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Minimal COVID-19 quieting measured in the deep offshore waters of the U.S. Outer Continental Shelf

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Abstract: Using a 2-year time series (2019–2020) of 1-min sound pressure level averages from seven sites, the extension of COVID-related quieting documented in coastal soundscapes to deep (approximately 200–900 m) waters off the southeastern United States was assessed. Sites ranged in distance to the continental shelf break and shipping lanes. Sound level decreases in 2020 were observed at sites closest to the shelf break and shipping lanes but were inconsistent with the timing of shipping changes related to a COVID-19 slowdown. These observations are consistent with increased numbers of vessel tracks in 2020 compared to 2019 at a majority of sites. © 2022 Author(s). All article content, except where otherwise noted, is licensed under a Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).

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1. Introduction

The World Health Organization declared the coronavirus disease (COVID-19) a global pandemic on 11 March 2020, which resulted in global movement or lockdown restrictions that reached maximum (strictest) levels in April (March *et al.*, 2021). Mobility restrictions impacted not only the magnitude of human ocean use but also the operating behavior and patterns of multiple marine sectors. Ocean soundscape studies examining the impact of COVID-19 mobility restrictions have predominantly focused on coastal or slope waters (Thomson and Barclay, 2020; Gabriele *et al.*, 2021; Dahl *et al.*, 2021; Leon-Lopez *et al.*, 2021; Basan *et al.*, 2021; Pine *et al.*, 2021) as opposed to offshore, outer continental shelf regions (Ryan *et al.*, 2021). General patterns resulting from coastal and continental slope soundscape studies indicate a reduction in low frequency (\leq 125 Hz) sound levels associated with the March–May time period of severe lockdown at most, but not all, recording sites that is attributed to a decrease in marine traffic activity. Specifically, the greatest decreases in sound levels were observed in regions experiencing significant reductions in marine tourism (passenger vessels) and recreational activity (Thomson and Barclay, 2020; Gabriele *et al.*, 2021; Pine *et al.*, 2021; Dine *et al.*, 2021). Decreases in low frequency sound observed within the lockdown period in deeper waters were related to reductions in commercial, large vessel traffic in certain areas (Ryan *et al.*, 2021; March *et al.*, 2021).

To better understand the impact of COVID-19 movement restrictions on the soundscape of deep, offshore waters without substantial recreational or tourist activity, a detailed examination of sound levels and marine traffic at seven sites along the U.S. eastern seaboard Outer Continental Shelf (OCS) between Virginia and Florida was made from recordings acquired as part of the Atlantic Deepwater Ecosystem Observatory Network (ADEON) program.¹ A direct year-year comparison accounted for the general seasonal patterns in vessel traffic, marine mammal vocal activity, and wind/weather patterns. The analysis was restricted to a 2019–2020 comparison, as increasing trends in marine traffic occupancy (estimated increase of \sim 3% in 2020) could result in a confounded COVID signal detection if the analysis included a comparison of years prior to 2019 with less overall marine traffic occupancy (March *et al.*, 2021). As such, we acknowledge that the 2019–2020 comparison may provide a slight underestimate of offshore, regional COVID-19 impacts.

2. Methods

The ADEON program deployed ocean bottom landers at seven sites along the U.S. eastern OCS from 2017 to 2020. The site locations varied in water depth (\sim 200–900 m), distance from shore (\sim 45–280 km) (Table 1), and distance from nearest



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				Location			
Site ID	Start date	End date	Months of data	Latitude	Longitude	Depth (m)	Distance from shore (km)
BLE	2017-11-29	2020-12-14	37	29° 15.05′ N	$078^{\circ} \ 21.07' \ W$	868	280
JAX	2017-12-01	2020-12-13	35	$30^\circ~29.61'~N$	$080^\circ \ 00.16' \ W$	317	140
CHB	2017-12-03	2020-12-11	36	32° 04.29' N	$078^{\circ} \ 22.28' \ W$	401	160
SAV	2017-11-27	2020-12-11	36	32° 02.64' N	$077^{\circ} \ 20.82' \ W$	790	216
WIL	2017-11-26	2020-12-10	36	33° 35.24′ N	076° 26.92' W	460	145
HAT	2017-11-24	2020-12-08	36	35° 12.08' N	$075^{\circ} \ 01.10' \ W$	291	45
VAC	2017-11-22	2020-07-07	27	$37^{\circ} \ 14.76' \ N$	$074^\circ~30.87'~W$	212	105

Table 1. Seven ADEON site deployment durations, locations, water depths, and closest distance to land. BLE, Blake Escarpment; JAX, Jacksonville; CHB, Charleston Bump; SAV, Savannah; WIL, Wilmington; HAT, Hatteras; VAC, Virginia Canyon.

shipping lane (see Fig. 3). Maintenance cruises recovered and re-deployed landers at 5–12 month intervals. One to two days of data collection were typically lost between recovery and re-deployment. The VAC lander was prematurely trawled in summer 2019 and 2020, which accounts for the smaller number of overall months of data with recordings (Table 1). Each lander was equipped with an AMAR acoustic recorder (JASCO Applied Sciences, Dartmouth, Canada) and M36-V35-100 hydrophones (Geospectrum Technologies Inc., Dartmouth, Canada) that were calibrated before deployment and on retrieval using a 42AA pistonphone calibrator at 250 Hz (G.R.A.S., Holte, Denmark). This analysis focuses on a detailed 2019–2020 comparison of sound pressure levels to understand potential COVID-19 impact in 2020.

2.1 Acoustic processing

Time series of 1-min decidecade sound pressure levels (SPLs) were analyzed to look for the possible effects of changes in vessel traffic sound contribution due to COVID-19. The decidecade band definitions and SPL were compliant with ISO 18 405:2017 (ISO, 2017); details of the analysis are available in the ADEON Data Processing Specification (Heaney *et al.*, 2020). Six decidecade bands were selected for analysis with nominal center frequencies of 20, 63, 125, 200, 630, and 3150 Hz. The 20 Hz band is associated with fin whale chorusing in the northern sections of the project area. The 63 and 125 Hz bands are associated with large vessel traffic and are the bands suggested for tracking good environmental status under the Marine Strategy Framework Directive (Dekeling *et al.*, 2014). In the southern parts of the project area, 125 Hz is also associated with minke whale chorusing in the winter months (Kiehbadroudinezhad *et al.*, 2021). The 200 Hz band is associated with smaller vessels, such as the fishing fleet that occurs around the HAT and VAC sites. Sound from wind and wave action at the surface peaks at 630 Hz. However, this frequency band also contains energy from vessels in the general area of a recorder (Wenz, 1962). Finally, 3150 Hz is expected to contain energy primarily from wind and wave action. Thus, if there was a COVID-19 signal present in the data, we expected to see the effects primarily in the 63 and 125 Hz bands; the other bands serve as controls to test whether there were measurable differences in wind or biologic sound patterns.

2.2 Statistical processing

The SPL time series were analyzed using change point analysis (CPA) (Chen and Gupta, 2000; Taylor, 2000; Pettitt, 1979). CPA identifies one or more points in a time series at which the trend in the variable of interest changes. To accomplish this, each point in the time series is evaluated to determine its ability to divide the time series into segments that are maximally different from each other; the points with the greatest impact are identified as change points. CPA identifies a user-specified number of change points rather than statistically significant change points, although Qian *et al.* (2003) noted that significance could be evaluated using an approximate χ^2 test. Variance and (non-parametric) confidence intervals associated with each change point identified can be calculated using bootstrapping (Efron and Tibshirani, 1993; Mooney and Duval, 1993). Among other applications, CPA has been used to analyze satellite imagery for forest change (Ghaderpour and Vujadinovic, 2020), detect changes in variability of waves and storm events (Killick *et al.*, 2010), and even explore Twitter tweets (Liu *et al.*, 2013).

Data from 2019 and 2020 for each of the seven sites were summarized by computing the median decidecade SPL per week. Weekly units appeared to provide the most useful trade-off between extremely noisy hourly summaries and overly smoothed monthly summaries. Analysis of weekly data also follows the precedent set by Thomson and Barclay (2020). Weeks from 2019 and 2020 were paired ordinally, i.e., week 1 for 2019 and for 2020, and the difference in median was calculated. The median was employed rather than the mean because the median is less impacted by outlier points. A negative difference in medians indicates that SPL was lower in 2020 than in 2019. Note that though a quieter 2020 may

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suggest a post-COVID decrease in SPL, it could equally indicate a noisier 2019 that could be caused by, for example, 2019 hurricanes, such as those that impacted this study.

A CPA of the median difference data was undertaken using the R library *mcp* ("multiple change point").² *mcp* allows one to specify the number of change points expected and also the "nature" of each change, i.e., abrupt or gradual. A "COVID-19 consistent" model comprised of four change points was defined. The first two change points were expected to represent a (1) relatively abrupt decrease in sound associated with a decrease in shipping sometime near week 10 (March 10–16 in 2020) and (2) subsequent gradual return to "normal" shipping-associated noise levels. The second two change points were necessitated by the occurrence of two hurricanes, Dorian (category 5) and Humberto (category 3), that overlapped in weeks 34–37 of 2019 (roughly August 24 to September 22) (Tripathy *et al.*, 2021). It was expected that these would identify a relatively abrupt 2020 SPL decrease relative to the 2019 hurricane-related SPL increase followed by a relatively abrupt return to gre-hurricane SPL levels. This CPA model was employed for all sites except VAC, for which data were only available from January to June in 2019 and 2020 due to premature lander recovery related to trawling activity. Thus, for VAC, a CPA comprising only the first two change points was defined, i.e., the potential impact of hurricane-related noise in August-September was not considered.

The appropriate CPA model was fit to the weekly data for each hydrophone individually. A CPA model consists of the (bootstrap) mean week and associated 95% confidence interval for each change point identified; the amount of change is determined by differencing the sound level of adjacent change points. The "COVID consistency" of such CPA models must be interpreted relative to real-world expectations of how shipping would have changed had it been affected by COVID. Though COVID's impact on the human population of the U.S. eastern seaboard started abruptly around week 11 (March 12) of 2020, it is uncertain whether shipping had already been affected by week 11. Hence, a COVID-consistent initial change point was defined as one showing an abrupt drop in sound level over a two-week period centered on week 11—rather than one showing an abrupt drop that occurred exactly during week 11. Table 2 shows the set of "fuzzy tolerances" developed to interpret the CPA models relative to COVID consistency and hurricane consistency; these are represented visually as gray zones in Fig. 1. These were defined based on scientific literature (e.g., March *et al.* 2021) and the authors' real-world expectations. Note that the unknown duration of the assumed gradual post-COVID return to a "pre-COVID normal" soundscape was accommodated by defining a relatively large (20 week) permissible bootstrap 95% confidence interval for change point 2, i.e., the period of time over which shipping activity may have rebounded. Finally, the magnitude of sound change (in dB) was not used to determine COVID consistency as this was unknown.

To aid understanding of CPA and its outputs, Fig. 1(a) shows a graphic example (HAT for 20 Hz). The three vertical dashed lines represent (left to right, respectively) the expected week of COVID onset, Hurricane Dorian, and Hurricane Humberto. The black points are the weekly raw data (not shown in other plots to reduce visual clutter). Three points are labeled with their 2019 and 2020 sound levels, i.e., (98104), (85, 84), and (11,485); these will be discussed in Sec. 3. The continuous multi-colored line from week 0 to week 50 is the CPA model. The color-coded vertical and sloped segments show the week when change occurred (*x* axis) and the magnitude of change (*y* axis); the black horizontal lines show periods within which no change points were detected. The gray zone represents the tolerances in Table 2; to be deemed COVID-consistent, a line must fall within the gray zone. Color-coding of vertical/sloped lines indicates various reasons that change points are or are not consistent with the hypothesized CPA model. (See the caption for Fig. 1.) In Fig. 1(a), the first two change points define an abrupt decrease (week 7) and then gradual rebound in sound level (week 13). Though this pattern—abrupt drop/gradual rebound—is COVID-consistent and similar to the gray zone representing COVID consistency, these two change points did not occur at the appropriate time; hence, these lines are colored orange. The final two change points showing an abrupt sound level drop (week 25) followed by an abrupt rebound (week 33) are not only inconsistent with the timing of the hurricane occurrence, but their 95% bootstrap confidence interval (not shown) was too wide to suggest a definitive and abrupt change; hence, the relevant lines are colored red.

2.3 Marine traffic processing

Large commercial vessels over 300 GT, vessels on international voyages, all vessels over 500GT regardless of destination, and all passenger vessels are required to carry Automated Identification System (AIS) transponders, which transmit their position via very high frequency (vhf) radio to nearby vessels every 2–10 s depending on local traffic systems. This system, originally designed for safe navigation and collision avoidance, is useful for tracking vessels globally for research purposes.

Table 2. Tolerances for a	determining if a o	change point is COVID-19-consistent. ('	These are represented	graphically	y as the gray zone in Fig. 1.)
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Change point	Related to	Expected nature	Mean range (weeks)	95% confidence interval width (weeks)
1	COVID	Abrupt	10-12	6
2		Gradual	15-25	20
3	Hurricanes Dorian and Humberto	Abrupt	33-37	4
4			37-41	



Sound Level Diff (2019-2020)

Raw Data and Change Points (20 Hz) (b) 20 Hz (a) [98,104] • HAT BLE 5 Raw Data • HAT 5 VAC 0 [85,84] 0 -5 -5 -10-15-10-20 -15-25 -20 -30 (c) 63 Hz (d) 125 Hz BLE HAT VAC 8 8 BLE HAT Ō VAC Sound Level Diff (2019-2020) 6 6 4 4 2 2 0 0 -2 -2 -4-4 (e) 200 Hz (f) 630 Hz BLE HAT 8 BLE • 8 HAT • VAC VAC Sound Level Diff (2019-2020) 6 6 4 4 2 2 0 0 -2 -2 -4 -6 ò 10 20 30 50 10 20 30 40 50 0 40 Week of the Year Week of the Year

Sound Level Difference 2019 to 2020 (+ values indicate a louder 2020 or quieter 2019)

Fig. 1. Change point analysis results. Lines that are vertical or sloped represent change points and are color-coded as follows: (1) green are COVID-consistent; (2) yellow are not COVID-consistent due to change point confidence interval width; (3) orange are not COVIDconsistent due to mean location; and (4) red are not COVID-consistent for both confidence interval width and mean location. The vertical gray dashed lines indicate the location/time of the onset of the COVID pandemic in 2020 near week 10 and of hurricanes Dorian and Humberto in 2019 near week 35. In Fig. 1(a), three points are labeled with their [2019, 2020] sound levels for illustration. (See discussion in Sec. 3.)

The signals are received by shore stations and satellites and synthesized into a single comprehensive dataset. For this research effort, AIS data were obtained for the duration of the experiment from Spire global satellite-based observations (Washington, DC), along with U.S. Coast Guard Navigation Center (NAVCEN), historical Nationwide Automated Identification System (NAIS) data, and National Oceanic and Atmospheric Administration (NOAA) marine Cadastre data, which derive from a network of shore-based towers. These datasets were combined and interpolated into a single dataset with consistent time intervals. Vessel entity resolution and type were obtained using vessel International Maritime Organization (IMO) ID number and Maritime Mobile Service Identity (MMSI) number.

Vessels within 500 km of each lander location and more than 2 km from shore were included in the analysis. To examine differences in local shipping in the vicinity of the ADEON landers, two types of analysis were performed. First,



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vessel density was computed for the whole experiment area using a simple kernel density tool in ESRI ArcGIS Pro (Redlands, CA). The second analysis calculated and compared the total vessel hours spent near each lander defined by a 100 km radius around the lander position.

3. Results

3.1 SPLs and patterns

To provide overall context of SPL and trends, data from 2017–2020 were analyzed and are presented to illustrate that neither 2019 nor 2020 was an anomalous year (Fig. 2). Figure 2 plots the monthly empirical probability density functions (EPDFs) for each site at 125 Hz. The EPDFs present the probability of different SPLs occurring based on the measured data, where the SPL that is most likely to occur is called the mode of the distribution. Each year is plotted as a different color. Across all sites, there are few differences between years in any of the months, including March–May.

3.2 Change point analysis

The result at HAT for 20 Hz was selected for presentation in exemplar Fig. 1(a) in part because the magnitude of initial sound level change—22 dB at the onset of the COVID pandemic—seemed excessively high. Seeing the raw data along with the CPA model provides a better understanding of the insight that a CPA model can provide. In response to the relatively large sound level change, shipping data for HAT were examined further. It was determined that in 2019 shipping tracks were generally closer to the HAT hydrophone than in 2020, resulting in a noisier 2019/quieter 2020. This is demonstrated

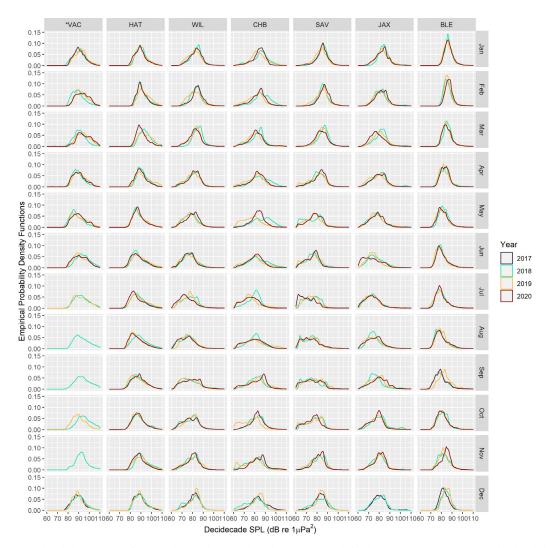


Fig. 2. Empirical probability density functions by site (horizontal) and month (vertical) for the 1-min SPLs in the 125 Hz decidecade band. *, VAC had less data than the other sites due to early recovery by trawling in July 2019 and 2020. Gridded lines are provided as a visual reference for comparisons.



by the three points labeled (98, 104), (85, 84), and (11, 485)—the sound levels in 2019 and 2020, respectively—in Fig. 1(a). Most notable is the week 12 point that had a median sound level of 114 dB in 2019 and 85 dB in 2020—a drop of 29 dB. However, that the two other points labeled in Fig. 1(a) had 2019 sound levels of 98 and 85 dB suggests that the week 12 point with a 2019 sound level of 114 dB (and comparable values most of the weeks from 7 to 30) implies that 2019 was unusually noisy rather than 2020 being unusually quiet.

To improve interpretability of CPA across all sites and decrease visual clutter, CPA model results without raw data are presented only for three sites—BLE, HAT, and VAC (Fig. 1). (The raw data coupled with the CPA results are presented individually for all sites and frequencies in supplementary Figs. 1 and 7.)³ Sites VAC and HAT were selected due to their nearest proximity to shipping lanes and, thus, were most likely to be impacted by a COVID-related change in shipping. For comparison, BLE was included as the site farthest from the shipping lanes and deemed least likely to be impacted by COVID-related change in shipping.

It is apparent that SPL did not conform to the *a priori* expectation of an abrupt COVID-related sound level impact across all sites and frequencies: almost none of the vertical/sloped lines indicate COVID consistency by being colored green. [Similar results were observed for the hydrophones for the other ADEON sites (WIL, SAV, JAX, and CHB); see supplementary Figs. 1–7.³] It is concluded, therefore, that the data from each of the ADEON hydrophones did not conform to the COVID-consistent CPA model defined, i.e., no COVID-related shipping impact was detected at any of the ADEON hydrophones. Moreover, there is little evidence in Fig. 1 to suggest that this conclusion would be altered if the "fuzzy tolerances" used to define COVID consistency (Table 2) were changed to reflect the possibilities that, for example, shipping—particularly shipping from Europe—dramatically decreased sooner than week 10 after China's January 9 (week 2, 2020) announcement of the discovery of a new coronavirus.

Conversely, there was a weak CPA detection of the joint Dorian/Humberto hurricane event. For all frequencies except 630 Hz, there was a pronounced 2019–2020 decrease and subsequent increase in sound level for change points near week 35 for at least one site. In most cases, the confidence interval width was overly wide, i.e., most lines are yellow. Moreover, the distance of each hydrophone from the eye of either hurricane was not considered—something that may have impacted results. There is arguably enough evidence in Fig. 1 to suggest that the CPA recorded the impact of hurricanes Dorian and Humberto.

3.3 Marine traffic patterns

The vessel density from 2020 was subtracted from the vessel density in 2019 (Fig. 3), and the resulting surface was averaged. The average difference in the number of ship hours per square km in the entire region was -2361 h/km^2 ; over the entire region, there were slightly more vessels under way at any in given time in 2020 when compared to 2019. It should be noted that the vessel density plotted in Figs. 3(a) and 3(b) ranges from 1000 to 150 000 h/km²/yr, while the differences plotted in Fig. 3(c) vary from $-10\ 000\ \text{to} + 10\ 000\ \text{h/km}^2/\text{yr}$. As such, the differences should be considered small and geographically variable, or "patchy." When total vessel transit hours are compared for each lander (Fig. 4), the differences were more subtle, with landers WIL, CHB, HAT, SAV, and JAX experiencing a reduction in total vessel hours within 100 km of the lander from 2020 when compared to the average of 2018–2019 (reductions of 3028, 9910, 6947, 5692, and 6752 h, respectively), whereas landers VAC and BLE experienced an increase in total vessel hours within 100 km (increase in 26 626 and 2960 h, respectively). When total vessel hours were considered by vessel type across the entire region (Fig. 4,

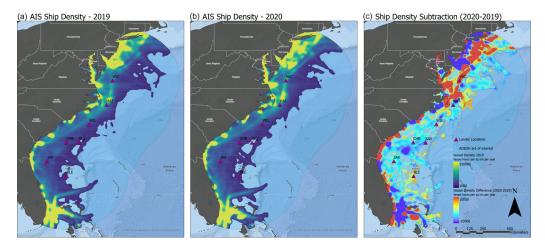


Fig. 3. Vessel density in ADEON region. (a) Global AIS vessel density in 2019; (b) global AIS vessel density in 2020; (c) vessel density subtraction between 2020 and 2019.



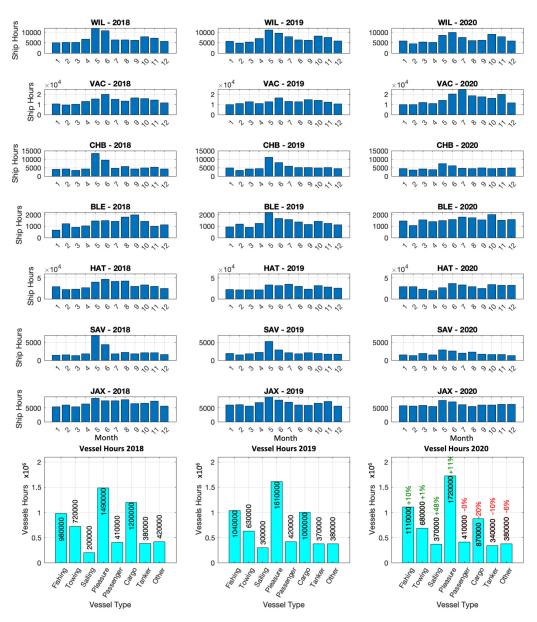


Fig. 4. Number of monthly vessel hours within 100 km of each ADEON lander in 2018–2020. The bottom row shows the number of annual vessel hours across the ADEON region categorized by vessel type. The 2020 vessel type hours shows the increase in fishing and recreational vessels in 2020 compared to the average in 2018–2019 (green text). There was a corresponding decrease in the commercial vessel types (red text).

bottom row), there was a marked increase (\geq 10%) in fishing, sailing, and pleasure craft in 2020 compared to the average in 2018–2019. At the same time, there was a marked decrease in cargo and tanker vessels.

4. Discussion

Combining information obtained from differences in ocean sound with marine traffic patterns provides information pertaining not only to the level of marine traffic but also the movements of the vessels, which ultimately affords insight into the marine sectors driving local and regional sound levels and ocean use. It would appear, based on sound levels and vessel tracks alone, that the COVID-19 pandemic had little impact in this region. Though the timing of change points could be anticipated, the pre- and post-change point differences in sound pressure level could not. The CPA did not detect a COVID-19-consistent decrease in sound levels from 2019 to 2020 at any of the seven sites and six frequencies. While we acknowledge that this analysis reflects only a weekly time step, examination of results for daily and monthly time steps reinforced this conclusion. Interestingly, the CPA appeared to weakly identify a change in the soundscape related to hurricanes Dorian and Humberto in 2019.



The qualitative analysis of vessel type transiting the area, however, did show a COVID-19-related shift in 2020 compared to 2018–2019. For example, while the total number of vessels did in fact remain fairly constant, there were more pleasure craft, fishing vessels, and sailboats in 2020 than in 2018–2019. There were correspondingly fewer cargo vessels and tankers in 2020. This is consistent with economics literature, which suggests that while international transport of goods by cargo ships and large tankers did decrease, domestic transport of bulk goods and industries such as fishing remained fairly consistent (March *et al.*, 2021).

Acknowledgments

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References and links

¹Information on the ADEON Program can be found at https://adeon.unh.edu/ (Last viewed September 1, 2022).

²Information on the R package mcp (multiple change point analysis) can be found at https://osf.io/fzqxv (Last viewed September 2, 2022). ³See supplementary material at https://www.scitation.org/doi/suppl/10.1121/10.0013999 for the results of change point analyses for all frequencies and sites in the same format as Fig. 1.

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