






# Global Biogeochemical Cycles®



## RESEARCH ARTICLE

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## Amplified Subsurface Signals of Ocean Acidification

Andrea J. Fassbender<sup>1</sup> , Brendan R. Carter<sup>1,2</sup> , Jonathan D. Sharp<sup>1,2</sup> , Yibin Huang<sup>1,3,4</sup> , Mar C. Arroyo<sup>1,4</sup> , and Hartmut Frenzel<sup>1,2</sup>

### Key Points:

- The largest changes in multiple metrics of ocean acidification (OA) occur below the sea surface due to carbonate system nonlinearities
- Across broad ocean realms, subsurface changes in the partial pressure of carbon dioxide gas ( $p\text{CO}_2$ ) driven by OA exceed the atmospheric  $p\text{CO}_2$  change
- Implications for ecosystem habitability, ocean carbon storage, and marine carbon dioxide removal strategies require investigation

### Supporting Information:

Supporting Information may be found in the online version of this article.

### Correspondence to:

A. J. Fassbender,  
[andrea.j.fassbender@noaa.gov](mailto:andrea.j.fassbender@noaa.gov)

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### Author Contributions:

**Conceptualization:** Andrea J. Fassbender

**Formal analysis:** Andrea J. Fassbender

**Methodology:** Andrea J. Fassbender, Brendan R. Carter, Jonathan D. Sharp, Yibin Huang

**Project Administration:** Andrea J. Fassbender

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<sup>1</sup>NOAA/OAR Pacific Marine Environmental Laboratory, Seattle, WA, USA, <sup>2</sup>Cooperative Institute for Climate, Ocean, and Ecosystem Studies, University of Washington, Seattle, WA, USA, <sup>3</sup>Cooperative Institute for Marine and Atmospheric Research, University of Hawai'i at Manoa, Honolulu, HI, USA, <sup>4</sup>Department of Ocean Sciences, University of California Santa Cruz, Santa Cruz, CA, USA

**Abstract** We evaluate the impact of anthropogenic carbon ( $C_{\text{ant}}$ ) accumulation on multiple ocean acidification (OA) metrics throughout the water column and across the major ocean basins using the GLODAPv2.2016b mapped product. OA is largely considered a surface-intensified process caused by the air-to-sea transfer of  $C_{\text{ant}}$ ; however, we find that the partial pressure of carbon dioxide gas ( $p\text{CO}_2$ ), Revelle sensitivity Factor (RF), and hydrogen ion concentration ( $[\text{H}^+]$ ) exhibit their largest responses to  $C_{\text{ant}}$  well below the surface (>100 m). This is because subsurface seawater is usually less well-buffered than surface seawater due to the accumulation of natural carbon from organic matter remineralization. pH and aragonite saturation state ( $\Omega_{\text{Ar}}$ ) do not exhibit spatially coherent amplified subsurface responses to  $C_{\text{ant}}$  accumulation in the GLODAPv2.2016b mapped product, though nonlinear characteristics of the carbonate system work to amplify subsurface changes in each OA metric evaluated except  $\Omega_{\text{Ar}}$ . Regional variability in the vertical gradients of natural and anthropogenic carbon create regional hot spots of subsurface intensified OA metric changes, with implications for vertical shifts in biologically relevant chemical thresholds.  $C_{\text{ant}}$  accumulation has resulted in subsurface  $p\text{CO}_2$ , RF, and  $[\text{H}^+]$  changes that significantly exceed their respective surface change magnitudes, sometimes by >100%, throughout large expanses of the ocean. Such interior ocean  $p\text{CO}_2$  changes are outpacing the atmospheric  $p\text{CO}_2$  change that drives OA itself. Re-emergence of these waters at the sea surface could lead to elevated  $\text{CO}_2$  evasion rates and reduced ocean carbon storage efficiency in high-latitude regions where waters do not have time to fully equilibrate with the atmosphere before subduction.

**Plain Language Summary** The chemistry of the upper ocean is changing due to the absorption of excess carbon in the atmosphere resulting from human activities, a process commonly referred to as ocean acidification (OA). The highest concentrations of excess carbon in the ocean are generally found at the surface; however, some of the largest chemical changes resulting from this carbon buildup are occurring below the sea surface. This subsurface intensification is caused by nonlinear responses of some chemical parameters to opposing vertical gradients of natural carbon versus excess carbon. Our findings emphasize the need to study multiple metrics of OA throughout the water column to comprehensively evaluate changes in the habitability of interior ocean realms and potential connections to ocean carbon storage timescales.

## 1. Introduction

Anthropogenic carbon ( $C_{\text{ant}}$ ) in the atmosphere is primarily transferred to the ocean through the air-sea exchange of carbon dioxide gas ( $\text{CO}_2$ ). To date, the ocean has absorbed ~25% of the total anthropogenic emissions since industrialization (Friedlingstein et al., 2022). Persistent growth in the atmospheric partial pressure of  $\text{CO}_2$  ( $p\text{CO}_2$ ) has caused persistent growth in upper ocean  $C_{\text{ant}}$  concentrations, with the highest values generally occurring at the sea surface. However, the accumulation of  $C_{\text{ant}}$  is not spatially uniform (Gruber et al., 2019; Sabine et al., 2004). Greater penetration of  $C_{\text{ant}}$  in deep water formation regions and the subtropics is caused by regional circulation that transports surface waters to the ocean interior (DeVries, 2014; Iudicone et al., 2016; Khatiwala et al., 2013).

In addition to circulation, heterogeneity in surface ocean carbonate chemistry influences the impact of increasing atmospheric  $p\text{CO}_2$  on dissolved inorganic carbon (DIC), and thus the efficiency of ocean  $C_{\text{ant}}$  accumulation (Revelle & Suess, 1957). Meridional surface gradients in temperature and salinity, in addition to physical and biological processes that can modulate local air-sea  $\text{CO}_2$  disequilibrium, dictate the meridional surface gradient in DIC concentration (Hamme et al., 2019; Volk & Hoffert, 1985) and the associated DIC-to-total alkalinity ratio (Wu et al., 2019); a measure of the carbonate system buffer capacity (Eggleston et al., 2010). The carbonate system

**Writing – original draft:** Andrea J. Fassbender  
**Writing – review & editing:** Andrea J. Fassbender, Brendan R. Carter, Jonathan D. Sharp, Yibin Huang, Mar C. Arroyo, Hartmut Frenzel

buffer capacity is often described using the Revelle sensitivity Factor (RF; Broecker et al., 1979; Middelburg et al., 2020), which is defined as the relative change in  $p\text{CO}_2$  associated with a relative change in DIC, assuming all other variables are held constant:

$$\text{RF} = (\Delta p\text{CO}_2 / p\text{CO}_2) (\Delta \text{DIC} / \text{DIC})^{-1} \quad (1)$$

For a given relative change in  $p\text{CO}_2$ , a low RF indicates that a relatively large change in DIC will occur, and a high RF indicates that a relatively small change in DIC will occur. The mean surface ocean RF is  $\sim 10$ , indicating that a 10% change in  $p\text{CO}_2$  is required to elicit a 1% change in DIC. However, spatial variability in the RF indicates that some areas of the ocean are more efficient than others at accumulating DIC for a given surface ocean  $p\text{CO}_2$  perturbation (Figure 1a and Figure S1 in Supporting Information S1; Fassbender et al., 2017). Below the surface, the RF increases with depth, more than doubling in many ocean regions, indicating an increase in the relative sensitivity of  $p\text{CO}_2$  to DIC (Figure 1c).

The rate at which surface ocean carbonate chemistry is changing has been well explored for a handful of ocean acidification (OA) metrics (Caldeira & Wickert, 2003; Jiang et al., 2023; Orr et al., 2005). Observation-based trends in surface ocean  $p\text{CO}_2$  (Fay & McKinley, 2013; Jiang et al., 2023; Sutton et al., 2019; Takahashi et al., 2014), hydrogen ion concentration ( $[\text{H}^+]$ ) (Fassbender et al., 2017; Jiang et al., 2023), pH ( $\text{pH} = -\log_{10}([\text{H}^+])$ ; Iida et al., 2021; Jiang et al., 2019, 2023; Lauvset et al., 2015), and the saturation state of aragonite ( $\Omega_{\text{Ar}}$ ; a calcium carbonate mineral polymorph; Bates et al., 2014; Feely et al., 2009; Iida et al., 2021) have been evaluated globally. Less attention has been given to carbonate chemistry changes occurring in the ocean interior where vertical DIC gradients greatly exceed horizontal DIC gradients across the open surface ocean (Figures 1b and 1d). Exceptions include a few global studies that have evaluated subsurface changes in calcium carbonate mineral saturation states and pH (Feely et al., 2004; Jiang et al., 2015; S. K. Lauvset et al., 2020) and regional studies that have evaluated subsurface changes in  $p\text{CO}_2$  (Arroyo et al., 2022; Chen et al., 2022),  $[\text{H}^+]$  (Arroyo et al., 2022; Fassbender et al., 2021), pH (Arroyo et al., 2022; Byrne et al., 2010; Carter et al., 2019; Chen et al., 2017; Dore et al., 2009; Fassbender et al., 2021), and aragonite saturation state ( $\Omega_{\text{Ar}}$ ) (Arroyo et al., 2022; Carter et al., 2019; Feely et al., 2018; Negrete-García et al., 2019). Some of these studies suggest that the largest OA metric responses to  $C_{\text{ant}}$  may be occurring below the sea surface (Arroyo et al., 2022; Carter et al., 2019; Fassbender et al., 2021; Lauvset et al., 2020).

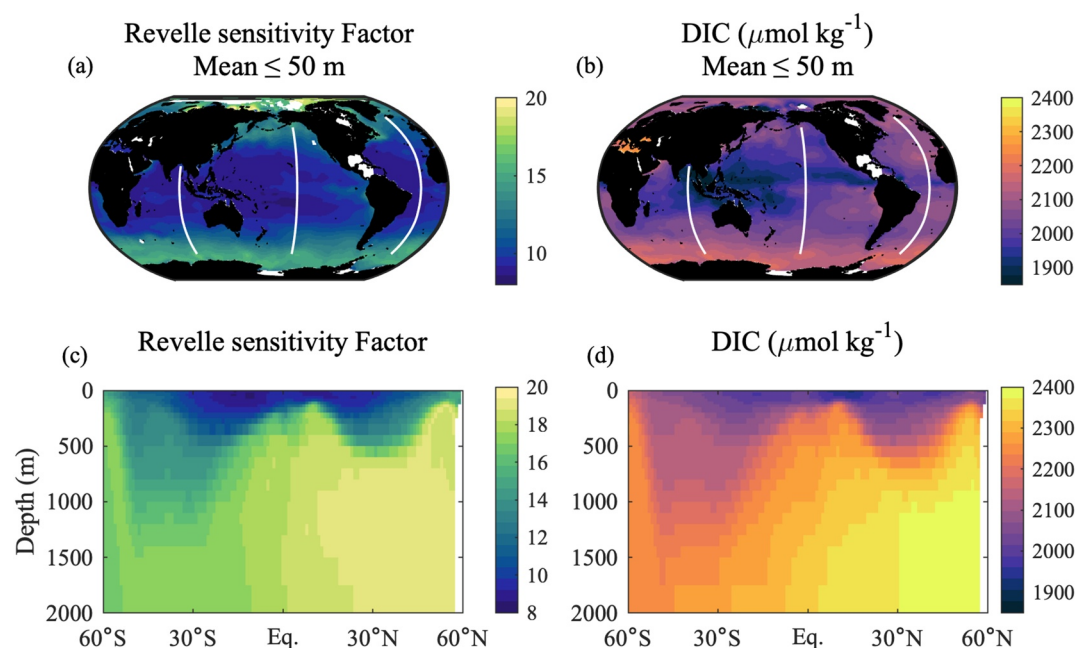
In the ocean interior, the three-dimensional habitats of marine species are shaped by environmental conditions (e.g., Deutsch et al., 2020; Howard et al., 2020) that evolve with natural variability and external forcing. Yet, few studies have evaluated how OA metrics influence the distributions of economically important species and their prey (e.g., Guinotte & Fabry, 2008). For example,  $\Omega_{\text{Ar}}$  is a valuable indicator of the energetic requirement to sustain net calcification (e.g., Bach, 2015) for species that may serve as prey for pelagic fish or be economically important in their own right (Cooley & Doney, 2009). Additionally, there is evidence that some fish species may be severely impacted by elevated seawater  $p\text{CO}_2$  levels that can make it difficult to expel  $\text{CO}_2$  from the gills, causing a buildup of  $\text{CO}_2$  in the blood (i.e., hypercapnia; Heuer & Grosell, 2014). Understanding how OA is evolving below the surface, where new mesopelagic fisheries may become important to feed the growing global population (Fjeld et al., 2023; Kourantidou & Jin, 2022), is a critical first step toward identifying potential downstream impacts of OA on marine species distributions and ecosystem health.

Building on prior studies, we evaluate the impact of  $C_{\text{ant}}$  accumulation on multiple commonly considered OA metrics throughout the water column and across the major ocean basins. We then quantify the impact of carbonate system nonlinearities on the  $C_{\text{ant}}$ -induced OA metric changes. The indirect impacts of  $C_{\text{ant}}$  on ocean circulation and the biological carbon pump through climate change are additional complications that we do not address in this study. Finally, we consider potential implications for interior ocean habitability, carbon storage efficiency, and impacts resulting from marine carbon dioxide removal strategies.

## 2. Methodology

### 2.1. OA Metric Changes Caused by $C_{\text{ant}}$

To quantify the impact of  $C_{\text{ant}}$  on each OA metric (i.e., pH,  $\Omega_{\text{Ar}}$ ,  $p\text{CO}_2$ ,  $[\text{H}^+]$ , and RF), we rely on a quality-controlled and internally consistent hydrographic data set curated by the Global Data Analysis Project (GLODAP; Olsen et al., 2016) that was previously mapped to a global  $1^\circ \times 1^\circ$  horizontal grid with 33 stand-



**Figure 1.** Average (a) Revelle sensitivity Factor (RF) and (b) dissolved inorganic carbon (DIC) concentration in the upper 50 m of the ocean. Interior ocean (c) RF and (d) DIC concentrations along 150.5°W (central white line in panels (a) and (b)). Panels a and c as well as b and d use consistent color scales to emphasize the larger interior ocean versus near-surface gradients in these parameters. Data are from the GLODAPv2.2016b mapped product, which is an annual climatology normalized to the year 2002 (Lauvset et al., 2016). White patches in panels (a) and (b) reflect regions lacking data. Panels (a) and (b) also show meridional transects (white lines) in the Atlantic (25.5°W) and Indian (90.5°E) Oceans that will be referenced in subsequent figures.

ard depth levels and normalized to the year 2002 as an annual climatology: the GLODAPv2.2016b mapped product (Key et al., 2015; Lauvset et al., 2016). Salinity ( $S$ ), temperature ( $T$ ), total alkalinity (TA), DIC, and nutrient (N; phosphate and silicate) data were used to compute pH,  $\Omega_{Ar}$ ,  $pCO_2$ ,  $[H^+]$ , and RF (Figure S2 in Supporting Information S1). All carbonate system calculations in our study were made in MATLAB using the CO2SYSv3 (version 3.2.0; Sharp et al., 2020) carbonate system calculator with the following user settings: total pH scale; equilibrium constants of Lueker et al. (2000); sulfate dissociation constant of Dickson et al. (1990); fluoride dissociation constant of Perez and Fraga (1987); and borate-to-salinity ratio of Lee et al. (2010).

$C_{ant}$  values included in the GLODAPv2.2016b mapped product were subtracted from the DIC values to estimate a quasi-preindustrial (PI) DIC concentration ( $DIC_{PI}$ ). The GLODAPv2.2016b mapped product does provide a  $DIC_{PI}$  field, but it is mapped from calculations of  $DIC_{PI}$  at observation locations and is nearly identical ( $0.0 \pm 0.2 \mu\text{mol kg}^{-1}$ ) to the mapped DIC minus mapped  $C_{ant}$ . We chose to deal with  $DIC_{PI}$  calculated from the mapped DIC and  $C_{ant}$  for consistency. Salinity, temperature, TA,  $DIC_{PI}$ , and nutrient data were then used to compute  $pH_{PI}$ ,  $\Omega_{Ar, PI}$ ,  $pCO_{2, PI}$ ,  $[H^+]_{PI}$ , and  $RF_{PI}$ . This approach isolates the influence of accumulated  $C_{ant}$  in setting ocean chemical conditions (in 2002 c.e.) but does not account for changes in temperature, salinity, ocean circulation, or biology that may have occurred since industrialization. Differences between the year 2002 and PI values are used to evaluate subsurface patterns of OA metric changes caused by accumulated  $C_{ant}$  (for a variable  $X$  this would be  $\Delta X^{C_{ant}}$ ; Figure S3 in Supporting Information S1), with an example calculation for pH shown here:

$$\Delta pH^{C_{ant}} = pH^{f(S,T,DIC,TA,N)} - pH_{PI}^{f(S,T,DIC_{PI},TA,N)} \quad (2)$$

We consider subsurface changes in each OA metric relative to the respective mean change within the upper 50 m of the local overlying water ( $\Delta pH^{C_{ant}} - \Delta pH^{C_{ant}}|_{0-50m}$ ). Local overlying waters do not typically reflect the origin conditions of the waters below; however, using the local, rather than global, mean change in near-surface waters as a reference helps to reveal how the influence of this feedback varies with depth (Figures S4 and S5 in Supporting Information S1).

## 2.2. Nonlinear Component of OA Metric Changes Caused by $C_{\text{ant}}$

To quantify how carbonate system nonlinearities may be contributing to the total change in each OA metric, we use previously published, globally mapped estimates of preformed properties (Carter et al., 2021) provided on the same grid as the GLODAPv2.2016b mapped product. These so-called preformed properties reflect the property concentrations that would be expected in the absence of carbon accumulated through organic matter remineralization (Figure S6 in Supporting Information S1) and calcium carbonate dissolution (Figure S7 in Supporting Information S1). The interior ocean preformed property estimates rely on the transport matrix output from a data-assimilation ocean circulation inverse model (OCIM: DeVries, 2014) to determine where interior ocean water masses were last near the ocean surface, and two alternative circulation products are used as a component of the uncertainty estimate for the product. OCIM in turn relies on GLODAP observations (Key et al., 2004) of potential temperature, salinity, radiocarbon, and CFC-11 to estimate the climatological mean state ocean circulation. Locally interpolated regression algorithms developed by Carter et al. (2017), which are also based on GLODAP observations, were used to estimate preformed property values at the base of the mixed layer. These values were propagated into the ocean interior using the OCIM transport matrix to estimate the interior ocean preformed property values. As a final step, Carter et al. (2021) regridded the preformed properties to match the GLODAPv2.2016b mapped product grid for public release of the files.

We focus on the biogenic component of natural carbon in the ocean due to its dominance in setting the vertical carbon gradient (DeVries, 2022; Sarmiento & Gruber, 2006) and because it is the addition of biogenic carbon, after natural and anthropogenic carbon have been added through air-sea exchange, that induces the nonlinear subsurface changes we aim to characterize (Figure S8 in Supporting Information S1). We subtract the preformed dissolved oxygen ( $O_{2,0}$ ) field from the GLODAPv2.2016b mapped product  $O_2$  field to estimate the true oxygen utilization (TOU). To convert TOU to respiratory DIC, we use the canonical respiratory quotient ( $O_2:C$ ) of  $(-170/117)$  that was estimated from mixed phytoplankton tows (Hedges et al., 2002) and interior ocean water mass analyses (Anderson & Sarmiento, 1994) to evaluate the bulk remineralized carbon pool in the ocean interior (sensitivity analysis presented in Text S1 and Figures S9–S10 in Supporting Information S1). We subtract preformed nitrate, silicate, and phosphate from the GLODAPv2.2016b mapped product fields for each parameter to determine their respiratory burdens. Following Carter et al. (2021), we compute potential alkalinity ( $pTA$ ) by subtracting the GLODAPv2.2016b mapped product nitrate field multiplied by 1.36 (Wolf-Gladrow et al., 2007) from the TA field to account for the minor influence of remineralization on TA. We perform the same calculation using the preformed TA ( $TA_0$ ) and preformed nitrate fields to estimate preformed potential TA ( $pTA_0$ ). The difference between  $pTA$  and  $pTA_0$  yields the calcium carbonate dissolution term ( $TA_{CaCO_3}$ ). Subtracting  $TA_0$  and  $TA_{CaCO_3}$  from the TA field yields the residual, remineralized TA component. We multiply  $TA_{CaCO_3}$  by 0.5 to calculate the DIC calcium carbonate dissolution component. Preformed DIC ( $DIC_0$ ) is then calculated by subtracting the respiratory and calcium carbonate DIC components from the GLODAPv2.2016b mapped product DIC field.

For each OA metric, the preindustrial preformed (PI,0) value is subtracted from the year 2002 preformed value to determine OA metric changes ( $\Delta X_0^{C_{\text{ant}}}$ ) in the absence of natural biogenic byproducts, with an example calculation for pH shown here:

$$\Delta pH_0^{C_{\text{ant}}} = pH_0^{f(S,T,DIC_0,TA_0,N_0)} - pH_{PI,0}^{f(S,T,DIC_{PI,0},TA_0,N_0)} \quad (3)$$

For each OA metric (e.g.,  $X$ ), we then evaluate the difference between  $C_{\text{ant}}$ -induced changes occurring with ( $\Delta X^{C_{\text{ant}}}$ ) and without ( $\Delta X_0^{C_{\text{ant}}}$ ) the background of natural biogenic carbon byproducts (hereafter referred to as natural carbon). This allows us to quantify how much of the OA metric response is caused by nonlinear carbonate chemistry effects induced by natural and anthropogenic carbon pool interactions (Figure S8 in Supporting Information S1), with an example calculation for pH shown here:

$$\Delta pH_{\text{Nonlinear}} = \Delta pH^{C_{\text{ant}}} - \Delta pH_0^{C_{\text{ant}}} \quad (4)$$

In the history of a water mass,  $C_{\text{ant}}$  accumulates before and during water mass formation and subduction, whereas natural carbon accumulates after water mass subduction. Therefore, this nonlinear effect should be considered the impact of  $C_{\text{ant}}$  upon the magnitude of change induced by natural carbon rather than the reverse. Nevertheless, hereafter we discuss the impact in the reverse sense because we are interested in how human emissions modulate the signals associated with natural environmental variability.

Our calculations rely on numerous assumptions and data products, each of which contains a degree of uncertainty. However, in Text S2, we describe a validation exercise based on independent output from a global ocean biogeochemistry model that reproduces the significant patterns that we highlight in our findings (Figure S11 in Supporting Information S1). This confirms that our findings are not spurious products of our methodological choices but are robust signals that are consistent with modern understanding of ocean circulation, biogeochemistry, and anthropogenic forcing. While this exercise shows that models already represent subsurface amplification of OA metric changes through carbonate system nonlinearities, our study serves to characterize and to call attention to this combination of unintuitive feedbacks and to provide observational evidence for its existence and extent in the real ocean.

### 2.3. Estimation of Uncertainties

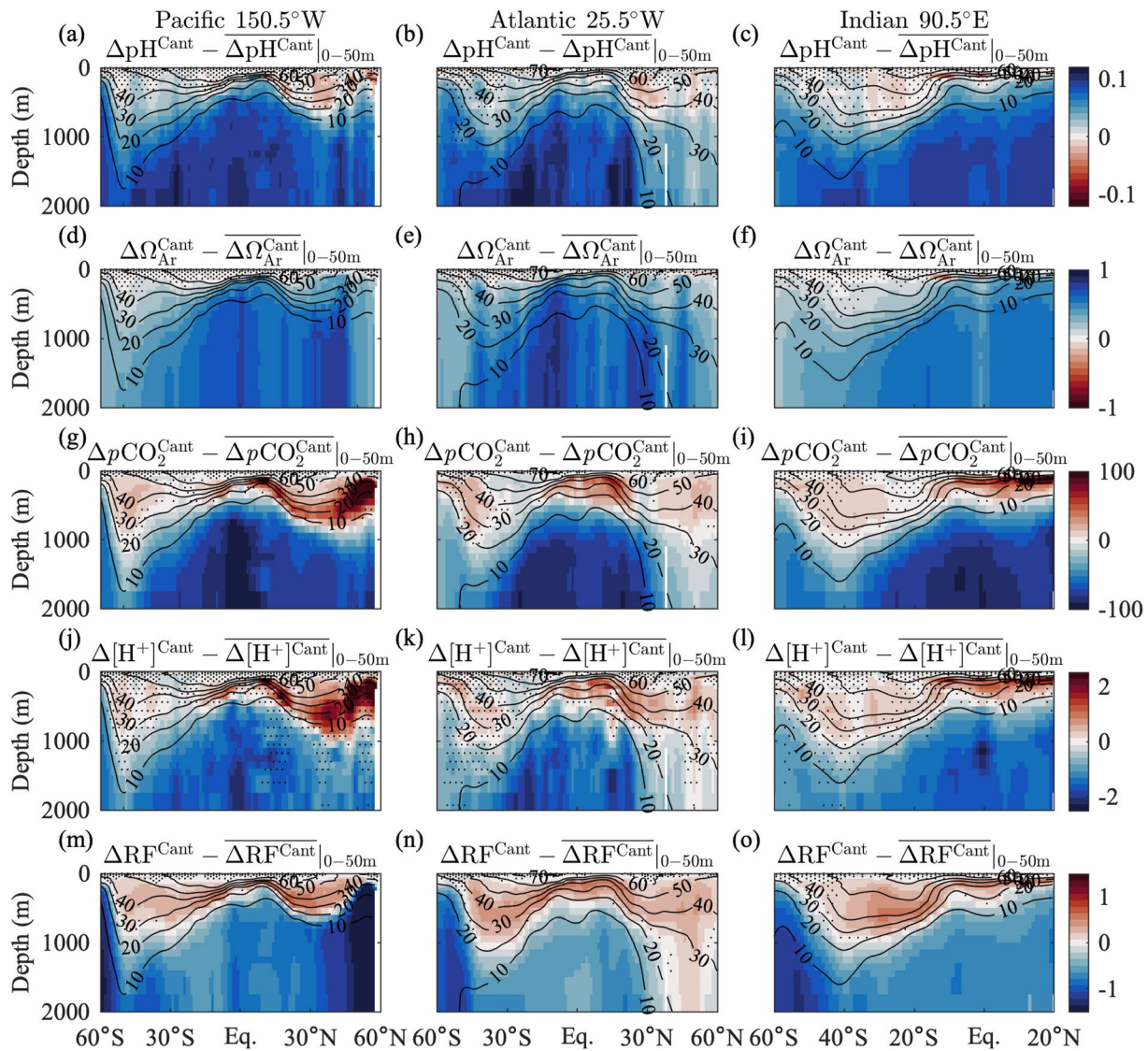
The GLODAPv2.2016b mapped product provides spatially resolved error fields for each parameter. These errors reflect mapping uncertainties and do not include measurement uncertainties or calculation errors (for pH and  $\Omega_{Ar}$ ), as mapping errors are thought to dominate (Lauvset et al., 2016; Olsen et al., 2016). We compute the  $[H^+]$  error directly from the provided pH and  $pH_{error}$  fields (Text S3). The Carter et al. (2021) preformed a property mapped product also provides spatially resolved error fields for each parameter. We use the error fields in Monte Carlo simulations and standard error propagation procedures (i.e., summing in quadrature) to estimate the uncertainty in the calculated values presented herein. For  $pCO_2$ , RF, and all PI values, we perform a 1,000 iteration Monte Carlo simulation of the CO2SYSv3 calculations while individually varying all input values around their provided errors in a Gaussian manner using a MATLAB pseudorandom number generator (randn) that produces a set of numbers with a mean equal to zero and standard deviation equal to one. We also calculate the change in each parameter from the PI period to the year 2002 within each simulation. The standard deviation across the 1,000 simulations for each parameter is used to estimate its uncertainty. Standard error propagation is used in subsequent calculations as needed. The computed uncertainties are used for stippling in various figures to convey statistical confidence.

## 3. Results

### 3.1. Identifying OA Metrics With Subsurface Intensified Changes

pH and  $\Omega_{Ar}$  do not display coherent, amplified subsurface  $C_{ant}$ -induced changes ( $\Delta X^{C_{ant}}$ ) relative to the local mean changes within the upper 50 m along the transects evaluated (Figure 2 and Figure S12 in Supporting Information S1). However, there are patchy regions of slightly elevated subsurface  $\Delta pH^{C_{ant}}$  that exceed the calculation uncertainties (Figures 2a–2c), and similar signals have been identified previously (Carter et al., 2019; Lauvset et al., 2020).  $pCO_2$  and  $[H^+]$  display amplified subsurface  $C_{ant}$ -induced changes, relative to the local mean changes within the upper 50 m, with the largest changes occurring at depths with moderate to low  $C_{ant}$  concentrations (Figure 2 and Figure S12 in Supporting Information S1). These features are spatially coherent and found throughout significant portions of each ocean transect, reflecting a signal that is global in nature. The largest subsurface  $\Delta pCO_2^{C_{ant}}$  and  $\Delta [H^+]^{C_{ant}}$  signals occur in the North Pacific (~100–500 m) where the waters are old (Figure S13 in Supporting Information S1), the vertical  $pCO_2$  and DIC gradients are steep (Figure S14 in Supporting Information S1), and carbonate system buffering is naturally weak (Figure 1c). In these areas, small changes in DIC have a large influence on  $pCO_2$  due to the elevated background  $pCO_2$ :DIC ratio (Figure S15a in Supporting Information S1; Equation 1; Fassbender et al., 2017). Similarly large subsurface  $\Delta pCO_2^{C_{ant}}$  and  $\Delta [H^+]^{C_{ant}}$  signals are found in the North Indian Ocean where  $C_{ant}$  penetration is shallow but the vertical  $pCO_2$ :DIC gradient is also shallow and steep (Figure S14 in Supporting Information S1). In the North Atlantic and Southern Oceans, where  $C_{ant}$  reaches deep into the interior, weaker vertical carbon gradients in the more recently ventilated waters cause subsurface  $\Delta pCO_2^{C_{ant}}$  and  $\Delta [H^+]^{C_{ant}}$  signals to exceed the near-surface changes by a much smaller magnitude. Larger GLODAPv2.2016b mapped product uncertainties in the Southern Ocean, due to data scarcity (Lauvset et al., 2016), cause most of the  $\Delta [H^+]^{C_{ant}}$  signals in this region to fall within the uncertainties of the calculation.

Like  $pCO_2$  and  $[H^+]$ , the RF exhibits amplified subsurface  $C_{ant}$ -induced changes relative to the local mean changes within the upper 50 m, with the largest changes occurring at depths with moderate to low  $C_{ant}$  concentrations (Figure 2). Poleward of  $\sim 45^\circ N$  in the Pacific Ocean, there is a large discrepancy in the vertical extent of subsurface  $\Delta RF^{C_{ant}}$  versus  $\Delta pCO_2^{C_{ant}}$  signals (Figure S3 in Supporting Information S1). These waters surpassed their minimum buffer capacity (or maximum RF) in the preindustrial ocean (Figures S12 and S16 in Supporting Information S1), such that the addition of  $C_{ant}$  causes  $\Delta RF^{C_{ant}}$  to be negative (Eggleston et al., 2010; Fassbender

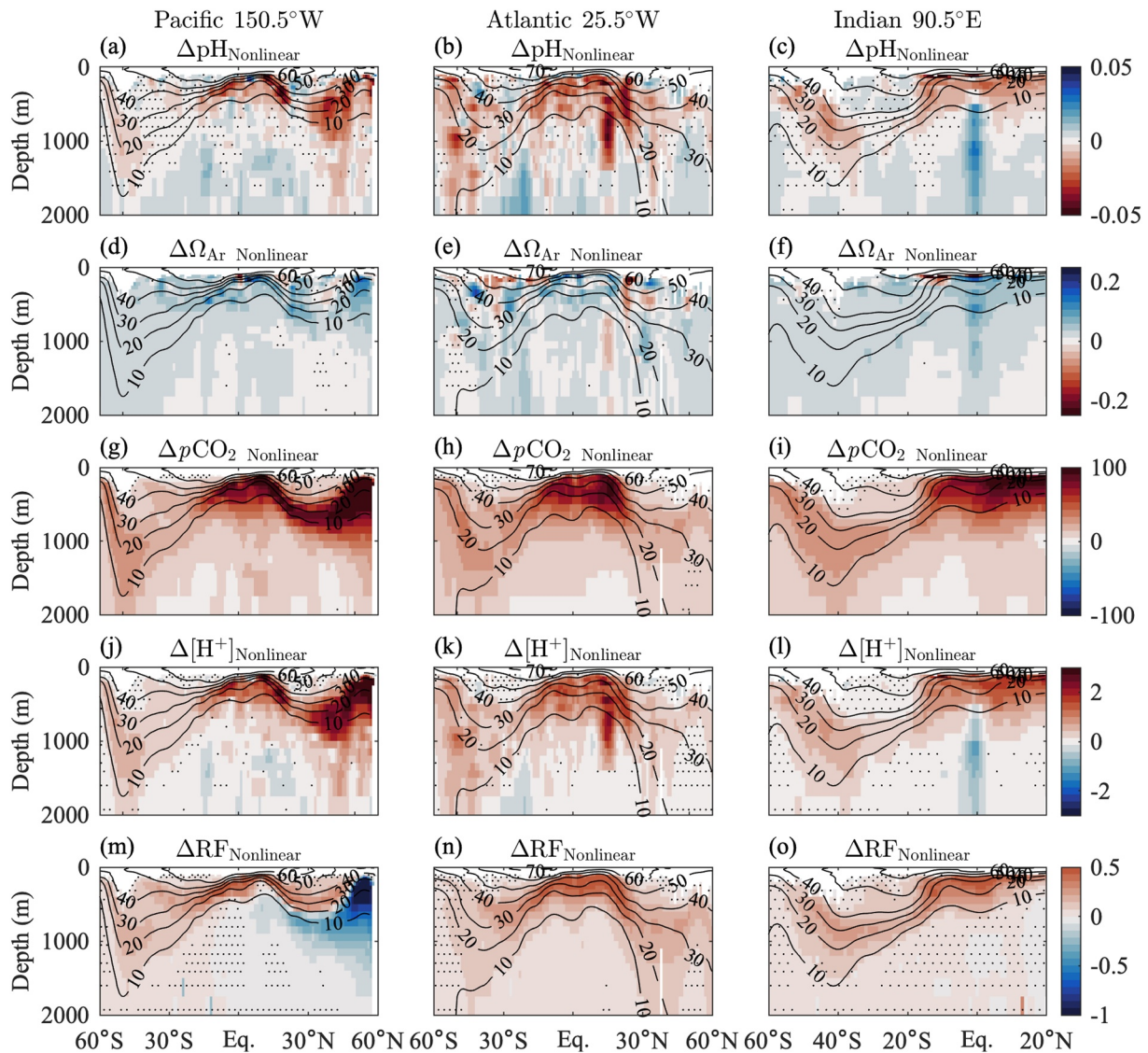


**Figure 2.**  $C_{\text{ant}}$ -induced ocean acidification metric changes ( $\Delta$ ), from the preindustrial period to the year 2002, relative to the local mean change in the upper 50 m for (a–c) pH, (d–f) aragonite saturation state ( $\Omega_{\text{Ar}}$ ), (g–i) partial pressure of carbon dioxide gas ( $p\text{CO}_2$ ;  $\mu\text{atm}$ ), (j–l)  $[\text{H}^+]$  ( $\text{nmol kg}^{-1}$ ), and the (m–o) Revelle sensitivity Factor. Results for the Pacific ( $150.5^\circ\text{W}$ ), Atlantic ( $25.5^\circ\text{W}$ ), and Indian ( $90.5^\circ\text{E}$ ) Oceans with meridional transect locations shown in Figure 1a. Black contours represent  $C_{\text{ant}}$  ( $\mu\text{mol kg}^{-1}$ ) in the year 2002. Red coloring indicates a subsurface change that is larger in magnitude than the local mean change in the upper 50 m. Stippling indicates where the magnitude of the change is smaller than the uncertainty.

et al., 2017). The maximum RF is found where DIC approximately equals TA (Figure S15b in Supporting Information S1). Where  $\text{DIC} < \text{TA}$ , as it is in much of the modern ocean, the RF increases with DIC additions, as carbonate ions are consumed to neutralize the added  $\text{CO}_2$  (Figure S15c in Supporting Information S1), thus diminishing the quantity of carbonate ions remaining to buffer the seawater against further changes. When  $\text{DIC} > \text{TA}$ , the carbonate ions have been largely consumed, leading to an approximately linear increase in  $p\text{CO}_2$  with increasing DIC (Figures S15a and S15c in Supporting Information S1). In these regions, the RF declines with added DIC, primarily due to a constant  $\Delta p\text{CO}_2/\Delta\text{DIC}$  and rapidly growing  $p\text{CO}_2$  denominator in Equation 1. Like  $p\text{CO}_2$ , subsurface  $\Delta\text{RF}^{C_{\text{ant}}}$  values throughout the Southern Ocean are larger than the uncertainties (Figures 2m–2o).

### 3.2. Nonlinear Interactions Between Natural and Anthropogenic Carbon Pools

Regional differences in vertical DIC and TA gradients caused by heterogeneous accumulation of biogenic and anthropogenic carbon (Figures S6 and S7 in Supporting Information S1) lead to regional differences in the nonlinear responses of OA metrics to natural and anthropogenic carbon pool interactions (Figure 3). Ocean  $C_{\text{ant}}$  distributions



**Figure 3.** Nonlinear component of ocean acidification (OA) metric changes ( $\Delta$ ) caused by interactions between  $C_{\text{ant}}$  and natural carbon accumulated from organic matter remineralization and calcium carbonate dissolution. Red and blue coloring indicate where the OA metric responses to  $C_{\text{ant}}$  are amplified or dampened, respectively, by carbonate system nonlinearities. Results are shown for (a–c) pH (d–f) aragonite saturation state ( $\Omega_{\text{Ar}}$ ), (g–i) partial pressure of carbon dioxide gas ( $p\text{CO}_2$ ;  $\mu\text{atm}$ ), (j–l)  $[\text{H}^+]$  ( $\text{nmol kg}^{-1}$ ), and the (m–o) Revelle sensitivity Factor. Black contours represent  $C_{\text{ant}}$  ( $\mu\text{mol kg}^{-1}$ ) in the year 2002. Results for the Pacific (150.5°W), Atlantic (25.5°W), and Indian (90.5°E) Oceans with meridional transect locations shown in Figure 1a. Stippling indicates where the magnitude of the change is smaller than the uncertainty.

reflect the uptake of a non-steady-state tracer sourced from the atmosphere and the passive redistribution of this surface signal into the ocean interior through ocean circulation. Biogeochemical feedback also have the potential to impact  $C_{\text{ant}}$  distributions, but the transient-tracer-based transit-time  $C_{\text{ant}}$  distribution estimates used in this study do not capture or represent these secondary controls on  $C_{\text{ant}}$  distributions. By contrast, vertical gradients in natural carbon primarily result from biological processes and are only secondarily controlled by the temperature-driven  $\text{CO}_2$  solubility prior to water mass subduction (i.e., the solubility pump) (Figure S6 in Supporting Information S1). Importantly, natural carbon tends to increase with water mass age while  $C_{\text{ant}}$  tends to decrease with water mass age. This leads to a decoupling of large-scale  $C_{\text{ant}}$  and natural carbon gradients along neutral density surfaces, creating hotspots for the emergence of nonlinear carbonate chemistry signals in the ocean interior.

Nonlinear interactions between natural and anthropogenic carbon pools are working to both dampen and amplify OA metric changes in different regions of the water column. For pH, nonlinearities amplify the decrease in pH throughout coherent regions of the subsurface ocean (Figure 3); however, this effect is small, accounting for <25% of the

total pH change in waters above the  $10 \mu\text{mol kg}^{-1} C_{\text{ant}}$  contour (Figure S17 in Supporting Information S1), where pH changes are greatest. As a result, nonlinear pH changes are not large enough to produce a coherent, elevated subsurface signal in the overall pH change or in the pH change relative to the upper 50 m in the GLODAPv2.2016b mapped product (Figure 2 and Figure S3 in Supporting Information S1). Model estimates of interior ocean nonlinear pH changes caused by  $C_{\text{ant}}$  accumulation (Figure S11 and Text S2 in Supporting Information S1) imply that subsurface amplified signals may be anticipated but are difficult to detect amid uncertainties in the underlying observational products. For  $\Omega_{\text{Ar}}$ , carbonate system nonlinearities dampen the decrease in  $\Omega_{\text{Ar}}$  throughout the water column, but the effect is small, accounting for <25% of the total  $\Omega_{\text{Ar}}$  change in most waters above the  $10 \mu\text{mol kg}^{-1} C_{\text{ant}}$  contour (Figure S17), where  $\Omega_{\text{Ar}}$  changes are greatest (Figure S3 in Supporting Information S1). Carbonate system nonlinearities work to significantly increase  $p\text{CO}_2$  and  $[\text{H}^+]$  changes below the surface, accounting for >70% of the total changes in waters laden with respiratory byproducts above the  $10 \mu\text{mol kg}^{-1} C_{\text{ant}}$  contour, where changes in these parameters are greatest (Figures S3, S6, and S17 in Supporting Information S1). For the RF, nonlinear contributions to the OA driven changes are predominantly small (<35% of the total RF change), excluding a large dampening signal in the mesopelagic North Pacific that is entirely explained by carbonate system nonlinearities (Figure S17 in Supporting Information S1). In this region the preindustrial DIC:TA ratio is already greater than 1 and increases in DIC from  $C_{\text{ant}}$  accumulation lead to declines in the RF (Figure S16 in Supporting Information S1). However, adding  $C_{\text{ant}}$  to the preformed PI values, for which the DIC:TA ratio is much less than 1, causes the RF to increase. Differencing these changes (Equation 4) leads to the large nonlinear reduction in the RF. In summary, carbonate system nonlinearities resulting from natural and anthropogenic carbon pool interactions mitigate  $C_{\text{ant}}$ -driven changes to  $\Omega_{\text{Ar}}$  and exacerbate changes to pH,  $p\text{CO}_2$ , and  $[\text{H}^+]$  in coherent spatial patterns. The RF responds similarly to  $p\text{CO}_2$  in regions where the DIC:TA ratio remains <1 (Figures S3 and S16 in Supporting Information S1).

### 3.3. Potential Implications for Habitat Compression

The largest  $[\text{H}^+]$  and  $p\text{CO}_2$  changes resulting from accumulated  $C_{\text{ant}}$  in the open ocean have occurred below the sea surface (Figure 2) in mesopelagic waters where organisms are also experiencing reductions in carbonate mineral saturation (Jiang et al., 2015) and dissolved oxygen levels (hypoxia;  $\text{O}_2 \leq 60 \mu\text{mol kg}^{-1}$ ; Breitburg et al., 2018; Oschlies et al., 2018). Elevated in situ  $p\text{CO}_2$  has been linked to negative impacts for a suite of sessile and low-vagility invertebrates (Vargas et al., 2022), and there is mixed evidence for adverse impacts on marine fishes through several biological mechanisms (Clements & Hunt, 2015; Esbaugh, 2018; Heuer & Grosell, 2014; Sundin, 2023). One of these mechanisms is a reduction in the efficiency at which  $\text{CO}_2$  is expelled during respiration, which can lead to a buildup of  $\text{CO}_2$  in the blood (i.e., hypercapnia; Nilsson et al., 2012; Perry & Gilmour, 2006). 1,000  $\mu\text{atm}$  is commonly used as a  $p\text{CO}_2$  threshold for when respiring marine organisms may experience stress (Arroyo et al., 2022; Feely et al., 2018; McNeil & Sasse, 2016).

The interior ocean  $p\text{CO}_2$  we have presented until now reflects the partial pressure that  $\text{CO}_2$  would have if it were an ideal gas that was unaffected by the overlying hydrostatic pressure. This is a useful parameter for considering the air-sea  $p\text{CO}_2$  gradient that would occur if subsurface waters were instantaneously and quasi-adiabatically brought to the sea surface where  $p\text{CO}_2$  and the fugacity of  $\text{CO}_2$  ( $f\text{CO}_2$ ) are quite similar (Humphreys et al., 2022). However, in the ocean interior, the influence of overlying pressure and non-ideal nature of  $\text{CO}_2$  may be an important consideration (Figure S18 in Supporting Information S1). Thus, we compute in situ  $f\text{CO}_2$  values (Text S4) and evaluate hypercapnia (hereafter equating to  $f\text{CO}_2 \geq 1,000 \mu\text{atm}$ ) in the ocean interior and its relation to patterns of low oxygen and  $\Omega_{\text{Ar}}$ .

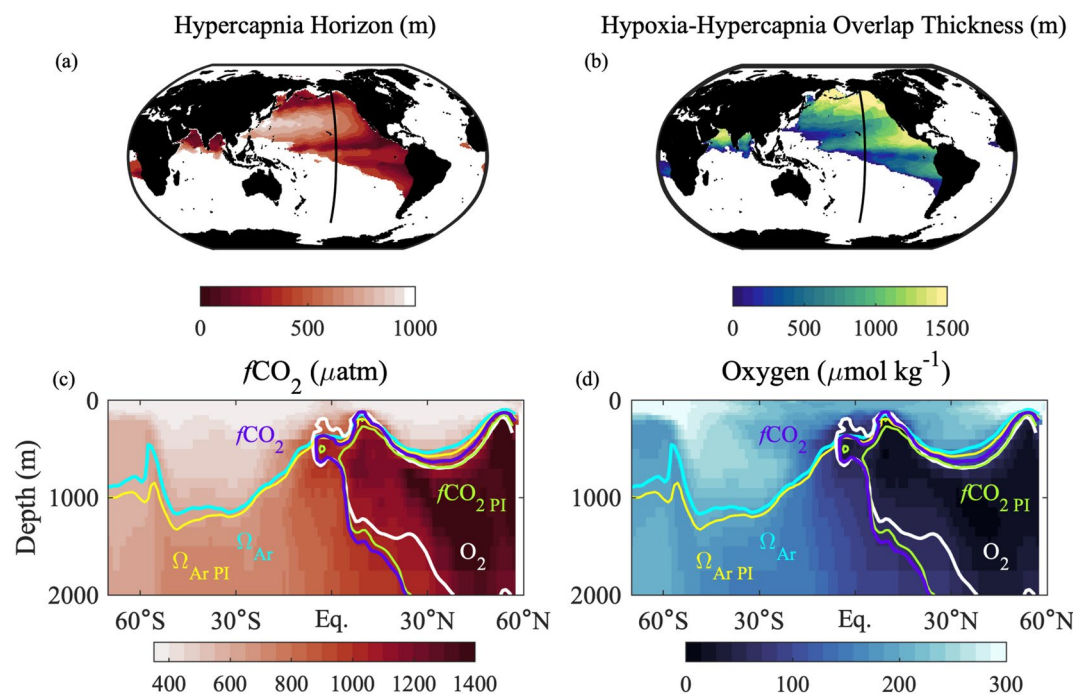
Hypercapnic conditions can be found at depths shallower than 500 m throughout large expanses of the Pacific Ocean as well as the Bay of Bengal, Arabian Sea, and off the west coast of Africa (Figure 4a).  $C_{\text{ant}}$ -driven  $f\text{CO}_2$  increases in the ocean interior have contributed to this signal, causing widespread shoaling of the hypercapnia horizon (~180 m along the Pacific transect; green vs. purple line in Figure 4c). A significant volume of hypercapnic water in the Eastern Equatorial Pacific, North Pacific Ocean, and North Indian Ocean is also hypoxic (Figure 4b). In the North Pacific, the hypoxia and hypercapnia horizons closely align with the aragonite saturation horizon at depths  $\leq 200$  m (Figure 4d).

## 4. Discussion

### 4.1. Amplified Subsurface Ocean Acidification

OA caused by the air-to-sea transfer of  $C_{\text{ant}}$  is intuitively thought to be a surface-intensified process, but this is not the case across broad ocean regions and for multiple OA metrics, including  $p\text{CO}_2$ , RF, and  $[\text{H}^+]$ . By the





**Figure 4.** Year 2002 (a) depth of the hypercapnia horizon ( $f\text{CO}_2 = 1,000 \mu\text{atm}$ ) and (b) thickness of overlap in simultaneously hypercapnic and hypoxic ( $\text{O}_2 \leq 60 \mu\text{mol kg}^{-1}$ ) waters. (c) Year 2002  $f\text{CO}_2$  and (d) dissolved oxygen concentration along North Pacific Section 150.5°W. Purple and green lines show the year 2002 and PI hypercapnia horizons ( $f\text{CO}_2$ ), respectively. Cyan and yellow lines show the year 2002 and PI aragonite saturation horizons ( $\Omega_{\text{Ar}}$ ), respectively. White lines show the year 2002 hypoxia horizon ( $\text{O}_2$ ).

year 2002, these parameters exhibited their largest responses to  $C_{\text{ant}}$  accumulation in the ocean interior, where waters are weakly buffered due to the buildup of remineralized organic material, and  $C_{\text{ant}}$  concentrations are moderate. Annual mean surface ocean  $p\text{CO}_2$  growth largely tracks atmospheric  $p\text{CO}_2$  growth, globally and over multi-decadal timescales (McKinley et al., 2017), increasing by  $\sim 90 \mu\text{atm}$  from the PI to the year 2002 (Figure S1b in Supporting Information S1). Subsurface  $\Delta p\text{CO}_2^{C_{\text{ant}}}$  values that exceed the upper 50 m mean  $\Delta p\text{CO}_2^{C_{\text{ant}}}$  value (Figure 2) are therefore outpacing the atmospheric  $p\text{CO}_2$  perturbation, more than doubling it in some regions of the North Pacific and North Indian Oceans. This is particularly notable since these waters reside below the local maximum annual mixed layer depth and have not been in contact with the atmosphere for some time (Figure S13 in Supporting Information S1).

Aragonite saturation state does not exhibit a subsurface intensified response to  $C_{\text{ant}}$  accumulation while pH exhibits an inconsistent subsurface intensified response to  $C_{\text{ant}}$  accumulation in the GLODAPv2.2016b mapped product. There are patches of slightly elevated  $C_{\text{ant}}$ -driven pH changes below the surface that exceed our calculation uncertainties, and the model analysis (Text S2) indicates that carbonate system nonlinearities are working to induce widespread subsurface pH change amplification (Figure S11 in Supporting Information S1). pH changes reflect relative  $[\text{H}^+]$  changes (Fassbender et al., 2021; Kwiatkowski & Orr, 2018), so small positive biases in the 2002 subsurface  $[\text{H}^+]$  values or negative biases in the  $C_{\text{ant}}$  estimates (which would cause negative biases in  $\Delta[\text{H}^+]^{C_{\text{ant}}}$ ) could be muting the large-scale  $\Delta\text{pH}^{C_{\text{ant}}}$  signal and causing the small and localized subsurface  $\Delta\text{pH}^{C_{\text{ant}}}$  minima that we find. Alternatively, these patches could reflect unaccounted for uncertainties associated with mapping  $C_{\text{ant}}$  and/or pH to a global scale to create the GLODAPv2.2016b mapped product. We find that carbonate system nonlinearities are working to amplify the subsurface responses of  $p\text{CO}_2$ , RF,  $[\text{H}^+]$ , and pH to  $C_{\text{ant}}$  accumulation, dominating the overall responses of  $p\text{CO}_2$  and  $[\text{H}^+]$  as well as the response of RF in some ocean regions. Continued OA may cause the patchy  $\Delta\text{pH}^{C_{\text{ant}}}$  minima to expand into coherent subsurface signals like those found in a recent analysis of 21st century Earth system model projections (Kwiatkowski et al., 2020). Nonlinear carbonate chemistry effects weakly mitigate reductions in  $\Omega_{\text{Ar}}$ , which has a surface intensified response to  $C_{\text{ant}}$  accumulation. Our findings therefore do not add significant new context to  $C_{\text{ant}}$ -driven  $\Omega_{\text{Ar}}$  changes relative to previous interior ocean analyses (e.g., Feely et al., 2004; Negrete-García et al., 2019).

## 4.2. Broader Implications

The OA metrics evaluated herein are not routinely incorporated into marine ecosystem models, which are forced with output from Earth system model projections to estimate future ocean biomass changes (Doney et al., 2020; Lotze et al., 2019; Tittensor et al., 2021). However, there is growing interest to understand how climate change, including OA, is impacting the marine environment, and to use this understanding to support ecosystem-based fishery management (Edited by In Bianchi & Skjoldal, 2008; Fletcher et al., 2010; Garcia & Cochrane, 2005; Marshall et al., 2019; Pikitch et al., 2004). A large body of experimental OA work suggests that species from more variable marine environments tend to have more phenotypic plasticity and are thus more tolerant of environmental variability (Boyd et al., 2016). However, most biological OA sensitivity studies use modern or preindustrial near-surface ocean conditions as a baseline mean state from which to conduct their experimental treatments (e.g., Cornwall & Hurd, 2015). Our findings suggest that, in some regions, OA metric changes in subsurface waters with weaker buffering can be significantly larger than surface changes (which may exhibit similar relative changes; Figure S19 in Supporting Information S1), indicating that experimental conditions thought to represent the distant future for the surface ocean may also represent a not-so-distant future for deeper layers of the water column. In addition to mean state considerations, Arroyo et al. (2022) determined that North Pacific waters with amplified subsurface OA changes regularly bathe the continental shelf during upwelling events in the California Current Large Marine Ecosystem (CCLME). Thus, the seasonal range of OA metric extremes on the shelf of the CCLME may have increased by significantly more than in overlying surface waters since the preindustrial period. Inverting the perception that OA impacts attenuate with depth may provide useful new context when designing OA laboratory experiments and interpreting relationships between organismal plasticity and environmental variability (e.g., Vargas et al., 2022).

The nonlinear amplification of interior ocean  $p\text{CO}_2$  changes associated with  $C_{\text{ant}}$  accumulation may have implications for anthropogenic carbon storage in the ocean.  $C_{\text{ant}}$  enters the ocean due to persistent growth in atmospheric  $p\text{CO}_2$  (presently  $\sim 2.5 \mu\text{atm yr}^{-1}$ ) that in turn causes persistent growth in surface ocean  $p\text{CO}_2$  at a rate that largely tracks the atmosphere; therefore, changes in sea-air  $p\text{CO}_2$  disequilibrium ( $\Delta p\text{CO}_{2, \text{Sea-Air}}$ ) have occurred gradually (McKinley et al., 2017). The re-emergence of subsurface waters that have experienced  $p\text{CO}_2$  changes  $>100\%$  larger than global surface ocean changes (Figure S5 in Supporting Information S1) could greatly increase the rate of  $\text{CO}_2$  evasion during water mass ventilation. In areas where water masses do not fully equilibrate with the atmosphere prior to subduction (e.g., the Southern Ocean), changes in the rate of  $\text{CO}_2$  evasion from the ocean could influence the level of sea-air equilibration reached and thus the amount and efficiency of carbon stored (Eggleston & Galbraith, 2018; Ito & Follows, 2013). With international goals to reduce atmospheric  $\text{CO}_2$  levels and eventually achieve net-zero  $\text{CO}_2$  emissions (International Energy Agency, 2021), this raises the question: where and when will waters experiencing amplified subsurface  $p\text{CO}_2$  changes re-emerge, and could this meaningfully impact ocean carbon storage efficiency?

While we have focused on the chemical changes associated with OA, the same concepts hold for other scenarios in which interior ocean carbon or alkalinity gradients are modified; as is the case for many mCDR strategies (National Academies of Sciences, Engineering, and Medicine, 2022). The efficacy and environmental implications of mCDR strategies will be depth-dependent for some key OA metrics. Like the RF, the Alkalinity sensitivity Factor (AF; Takahashi et al., 1993) describes the relative change in  $p\text{CO}_2$  associated with a relative change in TA, assuming all other variables are held constant. The AF is elevated at depth so that  $p\text{CO}_2$  is more sensitive to alkalinity addition below the surface (Figure S20). This enhanced sensitivity coupled with natural calcium carbonate dissolution (Figure S7) helps to partially compensate for  $p\text{CO}_2$  increases resulting from the remineralization of organic matter; however, there is much more carbon added through remineralization than calcium carbonate dissolution (Figure S6). While surface ocean alkalinity enhancement has largely been considered an mCDR strategy to mitigate climate change with the potential co-benefit of OA mitigation, the intentional addition of alkalinity below the surface could mitigate OA impacts that may be more deleterious than previously realized. As these waters will eventually return to the sea surface, mitigating extreme subsurface OA impacts could preemptively mitigate some of the most extreme surface OA impacts as well. Subsurface alkalinity addition could also mitigate future ocean-based  $\text{CO}_2$  emissions in regions where subsurface waters with large,  $C_{\text{ant}}$ -induced  $p\text{CO}_2$  perturbations are expected to re-emerge at the sea surface, such as eastern boundary upwelling regions or obduction hot spots. Some of the most abundant mineral sources of TA (e.g., carbonate minerals; Caserini et al., 2022) being considered for use in mCDR do not readily dissolve in modern surface ocean conditions (Kheshgi, 1995) but could dissolve while sinking through undersaturated portions of the water column (Figure 4).

This is commonly viewed as efficiency loss for mCDR. However, we show that the resulting mitigation of interior OA, and the potential for reductions in future ocean-based CO<sub>2</sub> emissions, could be disproportionately impactful.

## 5. Conclusions

The accumulation of anthropogenic carbon ( $C_{\text{ant}}$ ) in the ocean interior has resulted in subsurface (>100 m)  $p\text{CO}_2$ , RF, and  $[\text{H}^+]$  changes that significantly exceeded their respective surface change magnitudes, sometimes by >100%. These amplified subsurface changes can predominantly be attributed to nonlinear carbonate chemistry effects in weakly buffered waters that have experienced a significant amount of organic matter remineralization. Under these conditions,  $p\text{CO}_2$ , RF, and  $[\text{H}^+]$  have a stronger response to carbon addition than they do at the sea surface. Such subsurface amplified signals are not yet consistently discernible for pH within the GLODAPv2.2016b mapped product but may be anticipated, as nonlinear carbonate chemistry effects are also working to amplify the subsurface pH response to  $C_{\text{ant}}$  accumulation (Figure S11a–S11c in Supporting Information S1).  $C_{\text{ant}}$ -induced changes in  $\Omega_{\text{Ar}}$  are surface intensified, and are expected to remain so with  $C_{\text{ant}}$  accumulation because nonlinear carbonate chemistry effects weakly mitigate  $\Omega_{\text{Ar}}$  declines at depth. Further work is needed to evaluate how subsurface carbonate chemistry has changed and will continue to change beyond the year 2002, and what this could mean for ocean ecosystems that are under pressure from a variety of anthropogenic stressors, which may eventually include the impacts of mCDR. Determining where and when subsurface waters with large  $C_{\text{ant}}$ -induced  $p\text{CO}_2$  changes could meaningfully impact future ocean-based CO<sub>2</sub> emissions will be valuable for understanding marine carbon cycle feedbacks and developing informed ocean-based emissions reduction and negative emissions strategies.

## Data Availability Statement

All data used in this study are publicly available. The GLODAPv2.2016b mapped data product is available through NOAA's National Centers for Environmental Information: <https://www.nodc.noaa.gov/archive/arc0107/0162565/2.2/data/0-data/mapped/>. Preformed property estimates based on GLODAPv2 data are available through Zenodo: <https://zenodo.org/record/3745002>. The GOSML mixed layer climatology product is available at: <https://www.pmel.noaa.gov/gosml/>. Water mass ages based on GLODAPv2 data are available through NCEI: <https://www.ncei.noaa.gov/data/oceans/ncei/ocads/metadata/0226793.html>.

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## Erratum

The originally published version of this article contained a few typographical errors in the supporting information. The errors have been corrected, and this may be considered the authoritative version of record.