The ephemeral and elusive ocean carbon response to COVID-related emissions reductions

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Abstract

The decline in global emissions of carbon dioxide due to the COVID-19 pandemic provides a unique opportunity to investigate the sensitivity of the global carbon cycle and climate system to emissions reductions. Recent efforts to study the response to these emissions declines has not addressed their impact on the ocean, yet ocean carbon absorption is particularly susceptible to changing atmospheric carbon concentrations. Here, we use ensembles of simulations conducted with an Earth system model to explore the potential detection of COVID-related emissions reductions in the partial pressure difference in carbon dioxide between the surface ocean and overlying atmosphere (ΔpCO_2), a quantity that is regularly measured. We find a unique fingerprint in global-scale ΔpCO_2 that is attributable to COVID and potentially detectable in observations, but only with much larger emissions reductions than those that have been observed to date.

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Key Points:

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13	•	COVID-related emissions reductions will be imperceptible in surface ocean pH obser-
14		vations
15	•	The CanESM5 COVID ensemble predicts a unique fingerprint of COVID-related
16		emissions reductions in global mean ΔpCO_2 (pCO ₂ ^{oc} - pCO ₂ ^{atm})
17	•	The fingerprint is potentially detectable in global-scale observations of ΔpCO_2 , but
18		only with large emissions reductions

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19 Abstract

- ²⁰ The decline in global emissions of carbon dioxide due to the COVID-19 pandemic provides
- a unique opportunity to investigate the sensitivity of the global carbon cycle and climate sys-
- tem to emissions reductions. Recent efforts to study the response to these emissions declines
- has not addressed their impact on the ocean, yet ocean carbon absorption is particularly sus-
- ²⁴ ceptible to changing atmospheric carbon concentrations. Here, we use ensembles of simu-
- ²⁵ lations conducted with an Earth system model to explore the potential detection of COVID-
- related emissions reductions in the partial pressure difference in carbon dioxide between the
- surface ocean and overlying atmosphere (ΔpCO_2), a quantity that is regularly measured. We
- $_{28}$ find a unique fingerprint in global-scale ΔpCO_2 that is attributable to COVID and potentially
- detectable in observations, but only with much larger emissions reductions than those that
- ³⁰ have been observed to date.

Plain Language Summary

The COVID-19 pandemic is slowing the rate of fossil fuel use, and thus slowing the rise of carbon dioxide in the atmosphere. Here we explore what this change in fossil fuel use does

- to carbon in the ocean. We use a climate model to estimate the change in ocean-atmosphere
- carbon exchange and ocean acidity. Since we don't yet know how much we will slow our
- fossil fuel use due to COVID, we make several guesses and see how our model ocean re-
- sponds to each. We use the model to investigate whether the change that we model would
- ³⁸ be detectable in the real world observations. We find that it is nearly impossible to detect a
- ³⁹ COVID-related change in ocean acidity with observations. It might be possible to detect a
- 40 COVID-related change in ocean-atmosphere carbon exchange, but only if we drastically slow
- our emissions, and only if we have enough observation stations in place to record it.

42 **1 Introduction**

The socioeconomic disruptions associated with the COVID-19 pandemic have caused 43 an unprecedented drop in global emissions of carbon dioxide (CO_2) and other atmospheric 44 pollutants. The first half of 2020 was characterized by an 8.8% decrease in global CO₂ emis-45 sions relative to the first half of the previous year [Liu et al., 2020], with average daily emis-46 sions declines peaking at -26% in individual countries [Le Quéré et al., 2020]. The duration 47 and severity of the emissions decline in the latter half of 2020 and beyond is as yet unknown, 48 but 2020 emissions are likely to change by -6% to -13% [Friedlingstein et al., 2020] and con-49 tinued CO₂ emissions reductions are expected in 2021 [Liu et al., 2020]. The important role 50 of CO₂ emissions in the global carbon cycle and climate system motivates further research 51 on this topic. 52

Several research groups are actively studying the impact of the COVID-related emis-53 sions reductions on the atmosphere and climate system. The latest World Meteorological 54 Organization bulletin reports slight reductions in 2020 atmospheric CO₂ levels (-0.08 to -55 0.23 ppm) as a result of the COVID pandemic, though they emphasize that this reduction is 56 difficult to detect given typical year-to-year variations in atmospheric CO₂ [\pm 1 ppm; World 57 Meteorological Organization, 2020]. A recent modeling study concurs that COVID-related 58 reductions in atmospheric CO_2 levels are likely undetectable unless the emissions reductions 59 are substantially larger than observed, but also demonstrates that these short-term reductions 60 will have a long-term (decadal or longer) influence on atmospheric CO2 concentrations due 61 to the long-lived nature of CO₂ in the atmosphere [Fyfe et al., 2020]. Modeling studies sug-62 gest a modest or negligible impact of the emissions reductions on global atmospheric tem-63 perature [Forster et al., 2020; Fyfe et al., 2020]. To date, no study has described the impact 64 of COVID-related emissions reductions on the ocean. As the ocean carbon system is particu-65 larly susceptible to atmospheric CO₂ levels, further study on this topic is warranted. 66

Previous modeling work implies that the COVID-related CO2 emissions reductions and 67 the subsequent slowdown in the atmospheric CO_2 growth rate will have an immediate im-68 pact on ocean carbon uptake. Using an upper ocean box model that solves for the time rate 69 of change of dissolved inorganic carbon in the surface mixed layer, McKinley et al. [2020] 70 showed high sensitivity of air-sea CO_2 flux to slight variations in the growth rate of the at-71 mospheric partial pressure of CO_2 (p CO_2^{atm}) over the 1990s and 2000s. Using a global Earth 72 system model, Laughner et al. [in review] find an anomalous 70 Tg C yr⁻¹ reduction in 2020 73 sea-to-air CO₂ flux due to COVID. These findings prompt further investigation into the de-74 tection of COVID-related CO₂ emissions reductions in ocean carbon observations. 75

Here, we explore the potential to detect COVID-related CO2 emissions reductions in 76 two measurable quantities for ocean carbon: (1) ΔpCO_2 , which is the difference between the 77 partial pressure of CO_2 in the surface ocean (p CO_2^{oc}) and the overlying p CO_2^{atm} and deter-78 mines the direction and, along with wind speed and solubility, the magnitude of the sea-to-air 79 CO_2 flux, and (2) surface ocean pH, a measure of ocean acidity. Using ensembles of simu-80 lations conducted with a single Earth system model, we identify the fingerprint of COVID-81 related CO_2 emissions reductions in these observable quantities. We then treat the individual model ensemble members as possible observations and remark on the likelihood of finger-83 print detection in future ocean carbon measurements. 84

85 2 Methods

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2.1 CanESM5 COVID ensemble

Our primary numerical tool is the Canadian Earth System Model version 5 (CanESM5), 87 which consists of coupled atmosphere, ocean/sea ice, and land model components and was designed to make estimates of historical climate change and variability, to provide future cli-89 mate projections, and to initialize near-term predictions of the climate system [Swart et al., 90 2019]. The ocean component of the model is based on the Nucleus for European Modelling 91 of the Ocean (NEMO), but has been configured for use in CanESM5 with a nominal 1° hor-92 izontal resolution that refines to $1/3^{\circ}$ meridional grid spacing near the equator, 45 vertical 93 layers with varying thickness from 6 m in the surface to 250 m at depth, and a collection of 94 scientifically supported sub-grid scale mixing schemes [Swart et al., 2019]. The ocean bio-95 geochemical component of the model uses the Canadian Model for Ocean Carbon [CMOC; 96 Christian et al., 2010], a Nutrient, Phytoplankton, Zooplankton, Detritus (NPZD)-type bio-97 logical model with updated carbonate chemistry routines following the Ocean Model Inter-98 comparison Project biogeochemical (OMIP-BGC) protocol [Orr et al., 2017]. 99

We analyze output from a large ensemble of CanESM5 simulations forced with 4 dif-104 ferent CO_2 emission scenarios (Figure 1a). This model simulation configuration is described 105 in Fyfe et al. [2020], and hereafter referred to as the CanESM5 COVID ensemble. Briefly, 106 the first set of simulations (the control) consists of 30 ensemble members of CanESM5 in-107 tegrated over 2015-2019 under SSP2-4.5 CO₂ emissions and initialized with slightly per-108 turbed climate states to capture internal climate variability. The remaining 3 ensembles fol-109 low the same initialization procedure with 30 ensemble members each over 2019-2040, but 110 are forced with a COVID-like CO₂ emissions reduction that begins in December 2019 and 111 resolves by December 2021 (Figure 1a). Peak emissions reductions of 25% (COVID-like), 112 50% (2 × COVID-like), and 100% (4 × COVID-like) occur in May 2020 (Figure 1); these 113 scenarios correspond to 2020 annualized emissions reductions of 16%, 32%, and 63%, re-114 spectively [Fyfe et al., 2020]. 115

¹¹⁶ CanESM5 is an appropriate tool for the exploration of the ocean carbon response to ¹¹⁷ COVID-related emissions reductions. A previous evaluation of the CMIP6 historical simula-¹¹⁸ tion of CanESM5 via comparison with historical climatologies finds high spatial correlation ¹¹⁹ (r > 0.9) of modeled and observed three-dimensional potential temperature, nitrate, oxygen, ¹²⁰ and dissolved inorganic carbon [*Swart et al.*, 2019]. However, the same study finds lower



Figure 1. (a) Global-mean CO₂ emissions (Pg C yr⁻¹) for the (black) control/SSP2-4.5, (blue) COVIDlike, (green) $2 \times \text{COVID-like}$, and (red) $4 \times \text{COVID-like}$ scenarios. (b) Global-, annual-, and ensemble-mean surface (solid) pCO₂^{atm} and (dashed) pCO₂^{oc} anomaly (μ atm; difference from control) simulated in the CanESM5 ensembles under the COVID-like emission scenarios. Adapted from *Fyfe et al.* [2020].

spatial correlations (r = 0.7) between modeled and observation-based historical air-sea CO₂ 121 flux [Swart et al., 2019], prompting our further evaluation of ocean observables ΔpCO_2 and 122 surface ocean pH over the historical period. Figure ??a illustrates similar spatial patterns of 123 annual-mean ΔpCO_2 across the global ocean between the CanESM5 control ensemble mean 124 and version 2020 of the Landschützer et al. [2016] observation-based climatology [Land-125 schützer et al., 2020] over 2015-2018, though we note regional differences in the magni-126 tude and spatial extent of positive ΔpCO_2 across the equatorial Pacific, in the sign of ΔpCO_2 127 in the subtropical North Atlantic, and in the spatial extent of the positive ΔpCO_2 region in 128 the eastern subtropical North Pacific. We also note a lack of observation-based estimates of 129 ΔpCO_2 in the Arctic, where CanESM5 predicts large negative ΔpCO_2 values (Figure ??a,b). 130 The CanESM5 control ensemble is capable of capturing the phasing and magnitude in the 131 climatological seasonal cycle of ΔpCO_2 as measured at the the Woods Hole Oceanographic 132 Institution Hawaii Ocean Timeseries Site (WHOTS) buoy, though the spring minimum is 133 deeper in approximately half of the CanESM ensemble members than observed (Figure ??b). While the annual mean surface ocean pH over 2015-2018 exhibits similar spatial patterns be-135 tween modeled pH and an observation-based product [Gregor and Gruber, 2020], the mod-136 eled pH is generally lower than that from observation-based estimates (Figure ??). As with 137 ΔpCO_2 , a lack of observation-based climatological estimates of pH in the seasonally ice cov-138 ered Southern Ocean and Arctic precludes investigation of model-observation similarity in 139 these regions. CanESM5 produces rates of historical ocean carbon uptake that are consistent 140 with observational estimates of decadal mean CO2 fluxes and with independent estimates of 141 cumulative anthropogenic carbon uptake at the global scale [Swart et al., 2019], suggesting 142 that the simulated response of ocean carbon to atmospheric CO_2 changes is reliable at the 143 large scale. 144

2.2 Statistical approach

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We identify the COVID-related fingerprints in ΔpCO_2 and pH using CanESM5 COVID ensemble mean output that has been annually and globally averaged over 2019-2024. This 5year period captures the time during which we observe the largest anomalies in atmospheric and oceanic pCO₂ relative to the control ensemble across each of the COVID emissions scenarios (see also Figure 1b). We identify the fingerprint using ensemble and global-mean output to maximize the influence of external forcing and dampen the influence of internal variability on the fingerprint [*Lovenduski et al.*, 2016; *McKinley et al.*, 2016; *Schlunegger et al.*,
 2019, 2020]. The spatial pattern associated with the COVID-related fingerprint is estimated
 as the regression coefficient of the ensemble mean at each location and the standardized fingerprint (subtract mean and divide by standard deviation) over 2019-2024 for each emission
 scenario.

¹⁵⁷ Detection and attribution of the COVID signal is assessed by analyzing the set of 30 ¹⁵⁸ Pearson's correlation coefficients (*r*) produced when correlating individual ensemble mem-¹⁵⁹ bers with the corresponding fingerprint over 2019-2024. The statistical properties (mean, ¹⁶⁰ standard deviation) of these coefficients are estimated via Fisher *z*-transformation.

161 **3 Results**

The CanESM5 COVID ensemble predicts an anomalous decrease in surface pCO₂^{atm} 162 and pCO_2^{oc} due to the CO₂ emissions reduction, as evidenced by the negative anomalies in 163 annual mean, ensemble mean pCO_2^{atm} and pCO_2^{oc} calculated relative to the control/SSP2-4.5 emissions scenario (Figure 1b). Anomalously low pCO₂^{atm} peaks in 2021-2, approxi-165 mately 1-2 years after the largest emissions reduction, reflecting the mixing time of CO_2 in 166 the global atmosphere. At their peak, global mean anomalies in pCO_2^{atm} are -1.5, -2.7, and 167 -5.4 µatm for the COVID-like, 2× COVID-like, and 4× COVID-like emission scenarios, 168 respectively. Anomalously low pCO₂^{oc} peaks in 2023-4, approximately 1-2 years after the 169 largest pCO₂^{atm} reduction, reflecting the equilibration timescale of the surface ocean mixed 170 layer with atmospheric CO₂ perturbations [McKinley et al., 2020]. At their peak, global 171 mean anomalies in pCO₂^{oc} are smaller in magnitude than the pCO₂^{atm} anomalies for the cor-172 responding emission scenario (-1.2, -1.9, and -4.1 μ atm for the COVID-like, 2× COVID-like, 173 and 4× COVID-like emission scenarios, respectively). Unlike the CO₂ emissions anoma-174 lies (Figure 1a), the pCO₂^{atm} and pCO₂^{oc} anomalies persist for the duration of the simulations 175 (Figure 1b), due to the long-lived nature of CO_2 in the atmosphere [*Fyfe et al.*, 2020]. 176

The difference between the evolution of pCO₂^{atm} and pCO₂^{oc} following the COVID-182 like CO₂ emissions reductions creates a unique fingerprint in ΔpCO_2 across the CanESM5 183 COVID ensemble (Figure 2a-c). Figure 2 (top row) shows the evolution of the annual mean, 184 global mean ΔpCO_2 from the 30 individual ensemble members (light gray) and the ensemble 185 mean (black) across the three COVID scenarios. The fingerprint for each scenario is indi-186 cated as the colored part of the ensemble mean ΔpCO_2 , capturing the temporal behavior over 187 2019-2024 (Figure 2a-c). This fingerprint is characterized by an increase in ΔpCO_2 from 188 2019 to 2021, followed by a decrease over 2021-2024, and is most pronounced in the $4 \times$ COVID-like case and least pronounced in the COVID-like case. This inverted "V" fingerprint/time-190 series is unique; it arises due to the rapid slowdown and recovery of CO₂ emissions and the 191 ~ 1 year equilibration timescale for carbon between the atmosphere and the ocean mixed 192 layer [Figure 1b; McKinley et al., 2020]. In contrast, a typical year-on-year emissions re-193 duction scenario – for example, a scenario that limits warming to 1.5°C – generates a slowly-194 changing ΔpCO_2 whose fingerprint would be challenging to distinguish (not shown). 195

The evolution of ocean acidification under COVID-like emissions reductions produces 196 an almost imperceptible fingerprint in global mean surface ocean pH. Here, the large and 197 long-lived anthropogenic CO_2 burden in the atmosphere drives continued ocean carbon up-198 take and thus decreasing global pH relative to the base period in all ensemble members over 199 2019-2040 (Figure 2d-f). The rate of pH decrease briefly stagnates under COVID-like emis-200 sions reductions, with the biggest stagnation under the 4 × COVID-like emissions scenario 201 (Figure 2f). This fingerprint in surface ocean pH would be difficult to distinguish in the ob-202 servational record due to large measurement uncertainty relative to the projected rate of pH 203 decrease. Thus, for the remainder of our study, we focus our analysis efforts on the unique 204 ΔpCO_2 fingerprint brought about by COVID-related emissions reductions. 205



Figure 2. COVID-related fingerprints in global-mean, annual-mean (top row) ΔpCO_2 (pCO_2^{oc} - pCO_2^{atm} ; μ atm) and (bottom row) surface ocean pH, simulated with the CanESM5 COVID ensemble. Gray lines show individual ensemble members, black line shows the ensemble mean, and colored lines show the COVIDrelated fingerprint over 2019-2024 under the (first column) COVID-like, (second column) 2 × COVID-like, and (third column) 4 × COVID-like emission scenarios.



Figure 3. Spatial pattern of the COVID-related fingerprints in ΔpCO_2 (pCO_2^{oc} - pCO_2^{atm} ; μ atm) under the (a) COVID-like, (b) 2 × COVID-like, and (c) 4 × COVID-like emission scenarios, calculated as the regression coefficient of ΔpCO_2 onto the standardized fingerprints. Black open circles indicate the locations of buoys

capable of autonomous surface ocean pCO₂ measurements from *Sutton et al.* [2019].

The COVID-related fingerprints in ΔpCO_2 are characterized by a heterogeneous spatial pattern across the CanESM5 global ocean. Figure 3 shows the magnitude of the fingerprint signal at each location. The largest fingerprint signals (> 2 μ atm) manifest in the Arctic Ocean, the subtropical North Pacific, and the western subpolar North Atlantic (Figure 3). The fingerprint signals become more widespread with larger emissions reductions, such that a majority of the global ocean experiences a fingerprint signal in the 4 × COVID-like emissions scenario (Figure 3c).

Is it possible to detect our modeled ΔpCO_2 fingerprint in the real ocean, and to at-217 tribute the fingerprint to COVID-related emissions reductions? To answer this question, we 218 treat the individual CanESM5 COVID ensemble members as equally likely observations of 219 the recent past / near future and examine their correlation to the ensemble mean. Figure 4a 220 shows the range of correlation coefficients across the 30 ensemble members under the four 221 emission scenarios for the global mean ΔpCO_2 . The mean correlation coefficient is near zero 222 for the control simulation (not exactly zero due to the long term trend in ΔpCO_2 under SSP2-223 4.5), with a wide range; COVID-like emissions reductions increase the mean and narrow the 22/ range, supporting the attribution of the ΔpCO_2 signal to COVID. There is enhanced likelihood of detection of the COVID signal from global-mean ΔpCO_2 observations with more 226 severe reductions in emissions, as evidenced by the increasing mean correlation coefficient 227 with larger emissions reductions. However, the range of correlation coefficients is only sta-228 tistically different from zero (using the $\pm 1\sigma$ or 67% confidence interval) in the 4 × COVID-229 like scenario. Thus, while the evolution of the global mean ΔpCO_2 anomaly is potentially 230 detectable in observations and attributable to COVID emissions, a much larger emissions 231 reduction than observed to date would be required to truly detect the signal in the real ocean. 232

It is nearly impossible to detect the COVID-related fingerprint in ΔpCO_2 at a single 233 observational site due to high local internal variability and measurement uncertainty. Fig-234 ure 3 shows the location of buoys capable of near real-time autonomous surface ocean pCO_2 235 measurements (< 2 μ atm uncertainty) as open black circles; these 40 observational buoys 236 are discussed in detail in Sutton et al. [2019]. Both a strong signal (COVID fingerprint) and low noise (internal variability) are required for detection at a single site. In all emission sce-238 narios, the CanESM5 COVID ensemble predicts the strongest ΔpCO_2 fingerprint signals in 239 regions where few buoys are located, such as the Arctic and the western subpolar North At-240 lantic. Under extreme emission reductions, a strong and measurable (> 2 μ atm) fingerprint 241 signal begins to emerge at several of the buoy sites (Figure 3c). However, even at a subtrop-242 ical site with low internal variance, such as the WHOTS buoy, and under the most extreme 243 forcing scenario, the $\pm 1\sigma$ confidence interval of the fingerprint correlations encapsulates the 244 zero correlation line (Figure 4b). 245

²⁵¹ Detection of a COVID-related fingerprint in ΔpCO_2 from near real-time autonomous ²⁵² buoys is more likely when considering all 40 observational data streams simultaneously. Fig-²⁵³ ure 4c reveals that, akin to the global-mean, the subsampled model ΔpCO_2 averaged across ²⁵⁴ the 40 autonomous buoy locations has higher correlations with the fingerprint than that of ²⁵⁵ a single buoy location. Yet, it is still statistically unlikely to detect the fingerprint from this ²⁵⁶ subsampled mean unless there is a much larger emissions reduction than that which has been ²⁵⁷ observed to date.

4 Conclusions and Discussion

We use an ensemble of Earth system model simulations to identify and assess the detectability of a COVID-related fingerprint in ΔpCO_2 and surface ocean pH. Our study reveals a unique fingerprint in modeled global mean ΔpCO_2 anomalies under COVID-like CO₂ emissions reductions due to the rapid slowdown and recovery of the emissions and the equilibration timescale for carbon in the upper mixed layer of the ocean. We find no discernible COVID fingerprint for modeled surface ocean pH, but rather a slight slowing of the continuous pH decline due to ocean acidification. A detection and attribution analysis conducted



Figure 4. Detection and attribution of COVID-related fingerprints in ΔpCO_2 under four emission scenarios for (a) the modeled global-mean, (b) the WHOTS buoy location in the model, and (c) the mean of 40 autonomous buoy locations in the model, shown as the temporal correlation coefficients of individual ensemble members with the ensemble-mean fingerprint over 2019-2024. Small circles show the correlation coefficients from the 30 ensemble members, and the large circles show the mean correlation coefficients.

²⁶⁶ on individual model ensemble members shows that the ΔpCO_2 fingerprint is attributable to ²⁶⁷ COVID emissions and potentially detectable in global-scale observations in cases with large ²⁶⁸ emissions reductions. At local scales, however, observational detection is hampered by high ²⁶⁹ internal variability.

Our results indicate that the detection of a COVID-related ΔpCO_2 fingerprint in fu-270 ture observations is more attainable from global-scale estimates, rather than regional or lo-271 cal measurements. While this is expected due to the low magnitude of internal variability 272 at global scales and high variability at local scales [Diffenbaugh et al., 2020; Lovenduski 273 et al., 2016], it nevertheless suggests that a large network of global-scale pCO_2^{oc} observations 274 will be necessary to detect the COVID signal. Recent efforts to collect and process disparate 275 pCO₂^{oc} data streams into a single cohesive database [e.g., Sutton et al., 2019; Bakker et al., 276 2016] will be highly useful for detection efforts. Even so, the ocean carbon community will 277 continue to rely on observation-based, gap-filled surface ocean pCO_2 estimates to approxi-278 mate the global-mean ΔpCO_2 and its temporal evolution. Continued improvement upon and 279 testing of the reliability of these products is thus warranted [e.g., *Gloege et al.*, in review]. 280

The COVID-related fingerprint in ΔpCO_2 is unique to the COVID-like emissions trajectory, permitting our investigation of detection and attribution. A more difficult task that awaits our community is the detection of a continuous emissions reduction in ocean carbon that may come about to support climate change mitigation policy. This detection will be further challenged by to the relatively high uncertainty in the global carbon cycle [*Peters et al.*, 2017]. Yet, it will become necessary to demonstrate the efficacy of emissions reductions on ocean carbon in the near future.

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Supplement to: The ephemeral and elusive ocean carbon response to COVID-related emissions reductions

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- Figure S1. Comparison of modeled and observed ΔpCO_2 ($pCO_2^{oc} pCO_2^{atm}$). Annual-mean ΔpCO_2 from
- (a) the CanESM5 control ensemble mean, and (b) the observation-based Landschützer et al. [2016] climatol-
- $_{29}$ ogy over 2015-2018. (c) Seasonal cycle of ΔpCO_2 at the WHOTS buoy location (orange dot on inset map):
- $_{30}$ (gray) 30 CanESM5 control ensemble members in 2015 and (green) the observed ΔpCO_2 climatology (mean
- \pm one standard deviation) from *Sutton et al.* [2019].



- Figure S2. Comparison of modeled and observed surface ocean pH. Annual-mean pH from (a) the
- CanESM5 control ensemble mean, and (b) the observation-based *Gregor and Gruber* [2020] climatology
- over 2015-2018.