

Modeling SARS-CoV-2 RNA Degradation in Small and Large Sewersheds

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Water Impact Statement: Microbial decay in sewer collection systems poses a significant challenge for wastewater-based epidemiology (WBE) for COVID-19 among other diseases. This work facilitates the understanding of SARS-CoV-2 decay in small and large sewersheds and under various wastewater temperatures. With this information we proposed a novel approach to designing a reliable and sustainable sampling infrastructure for WBE.

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17	
18	Abstract
19	Wastewater-based epidemiology has played a significant role in monitoring the COVID-19
20	pandemic, yet little is known about degradation of SARS-CoV-2 in sewer networks. Here, we
21	used advanced sewershed modeling software to simulate SARS-CoV-2 RNA degradation in
22	sewersheds across Houston, TX under various temperatures and decay rates. Moreover, a novel
23	metric, population times travel time (PT), was proposed to identify localities with a greater
24	likelihood of undetected COVID-19 outbreaks and to aid in the placement of upstream samplers.
25	Findings suggest that travel time has a greater influence on RNA degradation across the
26	sewershed as compared to temperature. SARS-CoV-2 RNA degradation at median travel times

27	was approximately two times greater in 20°C wastewater between the small sewershed,
28	Chocolate Bayou, and the larger sewershed, 69th Street. Lastly, placement of upstream samplers
29	according to the PT metric can provide a more representative snapshot of disease incidence in
30	large sewersheds. This study helps to elucidate discrepancies between SARS-CoV-2 viral load in
31	wastewater and clinical incidence of COVID-19. Incorporating travel time and SARS-CoV-2
32	RNA decay can improve wastewater surveillance efforts.
33	
34	Keywords: COVID-19, Wastewater-based epidemiology, Coronaviruses, Decay, Travel time
35	
36	1. Introduction
37	
38	Municipal wastewater treatment plants collect untreated wastewater from communities ranging
39	from hundreds to millions of inhabitants per day within a given sewershed. This wastewater can
40	be scrutinized to obtain critical insights into biological and chemical markers that are reflective
41	of community health within the serviced population, an approach known as wastewater-based
42	epidemiology (WBE).
43	
44	In WBE, untreated wastewater is considered analogous to a population-wide urine and stool
45	sample. This representative sample can be used to evaluate community health and the prevalence
46	of certain diseases by directly measuring markers of concern. Viral monitoring in wastewater has
47	gained much attention considering that viruses do not replicate independent of a host cell and are
48	persistent in the environment. Several viral pathogens including hepatitis A virus, hepatitis E

virus, norovirus, sapovirus, astrovirus, and poliovirus have been monitored in wastewater for
community health tracking (1–5).

51

52 Recently, WBE has been recognized as a promising tool for tracking SARS-CoV-2, the causative 53 agent of Coronavirus Disease 2019 (COVID-19). SARS-CoV-2 is an enveloped positive-sense 54 RNA virus belonging to the *Coronaviridae* family. Although the primary transmission route of 55 SARS-CoV-2 is via respiratory droplets, evidence of fecal shedding of SARS-CoV-2 in infected 56 individuals has led to the global attention of WBE in the ongoing fight against COVID-19 (6). 57 Several studies have highlighted the potential for viral signals to precede clinical cases and 58 capture the extent of asymptomatic individuals that are not reported in health care facilities (7– 59 10).

Generally, evidence supports the utility of WBE as a public health and environmental tracking
tool for viral disease outbreaks. Still, in some cases discrepancies exist between viral signal in
wastewater and disease prevalence, specifically with SARS-CoV-2 (11).

63

64 Viral measurements from wastewater alone may not be sufficient for disease tracking. Considerations such as the environmental matrix, sampling regimen, sewer collection system, 65 viral stability, and disease characteristics are critical aspects to establishing correlations between 66 67 viral signal and disease incidence in the community (12). Among these critical considerations is 68 the stability of the virus and its genetic material in the sewershed. Microbial degradation plays a 69 significant role in determining what proportion of RNA shed in feces gets captured at the outfall 70 of a wastewater treatment plant (WWTP). To date, few studies have investigated RNA 71 degradation of SARS-CoV-2 in wastewater (13–16).

73 In two of the studies, temperature had a significant influence on variations between first-order 74 decay rates (11,13). Temperature was also found to have a greater impact on RNA degradation 75 than the sample matrix (15). Despite the agreement on the importance of temperature between 76 the two studies, Weidhaas et al., 2021 obtained a significantly higher decay constant (4.32 day^{-1}) 77 at 35°C than Ahmed et al., 2020 (0.24 day⁻¹) at 37°C for similar gene targets. This indicates that 78 there are other factors that have a notable influence on RNA degradation such as sample 79 preparation or wastewater composition. A recent study demonstrated that the abundance of the 80 SARS-CoV-2 N1 marker is associated with total organic carbon and pH (17). Furthermore, 81 Bivins et al. 2020 evaluated changes in decay constants when the starting viral titer was low as 82 compared to high titers. Low titers $(10^3 \text{ TCID}_{50} \text{ mL}^{-1})$ obtained a decay constant of 0.09 day⁻¹ at 83 20°C which was significantly lower than that of the high titer ($10^5 \text{ TCID}_{50} \text{ mL}^{-1}$) at the same 84 temperature, 0.67 day⁻¹.

85

86 From these studies it is evident that further work is needed to understand degradation of SARS-CoV-2 under various conditions. Moreover, only one study to date has explored degradation of 87 88 SARS-CoV-2 in sewer systems using a first-order decay rate derived from a study on the 89 infectivity of various coronaviruses in wastewater after 21 days (16,18). The authors found that 90 larger sewersheds further confound the effects of temperature on degradation. Indeed, it is 91 expected that longer travel times will create notable discrepancies between viral concentration 92 and COVID cases in communities. Furthermore, since upstream sampling provides high spatial 93 resolution and is more representative of the sampled population (16,19), the placement of 94 wastewater samplers in sewersheds remains an ongoing area of interest (20,21). Yet, to our

knowledge, no quantitative approaches for selecting upstream sampling locations to capture
outbreaks and minimize degradation of SARS-CoV-2 RNA have been proposed.

97

98 Upstream sampling refers to sampling within the sewer system from locations such as manholes, 99 as compared to sampling at the influent of a WWTP (downstream sampling). Several studies 100 have implemented upstream sampling for monitoring COVID-19 outbreaks in hospitals (22), 101 universities (23), and metropolitan neighborhoods (24). There are practical constraints that 102 dictate the selection of upstream sites, namely available resources, accessibility, and safety. 103 Moreover, sampling site selection based on travel time should be considered to further increase 104 the impact of upstream sampling on WBE outcomes.

105

106 Interestingly, Haak et al. 2022 found population density to be highly significant when comparing 107 SARS-CoV-2 RNA concentrations in wastewater between different neighborhoods within the 108 same sewershed. Though the effects of population density on SARS-CoV-2 stability in 109 wastewater are not fully understood, population density remains a significant factor in epidemics 110 and can facilitate the rate at which a disease disseminates within a community. A recent study 111 found population density to have a positive effect on the basic reproductive number (R_0) of 112 COVID-19 with R_0 increasing by an average of .11 when population density doubled (25). 113 Likewise, a study assessing the effect of several environmental and geographical factors on 114 COVID-19 cases found population density to be the best predictor of cases when looking at 81 115 provinces in Turkey (26). Consequently, the higher the population density, the more potential 116 there is for a disease outbreak. Considering its significance, population density can be a critical

117	component for identifying sampling locations based on potential hotspots for rapid disease
118	spread.
119	
120	Here, we model SARS-CoV-2 RNA degradation in sewersheds across Houston that vary in
121	service population and geographic area based on published and experimentally derived first-
122	order decay rates, wastewater temperature, and sewershed travel times. Finally, we propose a
123	novel metric for determining critical locations for placing upstream samplers to improve SARS-
124	CoV-2 monitoring in wastewater.
125	
126	2. Materials and Methods
127	
128	2.1. Study Area and Overview
129	
130	Houston has 39 sewersheds with a total service area covering approximately 1,451 km ² (358,580
131	acres). Of those, ten sewersheds were selected for this study based on the availability of
132	sewershed hydraulic models provided by Houston Public Works. The location and characteristics
133	of the selected sewersheds are detailed in Figure 1 and Table S1, respectively. Hydraulic
134	
	modeling was conducted to simulate performance metrics which were then used to compute
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135 136	modeling was conducted to simulate performance metrics which were then used to compute travel times for each sewershed. Multiple SARS-CoV-2 decay rates based on published and experimental studies were then used with the computed travel times to estimate viral RNA
135 136 137	modeling was conducted to simulate performance metrics which were then used to compute travel times for each sewershed. Multiple SARS-CoV-2 decay rates based on published and experimental studies were then used with the computed travel times to estimate viral RNA degradation in the sewersheds.



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- 140

Figure 1. Ten selected wastewater treatment plant service areas (sewersheds) are shown in blue.
Sims Bayou has overlapping service areas recognized as Sims Bayou North and South
sewersheds. The remainder of Houston's sewersheds are shown in green.

Sewershed Modeling

145 **2.2.**

146

Hydraulic modeling of sewersheds in this study was accomplished using the Infoworks ICM
software (ICM stands for Integrated Catchment Modeling). Developed by Innovyze®,
Infoworks ICM is a hydrodynamic model capable of simulating the hydrology and hydraulics

of aboveground surfaces as well as underground drainage networks based on the conservation
 of mass and momentum. Due to its robustness and versatility, Infoworks ICM has been used by
 numerous municipalities, like the City of Houston, for stormwater, flood control infrastructure,
 and sewer management.

154

155 In this study, Infoworks ICM models for ten sewersheds were obtained from the City of 156 Houston Public Works department. Each model represents the wastewater network and service 157 areas for a sewershed. The models were calibrated by Houston Public Works under dry and 158 wet weather conditions. At a minimum, two rainfall events are used for model calibration and 159 one event for verification. A previous study applied a similar approach using an Infoworks 160 ICM model and obtained strong correlations between observed and simulated water levels in a 161 pumping station during a rainfall event (27). Infoworks ICM provides separate solution 162 models for permeable planes, force mains, pressurized pipes or normal gravity flow. An ICM 163 model consists of a network of links and nodes, in which the links represent pipes or conduits, 164 and the nodes represent manholes or other control structures (e.g., outfall or WWTP). 165 Additionally, the model allows for either one or multiple outfall locations. Based on the 166 connectivity of the nodes and links, service areas that drain to any particular node could be 167 further separated into individual subcatchments. The gradient or slope of the link is calculated 168 using the provided starting and ending invert elevations.

169

170 ICM divides each conduit into a number of discrete computational points and regularly-spaced 171 segments with intervals that are 20 times the pipe diameter. Flow, velocity, and other 172 performance metrics are computed in each segment. Inflow can be added to certain nodes as point sources, but in this study, diurnal curves in the form of wastewater profiles with hourly
time steps were applied at corresponding subcatchments to represent wet and dry conditions.
With specified information of population and per capita flow, the wastewater profile can be
developed from a calibrated model and is designed to mimic dry weather flow as typically seen
during flow monitoring.

178

179

2.3. Computing Travel Time

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181 While various performance metrics such as head, flow, velocity, volume, and water depth are 182 computed by ICM, individual travel times for subcatchments are not. In a typical wastewater 183 system, the conduits are connected to a common outfall, which usually represents the local 184 WWTP. All model networks must have at least one common outfall, but networks are allowed to 185 have multiple outfalls which could represent wet-weather overflows, emergency bypasses, or 186 pump stations to a different wastewater system. Because there is not always a single common 187 outfall, a structured query language (SQL) script was developed to allow users to specify a 188 terminal point. Having terminal points enables travel time to be computed from any 189 subcatchment to the specified points. The user determines the number of iterations for the query, 190 the minimum assumed velocity, and the specific simulation time that the query would run. The 191 query then uses the trace tool, which selects all upstream conduits, nodes, and subcatchments to a 192 specified point and iterates the simulated results to determine a corresponding travel time based 193 on the cumulative conduit length travelled and velocity at the given point. In the case where 194 multiple flow paths exist, the query assumes that wastewater would always travel on the shortest 195 path, therefore computing the shortest travel time from the point of entry to the terminal point.

Lastly, the computed travel times for the entire model network were then exported into GIS forfurther analysis.

198

199 2.4. Identifying Decay Rate Studies

200

201 A literature search was conducted in October 2020 and again in February 2021 using Web of 202 Science and Google Scholar databases to identify studies with first-order degradation rates for 203 SARS-CoV-2 RNA. SARS-CoV-2 was used as a keyword paired with one or more of the 204 following: wastewater, degradation, decay, sewershed, persistence, fate, and survivability. The 205 criteria for inclusion were (1) peer-viewed journal articles (excluded reviews, metadata, pre-206 prints, editorial material), (2) a focus on SARS-CoV-2 in untreated wastewater samples or 207 simulated untreated wastewater, (3) includes at least one original, experimentally determined 208 decay rate for SARS-CoV-2 RNA.

209

210 **2.5. Decay of SARS-CoV-2 RNA in Sewage**

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Along with experimentally determined decay rates of SARS-CoV-2 from published literature, decay rates were also generated. To determine decay rates for SARS-CoV-2 RNA, roughly 1 gallon of wastewater influent was collected from a 24-hour composite sampler and transported on ice to Houston Public Works central processing laboratory. Approximately 500 mL of wastewater was collected in triplicate, stored in Nalgene bottles, and transported on ice to Rice University. The 500 mL bottles were weighed to accurately determine the volume of wastewater in each bottle. Next, each sample was poured into a sterilized 1 L Erlenmeyer flask containing a stir bar. Flasks were loosely capped with aluminum foil to prevent evaporation and placed on astir plate at the lowest possible setting to maintain a heterogenous mixture.

221

222 A 50 mL sample was immediately collected from each flask and concentrated via the HA 223 filtration method with beat beating as previously described here (28). HA filters were stored at -224 80°C. Wastewater from each flask was collected, concentrated, and stored via this method every 225 24 hours for the next 6 days. All wastewater samples were incubated at room temperature 226 (~20°C) in a Biosafety cabinet. After the 6 days, all stored samples were simultaneously 227 extracted using the Qiagen Allprep Powerviral DNA/RNA kit (Qiagen) with some modifications 228 to the manufacturer's protocol. Briefly, 7 μ L of \Box -Mercaptoethanol and 693 μ L of PM1 solution 229 were added to each bead tube containing the sample filters. Samples were then bead beaten at 230 3,500 rpm in a Mini-Beadbeater 24 (BioSpec) for 1 min, cooled on ice for 2 min, and bead 231 beaten once more for 1 min. Following bead beating, samples were centrifuged at 17,000 g for 2 232 min. Roughly 450 µL of sample lysate was extracted from each bead tube and transferred to a 233 QIAcube Connect (Qiagen) for automated extraction. Samples were eluted in 50 µL of nuclease-234 free water, stored at -20°C, and processed within 24 hours.

235

SARS-CoV-2 N1 and N2 gene targets were quantified in wastewater extracts using a previously described method (28). In short, a duplex reverse transcriptase digital droplet PCR (RT-ddPCR) was carried out using the One-Step RT-ddPCR Advanced kit for probes (Bio-Rad) on a QX200 AutoDG Droplet Digital PCR System (Bio-Rad) according the manufacturer's recommendations. Ten microliters of RNA extract, no template control, or positive control was transferred to a 12 μ L reaction mix containing final concentrations of 900 nmol of each primer and 250 nmol for each

242	probe. All reactions were performed in triplicate with thermocycling conditions detailed here				
243	(28). Samples were then read on a QX200 Droplet Reader (Bio-Rad) and analyzed using the				
244	QuantaSoft v1.7.4 software. The limit of quantification (LOQ) was previously determined as				
245	0.767 gene copies/ μ L of RNA according to a threshold of 3 positive droplets per 10,000 tota				
246	droplets as recommended by the manufacturer. A linear regression analysis was performed in R				
247	(29) to determine the decay rates for each target. Concentrations of SARS-CoV-2 were log-				
248	transformed to satisfy the assumptions of normality according to a visual inspection of the				
249	quantile-quantile (Q-Q) plots.				
250					
251	2.6. Estimation of SARS-CoV-2 RNA Degradation in Sewersheds Based on First-				
252	order Decay				
252 253	order Decay				
252 253 254	order Decay To the best of our knowledge, all experimentally-derived published decay rates for SARS-CoV-2				
252253254255	order Decay To the best of our knowledge, all experimentally-derived published decay rates for SARS-CoV-2 were included in this study. A temperature of 20°C was used to compare the influence of each				
 252 253 254 255 256 	order Decay To the best of our knowledge, all experimentally-derived published decay rates for SARS-CoV-2 were included in this study. A temperature of 20°C was used to compare the influence of each decay rate on the proportion of virus loss in select sewersheds across studies. The following				
 252 253 254 255 256 257 	order Decay To the best of our knowledge, all experimentally-derived published decay rates for SARS-CoV-2 were included in this study. A temperature of 20°C was used to compare the influence of each decay rate on the proportion of virus loss in select sewersheds across studies. The following formula is an approximation of the Arrhenius equation used to determine the dependence of first-				

260
$$\frac{k_2}{k_1} = Q_{10}^{(T_2 - T_1)/10}$$
(1)

261

where Q_{10} is the temperature coefficient, k_1 and k_2 are the lower and upper decay rate constants, respectively, and T_1 and T_2 are the temperatures in Celsius for the upper and lower rate constants, respectively. The temperature coefficient Q_{10} is the factor by which a rate changes

265 given a ten degree increase in temperature and is usually between 2 and 3 for biological systems 266 (31, 32).267 268 Eq (1) was used to estimate the decay rate at 20°C for the Weidhaas et al., 2021 study, using the 269 decay rates measured at 10 and 35°C. The temperature-dependent linear regression equation 270 reported by the authors was used to determine the decay rate of SARS-CoV-2 RNA at 20°C for 271 Ahmed et al., 2020. 272 273 The degradation of SARS-CoV-2 in the sewershed over time is expected to follow exponential decay as expressed in eq (2) where C(t) is the concentration of SARS-CoV-2 after time t, C_0 is 274 275 the initial concentration of SARS-CoV-2 released in the wastewater, and k is the first order decay rate. 276 277 $\frac{C(t)}{C_0} = e^{-kt}$ 278 (2) 279 280 Assuming an initial viral RNA proportion of 1 or 100%, eq (2) was substituted into eq (3) to 281 estimate the proportion of SARS-CoV-2 RNA loss (L) eq (4) or remaining (R) eq (5) at a given 282 time within the sewershed. 283 Proportion degraded = $1 - \frac{C(t)}{C_0}$ 284 (3) 285 $L = 1 - e^{-kt}$ 286 (4) 287

$$R = 1 - L \tag{5}$$

The half-life $t_{\frac{1}{2}}$ and t_{90} (the time for viral load to decrease by one log unit) for each decay rate kwere obtained from the published work or derived from the following formulas, respectively: $t_{\frac{1}{2}} = \frac{\ln (2)}{k}$ (6) $t_{90} = \frac{-\ln (0.1)}{k}$ (7)

295

296 **2.7. PT Metric for Identifying Hotspots**

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298 Aside from using travel time isochrones to determine the spatial distribution of viral RNA signal, 299 they could also be used in conjunction with population density information to help identify 300 potential viral hotspot areas. In this study, a normalized population times travel time (PT) metric 301 is introduced to identify critical locations for placing upstream samplers. Normalized PT maps 302 for the 69th Street sewershed were generated by multiplying population density information (P) 303 in each sub-sewershed area by their corresponding travel times (T), and then normalized by the 304 maximum PT value computed for the 69th Street and Chocolate Bayou sewersheds. The 305 resulting normalized PT maps have values that range from 0 (0%) to 1 (100%). Areas with low 306 PT values indicate a low likelihood of an undetected outbreak, due to low population density, 307 short travel times, or both. Conversely, areas with high PT values imply a higher likelihood of 308 undetected outbreaks. This is especially true for areas with the highest PT values (i.e., at or close 309 to 100%), signifying that those areas have both high population density and long travel times.

311 **3. Results and Discussion**

312

313 **3.1.** Impact of Weather Conditions on Wastewater Travel Time in Sewersheds

314

To assess the impact of wet weather on travel times, the ICM model was used to compute travel times under wet and dry conditions for each sewershed (**Figure 2**). Travel times under dry weather conditions were generally higher than wet conditions. The 69th Street and Chocolate Bayou sewersheds were used for further analysis due to the differences in characteristics, and because they represented the sewersheds with the largest and smallest service areas studied, respectively.

321 Median dry weather travel times for 69th Street and Chocolate Bayou were 523 min (s.d. = 322 217.58 min) and 220 min (s.d.= 152.12 min) with a comparable maximum dry weather travel

time of 1207 mins and 1123 mins, respectively (Figure 3).

Condition 🖨 Dry 🖨 Wet



Figure 2. Boxplot of travel times for select sewersheds under dry and wet weather conditions.
Horizontal lines represent the median travel time. Lower and upper whiskers represent the 25th
and 75th percentiles, respectively.

324

Figure 3. Heat map displaying travel time for 69th Street (a) and Chocolate Bayou (b).

Numbers indicate travel time isochrones in minutes from the WWTP outfall (indicated with ared star).

333

334 3.2. Impact of Decay Rate and Temperature on SARS-CoV-2 RNA in Transit to 335 Wastewater Treatment Plant

336

337 We determined the decay rates of SARS-CoV-2 N1 and N2 at 20°C using wastewater collected 338 from a sewershed in Houston to compare values using a Houston-specific wastewater to 339 previously published decay rates. After the fourth day of incubation, unclear concentration 340 dynamics occurred wherein the concentration of all targets slightly increased. Due to uncertainty 341 in the cause of this behavior, only the first few days were considered in the regression analysis. 342 Degradation of N1 and N2 showed similar behavior with decay rates of 0.84 day⁻¹ and 0.82 day⁻¹ 343 ¹, respectively. **Table S3** displays the linear regression parameters for each gene. A summary of 344 the ddPCR droplet statistics is detailed in Table S2. Our experimentally-determined decay rates 345 were within the range of published rates (Table 1). Decay rates listed in Table 1 were used to 346 evaluate the impact of decay rate and temperature on viral RNA degradation in Houston 347 sewersheds.

348

Table 1. Summary of reported decay rates, half-lives, and t_{90s} (the time for viral concentration to decrease by one log unit) for SARS-CoV-2 RNA targets in various studies at 20°C.

Page 19 of 29

Duration of Experiment (day)	Duration of Experiment (hr)	Target	Decay Rate, k (day ⁻¹)	Half Life, t _{1/2} (day)	t ₉₀ (day)	Comments	Reference
33	792	N1	0.15	4.78	15.88		Ahmed et al. 2020
1	24	N1, N2	1.75	0.40	1.31		Weidhaas et al. 2021
6	144	N1	0.84	0.83	2.74		In lab
7	168	Е	0.67	0.99	3.30	High titer	Bivins et al. 2020

351

352 There were significant differences in how the decay rates in Table 1 were determined, which 353 may explain the wide range of reported rates. Weidhaas et al. 2021 obtained the fastest decay 354 rates compared to studies considered with a rate of (1.75 day⁻¹) at 20°C. The authors measured 355 SARS-CoV-2 RNA in wastewater samples obtained from two different treatment plants 356 immediately after collection. These initial concentrations were then compared to concentrations 357 measured in replicate samples incubated at 4, 10, and 35°C for 1 to 22 hours. Ahmed et al., 2020 358 spiked SARS-CoV-2-negative wastewater samples with RNA extracted from gamma-irradiated 359 SARS-CoV-2 hCoV-19/Australia/VIC01/2020 isolate and incubated them at 4, 15, 25, and 37°C 360 over the course of 33 days in which RNA concentrations from those samples were measures 361 every few days.

362

363 Decay rates from Bivins et al., 2020 were the most congruent with results from our lab except 364 under low titer conditions (starting concentration of $10^3 \text{ TCID}_{50} \text{ mL}^{-1}$) (data not shown). The 365 decay rate under low titer conditions was significantly slower than all other reported decay rates 366 listed here (14). Here, the authors inoculated non-sterile wastewater with a SARS-CoV-2 isolate 367 from a clinical patient diagnosed with COVID-19 at low titer ($10^3 \text{ TCID}_{50} \text{ mL}^{-1}$) and high titer 368 ($10^5 \text{ TCID}_{50} \text{ mL}^{-1}$) concentrations. SARS-CoV-2 RNA was extracted and quantified in 20°C 369 inactivated wastewater samples over the course of 7 days. The decay rate associated with the 370 high titer SARS-CoV-2 concentration was selected from the Bivins et al., 2020 study because it 371 was more representative of concentrations previously measured in Houston sewersheds. Notably, 372 the fastest reported decay rates from Weidhaas et al., 2021 and our own experiments were 373 determined in samples that were not spiked with virus. This may have been due to the form of 374 the virus in wastewater samples, which is likely a mixture of intact, protected (enveloped and/or 375 intact capsid) virus, and degraded unprotected viral RNA. Degraded, unprotected viral RNA will 376 degrade much faster than intact, protected virus (33). A limited number of studies have 377 discriminated between the forms of SARS-CoV-2 in wastewater and have indicated the presence 378 of both intact virus and free RNA (33,34). As more knowledge on factors that impact the 379 different forms of virus becomes available, consideration should be taken when estimating or 380 selecting SARS-CoV-2 decay rates for sewershed modeling.

381

382 Given the ability to estimate decay rates at various temperatures for values obtained from Ahmed 383 et al., 2020 and Weidhaas et al., 2021, and because they represented the lowest and highest decay 384 rates reported to date, respectively, these studies were used to evaluate the effect of wastewater 385 temperature (20-30°C) on RNA degradation over time. As expected, viral RNA degradation 386 increases with increasing travel time. Moreover, travel time has a greater influence on 387 degradation as compared to temperature within the range of travel times estimated for the ten 388 sewersheds considered in this study (Figure 4). However, it is important to note that the impact 389 of temperature on RNA degradation increases with increasing travel times as displayed in Figure 390 **4**. For example, the difference in the percent of RNA degradation between 20 and 30°C is 0.6%

and 9.8% for Ahmed et al., 2020 and Weidhaas et al., 2021, respectively after a travel of 120 min

Similar findings were reported in a recent study that assessed SARS-CoV-2 RNA in sewersheds in Tempe, Arizona under varying wastewater temperatures (16). The authors concluded that under high temperature conditions in large sewersheds, viral concentration at outfalls may be less representative of disease incidence as compared to colder temperatures. Wastewater temperatures can fluctuate by as much as 27°C depending on geographical region and seasonal changes (35). Therefore, careful consideration of wastewater temperatures can be used to

402 improve disease prevalence estimations and explain discrepancies in correlations between the403 number of disease cases and virus concentrations.

404

405 The percent of SARS-CoV-2 RNA degradation in wastewater traveling from a given 406 geographical location within the 69th Street and Chocolate Bayou sewersheds to their 407 corresponding outfalls at the WWTPs was determined using travel time and decay rates from 408 Table 1. As expected, 69th Street showed greater variability in RNA degradation across the 409 sewershed as compared to Chocolate Bayou. Viral RNA degradation at a median travel time of 410 523 min for 69th Street were 5.13, 21.60, 26.29, and 47.08% for the 0.145, 0.670, 0.840, and 411 1.752 day⁻¹ decay rates, respectively. Chocolate Bayou obtained median percent degradations of 412 2.19, 9.73, 12.04, and 23.48% at a median travel time of 220 min (Figure 5). Taking into 413 consideration the decay rate obtained from our study, approximately a 25% reduction in viral 414 signal is estimated in the 69th Street sewershed compared to a 12% reduction for Chocolate 415 Bayou.

416

Decay rates of 0.840, and 1.752 day⁻¹ resulted in SARS-CoV-2 RNA degradation of 417 418 approximately \geq 50% when considering travel times between 1190 and 570 min, respectively. 419 Travel time range between 0-1123 min for the Chocolate Bayou sewershed, thus all regions 420 maintained less than a 50% reduction in viral signal for a decay rate of 0.840 day⁻¹. Despite a 421 greater reduction of viral signal in both sewersheds when considering a virus degradation rate of 422 1.752 day⁻¹, the fraction of the 69th Street sewershed with \geq 50% viral RNA degradation is 49.84% as compared to 2.98% for Chocolate Bayou. Consequently, virus decay is more critical 423 424 in the 69th Street sewershed due to the number of remote regions.

428	Figure 5: Geographical heat maps of SARS-CoV-2 RNA degradation for 69th Street (a, c, e, g)					
429	and Chocolate Bayou (b, d, f, h) under dry weather conditions and decay rates obtained or					
430	estimated from studies liste	d in Table 1.				
431						
432	3.3. Population	vs. Travel Time Metric				
433						
434	To account for virus deca	y across large sewersheds we propose PT, a novel metric used to				

facilitate the placement of upstream samplers and minimize travel times throughout sewersheds.
The PT metric identifies areas that are at high risk of a wide-spread COVID-19 outbreaks due to
population density and the outbreak is less likely to be fully captured in WBE due to prolonged
travel times. To evaluate the efficacy of this metric, we estimated PT values for all regions
within the 69th Street sewershed. Figure 6a illustrates a PT heatmap in the case of downstream
sampling only. Hotspots were identified in the northwest-central region of the sewershed.

441

A second simulation was carried out with three upstream samplers hypothetically placed in hotspots (higher PT values), located in the northwest-central region, that were expected to reduce travel times in the sub-sewershed areas and minimize PT throughout the sewershed (**Figure 6b**). Placement of samplers decreased the median travel time in zones A, B, and C as indicated in **Figure 6b** from 865, 840, and 869 min to 154, 129, and 313 min, respectively. Results here indicate that implementation of upstream samplers according to the PT metric can significantly reduce the number of hotspots in large sewersheds.

the ICM models, they may not strictly reflect transit of wastewater in the sewersheds, particularly in remote locations and during varying diurnal cycles. Still, findings here indicate that in-sewer decay may be an important factor to consider in WBE and when designing sampling campaigns.

465

466 **5.** Conclusion

468 A hydraulic modeling approach was applied to 10 Houston sewersheds to estimate travel times 469 and decay of SARS-CoV-2 from source to the WWTP outfall under various temperatures. Travel 470 time generally had a greater impact on viral RNA degradation than wastewater temperature. The 471 largest sewershed showed greater variability in viral RNA degradation due to longer travel times 472 with nearly half of the sewershed losing 50% or more of the viral signal when considering the 473 fastest decay rate. By incorporating a novel PT metric for placement of upstream samplers within 474 the largest sewershed, travel times reduced by more than 60%. This reduction is expected to 475 alleviate virus signal loss due to decay and discrepancies between wastewater and clinical cases 476 in wastewater surveillance efforts. This approach can be adopted in various localities to improve 477 sampling infrastructures and public health responses to local and global viral disease outbreaks.

478

479 **Conflicts of interest**

480 There are no conflicts to declare.

481

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