

Using Wastewater Flow to Understand Water System's Demand Behavior during COVID-19 Pandemic in an Urban Metropolitan City in Texas

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ABSTRACT

Social distancing policies (SDPs) implemented in response to COVID-19 pandemic have led to spatiotemporal variations in water demand. In contexts with limited availability of smart meter infrastructure, the lack of high-granular water demand data challenges utilities' understanding of such demand variations that are needed to respond to potential operational and water quality issues. Founded on the water and wastewater infrastructures' interdependencies, this study proposes the use of high-granular wastewater flow data as a proxy to understand the water demand variations during active SDPs. Enabled by a random-effects model of wastewater flow in an urban metropolitan city in Texas, we explore the impacts of various SDPs (e.g., stay home-work safe, reopening phases) using daily flow data gathered between March 19, 2019, and December 31, 2020. Results indicate an increase in residential flow that offset a decrease in nonresidential flow during the stay home-work safe period. Our results also show that the three reopening phases have statistically significant relationships to wastewater flow, although yielding marginal net effects at the system scale. These findings in regard to residential-nonresidential variations—explored through the wastewater flow—underscore behavioral changes in water demand at sub-system spatial scales. Our assessment can inform emergency response plans for pandemics in regard to water infrastructure planning, management, and operations, considering spatiotemporal changes in water demand.

Keywords: Wastewater flow, water demand, pandemic, data interdependencies, regression analysis.

INTRODUCTION

As the 2019 novel coronavirus (COVID-19) spread worldwide, governments enacted a number of measures for its containment, such as lockdown, social distancing, and work-from-home orders (Balacco et al. 2020; Sivakumar 2020)—referred hereafter to as *social distancing*

policies (SDPs). These SDPs altered the spatial distribution of water demand (e.g., people working from home) (Cooley et al. 2020; Kalbusch et al. 2020), as well as the traditional underlying consumption dynamics (e.g., delayed morning peaks) (Balacco et al. 2020). Water utilities need to understand these spatiotemporal changes in their water demands to identify and adequately respond to system vulnerabilities (Cooley et al. 2020). For instance, sudden spatiotemporal demand changes can exacerbate existing and reveal new operational issues, such as reduced pressure, increase in pipe breaks, and treatment capacity (Cooley et al. 2020). Additionally, the areas with reduced demand are at risk for water quality problems due to possible stagnant water inside the building plumbing or increased water age (Sivakumar 2020).

A recent investigation on US water utilities show that more than 20% of utilities did not know if they experienced demand changes in response to SDPs, or simply could not know due to lack of information or data availability (Spearing et al. 2020). Water demand analysis is often based on account-level demand data that corresponds to billing cycles collected at monthly or quarterly intervals (Pesantez et al. 2020). However, in times of crises (e.g., COVID-19 pandemic), the lack of near real-time data may hinder utilities' ability to know systems' changes in response to these crises and provide timely response to potential issues as they arise. Recently, municipalities and water utilities have been investing in smart meters to acquire near real-time account-level water demands at high temporal granularity levels (Pesantez et al. 2020). Unfortunately, however, the implementation of smart meters is still limited to date (Pesantez et al. 2020). As such, utilities without access to smart water meters are challenged to understand the demand changes due to COVID-19 SDPs and adequately respond to potential operational and water quality issues. An alternative approach to understanding these demand changes is to use wastewater flow data. This is due to the fact that water used by various customer classes (e.g., residential, commercial) within a community constitutes a significant portion of wastewater flowing into the wastewater infrastructures before entering the treatment plants. Treated wastewater is then discharged as effluent into receiving natural water resources (Zhang et al. 2019), demonstrating interdependencies across water and wastewater systems. Such water-wastewater data interdependencies offer a promising proxy to explore potential water system's demand behavioral changes in response to policy interventions, especially in contexts lacking water demand data available at the appropriate spatiotemporal granularity.

This study seeks to answer the following question: In times of a pandemic, can wastewater flow data be used to understand water system's demand behavior during active SDPs? The study analyzes daily wastewater flow data gathered between 2019 and 2020 in an urban metropolitan city in Texas. It specifically explores the impacts of various SDPs on wastewater flow using random-effects (RE) regression, taking into account factors that could influence flow variations. Our discussion demonstrates how the assessment of these impacts can provide an understanding of water system's demand behavior during SDPs. By empirically using water-wastewater data interdependencies, our study can inform emergency response plans for pandemics in regard to water infrastructure planning, management, and operations, considering spatiotemporal changes in water demand.

FACTORS IMPACTING WASTEWATER FLOW VARIATIONS

Wastewater flow volume is typically measured by sensor-based wastewater flow meters—each serves a certain geographic area across the network—and captured at various temporal granularity levels (e.g., hourly, daily) (Zhang et al. 2019). The flow volume is typically used for (1) designing, planning, operations, and management of wastewater treatment plants, through providing guidance on effluent quality, as well as identifying capacity risks (Fernandez et al. 2009; Mefrakis 2015; Mines et al. 2007; Zhang et al. 2019); (2) designing pipe capacity (Mefrakis 2015); and (3) providing information on inflow and infiltration (I/I)—i.e., water entering sewer pipes through leaking joints, cracks, breaks, and manhole covers—and whether cost-effective I/I corrections are needed (Mefrakis 2015). In this study, we propose the use of flow volume as a proxy to understand water demand changes during SDPs. It should be noted, though, that wastewater flow is affected by numerous factors—referred hereafter to as *socio-technical determinants*—that span the technical, environmental, and social dimensions within which a wastewater system exists or operates (Fernandez et al. 2009; Zhang et al. 2019).

Technical. Wastewater flow depends on its past values; for instance, daily wastewater flow correlates with the values for the previous day (i.e., 1-day lag) (Fernandez et al. 2009; Zhang et al. 2019). Additionally, the average daily flow—assessed by averaging all flows in a given year—influences wastewater flow variations (Mines et al. 2007).

Environmental. I/I-related fluctuations and climatic and seasonality variations can lead to changes in wastewater flow. Storm events contribute to flow variability (e.g., 3.08 times the dry weather flow) due to the I/I of water into sewers (Mines et al. 2007). For instance, the increase in rainfall amount (Zhang et al. 2019) and rainfall intensity (Mines et al. 2007) may increase wastewater flow, especially if the I/I measurement of sewer pipes is relatively high. Additionally, an increase in maximum air temperature may increase wastewater flow through I/I especially during dry periods, as people may want to water their lawns/gardens after several days of no rain (Bougadis et al. 2005; Zhang et al. 2019). Possible seasonal shifts in wastewater flow may also occur throughout a year, likely due to storm events in the spring and summer (Zhang et al. 2019). Wastewater flow patterns also differ across the days of the week, especially weekday versus weekend trends due to changes in residential water demand (e.g., delayed morning peaks) (Fernandez et al. 2009; Zhang et al. 2019).

Social. Wastewater flows may vary across geographic areas due to differences in water demand patterns across customer classes (e.g., residential, commercial) (Zhang et al. 2019). SDPs can impact wastewater flow due to reasons such as business closures or working from home.

This study seeks to assess the impacts of various SDPs (independent variables) on wastewater flow, considering the effects of the socio-technical determinants (control variables); that is, lag flow, average daily flow, maximum air temperature, rainfall amount, rainfall intensity, season/month, weekday, classification. The analyses provide an insight into water system's demand behavioral changes in response to these SDPs, enabling proactive water infrastructure planning and operations during pandemics.

MATERIAL AND METHODS

Study Site and Data Collection

This study focuses on a wastewater flow network in an urban metropolitan city in Texas. To help slow the spread of the virus, Texas governor Greg Abbott issued a number of COVID-19 SDPs (Texas Department of Health Services 2020). Our analysis focuses on four major SDPs—stay home-work safe and three reopening phases—that were put in place between March 19, 2020, and December 31, 2020. Starting March 19, 2020, until April 30, 2020, social distancing, business closures, and stay home-work safe orders were implemented; we refer to this period as *Stay Home-Work Safe*. Subsequently, multi-phase reopening orders were issued: some businesses were operating at 25% capacity during *Reopening Phase 1* (starting May 1, 2020); more businesses were reopening at 25-50% capacity during *Reopening Phase 2* (May 18, 2020); and continuing towards *Reopening Phase 3* with increasing capacity up to 75% (June 3, 2020).

Wastewater flow variations are analyzed between March 19, 2019, and December 31, 2020, allowing for one-year of data prior to the enactment of SDPs on March 19, 2020. The wastewater network in the study site is comprised of around 75 permanent flow meters. These meters serve a variety of customer classes, including residential, commercial, and institutional. We obtained from the local water utility the daily wastewater flow time series data (given in million gallons per day [MGD])—disaggregated at the area scales that are served by these flow meters. We examined the data completeness of the entire data set, as well as the areas' spatial distributions across the network. This yielded a sample of 15 areas that have complete flow data and are widely distributed across the network. Using the wastewater flow time series data, we assessed the lag flows, as well as average daily flow in the two years—prior to and during the enactment of SDPs.

The customer classification of wastewater flow breakdown for the various areas—i.e., residential versus non-residential—were obtained from the local water utility. Accordingly, we classified the 15 areas into three groups: nine mostly residential (at least 70% residential flow), two mostly nonresidential (at least 70% nonresidential flow), and four mixed residential-nonresidential areas. The daily maximum air temperature data was gathered from the National Oceanic and Atmospheric Administration (NOAA) for the weather stations within the study site and averaged (NOAA 2020), whereas the rainfall data were gathered from the platform that the local water utility uses to obtain more accurate rainfall data at the flow meter basin scale.

Regression Analysis: Random-effects Modeling

Prior to developing the RE model, we verified the normality in the distribution of wastewater flow data using the frequency distribution (histogram) and Shapiro-Wilk test (Ghasemi and Zahediasl 2012). We also examined the correlation matrix across influential factors to determine any possible collinearity issues (Chambers 1992). We plotted the relationships between wastewater flow and previous wastewater flows across multiple lag periods—e.g., 1-day lag of flow (i.e., flow in the previous day), 2-day lag of flow—to identify the lag with the highest correlation. For our wastewater flow time series, 1-day lag turned to be the best lagged flow determinant, aligning with the literature (Fernandez et al. 2009; Zhang et al. 2019). Additionally,

we plotted the wastewater flow with respect to the various factors to determine possible types of relationships. For instance, scatter plots were created with numerical variables (i.e., 1-day lag flow, average daily flow, maximum air temperature, rainfall amount, rainfall intensity), whereas box plots were created with categorical variables (i.e., weekday, season/month, classification, SDPs).

Given that the 15 areas serve as a sample that could potentially capture the behavior of the wastewater flow at the system scale, and in order to account for the spatial and temporal attributes, we applied RE regression based on panel data procedure (Frees 2004). Panel data is defined as a data set, in longitudinal format, that contains repeated observations of subjects over multiple time periods (Frees 2004; Polebitski and Palmer 2010). For this work, the subjects (i.e., spatial unit) are areas, and the repeated observations are changes in daily wastewater flow and influential factors (socio-technical determinants and SDPs) within each area over days (i.e., temporal unit) throughout the period of data record. The original pooled data set (i.e., 654 records) was thus transformed to a panel data set with 9,810 records. The RE regression model allows the intercept to vary across the spatial units when estimating the regression coefficients and is assumed to be a random variable that is uncorrelated with the explanatory variables (Polebitski and Palmer 2010)—see Eq. (1):

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

where S is the total number of spatial units (areas), T is the total number of temporal units (days) in the panel data, N is the number of influential factors, Y_{st} is the observed water demand for spatial unit s at temporal unit t , μ is the population mean, α_s is the unobserved spatial (area)-specific heterogeneity, X is the vector of influential factors (i.e., aforementioned socio-technical determinants, SDPs), β is the vector of estimated parameters, and ε_{st} is the error term. Given the incorporation of spatial and temporal attributes into coefficient estimates as well as the separation of area-specific effects from the error term, RE regression generates more reliable parameter estimates than a typical pooled OLS model (Polebitski and Palmer 2010). Important to note, fixed effects were tested, but results verified that random effects were instead needed for modelling our data given that the areas represented a sample of the population area (Hausman and Taylor 1981). To assess model fit, we used the coefficient of determination R^2 . Notably, 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 Results and Descriptive Statistics

Table 1 shows the descriptive statistics for the wastewater flow across the 15 areas. Almost half of the average total wastewater flow is concentrated in three areas—*Area 1*, *Area 2*, and *Area 15* (see Table 1). The average maximum air temperature is over 80 [°F], whereas the rainfall amounts range between 0.08 and 0.1 [in], reflecting the city’s typically long, hot summers and mild winters.

Table 1. Descriptive statistics for wastewater flow (in MGD) and customer classification across the areas

Variable	Customer Classification	Mean $\pm$ Std. Deviation	Median	Interquartile Range
<i>Area 1</i>	Mostly residential	15.16 $\pm$ 4.18	13.92	3.59
<i>Area 2</i>	Mostly residential	12.59 $\pm$ 1.61	12.35	1.45
<i>Area 3</i>	Mostly residential	5.38 $\pm$ 1.23	5.40	0.85
<i>Area 4</i>	Mixed residential-nonresidential	6.19 $\pm$ 2.27	5.49	2.03
<i>Area 5</i>	Mixed residential-nonresidential	3.00 $\pm$ 0.37	2.93	0.31
<i>Area 6</i>	Mostly residential	1.45 $\pm$ 0.26	1.40	0.17
<i>Area 7</i>	Mostly residential	3.41 $\pm$ 0.67	3.20	1.00
<i>Area 8</i>	Mostly nonresidential	3.23 $\pm$ 0.58	3.27	0.81
<i>Area 9</i>	Mixed residential-nonresidential	3.70 $\pm$ 1.27	3.28	0.61
<i>Area 10</i>	Mostly residential	3.42 $\pm$ 0.52	3.34	0.31
<i>Area 11</i>	Mixed residential-nonresidential	6.70 $\pm$ 1.33	6.45	0.90
<i>Area 12</i>	Mostly residential	7.91 $\pm$ 1.80	7.34	1.45
<i>Area 13</i>	Mostly residential	4.31 $\pm$ 0.45	4.30	0.57
<i>Area 14</i>	Mostly nonresidential	2.40 $\pm$ 0.58	2.21	0.53
<i>Area 15</i>	Mostly residential	22.87 $\pm$ 3.80	21.73	2.96

The initial scatter plots show linear relationships between the wastewater flow and “1-day lag flow” and “maximum air temperature”, whereas a logarithmic decay is likely shown with the “average daily flow”. However, no relationships are observed between wastewater flow and the “rainfall amount” and “rainfall intensity”; therefore, we excluded these two factors. The box plots show variability among the various levels of the categorical variables—i.e., “weekday”, “classification”, “SDPs”—except for the “season”. Therefore, to account for possible seasonal variations in flow, we used “month” instead of “season”, as more variability is shown among the 12 months of a year.

RE Regression Wastewater Flow Model

The wastewater flow was skewed to the right, so we adjusted it for normality using the Box-Cox transformation (Box and Cox 1964) prior to developing the RE regression model. No collinearity issues were found across the socio-technical determinants and SDPs. Table 2 summarizes the RE regression analysis. Regarding determinants of categorical data type (e.g., SDPs, weekday, month, classification), it should be noted that the RE regression 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*. The parameter estimates of the SDPs’ levels in the RE model (see Table 2) are relative to the reference level *Non-enactment of SDPs*. The three reopening phases show statistically significant relationships with the wastewater flow at 1% significance level. During the *Stay Home-Work Safe*, on the other hand, a

negative change in wastewater flow is detected by the model (see Table 2) but was statistically insignificant in relation to this SDPs period. These results are likely attributed to the fact that the decrease in nonresidential wastewater flow (e.g., commercial, institutional) and increase in residential flow have offset the change at the system scale. These findings in regard to residential-nonresidential variations, explored through the wastewater flow, underscore behavioral changes in water demand at sub-system spatial scales. This water demand behavior has also been confirmed by a recent investigation on water demand changes, exploring that many U.S. water utilities that saw no significant change in overall demand during social distancing attributed that to a shift between customer classes (Spearing et al. 2020). Our discussion demonstrates how the assessment of SDPs' impacts on wastewater flow can provide an insight into water system's demand behavioral changes in response to these SDPs.

When businesses began to operate at increasing capacity—upon the enactment of *Reopening Phase 1* and *Reopening Phase 2*—statistically significant positive changes in wastewater flow occurred at the system scale (see Table 2). Compared to non-enactment of SDPs, this still likely represents an increase in residential flow and a decrease in nonresidential flow, due to a majority of the population continuing to work from home and businesses not being fully operational. The model detected the net effect of these various changes to be a statistically significant, though marginal, positive changes in total flow—estimated at 0.004-0.007 MGD (i.e., 15-26.5 cubic meter per day (m^3D^{-1})) (see Table 2). While these flow changes at the system scale may not seem critical from an operational perspective (compared to an average daily flow of over 100 MGD), they further emphasize behavioral changes in wastewater flow at sub-system spatial scales. These underlying spatial changes in flow serve as an indicator of sub-system spatial changes in water demand, requiring utilities to closely investigate any potential operational and water quality issues across areas within the water infrastructure system. During *Reopening Phase 3*, the net effect of the underlying sub-system spatial changes in wastewater flow is a statistically significant negative change at the system scale, estimated at 0.0015 MGD (i.e., $5.7 \text{ m}^3\text{D}^{-1}$), with respect to the non-enactment of SDPs; the magnitude of this change is marginal too.

Regarding the control variables, the relationships between the wastewater flow and “1-day lag”, “average daily flow”, and “maximum air temperature” are statistically significant at 1% significance level. For instance, a statistically significant negative change in wastewater flow in response to increase in the average daily flow is shown, aligning with the literature (e.g., Fernandez et al. 2009). Results also show (1) statistically significant decrease in wastewater flow during weekends (i.e., Saturdays and Sundays) relative to Mondays' wastewater flows; and (2) no statistically significant changes in flows across weekdays, except for on Wednesdays. These findings align with the literature (e.g., Fernandez et al. 2009), exploring a decrease in the flow during the weekends and almost constant flow rates during the weekdays. Our results also show statistically significant seasonal changes in flow across the majority of months, indicating the largest shift in May (i.e., spring) relative to January's flow. Notably, statistically insignificant levels of categorical variables—such as levels *MN-11* (i.e., November) and *MN-12* (i.e., December) of the “month” variable—are retained in the model specification. This is because the

exclusion of a categorical variable's insignificant levels would change the reference level and its interpretation (Harrell 2015). Additionally, excluding insignificant independent variables would lead to biased estimates for regression coefficients and inflated p -values (Harrell 2015).

Table 2. RE regression results for wastewater flow model ^a

Variable	β_i [10^{-5} MGD]	Std. Error [10^{-5} MGD]	z	p
<i>intercept</i>	19,755	635.59	31.08	0.000***
Independent variables: Social Distancing Policies				
<i>SDPs-2</i> (i.e., Stay Home-Work Safe)	-37.03	84.08	-0.44	0.66
<i>SDPs-3</i> (i.e., Reopening Phase 1)	712.63	126.66	5.63	0.000***
<i>SDPs-4</i> (i.e., Reopening Phase 2)	407.63	121.58	3.35	0.000***
<i>SDPs-5</i> (i.e., Reopening Phase 3)	-147.05	40.08	-3.67	0.000***
Control variables: Socio-technical Determinants				
<i>LF</i>	77,124	643.21	119.90	0.000***
Log (<i>ADF</i>) ^b	-3,759	135.18	-27.81	0.000***
<i>MT</i>	28.15	2.04	13.78	0.000***
<i>MN-2</i> (i.e., Feb)	-213.23	106.68	-1.99	0.045*
<i>MN-3</i> (i.e., Mar)	-518.66	102.63	-5.05	0.000***
<i>MN-4</i> (i.e., Apr)	-840.32	104.77	-8.02	0.002**
<i>MN-5</i> (i.e., May)	-1,789.4	117.26	-15.26	0.000***
<i>MN-6</i> (i.e., Jun)	-1,003.6	107.31	-9.35	0.000***
<i>MN-7</i> (i.e., Jul)	-645.27	111.43	-5.79	0.000***
<i>MN-8</i> (i.e., Aug)	-657.81	115.20	-5.71	0.000***
<i>MN-9</i> (i.e., Sep)	-786.74	107.09	-7.35	0.000***
<i>MN-10</i> (i.e., Oct)	-294.53	98.54	-2.99	0.003**
<i>MN-11</i> (i.e., Nov)	50.50	94.48	0.53	0.59
<i>MN-12</i> (i.e., Dec)	144.70	93.05	1.55	0.12
<i>WD-2</i> (i.e., Tues)	71.53	60.43	1.18	0.24
<i>WD-3</i> (i.e., Wed)	-119.30	60.37	-1.98	0.048*
<i>WD-4</i> (i.e., Thurs)	-22.91	60.36	-0.38	0.7
<i>WD-5</i> (i.e., Fri)	85.68	60.52	1.42	0.16
<i>WD-6</i> (i.e., Sat)	-224.45	60.60	-3.71	0.000***
<i>WD-7</i> (i.e., Sun)	-248.70	60.48	-4.11	0.000***
<i>CL-2</i> (i.e., mostly residential)	195.99	136.02	1.44	0.15
<i>CL-3</i> (i.e., mostly nonresidential)	174.77	197.45	0.88	0.38

Note: *LF* = 1-day lag of wastewater flow, *ADF* = average daily flow, *MT* = maximum air temperature, *MN* = month, *WD* = weekday, *CL* = classification, *SDPs* = social distancing policies.

^a RE regression analysis. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Model information: Total sum of squares = 20.061; Residential sum of squares = 2.486; $R^2 = 0.88$; Adjusted $R^2 = 0.88$; Chi-squared statistic = 69,051.4; $p = 0.000^{***}$.

^b Logarithmic decay relationship between the wastewater flow and ADF.

STUDY CONTRIBUTIONS

This study contributes to the existing body of knowledge through proposing a new approach for understanding the water system's demand behavioral changes due to pandemic-induced SDPs, considering spatiotemporal changes in wastewater flow. Our analyses revealed that these water-wastewater data interdependencies can be leveraged by researchers to examine the changes in water demand behaviors in response to policy interventions, considering the impacts on wastewater flow. Such an advancement, in turn, contributes to pandemic planning literature in regard to water sector infrastructure services. Additionally, by considering spatiotemporal changes in water demand, this study contributes to practice through better informing emergency responses to pandemics in regard to water infrastructure planning, management, and operations. Building off of our empirical use of water-wastewater data interdependencies, utilities are better equipped to adequately respond to potential system vulnerabilities and provide resilient water sector services, especially in contexts with limited access to high-granular, real-time water demand data.

CONCLUSION

COVID-19 SDPs enacted worldwide to slow the spread of the virus have led to spatiotemporal shifts in water demand, creating potential operational and water quality vulnerabilities in water infrastructures. Understanding these variations is especially challenging in contexts with limited availability of smart meter infrastructure. In this study, we propose the use of wastewater flow as a proxy to understand demand changes in response to active SDPs. More specifically, this study assesses the impacts of SDPs on wastewater flow in an urban metropolitan city in Texas, while controlling for the effects of various socio-technical determinants. Our findings further demonstrate how understanding such wastewater flow variations can provide an insight into water system's demand behavioral changes during SDPs, enabling better-informed strategies for providing communities with continuous water sector services.

Future research avenues could include: (1) incorporating peak flows—e.g., peak wet weather flow and peak dry weather flow—under the technical dimension, and (2) identifying possible influential factors within other dimensions of the wastewater flow's operating environment (e.g., financial and institutional). Similar to the authors' ongoing research, such efforts can explore these factors' effects on the flow model estimates, and on our understanding to SDPs' impacts on spatiotemporal water demand variations in times of pandemics.

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