

1 Using Detrending to Assess SARS-CoV- 2 2 Wastewater Loads as a Leading 3 Indicator of Fluctuations in COVID-19 4 Cases at Fine Temporal Scales: 5 Correlations Across Twenty 6 Sewersheds in North Carolina 7

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32 Abstract

33 Wastewater surveillance emerged during the COVID-19 pandemic as a novel strategy
34 for tracking the burden of illness in communities. Previous work has shown that trends in
35 wastewater SARS-CoV-2 viral loads correlate well with reported COVID-19 case trends over
36 longer time periods (i.e., months). We used detrending time series to reveal shorter sub-trend
37 patterns (i.e., weeks) to identify leads or lags in the temporal alignment of the wastewater/case
38 relationship. Daily incident COVID-19 cases and twice-weekly wastewater SARS-CoV-2 viral
39 loads measured at 20 North Carolina sewersheds in 2021 were detrended using smoothing
40 ranges of ∞ , 16, 8, 4 and 2 weeks, to produce detrended cases and wastewater viral loads at
41 progressively finer time scales. For each sewershed and smoothing range, we calculated the
42 Spearman correlation between the cases and the wastewater viral loads with offsets of -7 to +7
43 days. We identified a conclusive lead/lag relationship at 15 of 20 sewersheds, with detrended
44 wastewater loads temporally leading detrended COVID-19 cases at 11 of these sites. For the 11
45 leading sites, the correlation between wastewater loads and cases was greatest for wastewater
46 loads sampled at a median lead time of 6 days before the cases were reported. Distinct lead/lag
47 relationships were the most pronounced after detrending with smoothing ranges of 4–8 weeks,
48 suggesting that SARS-CoV-2 wastewater viral loads can track fluctuations in COVID-19 case
49 incidence rates at fine time scales and may serve as a leading indicator in many settings. These
50 results could help public health officials identify, and deploy timely responses in, areas where
51 cases are increasing faster than the overall pandemic trend.

52 Introduction

53 The first lab-confirmed COVID-19 case was reported in North Carolina (NC) on March 3,
54 2020, and over the next two and a half years, the number of reported positive cases statewide
55 increased to more than three million [1,2]. However, the true burden of disease far exceeded
56 this number due to underreporting, access to testing, unreported at-home tests, asymptomatic
57 illness and other factors [3–5]. Testing was not uniformly distributed among populations due to
58 unequal availability and pervasive mistrust of public health recommendations by historically
59 marginalized persons [6–8]. As a result, there is need for non-clinical means of tracking COVID-
60 19 trends to augment case-based reporting.

61 One promising approach is wastewater-based epidemiology (WBE), which measures
62 substances shed in human feces and derived from a condition of interest, such as pathogen
63 nucleic acids or pharmaceutical metabolites, by sampling sewage containing human fecal waste
64 and byproducts of water usage [9]. WBE has been increasingly utilized to track COVID-19
65 infection trends at the community level by quantifying SARS-CoV-2 RNA in sewage. Twice-
66 weekly testing of SARS-CoV-2 loads in wastewater can provide information on changes in
67 COVID-19 burden in the sewershed population and can be used as a method to detect periods
68 of increasing COVID-19 cases from far fewer samples than required for clinical case reporting
69 since wastewater samples represent pooled samples of multiple individuals [10]. Unlike case-
70 based surveillance, wastewater surveillance does not rely on individual healthcare-seeking
71 behavior or access to testing, which are strongly impacted by well-documented societal
72 inequities [11]. Additionally, SARS-CoV-2 is shed in the feces of both symptomatic and
73 asymptomatic individuals, allowing the capture of data on a range of infected individuals [12–14]
74 at varying stages of infection. Numerous studies have shown that when clinical testing coverage
75 is high, wastewater SARS-CoV-2 loads and documented COVID-19 cases follow similar trends
76 and are highly correlated [15–18]. Therefore, given the cost and human resource savings, WBE

77 may provide an effective complement to case-based surveillance that addresses some of the
78 limitations of traditional clinical surveillance approaches.

79 However, the values typically measured in wastewater, such as viral genome copies per
80 liter, are not directly interpretable in terms of familiar population health metrics, like the
81 prevalence or incidence rate of infection in a defined population. To effectively inform public
82 health response and mitigation strategies using WBE, it is necessary to relate wastewater-
83 based measurements to interpretable population-level metrics. One critical aspect is the
84 temporal relationship between SARS-CoV-2 wastewater loads measured at a wastewater
85 treatment plant (WWTP) and reported COVID-19 cases in the corresponding sewershed served
86 by the plant [5,19]. Past work has demonstrated that increases in SARS-CoV-2 wastewater
87 loads may occur prior to a rise in lab-confirmed sewershed COVID-19 cases in a sewershed,
88 allowing for WBE to be used as an early warning system [4,20–22]. Such leading signals in
89 wastewater were reported during the earlier phases of the pandemic in some North Carolina
90 sewersheds [10,23] as well as during more recent pandemic phases [24].

91 As the pandemic becomes endemic, trends lasting several months have been widely
92 reported to anticipate trends in COVID-19 infections, as later indicated by population
93 surveillance metrics [21,22,25,26]. However, the time alignment between trends in wastewater
94 load and trends in cases can be difficult to determine since its small temporal lead or lag may be
95 eclipsed by the longer time scale of trends. In this situation, kernel detrending can be used to
96 remove these longer pandemic trends and reveal shorter-term fluctuations that may help identify
97 leads or lags in the temporal alignment of the detrended wastewater and detrended case
98 relationship [27–31]. While the correlation between wastewater-based measurements of
99 pathogens of concern and clinical cases over longer time periods (i.e., months) is useful for
100 informing longer-term public health response, much less is known about short-term sub-trends
101 (i.e., weekly or even daily), which may be more relevant for ongoing, day-to-day public health
102 decision making. Therefore, there is a need for research to better understand and anticipate

103 changes in COVID-19 incidence on shorter time scales to inform timely, targeted, and cost-
104 effective public health action, particularly at the local level. *Detrending* the wastewater and case
105 data is done by modeling these longer-term trends and removing them to obtain detrended
106 wastewater loads and detrended cases, also referred to as wastewater load residuals and case
107 residuals, respectively. If wastewater load residuals can predict a fine-scale fluctuation in case
108 residuals, then public health measures can be taken *locally* and for *short* durations in
109 sewersheds where cases are anticipated to rise at levels greater than that of the baseline trend.
110 This methodology may also be applicable for other pathogens beyond SARS-CoV-2 as
111 wastewater surveillance expands to new targets in the future.

112 Our work aims to contribute to previous studies by refining the time scale at which
113 correlations between wastewater and cases are assessed. Accordingly, we investigate the
114 temporal relationship (i.e., lead or lag) that maximizes correlation between detrended
115 wastewater SARS-CoV-2 viral loads and detrended COVID-19 clinical cases at the finest time-
116 scale possible for 20 sewersheds across North Carolina in 2021. Furthermore, to operationalize
117 this approach, we propose and validate a set of reproducible criteria that can be easily deployed
118 by public health agencies to support the application of WBE approaches beyond North Carolina.
119

120 Materials and Methods

121 Ongoing Wastewater-Based Epidemiology in North Carolina

122 In collaboration with University of North Carolina (UNC) system researchers, the North
123 Carolina Department of Health and Human Services (NCDHHS) was one of eight state health
124 departments initially funded by the Centers for Disease Control and Prevention (CDC) to
125 participate in the National Wastewater Surveillance System (NWSS). The NCDHHS NC
126 Wastewater Monitoring Network is a multi-disciplinary collaboration between epidemiologists,

127 laboratory scientists, water reclamation managers, environmental engineers, and public health
128 officials with promising applications for genomic, large-scale pathogen monitoring, as well as
129 COVID-19. The development of this state surveillance network benefited from a collaboration
130 funded by the North Carolina State Legislature among North Carolina universities at the start of
131 the pandemic in 2020. This group of experts created the NC Wastewater Pathogen Research
132 Network to develop sampling techniques, laboratory capabilities, and analysis of SARS-CoV-2
133 in wastewater [32]. The NC Wastewater Pathogen Research Network, in collaboration with
134 NCDHHS, established a strong foundation for WBE, and founding contributors continue to be
135 essential partners in the NC Wastewater Monitoring Network using a framework of innovative
136 research to inform public health surveillance and action in North Carolina.

137 As part of the NC Wastewater Monitoring Network data collection in 2021, wastewater
138 samples were collected twice per week by WWTP staff and shipped to the UNC-Chapel Hill
139 Institute of Marine Sciences (IMS, Morehead City, NC) for laboratory analysis. Samples were
140 analyzed for SARS-CoV-2 by reverse-transcription droplet digital polymerase chain reaction
141 (RT-ddPCR) following a standardized protocol [33], for which additional details are provided in
142 the Supplementary Material [34]. Sewer network spatial data (e.g., gravity mains, force mains,
143 manholes, pump stations) obtained from North Carolina wastewater utilities and local
144 geographic information systems departments were used to delineate a sewershed polygon
145 using ArcGIS Pro 2.8 (ESRI, Redlands, CA). COVID-19 clinical cases reported to NCDHHS
146 were geocoded in ArcMap 10.7.1 (ESRI) and matched to the sewershed within which they
147 resided using a custom composite geocoder built from state and county address data. Lastly,
148 wastewater sample results and recorded clinical cases in the sewershed were submitted to
149 NCDHHS and uploaded weekly the CDC NWSS analytics platform for epidemiologic trend
150 analysis. COVID-19 cases were given a date based on the following hierarchy: date of symptom
151 onset, date of specimen collection, and date of result. Daily incidence rates per 100,000
152 estimated sewershed population were calculated. Wastewater sample results were normalized

153 to flow within each municipal utility to represent a 24-hour viral load. These analyzed data are
154 posted publicly on the CDC COVID-19 Data Tracker and the NCDHHS COVID Dashboard
155 (<https://covid19.ncdhhs.gov/dashboard/wastewater-monitoring>).

156

157 Relating Wastewater Loads and COVID-19 Incidence

158 During a ten-month study period from January 2021 through October 2021, we
159 compared SARS-CoV-2 viral loads in influent wastewater collected at the 20 WWTPs in the NC
160 Wastewater Monitoring Network with COVID-19 incidence in the corresponding sewersheds.
161 Nine sites were sampled for the entire duration of the study period, two sites were sampled
162 beginning in January and ending before October 2021, and nine sites were added in the
163 summer and sampled from June 2021 through October 2021 (Table 1). We retrieved calculated
164 wastewater viral loads and clinical COVID-19 incidence rates in the sewershed for each of the
165 20 sites from the CDC NWSS analytics platform. Twice-weekly wastewater loads were provided
166 as the sample-specific geometric mean of measured N1 and N2 target copy numbers per liter
167 (L) of wastewater [35], normalized by multiplying by the average daily flow and dividing by the
168 estimated sewershed population. Half the target-specific limit of detection (LOD) was substituted
169 for the concentration when a target was not detected in the sample (see Supplemental
170 Material). The resulting population-normalized viral loads, with units of SARS-CoV-2 N gene
171 copies (GC) per person per day (pppd), were \log_{10} -transformed for all analyses, which were
172 conducted in R version 4.1.2 [36].

173 Table 1. Characteristics of NC Wastewater Monitoring Network Sites

WWTP Name	Population (2019)	Area (km ²)	Capacity (ML/day)	First Sample	Last Sample	Number of Samples
Newport	3,731	6.1	5	1/12/2021	8/18/2021	64
Pittsboro	3,799	10.3	3	1/5/2021	5/25/2021	39
Beaufort	3,992	7.4	7	1/5/2021	10/20/2021	83
Marion	7,793	22.9	14	6/17/2021	10/14/2021	35
Laurinburg	15,407	37.4	18	6/17/2021	10/19/2021	36
Roanoke Rapids	19,335	43.9	38	6/19/2021	10/20/2021	33
Wilson	51,285	164.4	64	6/19/2021	10/19/2021	33
New Hanover Co.	51,401	81.4	48	1/22/2021	10/20/2021	78
Wilmington	65,081	62.5	25	1/5/2021	10/20/2021	79
Charlotte 1	77,278	126	55	1/5/2021	10/19/2021	76
Chapel Hill	84,729	89.8	66	1/6/2021	10/20/2021	81
Greenville	94,194	95.2	80	1/5/2021	10/20/2021	81
South Durham	98,068	100.7	91	1/6/2021	10/20/2021	81
Charlotte 3	122,063	122.2	55	6/3/2021	10/19/2021	38
Greensboro	144,539	143.6	82	6/18/2021	10/20/2021	36
Charlotte 2	154,519	105.3	127	1/4/2021	10/19/2021	80
Fayetteville	159,000	250.8	95	6/19/2021	10/20/2021	36
Winston Salem	177,520	319.6	70	6/19/2021	10/20/2021	33
MSD of Buncombe Co.	188,927	534.4	182	6/19/2021	10/20/2021	33
Raleigh	551,534	536.7	341	1/6/2021	10/20/2021	74

174

175 Exponential kernel smoothing is a technique used in space/time geostatistics to estimate

176 spatial and temporal trends of environmental and health processes at a variety of spatial and

177 temporal scales [27–31]. Here, we used exponential kernel smoothing to estimate trends in

178 wastewater viral loads and COVID-19 incidence rates at different temporal scales. For each

179 observed response, a smoothed estimate was obtained as the average of all observations

180 weighted by an exponentially decaying function of the temporal distance from the estimation

181 time point. The rate of exponential decay was determined by a smoothing range parameter,

182 corresponding to the temporal duration below which variations in the response are smoothed

183 out of the mean trend to retain only those variations of greater duration than the smoothing

184 range. For a response $y(t)$ observed at time t , the smoothed estimate was obtained as the
185 mean trend $m_y(t;T)$ with smoothing range of duration T :

$$m_y(t;T) = \sum_{j=1}^N k_j y(t_j) \quad (1)$$

186 where $y(t_j), j=1, \dots, N$, are the observations at observation times t_j and the exponential kernel
187 smoothing weights k_j are given by

$$k_j = \frac{\exp\left(\frac{-3|t_j - t|}{T}\right)}{\sum_{j=1}^N \exp\left(\frac{-3|t_j - t|}{T}\right)} \quad (2)$$

188 Scaling the exponential decay function by -3 ensured that the influence of observations with
189 temporal distance equal to the smoothing range T was diminished by ~95%, with the estimation
190 point itself receiving the highest weight. As T increased, observations further away in time were
191 allowed greater influence on the mean trend, increasing the extent of smoothing until
192 converging to a constant value at the arithmetic mean of all the data for T of infinite duration.

193 As the mean trend $m_y(t;T)$ only retained variations in the response of greater duration
194 than the smoothing range T , we detrended the observed responses by subtracting the mean
195 trend estimated at time t to obtain the residual response:

$$\tilde{y}(t;T) = y(t) - m_y(t;T) \quad (3)$$

196 which captured the fluctuations around the trend at temporal scales shorter than the smoothing
197 range T (including any measurement error). In short, we decomposed the signal $y_i(t)$ into a time
198 trend $m_{y_i}(t;T)$ that captured variation of time scales greater than T and a detrended signal \tilde{y}_i
199 $(t;T)$ that captured fluctuations of time scale shorter than T , corresponding to the shorter-term
200 variations around pandemic trends that are of particular relevance to timely public health action.

201 To examine the time scales at which wastewater signals may lead (i.e., precede) or lag
202 (i.e., follow) clinical cases at North Carolina Wastewater Monitoring Network sites, we evaluated
203 the cross-correlation between *detrended* wastewater viral loads, denoted $\tilde{w}(t;T)$, and *detrended*

204 COVID-19 incidence rates $\tilde{y}(t;T)$ across various detrending kernel smoothing ranges for
205 observations from January – October, 2021. The cross-correlation between two time series was
206 determined as the set of correlations between pairs of observations for different temporal offsets
207 τ , given by

$$r(\tau;T) = \text{corr}(\tilde{w}(t + \tau;T), \tilde{y}(t;T)) \quad (4)$$

208 for which $\tau < 0$ indicated the detrended wastewater load signal leads the detrended signal
209 obtained from COVID-19 incidence rates; conversely, $\tau > 0$ indicated the signal from detrended
210 wastewater loads lags that of detrended COVID-19 incidence.

211 We examined detrended wastewater loads and detrended COVID-19 incidence rates
212 with detrending smoothing ranges of $T = \infty, 16, 8, 4$ and 2 weeks separately for each site.
213 Because subtracting a constant does not affect correlation estimates, using the $T = \infty$
214 detrended residuals was equivalent to performing the analysis without detrending. As we
215 anticipated nonlinear associations, we estimated Spearman rank correlations to assess the
216 monotonic relationships between the two surveillance systems for temporal offsets ranging from
217 $\tau = -7$ to $\tau = +7$ days. The optimal combination of detrending smoothing range and temporal
218 offset to characterize the lead/lag relationship between wastewater and incidence over relevant
219 time scales was identified for each site by applying a reproducible set of criteria. For each
220 detrending smoothing range T , starting from $T = \infty$ down to $T = 2$, we:

- 221 1. Identified the span of consecutive lead/lag values τ for which $r(\tau;T)$ was a statistically
222 significant positive correlation.
- 223 2. Accepted τ if (a) it was less than 7 days (identifiable), (b) it lasted at least 2 days
224 (persistent), and (c) it contained the maximum $r(\tau;T)$ value (predictive). Otherwise, it
225 was rejected and deemed inconclusive.

226 Finally, the optimal smoothing range was obtained by choosing the shortest detrending
227 smoothing range T that successfully identified a conclusive lead or lag. Detecting fluctuations

228 over a shorter duration is ideal because these can be addressed with more timely public health
229 measures. We selected criteria that favor identifiability, persistence, and predictivity; however,
230 this framework may easily be extended to additional or alternative criteria as required by the
231 specific application.

232 This analysis did not involve human subjects in its research.

233

234 Results

235 Charlotte 1 Sewershed Case Study

236 In this case study, we demonstrate the use of kernel detrending in the cross-correlation
237 analysis of SARS-CoV-2 wastewater loads and COVID-19 incidence in the Charlotte 1
238 sewershed. One of three WWTPs in the Charlotte metropolitan area monitored by the NC
239 Wastewater Monitoring Network during the study period, the Charlotte 1 sewershed covers 126
240 km² in the northeast of the city and serves approximately 80,000 people. From January to
241 October 2021, 76 wastewater samples were collected at Charlotte 1 with a SARS-CoV-2 RNA
242 detection frequency of 98% and a mean daily load of 9.2×10^6 GC pppd. The maximum load
243 was an order of magnitude higher at 4.7×10^7 GC pppd and the minimum load was 7.9×10^4 GC
244 pppd. A total of 6,039 COVID-19 cases were reported in the Charlotte 1 sewershed over the 10-
245 month study period, with a daily incidence rate of 30 cases/100,000 people on average and a
246 maximum of 132 cases/100,000 people. There was only one day with zero COVID-19 cases
247 reported (0.3%, n = 293 days).

248 Visual inspection of trends in the Charlotte 1 sewershed indicated the wastewater loads
249 generally mirrored the COVID-19 incidence rates, with a peak in January, a gradual decline
250 through July followed by a sharper increase in August and second peak around September
251 (Figure 1a and 1b). The mean trend was estimated at each time point for smoothing ranges of

252 $T = \infty, 16, 8, 4$ and 2 weeks. Using $T = \infty$ resulted in a flat (i.e. constant) trend line. Then, as
253 the kernel smoothing range became finer (i.e. $T = 16, 8, 4$ and 2 weeks), the trend line captured
254 more of the inflections in the wastewater and case trends.

255 Subtracting the various mean trends from the wastewater and case observations yielded
256 residuals retaining the variation in the observations at time scales shorter than the
257 corresponding smoothing range T . With an 8-week range, the detrended wastewater loads and
258 detrended cases demonstrated lower temporal variability compared to the variability seen
259 without detrending (Figures 1c and 1d). Scatterplots comparing the detrended wastewater loads
260 and detrended cases on the same day (i.e., temporal offset $\tau = 0$) are presented in Figures 1e
261 and 1f for detrending smoothing ranges $T = \infty$ weeks and $T = 8$ weeks, respectively. As
262 anticipated, we observed that the pairwise correspondence between detrended wastewater
263 loads and detrended cases declined with decreasing detrending smoothing range (i.e., as $T =$
264 $\infty, 16, 8, 4$ and 2 weeks) because more of the pandemic-scale trend was removed and only
265 shorter-term fluctuations remained. However, detrended residuals were significantly positively
266 correlated for all detrending smoothing ranges other than $T = 2$ (the shortest range considered,
267 Spearman's $\rho = 0.19, p = 0.11$).

268 We then calculated, for each detrending smoothing range T , not only the correlation for
269 detrended wastewater observations on the same day as each case date ($\tau = 0$), but also for
270 wastewater observations up to 7 days before ($\tau = -7$) and 7 days after ($\tau = +7$) each case date
271 (Figure 1g). Based on our proposed criteria, we determined the shortest smoothing range T to
272 conclusively identify a time offset τ for predicting detrended cases from detrended wastewater
273 loads in the Charlotte 1 sewershed was $T = 8$ weeks, which revealed positive correlations for
274 wastewater measured 0 to 3 days before cases were reported. This set of contiguous positive
275 correlations spanned more than 2 and fewer than 7 contiguous days and included the maximum
276 correlation value, satisfying our proposed criteria for identifiable and predictive lead/lag

277 relationships. Longer detrending smoothing ranges ($T = \infty$ and $T = 16$ weeks) demonstrated
278 significant positive correlations at all temporal offsets, suggesting that the lead/lag relationships
279 were not identifiable because they were dominated by overall pandemic trends that obscured
280 the short-term fluctuations relevant to timely public health action. Conversely, the shorter 4- and
281 2-week detrending smoothing ranges removed so much of the trend that the residuals were not
282 predictive at any contiguous sets of temporal offsets, rendering the lead/lag relationships
283 inconclusive. We therefore concluded that the finest detrending time-scale at which wastewater
284 loads predicted COVID-19 cases in the Charlotte 1 sewershed during our study period—based
285 on our reproducible criteria for identifiability, persistency and predictivity—was 8-weeks, and
286 that the correlation between detrended wastewater loads and detrended cases was greatest for
287 wastewater loads sampled with a lead time of 0 to 3 days before the cases were reported.

288 Figure 1. Kernel smoothing of the (A) SARS-CoV-2 wastewater loads (log GC pppd) and (B)
289 COVID-19 incidence (cases/100k) observed at Charlotte 1 sewershed from January to October
290 2021, using various range parameters indicated by the colored lines in the legend. The
291 smoothed estimates were subtracted from the observations to yield the (C) detrended
292 wastewater loads and (D) detrended cases, shown here for a detrending smoothing range of 8-
293 weeks. The pairwise correspondence of the detrended wastewater and case residuals on the
294 same day (i.e. temporal offset of zero) were compared in scatterplots with added spearman
295 correlation lines prior to evaluating any temporal offsets for detrending smoothing ranges of (E)
296 $T = \infty$ weeks and (F) $T = 8$ weeks. A cross-correlation plot (G) between the detrended
297 wastewater and case residuals was created for each detrending smoothing range and temporal
298 offset to be used with the criteria to assess the lead/lag relationship. Note: The temporal offset
299 values on the x-axis are in relation to the case date, such that negative values indicate the
300 correlation was performed when the wastewater preceded the cases and positive values
301 indicate the correlation was performed when the wastewater lagged the cases. Statistically
302 significant correlations are indicated with a filled-in circle and the intersecting line represents the
303 95% confidence interval.
304

305 Wastewater Loads and COVID-19 Incidence Across All Sites

306 The observed COVID-19 incidence rates and SARS-CoV-2 wastewater loads varied
307 across the 20 North Carolina sewersheds participating in this study (Figure 2). The sites were
308 distributed across North Carolina, covering approximately 20% of the population and about 2%
309 of the land area. There was a wide range in sewershed size, with the largest sewershed,
310 Raleigh, serving 551,534 people at a capacity of 341 ML/day and the smallest sewershed,
311 Newport, serving 3,731 people at a capacity of 5 ML/day. During the study period, the number
312 of samples collected per site ranged from 33 (Wilson, Buncombe, Roanoke Rapids, and
313 Winston-Salem) to 83 (Beaufort). SARS-CoV-2 RNA was detectable in 74% of the 1,129
314 wastewater samples across all 20 sites. Sewersheds with larger populations tended to have
315 higher detection frequencies, with 50% of all the non-detects occurring at the three smallest
316 sites with populations under 5,000 people. The lowest mean daily load was 5.0×10^5 GC pppd,
317 observed at Newport, while the highest mean daily load of 2.3×10^7 GC pppd was observed at
318 Fayetteville. The median mean daily load was 7.8×10^6 GC pppd, observed at Buncombe
319 County. There was a total of 122,444 COVID-19 cases reported across all 20 sites during the
320 study period, with the average daily incidence rate ranging from 1 case/100,000 people
321 (Pittsboro) to 148 cases/100,000 people (Raleigh). The median daily incidence rate was 16
322 cases/100,000 people, observed at South Durham. Comparable to the wastewater loads, the
323 three smallest sewersheds accounted for almost 75% of the observed days with zero reported
324 COVID-19 cases.

325 The maximum daily population normalized loads (henceforth referred to simply as loads)
326 for each site ranged from 4.7×10^6 GC pppd to 4.3×10^8 GC pppd, with most of these values
327 occurring in January or late August/early September, during which peaks in COVID-19 cases
328 were also observed with daily incidence rates as high as 235 cases/100,000 people. For the 10
329 sites that were sampled for the entire 10-month period, there was also a noticeable lull during

330 the period of May to July 2021 for both the wastewater loads and cases. All but one sewershed
331 had significant positive correlations between the wastewater loads and cases observed on the
332 same day, with the significant Spearman's coefficients ranging from $\rho = 0.38$ to $\rho = 0.85$, with a
333 median of $\rho = 0.72$. The smallest sewershed (Newport) had a non-significant correlation with a
334 coefficient of $\rho = 0.21$ and p-value of 0.09.

335 Figure 2. Time series of SARS-CoV-2 wastewater loads (log GC pppd) and COVID-19
336 incidence (cases/100k) for each of the 20 sites from January through October 2021. Note:
337 COVID-19 incidence is shown as a 7-day rolling average with the blue line. SARS-CoV-2
338 wastewater loads are depicted with the orange dots and a LOESS curve was fitted to these
339 values, depicted by the orange line (span=0.3).
340

341 Detrending Reveals Short-Term Associations

342 Applying each detrending smoothing range ($T = \infty, 16, 8, 4$ and 2 weeks) across
343 temporal offsets ($\tau = -7$ to $\tau = +7$ days) allowed us to evaluate the lead/lag relationship
344 between the detrended wastewater and case residuals at progressively finer time scales.
345 Correlation plots similar to Figure 1e were generated for all 20 sewersheds, and the proposed
346 criteria were used to identify the optimal detrending smoothing range for each site, which was
347 defined as the shortest kernel smoothing range that revealed an identifiable lead or lag (Figure
348 3). Eighteen of the 20 sewersheds exhibited statistically significant correlation coefficients at all
349 temporal offsets when $T = \infty$ weeks, indicating that additional detrending was needed to reveal
350 the fine time scale fluctuations required for a lead/lag analysis. Beaufort and Pittsboro were the
351 only sewersheds for which the $T = \infty$ weeks range was optimal for identifying the lead/lag
352 relationship; the detrended wastewater and case residuals were no longer significantly
353 correlated over any 2-day span of temporal offsets using shorter detrending smoothing ranges.

354 Of the remaining sewersheds, one site had an optimal detrending smoothing range of T
355 = 16 weeks, eight sites had an optimal detrending smoothing range of $T = 8$ weeks, and four
356 sites had an optimal detrending smoothing range of $T = 4$ weeks (Figure 3). As a general

357 pattern, the detrending smoothing ranges greater than the identified optimal T either had
358 significant positive correlations at all temporal offsets, such that no lead/lag pattern was
359 identifiable, or additional detrending allowed us to detect fluctuations over a shorter duration
360 while still meeting all the proposed criteria. Conversely, too much of the trend was removed
361 when using values for T smaller than the optimal detrending smoothing range, such that the
362 detrended residuals were no longer significantly correlated for any span of contiguous temporal
363 offsets. Five of the 20 sewersheds were deemed inconclusive as none of the detrending
364 smoothing ranges revealed an identifiable lead or lag between the detrended wastewater loads
365 and cases, according to the proposed criteria. We identified two reasons for this: 1) the span of
366 consecutive lead/lag values was longer than 7 days for larger T values (not identifiable) and
367 shorter than 2 days at smaller T values (not persistent), or 2) the longest range of consecutive
368 lead/lag values did not include the maximum correlation coefficient (not predictive). The
369 inconclusive nature of the lead/lag relationship in these sewersheds may be linked to the short
370 sampling duration or the small size of the sewershed as all five sites had data for only half of the
371 study duration and all but Buncombe County were among the smallest sewersheds.

372 Figure 3. Plots of Spearman correlation coefficient versus temporal offset at the optimal
373 detrending smoothing range for each of the 15 conclusive sites, ordered from longest lead to
374 longest lag. The highest correlation value is colored in red, the identified lead or lag span is
375 represented with brackets, and the optimal smoothing range is listed in the bottom right corner
376 of each plot. Note: The lead/lag relationship was inconclusive for Wilson, Laurinburg, Marion,
377 MSD of Buncombe County, and Roanoke Rapids, and these plots are therefore not presented.

378 Detrended wastewater loads were temporally leading detrended COVID-19 cases in 11
379 of the 15 sewersheds where we were able to identify optimal detrending smoothing ranges
380 (Figure 4). For these sites, the highest correlation was observed for wastewater loads sampled
381 at a median lead time of 6 days before the cases were reported, with a contiguous span of
382 elevated correlations lasting a median of 3 days. At four sewersheds, the correlation between
383 detrended wastewater loads and detrended cases was greatest when the detrended wastewater
384 loads were *lagging*, with the highest correlation identified at a median of 3.5 days after the
385 cases were reported and a median contiguous span of elevated correlations of 2 days. Although
386 the smaller sewersheds were more likely to be inconclusive, size did not seem to influence the
387 lead/lag relationship at the 15 conclusive sites, with about the same proportion of leading vs
388 lagging between groups of the smallest and largest sewersheds. However, the optimal
389 detrending smoothing range seemed to be related to the lead/lag relationship, as 64% (7/11) of
390 the leading sewersheds had an optimal detrending smoothing range of $T = 8$ weeks and 75%
391 (3/4) of the lagging sewersheds had an optimal detrending smoothing range of $T = 4$ weeks,
392 suggesting that it may be easier to identify detrended wastewater loads lagging detrended
393 COVID-19 cases at shorter detrending time scales. A summary of the optimal smoothing range,
394 relationship, span, and temporal offset with the highest correlation identified for each sewershed
395 is included in the Supplemental Material (Table S2).

396 Figure 4. Locations of NC Wastewater Monitoring Network sewersheds participating between
397 January and October 2021. In 11 sewersheds, detrended wastewater leads cases (lead), in 4
398 sewersheds detrended wastewater lags cases (lag) and in 5 sewersheds results were
399 inconclusive.

400

401 Discussion

402 Wastewater surveillance emerged during the pandemic as a potential leading indicator
403 of COVID-19 infection trends in the community. Although previous research analyzed the overall

404 correlation between SARS-CoV-2 wastewater loads and clinical cases, this analysis used kernel
405 detrending to characterize short-term relationships and identify sub-trends. By detrending
406 wastewater viral loads and cases in the sewershed using various kernel smoothing ranges, we
407 were able to characterize lead/lag relationships at 15 of the 20 North Carolina sewersheds
408 assessed using a set of reproducible criteria, reducing the proportion of inconclusive results
409 from 90% without detrending to 25% using the optimal detrending smoothing range.
410 Furthermore, we found that detrended wastewater loads temporally led detrended cases at
411 almost three times as many sewersheds (N=11) as sewersheds where detrended wastewater
412 loads lagged detrended cases (N=4), further highlighting the utility of wastewater as a leading
413 indicator of COVID-19 cases in North Carolina. The optimal detrending kernel smoothing range
414 that removed long-scale pandemic trends while retaining sufficient temporal correlation to
415 identify lead/lag relationships was in the range of 4 to 8 weeks at 12 of the 15 sites with
416 conclusive relationships. Because detrending with a given smoothing range retains only the
417 variation in the observations at time scales shorter than the corresponding timeframe, this
418 finding suggests that this approach is ideal for identifying the leading or lagging nature of
419 wastewater and case trends in most sewersheds experiencing a sustained period of increasing
420 SARS-CoV-2 infection rates lasting at least 4 to 8 weeks. A sustained 4 to 8 weeks increase in
421 COVID-19 incidence corresponding to the emergence of the Delta variant (B.1.617.2) in late
422 July 2021 was observed in wastewater loads at 19 of the 20 study sites, further supporting the
423 wider relevance of this range during the study period. However, due to onboarding schedules,
424 some sewersheds were only sampled for half of the study period, and the shorter sampling
425 history appeared related to inconclusive results at these sites.

426 A strength of our study is that we performed a lead/lag analysis across a wide-range of
427 WWTP systems, including both rural and urban municipal systems serving sewershed
428 populations ranging from under 4,000 to 550,000 people [16,24,37–39]. Although we identified a
429 leading relationship in the majority of North Carolina sewersheds, those within the same county

430 or in adjacent counties did not always exhibit the same lead/lag relationship nor have the same
431 optimal detrending smoothing range (Figure 4). For example, we found that detrended
432 wastewater loads led detrended cases at Charlotte 1 and Charlotte 3 but lagged detrended
433 cases at Charlotte 2 (Figure 4, Table S2). Wastewater led cases in both the Wilmington
434 sewershed and the sewershed encompassing surrounding areas of New Hanover County, but
435 the optimal detrending smoothing range was 8 weeks for the city and 16 weeks in the county,
436 which covers a larger land area but serves fewer people (Table 1). Differences in the temporal
437 relationship or optimal smoothing range at each sewershed could be due to conditions at a
438 given site: virus loads measured in wastewater can be impacted by sewer network infrastructure
439 age, sewer residence time, or weather [38,40,41], and clinical surveillance is subject to
440 underreporting due to testing access, home test usage, or fluctuations in populations from
441 tourists and commuters [42]. To minimize the potential impact of testing behavior on the
442 evaluation of relationships between SARS-CoV-2 loads and COVID-19 cases presented in this
443 work, we chose to perform the analysis for a period ending prior to November 2021, when
444 clinical testing penetration was still relatively high and home testing was not yet widely used in
445 North Carolina communities.

446 Given that site-specific conditions can influence wastewater results, public health
447 agencies leading wastewater surveillance programs in their jurisdictions may want to validate
448 their wastewater data against other foundational COVID-19 metrics to determine how
449 wastewater surveillance fits into their larger surveillance strategies. For states or jurisdictions
450 less familiar with wastewater data, a lead/lag analysis between wastewater loads and reported
451 cases would be a useful method to help understand the temporal relationship between
452 wastewater-based pathogen and other decision-making metrics. Our method can be employed
453 by public health agencies participating in CDC NWSS across the United States by using an R
454 Markdown document that applies set criteria to identify the leading or lagging relationships
455 between wastewater and reported cases [43]. As counts of reported cases become less reliable

456 over time due to an increase in non-reportable results from at-home-testing kits, as well as an
457 overall reduction in PCR-based, reportable, COVID-19 clinical testing, this method can be
458 adapted to utilize surveillance metrics besides cases, including hospitalizations, emergency
459 department visits (syndromic surveillance data), or mortality [17].

460 Results from our analysis characterizing the shortest time ranges at which wastewater
461 loads are associated with cases have been formative in elevating wastewater as a reliable
462 metric for tracking trends in North Carolina, not only to anticipate the start of long-term cycles
463 (such as the start of elevated rates in winter), but also for short duration fluctuations within any
464 given long-term cycle. The leading nature of wastewater-based COVID-19 findings at most sites
465 provides the foundation and rationale for including wastewater loads as an early warning metric
466 alongside reported cases, emergency department visits, and hospitalizations, which are
467 highlighted on statewide data surveillance dashboards such as the NCDHHS COVID-19
468 dashboard (<https://covid19.ncdhhs.gov/dashboard/wastewater-monitoring>).

469 In under two years, COVID-19 wastewater surveillance in the United States expanded
470 from 8 pilot state health agencies participating in the CDC National Wastewater Surveillance
471 System in 2020 to 46 states, 5 cities, 3 territories, and 7 tribes participating in 2022 [44].
472 Similarly, the global portal expanded to coverage of 70 countries, reporting for 3,807 sites,
473 indicating widespread use of wastewater surveillance data [45]. With the explosive growth in
474 both the academic literature on, and implementation of, wastewater surveillance programs
475 globally, public health professionals developed a wide range of approaches to utilizing
476 wastewater data for decision making. Our method shows how detrended wastewater loads can
477 predict *fine* scale fluctuations in detrended cases, which can allow public health officials to
478 respond more *locally* and *timely* when COVID-19 burden, or other disease burden as
479 wastewater surveillance expands to new targets, is increasing at levels *greater* than the
480 baseline trend. Examples of mitigation strategies that can be deployed at local levels and for
481 short durations, while being complementary to long lasting statewide measures, may include the

482 following: (a) officials could quickly alert local hospitals about a potential increase in cases
483 above the statewide trend and provide recommendations to community leaders to implement
484 short-duration restrictions, such as limiting indoor gatherings and reducing business capacity
485 [46]; (b) jurisdictions could mobilize pop-up testing and take steps to increase vaccination in the
486 community [47]; (c) increasing public health communications regarding masking, handwashing,
487 vaccination, and social distancing to help contain the spread of the virus; and d) interacting with
488 local public health officials and hospital administrators to indicate periods of higher ICU bed,
489 PPE, and medical staffing needs. This has already been observed during a large sport fishing
490 tournament that took place in a small coastal North Carolina watershed where NCDHHS
491 notified local health department and city officials of an increase in wastewater viral load. In
492 response to this increase, local health department and city officials reinforced recommended
493 mitigation strategies outlined in the Governor's Executive order to the event leadership, like
494 additional hand-washing stations and frequent disinfection of high touch surfaces (Nina Oliver,
495 Carteret County Health Director, personal communication, June 21-22 2021 & February 6,
496 2023). Local notices were also used to encourage the surrounding community to take
497 precautions through vaccinations, masking, social distancing, and frequent handwashing [48].
498 Immediately following the event, county and city officials met routinely to review wastewater, as
499 well as other COVID-19 metrics, and to ensure levels were decreasing (Nina Oliver, personal
500 communication, February 6, 2023).

501 As public health officials and the scientific community continue to rely on wastewater
502 surveillance both for large-scale pandemic decision-making and localized action as described
503 here, there is a growing need for increasing equitable access to wastewater services,
504 particularly in cases of municipal underbounding, and for investing in substantial infrastructure
505 improvements. This is especially important in jurisdictions like North Carolina, where half of
506 households rely on private septic and package treatment plants [49]. In some cases, racial
507 disparities in access to and disproportionate exclusion from municipal water and sewer service

508 have been documented [49–51]. In other areas, distance, lack of gradient, and groundwater
509 height play a role in decisions to use centralized versus decentralized waste treatment systems.
510 For wastewater to continue to be useful for disease tracking and public health decision-making
511 beyond COVID-19, additional resources are needed to achieve equitable access to centralized
512 wastewater treatment where it is desired and environmentally relevant. In other rural areas
513 where this is not the case, we need to improve our technical capabilities to characterize
514 decentralized waste systems.

515

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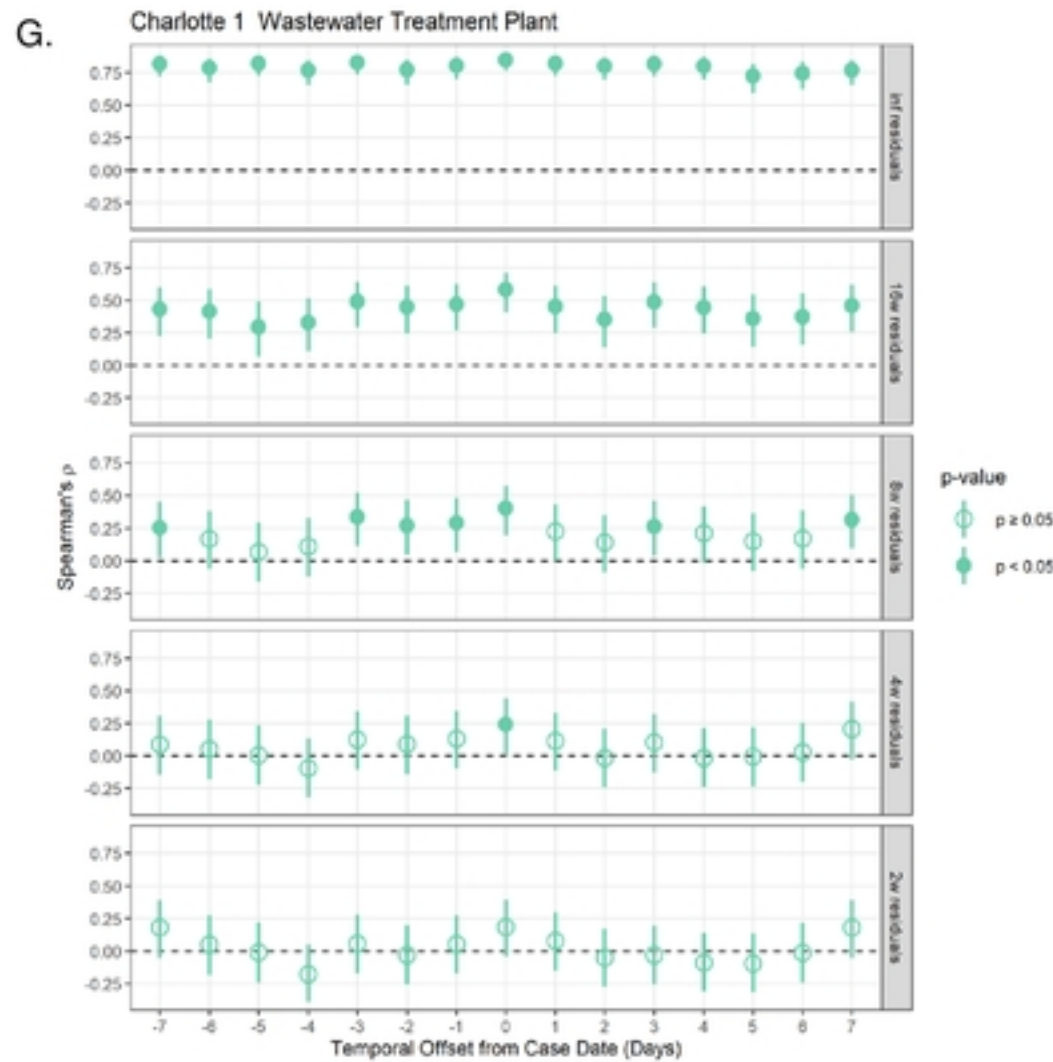
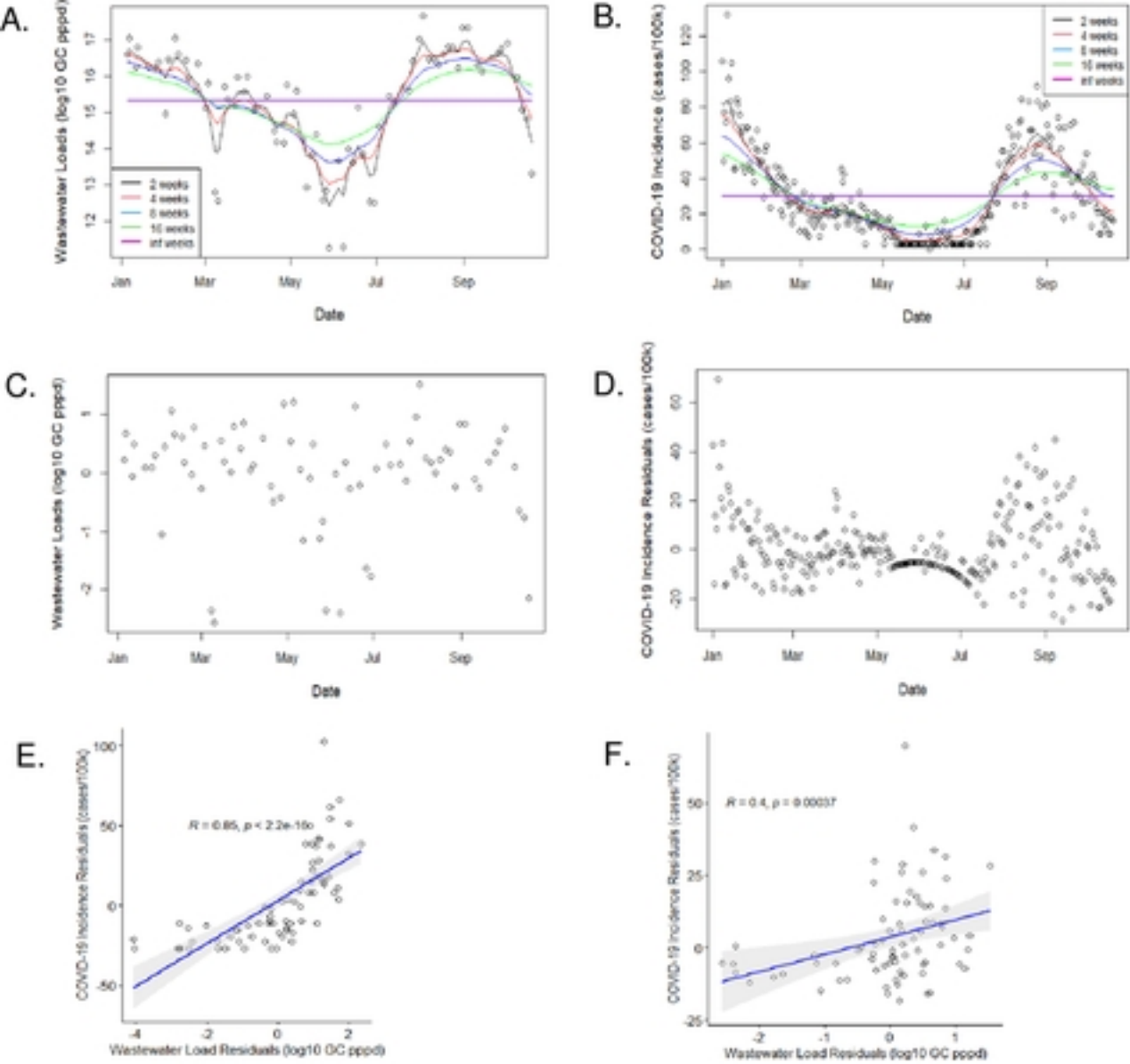


Fig1

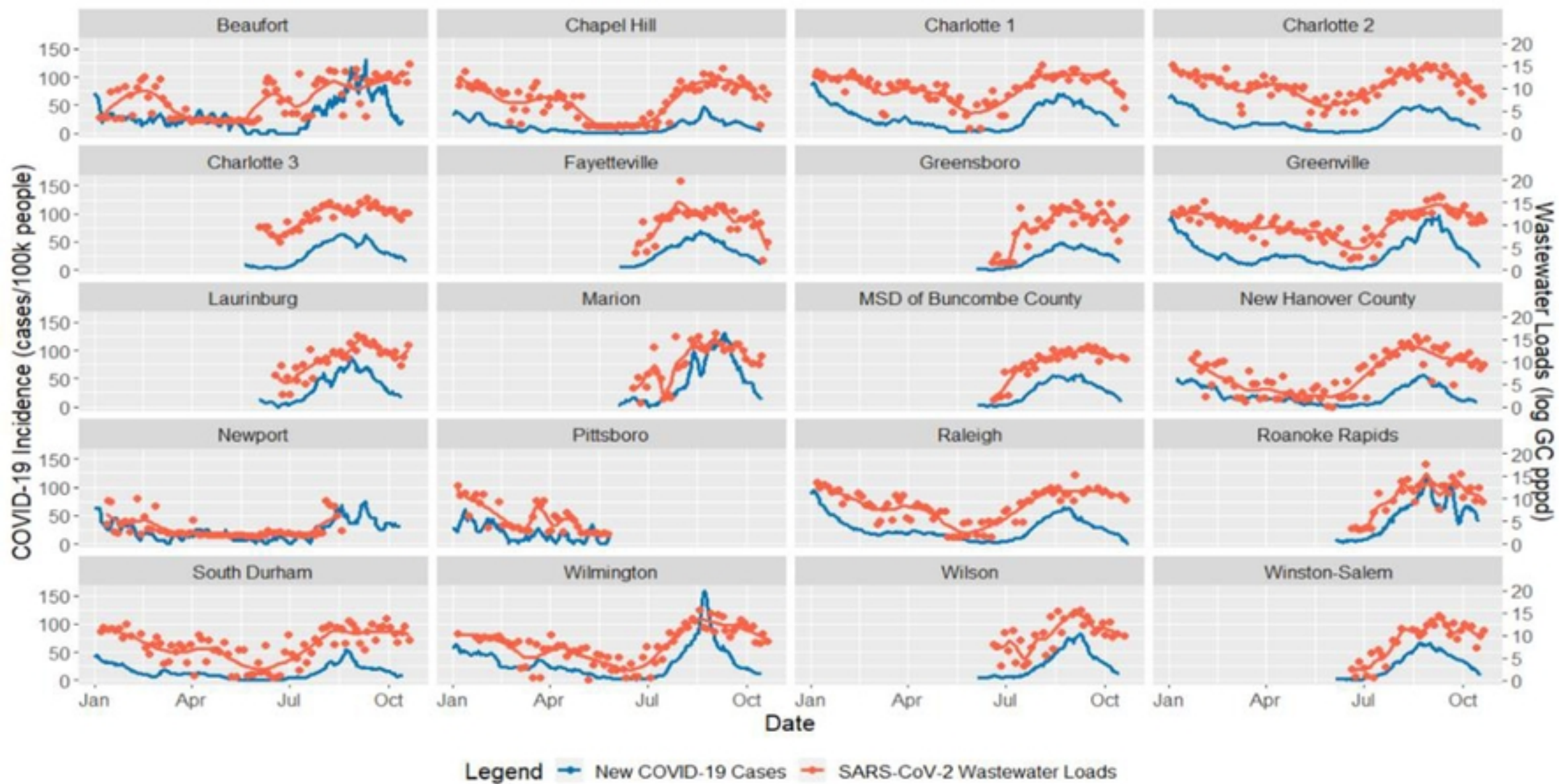


Fig2

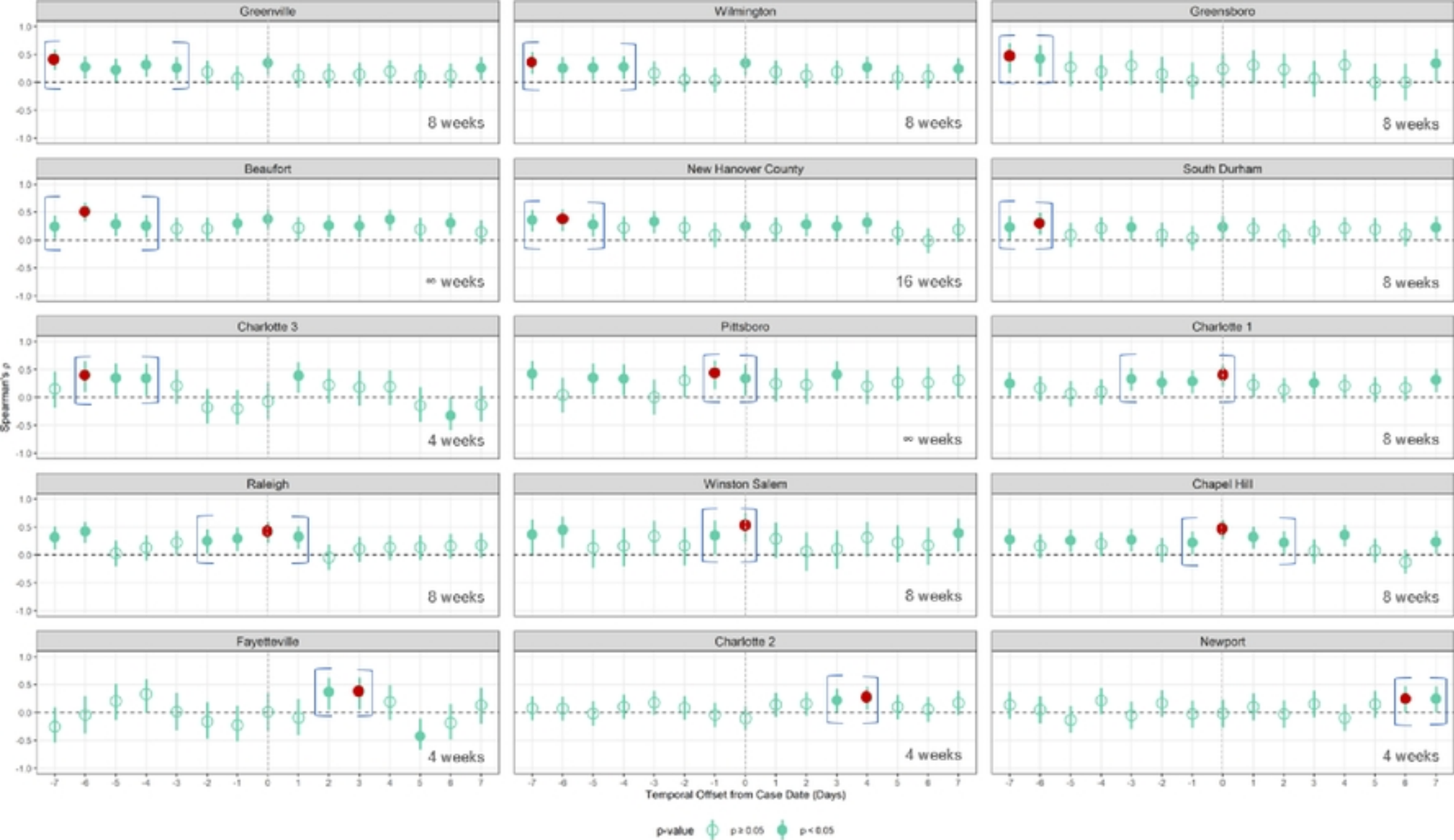


Fig3

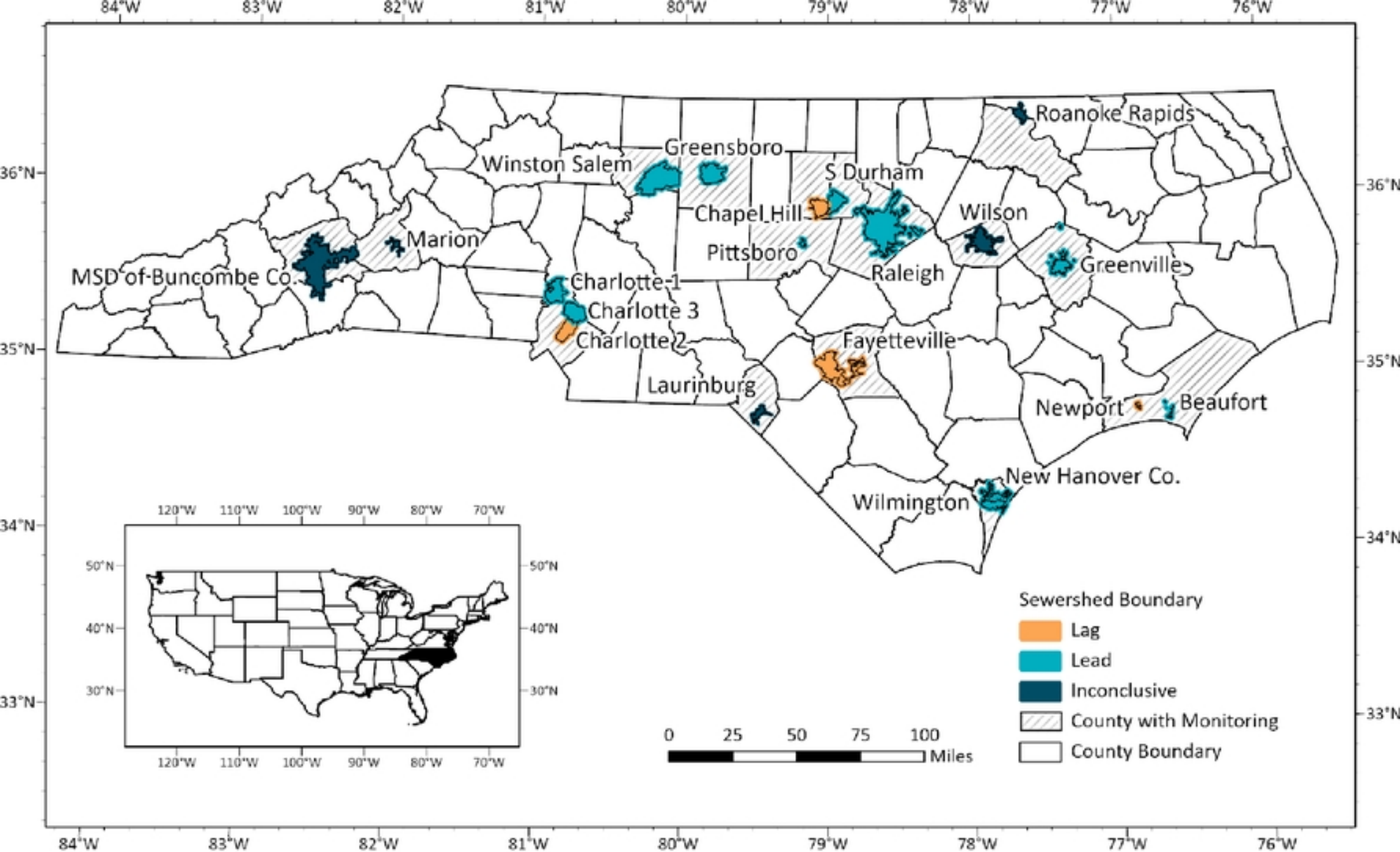


Fig4