No widespread signature of the COVID-19 quarantine period on water quality across a spectrum of coastal systems in the United States of America

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Abstract

During the recent COVID-19 related quarantine period, anecdotal evidence emerged pointing to a rapid, sharp improvement in water quality in some localities. Here we present results from an analysis of the impacts of the COVID-19 quarantine period using two long-term coastal water quality datasets. These datasets rely on sampling that operates at appropriate timescales to quantify the influence of reduced human activity on coastal water quality and span coastal ecosystems ranging from low human influence to highly urbanized systems. We tested two hypotheses: 1) reduced tourism during the COVID-19 quarantine period would lead to improved coastal water quality, and 2) water quality improvements would scale to the level of human influence, meaning that highly urbanized or tourist-centric watersheds would see greater improvement than more rural watersheds. A localized reduction in fecal indicator bacteria was observed in four highly impacted regions of the Texas (USA) coast, but this pattern was not widespread. In less impacted regions, the signature of natural, decadal environmental variability (e.g., dissolved oxygen and turbidity) overwhelmed any potential signature of reduced human activity. Results from this study add to the growing body of literature on the environmental impacts of the COVID-19 quarantine period, and when considered with existing literature, emphasize that coastal water quality improvements appear to be ephemeral and reserved for the most severely affected (by human activity) systems. Furthermore, results show the importance of assessing COVID-19 signatures against long-term, decadal datasets that adequately reveal a system's natural variation.

Keywords: COVID-19; coastal; water quality; bacteria; dissolved oxygen; turbidity

1. Introduction

Humans can have a considerable influence on coastal water quality, primarily through actions that result in pollutant discharge to waterbodies (Hopkinson et al. 1995; Bricker et al. 2008). For example, numerous studies have documented the growing prevalence of cultural eutrophication in coastal ecosystems worldwide (see e.g., Bricker et al. 2008), which arises from excessive nutrient (nitrogen and phosphorus) loadings from watersheds influenced by human activity. Indeed, coastal systems with watersheds that are urbanized or that have significant agricultural influence tend to be more prone to eutrophication than systems with less disturbed watersheds (NRC 2000; Bricker et al. 2008). Common symptoms of eutrophication include persistent algal blooms, occasionally including harmful taxa, as well as decreased light penetration and hypoxia/anoxia (NRC 2000; Bricker et al. 2008). Coastal systems with urbanized watersheds also tend to have a greater propensity for fecal bacterial pollution, which carries with it significant risks for human health (Mallin et al. 2001, 2009; Handler et al. 2006). Natural environmental variability, and rainfall in particular, also influences the magnitude of loadings and thus affects coastal water quality. For example, high rainfall conditions that lead to high river discharge to coastal systems often delivers significant quantities of pollutants and sediment, whereas drought conditions can lead to sharp reductions in loadings (e.g., Paerl et al. 2006; Wetz and Yoskowitz 2013).

During the recent COVID-19 related quarantine period, anecdotal evidence emerged pointing to a rapid, sharp improvement in water quality. For example, it was reported that canals in Venice, Italy, experienced an unprecedented (in modern times) improvement in visibility due to a reduction in human activity: "*Venice canals are clear enough to see fish as coronavirus halts* *tourism in the city*", March 18th, 2020 edition of ABC News, https://abcnews.go.com/International/venice-canals-clear-fish-coronavirus-halts-tourism-city/story?id=69662690. In particular, emphasis was placed on a reduction in tourists as being a major contributor to this improvement in estuarine water quality. Other studies have now been published from rivers, lakes, and coastal waters worldwide documenting localized improvements in various water quality constituents as a result of the COVID-19 quarantine period (Lotliker et al., 2021; Mishra et al., 2020; Yunus et al., 2020).

Observations of improved water quality highlight how the COVID-19 quarantine period and data collected during it may offer a rare opportunity to directly quantify human influence on aquatic ecosystems as well as potential recovery times from various forms of human influence. Nonetheless, assessments such as this are challenged by a need for long-term datasets in order to tease apart effects of the reduction in human influence from natural variability. For example, the aforementioned improvement in Venice's canal water clarity was subsequently attributed to a combination of reduced boating activity that would otherwise resuspend sediments, and a >50% reduction in precipitation in 2020 compared to historical conditions that resulted in less sediment-laden runoff and nutrients that would otherwise stimulate algal blooms (Braga et al., 2020).

Here we present results from an analysis of the impacts of the COVID-19 quarantine period using two coastal water quality datasets. These datasets rely on sampling that operates at appropriate timescales to quantify the influence of reduced human activity on coastal water quality and span coastal ecosystems ranging from low human influence to highly urbanized systems. They are also of long duration, allowing for shorter-term effects of the COVID-19 quarantine to be placed in a longer-term context and to separate out the effects of the quarantine from natural variability. The primary hypothesis was that reduced tourism during the COVID-19 quarantine period would lead to improved coastal water quality, namely lower fecal indicator bacterial abundance and turbidity as well as higher dissolved oxygen. A secondary hypothesis was that water quality improvements would scale to the level of human influence, meaning that highly urbanized or tourist-centric watersheds would see greater improvement than more rural watersheds.

2. Methods

2.1. Data acquisition:

Water quality data were obtained from the National Estuarine Research Reserve's (NERR; https://coast.noaa.gov/nerrs/) long-term water quality monitoring program and the Texas Beach Watch bacterial sampling program (https://cgis.glo.texas.gov/Beachwatch/). The NERR maintains long-term monitoring stations at sites throughout the United States. For this study, we utilized water temperature (ºC), salinity, dissolved oxygen (DO; % saturation) and turbidity (FNU/NTU) data from five NERR sites that are representative of various geographic regions of the United States that have distinct hydrologic drivers and different levels of human influence. These include three NERR sites from the southern United States where seasonal tourism and subsequent human influence on the environment would be most pronounced (North Inlet-Winyah Bay NERR, South Carolina; North Carolina NERR; Mission-Aransas NERR, Texas), one upwelling-influenced site on the United States West Coast (Elkhorn Slough NERR, California), and one urbanized site on the United States Northeast Coast (Narragansett Bay NERR, Rhode Island) (Figure 1; Supplemental Table 1).

The Texas Beach Watch program is managed by the Texas General Land Office and assesses the fecal indicator bacteria (FIB), enterococci, for the purpose of notifying the public via beach advisories when FIB levels are above the EPA's beach action value (USEPA, 2012). Routine water sampling has been on-going for over 15 years, with samples being collected on a weekly basis during peak season (i.e., March and May through September) and a bi-weekly basis during non-peak season. Data from 2009-2020 were obtained from 159 monitoring sites in 61 beaches throughout the following eight coastal counties: Jefferson, Harris, Galveston, Brazoria, Matagorda, Aransas, Nueces, and Cameron (coordinates available at www.texasbeachwatch.com). In accordance with an EPA-approved Quality Assurance Project Plan (QAPP) (Texas Beach Watch Program, 2015), enterococci were quantified using the Enterolert test method (IDEXX Laboratories, Westbrook, Maine, US) and reported as the most probable number (MPN) 100 mL^{-1}. A small subset of the earlier samples that were obtained in 2009 and 2010 were analyzed with the EPA 1600 membrane filtration method (USEPA, 2006), also in accordance with the QAPP, and reported as colony forming units (CFU) 100 mL^{-1}. For the purpose of this study, enterococci units are reported as MPN 100 mL^{-1}.

Hotel locations and visit patterns provide insights into coastal tourism activity (Silva et al., 2021). To assess coastal tourism prior to and during the COVID-19 pandemic, weekly hotel visits were obtained from SafeGraph (https://www.safegraph.com), which were generated from privacy-compliant and anonymized mobile device location data. This dataset includes visitor aggregations from 4.5 million points of interest in the U.S. The hotels were identified within the North American Industry Classification System (NAICS) code 721110. To capture hotel visits in the Texas Beach Watch and NERR stations, all hotels in the eight coastal counties in Texas where the Beach Watch sites were located and 13 counties whose centers are located within 30 miles of the five NERR sites were included.

2.2. Data analysis:

2.2.1. NERR water quality - High frequency water quality data including turbidity, salinity, DO, and water temperature were recorded in 15-minute intervals at the five NERR sites. Each site had 3-4 sampling stations from which data were utilized (see Table 1 for list of stations). States/counties in which the sites are located began implementing quarantine orders in the timeframe of mid-March, 2020. Data from March-July 2020 were compared to data from March-July 2010-2019 with a t-test using R (version 3.6.1) and RStudio (version 1.2.1335). Due to a non-normal distribution, turbidity data were log-transformed prior to analysis. Linear models were generated for each NERR station to relate deviations from the long-term average (i.e., daily mean values in 2020 minus daily mean values in 2010-2019) for response variables (DO and turbidity) to the explanatory variables (salinity, temperature, and weekly hotel visits as a proxy for coastal tourism). Finally, weekly visit patterns in 2020 were compared to 2019 with a t-test.

2.2.2. Beach Watch bacteria - The presence of censored data in the enterococci measurements required the use of censored statistical tests from the NADA package in R (Lee, 2017). Data from 2020 were compared to historical data (i.e., 2009-2019) using the cendiff test; as data had only been recorded through October 2020 at the time of this analysis, data from November and

December of each year were excluded from the comparison. Correlations between enterococci levels and weekly visits in 2020 were computed using the cenken test in R (Kendall's tau correlation coefficient) and weekly visit patterns in 2020 were compared to 2019 with a t-test.

3. Results

3.1. NERR water quality:

A sharp decline in the number of visits to hotels surrounding NERR stations occurred immediately following stay-at-home orders in March 2020 (Figure 2). Whereas North Inlet, North Carolina, and Mission-Aransas visits increased to pre-COVID (2019) levels by summer 2020, Elkhorn Slough and Narragansett Bay maintained lower levels of hotel visits throughout the entire timeframe of this study (t-test; $p < 0.05$).

March-July water temperature was significantly higher in Mission-Aransas during 2020 at all stations compared to 2010-2019 (Figure 3, Table 1). Elkhorn Slough and North Inlet had at least two stations with higher temperatures in 2020, while cooler temperatures were observed at Narragansett Bay. Water temperature trends were spatially variable in North Carolina. In general, the water temperature data showed a high degree of temporal variability in each estuary. Salinity was lower in 2020 compared to 2010-2019 at all stations in Elkhorn Slough, North Carolina, and North Inlet, but higher in Mission-Aransas (Figure 4, Table 1). Salinity trends were spatially variable in Narragansett Bay. Turbidity was higher in 2020 compared to 2010-2019 in North Inlet and Narragansett Bay, but spatially variable in the other three estuaries (Figure 5, Table 1). A high degree of temporal variability was also observed. DO was lower in North Inlet in 2020, but spatially variable in the other estuaries, with all sites showing a high degree of temporal variability (Figure 6, Table 1).

Deviations in salinity and temperature as well as hotel visits explained approximately 11-35% of the variance in turbidity and DO, depending on the site (Table 2). In the case of turbidity, four sites (Elkhorn Slough, Narragansett Bay, North Carolina, North Inlet) showed a significant negative correlation with salinity and none showed a positive correlation (Table 2). The relationship between turbidity and water temperature was less consistent, with a positive correlation observed in North Carolina and North Inlet and a negative correlation observed in Narragansett Bay (Table 2). In terms of weekly hotel visits, one site had a positive correlation with turbidity (Elkhorn Slough) and two sites had a negative correlation (North Carolina and North Inlet). In the case of DO, three sites (Elkhorn Slough, Mission-Aransas, North Inlet) showed a significant positive correlation with salinity and none showed a negative correlation (Table 2), while all five sites showed a negative correlation with water temperature. Two sites had a positive relationship between DO and hotel visits (Elkhorn Slough and Narragansett Bay) and two had a negative relationship between these variables (North Carolina and North Inlet).

3.2. Beach Watch bacteria:

Nearly every Texas county in this study had a notable decrease in weekly visits during the stay-at-home order in March-April, 2020, and the majority of counties also experienced significantly fewer visits in 2020 than 2019. The exception to this was Matagorda, which received more visits in 2020, and Aransas and Cameron, which had no difference in weekly visits (t-test; $p < 0.05$; Figure 7). To test if FIB levels were lower during the stay-at-home order compared to previous years, enterococci concentrations in March-July 2020 were compared to the historical concentrations from 2009-2019. In January through March of 2020, FIB levels tracked with historical concentrations with the exception of Matagorda, where FIB levels were slightly higher than the historical average (Figure 8). Following the quarantine orders in March, the counties showed diverging trends (Figure 8). The majority of counties showed increasing FIB levels that accompanied the onset of spring and early summer with the exception of Harris and Cameron. Nueces, Aransas, Jefferson, and Galveston exhibited positive correlations between enterococci and the number of weekly hotel visits (Kendall's tau: 0.17, 0.14, 0.12, and 0.05 respectively), whereas Matagorda exhibited an inverse correlation (Kendall's tau: -0.07). Cameron and Harris Counties did not experience significant relationships between these variables.

4. Discussion

The COVID-19 pandemic resulted in unprecedented changes to economic and social behaviors worldwide. One such change was the drastic reduction in the number of people traveling for vacations and holidays. This study set out to answer the question: *did the COVID-19 quarantine period lead to a reduction in human influence on coastal ecosystems, manifesting as improved water quality?* The primary hypothesis, that reduced tourism during the COVID-19 quarantine period would lead to improved coastal water quality, and the secondary hypothesis, that water quality improvements would scale to the level of human influence, were supported at four highly impacted regions where FIB concentrations decreased during the quarantine period. However, these hypotheses were generally not supported for other water quality indicators, such as dissolved oxygen and turbidity, that commonly demonstrate high natural environmental variability. An emerging theme from these results and current literature findings is that temporary, quarantine-associated water quality improvements appear to only occur in ecosystems severely impacted by human activity, such as those receiving significant quantities of industrial discharge or poorly treated sewage. Furthermore, an important theme from our analysis of the NERR data in particular is that natural climate variability can easily overwhelm the COVID-19 quarantine signature, emphasizing the need for data collections at appropriate timescales and datasets that are of sufficient duration to separate the signature of events such as a COVID-19 quarantine from this natural variability. We elaborate on these themes below.

4.1. Findings from the NERR data analysis – a key role for natural variability

Water temperature and salinity are integrative of the effects of natural environmental drivers such as weather and climatological conditions that affect air temperature and rainfall, wind-forcing of ocean circulation features (in the case of upwelling systems), and tides, among other factors. These same features are also important natural drivers of water quality indicators such as turbidity and DO through their effects on material loadings to coastal systems as well as on gas solubility (in the case of DO). Thus, water temperature and salinity can serve as proxies for the larger-scale drivers of variability in e.g., turbidity and DO, as well as other water quality indicators.

As observed in the Venice Canal, humans can have an important influence on estuarine turbidity, either as an artifact of what we put into a system (e.g., wastewater effluent that fuels algal blooms) or as a direct impact of activities such as boating (Braga et al., 2020). Nonetheless, results from this study suggest that natural environmental variability likely overwhelmed any signature of human influence on turbidity in the systems that were examined. For example, turbidity was negatively correlated with salinity at four NERR sites (Elkhorn Slough, Narragansett Bay, North Carolina, North Inlet), emphasizing the role of rainfall that either leads to increased (high rainfall, low salinity) or decreased (low rainfall, high salinity) particle loading from watersheds and turbidity in the estuary. In the case of Elkhorn Slough, turbidity was generally below average for the first half of 2020, but natural environmental variability can at least partially explain this as it coincided with above average salinities and below average late winter rainfall. Turbidity subsequently increased through mid-April as rainfall increased, but nonetheless turbidity remained below average through early June until upwelling commenced. We cannot rule out a role for decreased human activity in the below average turbidity as well, given its correlation with hotel visits and the low number of visits during that timeframe. In contrast to the below average turbidity in Elkhorn Slough during the first half of 2020, instances of above average turbidity were documented in Narragansett Bay (April-May 2020), North Carolina (early January, March-April 2020), and for much of the first half of 2020 at North Inlet. In each of these cases, the above average turbidity corresponded with either a sharp drop in salinity (Narragansett Bay) or prolonged periods of below average salinity (North Carolina, North Inlet), pointing to the likelihood of increased input of riverine particulate matter as a being a driver. It must be acknowledged that the R^2 for turbidity-environmental relationships was low, which indicates that other factors not represented by temperature or salinity may have also affected turbidity. One obvious factor is wind-driven resuspension of sediments, which is known to play a role in estuarine turbidity (Bever et al., 2018; McCarthy et al., 2018), with some systems being more susceptible than others.

DO is often used as an indicator of human influence on coastal environments, namely because it is affected by factors such as algal production and bacterial respiration that are themselves influenced by the eutrophication process (Cloern, 2001; Anderson et al., 2002; Rabalais et al., 2009, 2010). Indeed, both short- and long-term declines in DO have been linked to excessive algal production and subsequent biomass degradation in eutrophying waterbodies (Kemp et al., 2005; Diaz and Rosenberg, 2008; Rabalais et al., 2010). Watershed organic matter loadings can also fuel bacterial respiration (Paerl et al., 1998; Servais et al., 1987; Abril et al., 2002; Mallin et al., 2002; Petrone et al., 2009) and tend to be enhanced in systems with land use that is influenced by humans (Servais et al., 1987; Abril et al., 2002). In addition to biological influences, environmental variability also affects DO. For example, rainfall often modulates the loadings of organic matter, and both salinity and temperature directly affect DO solubility, with DO solubility showing inverse correlations with both. Because of the expected reduction in human waste streams during the COVID-19 quarantine period due to reduced tourism, we hypothesized that DO would be above average in 2020. The NERR data did not show this, however, and instead displayed a high degree of both short timescale and spatial variability in DO. Where significant trends were observed, ten out of seventeen sampling stations in the NERR system showed below average DO while only five out of seventeen showed above average DO. The below average DO was centered in the Elkhorn Slough, North Carolina, and North Inlet systems, which we attribute to higher riverine loadings of organic matter that fueled bacterial respiration, an observation supported by prolonged periods of below average salinity in those systems in 2020. At the five stations where DO was above average in 2020, three can be explained, at least in part, by higher oxygen solubility due to below average temperature (Potters Cove, T-Wharf of Narragansett Bay; Research Creek of North Carolina; Table 1). In the case of the North Carolina station, we cannot rule out a role for decreased human activity in the above average DO as well, given its negative correlation with hotel visits and the low number of visits for part of the record in 2020. Nonetheless, there are no other examples of reduced visitors leading to increased DO in this dataset. Thus, there was no obvious improvement in DO as a result of the COVID-19 quarantine. Only Copano West (Mission-Aransas) displayed above average DO that cannot be explained based on temperature and salinity.

4.2. Findings from the Beach Watch data analysis – conflicting site-specific patterns in relation to human populations

FIB levels were frequently higher in 2020 than the long-term average (i.e., 2009-2019), which agrees with a decade-long increase in enterococci throughout coastal Texas (Powers et al., 2021). This finding was particularly true in the months following the original stay-at-home order and throughout the summer. However, several counties also experienced lower FIB levels sporadically throughout 2020. This trend was prominent in Matagorda and Cameron, the latter of which has rarely recorded enterococci levels in exceedance of the beach action value in the past decade (Powers et al., 2021). In fact, Cameron was the only county in this study that has shown an inverse correlation between time and long-term measurements of enterococci (Powers et al., 2021). The low FIB levels may be attributed to watershed protection plans and subsequent water quality improvements that are taking place in the Lower Laguna Madre and Arroyo Colorado (TCEQ, 2020a; TCEQ, 2020b).

In terms of the number of hotel visits, Matagorda was the only county that received more visits in 2020 than 2019, although it did not see a simultaneous increase in FIB levels. Rather, this county showed a unique trend of lower levels of FIB accompanying an increase in visits. It is possible that the enterococci originated from animal sources other than humans, and wildlife inputs could be obfuscating the impacts of human fecal pollution. For example, Matagorda is home to many critical wildlife habitats, including several coastal bird rookeries and sanctuaries (Weber et al., 2015) and it has one of the largest cattle populations in coastal Texas (http://www.texascounties.net/statistics/cattle2017.htm).

Nueces, Aransas, Jefferson, and Galveston Counties experienced direct correlations between FIB and the number of hotel visits. This direct relationship suggests that a larger portion of enterococci in these counties may be attributed to human waste than in the other locations throughout the study. All four reported a spike in June, when anecdotal evidence from news reports indicated that there was a sharp increase in beach tourism due to the lifting of some COVID-19 restrictions (https://www.kristv.com/news/coronavirus/beaches-draw-crowds-saturday; https://www.kiiitv.com/article/news/beaches-will-remain-open-this-fourth-of-july-but-there-could-be-some-rule-changes-heres-why/503-58d8bab2-9af8-42aa-b16f-5b8c5ac6271e). These findings offer some support for our secondary hypothesis that water quality improvements would scale to the level of human influence, as all of these counties belong to a region characterized by high levels of coastal tourism. Nueces has previously been identified as a hotspot of bacterial pollution (TCEQ, 2018), and in September of 2020, the EPA and the city of Corpus Christi (Nueces) entered into a consent decree which requires the city to improve its sanitary sewer system to prevent violations of the Clean Water Act, including illegal discharge of sewage waste into receiving environments (https://www.epa.gov/sites/production/files/2020-09/documents/corpuschristi-cd.pdf). Furthermore, previous source tracking studies have identified abundant human waste in both Nueces and Aransas (Powers et al., 2020; Powers et al., In press). Nonetheless, the low correlation values in these counties and the lack of correlation elsewhere indicate that fecal bacteria pollution is likely influenced by a multitude of additional factors that were not included in this study, including rainfall, sanitary sewer overflows, onsite sewage facilities, and underlying infrastructure conditions (Converse et al., 2011; Passerat et al., 2011; Sauer et al., 2011; Sowah et al., 2017; Zeki et al., 2020).

5. Conclusions

Results from this study highlight the lack of a widespread impact of the COVID-19 quarantine period on estuarine water quality. In the 2020 NERR data, turbidity and DO variance from the long-term average could be explained largely by natural fluctuations in the environment, as denoted by salinity and temperature variability. This was despite inclusion of NERR sites spanning a continuum of watershed land uses from high impact (significant urban influence) to low impact (e.g., forests and wetlands), and susceptibility to pollutants as shown by the range of residence times. In the Texas bacterial data, four locations demonstrated a direct relationship between bacteria levels and the number of visits: Aransas, Jefferson, Galveston and Nueces Counties, which have a long history of impaired water quality due to suspected sewage infrastructure degradation. Overall, these results add to the growing body of literature on the environmental impacts of the COVID-19 quarantine period, and when considered with existing literature, emphasize that coastal water quality impacts appear to be ephemeral and reserved for the most severely affected (by human activity) systems. In addition, the results suggest caution is in order when interpreting conclusions from studies that lack historical baseline data or that do not account for natural variability.

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Figure Legends

Figure 1. Map of the National Estuarine Research Reserve study sites.

Figure 2. Number of weekly visits to hotels in 2019 (blue) compared to 2020 (red) in A) Elkhorn Slough, B) Mission Aransas, C) Narragansett Bay, D) North Carolina, and E) North Inlet.

Figure 3. Daily mean water temperature in 2020 compared to 2010-2019; shaded regions represent +/- standard deviation. A) Elkhorn Slough (n = 4 stations), B) Mission-Aransas (n = 3 stations), C) Narragansett Bay (n = 3 stations), D) North Carolina (n = 4 stations), E) North Inlet (n = 3 stations).

Figure 4. Daily mean salinity in 2020 compared to 2010-2019; shaded regions represent +/- standard deviation.
A) Elkhorn Slough (n = 4 stations), B) Mission-Aransas (n = 3 stations), C) Narragansett Bay (n = 3 stations), D) North Carolina (n = 4 stations), E) North Inlet (n = 3 stations).

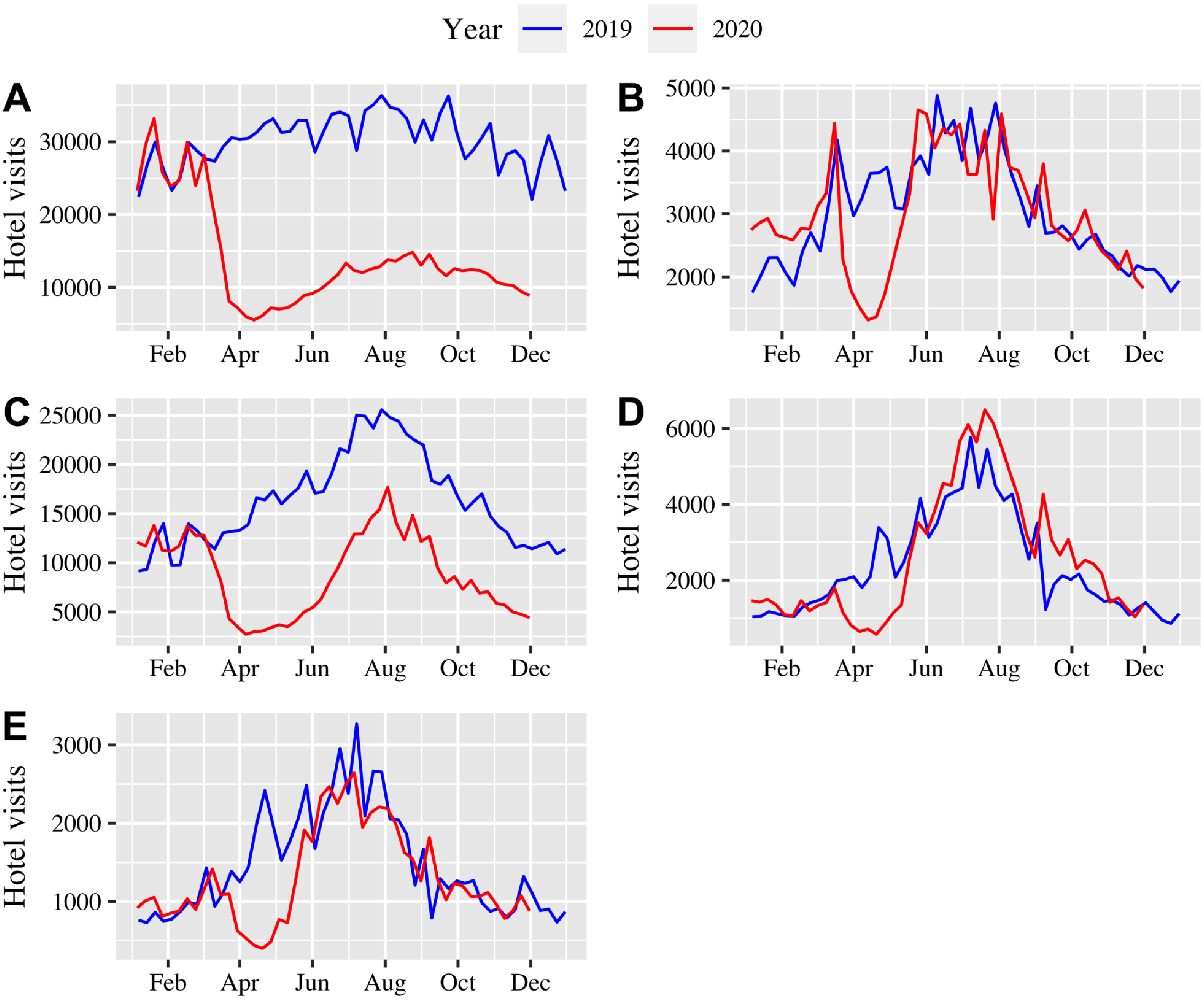
Figure 5. Daily mean turbidity in 2020 compared to 2010-2019; shaded regions represent +/- standard deviation.
A) Elkhorn Slough (n = 4 stations), B) Mission-Aransas (n = 3 stations), C) Narragansett Bay (n = 3 stations), D) North Carolina (n = 4 stations), E) North Inlet (n = 3 stations).

Figure 6. Daily mean dissolved oxygen (% saturation) in 2020 compared to 2010-2019; shaded regions represent +/- standard deviation.
A) Elkhorn Slough (n = 4 stations), B) Mission-Aransas (n = 3 stations), C) Narragansett Bay (n = 3 stations), D) North Carolina (n = 4 stations), E) North Inlet (n = 3 stations).

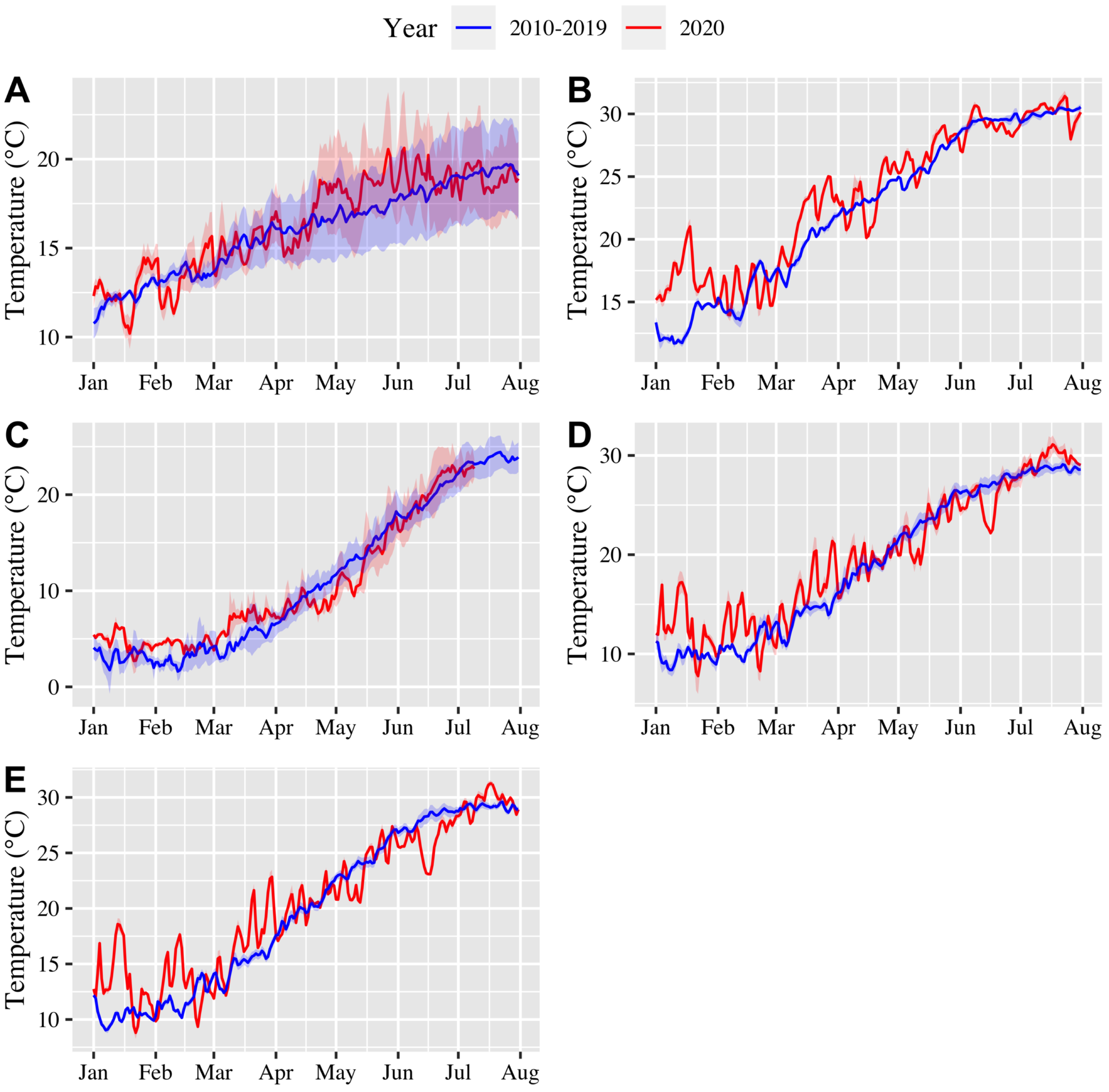
Figure 7. Number of weekly visits to hotels in 2019 (blue) compared to 2020 (red) in A) Jefferson, B) Harris, C) Galveston, D) Brazoria, E) Matagorda, F) Aransas, G) Nueces, and H) Cameron Counties of Texas (United States of America).

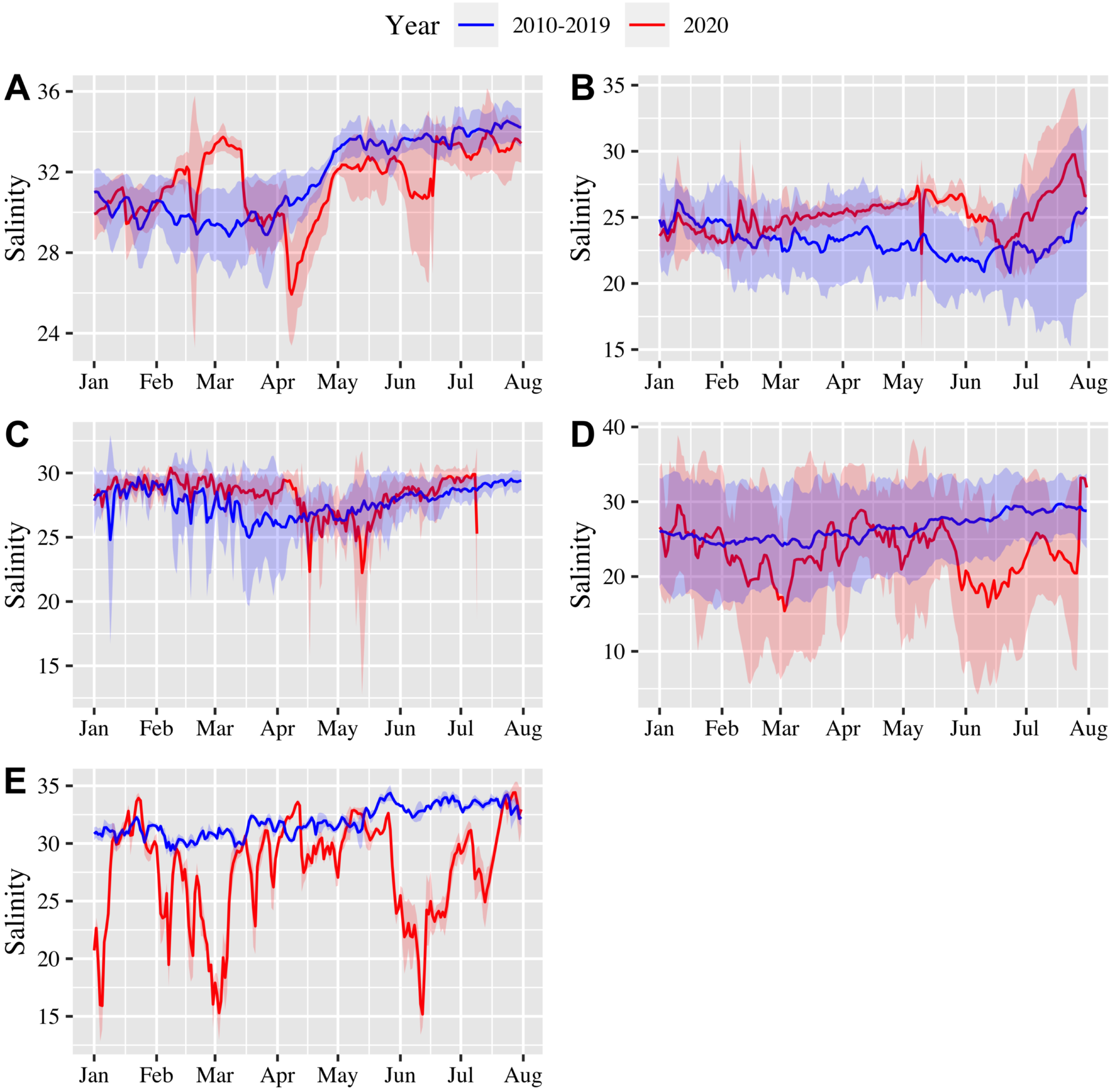
Figure 8. Concentration of enterococci (data aggregated based on daily median values) in 2020 (red triangles) compared to the long-term average in 2009-2019 (blue circles) in A) Jefferson, B) Harris, C) Galveston, D) Brazoria, E) Matagorda, F) Aransas, G) Nueces, and H) Cameron Counties. Loess curves are shown as red lines for 2020 data and blue lines for 2009-2019 data.


Narragansett Bay, RI
Elkhorn Slough, CA
North Carolina, NC
North Inlet-Winyah Bay, SC
Mission-Aransas, TX
Data sources: National Estuarine Research Reserve System

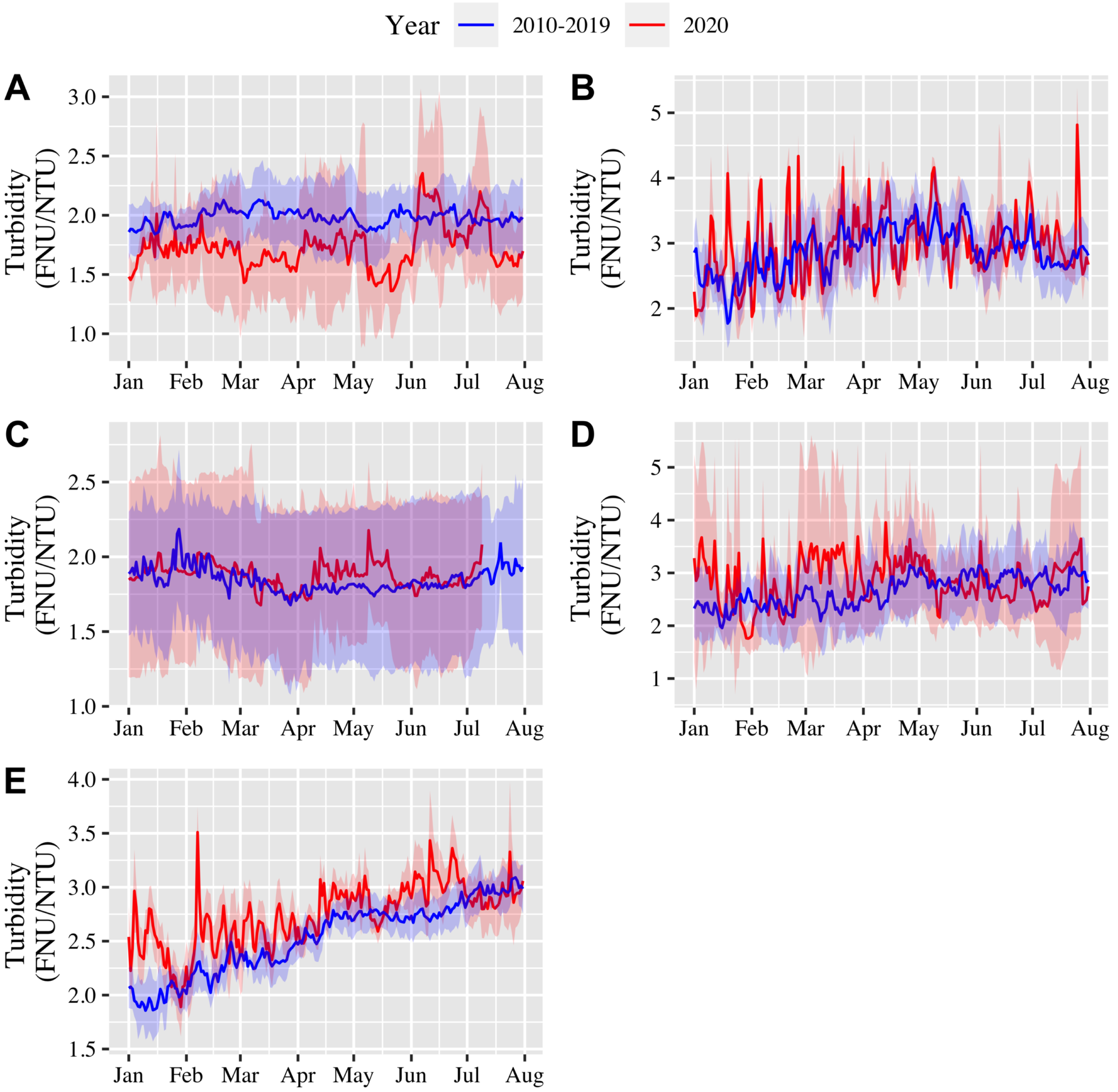


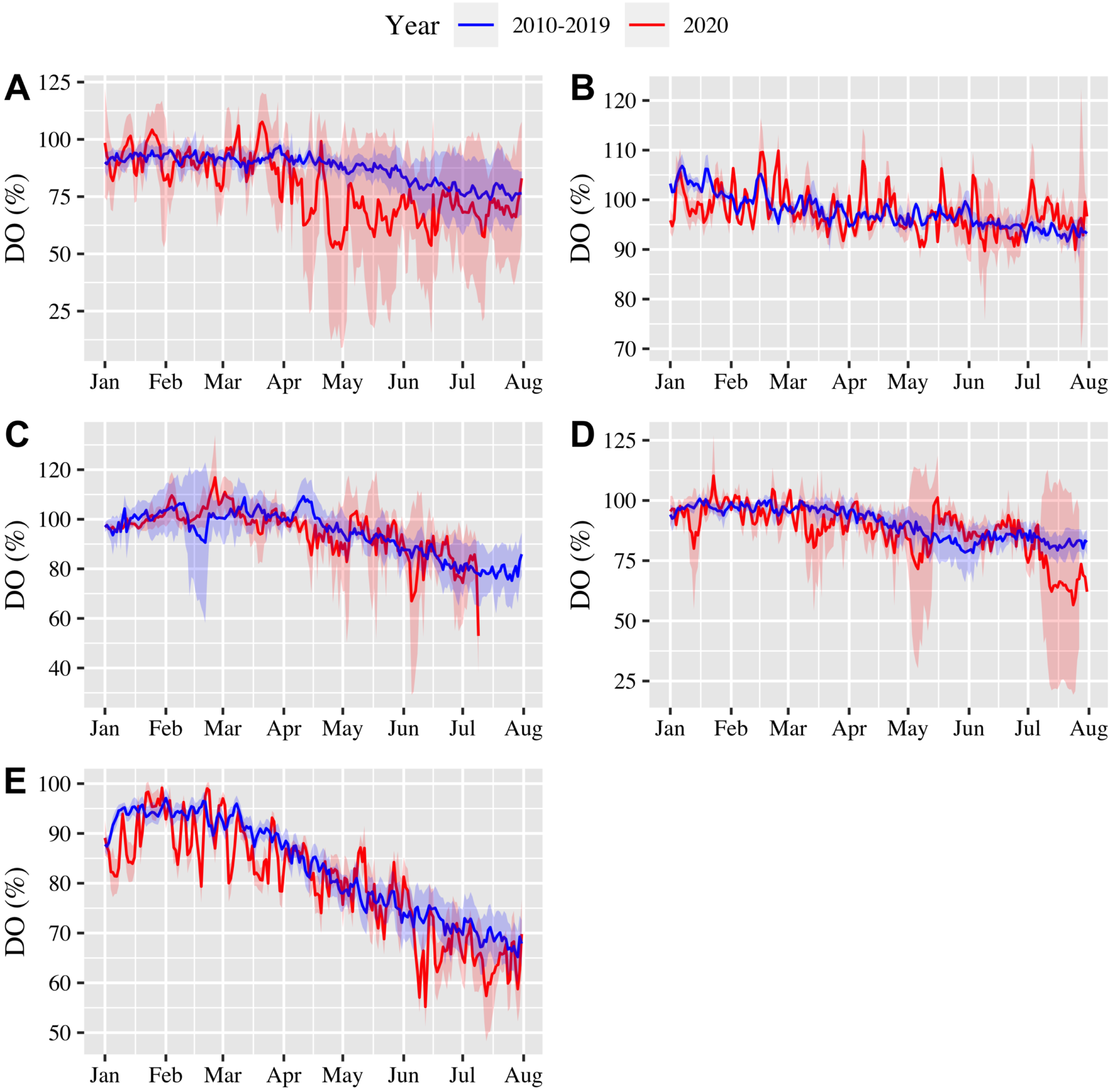
Year
2019
2020
A
B
C
D
E
Hotel visits
Feb
Apr
Jun
Aug
Oct
Dec


Year
2010-2019
2020
A
B
C
D
E
Temperature (°C)
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
10
15
20
25
30
0

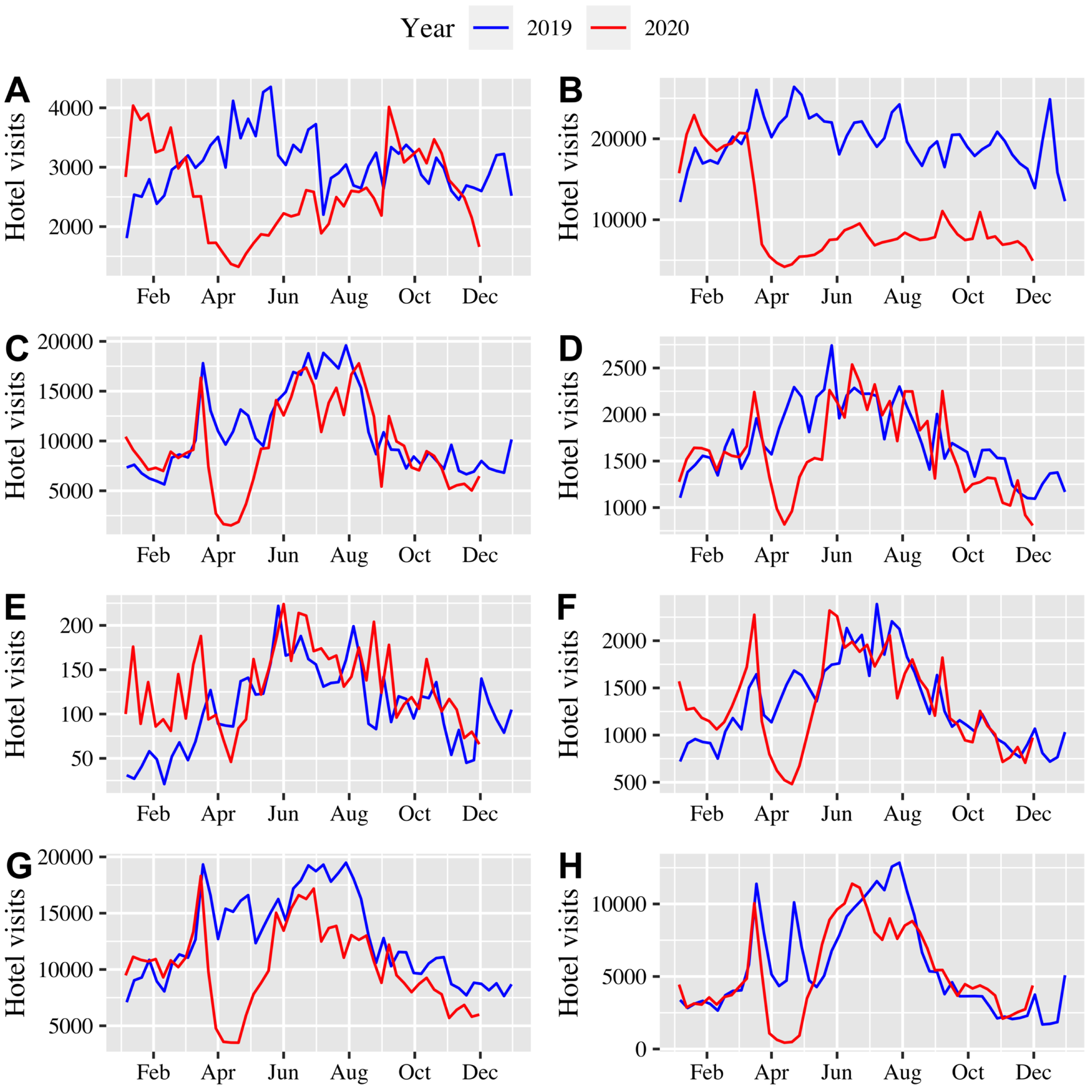


Year
2010-2019
2020
A
B
C
D
E
Salinity
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug


Year
2010-2019
2020
A
B
C
D
E
Turbidity (FNU/NTU)
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
3.0
2.5
2.0
1.5
1.0
5
4
3
2
1
4.0
3.5



Year
2010-2019
2020
A
B
C
D
E
DO (%)
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
125
100
75
50
25
120
110
90
80
70
60
40



Year
2019
2020
A
B
C
D
E
F
G
H
Hotel visits
Feb
Apr
Jun
Aug
Oct
Dec

Year
2009-2019
2020
A
B
C
D
E
F
G
H
Enterococci (logged MPN)
Feb
Apr
Jun
Aug
Oct
Dec

Table 1. Comparison of turbidity (FNU/NTU), salinity, dissolved oxygen (%), and water temperature (ºC) in 2020 (March-July) to average values from 2010-2019 (March-July). *Due to a non-normal distribution, turbidity data were log-transformed prior to analysis. Green boxes indicate the variable was significantly lower in 2020; red boxes indicate the variable was significantly higher in 2020 (t-test; $p < 0.001$). White boxes indicate no significant difference.

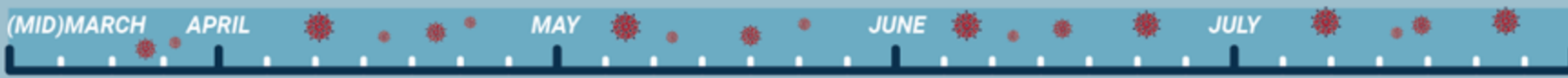
NERR site	Station name	Turbidity* (FNU/NTU)	Salinity	Dissolved oxygen (%)	Temperature (ºC)
Elkhorn Slough	Azevedo Pond				
	North Marsh				
	South Marsh				
	Vierra Mouth				
Mission-Aransas	Aransas Bay				
	Copano Bay East				
	Copano Bay West				
Narragansett Bay	Nag Creek				
	Potters Cove				
	T-Wharf Surface				
North Carolina	East Cribbing				
	Loosin Creek				
	Research Creek				
	Zeke's Basin				
North Inlet	Clambank				
	Debidue Creek				
	Oyster Landing				

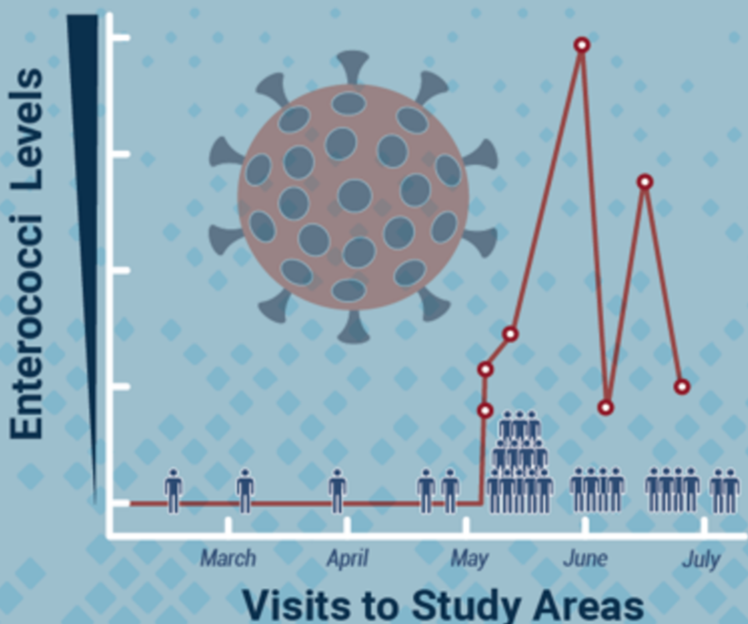
Table 2. Results of linear models relating deviations in explanatory variables to deviations in response variables ($p < 0.05$). ns = nonsignificant model.

NERR site	Response variable	Significant explanatory variable(s) and sign of relationship (+ or -)	Adjusted R^2
Elkhorn Slough	Turbidity	Salinity (-) Hotel visits (+)	0.27
	DO	Salinity (+) Temperature (-) Hotel visits (+)	0.35
Mission-Aransas	Turbidity	ns	ns
	DO	Salinity (+) Temperature (-)	0.15
Narragansett Bay	Turbidity	Salinity (-) Temperature (-)	0.30
	DO	Temperature (-) Hotel visits (+)	0.11
North Carolina	Turbidity	Salinity (-) Temperature (+) Hotel visits (-)	0.28
	DO	Temperature (-) Hotel visits (-)	0.19
North Inlet	Turbidity	Salinity (-) Temperature (+) Hotel visits (-)	0.32
	DO	Salinity (+) Temperature (-) Hotel visits (-)	0.33

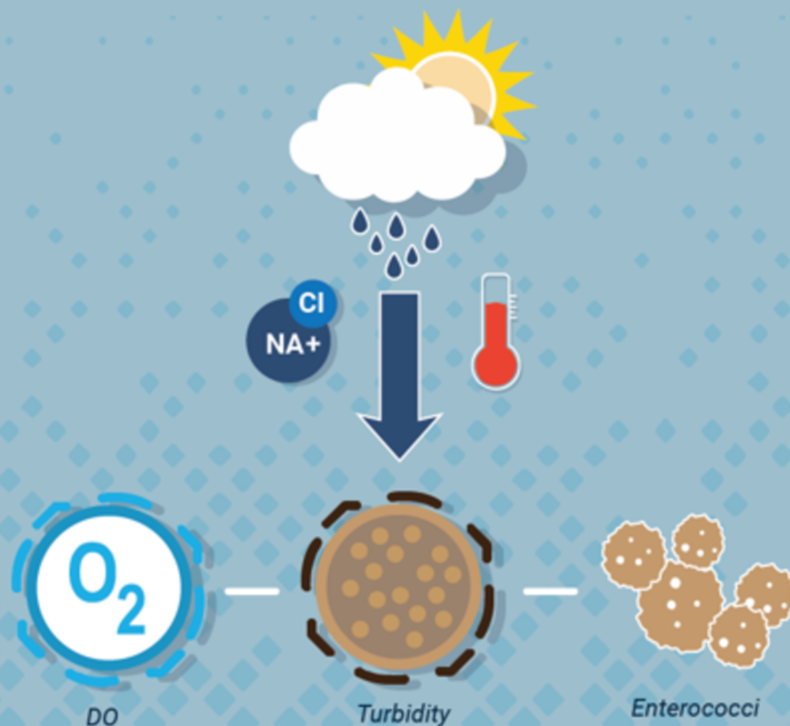
No widespread signature of the COVID-19 Quarantine Period on Water Quality Across a Spectrum of Estuarine Systems

QUARANTINE PERIOD TIMELINE





RESULT: Localized decrease in enterococci when there were fewer visitors.



RESULT: There were no widespread impacts of COVID-19 quarantine on water quality.