Impacts of COVID-19 Social Distancing Policies on Water Demand: A Population Dynamics Perspective

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ABSTRACT

Social distancing policies (SDPs) implemented in response to the COVID-19 pandemic have led to temporal and spatial shifts in water demand across cities. Water utilities need to understand these demand shifts to respond to potential operational and water-quality issues. Aided by a fixed-effects model of citywide water demand in Austin, Texas, we explore the impacts of various SDPs (e.g., time after the stay home-work safe order, reopening phases) using daily demand data gathered between 2013 and 2020. Our approach uses socio-technical determinants (e.g., climate, water conservation policy) with SDPs to model water demand, while accounting for spatial and temporal effects (e.g., geographic variations, weekday patterns). Results indicate shifts in behavior of residential and nonresidential demands that offset the change at the system scale, demonstrating a spatial redistribution of water demand after the stay home-work safe order. Our results show that some phases of Texas's reopening phases had statistically significant relationships to water demand. While this yielded only marginal net effects on overall demand, it underscores behavioral changes in demand at sub-system spatial scales. Our discussions shed light on SDPs' impacts on water demand. Equipped with our empirical findings, utilities can respond to potential

vulnerabilities in their systems, such as water-quality problems that may be related to changes in water pressure in response to demand variations.

Keywords: Water demand, socio-technical infrastructure systems, pandemic, population dynamics, operating environment, regression analysis

INTRODUCTION

Following the outbreak of the COVID-19 pandemic, governments worldwide have enacted a number of policies to slow the spread. These policies, referred to hereafter as social distancing policies (SDPs), include measures such as lockdowns, social distancing, and work-from-home orders (Balacco et al., 2020; Roidt et al., 2020; Sivakumar, 2020). These SDPs have impacted social activities (Balanzá–Martínez et al., 2020; Sheehan et al., 2020), businesses (Nicola et al., 2020), the natural environment (Aydın et al., 2020; Elsaid et al., 2021; He et al., 2020; Mostafa et al., 2021; Paleologos et al., 2020), and infrastructure system performance (Balacco et al., 2020; Hantoko et al., 2021; Kalbusch et al., 2020; Spearing et al., 2020). Scholars have already begun to explore the implications of SDPs; prior to COVID-19, there was, for various sectors, a dearth of pandemic-focused literature (Roidt et al., 2020; Spearing et al., 2020). Indeed, the COVID-19 pandemic has highlighted a gap in knowledge and practice regarding how SDPs may impact the water sector. As such, researchers are working to identify and understand the following issues: pandemic-related challenges to and responses of utilities (AWWA, 2020; Spearing et al., 2020; World Bank, 2020) as well as other water-sector companies (e.g., engineering and consulting firms) (Cotterill et al., 2020); water-demand changes and patterns (Balacco et al., 2020; Cooley et al., 2020; Kalbusch et al., 2020; Li et al., 2021; Rizvi et al., 2020); infrastructures' operational constraints (Cooley et al., 2020) and water-service-related quality issues (Cooley et al., 2020;

Sivakumar, 2020) in response to water-demand changes; natural water resource quality (Cooley et al., 2020; Lokhandwala and Gautam, 2020; Pant et al., 2021); water security (Cooley et al., 2020; Kassem and Jaafar, 2020; Rafa et al., 2020); and sensitivity of the water-energy nexus to pandemic lockdowns (Roidt et al., 2020).

Of interest to this study are the research efforts surrounding water demand and SDPs. SDPs have altered the spatial distribution of water demand (e.g., closure of businesses and working from home) (Cooley et al., 2020; Kalbusch et al., 2020). Moreover, they have altered the traditional underlying consumption dynamics (e.g., delayed morning peaks) (Balacco et al., 2020; Rizvi et al., 2020). A recent investigation (Spearing et al., 2020) into challenges confronting U.S. water utilities—challenges related specifically to technical system—reported the following: more than 20% of utilities were unsure whether they had experienced demand changes in response to SDPs; the uncertainty was due to lack of information or data availability, or they had simply not explored these impacts. Yet to identify and adequately respond to system vulnerabilities, water utilities need to understand the spatiotemporal changes in their water demand and what impacts they have on system performance (Cooley et al., 2020; Zhuang and Sela, 2020). Sudden demand changes can, for instance, (1) exacerbate existing and reveal new operational issues (e.g., pressure, pipe breaks, treatment capacity) (Cooley et al., 2020) and (2) lead to water-quality problems (Cooley et al., 2020; Sivakumar, 2020), especially in areas with reduced demand due to possible stagnant water inside the premise plumbing. When water demand is significantly lower than normal, say for an extended period of time, water may stagnate in the water distribution systems, something we might expect to see in commercial areas during a pandemic. This stagnation could reduce disinfectant residuals (e.g., chlorine, chloramine), leading to health risks (Gleick, 2020) if flushing operations are not implemented and/or the system is not well-looped; a looped piped system means that pipes are connected in a manner that allows water to keep flowing in several pathways, reducing the problems associated with water stagnation (National Research Council, 2007). Therefore, areas of a system that were already, prior to a pandemic, at risk for water-quality or operational issues, could be even more vulnerable during a pandemic (Spearing et al., 2020).

Framing of Social Distancing Policies

Here, we frame SDPs as a form of population dynamics. Population dynamics refers to a change in spatial distribution of socio-demographics or total population (Faust and Kaminsky, 2017). In this case, the total population remains relatively unchanged; however, the distribution of where a population interacts with a system shifts spatially on a daily basis due to policies, such as working from home and business closures. In this study, we seek to better understand the spatiotemporal changes in water demand in response to SDP intervention. Such sudden shifts in demands must be assessed with the consideration of the infrastructures' operating environment (Bakchan et al., 2021, 2020; Hamilton et al., 2015), that is, environmental, financial, social, and institutional considerations within which a system exists or operates. These considerations, along with the physical system, are referred to as *socio-technical dimensions*. In general, water demand is affected by numerous factors (Haque et al., 2015; House-Peters and Chang, 2011) that span these socio-technical dimensions; these factors are, henceforth, referred to as *socio-technical determinants*. Such determinants include climate (within the environmental dimension), water price (financial), water conservation policy (institutional), and population growth (social) (House-Peters and Chang, 2011). For instance, an increase in the maximum air temperature can lead to increases in water demand—especially during dry periods—largely due to increases in outdoor watering (Bougadis et al., 2005). Additionally, water demand varies across geographic areas (House-Peters and Chang, 2011) (e.g., residential areas versus commercial areas) and typically exhibits different patterns throughout weekdays (Cutore et al., 2008; Pesantez et al., 2020). We refer to these temporal and spatial trends as *spatial* and *temporal effects* in water demand. By framing pandemic-induced SDPs as population dynamics, this study considers the system's operating environment for assessing SDPs' impacts on the *temporal* behavior of water demand—i.e., changes in longitudinal demand. This is a major contribution over existing studies (e.g., Balacco et al., 2020; Cooley et al., 2020; Kalbusch et al., 2020; Li et al., 2021) that focus on pandemic-induced water-demand changes. Although their intellectual contributions to pandemic planning are important (further discussed in the subsequent section), these studies do not consider the socio-technical determinants, as well as spatial and temporal effects when studying water-demand changes. Failing to integrate these effects introduces uncertainty into knowing whether changes arose from policy intervention or from shifts in the operating environment. For instance, a reduction in citywide water demand could be attributed to a major increase in the rainfall amount (Bougadis et al., 2005) during that period rather than to the enactment of policies.

Existing Efforts on Pandemic-induced Water-Demand Changes and Hypothesis Development

Existing work (Balacco et al., 2020; Cooley et al., 2020; Kalbusch et al., 2020; Li et al., 2021) that explores pandemic planning in regard to water demand is limited, especially prior to the COVID-19 pandemic. A study (Balacco et al., 2020) conducted in southern Italy compared 2020 water-demand patterns to those of 2019. The authors found that in certain cities during the pandemic there was a noticeable decrease in demand due ultimately to an absence of commuters. Another work (Kalbusch et al., 2020), based in southern Brazil, examined changes in water consumption across various customer classes (e.g., residential, industrial), comparing the consumption in two-equal periods—before and after the enactment of SDPs. The authors noticed a drop in the commercial, industrial and public water consumption, and an increase in the residential consumption. Two other studies (Cooley et al., 2020; Spearing et al., 2020) suggested that such shifts in demand between customer classes could be the reason behind the insignificant change in overall demand during SDPs. As such, we broadly posit that business closures and work-from-home orders may lead to no change at the system scale. However, when businesses reopen and people start to go back to work, we expect to see more significant changes in overall demand. Accordingly, we formulate two hypotheses related to water demand changes during work-from-home periods and reopening of businesses (further discussed in the subsequent section).

Purpose, Research Questions, and Hypotheses

This study seeks to answer two questions: In times of a pandemic, what changes in water demand occur during imposed SDPs? To what extent are these demand changes a result of the SDPs, with attention given to the socio-technical determinants and considering spatial and temporal effects in water demand? To answer these questions, we formulate two hypotheses, as follows:

Hypothesis 1: At a system scale, there will be no significant change in water demand during business closures and work-from-home orders.

Hypothesis 2: At a system scale, there will be significant change in water demand during the reopening of businesses, subsequent to the work-from-home periods.

Our study is enabled by a fixed effects (FE) model of total water demand in Austin, Texas (TX), bounded at the service area of the local utility. The analysis explores the effects of various COVID-19 SDPs (e.g., business closures, reopening phases) that have been enacted since March 19, 2020, in Austin. Our proposed approach on water-demand changes during a pandemic provides further empirical evidence for the necessity of considering population dynamics through a lens of integrated operating environment for resilient water infrastructure systems. Furthermore, our work can inform emergency-response plans for pandemics in regard to water infrastructure planning, management, and operations, considering spatiotemporal changes in water demand. In fact, a survey (AWWA, 2020) of U.S. utilities found that 61% of utilities did not have a specific pandemic plan in place, prior to COVID-19, and they are in the process of developing one. By exploring the implications of SDPs on water demand, utilities can proactively plan for an adequate response to potential vulnerabilities in a system during pandemics.

MATERIALS AND METHODS

Operating Environment of Water Demand

Our proposed approach for the assessment of SDPs' impacts on the water demand considers the environmental, institutional, financial, and social effects—i.e., incorporating the physical system and its operating environment through the lens of population dynamics (see Figure 1). To identify the various socio-technical determinants of temporal water-demand patterns—spanning the five socio-technical dimensions—we turned to water-demand modelling and forecasting literature (see Table 1). Important to note, our approach captures the spatial and temporal effects in water demand via a fixed-effects regression model (Frees, 2004). More specifically, various location-specific variables exist within the social dimension, such as household characteristics (e.g., household size, housing typology) (Bisung et al., 2014; Donkor et al., 2014; House-Peters and Chang, 2011; Polebitski and Palmer, 2010), socio-demographics (e.g., age, gender, race, income, language, education) (Bisung et al., 2014; Donkor et al., 2014; House-Peters and Chang, 2011; Miller and Buys, 2008; Randolph and Troy, 2008), social capital (e.g., voter turnover, participation in local associations, norms) (Aldrich and Meyer, 2015; Bisung et al., 2014; Miller and Buys, 2008), and water conservation technological measures (e.g., low-flow fixtures and appliances) (Donkor et al., 2014; House-Peters and Chang, 2011; Williamson et al., 2002). While our study does not incorporate these variables as controls explicitly, the FE regression analysis does inherently capture their effects via the zone-based intercepts, i.e., fixed-effects (House-Peters and Chang, 2011; Polebitski and Palmer, 2010) (further discussed in the Regression Analysis section).

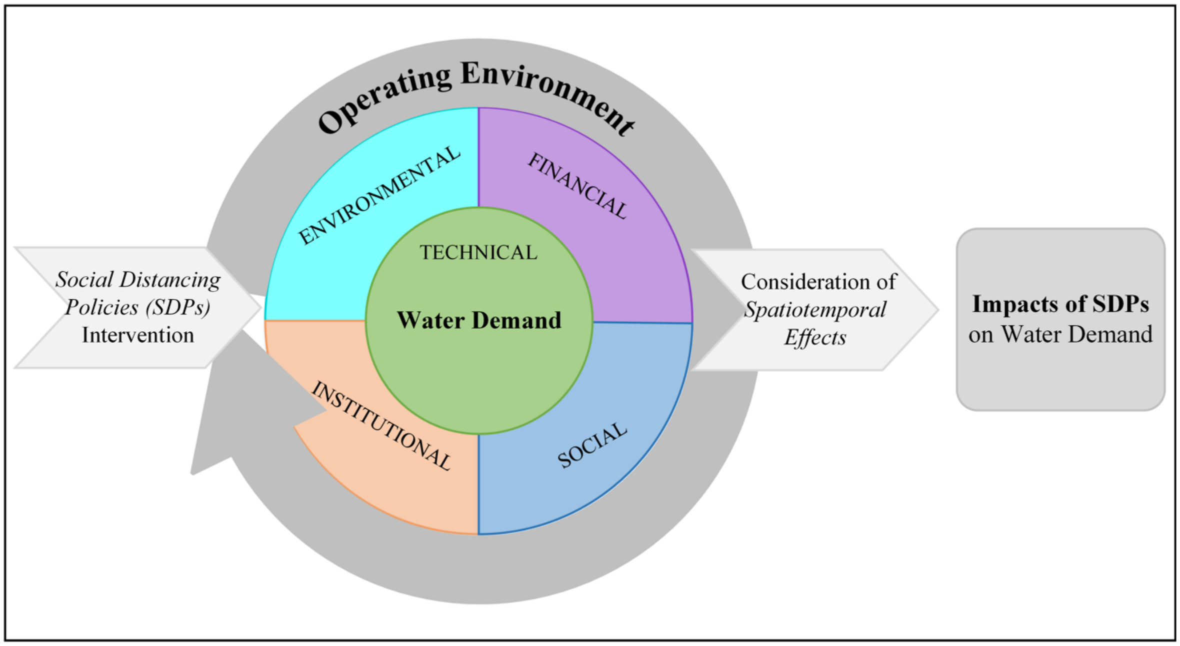

Figure 1. Conceptual representation for assessing SDPs' impacts in the context of population dynamics

Table 1. Primary socio-technical determinants of *temporal* water-demand patterns identified from literature

Socio-technical Determinant	Explanation/Reference
Technical	
Previous water demand (lagged)	▪ Water demand depends on its past values (Alhumoud, 2008; Bougadis et al., 2005; Hutton and Kapelan, 2015; Jain et al., 2001; Jain and Ormsbee, 2002; Jentgen et al., 2007; Pesantez et al., 2020; Wu and Zhou, 2010; Zhou et al., 2000); e.g., weekly water demand is highly correlated with water demand in the previous week (Jain et al., 2001)
Environmental	
Climatic	
Maximum air temperature	▪ Increases in water demand when maximum air temperature increases, especially during dry periods (Bougadis et al., 2005; Goodchild, 2003; House-Peters and Chang, 2011; Jain et al., 2001; Jain and Ormsbee, 2002; Jentgen et al., 2007; Pesantez et al., 2020; Zhou et al., 2000)
Rainfall amount	▪ Decreases in weekly water demand when there is increasing rainfall volume (Bougadis et al., 2005; Goodchild, 2003; House-Peters and Chang, 2011; Jain et al., 2001; Jain and Ormsbee, 2002; Jentgen et al., 2007)

Rainfall occurrence	▪ Decrease in water use when rainfall occurs (defined as rainfall amount > given threshold value) (Jain and Ormsbee, 2002; Maidment and Parzen, 1984); i.e., rainfall occurrence is set to 1, with rainfall amount greater than zero (Jain et al., 2001) or greater than 1 [in] (Maidment and Parzen, 1984) ▪ Decrease in water demand when rainfall occurs; rainfall amount has higher significant correlation than rainfall occurrence (Bougadis et al., 2005) ▪ Decrease in water demand when rainfall occurs; rainfall occurrence has higher significant correlation than rainfall amount (Jain et al., 2001)
Days since rain	▪ Water demand increases as the number of days since it has rained last increases, attributed to people watering their lawns/gardens after several days of no rain (Goodchild, 2003; Zhou et al., 2000)
Seasonality	
Season	▪ Seasonal impact (e.g. summer, winter) of water demand variations; summer demand is higher than winter demand (Arbués et al., 2003; Zhou et al., 2000)
Seasonal rainfall	▪ Defined in terms of the season and rainfall occurrence (Hansen and Narayanun, 1981) ▪ Impact of rainfall on water demand varies seasonally; the magnitude of water demand decrease in response to summer rainfall (i.e., rainfall occurring in summer) is higher than that due to winter rainfall (Hansen and Narayanun, 1981; Zhou et al., 2000)
Weekday	▪ Significant cyclic effect of the day of the week on water-demand patterns (Cutore et al., 2008; Gato et al., 2007; Pesantez et al., 2020; Rizvi et al., 2020; Zhou et al., 2000)
Institutional	
Water conservation policy	▪ Institutional level efforts for managing and restricting outdoor watering to promote better water conservation (Campbell et al., 2004; Kenney et al., 2008; Reynaud and Romano, 2018)
Financial	
Water price	▪ Water price increase can decrease water use (Burney et al., 2001; House-Peters and Chang, 2011; Reynaud and Romano, 2018); primarily affects long-term water demand planning and modelling (Donkor et al., 2014)
Social	
Population	▪ Impact of population change on long-term water demand modelling; water demand likely increases with the increase in population (Burney et al., 2001; House-Peters and Chang, 2011; Jain et al., 2001; Maidment and Parzen, 1984), especially without changes in water use efficiency and conservation policies

Study Site

Austin, TX is among the fastest growing U.S. cities, in terms of both economics and population (Leighton, 2019). Between 2010 and 2018, the population had increased by 22%—an average of 100 new residents moving to the city per day (U.S. Census Bureau, 2010). A major driver of Austin's population growth is its growing number of businesses (~ 4%) and technology companies

(~ 5%) (Leighton, 2019). This growth has given rise to increases in nonresidential water demand (e.g., commercial, industrial) over years.

Austin's water infrastructure system consists of nine major pressure zones (Austin Water, 2013). These zones are areas generally within lower and upper topography boundaries (elevation) to operate water pressure in the system within appropriate ranges (Austin Water, 2021a). The public water utility (Austin Water) has been investing in infrastructure advancement (Austin Water, 2020; Smart Cities Dive, 2020) across the various zones to promote system resilience and help support racial equity and environmental justice aligning with strategic direction efforts (Becker, 2017; City of Austin, 2018). In spite of these efforts, the shifts in water-demand behavior in response to COVID-19 SDPs may reveal new and varied technical challenges across the system, including the impacts of infrastructure's age and conditions (Busch, 2015). Examples of possible technical challenges include pipe breaks, water-quality issues, and impacted fire flow capabilities due to possible changes in water pressure in response to demand variations (Cooley et al., 2020). In fact, a recent study (Spearing et al., 2020) of U.S. water utilities reported that the COVID-19 pandemic amplified technical issues, and the repercussions of not addressing these issues could intensify them or make them occur earlier. By seeking to understand the implications of SDPs on water demand in Austin, our work can better inform emergency responses (City of Austin, 2020a, 2016) to pandemic-incurred challenges.

Data Collection

To limit human contact and help slow the spread, Austin enacted a number of COVID-19 SDPs (City of Austin, 2020b). Our analysis examines policies enacted between the time period of March 19, 2020, and December 10, 2020, to explore the impact of the SDPs on the water demand. *Stay Home-Work Safe* orders in Austin began on March 24, 2020. This included social distancing requirements, as well as some business closures. The *Stay Home-Work Safe* order was followed by general multi-phase reopening (Austin Texas, 2020a; Texas Department of Health Services, 2020; Texas State, 2020) when more businesses were reopening at increasing capacity limitations. It is important to note that policies relating to these SDPs were being implemented at the local, state, national and global levels, entering various stages of risk during the reopening phases (Austin Texas, 2020b). For the purposes of this study, the analysis was conducted looking at four SDPs phases based on the reopening phases outlined by the State of Texas.

We obtained from Austin Water the *daily* total water-demand time series—disaggregated across the nine pressure zones; this is treated water volume introduced to the water distribution system to provide water service. The water-demand time series records extend from January 1, 2013, to December 10, 2020, totaling 2,899 records of daily water demand (given in million gallons per day [MGD]). Hence, we possess a large sample prior to the enactment of SDPs, permitting us to better parse the impact of the SDPs. To explore SDPs-induced water-demand changes, we implemented the proposed approach (see Figure 1) and considered the major socio-technical determinants presented in Table 1, with the following exceptions: “rainfall occurrence,” “seasonal rainfall,” “population,” and “water price.” The specifics of the water conservation policy implemented throughout the period of record—i.e., mandatory outdoor watering restrictions—were obtained from Austin Water. The climatic data (i.e., daily maximum air temperature, daily rainfall amount) were gathered from the National Oceanic and Atmospheric Administration (NOAA) for the two weather stations within the study area and averaged (NOAA, 2020).

We excluded the “rainfall occurrence” determinant (a binary variable with value 1 for a rainfall amount greater than a given threshold value, such as 1 inch [in] rainfall used in the literature (Maidment and Parzen, 1984)) to avoid a multicollinearity (House-Peters and Chang, 2011) issue with the “rainfall amount” determinant. Similarly, we excluded the “seasonal rainfall” determinant to avoid a multicollinearity issue with the “season” and “rainfall occurrence” determinants (Hansen and Narayanun, 1981). We also excluded the “population” determinant, as conversations with the local utility suggested that the water conservation policy at the institutional level had already significantly contributed, more than the population growth, to water-demand changes in Austin. Austin Water has restricted outdoor watering schedules depending on conservation stages (Austin Water, 2021b), resulting in a major reduction—over years—in the average per capita water consumption (see Figure S1 in the Supporting Information). Further, recent incoming businesses (Leighton, 2019) caused a significant increase in nonresidential water demand leading to greater changes in water demand than that imposed by residential use (e.g., population). According to the literature (Burney et al., 2001; Levin et al., 2006; Miaou, 1990; Mohamed and Al-Mualla, 2010), “population” and “water price” determinants are more influential on water-demand changes when conducting long-term demand planning at a lower temporal resolution (e.g., monthly, yearly). To inform infrastructure developments, typical planning periods range from 20-30 years (Donkor et al., 2014). Given that we are analyzing water-demand changes at the system-daily scale over a relatively medium-range time period (8 years), we excluded the “water price” determinant.

Regression Analysis: Model Structure and Estimation

To gain an initial understanding of potential differences in water-demand patterns due to SDPs—prior to developing the regression model—we plotted the 2020 weekly moving average of the system’s daily water demand against that of 2019 (see Figure 2). Following this step and using regression analysis, we accounted for factors (e.g., socio-technical determinants) that impacted the demand changes we saw in the plot. Further, we plotted the nine zones’ daily water demand to better understand the spatial effects from the regression results (see Figure 3).

The preliminary step in assessing the impacts of influential factors on water demand is to verify the normality in the distribution of water demand data (Bougadis et al., 2005). We did so using the frequency distribution (histogram) and Shapiro-Wilk test (Ghasemi and Zahediasl, 2012). We also explored if periodicity (Ollech, 2019; Webel and Ollech, 2019) exists in the demand time series, which was non-existent; however, we did account for possible seasonal shifts in water demand through the seasonality-related determinants (see Table 1) considered in modelling. We examined correlations in the predictors using the correlation matrix (Chambers, 1992), as well as the Variance Inflation Factor (VIF) (Fox and Monette, 1992), to determine any possible collinearity across independent and control variables. We also plotted the relationships between water demand and previous water demand across multiple lag periods—e.g., 1-day lag of demand (i.e., demand in the previous day), 2-day lag of demand—to identify the lag with the highest correlation. For our water-demand time series, 1-day lag was the best lagged-demand determinant, aligning with the literature (Bougadis et al., 2005; Jain et al., 2001). To see the lag plots, refer to Figure S2 in the Supporting Information.

To control for the spatial and temporal effects in water demand, we applied FE regression—based on panel data procedure (Frees, 2004)—on water demand across the nine pressures zones. Panel data is defined as a data set—in longitudinal format—that contains repeated observations of multiple subjects over multiple time periods (Frees, 2004; Polebitski and Palmer, 2010). For this work, the subjects (i.e., spatial unit) are the nine pressure zones, and the repeated observations are changes in daily water demand, socio-technical determinants, and SDPs within each zone over days (i.e., temporal unit) throughout the period of data record. The original pooled data set (i.e., n=2,899 records) was thus transformed to a panel data set of n=26,083. The FE regression model allows the intercept term to vary across the spatial subjects when estimating the regression coefficients (Polebitski and Palmer, 2010)—see Eq. (1):

$$Y_{st} = \alpha_s + \sum_{i=1}^{N} X_{st,i}\beta_i + \varepsilon_{st}; \text{ with } s = 1, 2, \dots S; \text{ and } t = 1, 2, \dots T \quad (1)$$

where S is the total number of spatial units (zones), T is the total number of temporal units (days) in the panel data, N is the number of influential factors, Y_{st} is the dependent variable representing observed water demand for spatial unit s at temporal unit t, α_s is the unobserved spatial (zonal)-specific heterogeneity, X is the vector of influential factors (independent variables: SDPs; control variables: sociotechnical determinants), β is the vector of estimated parameters, and ε_{st} is the error term. By incorporating spatial and temporal attributes into coefficient estimates as well as the separation of zone-specific effects from the error term, FE regression generates more reliable parameter estimates compared to classical pooled OLS regression (Arbués et al., 2003). From a water-demand perspective, the analysis of demand while accounting for the effects of variations across the zones can provide a better understanding of the citywide water-demand changes due to SDPs. Important to note, random effects—i.e., spatial effects treated as random variable (Polebitski and Palmer, 2010)—were also tested, but results verified that fixed effects were more suitable for representing our data (Wallace and Hussain, 1969). To assess model fit (Zhou et al., 2000), we used the coefficient of determination R^2. Further, using the likelihood ratio test (Fox, 1997), we compared the fit of the five-level SDPs model (i.e., *Non-enactment of SDPs*, *Stay Home-Work Safe*, *Reopening Phase 1*, *Reopening Phase 2*, *Reopening Phase 3*) with that of a two-level SDPs model (*before SDPs*, *during SDPs*); results indicate a significant improvement by the five-level SDPs model, compared to the two-level SDPs model (see Table S1 in the Supporting Information). We performed all statistical analyses using *R* version 1.3.1093 (R Core Team, 2020) and various supporting packages (e.g., tidyverse, gplots, lmtest, plm, seastests, bestNormalize).

RESULTS AND DISCUSSION

Exploratory Analysis and Descriptive Statistics

Figure 2 compares the 2020 total water demand’s temporal patterns to those of 2019. Notably, the total water demand denotes the overall demand bounded at the service area of the local utility. We refer to this as the *system scale*, as it is geographically defined by the water infrastructure system. At the beginning of 2020, the average daily total demand (~123 MGD) was higher than that of 2019 (~111 MGD), with the increase possibly being attributed to a variety of socio-technical determinants; on March 24, 2020, however, when SDPs—*Stay Home-Work Safe*—were enacted, demand fell slightly below that of the corresponding dates in 2019. The largest relative decrease in average daily demand was on April 7, (-8.6%) when the city demand was ~11 MGD less than it was in 2019. By the end of April 2020, when businesses began to reopen in Austin (Texas Department of Health Services, 2020), citywide demand started to increase again, similar to levels prior to social distancing. Of course, these changes in water demand—depicted in Figure 2—cannot be attributed merely to SDPs, and it does emphasize the need for further investigations that consider the socio-technical determinants, as well as spatial and temporal effects.

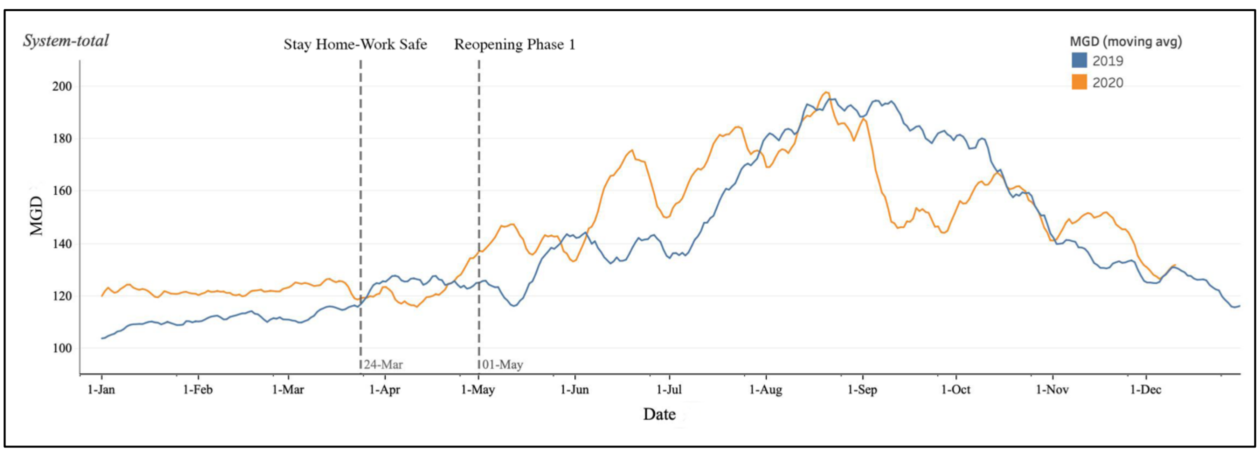

Figure 2. Comparison of 2020 average daily system-total water demand to that in 2019

Table 2 shows the descriptive statistics for the water demands (total, nine zones) and previously identified variables impacting water demands. Almost half of the average total water demand is consumed by two pressure zones—*Zone 1* and *Zone 2* (see Table 2). Furthermore, the average maximum air temperature and rainfall amounts are over 80 [˚F] and 0.1 [in], respectively, reflecting Austin's typically long, hot summers and mild winters. This trend is highlighted by the system's temporal water-demand behavior, shown in Figure 2, indicating a much higher water demand during summer months. Notably, throughout the period of data record, Austin Water implemented two stages of its water conservation policy. On May 18, 2016, the conservation stage was changed from *Stage 2* to *Stage 0*, specifying outdoor watering schedules (Austin Water, 2021b) throughout the week based on the customer class (e.g., residential, commercial), technology used (e.g., hose-end sprinklers, automatic irrigation), and whether the address number is odd or even (see Table S2 in the Supporting Information for further details).

Table 2. Descriptive statistics and categorical levels for water demands and influential variables (units in brackets)

Variable	Mean ± Std. Deviation	Median	Interquartile Range
Total water demand			
Total demand [MGD]	132.29 ± 24.19	125.67	33.45
Water demands across zones			
Zone 1 [MGD]	30.16 ± 7.50	27.17	9.90
Zone 2 [MGD]	30.20 ± 6.36	30.19	8.38
Zone 3 [MGD]	23.33 ± 5.26	22.50	7.66
Zone 4 [MGD]	11.88 ± 3.18	11.10	4.47
Zone 5 [MGD]	2.26 ± 0.88	2.06	1.06
Zone 6 [MGD]	20.52 ± 3.84	20.06	4.68
Zone 7 [MGD]	10.69 ± 2.85	9.98	2.96
Zone 8 [MGD]	3.24 ± 1.42	2.95	1.62
Zone 9 [MGD]	1.18 ± 0.68	0.97	0.48
Control variables: Socio-technical determinants			
1-day lag of demand [a] [MGD]	–	–	–
Maximum air temperature [˚F]	81.23 ± 14.94	83.5	21.97
Rainfall amount [in]	0.11 ± 0.43	0	0.005

Days since rain [days]	8.06 ± 8.41	5	10
Season	1 – Winter, 2 – Spring, 3 – Summer, 4 – Autumn		
Weekday	1 – Mon, 2 – Tue, 3 – Wed, 4 – Thurs, 5 – Fri, 6 – Sat, 7 – Sun		
Water conservation policy	0 – Stage-2 conservation, 1 – Stage-0 conservation		
Independent variables: Social distancing policies			
SDPs	1 – Non-enactment of SDPs, 2 – Stay Home-Work Safe, 3 – Reopening Phase 1, 4 – Reopening Phase 2, 5 – Reopening Phase 3		

[a] Descriptive statistics values for the lag demand of system-total and nine pressure zones are the same as their corresponding water demands.

FE Regression Water Demand Model

The water-demand was skewed to the right, so we adjusted it for normality using the Box-Cox transformation (Box and Cox, 1964) prior to developing the FE regression model. Further, no collinearity issues were found across the socio-technical determinants and SDPs (refer to Table S3 and Table S4 in the Supporting Information for the correlation matrix and VIF values, respectively). Table 3 summarizes the FE regression analysis of the relationships between the water demand and various SDPs' levels, while also considering the socio-technical determinants' effects. For the regression analysis of relationships with the socio-technical determinants and fixed effects of the nine zones, see Table S5 and Table S6 in the Supporting Information, respectively. Notably, the relationships between the water-demand and socio-technical determinants are all statistically significant at 1% significance level (Table S5). The sign of behavioral demand changes in response to these socio-technical determinants align with the literature (Bougadis et al., 2005; Goodchild, 2003; House-Peters and Chang, 2011; Jain et al., 2001; Jain and Ormsbee, 2002; Jentgen et al., 2007; Zhou et al., 2000); refer to the FE Regression Results section in the Supporting Information for further details.

Regarding the determinants of categorical data type (e.g., SDPs, season, weekday), it should be noted that the model assesses parameter estimates for the various categorical levels relative to a reference level. For instance, the "SDPs" determinant has five categorical levels: *Non-enactment of SDPs*, *Stay Home-Work Safe*, *Reopening Phase 1*, *Reopening Phase 2*, and *Reopening Phase 3* (see Table 2). The parameter estimates of the SDPs' levels in the FE model—shown in Table 3—are relative to the reference level *Non-enactment of SDPs*, assessed at -0.004 MGD (p = 0.49), 0.021 MGD (0.025), 0.014 MGD (0.144), and 0.025 MGD (0.000), respectively. In the following section, we discuss the relationships with SDPs and how the consideration of the spatial and temporal effects in water demand provides a better understanding of these relationships.

Table 3. Regression results of SDPs' relationships with the water demand [a]

SDPs Variable [b]	β_i [10^{-5} MGD]	Std. Error [10^{-5} MGD]	t	p
Water Demand (panel data set, n = 26,083 records)				
Stay Home-Work Safe	-423.81	614.30	-0.69	0.49
Reopening Phase 1	2,142.5	954.11	2.25	0.025^{*}
Reopening Phase 2	1,435.6	982.74	1.46	0.144
Reopening Phase 3	2,483.5	308.15	8.06	0.000^{***}

Note: The full FE model, including regression results of socio-technical determinants (control variables), is included in Table S5 in the supporting information.

[a] FE regression analysis; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

[b] Reference level: *Non-enactment of SDPs*

Model information: Total sum of squares = 1463.9; Residential sum of squares = 350.2; R^2 = 0.76; Adjusted R^2 = 0.76; F-statistic = 4601.77; $p = 0.000^{***}$.

Discussion

Demand Changes during Stay Home-Work Safe Period (Hypothesis 1)

Our descriptive (Figure 2) and regression (Table 3) analyses are well aligned. After the *Stay Home-Work Safe* order, the model detected a negative change in water demand (see Table 3), aligning with the temporal total demand patterns in Figure 2. This demand behavior aligns with a recent study (Cooley et al., 2020) on water-demand changes in several U.S. communities during social distancing. That study reported a reduction in total demand during April 2020 across larger metropolitan systems—including Austin's (TX). According to the study, in Austin, a 5% decrease relative to expected April demands was attributed to reduced commercial demands due to the *Stay Home-Work Safe* order (Clifton, 2020; Cooley et al., 2020). By considering sociotechnical determinants and accounting for the variations across the nine zones, however, our analysis reveals that the negative change in Austin's water demand experienced during April 2020 was statistically insignificant in relation to the *Stay Home-Work Safe* order (see Table 3). These results may likely be attributed to the fact that the decrease in nonresidential water demand (e.g., commercial, institutional) had offset an increase in residential demand at the system scale, suggesting a spatial redistribution of water demand following the *Stay Home-Work* Safe order. This demand behavior at the system scale is further supported by the demand patterns at a finer spatial resolution (see Figure 3). Water-demand patterns across the nine individual zones appeared to be affected by the imposed SDPs, especially during the *Stay Home-Work Safe* period between March 24, 2020, and April 30, 2020 (Figure 3). For instance, a sizable decrease occurred in the average daily water demand in *Zone 1*—a mostly nonresidential zone—likely due to business closures following the *Stay Home-Work Safe* order (Austin Texas, 2020c). On the other hand, a marginal decrease was seen in the average daily water demand in *Zone 7*—a mixed residential-nonresidential zone. Residential demand increased due to work-from-home orders as well as to a surge in hygiene and cleaning practices to limit the virus spread (Kalbusch et al., 2020). As such, in mixed residential-nonresidential zones—such as *Zone 7*—the increase in residential demand had likely offset the decrease in nonresidential demand during the *Stay Home-Work Safe* period, resulting in a marginal drop in demand. Given such spatial redistribution of water demand across the zones, the (negative) net effect of these spatial demand changes at the system scale was not detected by the model as statistically significant. These findings align with the literature (Spearing et al., 2020), which has explained that many U.S. water utilities saw no significant change in overall demand, dependent on the utility's customer composition, during social distancing because of a shift between customer classes. Another study (Cooley et al., 2020) on COVID-19's impacts on water demand emphasized that the net effect of changes between residential and nonresidential demand varied from community to community, depending on their relative proportions from the overall demand.

Figure 3. Comparison of 2020 average daily water demands across nine zones to those in 2019

Demand Changes during Reopening Phases (Hypothesis 2)

As shown in Table 3, only the *Reopening Phase 1* and *Reopening Phase 3* show statistically significant relationships with the water demand at 5% and 1% significance levels, respectively. When some businesses were allowed to operate at 25% capacity—*Reopening Phase 1* enacted on

May 1, 2020—there occurred a statistically significant positive change in water demand (see Table 3), estimated at 0.021MGD (i.e., 81.1 cubic meter per day [m^3D^{-1}]). During this reopening phase, there was still an increase in residential demand as compared to pre-pandemic due to a majority of the population continuing to both work from home and practice social distancing. However, the magnitude of this increase was likely smaller than that experienced soon after the *Stay Home-Work* Safe order, similarly for the magnitude of the nonresidential demand decrease given the 25% businesses' operational capacity potential. What may also be expected during this phase is an increase in water demand from additional maintenance activities (e.g., flushing), which water utilities typically implement to alleviate potential water-quality issues associated with stagnant water inside pipes due to business closures following the *Stay Home-Work* Safe order (Cooley et al., 2020; Gleick, 2020; Proctor et al., 2020). The magnitude of demand increase from additional maintenance activities may be insufficient to solely cause significant shifts in total demand. Nevertheless, it is a contributor to the collective changes occurring at the system scale during this period. For the case of Austin, additional pandemic-related line flushing activities were not needed; key contributors to this include system connectivity and looping (refer to Figure S3 in the Supporting Information for further details). Additionally, in the spatial distribution of water demand across the system, even in some mostly commercial areas, there are also residential customers who were using water throughout the pandemic, thereby preventing water stagnation and alleviating the need for the utility to perform pandemic-related flushing. Onsite flushing at the customer level to maintain water quality inside the premise plumbing occurred, but the water use for these flushing activities was reflected in their metered water use. In fact, the model detected the net effect of these various changes to be a statistically significant, though marginal, positive change in total water demand of less than 0.2% (compared to an average daily demand of 123

MGD). While the magnitude of SDPs' effects on total water demand—analyzed at the system scale—may not seem large enough to matter from an operational perspective, it should be noted that it emphasizes a behavioral change of the underlying spatial demands at sub-system scales. Such behavioral changes still require a closer investigation to identify any potential operational and water-quality issues across areas within the system. The behavior of changes in residential and nonresidential demands during *Reopening Phase 2* is similar to that during *Reopening Phase 1*, excluding the contributions from additional maintenance activities, though neither change is statistically significant (see Table 3).

During *Reopening Phase 3*, people were more involved in public activities, and some businesses were allowed to operate at up to 75% capacity. Compared to the period before the pandemic, this still likely represents an increase in residential demand and a decrease in nonresidential demand. These demand changes could be due to Austin not completely lifting additional pandemic-related recommended hygiene and cleaning practices and stay home-work safe orders, as well as businesses not being fully operational. The net effect of these spatial changes in demand is a statistically significant positive change in total water demand, estimated at 0.025 MGD (i.e., 94 m^3D^{-1}) with respect to the non-enactment of SDPs. As with *Reopening Phase 1*, the magnitude of this change is marginal. In the third reopening phase, the decrease in nonresidential demand was less as compared to previous reopening phases. As such, the impact of the residential demand increase on the overall water demand was detected by the model as statistically significant.

Our analysis assessed the impacts of SDPs on water-demand changes using demand data disaggregated by pressure zone throughout the service area. However, the disaggregation of demand data across customer classes (e.g., commercial, industrial, residential, institutional) would have provided a deeper understanding of the underlying spatial water-demand redistributions that shaped the net effect at the system scale. Such higher spatial resolution data, for instance, would have enabled more accurate assessment of the magnitudes of spatial changes (e.g., residential increase, nonresidential decrease). Consequently, we would possess a more comprehensive understanding of their operational effects throughout the system. In this regard, Advanced Metering Infrastructure (AMI aka "smart meters") can provide near real-time water-demand monitoring, disaggregated at higher temporal and spatial resolutions (Cooley et al., 2020; Pesantez et al., 2020). Such advancement could help provide the continued operation and management of water infrastructure, especially with the ongoing pandemic-induced socio-technical challenges (e.g., operation outside design conditions, reduced staff, revenue loss) (Cooley et al., 2020; Spearing et al., 2020). For this reason, the pandemic may be expected to reinforce and accelerate the need to expand the application of digital monitoring and operational technologies (Bindler, 2020); indeed, such expansion is high on Austin Water's agenda, as at the time of data collection the utility was piloting project for a new system-wide AMI (Austin Water, 2020).

To further support the urgent need for utility-infrastructure investments, federal and state policy needs to address gaps in infrastructure funding (Cooley et al., 2020; Spearing et al., 2020). For instance, funding should be prioritized for capital projects and infrastructure upgrades to (1) ensure continuous operations during crises, such as COVID-19 and future pandemics; (2) provide more granular understanding on water demand behaviors; and, therefore, (3) help identify and address spatial discrepancies in the level of service, thereby enabling more equitable water-sector services.

STUDY IMPLICATIONS AND CONCLUSIONS

In this work, we have viewed pandemic-induced SDPs as population dynamics through a lens of integrated operating environments. Doing so offers a powerful means to empirically understand the temporal demand behavior of socio-technical water infrastructures during pandemics. We have thus presented an integrated approach for how future research may be conducted considering socio-technical determinants, as well as spatial and temporal effects in water demand. By increasing infrastructure resilience through improved understanding of SDPs' impacts on water demand, our approach contributes to global conversations on sustainable development (UN-CSD, 2012; UN-SDG, 2015). Additionally, our study provides valuable information to water utilities as they plan for future disasters or develop pandemic response plans; it also enables them to respond adequately to potential system vulnerabilities. To adapt to changing operating environments, such responses may include (1) operating water treatment plants at reduced production levels when demand drops; or (2) prioritizing resource allocation based on demand-capacity management strategies in case of increased demand, such as limiting outdoor watering to maintain continuous service to critical customers (e.g., hospitals). These practices can improve the resilience of water resources, which is fundamental to limiting the evolution of a pandemic (Kalbusch et al., 2020).

The applicability of the proposed approach may also be extended to other infrastructure sectors (e.g., energy) or other types of extreme events (e.g., humanitarian crises, compounded disasters) that trigger shifts in the population dynamics or operating environment. Such application would shed light on the impacts of policy interventions with an infrastructure's demand behavior. Our study also sets the stage to extend the limited literature on pandemic planning and population dynamics by conducting the assessment at higher temporal and spatial resolutions (e.g., disaggregation across customer classes, household-level), using case data in varying geographic contexts. Considering additional geographic contexts would provide a more comprehensive understanding of how aspects of the operating environment impact the analysis of demand changes in response to policy interventions.

Additional research is needed to incorporate time series analysis (e.g., ARIMA; Gardner et al., 1980) with FE regression—through hybrid modelling—to consider the inherent autocorrelation structure of a water-demand pattern over time (Jain et al., 2001; Maidment and Parzen, 1984), thereby improving the performance of the model. Future research could also consider the integration of schedules related to maintenance operational activities—such as flushing performed by utilities and possible operational changes in treatment plants during the imposed SDPs—in the temporal modelling. Such investigation could explore the impacts of these activities on water demand and the feasibility of incorporating them as contributing factors within the technical dimension of the operating environment. As researchers continue to improve our understanding of how policy initiatives impact water demand considering the operating environments of infrastructure systems, utilities will be able to implement better-informed strategies for providing communities with continuous water-sector services.

ASSOCIATED CONTENT

Supporting Information

- Yearly water pumpage and population variations in Austin, TX
- Lagged plots
- Likelihood ratio test results
- Water conservation policies in Austin, TX
- Correlation assessment
- Full table of FE regression results
- Fixed effects of pressure zones
- Operational line flushing activities in Austin, TX

AUTHOR CONTRIBUTIONS

The manuscript was written through contributions of all authors, as follows: Conceptualization and design, A.B. and K.F.; Data collection and curation: A.B.; Statistical modelling and software, A.B. and A.R.; Model Verification and Validation, A.B., A.R., and K.F.; Visualization and Data Analysis, A.B.; Writing - original draft, A.B.; Writing - review and editing, A.B., A.R., and K.F.; Supervision: K.F. All authors have given approval to the final version of the manuscript.

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