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Leveraging water-wastewater data interdependencies to understand infrastructure systems’ behaviors during COVID-19 pandemic

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ABSTRACT

Social distancing policies (SDPs) implemented worldwide in response to COVID-19 pandemic have led to spatiotemporal variations in water demand and wastewater flow, creating potential operational and service-related quality issues in water-sector infrastructure. Understanding water-demand variations is especially challenging in contexts with limited availability of smart meter infrastructure, hindering utilities’ ability to respond in real time to identified system vulnerabilities. Leveraging water and wastewater infrastructures’ interdependencies, this study proposes the use of high-granular wastewater-flow data as a proxy to understand both water and wastewater systems’ behaviors 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-safe, reopening phases) using daily flow data gathered between March 19, 2019, and December 31, 2020. Results indicate an increase in residential flow that offsets a decrease in nonresidential flow, demonstrating a spatial redistribution of wastewater flow during the stay home-work safe period. Our results show that the three reopening phases had statistically significant relationships to wastewater flow. While this yielded only marginal net effects on overall wastewater flow, it serves as an indicator of behavioral changes in water demand at subsystem spatial scales given demand-flow interdependencies. Our assessment should enable utilities without smart meters in their water system to proactively target their operational response during pandemics, such as (1) monitoring wastewater-flow velocity to alleviate potential blockages in sewer pipes in case of decreased flows, and (2) closely investigating any consequential water-quality problems due to decreased demands.

1. Introduction

As the 2019 novel coronavirus (COVID-19) spread worldwide, governments enacted a number of measures for its containment, such as lockdown, social distancing recommendations, 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) (Balacco et al., 2022a), as well as the traditional underlying consumption dynamics (e.g., delayed morning peaks) (Balacco et al., 2020). Given water and wastewater systems’ interdependencies (Faust et al., 2017)—i.e., bidirectional relationships and influences between both infrastructures (Rinaldi et al., 2001)—such SDPs can also lead to wastewater-flow variations. This is due to the fact that water used by various customer classes (e.g., residential, nonresidential) within a community constitutes a significant portion of wastewater flowing into the wastewater infrastructures before entering the treatment plants (Grigg, 2012; Malik et al., 2015); other wastewater sources include toilets sewage, as well as stormwater in some communities (NSFC, 1997). Treated wastewater is then discharged as effluent into receiving natural water resources (National Institute of Standards and Technology, 2015).

Water utilities need to understand these spatiotemporal changes in their demands-flows and consequential impacts on the technical performance of water-sector (water and wastewater) infrastructure to identify and adequately respond to system vulnerabilities (Cooley et al., 2020). For instance, sudden spatiotemporal water-demand changes can exacerbate existing and reveal new operational issues, such as reduced pressure, increase in pipe breaks, or 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). This stagnation could reduce disinfectant residuals, leading to health risks (Gleick, 2020) if flushing operations are not implemented or the system is not well-looped (National Research Council, 2007). From a wastewater-flow perspective, sudden spatiotemporal flow changes may impact influential characteristics, as well as introduce capacity risks and costs (Zhang et al., 2019). Changes in flow quality, for instance, could influence treatment operation results and have consequential environmental risks, such as the quality of natural water resources (Malik et al., 2015). On the other hand, a decrease in wastewater flow may cause blockages in the sewer pipes due to a decrease in flow velocity (WGI, 2015). On the other hand, a decrease in wastewater flow may cause blockages in the sewer pipes due to a decrease in flow velocity (WGI, 2020). In this regard, insufficient flow velocities can increase retention time within the pipes, resulting in undesirable sedimentation of solid particles (WGI, 2020).

A recent investigation of U.S. water utilities, however, show that more than 20% of utilities were not proactive in responding to potential pandemic-related operational and service-quality issues due to lack of information or demand data availability (Spearing et al., 2020). Even though many municipalities and water utilities have been recently investing in smart meter infrastructure to acquire near, real-time water-demand data (Berglund et al., 2020), unfortunately, the implementation is still limited to date (Pesantez et al., 2020). This leaves many utilities with account-level demand data that corresponds to billing cycles collected at monthly or quarterly intervals to inform their water-demand analyses (Pesantez et al., 2020), and as such, delayed information on changes in water-sector use behavior. 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. If wastewater infrastructure system is metered, though, wastewater-flow data could fill this gap in regard to water-demand data availability given the water and wastewater systems’ interdependencies (Faust et al., 2017), such as the case presented here. In this study, to enable utilities lacking smart meter infrastructure to understand both water and wastewater infrastructures’ behavioral changes during SDPs, we propose an integrated approach that leverages demand-flow data interdependencies. Specifically, we focus on one dependency, that is, the use of wastewater-flow data to inform water-demand changes.

1.1. Existing efforts on pandemic-induced wastewater-flow changes

Wastewater-flow volume is often measured by sensor-based wastewater-flow meters in many utilities—each serves a certain geographic area across the network—and captured at various temporal granularity levels (e.g., hourly, daily) (Zhang et al., 2019). Utilities often use flow volume 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; 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).

Prior to COVID-19 pandemic, there was a dearth of pandemic-focused literature for various sectors (Roldi et al., 2020; Spearing et al., 2020). Indeed, the pandemic highlighted gaps in literature and practice regarding the implications across the water sector, spurring research efforts. For wastewater specifically—of interest to this study—existing COVID-19 focused research has focused mainly on the use of wastewater as a transmission means to detect outbreaks in communities (e.g., Li et al., 2021; Mota et al., 2021; Saguti et al., 2021). Li et al. (2021), for example, tracked the daily dynamics of COVID-19 virus in the wastewater from two wastewater treatment plants in Honolulu. They observed inter-day fluctuations during a rapidly expanding COVID-19 outbreak, with a significant decrease as a result of the lockdown put in place to control the outbreak. Another study based in Brazil (Mota et al., 2021) monitored sewers to identify hotspots of COVID-19 infections across a large city. Similarly, in Sweden, Saguti et al. (2021) discovered peaks of COVID-19 virus in the wastewater preceding those of hospitalized patients with COVID-19. Other work (e.g., Keshaviah et al., 2021; Venugopal et al., 2020) has focused on wastewater surveillance technologies for enabling such viral detections. Keshaviah et al. (2021), for instance, developed a dynamic national wastewater surveillance system coupled with its enabling environment, including coordination across entities involved with surveillance, government funding, and policymaking. Aside from the focus on wastewater monitoring and detection technologies, researchers have also investigated disinfection technologies of wastewater during COVID-19 to reduce the health risks to the public and environment (e.g., Gheraout and Elboughdiri, 2020; Wang et al., 2020). To the best of authors’ knowledge, researchers have yet to analyze wastewater-flow variations for the identification and understanding of both water and wastewater infrastructures’ operational constraints and water-sector service-related quality issues.

1.2. 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 context, 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. To better understand the water and wastewater systems’ behavioral changes in response to SDPs, sudden shifts in wastewater flow must be assessed with the consideration of the infrastructures’ operating environment (Bakchan et al., 2020, 2021, 2022b; 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, wastewater flow is affected by numerous factors (Shakeri et al., 2021; Zhang et al., 2019)—referred hereafter to as socio-technical determinants—that span these socio-technical dimensions. Such determinants include flows during previous days (within the technical dimension), climate (environmental), and customer classes (social). Storm events, for example, contribute to flow variability 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, wastewater flow may vary across geographic areas due to differences in water-demand patterns across customer classes (Zhang et al., 2019) (e.g., residential, commercial) and typically exhibit different patterns across the days of the week (Fernandez et al., 2009; Zhang et al., 2019). These spatial and time trends are referred to as spatial and temporal effects in wastewater flow. 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 wastewater flow—i.e., changes in longitudinal flow.

1.3. Purpose and research questions

This study seeks to answer two questions: In times of a pandemic, what changes in wastewater flow occur during imposed SDPs, considering socio-technical determinants and spatial and temporal effects in flow? How can assessing these flow variations contribute to understanding water-demand changes in response to SDPs? Our study is enabled by a random effects (RE) model of daily wastewater flow gathered between 2019 and 2020 in an urban metropolitan city in Texas. The analysis explores the effects of various COVID-19 SDPs that have been enacted between March 19, 2020, and December 31, 2020.
Our discussion demonstrates how the assessment of these impacts can provide an understanding of both water and wastewater systems’ demand behaviors during active SDPs. By filling such data gaps, resource-constrained utilities—especially those lacking smart meter infrastructure that can provide near, real-time water-demand data—can proactively plan for an adequate response to potential vulnerabilities in water-sector systems during pandemics. By empirically using water-wastewater data interdependencies, our study should inform emergency response plans for pandemics in regard to water-sector infrastructure, considering demand-flow spatiotemporal variations. The development of such response plans has been high on the majority of U.S. utilities’ agendas, as they were lacking prior to COVID-19 (AWWA, 2020).

2. Materials and methods

2.1. Operating environment of wastewater flow

Our assessment of SDPs’ impacts on the spatiotemporal wastewater flow considers the infrastructures’ environmental, institutional, financial, and social aspects. Our approach (1) captures the spatial and temporal effects in wastewater flow by incorporating the spatial and temporal-based variations into the model specification (Frees, 2004) (further discussed in the Regression Analysis section) and (2) uses such flow assessment to explore water-demand and wastewater-flow behavioral changes in times of SDP intervention. To identify the various socio-technical determinants of temporal wastewater-flow patterns, we turned to wastewater-flow modelling and forecasting literature (see Table 1). Given water-wastewater systems’ interdependencies, we also turned to water-demand modelling and forecasting literature to identify additional socio-technical determinants (see Table 1). Important to note, our approach captures the spatial and temporal effects in wastewater flow via a random-effects regression model (Frees, 2004). More specifically, various location-specific variables exist within the social dimension, which may impact water-demand variations and consequentially wastewater-flow variations. Such variables include household characteristics (e.g., household size, housing typology) (Donkor et al., 2014; House-Peters and Chang, 2011), socio-demographics (e.g., age, gender, race, income) (Miller and Buys, 2008; Randolph and Troy, 2008), social capital (e.g., voter turnover, norms) (Aldrich and Meyer, 2015; Bisung et al., 2014), and water conservation technological measures (e.g., low-flow fixtures and appliances) (House-Peters and Chang, 2011; Williamson et al., 2002). In the context of pandemic-induced policies, such variables also include percentage of commuters (incoming, outgoing) (Balacco et al., 2020). While our study does not incorporate these variables as controls explicitly, the RE regression analysis does inherently capture their effects via the area-based intercepts, i.e., random-effects (Polebitski and Palmer, 2010) (further discussed in the Regression Analysis section).

2.2. Study site and data collection

To demonstrate our proposed approach, this study focuses on a wastewater-flow network in an urban metropolitan city in Texas. The city has been experiencing economic and population growth. As of July 2021, the population has increased by around 2% during one-year-period, primarily attributed to the growing number of businesses (Census Bureau, 2022). This growth has led to an increase in non-residential water demand (e.g., commercial).

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 various SDPs 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. During this period, COVID-19 quarantine restrictions were enforced in Texas cities (DHSH, 2020).

Table 1: Socio-technical determinants of temporal wastewater-flow patterns identified from literature.

| Socio-technical Determinant | Explanation/Reference |
|----------------------------|-----------------------|
| **Technical**              |                       |
| Average daily flow         | Assessed by averaging all flows in a given year (Mines et al., 2007) |
| Previous wastewater flow   | Wastewater flow depends on its past values (Fernandez et al., 2009; Zhang et al., 2019); e.g., daily wastewater flow correlates with the values for the previous day (i.e., 1-day lag) (Fernandez et al., 2009) |
| **Environmental**          |                       |
| Maximum air temperature    | Increases in maximum air temperature may increase wastewater flow; this is due to potential increase in water use (e.g., showering), which may consequently lead to wastewater-flow variations (Bougadis et al., 2005; Goodchild, 2003; Zhou et al., 2006) |
| Rainfall amount            | Increases in wastewater-flow rate when there is increasing rainfall volume (El-Din and Smith, 2002; Wei et al., 2013; Zhang et al., 2019) |
| Rainfall intensity         | Moderate to high correlations between wastewater flow and rainfall amount (Mines et al., 2007) |
| **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**                 |                       |
| Customer classification    | Wastewater flow may vary across geographic areas due to differences in water-demand patterns across customer classes (e.g., residential, commercial) (Burney et al., 2001; Zhang et al., 2019) |
| 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; Romano et al., 2016), especially without changes in water use efficiency and conservation policies |
|                          | Changes in water demand consequentially impact wastewater-flow variations, given these systems’ interdependencies (Zhang et al., 2019) |
The stay home-work safe order was followed by general multi-phase reopening (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. 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—referred to hereafter as Stay Home-Work Safe, Reopening Phase 1, Reopening Phase 2, and Reopening Phase 3.

Our study analyzes wastewater-flow variations between March 19, 2019, and December 31, 2020, allowing for one-year of data prior to the enactment of SDPs on March 19, 2020. Important to note, at the time of data collection, smart meters were not implemented within the water infrastructure system in the study site; instead, the water billing data has been collected and reported at a monthly timescale. For this reason, we turned to wastewater-flow data—available at higher temporal and spatial resolutions—to better understand water-demand and wastewater-flow changes, serving as a promising case to demonstrate our approach in regard to leveraging water-wastewater data interdependencies.

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 wastewater-flow time series data at 5-min, 15-min, and daily temporal resolutions (given in million gallons per day [MGD])—disaggregated at the area scales that are served by these flow meters. The daily wastewater-flow data was used for regression model development to understand the system’s behavior on a daily basis due to policies, whereas the 15-min flow data was used to understand the spatial effects from regression results (further discussed in the Regression Analysis section). To determine the appropriate sample for model development, we first examined the data completeness of the entire daily data set (i.e., no date gaps) and only considered areas with complete data records. Subsequently, we conducted data quality assessment using these areas’ 5-min resolution flow data. In this regard, we inspected each of these meters’ wastewater-flow quarterly hydrographs for all quarters over the period of analysis and assessed corresponding flow measures—i.e., minimum, maximum, and average flows. Accordingly, we excluded areas with flow data that do not lie within their expected flow measures and not associated with specific events that may cause technically feasible variations (e.g., flow peaks due to rain events). This process yielded a sample of 15 areas that have complete, high quality flow data. We further examined these 15 areas’ spatial distributions across the network, confirming that they are widely distributed across the network (see Fig. 1). Using the wastewater-flow time series data, we assessed the average daily flow within the two years—prior to (March 19, 2019–March 18, 2020) and during the enactment of SDPs (March 19, 2020–December 31, 2020).

The customer classification of wastewater flow breakdown for the various areas—i.e., residential versus nonresidential—were also 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 area and averaged (NOAA, 2020). The rainfall data, on the other hand, were gathered from the platform that the local water utility uses to obtain more accurate rainfall data at the flow meter basin scale.

We excluded the “water conservation policy” determinant, as there were no changes to allowed outdoor watering schedules throughout the study period; the latest changes to the conservation stage were made in 2016. We also excluded the “population” and “water price” determinants. According to the literature (Burney et al., 2001; Levin et al., 2006; Miaou, 1990; Mohamed and Al-Mualla, 2010), these two 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 to 30 years (Donkor et al., 2014). Given that we are exploring possible behavioral changes in water demand and wastewater flow at the system-daily spatiotemporal scale over a relatively short-range time period (2 years), we excluded both “population” and “water price” determinants. Also, important to note, the water price did not change throughout the study period.

2.3. Regression analysis: Model structure and estimation

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). Further, 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, 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 control for the spatial and temporal effects in flow, 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 has similar basic form as the typical OLS regression, except that the intercept is allowed 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):

$$Y_{st} = \alpha_s + \sum_{i=1}^{N} X_{st,i} \beta_i + \epsilon_{st}; \text{ with } s = 1, 2, \ldots S; \text{ and } t = 1, 2, \ldots T$$

(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 wastewater flow for spatial unit $s$ at temporal unit $t$, $\alpha$ is the unobserved spatial (area)-specific heterogeneity, $X$ is the vector of influential factors (independent variables: SDPs; control variables: socio-technical determinants), $\beta$ is the vector of estimated parameters, and $\epsilon$ is the error term. Given the incorporation of spatial and temporal effects into coefficient estimates as well as the separation of area-specific effects from the error term, RE regression generates reliable parameter estimates (Polebitski and Palmer, 2010). Important to note, a fixed effects regression model—i.e., fixed parameters assigned to each spatial unit to account for variability—was also developed, but results verified that random effects were instead needed for modelling our data (Hausman and Taylor, 1981). These results confirm that the sample of 15 areas is sufficient to capture the wastewater infrastructure system’s behavior; this is an important improvement of the panel data approach to temporal econometric water-sector demand analysis by incorporating both temporal and subject-based variability into coefficient estimates (Frees, 2004; House-Peters and Chang, 2011). To assess model fit, we used the coefficient of determination $R^2$. Notably, we performed all statistical analyses using R version 1.3.1093 (Core Team, 2020) and various supporting packages (e.g., tidyverse, gplots, lmtest, plm, seastests, bestNormalize).

To better understand the spatial effects from the regression results, we plotted the flow diurnal patterns during SDPs to those prior to SDP enactment using 15-min flow data (see Fig. 2). We chose two dry weeks (i.e., no precipitation) to exclude possible spikes in flow from storm events throughout the various seasons.

3. Results

3.1. Exploratory analysis and descriptive statistics

Table 2 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 2). The average maximum air temperature is over 80 $^\circ$F, whereas the rainfall amounts range between 0.08 and 0.1 [in], reflecting the city’s

![Fig. 2. Comparison of wastewater diurnal patterns—prior to and during SDPs—across weekdays for select areas within different customer classification groups (15-min data granularity).](image-url)
shown with the is likely attributed to sewer pipes across the 15 referenced flow meters as wastewater flow, in the context of modelling and results. Further, no statistics of wastewater flow (Table 2) is also presented in the relative to a reference level. For instance, the season not having major I/I contributions. The box plots indicate variability between wastewater flow and the relation matrix). RE regression model. Henceforth, we refer to this transformed variable transformed using the Box-Cox transformation (Box and Cox, 1964) typically long, hot summers and mild winters. Notably, descriptive statistics for wastewater flow (Table 2) is also presented in the Table S3 in the Supporting Information. The wastewater flow was heavily skewed to the right, so it was transformed using the Box-Cox transformation (Box and Cox, 1964) (\(\lambda = -0.24\)) to meet the distributional (normality) assumptions of the RE regression model. Henceforth, we refer to this transformed variable as wastewater flow, in the context of modelling and results. Further, no collinearity issues were found across the socio-technical determinants and SDPs (refer to Table S1 in the Supporting Information for the correlation matrix).

From exploratory analysis, 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” (see Fig. S1 in the Supporting Information). However, interestingly, no relationships are observed between wastewater flow and the “rainfall amount” and “rainfall intensity” for our data set; therefore, we excluded these two factors. This is likely attributed to sewer pipes across the 15 referenced flow meters not having major L/I contributions. The box plots indicate 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 (see Fig. S2 in the Supporting Information).

### 3.2. RE regression wastewater flow model

Table 3 summarizes the RE regression analysis; for the random effects of the 15 areas, see Table S2 in the Supporting Information. 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 (Fernandez et al., 2009). Regarding determinants of categorical data type (e.g., weekday, month, classification, SDPs), it should be noted that the RE regression model assesses parameter estimates for the levels of the categorical variables relative to a reference level. For instance, the “weekday” determinant has seven levels: WD–1 (i.e., Monday) to WD–7 (i.e., Sunday); the parameter estimates of the levels WD–2 to WD–7 in the RE model are relative to WD–1 (see Table 3). Similarly, the reference levels for the “month” and “classification” determinants are MN–1 and CL–1, respectively (see Table 3). Results show (1) statistically significant decrease in wastewater flow during weekdays (i.e., Saturdays and Sundays) relative to Mondays’ wastewater flows; and (2) no statistically significant changes in flows between weekdays, except for on Wednesdays. In this regard, a statistically significant decrease in Wednesday flow. These findings align with the literature (Fernandez et al., 2009), exploring a decrease in the flow levels in the RE model (see Table 3) are relative to the reference level Non-enactment of SDPs.

### 4. Discussion

#### 4.1. Changes during stay home-work safe period

During the Stay Home-Work Safe period, on the other hand, a negative change in wastewater flow is detected by the model (see Table 3) but was statistically insignificant in relation to this SDPs period. These

### Table 2

| Variable | Customer Classification | Mean ± Std. Deviation | Median | Interquartile Range |
|----------|-------------------------|-----------------------|--------|---------------------|
| Area 1   | Mostly residential      | 15.16 ± 4.18          | 13.92  | 3.59                |
| Area 2   | Mostly residential      | 12.59 ± 1.61          | 12.35  | 1.45                |
| Area 3   | Mostly residential      | 5.38 ± 1.23           | 5.40   | 0.85                |
| Area 4   | Mixed residential       | 7.19 ± 0.27           | 5.49   | 2.03                |
| Area 5   | Mixed residential       | 3.00 ± 0.37           | 2.93   | 0.31                |
| Area 6   | Mostly residential      | 1.45 ± 0.26           | 1.40   | 0.17                |
| Area 7   | Mostly residential      | 3.41 ± 0.06           | 3.20   | 1.00                |
| Area 8   | Mostly nonresidential   | 3.23 ± 0.58           | 3.27   | 0.81                |
| Area 9   | Mixed residential       | 3.70 ± 1.27           | 3.28   | 0.61                |
| Area10   | Mostly residential      | 3.42 ± 0.52           | 3.34   | 0.31                |
| Area11   | Mixed residential       | 6.70 ± 1.33           | 6.45   | 0.90                |
| Area12   | Mostly residential      | 7.91 ± 1.90           | 7.34   | 1.45                |
| Area13   | Mostly residential      | 4.31 ± 0.45           | 4.30   | 0.57                |
| Area14   | Mostly residential      | 2.40 ± 0.58           | 2.21   | 0.53                |
| Area15   | Mostly residential      | 22.87 ± 3.80          | 21.73  | 2.96                |

### Table 3

| Variable | \(\beta_{10}^{[10^{-5}]}\) | Std. Error \(\times 10^{-5}\) | z | p |
|----------|----------------------------|-----------------------------|---|---|
| intercept| 19,755.00                  | 635.59                      | 31.08 | 0.000*** |
| Independent variables: Socio-distancing policies |                      |                            |      |      |
| SDPs–2 (i.e., Stay Home–Work Safe) | -37.03                  | 84.08                      | -0.44 | 0.66 |
| SDPs–3 (i.e., Reopening Phase 1) | 712.63                   | 126.66                      | 5.63 | 0.000*** |
| SDPs–4 (i.e., Reopening Phase 2) | 407.63                   | 121.58                      | 3.35 | 0.000*** |
| SDPs–5 (i.e., Reopening Phase 3) | -147.05                  | 40.08                      | -3.67 | 0.000*** |
| Control variables: Socio-technical determinants |                      |                            |      |      |
| LF     | 77,124.00                   | 643.21                      | 119.90 | 0.000*** |
| Log (ADF) b | -3,759.00                  | 135.18                      | -27.81 | 0.000*** |
| MN–1  | 28.15                      | 2.04                       | 13.78 | 0.000*** |
| MN–2  | -213.23                    | 106.68                      | -1.99 | 0.045*  |
| MN–3  | -518.66                    | 102.63                      | -5.05 | 0.000**  |
| MN–4  | -840.32                    | 104.77                      | -8.02 | 0.002**  |
| MN–5  | -1,789.40                  | 117.26                      | -15.26 | 0.000*** |
| MN–6  | -1,663.60                  | 107.31                      | -9.35 | 0.000*** |
| MN–7  | -645.27                    | 111.43                      | -5.79 | 0.000*** |
| MN–8  | -657.81                    | 115.20                      | -5.71 | 0.000*** |
| MN–9  | -786.74                    | 107.09                      | -7.35 | 0.000*** |
| MN–10 | -294.53                    | 98.54                       | -2.99 | 0.003**  |
| MN–11 | 50.50                      | 94.49                       | 0.53  | 0.59    |
| MN–12 | 144.70                     | 93.05                       | 1.55  | 0.12    |
| WD–2  | 71.53                      | 60.43                       | 1.18  | 0.24    |
| WD–3  | -119.30                    | 60.37                       | -1.98 | 0.048*  |
| WD–4  | -22.91                     | 60.36                       | -0.38 | 0.70    |
| WD–5  | 85.68                      | 60.52                       | 1.42  | 0.16    |
| WD–6  | -224.45                    | 60.60                       | -3.71 | 0.000*** |
| WD–7  | -248.70                    | 60.48                       | -4.11 | 0.000*** |
| CL–2  | 195.99                     | 136.02                      | 1.44  | 0.15    |
| CL–3  | 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; Residual 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.
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. This flow behavior at the system scale is further supported by the flow patterns at a finer spatial resolution (see Fig. 2). Diurnal flow patterns across the various areas appeared to be affected by the imposed SDPs, especially during the Stay Home-Work Safe period (Fig. 2). For instance, in Area 1—a mostly residential area—a sizable increase (34% relative change) was seen in the flows throughout weekdays when SDPs were enacted, where the peak flow had increased from 16.5 to 22 MGD (see Fig. 2). Such increase in residential flow is likely attributed to people working from home in response to the work-from-home orders, as well as the surge for hygiene and cleaning practices for limiting the coronavirus spread (Kalbush et al., 2020). On the other hand, a sizable decrease occurred in the wastewater flow in Area 8—a mostly nonresidential area—likely due to business closures following the Stay Home-Work Safe order (Texas Department of Health Services, 2020); the peak flow relatively dropped by 47%, from 5 MGD prior to the enactment of SDPs to 2.7 MGD during SDPs (see Fig. 2). These wastewater-flow behavioral changes across Area 1 and Area 8 suggest a spatial redistribution of flow between customer classes (e.g., residential, nonresidential) following the Stay Home-Work Safe order. In Area 10—a mixed residential-nonresidential area—the diurnal flow patterns during SDPs were relatively similar to those prior to SDPs (see Fig. 2). The increase in residential flow had likely offset the decrease in nonresidential flow during the Stay Home-Work Safe period, resulting in a marginal change in flow. Such a system’s behavior has also been confirmed by a recent investigation (Spearing et al., 2020) on water-sector systems’ demands changes, exploring that many U.S. water utilities that saw no significant change in overall demand across a service area during social distancing attributed that to a shift between customer classes. From an operational perspective, even though there were no major flow changes experienced at the system scale, the behavioral flow changes at sub-system spatial scales may cause operational challenges across areas within the wastewater infrastructure system. For instance, in areas with reduced flows, blockages may occur in sewer pipes due to reduced flow velocity (WGI, 2020); this is something we might expect to see in commercial areas during a pandemic due to business closures in response to work-from-home orders. If blockages are determined in the main sewer line, utilities need to respond immediately to clear the blockages and avoid sewer backups. For the case of the study site, conversations with the utility’s operations manager have revealed that major sewer blockages were not experienced during the Stay Home-Work Safe period due to the spatial distribution of customer classes across the system. Even in mostly commercial areas, there are also residential customers who were generating wastewater flows throughout the pandemic, thereby preventing the reduction in flow velocity and sedimentation of solid particles in sewer pipes.

In addition to informing such operational response in regard to the wastewater system, these findings in regard to residential-nonresidential variations—explored through the wastewater flow—underscore behavioral changes in water demand at sub-system spatial scales. For instance, the flow reduction seen in certain areas may also indicate a reduction in water demand, requiring utilities to investigate any potential water-quality problems that may be associated with water stagnation (Cleik, 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. Such understanding to both water and wastewater behavioral changes enables utilities—especially those constrained by lack of information or water-demand data availability—to proactively target their operational response during pandemics.

4.2. Changes during reopening phases

As shown in Table 3, the three reopening phases show statistically significant relationships with the wastewater flow at 1% significance level. When some businesses were allowed 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 3). Compared to pre-pandemic, this still likely represents an increase in residential flow and a decrease in nonresidential flow, due to most of the population continuing to work from home and businesses not operating at full capacity. 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$^3$/D)) (see Table 3). 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. However, as with the case during Stay Home-Work Safe period, such flow variations 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, 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 enactment of SDPs, there has been still an increase in residential demand and a decrease in nonresidential demand. The net effect of these 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 m$^3$/D), with respect to the non-enactment of SDPs; the magnitude of this change is marginal too.

This analysis provided an insight into water and wastewater systems’ behavioral changes in response to SDPs by assessing the impacts of these SDPs on wastewater flow using flow data disaggregated by flow meter- area. This study emphasizes that high-resolution, timely data can reveal demand changes that would otherwise not be possible without it, further underscoring the need to expand the application of digital monitoring and operational technologies in the water sector. Such an implementation can provide access to water-demand and wastewater-flow data disaggregated by customer class (e.g., residential, commercial, industrial, institutional), potentially revealing new insights into water-wastewater data interdependencies. Better understanding such data interdependencies helps reduce the epistemic uncertainty around water-sector infrastructures’ demand changes during pandemics and other disruptive events.

To further support the urgent need for utility infrastructure investments, federal and state policy should address gaps in infrastructure funding to prioritize capital projects and infrastructure upgrades (Cooley et al., 2020; Spearing et al., 2020). Such funding would (1) enable proactive water infrastructure planning and operations during crises, such as COVID-19 and future pandemics, to ensure continuous service provision; and (2) help identify and address spatial discrepancies in the level of service, thereby enabling more equitable water-sector services.

5. Study implications and conclusions

5.1. Implications

The framing of pandemic-induced SDPs as population dynamics through a lens of integrated operating environments offers a means to empirically understand the temporal demand behavior of socio-technical water-sector infrastructures during pandemics. This research presents an integrated approach for understanding both water and wastewater systems’ behavioral changes due to pandemic-induced SDPs, considering spatial and temporal changes in wastewater flow. Our analyses demonstrated that these water-wastewater data interdependencies can be leveraged by researchers to examine changes in
water-demand behaviors. This is especially promising in contexts with limited access to high-granular, real-time water-demand data. Such an advancement, in turn, contributes to pandemic planning literature in regard to water-sector infrastructure services. By increasing infrastructure resilience through improved understanding of SDPs’ impacts on demand-flow variations, our approach contributes to global conversations on sustainable development (UN-CSD, 2012; UN-SDG, 2015).

Building off of our empirical use of water-wastewater data interdependencies, resource-constrained utilities are better equipped to adequately respond to potential system vulnerabilities and provide resilient water-sector services. To adapt to changing operating environments, such responses may include (1) operating wastewater treatment plants at reduced levels when flow drops to maintain operation results and costs efficiencies; or (2) monitoring wastewater-flow velocity to alleviate any potential blockages in the sewer pipes in case of decreased flows. From a water-demand perspective, utilities may (1) prioritize resource allocation based on demand-capacity management strategies in case of increased demands to maintain continuous service to critical customers (e.g., hospitals) during pandemics; or (2) operate water treatment plants at reduced production levels when demand drops.

5.2. Applicability and future research

The applicability of the proposed approach may be also extended to other infrastructure sectors (e.g., energy) or other types of extreme events (e.g., humanitarian crises, natural hazards, compounded disasters) that might trigger shifts in the population dynamics or operating environments to understand the impacts of policy interventions on infrastructures’ demand behavior. Our study also sets the stage to extend the limited literature on pandemic planning and population dynamics by conducting the assessment using case data in varying geographic contexts. Considering additional geographic contexts would provide more comprehensive understanding of how aspects of the operating environment impact the analysis of water-wastewater data interdependencies in times of policy interventions.

Our approach captures the spatial and temporal effects in wastewater flow via a RE regression model. Additional research is called for to incorporate time series analysis (e.g., ARIMA; Gardner et al., 1980) with RE regression—through hybrid modelling—to consider the inherent autocorrelation structure of a wastewater-flow pattern over time (Jain et al., 2001; Maidment and Parzen, 1984), thereby improving the performance of the assessment models. Future research could also consider the integration of schedules related to operational activities—such as possible operational changes in wastewater treatment plants during the imposed SDPs—in the temporal modelling. Such investigation could explore the impacts of these activities on wastewater flow and the feasibility of incorporating them as impacting factors within the technical dimension of the operating environment. Furthermore, future research efforts are needed to (1) incorporate peak flows—e.g., peak wet weather flow and peak dry weather flow—under the technical dimension, and (2) identify additional influential factors within the financial and institutional dimensions of the wastewater flow’s operating environment. 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. As researchers continue to improve our understanding of disasters-induced policies’ impacts on water-wastewater data interdependencies considering infrastructures’ operating environments, utilities will be able to implement better-informed strategies for providing communities with continuous water-sector services.

CRediT authorship contribution statement

Amal Bakchan: Conceptualization, Data collection & curation, Software, Model verification & validation, Visualization, Formal analysis, Writing – original draft, Writing – review & editing.

Araikajoti Roy: Software, Model verification & validation, Writing – review & editing.

Kasey M. Faust: Conceptualization, Model verification & validation, Writing – review & editing, Supervision, All authors have given approval to the final version of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2022.132962.

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