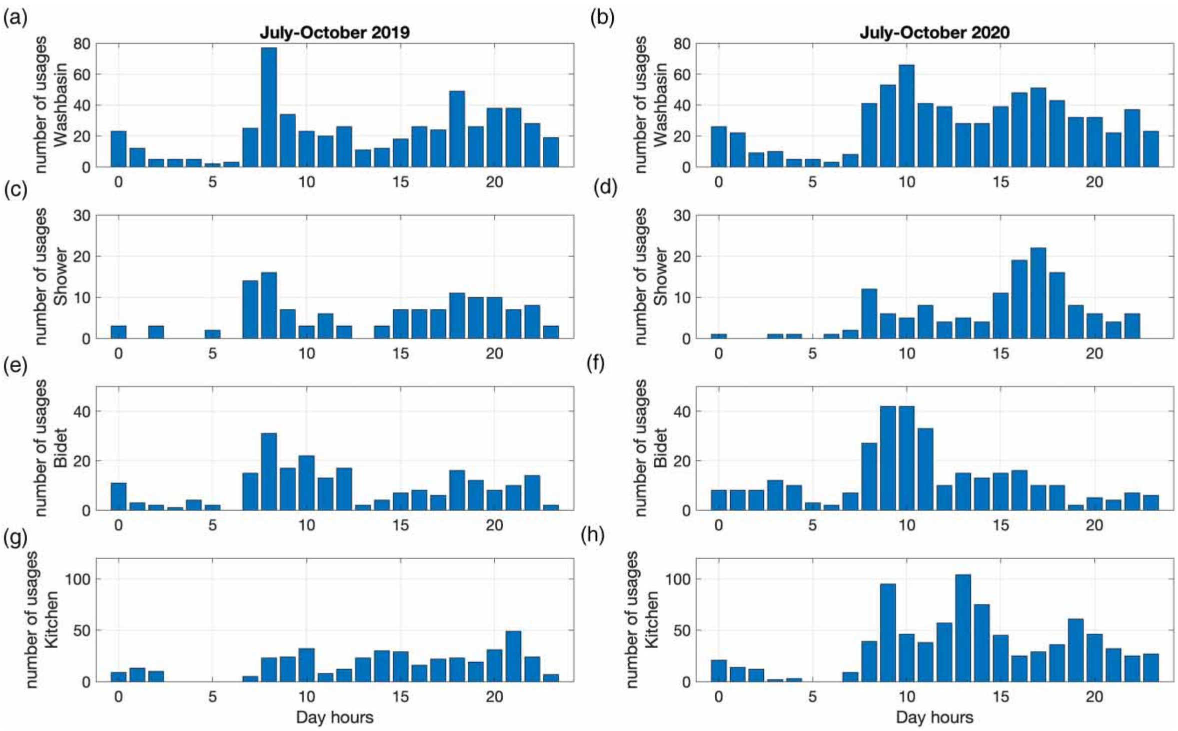

Figure 3 | (a)–(h) Number of users during day hours for different fixtures evaluated on the same 4 months of measurements (July–October) of different years 2019 and 2020: (a) Washbasin 2019, (b) Washbasin 2020, (c) Bidet 2019, (d) Bidet 2020, (e) Shower 2019, (f) Shower 2020, (g) Kitchen 2019, and (h) Kitchen 2020.

2020. The comparison of hourly frequencies of usages between years 2019 and 2020 underlines that after COVID-19 lockdown, the usages of each fixture increased and occurred at almost any hour of the day (i.e. shower and kitchen). In 2019, shower usage (77 times) and washbasin usage (31 times) constituted the morning peak at 08:00, while the usages of bidet and kitchen were less likely. Conversely, in 2020, the morning demand peak at 08:00 was the combined effect of three fixtures: washbasin usage (66), bidet usage (42), and kitchen usage (97 times), while the evening demand peak at 17:00 was caused by washbasin usage (51 times), shower usage (22 times), and kitchen usage (38 times). Furthermore, the high values of 2020 consumption pattern between 08:00 and 16:00 arise from staying a lot of time at home and, consequently, consuming more water to prepare food and wash, because, as reported in Figure 3(b) and 3(h), a significant increase of usages is accounted for washbasin and kitchen. To conclude, the availability of high-resolution data at the end-use level has allowed investigating the cause of alteration in water consumption patterns.

In the case of data aggregated at the household level, it is very complex to develop models that can identify user behaviors based on consumption data because they depend on multiple factors and change user by user. Then, it is mandatory to involve sophisticated machine learning algorithms to break down the total consumption data at the household level into the different end-use categories to infer the same consideration about users' behavior. On this side, disaggregation is one of the most used machine learning techniques able to understand how much of household water consumption belongs to a single fixture in the house useful to infer detailed information on users' behavior.

Figure 4 shows the number of usages during weekdays related to the use of the fixture kitchen evaluated for each month of the monitoring periods. The kitchen faucet was used as an example to compare the way kitchen fixture has been used before and during remote working. The same graphics related to bidet, washbasin, and shower are reported in the Supplementary Materials, respectively, in Figures S1, S2, and S3.

Observing the use of the mentioned fixtures, the general trend of the number of usages increased significantly in 2020, confirming the permanence at the home of the customer in remote working during all day. This increment emerged notably by comparing weekly water usage between August 2019 and 2020. Furthermore, observing water usage during August 2019, it can be seen on Wednesday as a clear habit of the user who is generally away from home.

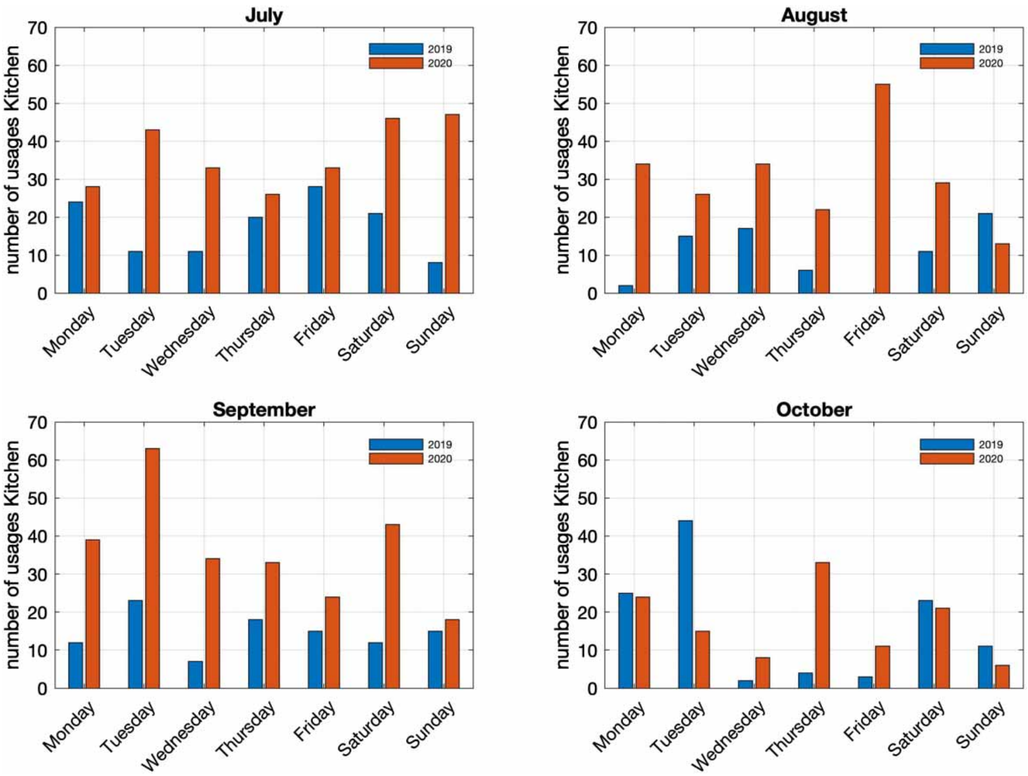

Figure 4 | The figure shows the variability of water usage related to the use of the fixture kitchen during weekdays among the 4 months (July–October) of detection in two different years 2019 and 2020.

Looking at the fixtures, it can be noted that kitchen usage almost doubled from 2019 to 2020 and their distribution appeared more uniform throughout the week during this period than in the year 2019 alone. Shower usage distribution during weekdays is quite similar between the two monitoring periods, but high usage can be observed in September 2020, as reported in Supplementary Material, Figure S1. Then, washbasin and bidet water usages show a change in the weekly distribution. In 2019 and 2020 in the months of July and August, the distribution appeared quite different as water use increases significantly in the year 2020, while from September to October (2019 and 2020) water distribution appears quite similar, as reported in Figures S2 and S3 in the Supplementary Material.

Weekly and monthly distribution, as shown in Figure 4 and Supplementary Material, Figures S1–S3, evaluated on a larger scale, can support water utilities to improve and optimize water storage and pump schedules (Menke *et al.* 2016).

CONCLUSIONS

This paper presents a statistical analysis of water end-use consumption data, before and after the impact of COVID-19, to highlight how high-resolution water end-use consumption, measured with an IoT system, can contribute to understand and profile users' behaviors.

The study is based on the public dataset WEUSED-TO of real water end-use consumption data gathered in a residential apartment used as a case study.

Starting from the authors' previous work (Di Mauro *et al.* 2019, 2020), the paper represents an update of the case study and the statistical analysis of the generated dataset. The pandemic represented an opportunity to observe the modified behaviors of a single householder who changed from a worker to a smart worker profile.

The availability of the IoT high-resolution data has allowed us to identify the impact of user behavior on demand peak, and how an alteration of lifestyle can affect water usage.

The first results, as also reported by other international studies, confirmed that COVID-19 sanitary emergency changed the residential water consumption pattern significantly, stressing on water utility as a solution for the increasing water demand peak and frequency. Moreover, data collected in the case study and statistical analysis of daily, weekly, and monthly water consumption have highlighted how single end-use categories are crucial for identifying customer behaviors that impact on water demand peak.

The results also showed how disaggregated water consumption can help to understand water usage in the domestic environment by promoting water-saving and providing precious information on water utilities for water user profiling. Customers' profiling represents a crucial aspect to improve users' awareness, promote sustainable behaviors able to reduce water waste, and help water utilities in their decision systems.

Moreover, residential water demand modeling and side management can impact also on the existing nexus between energy and water. A comprehensive evaluation of water-related energy use within residential activities can bring valuable insights into water conservation and sustainable urban planning through a behavioral change.

Nevertheless, customer profiling is still a challenge in the water sector due to the cost and intrusiveness of metering devices at the fixture level. On this side, the data collected in this study are potentially eligible as numerical benchmarks for training and testing end-use disaggregation algorithms in order to avoid sensors' placement. The water consumption measures collected from a single householder can simplify the application of complex disaggregation methods in the water sector. Furthermore, data sampled with a high temporal frequency can offer new possibilities on disaggregation techniques, demand-side management, and forecasting.

DATA AVAILABILITY STATEMENT

All relevant data are available from an online repository or repositories (https://github.com/Water-End-Use-Dataset-Tools/WEUSEDTO).

REFERENCES

Abu-Bakar, H., Williams, L. & Hallett, S. H. 2021 Quantifying the impact of the COVID-19 lockdown on household water consumption patterns in England. *Npj Clean Water* **4**(1). https://doi.org/10.1038/s41545-021-00103-8.

Baker, S. R., Farrokhnia, R. A., Meyer, S., Pagel, M. & Yannelis, C. 2020 How does household spending respond to an epidemic? Consumption during the 2020 COVID-19 pandemic. *Rev. Asset Pricing Stud.* **10**, 834–862.

Beal, C. D. & Stewart, R. A. 2014 Identifying residential water end uses underpinning peak day and peak hour demand. *Journal of Water Resources Planning and Management* **140** (7), 04014008. https://doi.org/10.1061/(asce)wr.1943-5452.0000357.

Beal, C. D., Stewart, R. A. & Fielding, K. 2013 A novel mixed method smart metering approach to reconciling differences between perceived and actual residential end use water consumption. *J. Cleaner Prod.* **60**, 116–128.

Cary, J. W. 2008 Influencing attitudes and changing consumers' household water consumption behaviour. *Water Sci. Technol. Water Supply* **8**, 325–330.

Cufoglu, A. 2014 User profiling – a short review. *Int. J. Comput. Appl.* **108**, 1–9.

Di Mauro, A., Di Nardo, A., Santonastaso, G. F. & Venticinque, S. 2019 An IoT system for monitoring and data collection of residential water end-use consumption. In: *Proc. Int. Conf. Comput. Commun. Networks, ICCCN*, 2019 July.

Di Mauro, A., Di Nardo, A., Santonastaso, G. F. & Venticinque, S. 2020 Development of an IoT system for the generation of a database of residential water end-use consumption time series. *Environ. Sci. Proc.* **2**, 20.

Di Mauro, A., Venticinque, S., Santonastaso, G. F. & Di Nardo, A. 2021a WEUSEDTO – Water End USE Dataset and TOols: an open water end use consumption dataset and data analytics tools. *Software X* (in preparation).

Di Mauro, A., Cominola, A., Castelletti, A. & Di Nardo, A. 2021b Urban water consumption at multiple spatial and temporal scales. A review of existing datasets. *Water (Switzerland)* **13**, 1–31.

Eke, C. I., Norman, A. A., Shuib, L. & Nweke, H. F. 2019 A survey of user profiling: State-of-the-art, challenges, and solutions. *IEEE Access* **7**, 144907–144924. https://doi.org/10.1109/ACCESS.2019.2944243.

Fu, Y. & Wu, W. 2014 Behaviour interventions for water end use: an integrated model. In: *ICAC 2014 – Proc. 20th Int. Conf. Autom. Comput. Futur. Autom. Comput. Manuf*.

Gerland, P., Raftery, A. E., Ševčíková, H., Li, N., Gu, D., Spoorenberg, T., Alkema, L., Fosdick, B. K., Chunn, J., Lalic, N., Bay, G., Buettner, T., Heilig, G. K. & Wilmoth, J. 2014 World population stabilization unlikely this century. *Science* **346**, 234–237. https://doi.org/10.1126/science.1257469.

Kalbusch, A., Henning, E., Brikalski, M. P., Luca, F. V. & de Konrath, A. C. 2020 Impact of coronavirus (COVID-19) spread-prevention actions on urban water consumption. *Resour. Conserv. Recycl.* **163**. https://doi.org/10.1016/j.resconrec.2020.105098.

Menke, R., Abraham, E., Parpas, P. & Stoianov, I. 2016 Demonstrating demand response from water distribution system through pump scheduling. *Appl. Energy* **170**, 377–387.

Nguyen, K. A., Stewart, R. A. & Zhang, H. 2013 An intelligent pattern recognition model to automate the categorisation of residential water end-use events. *Environ. Model. Softw.* **47**, 108–127. https://doi.org/10.1016/j.envsoft.2013.05.002.

Ociepa, E., Mrowiec, M. & Deska, I. 2019 Analysis of water losses and assessment of initiatives aimed at their reduction in selected water supply systems. *Water (Switzerland)* **11** (5). https://doi.org/10.3390/w11051037.

Rahim, M. S., Nguyen, K. A., Stewart, R. A., Giurco, D. & Blumenstein, M. 2021 Advanced household profiling using digital water meters. *J. Environ. Manage.* **288**, 112377. https://doi.org/10.1016/j.jenvman.2021.112377.

Swan, L. G. & Ugursal, V. I. 2009 Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. *Renew. Sustain. Energy Rev.* **13**, 1819–1835.

The United Nations World Water Development Report 2018 *Nature-Based Solutions for Water*. United Nations Educational, Scientific and Cultural Organization, Paris, France. Available from: https://www.unwater.org/publications/world-water-development-report-2018/ (accessed 24 September 2021).

Willis, R. M., Stewart, R. A., Giurco, D. P., Talebpour, M. R. & Mousavinejad, A. 2013 End use water consumption in households: impact of socio-demographic factors and efficient devices. *J. Cleaner Prod.* **60**, 107–115. https://doi.org/10.1016/j.jclepro.2011.08.006.

First received 13 July 2021; accepted in revised form 22 October 2021. Available online 6 November 2021