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WATER CONSUMPTION VARIATION IN LATIN AMERICA DUE TO COVID-19 PANDEMIC

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Abstract

To stop the spread of the COVID-19 pandemic, governments all over the world have applied social distancing measures, which have drastically altered people's lifestyles. Many studies suggest that the water sector, including its demand and supply, has been strongly affected by these regulations. The importance of hygiene practices confers a crucial role to potable water availability as an ally for tackling the spread of the virus, heightening the alteration of water demand patterns during the ongoing pandemic. Therefore, this research aimed to assess the impact of the pandemic on the water consumption patterns in four Latin-American cities and the differences among the type of users. The case studies include two Colombian and two Mexican cities known for their important industrial and touristic features. The outcomes reveal a diminishing effect on water consumption for industrial and commercial customers. Touristic cities were the most affected, even experiencing decreased domestic water demand. Understanding these changes and challenges is essential for keeping and improving the resilience of water systems in different scenarios, especially under fluctuating environmental conditions.

Keywords
Water demand, COVID-19 pandemic, touristic cities, industrial cities.

1 INTRODUCTION

The COVID-19 pandemic was declared by the World Health Organization – WHO on March 11, 2020. The rapid propagation of the COVID-19 disease, caused by the SARS-CoV-2 virus, forced the governments to apply measures to prevent the spread of the virus. Social distancing measures, along with face mask use, constant hand washing, and disinfection of frequently touched surfaces, are standard measures implemented by governments to tackle the spread of the disease. The goal of social distancing measures is to slow down the spread of the virus so that the medical system has enough capacity for treating the sick. Thus, stay-at-home orders have been applied in many countries so that only businesses classified as "essential" could operate in person. These measures abruptly altered the habits of people all over the world, forcing individuals to perform their daily activities from home and, consequently, driving changes in the water consumption patterns of cities, both in daily and in total volumes consumed locally.

Studies have shown that changes in water consumption vary from one city to another because of environmental, socioeconomic, and sociocultural characteristics. A study performed in Hamburg, Germany, revealed an increase of 14.3% in daily water consumption, with a delay of 1-2 hours in the morning peak and a higher peak in the evenings during weekdays [1]. A similar research for five towns in Puglia, Italy, showed a shift of 2-2.5 hours in the morning water use peak for two small towns (Cellemare and Lizzano), while a drop was observed in the peaks and base water demand in the two biggest municipalities (Bari and Molfetta) [2]. This finding relates to that exposed by Bich-Ngoc and Teller [3], who investigated the effect of the lockdown measures and the outbound tourism on water consumption in Liège, Belgium. Liège is a particular case since the historical data shows a lower consumption in the summer months due to people leaving the city. Through a statistical model, the authors found that water demand increased significantly when evaluating restricted trips scenarios [3] as the pandemic spawned. Consistently, the towns that receive a large number of commuters every day, such as Bari and Molfetta, experienced the contrary effect, meaning a decrease in the water consumption because of commuting limitations [2].

Furthermore, the studies mentioned above focused mainly on domestic water consumption; nevertheless, it is evident that the impacts differ according to the different types of water demand. For example, a study conducted in Henderson, Nevada, demonstrated an increase of 11.7-13.1% in residential, a drop of 34.1-35.7% and 55.8-66.2% in commercial and in schools water average daily demand, respectively [4]. Likewise, results obtained from a study in Joinville, Brazil, show a statistically significant decrease of 42%, 53%, and 30% for commercial, industrial, and public water demand, respectively, while a conceivable increase of 11% in residential water demand was recorded [5].

Moreover, the effect of other parameters plays an important role in analysing the sole effect of the pandemic on water consumption. That is why many investigators apply regression models for controlling variables such as seasonality, water price, customer income, weather variations, among others. For instance, researchers demonstrated for residential buildings in Dubai that fasting during Ramadan month modifies water usage patterns [6], which shows how sociocultural aspects are also essential factors to consider. Regarding COVID-19, the same authors observed how daily residential consumption increased (even more during Ramadan month) due to stay-at-home restrictions and augmented cleaning practices [6]. Relatable results from a study with data from several water utilities in California were obtained when applying a multivariate regression model for forecasting residential, commercial, industrial, and institutional (CII) and total water use. The model included variables for seasonality, mandatory and voluntary drought restriction measures, precipitation, temperature, evapotranspiration, water rates, population, and annual inflation [7]. Additionally, the authors demonstrated through an impact index that the influence of the pandemic on water consumption was mildly more substantial than the combined effect of all other factors [7]. This conclusion reflects the relevance of the COVID-19 pandemic in altering water demand patterns.

As expected, all these changes have imposed challenges for water utilities, including effects on financial aspects, like revenues and bills, and operational aspects, such as water quality. Regarding financial features, utilities were faced with suspensions on cut-offs, commercial income reduction, major misconduct in water bill payments, and reduced customer upgrowth [8]. Also, utilities have been impacted monetarily due to augmented domestic and reduced non-domestic water consumption. Concerning operational aspects, as rapid variations in water usage occurred, water infrastructure may have been affected because system operations are designed based on historical demands [9]. Moreover, regular flows maintain drinking water distribution systems absent of leached minerals, corrosion, and microorganisms that could affect tap water quality [9]. Consequently, health risks are present, and water utilities must manage and advertise to customers to avoid potential disease outbreaks. Furthermore, the social distancing measures also affected water utility operations as many workers started to work remotely, and they should operate the systems with reduced skilled staff, carrying off institutional knowledge [8]. Thus, the pandemic obligated numerous water utilities to work in non-designed conditions and with decreased workforce and financial capabilities [10].

This paper aimed to assess the effect of the pandemic on domestic, commercial, industrial, and total water demand in four cities of Latin America. There are several studies of the pandemic impacts on water demand in developed nations, but there are not sufficient records from the Global South. Hence, this study contributes to the progress in water-related research in developing countries. Following this introduction, the four case studies are presented, and the data used for the analysis is described. Then, the following section details the employed methods for estimating the impact of COVID-19 on water demand, which was performed with a regression model and with neural network approaches. Subsequently, the results and discussion of the water demand variation magnitude are presented, and an analysis of the factors influencing these changes and the differences between each city. Finally, conclusions are given on how the results are valuable for water utilities planning and management operations.

2 CASE STUDIES AND DATA

Water demand data for two Colombian and two Mexican cities was obtained from each water utility as the monthly billed water volumes from January 2016 until December 2020. Figure 1 shows the water demand proportion in each city as the average of pre-pandemic data, meaning records before March 2020. Additionally, the number of inhabitants in the metropolitan areas for 2020 is presented as a reference value of the size of the cities.

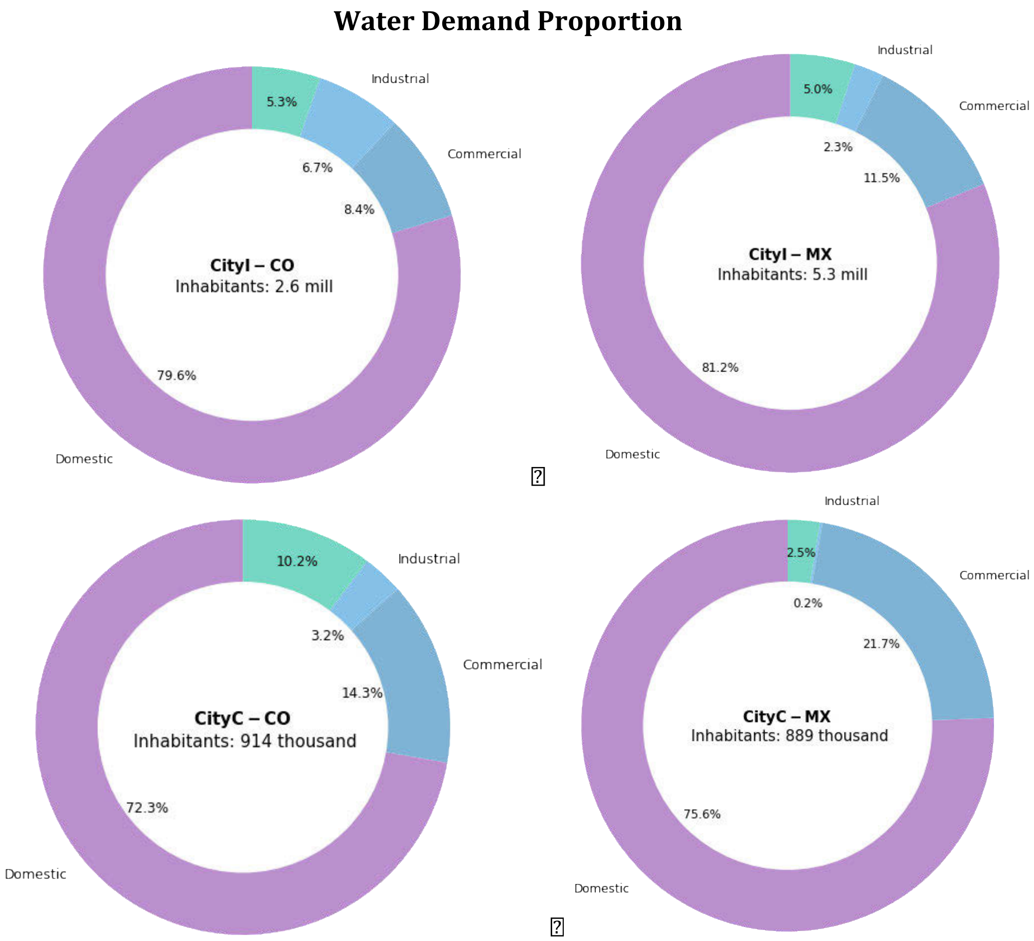

Figure 1. Water demand proportion by domestic, commercial, and industrial categories in each case study, as well as number of inhabitants of the corresponding metropolitan area.

The four cities were carefully chosen for their industrial and commercial characteristics. One in each country performs diverse economic activities (with substantial industrial water demand), and the other is an important touristic city (predominance of commercial demand). The case studies have been named accordingly: City I prefix corresponds to cities with diverse activities and City C to touristic cities. The endings -CO and -MX mean a Colombian or Mexican city, respectively.

As Figure 1 presents, the domestic water demand predominates in all cities, showing the importance of residential users for defining water usage patterns. In contrast, non-domestic water demand represents less than 30% of the total demand in the four case studies. Changes in domestic demands are expected to drastically influence water distribution systems' operations, while only abrupt variations in non-domestic demand would impact the urban water systems.

According to the predominance of commercial and industrial customers in each city, the pandemic might have affected water usage differently. This research focuses on understanding these dissimilarities among the case studies. For instance, an enormous impact on commercial demand can be anticipated in both touristic cities (City C–CO and C–MX) due to travel restrictions. Therefore, the non-domestic water demand changes are more critical in C-cities than in I-cities because of the high commercial proportion out of the total demand.

Moreover, in addition to water demand data, this study also employed temperature information for the analysis. Maximum temperatures for the entire service areas were calculated using monthly data from several meteorological stations distributed throughout the cities. Noteworthy, temperature information was not available for City C-MX, so the analysis was performed without it.

3 METHODS

We analysed the temporal variation of water consumption by comparing the observed water demand during the pandemic with a forecasted non-pandemic scenario. The historic non-pandemic water volumes were used to train and validate water demand models, which were used to forecast the expected demand as if the pandemic did not occur. Different modelling approaches were employed to validate and compare the results: Multivariate Regression Models (MVRM) and Artificial Neural Networks (ANN). Hence, data from January 2016 to February 2020 was used to fit the models to historical water usage patterns. Then, the non-pandemic water demand scenario for March to December 2020 was estimated with those models.

3.1 Multivariate Regression Model

The first approach implemented multivariate ordinary least squares linear regression models using water demand time series. Equation (1) presents the general form of the model. y is a vector representing the volumetric water use per month, X is the matrix containing the values for the n predictor variables in each month, β is the vector with the n related regression coefficients, and E is the vector for the error terms associated with the monthly water use estimations.

$$y = X\beta + E \tag{1}$$

R Software was used to implement the models through the *lm* function [11]. The unbiased estimators are calculated with Equation (2) and are used to produce unbiased least-square estimations of the water volumes $\hat{y}$, with errors $\hat{E}$ following a normal distribution with a mean equal to zero and minimizing the covariance [7].

$$\hat{\beta} = (X^T X)^{-1} X^T y \tag{2}$$

It is essential to break down the total water use by sector for obtaining better-modelled water demand results. Therefore, the models were fitted for each category of water demand: domestic, commercial, industrial, and total demand. Regarding the explanatory variables, at first several variables, including precipitation, commuting population, and water tariffs, were evaluated. However, not all the estimators' results showed statistical significance, so fewer variables were considered to avoid noise affecting the results. In fact, Bich-Ngoc and Teller [3] exposed that evaluating meteorological variables, like daily maximum temperature, has been frequently used to forecast short-term variations in the water demand. At the same time, socioeconomic factors, such as income, are more relevant when modelling demand in a long-term period. Hence, since the predictions were only extended to 10 months for this study, 14 explanatory variables were used: 12 binary variables representing seasonality by month and 2 continuous variables for maximum temperature and the number of users over time.

Once the models were fitted, R-squared results and p-values were analysed to assess the fitting results and the influence of the estimator variables on water consumption. Afterward, the matrix X was augmented to include values corresponding to the pandemic, namely, the values from March to December 2020. The augmented X matrix and the regression coefficients vector $\hat{\beta}$ obtained from the historical data were employed to calculate the water volumes in the non-pandemic scenario. These modelled water volumes were used to analyse the differences between the non-pandemic scenario and the experienced pandemic situation.

3.2 Artificial Neural Networks

As water utilities require consumption predictions for operational reasons and updating pricing policies, ANN are one of the principal approaches used to predict water demand [12]. ANN imitate the human brain by performing non-linear calculations in a certain number of neurons, which receive input values that are transformed and transferred to other neurons or the output [13]. The great advantage of ANN is learning based on initial observations and producing equivalent outputs with new input data. Neural networks can work with a single or multiple layers. Several learning algorithms allow the communication between neurons to determine the weights, which are values assigned to every variable from the input layer to the hidden layer [13]. The weights' modification allows the network to adapt to reduce the error between the expected output and the result from the network.

Like the regression model, we used artificial neural networks to model domestic, commercial, industrial, and total water demand. The implementation of ANN in this study was executed using R software by feeding the network and training it with a different number of neurons and layers until the best performance was reached. The *neuralnet* package was used for this aim, using the Resilient Backpropagation algorithm to train the network [14].

Moreover, the data series were normalized before training the networks to adjust the variables to the same scale. The R-squared values from the validation set were used for modifying the number of neurons and layers until the best model fitting was reached. Then, the trained and validated ANN was used to estimate the expected water consumption in a non-pandemic scenario.

Regarding the validation of the models, different approaches were used depending on the city analysed. The entire data sets were randomly divided into training (80%) and validation sets (20%) for the Colombian cities. In contrast, the models were trained with information from 2016 to 2018 and validated with 2019 records for Mexican cities. This approach is due to the seasonality relevance in each city. As can be noticed in the results, the water demand records are clearly influenced by the time of the year in the MX cities. Commercial demand in City C – CO also shows a relation with seasons; however, better water demand estimates were obtained when training the network with the aleatory approach.

4 RESULTS AND DISCUSSION

4.1 Water Demand Estimation

We used the multivariate regression model results to study the influence of the predictors on the water demand through the computed models. For this aim, Table 1 presents the significance of the explanatory variables measured through the obtained p-values.

Table 1. Explicative variables significance for each computed model (D: Domestic, C: Commercial, I: Industrial, T: Total). Temperature information for City C – MX was not used. p-Value codes: 0 (***), <0.001 (**), <0.01 (*), <0.05 (.)

Explicative variables	**City I – CO**				**City I – MX**				**City C – CO**				**City C – MX**			
	D	C	I	T	D	C	I	T	D	C	I	T	D	C	I	T
Seasonality (12 variables)	***			***	*	*		**			**		*	**	**	**
Temperature					.	*		.			**		-	-	-	-
Number of users	***	***		***	***	***		***	***	***	***	***	***		***	***

The statistical significance of the chosen explicative variables differs for each city according to its socio-economic and environmental conditions. The number of users, which is directly related to water demand, is a relevant variable for most cases. However, industrial demand in I cities does not relate directly to any variable, not even the number of users. These observations showcase how industrial water use is usually unpredictable due to its high variability. In contrast, in the cities where the industrial demand is not predominant (C cities), all the variables are significant, but this is due to the small magnitude of the water volumes.

Moreover, the seasonality condition is prevailing for MX cities. This condition shows the effect of yearly temperature variations on water demand. Hence, the usage of temperature and months as seasonal variables can explain the interannual variations in water consumption. We found for City C-MX that monthly seasonality is enough to represent the tourism-related patterns adequately. In the case of the Colombian cities, the demand is not directly associated with the time of the year. This observation is due to the country's geographic position, affected by tropical weather.

Although not all variables were statistically significant, both approaches employed for water demand forecasting showed a good performance. Different validation sets were studied since the models were trained with different approximations due to the seasonality relevance (see Methods section). Nevertheless, Figure 2 presents the R-squared values for the estimated water volumes between January 2016 and February 2020 to compare both methods consistently. It can be noticed that ANN results for CO cities are much better than the MVRM outcomes. The same conclusion was obtained for industrial demand for MX cities. In contrast, the MVRM approach shows enhanced models' fit for Mexican cities' domestic, commercial, and total water demand.

Nevertheless, all R-squared values show outstanding performance, with values over 0.7 except for some industrial and commercial water use estimations. The worst fitting outcomes relate to industrial demand in City I – CO with MVRM, where the industrial economic sector is remarkably relevant. Similarly, the ANN commercial model fit in City C – MX is not particularly good, where commercial users are the most relevant among non-domestic customers. As previously discussed, forecasting commercial and industrial water demand is problematic due to the unpredictable changes that might occur due to governmental or institutional measures. Therefore, both approaches allow for choosing the best water demand estimations and better approximating what really would have happened if the pandemic had not occurred.

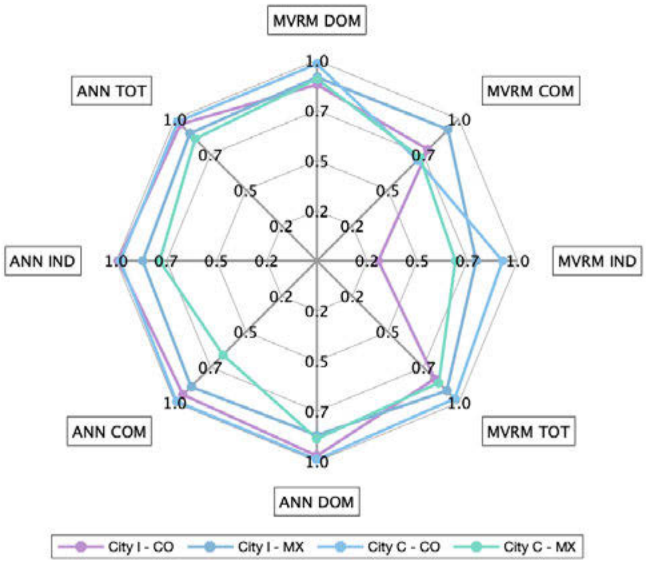

Figure 2. MVRM and ANN models' R-Squared results for domestic, commercial, industrial, and total water demand in the four case studies.

The performance of the models can also be graphically assessed through the time series comparison presented in Figure 3. This graph shows the reported water volumes from January 2016 to December 2020, and the predicted data using MVRM and ANN approaches. All models present a superb fit when comparing the pre-pandemic data. Industrial demand is the most problematic in all cities; however, it gives a good approximation of water demand with enough precision to analyse the pandemic impact.

Moreover, the pandemic effect is clearly evidenced by the data presented from March 2020 forward, highlighted by the red lines. The predicted water volumes show high similarity between the MVRM and ANN methods, giving reliability to the analysis and the estimated pandemic impacts. The only results that have an appreciable inconsistency between both approaches are for industrial demand in the commercial cities. The neural networks tend to underestimate the water volumes, even obtaining similar demands as the pandemic-affected values. In contrast, the MVRM exaggerates the increasing tendency. These anomalies might be related to the small magnitude of the demands as it only accounts for 3.2% and 0.2% of the total demand in City C – CO and – MX, respectively. Hence, it is not possible to state which estimations are better. However, it is preferable to assume an increasing trend since only unexpected events, like the pandemic, might generate such a decrease in industrial demand.

Further, according to both methods of water demand estimation, the domestic component in the CO cities shows a higher trend with time than in the MX cities. It could be related to the economic context of the case studies, despite the constant increase of users billed for each case. In addition, as domestic water use is predominant, with contributions to the total demand of over 70% in all cities, the same patterns are reflected in the total water use.

A similar increasing trend with time is exhibited for commercial use for the four study cases; however, the effect of lockdown breaks the tendency along the pandemic year 2020. In contrast, the industrial component of water demand shows a decreasing and stagnant tendency with time for three cities, excluding City C – MX. This finding could be part of urban development in Latin-American cities, which are implementing industrial hubs out of urban areas.

Finally, the seasonal variation of water demand for Colombian cities is not noticeable because of their geographical location, as previously discussed. Nevertheless, there is some effect of the annual seasonality on domestic and commercial water demand for City C-CO, related to tourism economic activities. On the other hand, City I – MX has a clear and marked water use pattern, showing peaks in the middle of the year. The same observation can be duplicated for City C – MX, but changes occur in a milder magnitude since its population is smaller.

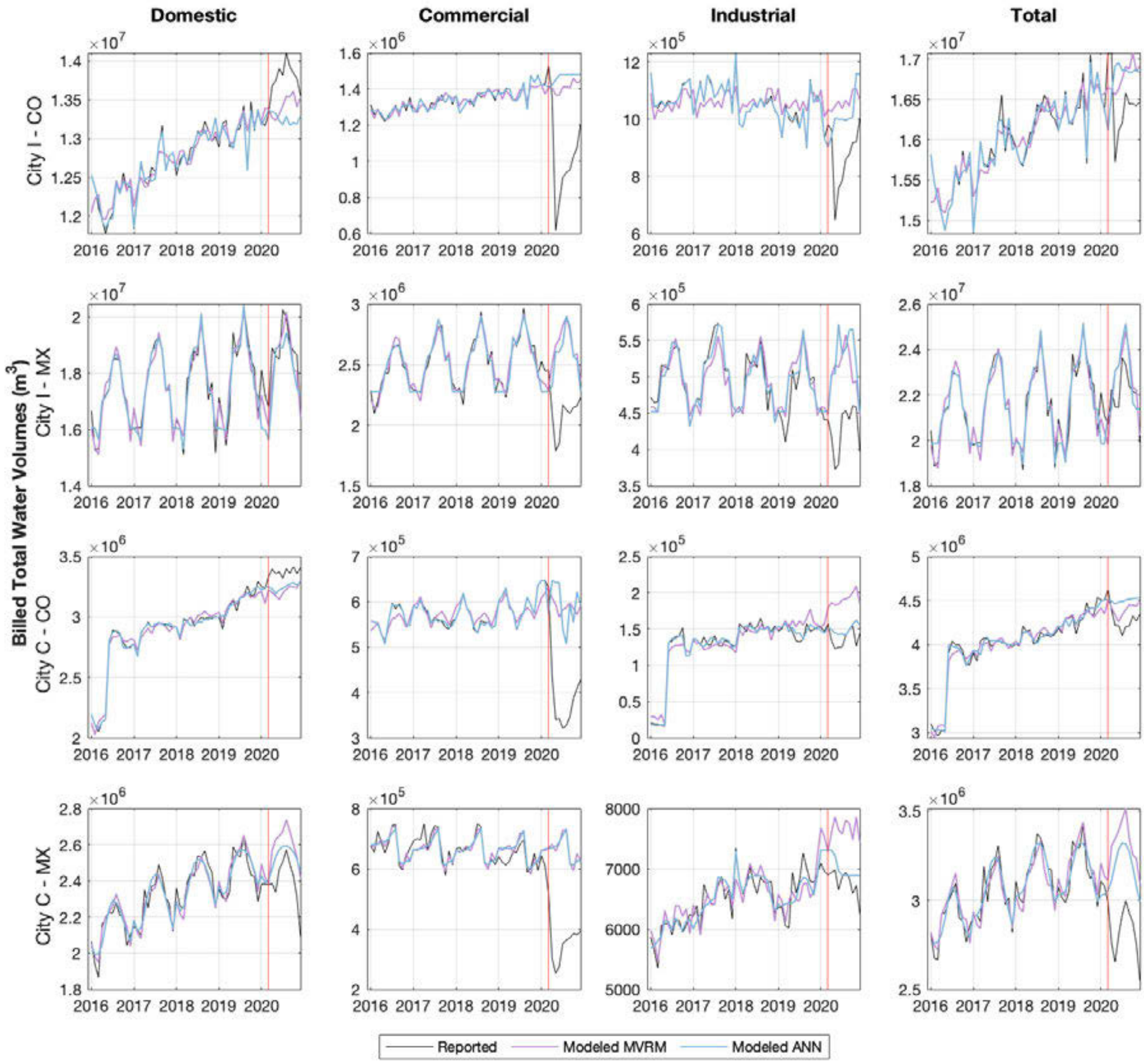

Figure 3. Reported and modelled domestic, commercial, industrial, and total water demand data in the four case studies. The red line marks March 2020, when the pandemic started, and the period for which data was forecasted.

4.2 Variation of water demand during the pandemic

The bibliographic review exposed how the pandemic influenced an upsurge in domestic water demand as people spent more time in their households due to lockdown measures. As Figure 4 presents, the same effect was obtained for industrial cities and City C – CO, with similar increases every month. Considering the models with the best fit results, the domestic component of water demand increased on average by 4% in CO cities and by 1% in City I – MX.

The extent of these increases does not seem influential. However, when contemplating the magnitude order of the residential water use, these surges represent a significant amount of water. Nonetheless, the evaluation of the total water demand changes reveals how the decreases in non-domestic water usage are more influential and balance the increased domestic demand. The total demand presents almost no variation or a moderate decrease. The average diminutions were 2% in City I-CO, 3% in City I-MX, 5% in City C-CO, and 15% in City C-MX.

Further, domestic water demand in City C–MX decreased 7% since the beginning of the pandemic. Lately, it has been more habitual for visitors to arrive at residential dwellings in touristic cities, such as Airbnb's, since it could be more economical than a regular hotel. Therefore, although residential users consume 75.6% of the total demand, this percentage might not relate entirely to the water use of City C – MX's inhabitants. According to 2019 data, the number of monthly tourists reaches the same number of inhabitants for the high seasons [15]. Hence, the decrease in the domestic water demand could be explained by the commuting limitations that the pandemic triggered. The same effect is not present in City C – CO's records because the number of monthly visitors does not exceed 3% of the number of inhabitants, even during the high seasons [16].

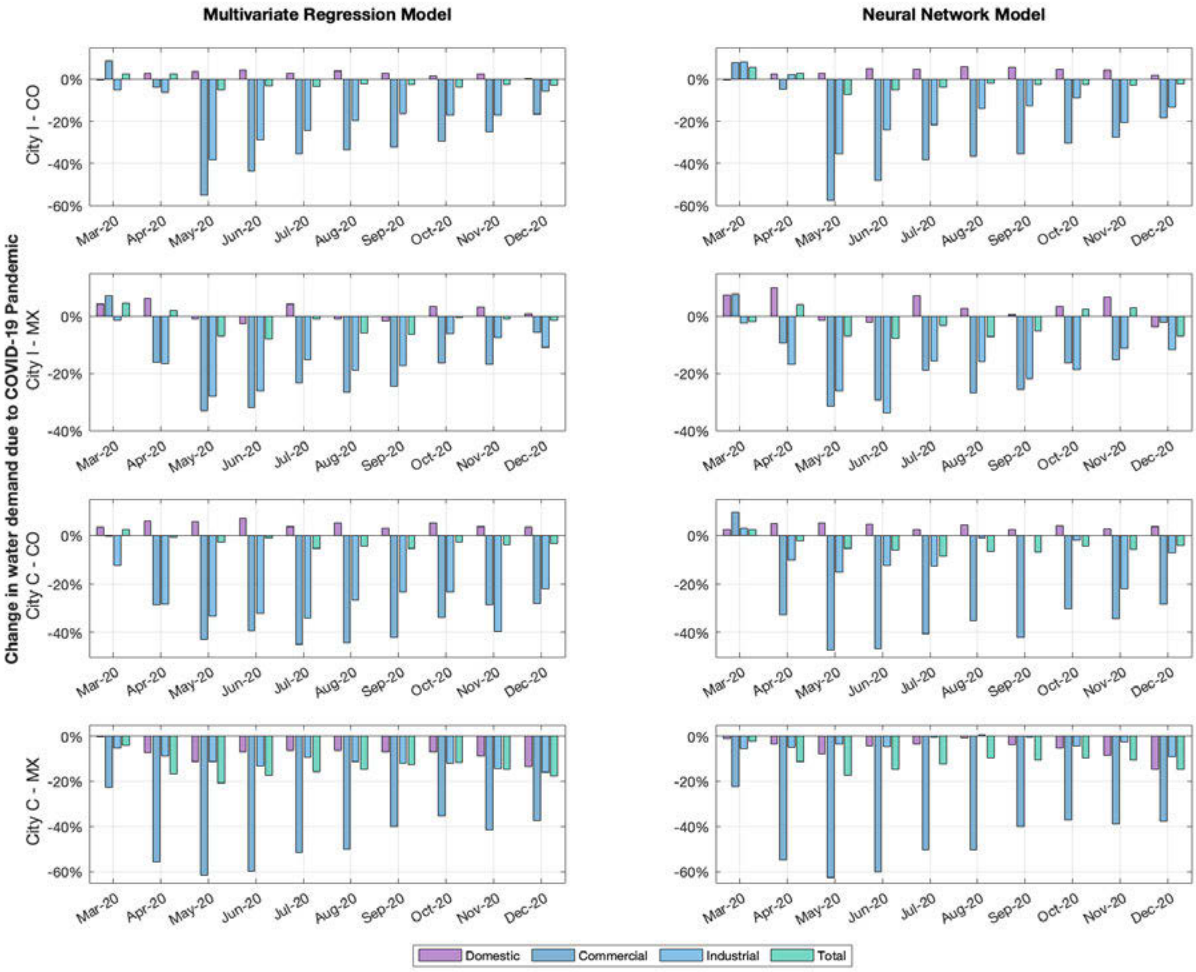

Figure 4. Change in domestic, commercial, industrial, and total water demand due to COVID-19 pandemic with MVRM and ANN estimates in the four case studies.

As it is shown by Irwin, McCoy & McDonough [4], Kalbusch et al. [5], Li et al. [7], among other studies, the non-domestic water demand was the most affected because of the pandemic. Indeed, the data from this research shows a noticeable fall in non-domestic water demand in the following four months after the global pandemic declaration. The variation of commercial water demand due to lockdown measures for industrial cities is about -29% in -CO and -19% in -MX compared to estimates based on the best-validated model. The drop is much more drastic in the commercial cities, with diminutions of 33% and 46% in City C – CO and – MX, respectively. The largest diminution in the C-MX case study compared to C-CO is essentially related to the number of commuters entering the city. More notably, as discussed in previous statements, the importance of tourism in both commercial cities significantly affects water demand since lockdown measures implied the impossibility to travel. Additionally, a considerable fraction of the commercial demand drop is related to ordinary commerce frequented by inhabitants. Hence, the closure of shops and related establishments could explain the decrease in cities I-CO and -MX.

Regarding industrial demand, the data reveals similar down-falling variation in the first three months of the pandemic. Nonetheless, the time series show some recovery in industrial consumption during the remaining months of the year. According to the model estimations, the average decrease in industrial demand was 14% in City I – CO, 18% in City I – MX, 8% in City C – CO, and 3% in City C – MX. The relevance of industrial demand is evidenced when comparing the values for C-cities and I-cities. The industrial decreases are not as abrupt as those obtained for commercial demand. Thus, it is evident how the pandemic affected touristic cities more drastically.

Moreover, the changes in non-domestic water consumption have been consistent with the increase in domestic demand for cities I-CO, I-MX, and C-CO. One might argue that commercial and industrial demand was transferred to households due to work-home activities. However, the cumulative values of non-domestic consumption are higher than those for residential customers. Hence, there is low evidence of volumetric compensation between domestic and non-domestic demand.

5 CONCLUSIONS

This research revealed how the main effect of the pandemic lockdown is the decreased non-domestic water consumption in the commercial and industrial cities analysed. This effect is linked to a slight increase in domestic water demand due to work-at-home activities, another main effect of lockdown restrictions. However, the case of one of the commercial case studies, City C-MX, shows a particular behaviour most probably due to a decline in domestic water demand due to tourism home-ownership renting dropping.

Regarding the employed methods, we can establish that both approaches for water demand estimation can address similar results, which is a relevant sign of a good level of reliability for the demand predictions. Based on the results, we can expect noticeable changes in the consumption patterns due to the effect of home working activities and their consequences on new working schemes in non-domestic sectors. We consider that these findings are related to the expected effect on the post-pandemic water demand behaviour. Hence, these demand variations should be considered in the near future investment and operations master plans for water utilities.

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