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Automatic Detection of Water Consumption Temporal Patterns in a Residential Area in Northen Italy

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Abstract
One of the main challenges for city development is to ensure a sustainable water resource management for the water supply system. A clear identification of the urban water consumption patterns supports policy and decision makers in managing the water resources, satisfying the total demand and, at the same time, reducing losses and identifying potential leakages or other issues in the distribution network. High resolution smart meters have widely shown to be an efficient tool to measure in-pipe water consumption. The collected data can be used to identify water demand patterns at different temporal and spatial scales, reaching the end-uses level. Water consumption patterns at building level can be influenced by multiple factors, such as socio-demographic aspects, seasonality, and house characteristics. The presence of a garden that requires summer irrigation strongly alters the daily consumption pattern. In this framework, we present an innovative approach to automatically detect the presence of garden irrigation, identifying daily average water consumption patterns with and without it. The proposed methodology was tested in a residential area in Northen Italy, where 23 smart meters recorded data at 1-minute resolution for two years. Results show very good performances in distinguishing between days with and without garden irrigation. The derived average normalized water consumption patterns for both scenarios can help decision makers and water managers to regulate the pressure regimes in the distribution network correctly.

Highlights

- High resolution smart meter data have been used to identify water consumption patterns;
- Automatic detection criteria to classify days with and without garden irrigation are designed;
- Normalized average water consumption patterns with and without irrigation are proposed.

Keywords Domestic water use · Water consumption pattern · Automatic detection · High resolution smart meter data

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1 Introduction

The intense drought that hit the North of Italy, and more in general, the whole of Europe, during summer 2022 (Montanari et al. 2023), highlighted how important it is to adopt correct water management strategies, even in highly industrialized and rich countries. The effects of climate changes, due to the rise of the average temperature and the decrease of mean annual precipitation (IPCC, 2022), are limiting freshwater availability. At the same time, the constant growth of the worldwide population, which is expected to reach 9.7 billion in 2050 (UN, 2018), increases the global water demand, hindering the possibility of ensuring clean water for everyone.

Besides the potential use of unconventional resources, such as reuse of grey water, desalinization or fog water (Karimidastenaei et al. 2022), maximizing the efficiency of the available water supply system is the first step towards a sustainable use of the water resource. Precisely characterizing the urban water consumption patterns and defining the influencing factors could support politicians and decision makers towards a sustainable water management (He et al. 2021).

Multiple studies investigated the water consumption and the aspects that have an impact on it (Abu-Bakar et al. 2021b; Cominola et al. 2023): number of people in the household, income, house dimensions and characteristics, such as the presence of a swimming pool or a garden, as well as climatic conditions, such as rainfall seasonality or heatwave exposure, and additional water request due to tourism fluctuations can influence the total water consumption and related patterns (Domene and Saurí 2006; Mazzoni et al. 2022; Romano et al. 2014). Furthermore, it has been demonstrated that an increase in water price is likely to lead most European households to reduce water consumption (Romano et al. 2014). Cominola et al. (2023) provided an intensive review of determinants that influence water demand at household level, showing that the most investigated factors in the literature are income, household dimension and age, while the most influential, besides the socio-demographic characteristics, are the house characteristics and the presence of a garden. Finally, it is important to consider that these factors act at different temporal scales: the long-term changes related to the population and income determine a slow change in the water consumption. Climate seasonality of rainfall and heatwaves, on the other hand, lead to an immediate fluctuation in the water demand.

To support sustainable water management strategies, besides the estimation of the total water consumption, it is important to identify the water consumption variability, classifying the daily water consumption patterns (Rondinel-Oviedo and Sarmiento-Pastor 2020). In fact, if the water consumption patterns that generate intense flows are well known and monitored, the pressure regimes and/or the hourly costs can be adjusted accordingly. If the water consumption in a specific time window is particularly high, for example, deciding to increase the pressure only during that specific period and reducing it during the rest of the day will limit the water losses when pressure is lower, saving energy for pumping.

The availability of measurements recorded by smart meters, at different spatial and temporal scale, makes it possible not only to estimate the water consumption, but also to identify water consumption patterns and to build water consumption models (Di Mauro et al. 2021; Reddy et al., 2024), as well as to highlight water losses (Alvisi et al. 2019) and leakages in the water supply system (Serafeim et al. 2022a, b), and to monitor and promote water conservation (Cominola et al. 2021). Moreover, smart meters allow fine temporal scales to be addressed, moving from a monthly and daily scale to sub-hourly measurements (Di Mauro et al. 2021).

Based on data collected by smart meters in the city of Kalgoorlie-Boulder in Australia, Cardell-Oliver (2013), identified four types of signature patterns (continuous flow days, exceptional peak use days, programmed patterns with recurrent hours, and normal use partitioned by season and period of the day), highlighting the most significant and prevalent population behaviours. Following a similar approach, Abu-Bakar et al. (2021a) classified, from the analysis of more than 10,000 monitored households in England, the water consumption in 4 main patterns, labelled accordingly to the predominant peak demand times.

Several studies used the high-resolution data recorded from smart meters to monitor and investigate end-use events, aiming to identify water use patterns for each single end-use, to support decision making regarding water consumption and suggesting more efficient approaches (Arsene et al. 2023; Heydari et al. 2022; Kumar et al. 2021; Meyer et al. 2021; Otaki et al. 2017). Most of these works aim to distinguish between indoor and outdoor water use, based on an event duration, volume, and intensity analysis (Meyer et al. 2021), while others focused on specific indoor uses, such as sinks and toilets (Arsene et al. 2023).

However, knowledge about the temporal patterns is not conclusive since external events can change the habits of the inhabitants and thus water consumption, for example during the COVID-19 period (Rizvi et al. 2020). Balacco et al. (2023), for example, observed a general decrease in water consumption and a morning peak shift during the pandemic period. They also showed how the water consumption has not returned to the pre-pandemic values yet, underlining how COVID-19 changed lifestyles, since many people changed their habits, spending more working time at home after the pandemic period. Similar variations in the water demand patterns, with a more spread out consumption during the day, and a decrease and a delay in the morning peaks have been observed in a residential area in Rovigo by Alvisi et al. (2021). An increase in the water consumption has been observed in Turkey (ÜÇLER 2022) and Saudi Arabia (Almulhim and Aina 2022), while a decrease has been recorded in the Balearic Islands, most likely related to the halt of tourism fluxes (Garcia et al. 2023).

To provide an effective support to the policy makers and water managers, it is, hence, important not only to identify the most relevant influencing factors, but also to evaluate how they modify the water consumption patterns. Although it is well known that the presence of an irrigated garden is one of the most influencing factors (Cominola et al. 2023), the actual changes in the water consumption patterns are still poorly investigated. In this context, we provide an innovative automatic approach to identify the signature of irrigation for domestic garden irrigation in water consumption patterns, based on high-resolution continuous measurements. The proposed approach is validated using data collected at 1-minute temporal resolution, during a two-year campaign (2019–2020), by 23 smart meters, installed in a residential area in Northern Italy by the Blue Gold company.

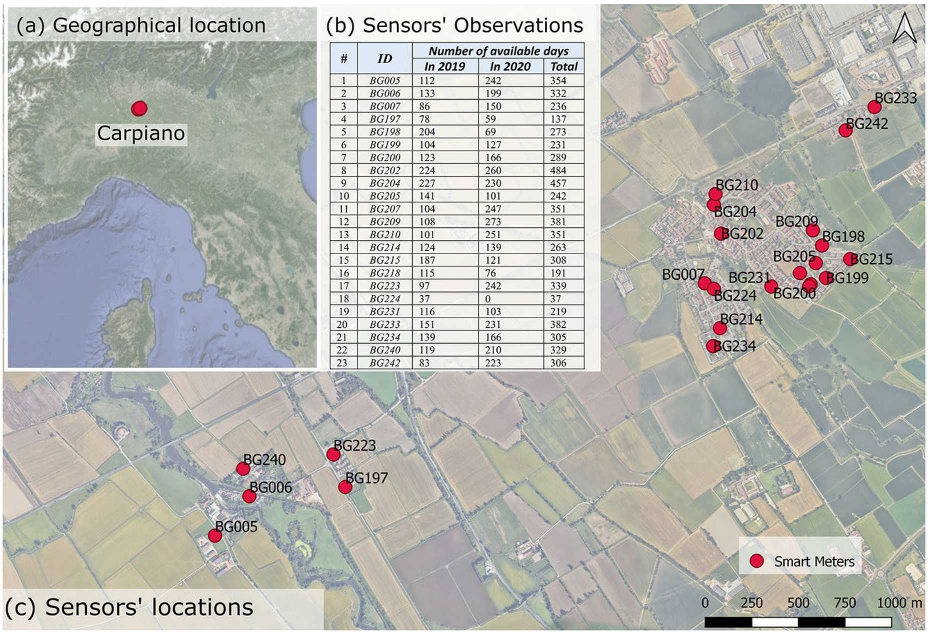
The paper is structured as follows. Sect. 2 introduces the case study and the available data from the smart meters, while Sect. 3 presents the proposed methodology developed to automatically identify the domestic water consumption patterns, highlighting days with and without garden irrigations. Results are illustrated in Sect. 4, where the average consumption patterns with and without irrigation are illustrated, compared, and discussed. Sect. 5, summarizes the main conclusions and suggests possible research pathways.

2 Case Study

To investigate and classify the domestic water consumption patterns, the Municipality of Carpiano (Fig. 1(a), Italy) was chosen as the case study. Carpiano is a small village, with about 4000 inhabitants and a surface of 17 km^2. The residential areas are spread in a historical agricultural area, as shown in Fig. 1, where 23 buildings with multiple apartments connected to the water supply network of Carpiano were monitored from 1 January 2019 to 31 December 2020, collecting 2 years of data. Specifically, water consumption of each building was recorded at 1-minute resolution by 23 smart meters produced by the Blue Gold company.

Although the location of the 23 smart meters is well known and shown in Fig. 1(b), for privacy reasons (Salomons et al. 2020), information about the demographic and socio-economic characteristics of the households living in the buildings monitored by the sensors is not available. However, with the use of satellite imagery, such as the images provided by Google Maps, it was possible to establish the dimensions, the number of floors and the presence of a garden of each connected building.

The installed smart meters ensure a continuous monitoring of the system, measuring water pressure, levels, flow rate, consumption, temperature, and turbidity at 1-minute resolution. Collected data are then transmitted and remotely available through an online platform. The Blue Gold smart devices are certified with IP68 protection, can be easily with a basic smartphone, and their small dimension ensures installation also in small manholes, adapting to existing infrastructures.



#	ID	Number of available days		
		In 2019	In 2020	Total
1	BG005	112	242	354
2	BG006	133	199	332
3	BG007	86	150	236
4	BG197	78	59	137
5	BG198	204	69	273
6	BG199	104	127	231
7	BG200	123	166	289
8	BG202	224	260	484
9	BG204	227	230	457
10	BG205	141	101	242
11	BG207	104	247	351
12	BG209	108	273	381
13	BG210	101	251	351
14	BG214	124	139	263
15	BG215	187	121	308
16	BG218	115	76	191
17	BG223	97	242	339
18	BG224	37	0	37
19	BG231	116	103	219
20	BG233	151	231	382
21	BG234	139	166	305
22	BG240	119	210	329
23	BG242	83	223	306

Fig. 1 (**a**) Geographical location of Carpiano (MI, Italy) and (**b**) observations and (**c**) locations of the smart meters (see coloured version)

3 Methodology

3.1 Water Consumption

Observations collected from the 23 smart meters during 2019 and 2020 were analysed to identify the daily water consumption for each building or residential complex. The dataset was first pre-processed to detect and exclude measurements that can be affected by errors (Khaki and Mortazavi 2022). With this aim, two criteria have been implemented. Since the aim of this work is to identify the water consumption patterns at daily scale, a first criterion consists in discarding days with more than 10% of missing data, thus retaining only days with at least 90% of 1-minute resolution data. Moreover, since each sensor is connected to a building with more than one household, a very low water consumption value is more likely to be attributable to the presence of leakages than to a real consumption. Thus, as a second criterion, days with low consumptions (in our case below a threshold of 500 l/d) have been excluded from the analysis. These two conditions ensure the use of reliable data for a reliable detection of water consumption patterns. Figure 1(b) summarizes, for each sensor, the number of days that are considered reliable for the study.

3.2 Automatic Detection of Water Consumption Patterns

After identifying the days with enough data and removing the measurements suspected to be affected by errors as described in Sect. 3.1, the obtained dataset has been used to classify the water consumption patterns. Figure 2 provides a schematic representation of the procedure proposed to identify days with garden irrigation and defining an average water consumption pattern. The first step is to define, for each utility u and for each day d, the volume of the cumulative water consumption $V_{u,d,j}$ from midnight to $t = j\Delta t$, where Δt is a discrete time step (in our case $\Delta t = 1min$), and $j = 1, ..1day/\Delta t$ is a time-step counter within day d:

$$V_{u,d,j} = \sum {}_{s=1}^{j} \left(\frac{Q_s + Q_{s-1}}{2} \right) \cdot \Delta t \tag{1}$$

where Q_s is the flow rate at time $t = s\Delta t$.

The cumulative water consumption curve in Eq. (1) is non decreasing and ranges from 0 for j=0 (at the beginning of day d) to $V_{u,d}$ (daily total water consumption) when $j = 1, ..1day/\Delta t$ (i.e. at the end of the same day).

To compare the patterns of utilities with different water consumption, let us introduce the normalized cumulative water consumption $R_{u,d,j}$ by dividing the cumulative water consumption $V_{u,d,j}$ in Eq. (1) by the total water consumption $V_{u,d}$ the same day *d*:

$$R_{u,d,j} = \frac{V_{u,d,j}}{V_{u,d}} \quad j = 0, \ldots, 1day/\Delta t \tag{2}$$

The normalized cumulative water consumption curve varies from 0 for $j = 0$ to 1 for $j = 1, ..1day/\Delta t$, regardless of the daily total water consumption of the considered utility.

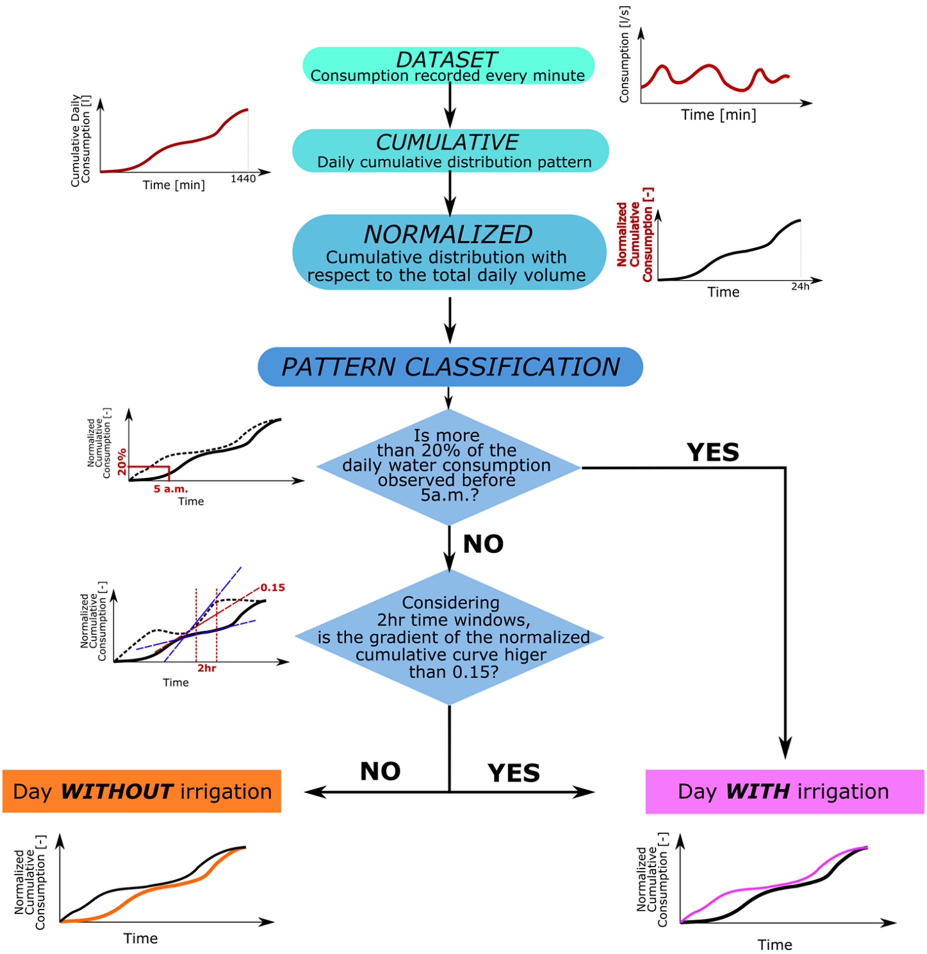


Fig. 2 Schematic representation of the pattern identification procedure

Normalized cumulative curves are then analyzed to classify the water consumption patterns, applying criteria to select whether the days are characterized by garden irrigation or not. In this work, two main assumptions have been considered to define the selection criteria, so if either of the following two criteria is satisfied, we classify “day with irrigation”. First of all, due to agronomic reasons, gardens are usually irrigated at night and in the early morning, when the soil is not directly exposed to the sun, thus temperatures and consequently evaporation are lower (Yacoubi et al. 2010). Most common summer irrigation schedules for domestic gardens follow this rule, and irrigation is set between 2 a.m. and 5 a.m. Thus, if the gardens are irrigated, we will observe a high water consumption during the first hours of the day, while if there is no irrigation, low water consumption is, hence, expected from midnight to 5 a.m. Following this assumption, we can define the first criterion, based on the percentage of total water consumption before 5a.m.: if more than 20% of the daily water consumption is observed in the early morning, that specific day is characterized as “day with irrigation”. The second assumption is based on the fact that, when the gardens are irrigated, the water consumption is extremely higher than the usual one. Hence, if we observe an unexpected high gradient in the cumulative normalized curve, which corresponds to a temporary increase in the water consumption, we can assume that this is caused by irrigation. Based on this assumption, the second criterion has been defined by analyzing if the average gradient of the normalized cumulative curve in a 2-hour time window overpasses a given threshold, which in this case is supposed equal to 0.15. Hence, if $R_{u,d,j} - R_{u,d,j-120} > 0.15$for at least one j, the day is classified as "day with irrigation". Applying the proposed approach to each day, as also illustrated in Fig. 2, enables them to be classified, and subsequently the average of the cumulative water consumption patterns for days with irrigation and days without it to be estimated.

Thanks to the normalization of the water consumption, this process enables days characterized by irrigation and days without it to be distinguished, regardless of the volume of water used and the number of households connected to each smart meter. This approach, moreover, allows multiple smart meter records to be directly compared, and general patterns, representative of the entire area to be identified.

A supplementary analysis on cumulative curves has been carried out by comparing the median of the normalized cumulative curves from July, when irrigation is mostly expected, with the ones of winter months, i.e., from November to February. For each sensor, the sums of the differences at 1-min time step between the July median of the normalized cumulative curves and the winter month medians have been calculated. Utilities that show high values of this factor are expected to have gardens irrigated during summer, while buildings with values closer to zero do not show significant differences between summer and winter water consumption.

Once days with and without irrigation are identified and separated, it is possible to estimate the normalized water consumption pattern $\tilde{Q}_{u,d,j}$ for each utility *u*, at time $t = j\Delta t$ from midnight of each day *d* as:

$$\tilde{Q}_{u,d,j} = \frac{Q_{u,d,j}}{?Q_{u,d}?} \tag{3}$$

where $\langle Q_{u,d} \rangle$ is the daily average water consumption. These curves enable the normalized daily pattern of the water consumption to be visualized and constitute a valuable tool for decision makers and water managers.

Following this approach, it is possible to analyze the influence of specific factors, such as climate effects, which might impact the citizens' behaviour, and consequently, vary the water consumption patterns. Focusing on the days without irrigation, we can select three main seasons (Oct-Jan, Feb-May, Jun-Sept) and estimate the seasonal average water consumption patterns. The comparison among the three curves highlights how climatic variations could affect the citizens' behaviour in terms of water consumption patterns. Moreover, thanks to the data availability for the years 2019 and 2020, it is possible to evaluate how COVID-19 changed the water consumption behaviour. The comparison between the average water consumption pattern of 2019 with the one of 2020, enables the differences between pre-COVID-19 and during the confinement to be underlined.

4 Results

4.1 Water Consumption

The daily water consumption for each of the 23 utilities was obtained by applying the criteria described in previous Sect. 3. The variability of the daily consumption during the period 2019–2020, for each utility is summarized by the boxplots shown in Fig. 3. In the same figure, the average water consumption during the single years is also highlighted, with a blue circle for 2019 and a red one for 2020. Each utility presents a different daily water consumption and a different variability during the two years of recorded data. Although most of the utilities showed an average daily water consumption lower than 10’000 l, the variability is relatively high, ranging from a minimum of 2761 l, recorded in BG233, to a maximum of 29,634 l, in BG209. The observed differences can depend on multiple factors, mostly related to the fact that utility characteristics, such as number and surface of the connected apartments, number of the household members and presence of gardens, are not available for privacy reasons.

Interestingly, the highest variability in daily consumption has been observed by the sensors BG209, BG214, BG234, where the location of the smart meter is compatible with the presence of a garden, which is probably irrigated during the warmest days. The potential presence of an irrigated garden has been verified by comparing the position of the smart meters and the typologies of the surrounding buildings, which are most likely to be connected to the sensors. On the contrary, it was not possible to find a unique link between

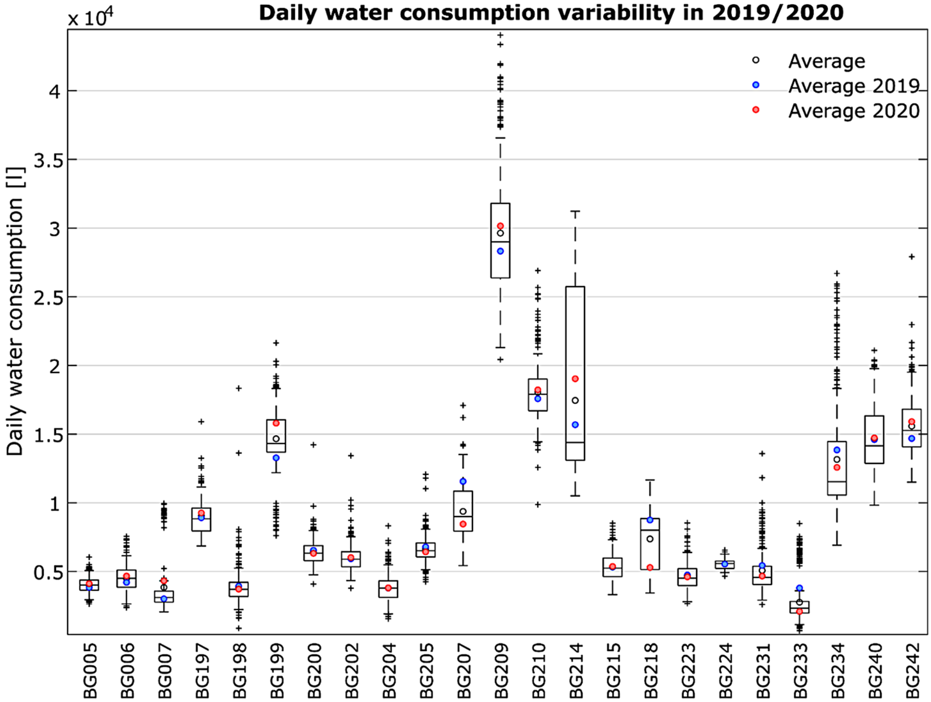


Fig. 3 Daily water consumption variability, recorded by the 23 smart meters

mean, variance or the coefficient of variation and the occurrence of summer irrigation, which has been automatically detected following the methodology illustrated in Sect. 3.2.

Moreover, from the comparison between average daily water consumption in 2019 and in 2020, it is not possible to identify a unique behaviour: some utilities increased the daily water consumption during the COVID-19 pandemic, while some others present the opposite trend, with a reduction of the daily water consumption. The deviation from 2019 varies from a reduction of 45% (BG233) to an increase of 43% (BG007), confirming the disagreement found in the literature about the effects of COVID-19 on the daily water consumption (Garcia et al. 2023; ÜÇLER 2022).

4.2 Automatic Detection of Domestic Water Consumption Patterns

To directly compare water consumption patterns recorded by the 23 smart meters, the normalized cumulative daily consumptions have been estimated. Figure 4a illustrates, as an example, the normalized cumulative consumptions recorded by BG240. The cumulative water consumption patterns are quite homogeneous and can be divided into two classes, the first one with a higher water consumption before 5 am, and the second one characterized by lower gradients. The first class of patterns is observed only for the utilities serving also a garden and only during the summer months (Fig. 4b), i.e., July, August and partially in June and September. From these considerations, we can assume that this class of patterns represents the days with domestic irrigation. Figure 4b plots, as an example, the daily normalized cumulative consumption for some representative months. During the autumn and winter months (e.g., Fig. 4b February) we observe only water consumption curves without irrigation. On the other hand, in summer (e.g., Fig. 4b July), only days with irrigation have been recorded. June and September, instead, exhibit a transient behaviour, with some days with irrigation and some without, the latter likely corresponding to periods with lower temperatures or rainfall.

The supplementary analysis on cumulative curves described in Sect. 3.2, where the median of the normalized cumulative curves of July is compared to the ones of winter months, i.e., from November to February is plotted in Fig. 4c. For utilities without gardens, this value is expected to be close to zero since no significant difference in the daily water consumption patterns is observed. On the other hand, the presence of garden irrigation is confirmed when the sum of the difference between the two curves shows high values. Due to the lack of data in July and/or winter months, few sensors (BG197, BG224 and BG242) have been excluded from this analysis. The blue area in Fig. 4c separates two different patterns, dividing the utilities with garden irrigation (above the blue area) from the ones without it (below the blue area). These results confirm the automatic identification as emerges from the method depicted in Sect. 3.2.

4.3 Domestic Patterns with and Without Irrigation

Following the criteria described in Sect. 3.2, it was possible to identify and select the days in which the water consumption is higher due to the presence of garden irrigation. The amount of water requested daily to satisfy the irrigation needs is different for each utility, due to different garden sizes, but the temporal pattern is quite similar, with most of the irrigation happening at night and in the early morning. For this reason, the normalized patterns have

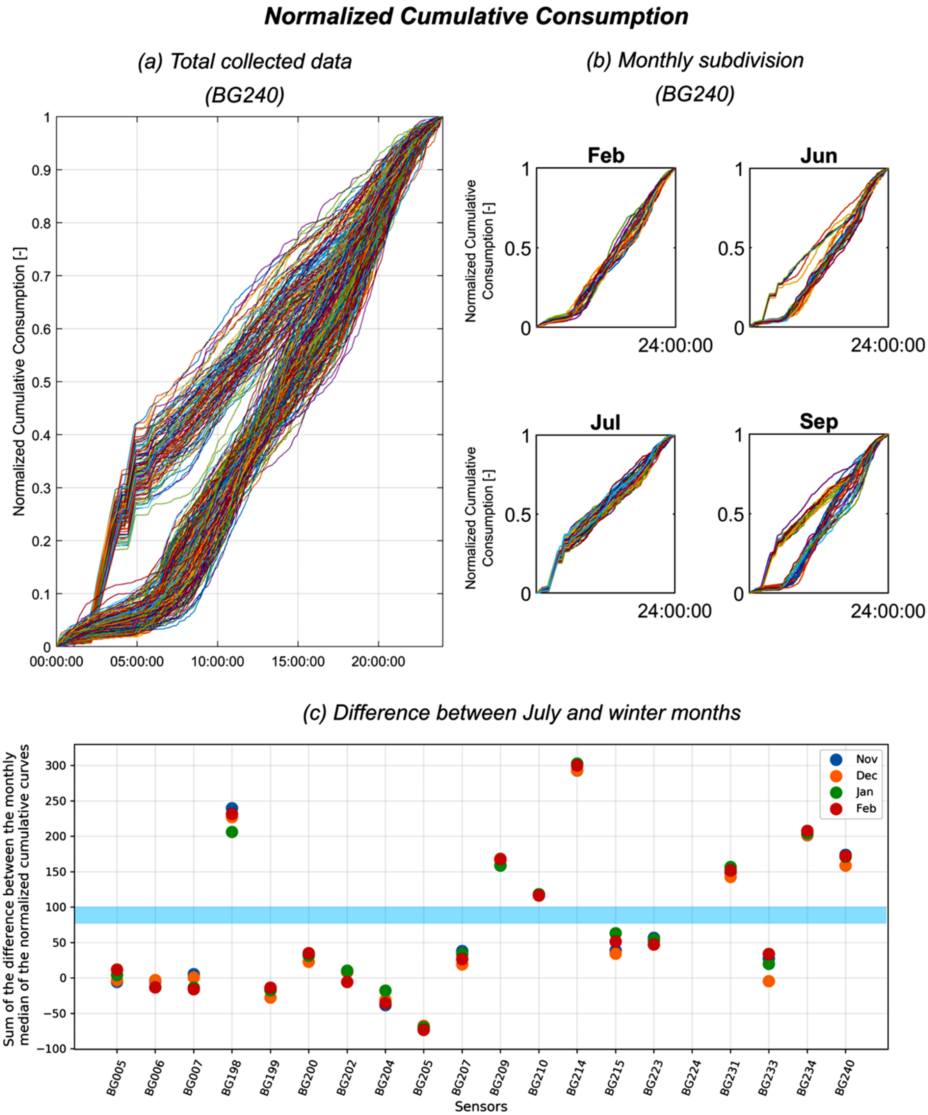


Fig. 4 Normalized cumulated water consumption (**a**)Total water consumption for BG240 (**b**)Monthly water consumption for selected months, i.e., February, June, July and September, for BG240 (**c**) Cumulative difference between the median of the normalized cumulative curves of July and of the winter months, i.e., November, December, January and February. The blue area highlights the separation between utilities with and without irrigation. Sensors with few data in the investigated months are excluded from this analysis

been investigated, enabling behaviours of utilities characterized by different consumptions to be compared. Figure 5 shows the daily normalized cumulative water consumption for days with irrigation. The red line highlights the average cumulative curve, while the dashed black lines define the bounds between the 5 and 95 percentiles. The high gradient that char-

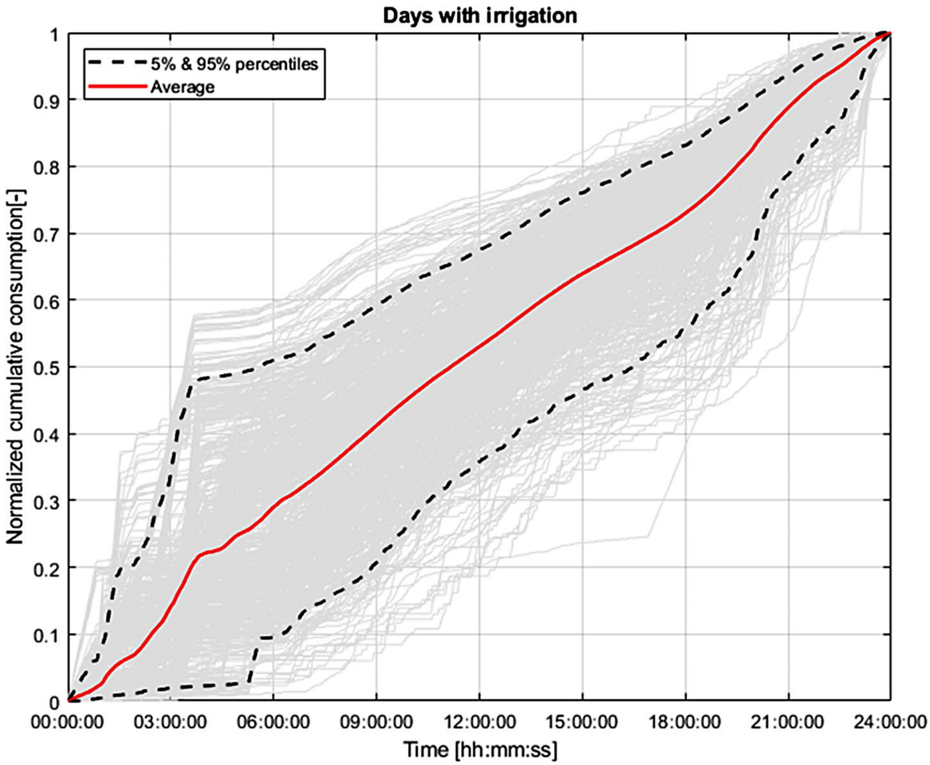


Fig. 5 Water consumption pattern variability for days with irrigation

acterizes the average curve between 2 a.m. and 5 a.m. underlines the presence of high water consumption due to garden irrigation.

To better understand the differences between water consumption patterns with and without irrigation, Fig. 6 illustrates the two average patterns, together with the bound between the 5 and 95 percentiles. Data are plotted using a moving average with a 60-min time window to smooth the noise.

The average of the normalized water consumption patterns without domestic irrigation is aligned with the water consumption patterns expected for a residential area in a small town: the main water consumption peak is observed in the evening, around 8 p.m., which corresponds to dinnertime. Two smaller peaks are recorded, the first one in the early morning, around 7:30 a.m, and the second one around lunchtime (at 1 p.m.), suggesting that, in this urban residential area, most of the residents have their lunch break at home. As expected, the water consumption is lower in the afternoon, and it is close to zero during the night (from 2 a.m. to 5 a.m.).

While the days without irrigation follow a well-known water consumption pattern for a residential area, similar to the ones presented in the literature (Rizvi et al. 2020), days characterized by irrigation show a different behaviour. Comparing the two patterns, it is clear that the main differences are observable during the night and in the early morning, from 11p.m. to 5 a.m. During the rest of the day no significant difference between days with and without irrigation is observed. It is also worth mentioning that the maximum relative peak

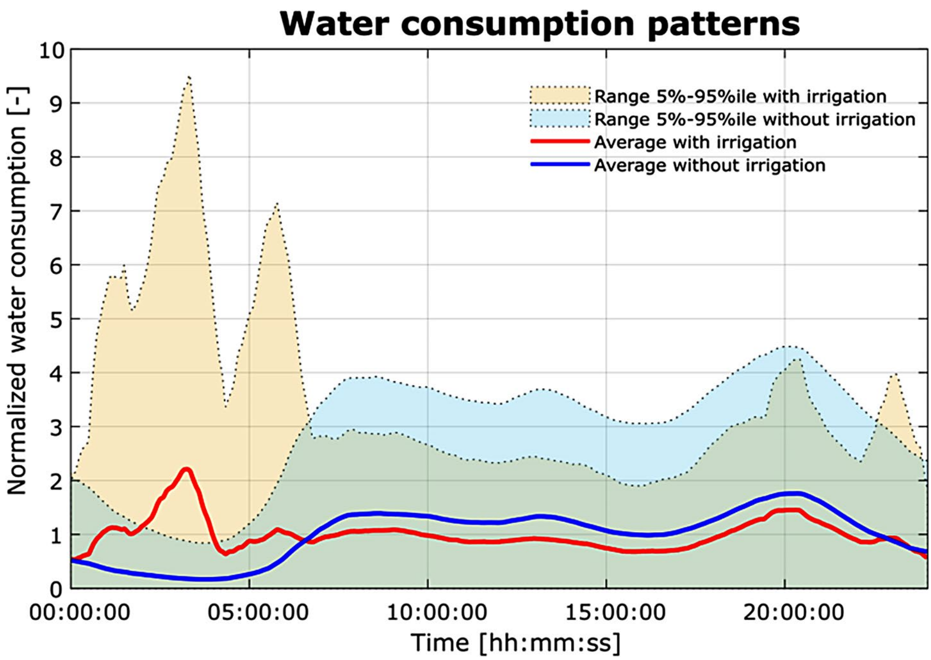


Fig. 6 Water consumption pattern variability for days with and without irrigation

of water request without irrigation is about 1.7 (line blue in Fig. 6), the maximum relative peak in days with irrigation is about 2.3 (line red in Fig. 6) and occurs in summer, when days are hot and dry, the water consumption is usually higher, not only due to garden irrigation, but also for personal uses.

In Fig. 7a the average water consumption patterns observed in three four-month periods (Jun-Sept, Oct-Jan and Feb-May) are illustrated to investigate how the different seasons affect the water consumption, without considering the days with irrigation. The average water consumption pattern seems not to be influenced by the seasonal climatic variability since no significant differences are observed between the three investigated periods.

Finally, the availability of data from both 2019 (pre-COVID-19) and 2020 (COVID-19) enabled how the confinement affected the water consumption to be investigated. In Fig. 7b, the average pattern observed in 2019 is compared with the one recorded in 2020. A small shift to the right in the morning peak and a flatter morning pattern is observed in 2020, suggesting that, due to the confinements, residents changed their morning habits slightly, getting up a bit later and most likely working from home. These results confirm what observed in Southern Italy. Those variation in the water consumption pattern are, however, small and limited only to the morning. Besides the small changes in the morning water consumption habits, no significant differences in terms of water consumption pattern have been detected between the pre-pandemic and pandemic situations, suggesting that COVID-19 did not have a relevant impact on the water consumption habits of the residents of the investigated urban area.

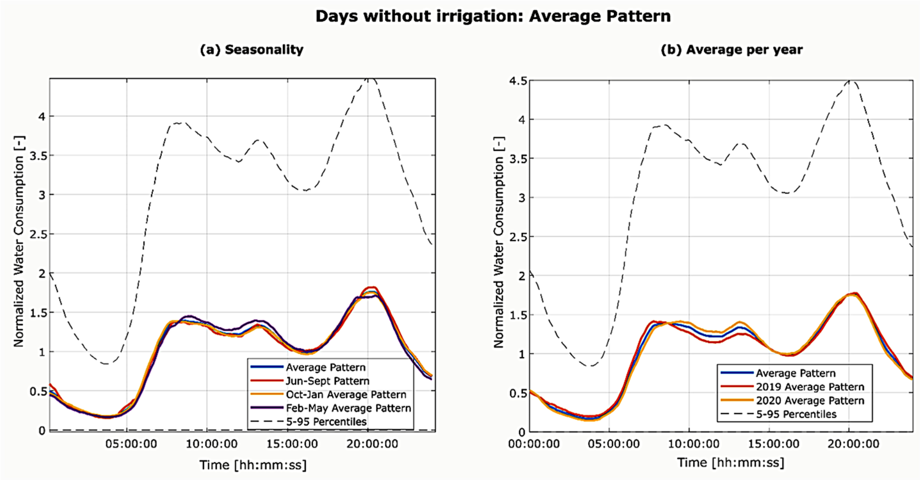


Fig. 7 Average water consumption pattern and water consumption pattern variability for days without irrigation. Solid lines indicate the average water consumption patterns, while dashed lines highlight the 5th and 95th percentile (**a**) Comparison among seasons. (**b**) Comparison between 2019 and 2020

5 Conclusions

This work presents an innovative methodology based on cumulative water consumption to automatically detect the presence of garden irrigation in the daily water consumption patterns. Moreover, normalized daily average water consumption patterns have been identified for both days with and without garden irrigation, enabling the impact that the presence of a domestic garden has on the daily water consumption to be characterized and quantified. In addition, this novel approach ensures a strategic support for water managers to regulate water pressure in the distribution systems properly. Thanks to the high-resolution smart meter data collected by the Blue Gold company, the proposed approach has been tested in a residential area of the municipality of Carpiano (Northern Italy). Data were collected from 23 smart meters, for the period from January 2019 to December 2020, enabling not only the seasonality effects to be investigated, but also how the confinement during the Covid-19 pandemic influenced the water consumption patterns.

Results showed how the proposed approach can automatically classify the daily water consumption patterns, separating days with and without irrigation. Focusing only on the days without irrigation, the average normalized daily water consumption pattern is aligned with the patterns available in the literature, with peaks at 8 a.m. in the morning, at lunchtime, around 1 p.m., and in the evening around 8 p.m., and lower consumption during the night. No significant differences have been observed among average water consumption patterns recorded in different seasons. On the other hand, in 2020 a small shift of the morning peak and a flatter morning pattern were recorded, highlighting how the confinement due to Covid-19, changed the habits and consequently the water consumption. Days characterized by garden irrigation, on the other hand, present quite different water consumption patterns, with high peaks during the night and early morning, between 11p.m. and 5 a.m. Such differences in water consumption patterns could support water managers in regulating the pressure regimes, increasing the night pressure only during the summer days.

In order to improve the validation of the proposed approach, multiple residential areas, characterized by different climatological and socioeconomic factors should be monitored and their water consumption patterns should be estimated. A large-scale investigation, with a consequent mapping of the water consumption patterns, is a promising and powerful instrument for water managers, policy makers and other stakeholders, ensuring a relevant contribution towards a sustainable water resource management and for the creation of resilient cities.

Author Contributions All authors contributed to the study conception and design. Material preparation and data collection were performed by Andrea Delogu and Martina Gandolfi. Analyses were performed by Pietro Biddau and Elena Cristiano, with the supervision of Francesco Viola, Roberto Deidda and Andrea Delogu. The first draft of the manuscript was written by Elena Cristiano and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Declarations

Competing Interests The authors have no relevant financial or non-financial interests to disclose.

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