Wastewater monitoring outperforms case numbers as a tool to track COVID-19 incidence dynamics when test positivity rates are high

Xavier Fernandez-Cassi¹, Andreas Scheidegger², Carola Bänziger², Federica Cariti¹, Alex Tuñas Corzon¹, Pravin Ganesanandamoorthy², Joseph C. Lemaitre³, Christoph Ort², Timothy R. Julian^{2,4,5}, Tamar Kohn^{1*}

¹ Laboratory of Environmental Chemistry, School of Architecture, Civil and Environmental Engineering, École Polytechnique Fédérale de Lausanne (EPFL), CH-1015 Lausanne, Switzerland

² Swiss Federal Institute of Aquatic Science and Technology (Eawag), 8600 Dübendorf, Switzerland

³ Laboratory of Ecohydrology, School of Architecture, Civil and Environmental Engineering, École Polytechnique Fédérale de Lausanne (EPFL), CH-1015 Lausanne, Switzerland

⁴ Swiss Tropical and Public Health Institute, CH-4051 Basel, Switzerland

⁵ University of Basel, CH-4055 Basel, Switzerland

^{*} To whom correspondence should be addressed: e-mail: tamar.kohn@epfl.ch; phone: +41 21 69 30891.

Abstract

Wastewater-based epidemiology (WBE) has been shown to coincide with, or anticipate, confirmed COVID-19 case numbers. During periods with high test positivity rates, however, case numbers may be underreported, whereas wastewater does not suffer from this limitation. Here we investigated how the dynamics of new COVID-19 infections estimated based on wastewater monitoring or confirmed cases compare to true COVID-19 incidence dynamics. We focused on the first pandemic wave in Switzerland (February to April, 2020), when test positivity ranged up to 26%. SARS-CoV-2 RNA loads were determined 2-4 times per week in three Swiss wastewater treatment plants (Lugano, Lausanne and Zurich). Wastewater and case data were combined with a shedding load distribution and an infection-to-case confirmation delay distribution, respectively, to estimate incidence dynamics. Finally, the estimates were compared to reference incidence dynamics determined by a validated compartmental model. Incidence dynamics estimated based on wastewater data were found to better track the timing and shape of the reference infection peak compared to estimates based on confirmed cases. In contrast, case confirmations provided a better estimate of the subsequent decline in infections. Under a regime of high-test positivity rates, WBE thus provides critical information that is complementary to clinical data to monitor the pandemic trajectory.

Keywords

18 Sewage, new infections, compartmental model, shedding load distribution, SARS-CoV-2, disease dynamics

1. Introduction

19

20

21

22

23

24

25

26

27

28

29

30

31

32

33

34

35

36

37

38

39

40

41

Wastewater-based epidemiology (WBE), a form of environmental surveillance of infectious diseases, has long been suggested as a sensitive tool to monitor pathogen circulation in a population¹⁻³. Many pathogens, both enteric and otherwise, are excreted from infected individuals into the sewage system via feces, saliva or other bodily fluids¹. The principle underlying WBE is that the pathogen concentrations or loads in sewage are proportional to the number of infected individuals among the population contributing to the sewage, and can thus inform on the presence and trajectory of a disease outbreak. For example, norovirus concentrations in sewage were found to closely track the dynamics gastroenteritis cases over several years in Japan⁴. WBE can inform not only on the presence and dynamics of a pathogen but may also capture the emergence of new strains or variants before they become widespread in a population^{4,5}. WBE has received renewed attention during the COVID-19 pandemic, when it was recognized that SARS-CoV-2 RNA is excreted in feces ⁶ and can be detected in wastewater⁷⁻⁹ and sludge^{10,11}. Several studies have shown that the dynamics of SARS-CoV-2 RNA in raw wastewater or sludge coincide with, or even anticipate, the dynamics of confirmed cases^{7,10,11}. In addition, WBE was able to capture the introduction and spread of SARS-CoV-2 variants of concern¹², and identify mutations that were not captured in clinical samples¹³. WBE may thus serve as a useful tool to support COVID-19 monitoring, and WBE data have already been integrated into multiple national or local COVID-19 dashboards^{14–17}. While WBE will never replace case reporting, it can be used to strengthen the understanding of infectious disease dynamics as it holds important benefits over clinical tests. Specifically, WBE captures both symptomatic and asymptomatic virus shedders; WBE data are not affected by testing capacity, strategy or compliance; and WBE allows the monitoring of a large population with few samples. The advantages of WBE over clinical testing are particularly important when test capacity is exceeded and hence may be insufficient to accurately capture case numbers. According to the WHO, the test positivity rate should

remain < 5% to confidently track disease dynamics¹⁸. Under regimes with a positivity rate > 5%, WBE may

thus better reflect true disease dynamics than clinical case numbers.

In this study we evaluated the use of wastewater monitoring as a tool to track COVID-19 dynamics. We

hypothesized that under high test positivity rates, wastewater provides an improved estimate of the

dynamics of new infections (incidence dynamics) compared to confirmed case numbers. We focused on

the first wave of the COVID-19 pandemic in Switzerland, which lasted from late February to April 2020.

The test positivity rate during this period ranged up to 26 % (Figure S1). Wastewater was monitored 2-4

times per week in two locations (Lugano, Lausanne) that were strongly affected, and one location (Zurich)

that experienced a milder wave. We did not directly evaluate SARS-CoV-2 RNA loads measured in

wastewater against the number of confirmed cases. Instead, we use these metrics to estimate the

incidence dynamics over time. This allowed us to compare both the wastewater- and the case number-

derived incidence dynamics to reference incidence dynamics determined retrospectively by a

compartmental (Susceptible-Exposed-Infected-Recovered; SEIR) model and consistent with

seroprevalence studies conducted in the region¹⁹.

2. Materials and Methods

42

43

44

45

46

47

48

49

50

51

52

53

54

55

56

57

58

59

60

61

62

63

2.1. Experimental approach

We determined the concentration and daily loads of SARS-CoV-2 RNA in longitudinal samples of raw

wastewater collected from three Swiss wastewater treatment plants (WWTPs). In each sample, we

analyzed two SARS-CoV-2 gene targets (N1 and N2). In addition, we determined virus recovery by means

of an externally added viral surrogate of SARS-CoV-2. Finally, we monitored the fecal strength in each

sample via the analysis of pepper mild mottle virus (PMMoV), a plant virus that occurs in wastewater at

high and constant concentrations^{20,21}.

2.2. Sample collection and storage

20 °C for up to 5 months.

24-h composite influent samples were collected 2-4 times per week between February 26 and April 30, 2020 from three Swiss WWTPs: Lausanne (STEP de Vidy; population connected: 240'000; 25 samples), Lugano (CDA Bioggio; population connected: 125'000; 31 samples); and Zürich (ARA Werdhölzli: population connected: 450'000; 22 samples). After collection, the wastewater samples were stored at -

2.3. Preparation of viral surrogate stock solutions

Three enveloped viruses were assessed as external recovery controls, namely Murine Hepatitis Virus (MHV, *Coronaviridae, betacoronavirus*), *Pseudomonas virus* Φ6 (*Cystoviridae, cystovirus*) and Murine Sendai virus (*Paramyxoviridae, respirovirus*). Murine Hepatitis Virus strain MHV-A59 (kindly donated by Volker Thiel, University of Bern) was propagated in DBT cells (kindly donated by Krista Rule Wigginton, University of Michigan) as described elsewhere²². Five days post-infection the viral particles were released from infected cells by three cycles of freezing/thawing. Cell supernatants were centrifuged at 3000 *xg* to pellet down cell debris and the supernatant was clarified through a 0.22 μm filter. The resulting stock solution had a concentration of 7.8x10⁹ genome copies (gc)/ml. Bacteriophage Φ6 (DSMZ nº 21518, strain HER 102) was propagated in *P. syringae* (DSMZ nº 21482, strain HER1102) according to the provider's instructions. After propagation, bacterial cultures were centrifuged at 8000 *xg* for 10 min and cell debris was removed by passing the supernatant through a 0.22 μm filter. The final stock solution had a concentration of 8.0x10⁹ gc/ml. Finally, Sendai virus propagated in embryonated eggs was kindly donated by Dominique Garcin (University of Geneva) and was used without further treatment. These solutions had a concentration of 1.3x10⁹ gc/ml.

2.4. Sample concentration and nucleic acid extraction

86

87

88

89

90

91

92

93

94

95

96

97

98

99

100

101

102

103

104

105

106

107

Samples from Lugano and Lausanne were processed at EPFL, and samples from Zürich were processed at Eawag. Prior to processing, samples were thawed at room temperature. For each sample, two replicate aliquots of 50 ml wastewater were processed. The 50 ml aliquots were spiked with MHV (Lausanne or Lugano) or Sendai virus (Zürich) at a concentration of approximately 1x10⁶ gc/50 ml, and were stirred for 20 minutes to ensure the homogenization of the sample. Then they were pre-filtered using 2 µm glass fiber pre-filters (Merck, cat nº AP2007500) placed on the top of 0.22 μm SteriCup filters (Merck, cat nº SCGVU02RE). After filtration, the filter units were rinsed with 10 ml of ultrapure water to ensure that no wastewater was retained in the dead volume. The filtrates (approximately 60 ml) were transferred to a centrifugal filter unit with a size cut-off of 100 kDa (Centricon Plus-70; Millipore cat nº UFC701008), and were centrifuged for 30 min at 3000xq. To collect the concentrate, the centrifugal filter was inverted and centrifuged for 3 min at 1000xq. The resulting viral concentrate volume ranged from 180 to 300 μL. Viral concentrates were extracted in their entirety using the Qiagen RNA Viral Mini Kit (Qiagen cat nº 22906, Valencia, CA, USA) following the manufacturer's protocol for higher volumes. Nucleic acids were eluted using 80 µl of AVE buffer. For each processed batch of samples, a negative extraction control using water was included. The extracted nucleic acids were passed through a Zymo OneStep PCR Inhibitor Removal column (Zymo Research, cat nº D6030) to remove PCR inhibitors following the protocol provided by the manufacturer. In addition to the longitudinal samples, seven wastewater samples were collected in Lausanne to test the recovery of different SARS-CoV-2 surrogates. These samples were spiked with MHV, Sendai virus and Φ6 at a concentration of approximately 10⁶ gc/50 ml each. Samples were then concentrated and nucleic acids were extracted as described above.

109

110

111

112

113

114

115

116

117

118

119

120

121

122

123

124

125

126

127

128

129

130

2.5. Quantification of SARS-CoV-2 N1 and N2 genes, viral surrogates and PMMoV by RT-gPCR All RNA extracts of the longitudinal samples were analyzed by RT-qPCR for four viral targets: The N1 and N2 genes of SARS-CoV-2, the surrogate virus and PMMoV. All N1, N2 and MHV analyses, as well as PMMoV analyses for Lugano and Lausanne were performed at EPFL. PMMoV and Sendai virus analyses for Zürich were performed at Eawag. The samples to test surrogate virus recovery were analyzed at EPFL for three viral targets: MHV, Sendai virus and Φ6. To detect the presence of SARS-CoV-2 RNA, the CDC N1 and N2 assays were used²³. PMMoV and MHV were analyzed by previously reported assays^{24–26}. The design for primers and probes for Φ6 were adapted from Gendron et al²⁷ according to the suggestion of Heather Bischel (University of California, Davis). For Sendai virus, primers and probes were designed for the purpose of this project. A summary of all primers and probes and the RT-qPCR protocols is given in the Supporting Information (Table S1). To calibrate the different RT-qPCR assays, standard curves for each viral target were generated using either double-stranded DNA gblocks gene fragments (viral surrogates and PMMoV), or a 2019-nCoV N positive control plasmid (cat nº 10006625, SARS-CoV-2 N1 and N2). Both gBlocks and plasmids were purchased from Integrated DNA Technologies (Coralville, IA, USA). RT-qPCR amplifications were performed in 25 µl reactions using RNA UltraSense™ One-Step Quantitative RT-PCR System (Invitrogen, cat nº 11732-927), amended with 4 μl of bovine serum albumin (2 mg/ml) on a Mic qPCR Cycler (Bio Molecular Systems). In each RT-qPCR reaction, 5 μl of RNA extract or calibration standard were used. For PMMoV, the RNA extract was diluted 1:10 prior to RT-qPCR analysis. All RT-qPCR runs included no-template controls and negative extraction controls to monitor for contamination during the extraction and amplification process. The preparation of PCR mastermix and standards, as well as sample loading were performed in separate locations to avoid contamination. Cq determination was performed using the micPCR software (v2; Bio Molecular Systems).

RT-qPCR limits of detection (LOD) were determined as the lowest concentration (N1, N2 and MHV) or the lowest standard (PMMoV, Sendai, Φ 6) with a 95% or greater detection probability. The limit of detection (LOD) for each gene target were determined from pooled standard curves ($n \ge 3$) in R using the Generic qPCR Limit of Detection (LOD) / Limit of Quantification (LOQ) calculator²⁸. Samples with a measurable RT-qPCR signal < LOD were assigned the concentration of the LOD of the respective assay. Samples which yielded no detectable RT-qCR signal were set to the theoretical minimal LOD (3 gc/reaction)²⁹.

2.6. RT-qPCR inhibition

To check for inhibition during RT-qPCR reactions, 4 μ l of each zymo-treated RNA extract were amended with 1 μ l of a synthetic SARS-CoV-2 RNA reference material (EURM-019, Joint Research Center) at a concentration of approximately 10⁵ gc/ μ L. RNA extracts were analyzed for the SARS-CoV-2 N1 target by the RT-qPCR protocol described above, and the resulting Cq values were compared between samples. Samples were considered inhibited when Cq was > 1.5 cycles beyond the average Cq measured at a given site. All inhibition tests were conducted at EPFL.

2.7. Recovery

Recovery was calculated as the ratio of surrogate virus recovered after sample processing and the virus originally spiked into 50 ml of unfiltered wastewater (equation 1):

147 Recovery=
$$\frac{\text{virus measured per } \mu \text{l RNA extract x RNA extraction volume (80 } \mu \text{l})}{\text{virus spiked into 50 ml of wastewater}}$$
 (1)

2.8. Determination of RNA loads

Genome copies (gc) per reaction were converted to units of load (gc/day) by determining the gc concentration per liter of wastewater and multiplication by the wastewater flow rate of corresponding day according to equation 2:

152 Load
$$(gc/day) = \frac{C_{PCR} \times V_{extract} / V_{PCR}}{V_{sample} \times Q}$$
 (2)

Where C_{PCR} is the template concentration (gc/reaction) determined by RT-qPCR, $V_{extract}$ is the total volume of RNA extract (80 μ L), V_{PCR} is the volume of extract analyzed by RT-qPCR (5 μ L), V_{sample} is the volume of the wastewater sample (0.05 L), and Q is the wastewater flow rate on a given sampling day measured and provided by the WWTPs included in this study (L/day).

2.9. Storage test

To determine if storage at -20 °C had a detrimental effect on SARS-CoV-2 RNA concentrations in wastewater, a control experiment was conducted. A batch of wastewater influent from Lausanne was collected and stored for a month in four different conditions: 1) unprocessed wastewater at 4 °C; 2) unprocessed wastewater at -20 °C; 3) concentrated wastewater (after filtration and ultracentrifugation) at -20 °C; and 4) zymo-treated RNA extract at -20 °C. All tests were conducted in duplicate. After one month, all samples were fully processed and immediately analyzed for the N1 gene target by RT-qPCR as described above.

2.10. Epidemiological data

Confirmed case numbers for each WWTP catchment were kindly provided by the Swiss Federal Office of Public Health.

2.11. Incidence estimates

Reference infection numbers were determined by an SEIR model described previously ¹⁹. This model is based on cantonal hospitalization data, intensive care unit visits and deaths, but not case numbers. This is to avoid any influence from changes in test strategies and test capacity over the time period considered. The modeled incidence includes both symptomatic and asymptomatic new infections. The model was

validated against a seroprevalence study conducted in the region, and we therefore consider it herein as the reference incidence.

Incidence was additionally estimated based on longitudinal data of SARS-CoV-2 loads in wastewater and based on confirmed cases. Both these metrics measured at time t reflect an aggregate of infections that occurred over a time span preceding the measurement. A deconvolution of these aggregated quantities allows for the reconstruction of daily infections. This requires an assumption of the extent by which previous infections influence the aggregated quantities. This assumption is expressed by time delay-dependent weight $\omega(\tau)$, where τ is the time (days) since infection. The measured aggregated quantity A at time t can be approximated by a weighted sum of all infections t that occurred up to time t:

182
$$A_t \approx \sum_{\tau=0}^{\infty} \omega(\tau) I_{t-\tau}$$
 (3)

The infections I over a time range of interest can be estimated via non-negative least squares regression.

As fast fluctuations in the number of daily infections seems unreasonable, an additional constraint was

added to enforce smoothness comparable to the infection numbers of the SEIR model (see Supporting

Information).

To obtain the wastewater-derived incidence, the weights of the deconvolution, $\omega(\tau)$, are given by the shedding load profile (SLP) that describes the average amount of virus shed by a patient τ days after infection. The SLP can be decomposed into the relative shedding load probability distribution (SLD) and the absolute viral load shed during the course of the disease (L) (equation 4):

191
$$SLP(\tau) = L \times SLD(\tau)$$
 (4)

The SLD was constructed by combining the gastrointestinal viral load as a function of time after symptom onset with the time between infection and symptoms. Virus shedding was modelled based on data

reviewed by Benefield et al.³⁰, and could be well described by a gamma distribution with a mean of 6.73 days and a standard deviation (sd) of 6.98 days. The time between infection and symptoms was also modeled by a gamma distribution based on Linton et al.³¹ (mean = 5.3 days, sd = 3.2 days). The convolution of these two distributions was used as the SLD (shown in Figure 1a) with a mean = 11.73 days and an sd = 7.68 days.

If L is known with small uncertainty, the absolute number of infections can be estimated. However, although the different SLDs have a comparable shape across literature, the loads L are highly variable ^{32,33}. Therefore, we applied the SLD, which still yields an estimate that is proportional to that obtained by using the correct but unknown SLP.

For the case number-derived incidence, (τ) was defined by the distribution combining the delays from infection to symptom onset (gamma mean= 5.3 days; sd = 3.2 days), and from symptom onset to case confirmation (gamma mean= 5.5 days, sd = 3.8 days³⁴). The resulting delay distribution from infection to case confirmation is visualized in Figure 1b.

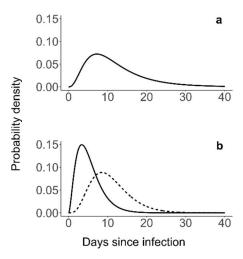


Figure 1: a) Shedding load distribution to describe the relative distribution of the SARS shedding load, based on the delay distribution from infection to symptom onset by Linton et al. 31 , combined with the gastrointestinal viral load

211

212

213

214

215

216

217

218

219

220

221

222

223

224

225

226

227

228

229

dynamics according to Benefield et al.³⁰ b) Delay distribution from infection to symptom onset according to Linton et al.³¹ (solid line), and combined with an additional delay from symptom onset to case confirmation based on Bi et al.³⁴ (dashed line). 2.12. Data analysis All statistical analyses were performed in R³⁵. The non-negative least-square regression for the incidence estimations was implemented with the package 'CVXR' ³⁶ and delay distributions were computed with the R package 'distr'³⁷. 2.13. Data availability Data will be made available on an institutional repository upon acceptance of the manuscript. 3. Results and Discussion 3.1. Method performance 3.1.1. PCR efficiency and LOD. PCR efficiencies for all targets ranged from 94-111% (Table S2). The R² of the pooled standard curves were ≥ 0.95. No amplification signal was measured in the non-template and negative extraction controls confirming the absence of contamination during sample processing. The LOD corresponded to 4.2 gc/ml wastewater and 2.6 gc/ml wastewater for the SARS-CoV-2 N1 and N2 genes, respectively. The LODs reflect the difficulty of producing accurate calibration curves for SARS-CoV-2 in the low template range based on plasmid standards. This limitation, which was also reported by others 38,39 highlights the need for improved qPCR standards and more sensitive RT-qPCR assays to minimize variability and false negative results in SARS-CoV-2 RNA quantification. The LODs of the other targets are listed in Table S2.

231

232

233

234

235

236

237

238

239

240

241

242

243

244

245

246

247

248

249

250

251

3.1.2. PCR Inhibition. Spiking RNA extracts with synthetic SARS-CoV-2 RNA reference material revealed minimal PCR inhibition on most samples. Specifically, with the exception of three samples from Lugano, all spiked RNA extracts exhibited N1 Cq values that fell within or only minimally beyond 1.5 cycles of the median Cq of a given WWTP (Figure S2). 3.1.3. Reproducibility: We compared quantifiable N1 concentrations determined in biological as well as in technical replicate samples (Figure S3). A good correlation (r=0.89) was obtained among biological replicates, indicating a high reproducibility of the overall processing pipeline. A good reproducibility was also found for technical replicates (r=0.78). 3.1.4. Recovery. Three enveloped viruses - MHV, Sendai virus and Φ6 - were evaluated as SARS-CoV-2 surrogates to monitor virus recovery in our sample processing pipeline. As a member of the Coronaviridae family, MHV is the most similar to SARS-CoV-2 in terms of size (120 nm diameter) and genome structure (single-stranded RNA). Sendai virus has a single-stranded RNA genome, but is slightly larger in diameter than SARS-CoV-2 (150 nm). Besides SARS-CoV-2, this virus may also serve as a surrogate for viruses with pandemic potential in the *Paramyxoviridae* family, such as measles virus. The novel RT-qPCR assay developed herein was able to quantify its concentration down to an LOD of 4.2 gc/ml (Table S2). Finally, Φ6 is the least similar surrogate to SARS-CoV-2. It has a smaller diameter (85 nm) and a different genome structure (double-stranded RNA). In seven wastewater samples spiked with all three surrogate viruses, MHV and Sendai virus exhibited similar recoveries that mostly ranged from 0.1-1% (Figure S4). This range corresponds well to that reported by other groups using a similar processing pipeline ⁴⁰. If determined using Φ6, recoveries were 10- to 100-fold higher and more constant across samples. This confirms previous reports that recoveries depend strongly on the surrogate virus used 40. Despite the better recovery of Φ 6, we decided to utilize

253

254

255

256

257

258

259

260

261

262

263

264

265

266

267

268

269

270

271

272

273

274

MHV or Sendai virus as recovery controls in this work, due to their higher structural similarity with SARS-CoV-2. The recoveries in the samples from Lugano and Lausanne were determined using MHV (Figure S5). Recoveries were similar for both sites and mostly fell into the 0.1-1% range, with average values of 0.95% and 0.74% for Lugano and Lausanne, respectively. In the samples from Zurich, Sendai virus was used as the surrogate. Compared to Lugano and Lausanne, the recoveries were significantly lower, with an average of 0.17% (one-way ANOVA, F=6.82, p < 0.002) (Figure S5). The lower recovery is unlikely to be a result of the use of Sendai virus, since MHV and Sendai virus yielded similar recoveries if assessed in the same sample (Figure S4). Instead, the lower recoveries in the Zurich samples may reflect the higher solids content in this WWTP. Enveloped viruses partition to wastewater solids⁴¹, and hence a higher solids content leads to a reduced recovery of the surrogate virus from the liquid wastewater fraction. 3.1.5. Fecal load: The daily load of PMMoV was used as an indicator of the fecal load entering the WWTP. On average, the PMMoV loads corresponded to 8.9x10¹⁵ gc/day (Lugano), 3.1x10¹⁶ gc/day (Lausanne) and 1.8x10¹⁶ gc/day (Zurich) (Figure S6). In all but five samples the PMMoV load fell within the range of $5x10^{15}$ to $5x10^{16}$ gc/day. The narrow range of the measured PMMoV loads further confirms the consistency of our virus concentration and extraction process. 3.1.6. Effect of storage conditions on RNA stability. As shown in Figure 2, different storage procedures exert significantly different effects on SARS-CoV-2 RNA stability (one-way ANOVA, F=12.8, p < 0.001). Storing raw wastewater at 4 °C or -20 °C for a month resulted in lower concentrations of SARS-CoV-2 RNA compared to samples stored as concentrates or RNA extracts at -20 °C (Tukey-Kramer, p < 0.02). The storage protocol used herein (raw wastewater at -20 °C) had to be implemented before storage tests could be completed, and likely led to significant RNA decay. In future studies, wastewater samples should immediately be concentrated or extracted prior to storage.

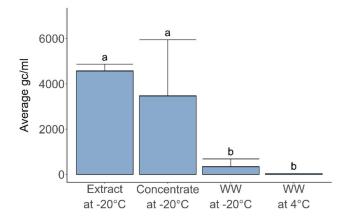


Figure 2: Effect of sample storage over one month under different conditions on SARS-CoV-2 RNA concentrations (N1 gene, gc/ml wastewater). Error bars represent standard deviations of replicate samples. Samples stored as non-processed raw wastewater (WW) at 4 °C or -20 °C exhibited lower concentrations compared to samples stored at -20 °C as concentrate (post ultrafiltration) or RNA extracts. Indices a and b denote experimental conditions yielding statistically different sample means.

3.2. Longitudinal trends SARS-CoV-2 RNA loads and confirmed cases

Concentrations of SARS-CoV-2 N1 and N2 genes in longitudinal samples are shown in Figure S7. The earliest detection of the N1 gene occurred in wastewater from Lugano on February 28 2020, four days after the first case was observed in Switzerland. This confirms earlier reports that wastewater can serve as a sensitive indicator for virus circulation, even during periods of low disease prevalence ^{7,8,42,43}.

N1 and N2 concentrations exhibited similar temporal trends, though N1 concentrations were on average 3-fold higher (Figure S7). Higher concentrations of the N1 gene were also reported by others ^{38,44}, though some studies have reported the N2 gene to yield higher results^{7,45}. Given the superior quantification by N1 in this work, only this gene target was considered for all subsequent analyses.

We did not normalize N1 concentrations by fecal strength (PMMoV concentration) as suggested elsewhere^{44,46}, because PMMoV concentrations were similar in all samples and were not correlated with

293

294

295

296

297

298

299

300

301

302

303

304

305

306

307

308

309

310

311

312

313

314

N1 concentrations (r=0.02-0.04) (Figure S8). We also did not correct N1 concentrations for recovery, because there was high inter-sample variation across the three surrogates tested, and it is uncertain which - if any - externally added surrogate accurately mimics the fate of SARS-CoV-2 during sample processing^{11,39}. Recovery values were strictly used for data quality control. Specifically, samples were excluded if two criteria were simultaneously met: the recovery of a sample was > 3x the median recovery for the site under consideration; and the concentrations measured by N1 and N2 differed by more than a factor 5. This led to the exclusion of one biological replicate on three sampling days in Lugano (March 18-19 and April 5), and both replicates for a single day in Lausanne (March 28). Among the three WWTPs studied, Lausanne had the highest number of confirmed cases in its catchment (Figure 3). Case numbers were similar in the catchments of the Lugano and Zurich WWTPs, even though Zurich's catchment encompasses approximately 3.6-fold more inhabitants than Lugano's, and 1.9-fold more than Lausanne's. Consequently, the N1 concentrations in the Zurich WWTP were expected to be lower compared to Lugano and Lausanne, as confirmed by our measurements (Figure S7). To enable a direct comparison among WWTPs, we converted N1 concentrations into units of daily N1 load (equation 2). This unit accounts for differences in catchment size (via the daily wastewater flow rate), and also incorporates daily variability in the wastewater flow of a given WWTP. Similar to data from other studies 10,11,38, there was considerable day-to-day variability in both the N1 loads and the number of confirmed cases (Figure 3). The variability in confirmed cases is increased by the fact that Switzerland reduces testing and reporting on weekends. To facilitate the visualization of pandemic trends in wastewater and case data, we therefore calculated weekly averages (Monday - Sunday) for each data set. The corresponding results are shown as solid lines in Figure 3. As is evident, both data sets feature a prominent peak in late March. However, the wastewater peak shape is narrow, whereas the number of confirmed cases remained high for 2-3 weeks.

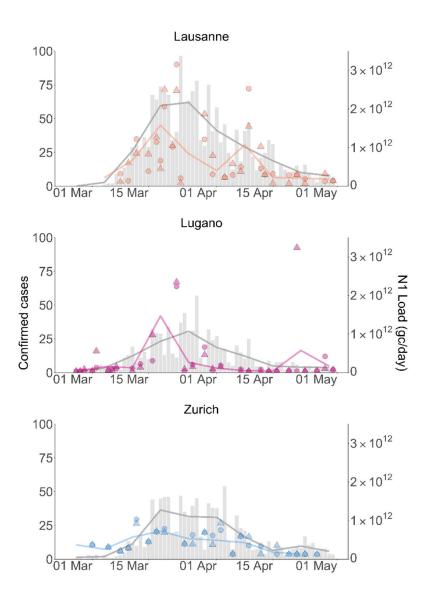


Figure 3: SARS-CoV-2 RNA (N1) loads and confirmed cases for the Lausanne, Lugano and Zurich WWTP catchments from February 26 until April 30, 2020. Data points represent wastewater data (average of technical replicates). Circles and triangles indicate biological replicates. Grey bars show confirmed cases. Lines connect weekly (Monday-Sunday) averages of SARS-CoV-2 RNA loads or confirmed cases.

Despite the similarity in confirmed case numbers in the catchment, measured SARS-CoV-2 RNA loads were higher in the Lugano WWTP than in Zurich WWTP. There are a number of potential methodological explanations for this, including lower virus recovery in Zurich (Figure S5), lower precision in quantifying low SARS-CoV-2 RNA copy numbers (Figure S7), and our sample storage protocol, which in retrospect was

found to be non ideal (Figure 2). The Zurich WWTP is located in the area of lowest disease prevalence and thus had the lowest starting concentrations of SARS-CoV-2 RNA among the WWTPs sampled. Further decay during storage of the Zurich samples may have lowered the concentrations below the LOD in all but the samples taken during the peak of the first wave.

3.3. Comparison of incidence dynamics from wastewater data, case numbers and SEIR models

To assess the ability to track disease dynamics with SARS-CoV-2 loads in wastewater and confirmed cases, both data sets were used to estimate disease incidence over time (by deconvoluting the signals, see Materials and Methods). The resulting trends were compared to the reference incidence determined by an SEIR model ¹⁹. While the SEIR model reports absolute infection numbers, this determination is currently not feasible for wastewater- or case number-derived estimates. For wastewater, estimating absolute infection numbers would require a better understanding of the magnitude of the shedding load L (equation 4), the decay kinetics of SARS-CoV-2 RNA in the sewer system, and the true recovery of SARS-CoV-2 in our sample processing pipeline. These parameters are currently not available, but may become better known in the future. For case numbers, the ratio of confirmed to total cases would have to be known, yet this parameter is associated with considerable uncertainty and likely variability during the first wave of the pandemic. We therefore only compared the incidence dynamics, but not the absolute incidence per day.

As shown in Figure 4, both wastewater- and case number-derived incidence exhibited a pronounced peak in mid-March. In Lausanne, the wastewater-derived incidence exhibited the highest number of infections from March 13-15, which matches the peak of infections determined by the SEIR model. If estimated based on confirmed cases, the highest number of new infections occurred from March 9-11. Considering the delay distributions from infection to case confirmation, this time range mainly reflects cases observed from March 17-24, coinciding with Swiss-wide positivity rates > 10% (Figure S1). The premature timing of

348

349

350

351

352

353

354

355

356

357

358

359

360

361

362

363

364

365

366

367

368

the peak may indicate that case numbers were truncated when testing capacity was exceeded and positivity rates were high. In Lugano, wastewater-based incidence estimates yielded the highest infection numbers from March 10-12. This time frame partly overlapped with the SEIR-modelled infection peak, which occurred from March 12-14. In contrast, the incidence peak determined from confirmed cases appeared later (March 17-19) and differed in shape compared to the other incidence estimates. This is another indication testing capacity during this period was insufficient to capture the full extent of the rise in cases during the height of the first wave. In both locations, the decline in new infections was better captured by case number- than by wastewaterbased incidence estimates. In Lausanne, the case number-based incidence exhibited a slow decay in new infections from mid-March to late April, similar to the reference incidence dynamics. In contrast, the decay in the wastewater-based incidence was faster. In Lugano the case number-derived incidence was also able to capture the tail end of the wave, whereas new infections based on wastewater data rapidly dropped to the baseline. Finally, the wastewater-based incidence dynamics in both locations exhibited a second, smaller peak in April, which was driven by few high load measurements in each location. In Lausanne this feature also appeared in the corresponding case number-derived incidence dynamics and thus reflects a local spike in infections. In contrast, the origin of the second peak in Lugano is not evident. It may stem from one or more shedders that are not permanent inhabitants of the Lugano WWTP catchment and were therefore not included in the catchment-specific case numbers (e.g., commuters or external patients hospitalized within the catchment). The April peaks were not apparent in the SEIR model, which may be explained by differences in the type of input data used to determine incidence dynamics. Whereas wastewater loads and case numbers were catchment-specific, the SEIR model was based on data for the entire canton. Local spikes in case numbers would thus appear attenuated in the reference incidence.

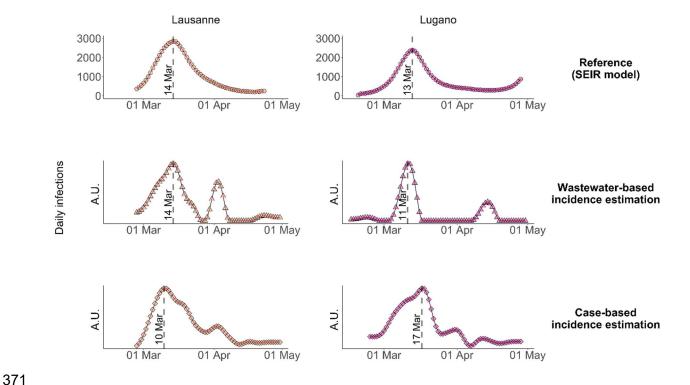


Figure 4. Comparison of COVID19 incidence dynamics estimated by the SEIR model, determined based on SARS-CoV-2 RNA loads in wastewater and based on confirmed case numbers. Incidence dynamics were determined by deconvolution of the wastewater loads and case numbers shown in Figure 3. The Zurich WWTP was not included in this analysis, because most wastewater samples yielded non-detectable SARS-CoV-2 RNA concentrations. A.U. = arbitrary units.

4. Conclusions

Our findings demonstrate that both confirmed case numbers and wastewater analysis are useful and independent metrics to estimate COVID-19 incidence dynamics. Wastewater outperformed case numbers with respect to the timing and shape of the peak incidence, whereas confirmed case numbers were a better indicator for incidence decline. In combination, the two metrics yielded complementary

383

384

385

386

387

388

389

390

391

392

393

394

395

396

397

398

399

400

401

402

403

404

information on incidence dynamics that correspond well to the reference dynamics determined by compartmental models. It is important to consider that all three approaches rely on a number of assumptions, all of which are associated with a degree of uncertainty. For example, the SEIR model is based exclusively on data pertaining to severe COVID-19 cases (hospitalizations, deaths), and may thus miss events among age classes that have a low severity rate but normal virus shedding. Wastewater-derived incidence dynamics suffer from uncertainties in the accuracy of the SLD. And cases-number derived estimates rely on the delay distribution between infection and case confirmation, which may vary with time and location. While the sources of uncertainties of these assumptions are conceptually understood, they remain difficult to quantify due to the lack of reference data. It is therefore important and encouraging that despite these uncertainties, comparable incidence dynamics were obtained with three independent approaches. Differences in the incidence dynamics determined by wastewater and confirmed cases may ultimately also be exploited to inform on the duration and degree of clinical undertesting. To do so, however, both incidence estimates need to be further advanced. In future work, wastewater-derived estimates can be enhanced by increasing the wastewater sampling frequency to smooth out measurement outliers, developing more sensitive assays to quantify the viral RNA at low concentrations, better determining SARS-CoV-2 RNA recovery from wastewater, and establishing a representative shedding load profile. Case number-derived incidence estimates can be improved by taking into account variations in the delay distributions from symptom onset to case confirmation. In Switzerland, the mean delay varied from 3 to 8 days during the first wave ⁴⁷, yet herein it was held constant at 5.5 days. Compared to the compartmental model, which relies on hospitalization and deaths, WBE can determine incidence dynamics with a faster turnaround time (RNA loads can be measured within 24 hours after sampling). Compared to clinical tests, an additional advantage of WBE is that a much lower number of samples is required to determine incidence dynamics with reasonable accuracy. During high positivity rate regimes, WBE can thus yield information on the trajectory of a pandemic that is potentially more precise, more readily available and more economical than information from clinical data. We contend that WBE should be included by epidemiologists and public health agencies as a useful pandemic monitoring tool during periods with high test positivity rates.

Acknowledgements

This work was supported by the Swiss National Science Foundation (project 31CA30_196538), Eawag discretionary funds, and an EPFL COVID-19 grant. XFC was a fellow of the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska—Curie Grant Agreement No. 754462. We thank the operators of the Lugano, Lausanne and Zurich WWTPs for providing samples, the Swiss Federal Office of Public Health for catchment-specific case numbers, Jana Huisman for valuable input on SLDs, and Marie-Helene Corre, Elyse Stachler and Lea Caduff for lab assistance.

Appendix A: Supporting Information

Supporting information to this article can be found online at https://doi.org/xxx.

References

420

421 (1) Sinclair, R. G.; Choi, C. Y.; Riley, M. R.; Gerba, C. P. Pathogen surveillance through monitoring of 422 sewer systems. Adv Appl Microbiol 2008, 65, 249-269. 423 (2) Fernandez-Cassi, X.; Timoneda, N.; Martínez-Puchol, S.; Rusiñol, M.; Rodriguez-Manzano, J.; 424 Figuerola, N.; Bofill-Mas, S.; Abril, J. F.; Girones, R. Metagenomics for the study of viruses in urban 425 sewage as a tool for public health surveillance. Sci. Total Environ. 2018, 618, 870–880. 426 (3) Hovi, T.; Shulman, L. M.; van der Avoort, H.; Deshpande, J.; Roivainen, M.; DE Gourville, E. M. Role 427 of environmental poliovirus surveillance in global polio eradication and beyond. Epidemiol. Infect. 428 2012, 140, 1–13. 429 (4) Kazama, S.; Miura, T.; Masago, Y.; Konta, Y.; Tohma, K.; Manaka, T.; Liu, X.; Nakayama, D.; Tanno, 430 T.; Saito, M.; et al. Environmental surveillance of norovirus genogroups I and II for sensitive 431 detection of epidemic variants. Appl. Environ. Microbiol. 2017, 83. 432 (5) Bisseux, M.; Debroas, D.; Mirand, A.; Archimbaud, C.; Peigue-Lafeuille, H.; Bailly, J.-L.; Henquell, C. 433 Monitoring of enterovirus diversity in wastewater by ultra-deep sequencing: An effective 434 complementary tool for clinical enterovirus surveillance. Water Res. 2020, 169, 115246. 435 Wu, Y.; Guo, C.; Tang, L.; Hong, Z.; Zhou, J.; Dong, X.; Yin, H.; Xiao, Q.; Tang, Y.; Qu, X.; et al. (6)436 Prolonged presence of SARS-CoV-2 viral RNA in faecal samples. Lancet Gastroenterol. Hepatol. 437 2020, 5, 434-435. 438 (7) Medema, G.; Heijnen, L.; Elsinga, G.; Italiaander, R.; Brouwer, A. Presence of SARS-Coronavirus-2 439 RNA in Sewage and Correlation with Reported COVID-19 Prevalence in the early stage of the 440 epidemic in The Netherlands. Environ. Sci. Technol. Lett. 2020. 441 (8) Randazzo, W.; Truchado, P.; Cuevas-Ferrando, E.; Simón, P.; Allende, A.; Sánchez, G. SARS-CoV-2 442 RNA in wastewater anticipated COVID-19 occurrence in a low prevalence area. Water Res. 2020, 443 *181*, 115942.

444	(9)	Ahmed, W.; Angel, N.; Edson, J.; Bibby, K.; Bivins, A.; O'Brien, J. W.; Choi, P. M.; Kitajima, M.;
445		Simpson, S. L.; Li, J.; et al. First confirmed detection of SARS-CoV-2 in untreated wastewater in
446		Australia: A proof of concept for the wastewater surveillance of COVID-19 in the community. Sci.
447		Total Environ. 2020, 728, 138764.
448	(10)	Peccia, J.; Zulli, A.; Brackney, D. E.; Grubaugh, N. D.; Kaplan, E. H.; Casanovas-Massana, A.; Ko, A.
449		I.; Malik, A. A.; Wang, D.; Wang, M.; et al. Measurement of SARS-CoV-2 RNA in wastewater tracks
450		community infection dynamics. Nat. Biotechnol. 2020, 38, 1164–1167.
451	(11)	Graham, K. E.; Loeb, S. K.; Wolfe, M. K.; Catoe, D.; Sinnott-Armstrong, N.; Kim, S.; Yamahara, K. M.;
452		Sassoubre, L. M.; Mendoza Grijalva, L. M.; Roldan-Hernandez, L.; et al. SARS-CoV-2 RNA in
453		wastewater settled solids is associated with COVID-19 cases in a large urban sewershed. Environ.
454		Sci. Technol. 2021, 55, 488–498.
455	(12)	Jahn, K.; Dreifuss, D.; Topolsky, I.; Kull, A.; Ganesanandamoorthy, P.; Fernandez-Cassi, X.; Bänziger,
456		C.; Stachler, E.; Fuhrmann, L.; Jablonski, K. P.; et al. Detection of SARS-CoV-2 variants in Switzerland
457		by genomic analysis of wastewater samples. <i>medRxiv</i> 2021.01.08.21249379; doi:
458		https://doi.org/10.1101/2021.01.08.21249379.
459	(13)	Crits-Christoph, A.; Kantor, R. S.; Olm, M. R.; Whitney, O. N.; Al-Shayeb, B.; Lou, Y. C.; Flamholz, A.;
460		Kennedy, L. C.; Greenwald, H.; Hinkle, A.; et al. Genome sequencing of sewage detects regionally
461		prevalent SARS-CoV-2 variants. <i>MBio</i> 2021, <i>12</i> .
462	(14)	The Cambridge Public Health Department (CPHD). Cambridge COVID-19 Data Center
463		https://cityofcambridge.shinyapps.io/COVID19/#shiny-tab-wastewater (accessed Mar 1, 2021).
464	(15)	Victoria State Government - Health and Human Services. Wastewater monitoring - coronavirus
465		(COVID-19) https://www.dhhs.vic.gov.au/wastewater-monitoring-covid-19 (accessed Mar 1,
466		2021).

467	(16)	Queensland Government. Wastewater surveillance program results
468		https://www.qld.gov.au/health/conditions/health-alerts/coronavirus-covid-19/current-
469		status/wastewater (accessed Mar 1, 2021).
470	(17)	Rijksoverheid. Early indicators - Virus particles in wastewater
471		https://coronadashboard.government.nl/landelijk/rioolwater (accessed Mar 1, 2021).
472	(18)	World Health Organization. Public health criteria to adjust public health and social measures in
473		the context of COVID-19: annex to considerations in adjusting public health and social measures in
474		the context of COVID-19, 12 May 2020.; WHO/2019-
475		nCoV/Adjusting_PH_measures/Criteria/2020.1; World Health Organization, 2020.
476	(19)	Lemaitre, J. C.; Perez-Saez, J.; Azman, A. S.; Rinaldo, A.; Fellay, J. Assessing the impact of non-
477		pharmaceutical interventions on SARS-CoV-2 transmission in Switzerland. Swiss Med Wkly 2020,
478		<i>150</i> , w20295.
479	(20)	Kitajima, M.; Iker, B. C.; Pepper, I. L.; Gerba, C. P. Relative abundance and treatment reduction of
480		viruses during wastewater treatment processesidentification of potential viral indicators. Sci.
481		Total Environ. 2014, 488-489, 290–296.
482	(21)	Symonds, E. M.; Nguyen, K. H.; Harwood, V. J.; Breitbart, M. Pepper mild mottle virus: A plant
483		pathogen with a greater purpose in (waste)water treatment development and public health
484		management. Water Res. 2018, 144, 1–12.
485	(22)	Leibowitz, J.; Kaufman, G.; Liu, P. Coronaviruses: propagation, quantification, storage, and
486		construction of recombinant mouse hepatitis virus. Curr Protoc Microbiol 2011, Chapter 15, Unit
487		15E.1.
488	(23)	Lu, X.; Wang, L.; Sakthivel, S. K.; Whitaker, B.; Murray, J.; Kamili, S.; Lynch, B.; Malapati, L.; Burke,
489		S. A.; Harcourt, J.; et al. US CDC Real-Time Reverse Transcription PCR Panel for Detection of Severe
490		Acute Respiratory Syndrome Coronavirus 2. Emerging Infect. Dis. 2020, 26.

491	(24)	Besselsen, D. G.; Wagner, A. M.; Loganbill, J. K. Detection of rodent coronaviruses by use of
492		fluorogenic reverse transcriptase-polymerase chain reaction analysis. Comp Med 2002, 52, 111–
493		116.
494	(25)	Haramoto, E.; Kitajima, M.; Kishida, N.; Konno, Y.; Katayama, H.; Asami, M.; Akiba, M. Occurrence
495		of pepper mild mottle virus in drinking water sources in Japan. Appl. Environ. Microbiol. 2013, 79,
496		7413–7418.
497	(26)	Zhang, T.; Breitbart, M.; Lee, W. H.; Run, JQ.; Wei, C. L.; Soh, S. W. L.; Hibberd, M. L.; Liu, E. T.;
498		Rohwer, F.; Ruan, Y. RNA viral community in human feces: prevalence of plant pathogenic viruses.
499		PLoS Biol. 2006, 4, e3.
500	(27)	Gendron, L.; Verreault, D.; Veillette, M.; Moineau, S.; Duchaine, C. Evaluation of filters for the
501		sampling and quantification of RNA phage aerosols. Aerosol Science and Technology 2010, 44,
502		893–901.
503	(28)	Merkes, C. M.; Klymus K.E.; Allison M.J.; Goldberg C.; Helbing C.C.; Hunter M.E.; Jackson C.A.; Lance
504		R.F.; Mangan A.M.; Monroe E.M.; Piaggio A.J.; Stokdyk J.P.; Wilson C.C.; Richter C. (2019) Generic
505		qPCR Limit of Detection (LOD) / Limit of Quantification (LOQ) calculator. R Script. Available at:
506		https://github.com/cmerkes/qPCR_LOD_Calc. DOI: https://doi.org/10.5066/P9GT00GB.
507	(29)	Ståhlberg, A.; Kubista, M. The workflow of single-cell expression profiling using quantitative real-
508		time PCR. Expert Rev Mol Diagn 2014, 14, 323–331.
509	(30)	Benefield, A. E.; Skrip, L. A.; Clement, A.; Althouse, R. A.; Chang, S.; Althouse, B. M. SARS-CoV-2
510		viral load peaks prior to symptom onset: a systematic review and individual-pooled analysis of
511		coronavirus viral load from 66 studies. <i>medRxiv</i> 2020.09.28.20202028; doi:
512		https://doi.org/10.1101/2020.09.28.20202028.
513	(31)	Linton, N. M.; Kobayashi, T.; Yang, Y.; Hayashi, K.; Akhmetzhanov, A. R.; Jung, SM.; Yuan, B.;
514		Kinoshita, R.; Nishiura, H. Incubation Period and Other Epidemiological Characteristics of 2019

515		Novel Coronavirus Infections with Right Truncation: A Statistical Analysis of Publicly Available Case
516		Data. J Clin Med 2020, 9.
517	(32)	Liu, P.; Cai, J.; Jia, R.; Xia, S.; Wang, X.; Cao, L.; Zeng, M.; Xu, J. Dynamic surveillance of SARS-CoV-
518		2 shedding and neutralizing antibody in children with COVID-19. Emerg. Microbes Infect. 2020, 9,
519		1254–1258.
520	(33)	Han, M. S.; Seong, MW.; Heo, E. Y.; Park, J. H.; Kim, N.; Shin, S.; Cho, S. I.; Park, S. S.; Choi, E. H.
521		Sequential analysis of viral load in a neonate and her mother infected with severe acute
522		respiratory syndrome coronavirus 2. Clin. Infect. Dis. 2020, 71, 2236–2239.
523	(34)	Bi, Q.; Wu, Y.; Mei, S.; Ye, C.; Zou, X.; Zhang, Z.; Liu, X.; Wei, L.; Truelove, S. A.; Zhang, T.; et al.
524		Epidemiology and transmission of COVID-19 in 391 cases and 1286 of their close contacts in
525		Shenzhen, China: a retrospective cohort study. Lancet Infect. Dis. 2020, 20, 911–919.
526	(35)	R Core Team. R: A language and environment for statistical computing. <i>R foundation for statistical</i>
527		computing, Vienna, Austria 2016. https://www.R-project.org/
528	(36)	Fu, A.; Narasimhan, B.; Boyd, S. cvxr: an r package for disciplined convex optimization. J Stat Softw
529		
		2020, 94.
530	(37)	2020, 94. Ruckdeschel, P.; Kohl, M. General Purpose Convolution Algorithm in S 4 Classes by Means of FFT. J
530 531	(37)	
	(37)	Ruckdeschel, P.; Kohl, M. General Purpose Convolution Algorithm in S 4 Classes by Means of FFT. J
531		Ruckdeschel, P.; Kohl, M. General Purpose Convolution Algorithm in <i>S</i> 4 Classes by Means of FFT. <i>J</i> Stat Softw 2014, 59, 1–25.
531 532		Ruckdeschel, P.; Kohl, M. General Purpose Convolution Algorithm in <i>S</i> 4 Classes by Means of FFT. <i>J</i> Stat Softw 2014, 59, 1–25. Gerrity, D.; Papp, K.; Stoker, M.; Sims, A.; Frehner, W. Early-pandemic wastewater surveillance of
531532533		Ruckdeschel, P.; Kohl, M. General Purpose Convolution Algorithm in S 4 Classes by Means of FFT. J Stat Softw 2014, 59, 1–25. Gerrity, D.; Papp, K.; Stoker, M.; Sims, A.; Frehner, W. Early-pandemic wastewater surveillance of SARS-CoV-2 in Southern Nevada: Methodology, occurrence, and incidence/prevalence
531532533534	(38)	Ruckdeschel, P.; Kohl, M. General Purpose Convolution Algorithm in S 4 Classes by Means of FFT. <i>J Stat Softw</i> 2014, <i>59</i> , 1–25. Gerrity, D.; Papp, K.; Stoker, M.; Sims, A.; Frehner, W. Early-pandemic wastewater surveillance of SARS-CoV-2 in Southern Nevada: Methodology, occurrence, and incidence/prevalence considerations. <i>Water Research X</i> 2021, <i>10</i> , 100086.
531532533534535	(38)	Ruckdeschel, P.; Kohl, M. General Purpose Convolution Algorithm in S 4 Classes by Means of FFT. <i>J Stat Softw</i> 2014, <i>59</i> , 1–25. Gerrity, D.; Papp, K.; Stoker, M.; Sims, A.; Frehner, W. Early-pandemic wastewater surveillance of SARS-CoV-2 in Southern Nevada: Methodology, occurrence, and incidence/prevalence considerations. <i>Water Research X</i> 2021, <i>10</i> , 100086. Chik, A. H. S.; Glier, M. B.; Servos, M.; Mangat, C. S.; Pang, XL.; Qiu, Y.; D'Aoust, P. M.; Burnet, J

539	(40)	Pecson, B. M.; Darby, E.; Haas, C. N.; Amha, Y. M.; Bartolo, M.; Danielson, R.; Dearborn, Y.; Di
540		Giovanni, G.; Ferguson, C.; Fevig, S.; et al. Reproducibility and sensitivity of 36 methods to quantify
541		the SARS-CoV-2 genetic signal in raw wastewater: findings from an interlaboratory methods
542		evaluation in the U.S. Environ. Sci.: Water Res. Technol. 2021.
543	(41)	Ye, Y.; Ellenberg, R. M.; Graham, K. E.; Wigginton, K. R. Survivability, partitioning, and recovery of
544		enveloped viruses in untreated municipal wastewater. <i>Environ. Sci. Technol.</i> 2016, <i>50</i> , 5077–5085.
545	(42)	La Rosa, G.; Iaconelli, M.; Mancini, P.; Bonanno Ferraro, G.; Veneri, C.; Bonadonna, L.; Lucentini,
546		L.; Suffredini, E. First detection of SARS-CoV-2 in untreated wastewaters in Italy. Sci. Total Environ.
547		2020 <i>, 736</i> , 139652.
548	(43)	Ahmed, W.; Tscharke, B.; Bertsch, P. M.; Bibby, K.; Bivins, A.; Choi, P.; Clarke, L.; Dwyer, J.; Edson,
549		J.; Nguyen, T. M. H.; et al. SARS-CoV-2 RNA monitoring in wastewater as a potential early warning
550		system for COVID-19 transmission in the community: A temporal case study. Sci. Total Environ.
551		2021 <i>, 761</i> , 144216.
552	(44)	D'Aoust, P. M.; Mercier, E.; Montpetit, D.; Jia, JJ.; Alexandrov, I.; Neault, N.; Baig, A. T.; Mayne,
553		J.; Zhang, X.; Alain, T.; et al. Quantitative analysis of SARS-CoV-2 RNA from wastewater solids in
554		communities with low COVID-19 incidence and prevalence. Water Res. 2021, 188, 116560.
555	(45)	Gonzalez, R.; Curtis, K.; Bivins, A.; Bibby, K.; Weir, M. H.; Yetka, K.; Thompson, H.; Keeling, D.;
556		Mitchell, J.; Gonzalez, D. COVID-19 surveillance in Southeastern Virginia using wastewater-based
557		epidemiology. Water Res. 2020, 186, 116296.
558	(46)	Wu, F.; Zhang, J.; Xiao, A.; Gu, X.; Lee, W. L.; Armas, F.; Kauffman, K.; Hanage, W.; Matus, M.;
559		Ghaeli, N.; et al. SARS-CoV-2 Titers in Wastewater Are Higher than Expected from Clinically
560		Confirmed Cases. mSystems 2020, 5.

(47) Huisman, J. S.; Scire, J.; Angst, D. C.; Neher, R. A.; Bonhoeffer, S.; Stadler, T. Estimation and worldwide monitoring of the effective reproductive number of SARS-CoV-2. *medRxiv* 2020.11.26.20239368; doi: https://doi.org/10.1101/2020.11.26.20239368.