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Research article

Water demand profile before and during COVID-19 pandemic in a Brazilian social housing complex

C. Cominato [a], J. Sborz [a], A. Kalbusch [a,*], E. Henning [b]

[a] *Santa Catarina State University, Civil Engineering Department, 89.219-710, Joinville, SC, Brazil*
[b] *Santa Catarina State University, Mathematics Department, 89.219-710, Joinville, SC, Brazil*

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ABSTRACT

The COVID-19 pandemic has changed the way resources are consumed around the world. The relationship between the pandemic and water consumption has important implications for the management of water use and must be evaluated in depth. The main goal of this research paper is to establish a comparison between pre-pandemic and pandemic water consumption profiles for 14 social-housing buildings located in Joinville, Southern Brazil. Telemetry data from each apartment were collected on an hourly basis before and during the COVID-19 pandemic. The analysis was based on descriptive statistics on the hourly and daily water consumption in addition to its profile plots. The best probability distribution fitting was also determined. To assess the differences in water consumption due to de pandemic, the Wilcoxon-Mann-Whitney test was employed and a Generalized Linear Model with mixed effects was fitted to the data. The Lognormal distribution was shown to be the most appropriate to model the water consumption data. Due to the COVID-19 pandemic, the two daily peak consumption periods changed from 12 h to 15 h and from 19 h to 21 h. The COVID-19 pandemic also impacted daily water consumption, leading to a small, yet significant, increase in demand in the first quarter of the pandemic period.

1. Introduction

The supply of water, both in terms of quantity and quality, observing safety and protection criteria, closely correlates to urban and community development (Dettori et al., 2022; Bhering et al., 2021). Understanding the patterns of residential water demand is essential to optimize urban water distribution (Beal; Stewart, 2014). For instance, peaking factors, such as the average daily peak hour, the peak day or even the annual peak hour, are decisive to evaluate how appropriate the pipe infrastructure is (Beal; Stewart, 2014). Balacco et al. (2017) add that peak water demand is one of the most relevant inputs when designing water distribution systems.

Defining the appropriate probability distribution can support design and management solutions for water distribution systems since it helps to characterize the maximum daily water demand (Gargano et al., 2017). The peak frequency and the probability of exceeding the peaking factor are important water consumption characteristics that can be found with the help of an appropriate statistical distribution fitting (Surendran and Tota-Maharaj, 2018). Kossieris and Makropoulos (2018) decomposed the residential hourly water demand as a mix of a discrete (probability mass concentrated at zero) and a continuous part, the latter described by a probabilistic model for the nonzero demand. Understanding which probabilistic models are more suitable to describe the nonzero demand values is very important (Kossieris and Makropoulos, 2018).

Even though an increasing number of studies on water demand modelling have been reported (Cominola et al., 2018), regional studies are important to understand the determinants of water consumption and how they relate in diverse contexts (Bich-Ngoc and Teller, 2018). Besides investigating the residential water consumption in social housings in Joinville in terms of hourly demand and probability distribution, the present study considers the impact of the COVID-19 pandemic on water consumption, since the analyzed consumption data encompass measurements from 2019 to 2021. Similarly to local water consumption particularities, the pandemic was perceived and managed differently across the globe (Hale et al., 2021), which may accentuate differences and similarities between residential water consumption profiles worldwide.

In late December 2019, the World Health Organization announced the emergence of unknown flu cases in the city of Wuhan, China, and declared it a public health emergency of international concern (Sohrabi

* Corresponding author.
E-mail address: andreza.kalbusch@udesc.br (A. Kalbusch).

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et al., 2020; Lüdtke et al., 2021). In the beginning of the following year, the causative agent was named Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), and the disease, COVID-19 (Sohrabi et al., 2020). Given its easy and fast spread, it was characterized as a worldwide pandemic (World Health Organization, 2020) forcing governments around the world, including Brazil, to take actions to contain the fast advance of the disease. Those measures included the closing of borders, travel restrictions and quarantines, which dramatically changed the way society lived (Balacco et al., 2020; Bich-Ngoc and Teller, 2020; de Haas et al., 2020). Brazilian states and cities issued decrees establishing measures to reduce COVID-19 infections, including the closing of services considered non-essential such as businesses, schools and workplaces for a period of quarantine. The Santa Catarina state government published a decree on March 17th, 2020, declaring a state of emergency throughout its territory, including the city of Joinville (Santa Catarina, 2020). The sudden change in people's routines, encouraged by social distancing policies, employees working from home and limited physical interactions, should influence water consumption (Balacco et al., 2020).

Since several countries enacted their lockdown in March 2020 (Bich-Ngoc and Teller, 2020; Hale et al., 2021), changes in the water consumption pattern were noticed in cities around the world (Bich-Ngoc and Teller, 2020; Feizizadeh et al., 2021). Overall, studies on the COVID-19 impact on water consumption focused on total water demand and changes related to peak hourly consumption (Abu-Bakar et al., 2021). In Brazil, data from 26 days before and after the lockdown were analyzed, revealing an 11% increase in domestic water consumption (Kalbusch et al., 2020). In a case study in Italian cities, Balacco et al. (2020) reported changes in the hourly consumption pattern during the first stage of lockdown. In Germany, Lüdtke et al. (2021) found that hourly water consumption patterns changed significantly during the first wave of COVID-19 and reinforced the need to investigate behavioral changes related to water use to understand the long-term consequences on water supply systems worldwide. Behavioral changes induced by the pandemic, such as employees working from home, homeschooling and the adoption of stricter hygiene practices may alter daily consumption patterns, which can pose a critical challenge for water utilities (Lüdtke et al., 2021). Therefore, understanding the impact of different consumption patterns during the COVID-19 pandemic can improve the accuracy of demand forecasting (Abu-Bakar et al., 2021). This research paper aims to establish a comparison between the hourly consumption profiles before and during the coronavirus pandemic, as well as the effects on the daily water consumption in 14 social housing buildings located in Joinville, Southern Brazil. Additionally, the probabilistic aspects of water consumption were investigated, aiming to fit a suitable statistical distribution to the water consumption pattern.

2. Materials and methods

The data were collected from 280 apartments in a social housing intervention in Joinville (Southern Brazil) by the water utility *Companhia Águas de Joinville.* The consumption was measured through water meters attached to a telemetry system in each apartment. Each apartment has 2 individual meters: one for hot and one for cold water. In this study, the analyzed water consumption was the total for each apartment, that is, the sum of hot and cold water consumption.

The apartments have an approximate area of 40 m^2 each and are equipped with a showerhead, a toilet, a sink, a kitchen tap and a laundry tap. The shower is the only plumbing fixture provided with hot water, which comes from the solar heating system. The analysis covered a sample of 14 5-story buildings with 4 apartments per floor, adding up to 280 apartments. Each building has a 15 000 L water tank serving all 20 apartments, with 9 950 L for consumption and 5 050 L as a technical firefighting reserve. The buildings' information was provided by the construction company.

Information about the residents was collected through face-to-face interviews in July and August 2019. This project was approved by the Research Ethics Committee of Santa Catarina State University, in Brazil (CAAE 14122819.4.0000.0118) and written informed consent was obtained from the interviewees. The property ownership of apartments in this type of social housing project cannot be transferred during 10 years, and renting conditions are very strict, according to the Brazilian federal law 11 977 (Brasil, 2009). Therefore, the number of occupants during the analyzed period was assumed constant. The per capita domestic water consumption was calculated dividing the water consumption of each apartment by the number of its occupants, defined during the interview.

The collection of domestic water consumption data was carried out between March 1st, 2019 and May 31st, 2021, totaling 822 days. The outliers, due to possible measurement errors, were removed from the data set. Therefore, the final sample included 254 apartments. The per capita consumption analysis was performed for 90 apartments whose residents agreed to participate in the interview phase and informed the number of occupants. The analyses were performed with the R software (R Core Team, 2021).

2.1. Probability distribution fitting

The average per capita water consumption per day per apartment was calculated to fit a probability distribution to the data. The averages were then plotted to a histogram so that the likely best fitting distributions could be visualized. The normal distribution was also tested as a reference because of its widespread understanding.

Once the distributions were chosen, the R packages fitdistrplus (Delignette-Muller and Dutang, 2015) and goftest (Faraway et al., 2019) were respectively employed to fit the possible distributions to the data and to analyze the goodness of fit using the Anderson-Darling (AD) and Kolmogorov-Smirnov (KS) tests. To fit the log-logistic distribution, frequently considered a good fitting for water consumption distribution (Surendran and Tota-Maharaj, 2018), the R package flexsurv (Jackson, 2016) was also used. The parameters for the distributions (*i.e.* mean, standard deviation) were defined with the distributions fitted to the data, as in the work of Surendran and Tota-Maharaj (2018). The parameter estimation used the maximum likelihood method.

Finally, the best fitting was chosen based on the maximization of the loglikelihood and the minimization of the Akaike information criterion (AIC), the Bayesian information criterion (BIC), the Anderson-Darling distance (AD D) and the Kolmogorov-Smirnov distance (KS D). The best model was required to have significant p-values ($\alpha = 0.05$) for both the AD and the KS tests.

2.2. Hourly and daily water consumption analysis

For the analysis of hourly water consumption data, the last measurement for each hour and apartment was selected, considering hot and cold water consumption data. For the daily analysis, the last water consumption measurement of each day was considered. Hourly and daily consumption was divided by the number of occupants of each apartment to obtain the per capita water consumption.

The analysis was conducted considering the pre-pandemic period, between March 1st, 2019, and March 16th, 2020, and the pandemic period, from March 17th, 2020, to May 31st, 2021. The data were split this way because, on March 17th, 2020, the first decree was issued declaring a state of emergency and lockdown in the state of Santa Catarina (Santa Catarina, 2020), where the city of Joinville is located. Thus, the total per capita water consumption data were analyzed considering the average hourly and daily water consumption in the pre-pandemic and pandemic periods.

Two methods were employed to compare the daily water consumption in the pre- and pandemic periods. First, the non-parametric Wilcoxon-Mann-Whitney test was applied. This test was chosen due to the non normality of the data (Krzywinski; Altman, 2014). The analyses were made using complete periods (before and during the pandemic), comparing daily water consumption per month in each period.

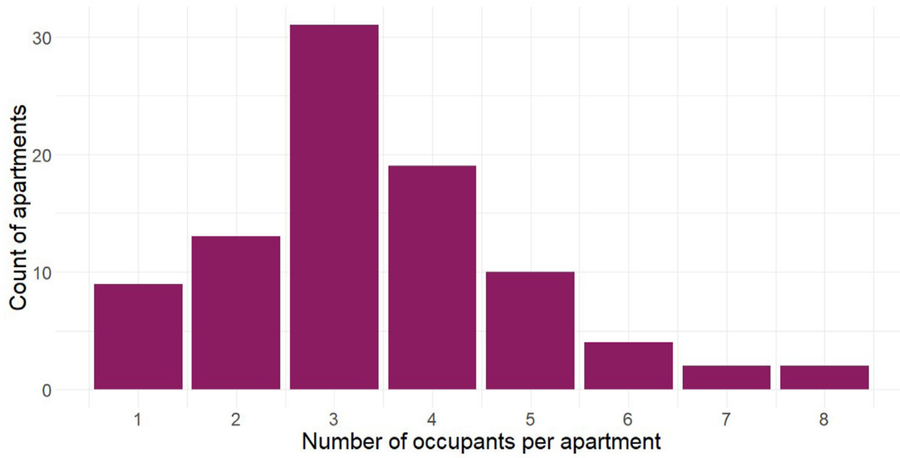

Figure 1. Bar chart of the number of occupants per apartment.

Table 1. Monthly income per household.

Number of minimum wages	0 ⊣ 1	1 ⊣ 2	2 ⊣ 3	3 ⊣ 4	4 ⊣ 5	5 ⊣ 6	6 ⊣ 7
Count of apartments	24	34	10	4	2	2	1

Table 2. Level of education.

Level of education/Status	Complete	Ongoing	Incomplete
Primary school	8 (3.32%)	6 (2.50%)	5 (2.07%)
Middle school	22 (9.13%)	67 (27.80%)	29 (12.03%)
High school	52 (21.58%)	13 (5.39%)	20 (8.29%)
University/College	10 (4.14%)	2 (0.83%)	7 (2.90%)

Additionally, a generalized linear mixed effect model was fitted to test for changes in water consumption in the pre-pandemic and pandemic periods. Models with mixed effects were used by Menneer et al. (2021) and Lüdtke et al. (2021) to analyze changes in water consumption due to the COVID-19 pandemic. The model was chosen on account of the repeated measures for each apartment and, as in Menneer et al. (2021), the property registration number was included as a random effect to represent the change within each apartment, to capture the repeated measures. The variable number of residents per apartment was also included.

Models were implemented using R version 4.1.1 (R Core Team, 2021) and the lme 4 package (Bates et al., 2015). The Pseudo-R-squared for Generalized Mixed-Effect models was calculated with the MuMIn package (Barton, 2020). The adopted level of significance was $\alpha = 0.05$.

3. Results and discussion

3.1. *Socioeconomic information*

This section presents information on households' occupancy, age, income, formal education, and employment of the residents. The number of occupants ranged from 1 to 8, with both the median and the mean approximately equal to 3. Figure 1 shows a bar chart of the number of residents. The residents age varied from 0 (newborns) to 79 years old, with a median of 24 years and a mean of about 27 years. The first quartile was 11 years, indicating an expressive presence of children.

From the 90 households, 12 did prefer not to disclose their income, and one stated that it was variable. For the 77 households with provided monthly income information, it ranged from none to 7 minimum wages, although the majority of the households had an income of up to 2 minimum wages (which was one requisite to be eligible for these social housing apartments) as shown in Table 1.

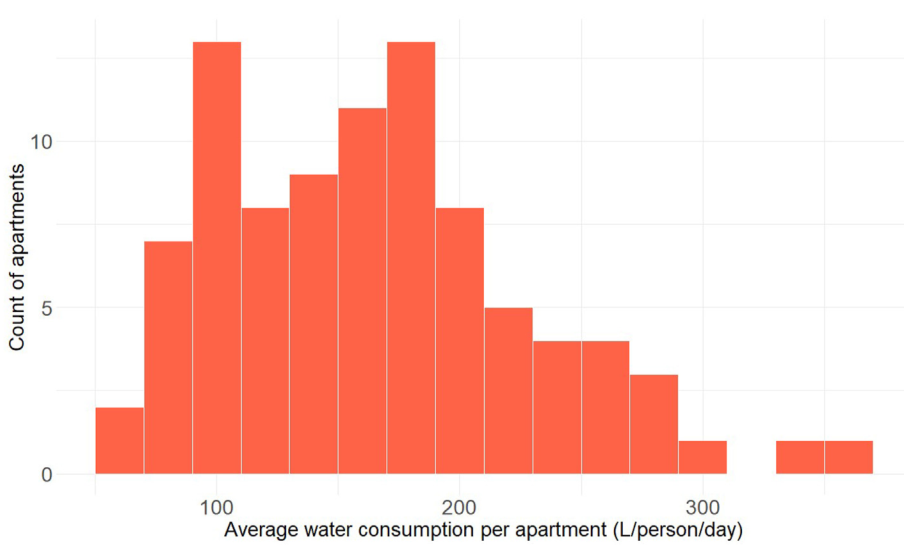

Figure 2. Histogram of average per capita water consumption per apartment.

Table 3. Goodness-of-fit results for the probability distributions to the data.

Distribution	Loglikelihood	AIC	BIC	KS D	AD D
Normal	-501.3455	1 006.69	1 011.69	0.071599	0.87775
Weibull	-499.1462	1 002.29	1 007.29	0.062216	0.61466
Lognormal	-495.8994	995.80	1 000.80	0.072372	0.36483
Gamma	-495.9073	995.81	1 000.81	0.062339	0.28227
Log-logistic	-498.1273	1 000.26	1 005.25	0.071507	0.48081

Considering the residents that were 16 years old or older, 52.7% were unemployed and 45.41% had a job (the others did not provide that information). Regarding formal education, residents that were 6 years old or younger were not considered. Only 2.6% had never attended school. Table 2 shows that most residents (27%) were currently enrolled in middle-school, which is expected due to the large number of children in the complex.

3.2. Probability distribution fitting

Figure 2 shows the histogram of the average daily per capita water consumption per apartment, which presents a positive skewness. Therefore, the data were fitted to distributions that are appropriate and to the normal distribution for reference.

Normal, Weibull, Lognormal, Gamma and Log-logistic distributions were fitted to the data and tested. All distributions presented significant p-values for both the KS and the AD tests. Table 3 presents the loglikelihood, AIC, BIC, AD D, KS D results for the acceptable distributions (p-value $>$ 0.05).

The Lognormal and Gamma distributions presented adequate values considering the fitting criteria. As Table 3 shows, the Lognormal is the best fitting distribution for all criteria, except for the KS distance and AD distance, for which the best option would be the Gamma distribution. Nonetheless, Surendran and Tota-Maharaj (2018) defended that the KS test is not suitable for water consumption data, since it is more sensitive near the center than at the tails of the distribution and, therefore, is inappropriate to catch the effects of high consumption data at the tail. Many studies have found the log-logistic distribution to best fit the water consumption, although the Gamma distribution was not considered in those cases (Surendran and Tota-Maharaj, 2018; Gargano et al., 2017). Kossieris and Makropoulos (2018) found that the Gamma and Weibull distributions were the best options to describe water demand at fine time scales. According to Surendran and Tota-Maharaj (2018), water

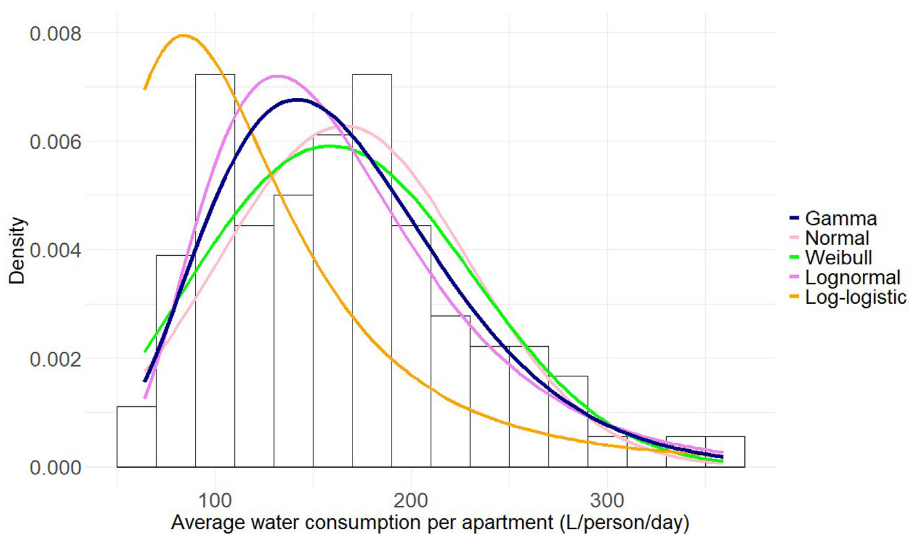

Figure 3. Curves of the density function for each fitted probability distribution.

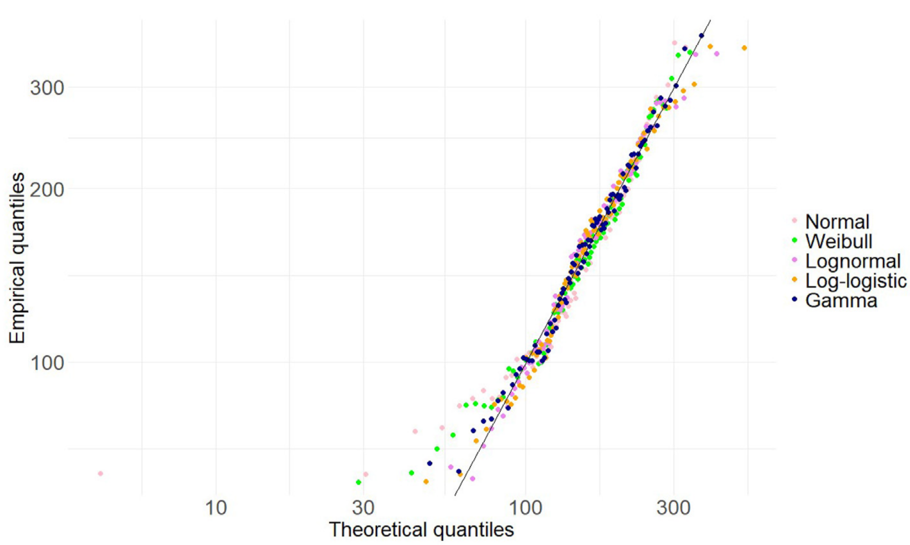

Figure 4. QQ-plots for each fitted probability.

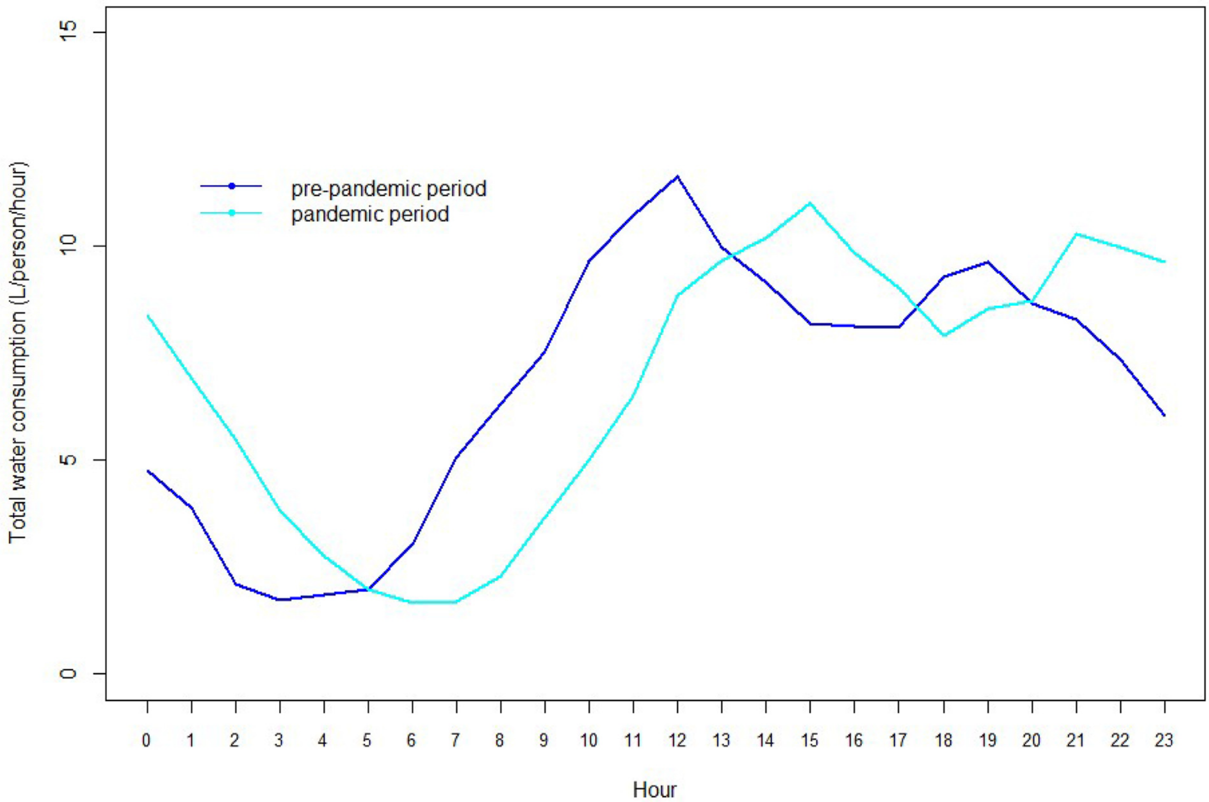

Figure 5. Hourly water consumption profile for the pre-pandemic and pandemic periods.

consumption is a positively-skewed random variable, which indicates the suitability of the Lognormal distribution for the data. Lee and Derrible (2020) applied the Lognormal distribution to adjust several prediction models for residential water consumption in the United States.

Figure 3 shows the distribution fitting versus the density. As expected, the normal distribution is the furthest from a good data fitting due to its symmetry properties, which do not match the data trend. The QQ-plot, frequently used as a goodness-of-fit checking reference, is presented on Figure 4, which shows that the Lognormal distribution presents the best fitting, since its distribution points are closer to the line.

3.3. Hourly and daily water consumption analysis

The total water consumption profiles for the pre-pandemic and pandemic periods were similar, with a well-defined pattern, showing only a shift of the peak during the day, which moved from 12 h before the pandemic to 15 h during the pandemic. The water consumption peak during the day was 11.63 L/person/hour and 11.00 L/person/hour, respectively, averaging the data before and after March 17th, 2020. A similar situation occurred for the night period, in which the water consumption peak changed from 19 h (9.63 L/person/hour before the pandemic) to 21 h (10.28 L/person/day during the pandemic). These results are presented in Figure 5.

The water consumption profile for the pre-pandemic period identified in Figure 5 is close to what has been reported in the literature so far. It decreases between midnight and the early morning, followed by a peak at about noon, then dropping until the end of the day, when it goes back up. Such behavior is consistent with results obtained by Rizvi et al. (2020), who studied the hourly domestic water consumption profile in the United Arab Emirates. Cole and Stewart (2013) also reported two major peaks during the day in a study that analyzed the hourly residential water consumption in the Harvey Bay, Australia, with higher peaks appearing in the early morning and evening. Beal and Stewart (2014) also concluded that the average daily water use typically presents two peaks when analyzing data from South East Queensland, Australia. The peaks were around 9 h and 19 h (Beal and Stewart, 2014), therefore the morning peak occurred earlier than that observed in the present study. In a study conducted in Southern Italy (Puglia region), the first urban water consumption peak was reported during the early morning and two other smaller peaks were observed at noon and during late afternoon (Balacco et al., 2017).

The first peak occurring at noon and not early in the morning can be explained by the fact that, in Brazil, lunch is usually had at home in medium-sized cities (Carús et al., 2014) while, in other countries, because of cultural differences and full-time schooling, this may not happen (Barbosa, 2010). In fact, Dzimińska et al. (2021) found a profile comparable to the one observed in the present work when analyzing the pre-pandemic water consumption on work-free days. They also noticed two peaks and, for workdays, the first appeared earlier in the morning than in the present study.

The comparison analysis between periods before and during the pandemic is also consistent with what has been found in other cities around the world. In a study that analyzed the water consumption before and during the pandemic period, Balacco et al. (2020) reported a delay in water consumption during the pandemic, as the morning peak was delayed by 2–2.5 h. In addition, Lüdtke et al. (2021) found that the domestic water consumption peaks in German cities shifted around 2 h Alvisi et al. (2021) analyzed hourly water consumption in a residential

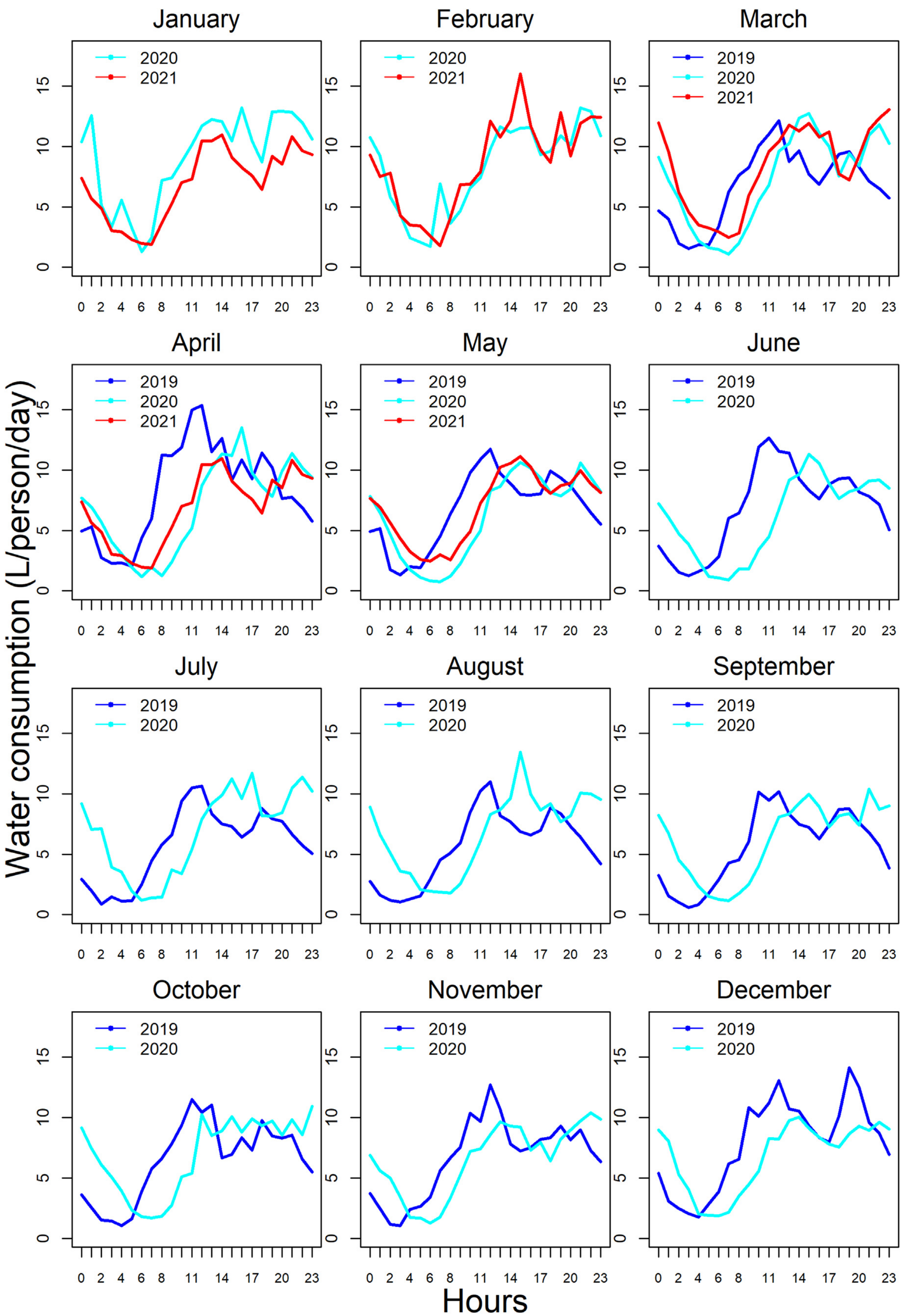

Figure 6. Water consumption profiles per year per month.

Table 4. Average daily water consumption (L/person/day) and Wilcoxon test results.

Quarter	Pre-pandemic		During pandemic		p-value	Sig.
	Month	Average water consumption	Month	Average water consumption		
1	Mar/19 Apr/19 May/19	147.95	Mar/20 Apr/20 May/20	154.3	0.0135	*
2	Jun/19 Jul/19 Aug/19	142.65	Jun/20 Jul/20 Aug/20	146.22	0.7107	
3	Sep/19 Oct/19 Nov/19	144.38	Sep/20 Oct/20 Nov/20	153.10	0.5008	
4	Dec/19 Jan/20 Feb/20	158.59	Dec/20 Jan/21 Feb/21	156.62	0.09379	°
5	Mar/19 Apr/19 May/19	147.95	Mar/21 Apr/21 May/21	143.91	$\leq$0.001	***

Significance °$p \leq 0.10$, *$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$.

district metered area in the city of Rovigo, northern Italy, also reporting a delay of about 2 h in the morning peak water consumption on weekdays during lockdown. The domestic hourly water consumption profile per month can be seen in Figure 6.

From March to December, the peaks in the profile shifted approximately 2 h in each month in the pandemic period. Table 4 presents the average per capita water consumption (L/person/day) and the results of the Wilcoxon test to compare consumption in the pre-pandemic and pandemic periods.

The analysis presented in Table 4 showed an increase in the average water consumption in the first three quarters of the COVID-19 pandemic, when compared to the previous year. However, the increase was only confirmed to be significant (p-value ≤ 0.05) in the Wilcoxon test in the beginning of the pandemic. Water consumption data from March to May 2021 show that the consumption was significantly reduced when compared to data for the same months in 2019, before the pandemic. Considering the whole period (pre- and pandemic), there was a slight, not significant, increase in mean water consumption (p-value $= 0.2564$). The descriptive statistics analysis of daily water consumption for the pre-pandemic and pandemic is shown in Table 5.

A generalized linear model with mixed effects was fitted with the dependent variable following a Lognormal distribution. The results show an increase in water consumption in the pandemic period (p-value $<$ 0.001). Table 6 shows the statistics of the model. The number of residents also affects water consumption (p-value < 0.001), so households with more residents present a lower per capita consumption (Hussien et al., 2016; Villarín et al., 2019). A model containing only the variable period was additionally fitted, also indicating that the effects of the pandemic period on the consumption were significant. Nonetheless, when comparing both models (with and without the variable number of residents), the model that accounted for the effects of the number of residents and the pandemic period was a significantly better fitting than the other ($\chi^2 = 22.763$; p-value < 0.001). The model residuals are independent and normally distributed. The values of R^2, marginal and conditional, equal 11% and 36%, respectively.

The results in Tables 4, 5, and 6 show a slight increase in the mean water consumption, especially in the beginning of the pandemic. The daily water consumption has also increased in other cities around the world due to the pandemic. Rizvi et al. (2020) reported that, during this period, many people stayed in their homes due to campaigns to contain the spread of the disease. Also, Lüdtke et al. (2021) found that, during the COVID-19 pandemic period, the daily water consumption increased 14.3% in a case study conducted in northern Germany. Alvisi et al. (2021) conducted a study in a residential district metered area in the city of Rovigo, Northern Italy, to assess the impact of the restrictions imposed to fight the COVID-19 pandemic and concluded that the average water consumption in April 2020 increased approximately 18% compared to April 2019.

Rouleau and Gosselin (2021) compared energy and hot water consumption in a social housing building with 40 residential units in Quebec, Canada, before and after the COVID-19 lockdown. The authors found a change in the consumption pattern, especially in the first two months of the restrictions. In this study, the analysis showed a 4.29% increase in the mean water consumption in the first quarter of the pandemic period (from March 2020 to May 2020), which was proven significant through the Wilcoxon test. The analysis from June 2020 to November 2020, in comparison to the same period in the previous year, also showed an increase in the mean water consumption, but the results were not significant according to the Wilcoxon test. From December 2020 to May 2021, the mean water consumption decreased, with significant results based on the Wilcoxon test from March to May 2021.

Many low-income Brazilians have informal jobs, or work in positions with no possibility of working from home, and may face barriers to comply with social distancing measures, especially due to financial restrictions (Torres et al., 2021). During the interviews, many residents complained about the cost of water. Even though they started spending more time at home, they may have make an effort to save on water. Their occupation may also have affected the way they consumed water during the pandemic. By the time of the interviews, only 2.53% of the working residents worked from home. Besides, 21.52% of the working residents worked in stores, 7.60% in offices, 24.05% in factories and 46.83% in the services sector. Services include cleaning, delivering, security and others,

Table 6. Regression model statistics.

Coefficient	Estimate	Standard error	p-value
Intercept	5.2934	0.0784	<0.001 ***
Period (pre-pandemic = 0; pandemic = 1)	0.0401	0.0062	<0.001 ***
Number of residents	-0.1060	0.0208	<0.001 ***

Significance °$p \leq 0.10$, *$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$.

Table 5. Descriptive statistics of water consumption (L/person/day) for the pre-pandemic and pandemic periods.

Period	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	sd
Pre-pandemic	14.43	88.00	134.00	148.06	195.00	380.00	77.58
During pandemic	12.62	81.33	131.33	150.70	204.17	415.25	87.32

and were usually related to self-employment or casual work. Those groups were especially vulnerable during the pandemic due to the lack of access to paid or sick leaves and other ways of income stability according to the International Labour Organization (ILO, 2020).

Fuentes et al. (2018) compared the daily domestic hot water consumption profiles for low-income dwellings in Manresa (Spain), obtained from Vogt et al. (2015), with the average European residential profiles, obtained from Knight et al. (2007). Fuentes et al. (2018) concluded that the hot water consumption profiles for low-income households present peaks in the morning, in the evening, and around lunch time, due to cooking. The authors state that the weekday profile indicates occupancy during the whole day, which may explain the smaller increase found in this research compared to other studies on the impact of the pandemic on residential water consumption.

The socioeconomic analysis presented in section 3.1 showed the expressive presence of children in the apartments. It also showed that 52.7% of the residents aged 16 or more were unemployed, which explains the occupancy during the day, even in the period before the pandemic. Furthermore, the water consumption peaks are consistent with the analysis performed by Fuentes et al. (2018). However, due to the COVID-19 pandemic, the two daily peak consumption times shifted from 12 h to 15 h and from 19 h to 21 h.

Assessing the consumption of natural resources in face of adverse situations for humanity, such as the COVID-19 pandemic, is important so that measures can be adopted to secure the supply. Ensuring access to safe water is necessary and, especially in regions of greater vulnerability, should be a priority (Siddique et al., 2021). Water consumption in residential units represents a significant portion of urban water demand and an in-depth understanding of how it is consumed is necessary for planned actions that guarantee access to water in situations such as the outbreak of a pandemic.

4. Conclusions

This research paper established a comparison of the hourly water consumption profile between the periods before and during the coronavirus pandemic, as well as the effects of the pandemic on daily water consumption in 14 social housing buildings located in the city of Joinville, southern region of Brazil. It also sought to determine the probability distribution that best represents the daily water consumption. The results showed that the distribution of water consumption is asymmetric, and the Lognormal distribution was the one that best fitted the data. The analyses showed that water consumption had a slight, but significant, increase in the period. Peak water consumption times also changed.

Understanding the probability distribution allows the determination of expected consumption values and, from that, an investigation on the probability of changes occurring. With such investigation, progress in the research of water consumption in social housings is possible, adequately modeling the phenomenon and allowing the simulation of scenarios with more accurate results. In addition, the construction of water consumption profiles is essential to plan conservation strategies. The results of this research can help managers to develop and deploy actions aimed at guaranteeing the supply of water, in adequate quantity and quality for social housing complexes in the city of Joinville.

The analyzed data was based on a case-study scenario in which units were built with similar characteristics, except for geographic orientation and floor. Moreover, some limitations of this research work that can lead to future explorations must be highlighted. For instance, data on lockdown conditions (i.e. occupancy rates, water use habits, residents' health, building type, etc.) could provide important insight on their effects on water consumption. The household income may have changed during the lockdown, but the need for face-to-face conversations to communicate with the residents along with the safety restrictions prevented the access to this type of information. In addition, a sample with different types of dwellings or low-income neighborhoods is recommended in future studies to allow the results to be generalized to broader contexts.

Declarations

Author contribution statement

Cominato, C: Conceived and designed the interviews; Analyzed and interpreted the data; Materials, analysis tools or data; Wrote the paper.

Sborz, J: Conceived and designed the interviews; Performed the interviews; Analyzed and interpreted the data; Materials, analysis tools or data; Wrote the paper.

Kalbusch, A: Conceived and designed the interviews; Analyzed and interpreted the data; Wrote the paper.

Henning, E: Conceived and designed the interviews; Analyzed and interpreted the data; Materials, analysis tools or data; Wrote the paper.

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Data availability statement

The authors do not have permission to share data.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

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