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Seasonal variability of the surface ocean carbon cycle: a synthesis

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Abstract

The seasonal cycle is the dominant mode of variability in the air-sea CO_2 flux in most regions of the global ocean, yet discrepancies between different seasonality estimates are rather large. As part of the Regional Carbon Cycle Assessment and Processes phase 2 project (RECCAP2), we synthesize surface ocean pCO$_2$ and air-sea CO_2 flux seasonality from models and observation-based estimates, focusing on both a modern climatology and decadal changes between the 1980s and 2010s. Four main findings emerge: First, global ocean biogeochemistry models (GOBMs) and observation-based estimates (pCO$_2$ products) of surface pCO$_2$ seasonality disagree, primarily due to discrepancies in the seasonal variability in surface DIC. Second, the seasonal cycle in pCO$_2$ has increased in amplitude over the last three decades in both pCO$_2$ products and GOBMs. Third, decadal increases in pCO$_2$ seasonal cycle amplitudes in subtropical biomes for both pCO$_2$ products and GOBMs are driven by increasing DIC concentrations stemming from the uptake of anthropogenic CO_2 (C_{ant}). In subpolar and Southern Ocean biomes, however, the seasonality change for GOBMs is dominated by C_{ant} invasion, whereas for pCO$_2$ products an indeterminate combination of C_{ant} invasion and climate change modulates the changes. Fourth, we have shown that biome-aggregated decadal changes in the amplitude of pCO$_2$ seasonal variability are largely detectable against both mapping uncertainty (reducible) and natural variability uncertainty (irreducible), but not at the gridpoint scale over much of the northern subpolar oceans and over the Southern Ocean, underscoring the importance of sustained high-quality seasonally-resolved measurements over these regions.

Plain Language Summary

Changes in the amplitude of seasonal variations in the surface ocean carbon dioxide partial pressure (pCO$_2$) over the period 1985-2018 are described over the historical period spanning 1985-2018, using both observation-based and model-based estimates. We identify increasing pCO$_2$ seasonality over most regions that is largely driven by the impact of the invasion flux of anthropogenic carbon into the surface ocean, with observation-based products also revealing

important modulations of pCO$_2$ seasonality in high latitude regions also being impacted by perturbations to the climate system. We also identified that there are important discrepancies between observation-based and modeled pCO$_2$ seasonality over global scales, with much of this likely associated with systematic biases in model representations of the seasonal cycle in surface dissolved inorganic carbon (DIC). Both reducible and irreducible forms of uncertainty in monitoring pCO$_2$ seasonality changes are quantified, with both cases highlighting the need for sustained seasonally-resolving measurements over the high latitudes as part of an optimized marine carbon observing system.

Key points:

(1) Changes in pCO$_2$ seasonal cycle amplitude over 1985-2018 are detectable against both mapping uncertainty and natural variability uncertainty.
(2) The dominant driver of pCO$_2$ amplitude increases over decadal timescales is attributed to the direct effect of C$_{ant}$ invasion.
(3) A discrepancy is identified with surface DIC variability being systematically lower in GOBMs than in surface DIC observation-based products.

1 Introduction

How is the ocean carbon cycle changing as a consequence of sustained increases in emissions of carbon to the atmosphere? Important steps toward answering this question over the last several decades have been provided via estimates of ocean carbon uptake from both interior hydrographic measurements (Gruber et al., 2019; Sabine et al., 2004), surface fluxes inferred from measurements of the sea surface partial pressure of CO$_2$ (pCO$_2$) (Chau et al., 2022; Gregor et al., 2019; Landschützer et al., 2014; Rödenbeck et al., 2015), global ocean biogeochemistry model simulations (Friedlingstein, et al., 2022; Hauck et al., 2020; Orr et al., 2001) and ocean inverse models (Gloor et al., 2003; Gruber et al., 2009). A first global synthesis was performed roughly a decade ago through the REgional Carbon Cycle Assessment and Processes (RECCAP) project (https://www.globalcarbonproject.org/reccap), highlighting the inevitable forced carbon cycle changes, while also identifying sources of uncertainty.

In a parallel direction of inquiry, it has also become clear that the seasonal cycle in surface ocean pCO_2 (and thereby air-sea CO_2 flux) has been changing, with this first identified in modeling studies (Rodgers et al., 2008; Riebesell et al., 2009; Gorgues et al., 2010; Hauck and Völker, 2015; Gallego et al., 2018) and subsequently inferred from observational constraints (Fassbender et al., 2018; Landschützer et al., 2018) and more recently also identified from changes in the seasonal cycle of atmospheric CO_2 induced by air-sea CO_2 fluxes in the Southern Ocean (Yun et al., 2022). Studies to date show that the dominant drivers of this trend towards increasing pCO_2 seasonal amplitude are the increasing surface concentrations of dissolved inorganic carbon (DIC), due to the invasion of anthropogenic CO_2 into the ocean, and the associated decline in surface ocean buffering capacity. The trend towards increased seasonal amplitude is also expected to be modulated by natural variability and by warming (Schlunegger et al., 2019). The net effect of warming in high emission projections by the end of the 21st century is to enhance increases in the seasonal amplitude of CO_2 fluxes over the expansive subtropical domain by approximately 15% (Rodgers et al., 2020).

Our synthesis effort builds on the earlier studies of Fassbender et al. (2018), Landschützer et al. (2018), and Fassbender et al. (2022), but here we rely on a greatly expanded set of pCO_2 products and GOBMs, spanning the time period 1985 to 2018, to assess the drivers of multi-decadal changes in the seasonal cycle of surface pCO_2. Such changes are of interest for three primary reasons. First, they may impact stressors of marine ecosystems, as emphasized in the analysis of future changes in pH, hydrogen ion concentration, and calcium carbonate mineral saturation state seasonality by Kwiatkowski and Orr (2018). Second, they can have potential impacts for climate feedback mechanisms, as demonstrated by Fassbender et al. (2022) for 21st century climate change under both strong and moderate CO_2 emissions pathways. Third, they will have implications for optimizing the design of the global marine carbon observing system, as summer-biased measurements can lead to significant errors for a system where the seasonal cycle itself is not stationary.

For the majority of the global ocean, the seasonal cycle in sea surface pCO_2 exhibits strong variability that is up to two orders of magnitude larger than the seasonal cycle in atmospheric pCO_2 (e.g. Takahashi et al., 2002). Seasonal variations in pCO_2 reflect the interplay of four principal underlying drivers: sea surface temperature (SST), sea surface salinity (SSS), dissolved inorganic carbon concentrations (DIC), and total alkalinity (TA) (Takahashi et al., 1993, 2002). Variations in these drivers are the result of changes in ocean circulation and mixing, biological processes, as well as exchanges of heat, freshwater, and carbon with the atmosphere. While the temperature-driven or thermal component of observed pCO_2 seasonality is well constrained by laboratory studies and by high-quality satellite-derived SST products, this is not the case for the other drivers. Therefore, observational studies often refer to changes related to DIC, TA, or salinity collectively as changes in the nonthermal component (Takahashi et al., 1993, 2002). Importantly, thermal and nonthermal drivers of pCO_2 seasonality are typically found to be opposed in phase and large in amplitude relative to the resulting net pCO_2 variations. For this reason, skillful modeling of seasonal pCO_2 cycling can be compromised if any of the underlying processes are not well-represented, both for the amplitude and the phase/timing of seasonality changes. Therefore, state-of-the-art models still face challenges in skillfully simulating the seasonal cycle of pCO_2 in regions that are known to be important for CO_2 exchange with the atmosphere (Anav et al., 2013; Goris et al., 2018; Kessler amd Tjiputra, 2016; Mongwe et al., 2018; Pilcher et al., 2015). For the important case of the North Atlantic, it has been shown that future carbon uptake in ESM projections can be constrained by diagnosing the timing and magnitude of modeled seasonal variations in pCO_2 (Goris et al., 2018). Similarly, Nevison et al. (2016) demonstrated, for the Southern Ocean, that the way an ESM represents the seasonal carbon cycle is related to the model's projected carbon uptake. A much weaker seasonal cycle than in higher latitudes is observed in the tropics, where seasonal pCO_2 amplitudes are obscured by interannual variability. In polar latitudes where there is seasonal ice cover, the challenge of data sparsity associated with the difficulty of sampling pCO_2 through the seasonal cycle presents challenges and uncertainty that are beyond the scope of this study.

An important source of uncertainty with detecting anthropogenic trends in the carbon cycle is natural variability. As a matter of definition, we consider the forced anthropogenic signal to represent the sum total of the effects of anthropogenic forcing on atmospheric radiation (greenhouse gases, anthropogenic aerosols, etc.) and thereby warming ensuing physical and biogeochemical state changes in the ocean, as well as the effect of the invasion flux of anthropogenic carbon into the ocean. For the analysis presented here, even if pCO$_2$ products were able to perfectly resolve multi-decadal changes in the seasonal amplitude of sea surface pCO$_2$ over 1985 to 2018, it would not be possible to confidently isolate the anthropogenic trend from the impacts of natural variability. Given that natural variability is an intrinsic property of the Earth system, natural variability uncertainty is understood to be an irreducible form of uncertainty that can nevertheless be quantified. To address the degree to which natural variability obscures detection of anthropogenic trends, we include analyses of large ensemble (LE) simulations with Earth system models (ESMs) in this study. LE simulations were considered previously in the study of Schlunegger et al. (2019) for the case of 21st century climate change projections under strong emissions, and they showed that over the subtropics forced changes in ΔpCO$_2$ seasonal amplitude are more emergent than forced trends in annual mean ΔpCO$_2$.

Previous research has pointed towards significant model biases in representing the seasonal cycle of pCO$_2$ and its underlying drivers (Goris et al., 2018; Mongwe et al., 2018; Rodgers et al., 2014). The question naturally arises as to whether models have improved since the evaluation of seasonal variability in an early generation of prognostic biogeochemistry models (McKinley et al., 2006; Tjiputra et al., 2012). For the case of the North Pacific, the forward models in McKinley et al. (2006) had their seasonal cycles in pCO$_2$ evaluated directly against time series measurements from observing stations spanning the subpolar and subtropical gyres to identify non-trivial biases in models. Our study differs in that, rather than direct comparisons with time series stations, our observation-based data sources consist of mapped global sea surface pCO$_2$ products constructed from the same underlying ungridded SOCAT (Surface Ocean CO$_2$ Atlas; Pfeil et al., 2013) data, as well as ocean interior seasonal climatological fields of DIC.

More extensive analyses for the regions with seasonal ice cover, which are not considered here due to their sparsity of carbon observations for estimating the seasonal cycle, will be provided by the Arctic and Southern Ocean regional contributions to RECCAP2. Our analysis and synthesis is developed using a diverse set of resources: nine observationally-based $p\mathrm{CO_2}$ products, three of which include associated time-varying monthly surface DIC and TA fields; two independent three-dimensional seasonally-resolved DIC climatologies; hindcast simulations from eleven GOBMs; five large ensemble simulations; and individual realizations of 11 CMIP6 models.

This paper is structured as follows. We begin in the methods section by introducing the RECCAP2 $p\mathrm{CO_2}$ products and GOBMs, along with ancillary products used for this study. In the main results section, we present a descriptive account of changes in $p\mathrm{CO_2}$ seasonality as well as discrepancies between $p\mathrm{CO_2}$ products and GOBMs, followed by attribution of these changes and discrepancies to their drivers. We finally present an analysis focused on identifying detectability of forced/anthropogenic signals, as well as an assessment of the robustness of our chosen biome aggregation for detectability of the forced changes in seasonality to changes due to natural variability. Our objective is to present a synthesis of the carbon cycle community's current knowledge of how the seasonal cycle of sea surface $p\mathrm{CO_2}$ and the air-sea $\mathrm{CO_2}$ exchange has been changing over the last three decades.

2 Methods

2.1 Considered regions

Ocean biomes offer a number of advantages as aggregation regions for studying the global carbon cycle (Fay and McKinley, 2014). For our interests in seasonality, biomes appropriately reflect the structures that are determined by real-world interactions between ocean circulation and biogeochemistry. For all of the oceanic studies within RECCAP2, a discrete number of ocean biomes based on Fay and McKinley (2014) are used to facilitate consistent intercomparison between regions (described in the RECCAP2 Global Ocean contribution by DeVries et al., submitted to the RECCAP2 special issue). This study analyzes $p\mathrm{CO_2}$ and $\mathrm{CO_2}$

flux seasonality for six biomes (**Table 1** and central panel of **Fig. 1**) aggregated from the aforementioned. Our decision to aggregate some biomes and exclude others is based on the following: First, this is a synthesis study and the seasonal cycle in surface ocean pCO_2 exhibits important similarities across the subtropics of each hemisphere. Second, we have elected to not include either the Arctic, the Bering Sea, or the regions of the Southern Ocean that are impacted by ice cover, with the analysis of those regions left to the individual regional RECCAP2 studies. Third, we have chosen to not include the equatorial regions, given that the seasonal cycle there is relatively weak and often obscured by large interannual variability.

Thus, our six aggregated biomes (**Table 1** and **Fig. 1**) consist of North Atlantic subpolar seasonally stratified (NA-SPSS), North Pacific subpolar seasonally stratified (NP-SPSS), Northern Hemisphere subtropical seasonally stratified (NH-STSS), Northern Hemisphere subtropical permanently stratified (NH-STPS), Southern Hemisphere subtropical permanently stratified (SH-STPS), and Southern Hemisphere seasonally stratified (subpolar and subtropical combined, SH-SS). We have elected to keep the North Atlantic and North Pacific subpolar biomes separate in our analysis in light of important differences that arise in their seasonal cycles.

Besides the aggregation as designated in **Table 1**, adjustments have been taken to avoid confounding changes in observational coverage with seasonality or changes in seasonality. We limit our analysis to regions that have valid observation-based (and GOBM) fields for the whole time period 1985-2018 for all pCO_2 products and for all variables considered in this study (CO_2 fluxes, pCO_2, SST, SSS, surface DIC, and surface TA). Thereby we make sure that the same region is considered for all variables over the whole seasonal cycle but also over the whole observational period (see **Fig.1**).

2.2. Temporal filtering of RECCAP2 products

In general, the monthly mean pCO_2 products and GOBMs considered here can be expected to represent pCO_2 seasonality modulations that are sustained through the combined effects of the invasion flux of C_{ant}, natural variability, and warming. In order to identify the amplitude of the seasonal cycle (with its modulations), we follow Landschützer et al. (2018) in using a quadratic polynomial fit to remove the decadal trend from monthly time series over 1985-2018. Our analysis through the majority of this manuscript characterizes multi-decadal changes in pCO_2 seasonal variations by considering differences between the five-year intervals 1985-1989 and 2014-2018. We also investigated the degree to which the main results are sensitive to the choice of five-year versus 10-year versus 15-year intervals for describing climatologies (**Fig. S3**), and upon finding that the results are relatively insensitive to the approach we opted to use the difference between the two five-year intervals 1985-1989 and 2014-2018. As such, our approach is consistent with that used by Landschützer et al. (2018), who also used five-year climatologies in calculating decadal changes.

2.3. Surface observation-based products of pCO_2, DIC, and TA

Observation-based pCO_2 products that are compared for their representation of pCO_2 seasonality are listed in **Table 2**. All of these products are built on surface ocean pCO_2 measurements within the Surface Ocean CO_2 Atlas database (SOCAT, Bakker et al., 2016) yet they differ significantly in the way they spatiotemporally interpolate or map the sparse observations. Methodologically they include multiple linear regression (Iida et al., 2021), gradient boosted decision trees (Gloege et al., 2022), neural networks (Chau et al., 2022; Landschützer et al., 2016; Zeng et al., 2022), ensembles of various machine learning approaches (Gregor et al., 2019; Gregor and Gruber, 2021), and a Bayesian approach that is additionally constrained by mixed-layer dynamics (Rödenbeck et al., 2013, 2022). Additionally, one neural network product applies adjustments to the SOCAT data to account for temperature gradients between the ocean surface and the depth of the seawater intake on the observing ships and for the cold skin layer effect (Watson et al., 2020).

Of central importance to our study is that three of these products (JMAMLR, OceanSODA-ETHZ, and CMEMS-LSCE-FFNN) additionally provide time-varying surface DIC and TA products spanning 1985-2018. While we use all available *p*CO_2 products listed in **Table 2** for our analysis of seasonal cycles of CO_2-fluxes and *p*CO_2, our analysis greatly benefits from using these three products to attribute changes of *p*CO_2 seasonality to its drivers. We will refer to them as the pCO_2/TA products. We provide a summary of how DIC and TA are derived for these three *p*CO_2 products in the **Supplementary Materials**, but we refer the reader to the papers cited in **Table 2** for a more complete description of methods for the individual observation-based products.

2.4. Three-dimensional DIC climatologies

For our evaluation of seasonal variability in surface DIC concentrations, we consider two three-dimensional DIC climatologies constructed from observational products: the Mapped Observation-Based Oceanic DIC (MOBO-DIC) product by Keppler et al. (2020a, 2020b), and the NNGv2LDEO monthly climatology of interior DIC by Broullón et al. (2020). Unlike the *p*CO_2/TA products, these products are based on direct observations of DIC and as such provide an independent estimate of surface DIC seasonality, with the caveat that they offer a climatological view only. Both of these three-dimensional DIC climatologies are described in greater detail in the **Supplementary Materials**.

2.5. Global Ocean Biogeochemistry Models (GOBMs)

Global ocean biogeochemistry models (GOBMs) are compared against the *p*CO_2 products for modulations of CO_2 fluxes and *p*CO_2 for the six aggregated biomes over the period 1985-2018. Many of the GOBMs considered here have contributed to the Global Carbon Project's estimate of the ocean carbon sink (Friedlingstein et al., 2022), and have been evaluated by Hauck et al. (2020). Both the phase and amplitude of seasonal variability in the GOBMs will be evaluated against the *p*CO_2 products, as will the behavior of the drivers (SST, DIC, SSS, and TA). The GOBMs are listed in **Table 3**, and they are further described for their initialization, forcing, and resolution in the submitted global RECCAP2 study of DeVries et al. All but one of the GOBMs listed in **Table 3** provide the full suite of variables and timescales needed for this analysis. The exception is the CCSM model for which output is available only through 2017 (rather than 2018). For this model alone we construct climatologies over 2014-2017. Additionally we have included the abiotic data-assimilation model OCIM (DeVries, 2014, 2022) where appropriate in our analysis. Although more commonly applied to the uptake of anthropogenic carbon, the abiotic nature of the OCIM model is of value as an endmember case in evaluating potential biotic biases in the GOBMs.

Air-sea heat fluxes for the GOBMs used throughout RECCAP2 are calculated with bulk formulae following the protocols of Large and Yeager (2009). This method does not impose a specific nudging or restoring of simulated sea surface temperature (SST) to observed SST, but rather imposes a negative feedback to SST through heat fluxes determined using observed surface boundary layer atmospheric temperatures. In this way, the simulation of seasonal variations in SST shows strong fidelity to observations when aggregated over biome scales.

2.6. Attribution Analysis

2.6.1 Attribution of drivers of the climatological seasonal cycle in $p\mathrm{CO_2}$

The first stage of the attribution analysis has the goal of identifying the mechanisms responsible for discrepancies between $p\mathrm{CO_2}$ products and GOBMs in representing the climatological seasonal cycle of $p\mathrm{CO_2}$. We will consider both a decomposition into thermal and nonthermal drivers, using the analysis methods presented by Fassbender et al. (2022). The thermal/nonthermal decomposition provides a valuable means to identify spatially regions where seasonal SST variations are or are not the dominant driver of seasonal variations in $p\mathrm{CO_2}$. We will also apply the Taylor Series decomposition method previously considered by Sarmiento and Gruber (2006). A Taylor Series decomposition is a more extensive decomposition into individual drivers of the seasonal cycle in pCO_2, where we are specifically interested in parsing the contributions of SST, SSS, DIC, and TA. In this way we will evaluate any discrepancies that may call into question the fidelity of modeled pCO_2 to the real ocean. This analysis is possible for all GOBMs and the three observation-based products that include DIC and TA.

Additionally mixed layer depth (MLD) products will be used as part of our attribution analysis. For the sake of consistency with our choice of the relatively data-rich period 2014-2018 for evaluating climatologies of pertinent variables, we present a MLD product for this period 2014-2018 derived from the gridded monthly Argo product of Roemmich and Gilson (2009) for temperature and salinity. We define MLD by a density threshold through application of the MLD definition of Holte and Talley (2009).

2.6.2 Attribution of decadal changes in the seasonal cycle of pCO_2

The second stage of attribution analysis consists of applying the method of Fassbender et al. (2022) to identify the drivers of decadal changes in pCO_2 seasonality over 1985-2018. The method provides a means to separate the impacts of the invasion flux of anthropogenic carbon from the atmosphere from other climate signals that can modulate the seasonal cycle in pCO_2. More specifically, the goal for this work will be to identify the direct impact of an increase in the anthropogenic carbon (C_{ant}) content (i.e., a decrease of the surface ocean buffering capacity) relative to climate change and natural variability impacts on pCO_2 seasonality changes over 1985-2018. The original application by Fassbender et al. (2022) was for 21st century LE projections with an ESM, where the ensemble mean was applied to identify the forced component of change. Here our intention is to apply the method to the period 1985-2018 for all GOBMs (**Table 3)** and gridded pCO_2 products that include associated monthly DIC and TA fields along with SST and SSS. A description of the method is provided in the **Supplementary Materials.**

2.7. Uncertainty analysis for detecting the anthropogenic signal

As in the study of Fassbender et al. (2022), we apply large ensemble (LE) simulations with ESMs to aid in our interpretation of forced changes in pCO$_2$ seasonality in the presence of non-negligible background variability. Whereas Fassbender et al. (2022) focused on centennial timescale projections and could rely on the ensemble mean to isolate forced signals, we are here faced with a different challenge of interpreting historical records for which we have only three out of nine pCO$_2$ products that are viable for attribution analysis, all aiming to represent the same individual realization experienced by the chaotic Earth system. Thus, LE simulations will be applied to interpret changes measured over the historical period 1985-2018 to estimate uncertainty in isolating a forced change in the presence of natural background variability.

The LE models considered here are listed in **Table 4**. The first set of models were run under CMIP5 protocols using historical/RCP8.5 forcing (CanESM2, ESM2M, and CESM1) and the second set were run under CMIP6 protocols with historical/SSP3-7.0 forcing (CanESM5 and CESM2). Such a mix of CMIP5 and CMIP6 is appropriate to our interest in the historical period spanning 1985-2018, as the total radiative forcing component for the CMIP5 and CMIP6 forcing pathways is very similar through 2018 (Riahi et al., 2017). These LE outputs are not part of the resources made available through RECCAP2, but were rather collected by the authors through a modest expansion of the collection of LE models considered by Schlunegger et al. (2020) and Gloege et al. (2021). We are particularly interested in evaluating confidence levels for emergent changes between the time intervals 1985-1989 and 2014-2018, where the ensemble mean changes (signal) and natural variability in the changes (noise) provide a means to identify the signal-to-noise ratio (SNR) to characterize the degree of emergence or detectability.

For the attribution of decadal changes in pCO$_2$ seasonal amplitude, we have applied the CESM2-LE, as this was deemed to have better correspondence with climatological pCO$_2$ variability over biome scales than the other models (this will be addressed in **Fig. 12a**). The application of CESM2-LE will allow us to address the degree of confidence that we have in distinguishing the impact of the invasion flux of anthropogenic carbon from climate-driven perturbations. CESM2-LE is also applied to identify the degree to which thermal and nonthermal drivers of $p\mathrm{CO_2}$ seasonality changes are emergent.

2.8. CMIP6 models

This study also includes analyses of 11 CMIP6 ESMs that are evaluated for their agreement with the $p\mathrm{CO_2}$ products over biome scales, with the models listed in **Table 6**. As ESMs are used for future projections of the ocean carbon sink, it is of interest to assess their fidelity in reproducing the seasonal cycle and its underlying processes. The CMIP6 models are not intended to correspond to coupled versions of the GOBMs considered here, but our goal is rather to identify similarities or discrepancies between these models, the GOBMs, and observational $p\mathrm{CO_2}$ products. For the CMIP6 models we have opted to focus on a slightly different period, namely the five years (2010-2014) at the end of the historical component of CMIP6 simulations, rather than the 2014-2018 interval considered for the GOBMs.

3 Results

3.1. Overview of Multi-Decadal Changes in $\mathrm{CO_2}$ Flux and $p\mathrm{CO_2}$ seasonality

The evolution of air-sea $\mathrm{CO_2}$ flux seasonality, considered as averages over the six biomes, is shown in **Fig. 1** as time series of the annual minimum and annual maximum of the monthly air-sea $\mathrm{CO_2}$ fluxes for the $p\mathrm{CO_2}$ products and GOBMs. Here, we have chosen to show the maximum and minimum of the fluxes to represent the full range of the seasonal cycle. One should keep in mind that the across-product ensemble spread also includes the impacts of wind speed on gas exchange that are not treated the same way across products (more details are provided in the submitted DeVries et al. global ocean contribution to RECCAP2).

A prominent feature in **Fig. 1** is that the amplitude of the seasonal cycle in CO_2 fluxes is consistently larger for the GOBMs than it is for the $p$$CO_2$ products, across all biomes (see also **Fig. S1)**. From the RECCAP2 GOBMs alone it is not possible to determine the degree to which these internal disagreements reflect structural differences between the GOBMs and the degree to which it represents differences in forcing of the GOBMs. It is also worth noting that both the GOBMs and $p$$CO_2$ products exhibit a non-negligible degree of natural variability (interannual to decadal), for both the maxima and minima.

A decadal trend towards increased seasonal amplitude of biome-integrated CO_2 fluxes is evident over the subtropical biomes, as well as for NP-SPSS, whereas for NA-SPSS and SH-SS biomes this is less evident (especially in the $p$$CO_2$ products, see also **Fig. S1**). The increase in the amplitude, where it exists, can be accounted for mainly by a decrease of the annual minima (i.e., an increase of the uptake flux), whereas the annual flux maxima remained comparably constant over time. To better constrain whether there are discernable decreases in the spread amongst the $p$$CO_2$ products over 1985-2018 as $p$$CO_2$ observations increase, the biome-averaged $p$$CO_2$ for seasonal maximum and seasonal minimum are shown in **Fig. S2**, where although there is a decrease for both NA-SSS, SH-STPS, and SH-SS between 1985 and 2018, for the other biomes the changes are rather small. The broad-scale view of the evolution of CO_2 fluxes in **Fig. 1** serves to motivate much of the analysis that follows, with emphasis devoted to $p$$CO_2$ rather than CO_2 fluxes as a means to facilitate attribution and mechanistic understanding. Nevertheless we will return to CO_2 fluxes in the discussion of decadal trends in seasonal cycle amplitude.

3.1.1 Climatological seasonal cycle of *p*CO_2 and multi decadal changes

The climatological monthly $p$$CO_2$ seasonal cycle over 2014-2018 as a zonal mean is shown in **Fig. 2.** For the $p$$CO_2$ products (**Fig. 2a**), $p$$CO_2$ is highest in the subtropics in summer and highest in the Northern Hemisphere subpolar region and in the Southern Ocean in winter. The GOBMs (**Fig. 2e**) are in agreement with the $p$$CO_2$ products in their seasonal phasing in the subtropics but are in disagreement in the Northern Hemisphere subpolar regions and the

Southern Ocean. As a measure of the internal consistency across the nine pCO_2 products and the 11 GOBMs for this 2014-2018 climatology, the standard deviation is calculated month-by-month across the pCO_2 products (**Fig. 2b**) and across the GOBMs (**Fig. 2f**). From this we learn that the agreement across the pCO_2 products is robust (<10% disagreement relative to the annual cycle amplitude), whereas internal disagreements are much larger across the GOBMs (larger than 20% of the annual cycle amplitude at some locations), with the GOBMs diverging the most north of 30°N and south of 30°S. For the Northern Hemisphere subpolar regions, the disagreement in the GOBMs is largest in summer, and over the Southern Ocean it is largest in summer and in late winter.

We also consider the multi-decadal changes in the climatological monthly pCO_2 seasonal cycle between 1985-1989 and 2014-2018 for the pCO_2 products (**Fig. 2c**) and for the GOBMs (**Fig. 2g**). For both the pCO_2 products and the GOBMs (**Fig. 2c** and **Fig. 2g**, respectively), the meridional patterns of increases in seasonal amplitude to first order reflect and amplification of the climatological seasonal cycle in the Northern Hemisphere subtropical and subpolar biomes. However, this is less clear in the Southern Hemisphere subtropics and the Southern Ocean.

3.1.2 Spatial structure in the seasonal amplitude change

To understand the spatial structure of the amplitude change and the coherence between pCO_2 products and between GOBMs, maps of changes in the amplitude of the pCO_2 seasonal cycle between 1985-1989 and 2014-2018 are shown for the pCO_2 products in **Fig. 3a** and for the GOBMS in **Fig. 3b**. We use two definitions for the amplitude assessment: winter minus summer (JFM minus JAS for the Northern Hemisphere and JAS minus JFM for the Southern Hemisphere) in **Figs. 3a** and **3b** and climatological monthly maximum minus minimum in **Figs. 3c** and **3d**. For both the GOBMs and the pCO_2 products, regions where the multi-decadal trends are not significant (defined using a one standard deviation threshold) are stippled. From this we can see that the Northern Hemisphere has more significant changes than the Southern Hemisphere. Nevertheless for both hemispheres for GOBMs and pCO_2

products the broadest regions of significant changes are in the subtropics, although there is also a significant trend in the eastern subpolar North Pacific.

The two different definitions of seasonal amplitude (winter-minus-summer and maximum-minus-minimum) result in very similar large-scale patterns, although, due to their definition, with largely opposite sign. While for the maximum-minus-minimum definition positive changes always indicate an increase in seasonal amplitude, the winter-minus-summer amplitude is negative over the subtropical domain and positive in high latitudes, such that negative (positive) values for the multi-decadal amplitude change in **Fig. 3**a and **3b** over the subtropics (high latitudes) also indicate an amplitude increase. Phasing differences in seasonality are treated differently with the two definitions, since winter-minus-summer refers to fixed time intervals while the maximum and minimum can occur at any time throughout the year. While the winter-minus-summer definition highlights differences in phasing between $p\mathrm{CO}_2$ products and GOBMs, it conceals some of the changes in the seasonal amplitude, specifically if the maximum or minimum of the seasonal cycle occurs outside of winter or summer months (as seen in **Fig. 3d** in the high latitude North Atlantic and North Pacific, where the discrepancy between GOBMs and $p\mathrm{CO}_2$ products is much larger for the winter-minus-summer definition).

For the remainder of our analysis we will use the winter minus summer definition of seasonality due to its simplicity when it comes to analysis of multiple models and products, and also for consistency with previous work (e.g., Landschützer et al., 2018), keeping in mind that the specifics of this definition (the choice of JFM and JAS for defining seasonal amplitude) are sensitive to phasing differences between GOBMs and $p\mathrm{CO}_2$ products. The sensitivity of the choice of five-year versus 10-year versus 15-year climatologies for the case of the $p\mathrm{CO}_2$ products (**Fig. S3**) indicates that the results are robust to the length of the climatologies, the main difference being that using 10-year or 15-year climatologies shortens the effective decadal-change interval and weakens the signal of interest.

The fields shown in **Fig. 3a** and **3c** reveal important information about uncertainty in detecting multi-decadal changes in pCO_2 seasonality using pCO_2 products. As all of the products are based upon the same un-gridded SOCAT data product, differences in multi-decadal changes shown in **Fig. 3a** and **3c** are due to mapping differences rather than differences in the basis data itself. As such, the stippled regions indicate where mapping uncertainty is large relative to resolved decadal changes. We interpret mapping uncertainty to be a reducible variety of uncertainty, in that with improved data coverage and expansion of the ocean observing system the products should be expected to converge.

For the GOBMs (**Figs. 3b** and **3d**) the regions of significance are very similar to what is shown for the pCO_2 products, but the underlying reasons for uncertainty are of course fundamentally different. For the GOBMs, regions where trends are not significant reflect the combined effect of structural differences between models and differences in GOBM forcing (described in the submitted global RECCAP2 contribution of DeVries et al. for differences in forcing). The uncertainty in **Fig. 3b** and **3d** for the GOBMs should also be considered as a reducible variety of uncertainty.

Nevertheless it should also be noted that for both pCO_2 products and GOBMs that it is the subtropics where the thermal component of pCO_2 seasonality has the weakest opposition from the nonthermal component that there is emergence. Thus both mapping uncertainty and presumably structural uncertainty with GOBMs are mostly problematic in regions where the nonthermal drivers become important. This will be discussed further in subsequent analyses of this study.

3.1.3 Biome aggregated climatologies

Climatological monthly anomalies in pCO_2 and its primary drivers, SST and surface DIC, relative to their annual means are displayed in **Fig. 4** as (area-weighted) averages across the RECCAP2 biome regions. A first comparison between the full collection of pCO_2 products (blue) and all GOBMs (green) is shown in the first column of **Fig. 4** by biome region, where continuous lines and associated shading represents the mean and one standard deviation, respectively. Our first objective is to identify discrepancies between the GOBMs and the pCO$_2$ products, with such discrepancies to be addressed subsequently in the **Attribution** section of the paper.

In broad terms, the seasonal phasing agreement between GOBMs and pCO$_2$ products is best in subtropical biomes (NH-STSS, NH-STPS, and SH-STPS) and worst in the Northern Hemisphere subpolar and the Southern Ocean biomes (NA-SPSS, NP-SPSS, and SH-SS). In the NA-SPSS and NP-SPSS biomes, GOBMs consistently represent seasonal pCO$_2$ minima that occur earlier than in the pCO$_2$ products, and that are weaker for NA-SPSS. For NA-SPSS and NP-SPSS, after the spring minimum in pCO$_2$ in the GOBMS there is an increase towards a maximum in August, whereas the pCO$_2$ products remain low throughout the summer before increasing in autumn and winter towards a maximum in January/February. Analogous to what is found in the Northern Hemisphere subpolar biomes, there are also discrepancies in phasing for the GOBMs relative to the pCO$_2$ products for SH-SS. For the higher latitude regions where phasing in models diverges greatly from that seen in the pCO$_2$ products, it is widely understood that the early summer minimum in pCO$_2$ (as seen in pCO$_2$ products) is directly related to biological drawdown of DIC (Gregor and Gruber, 2021). It is a known bias of coupled models that primary production is often not realistically sustained through summer after a pronounced spring bloom. This has been shown in the North Atlantic (Goris et al., 2018), and more broadly for the high latitudes of both hemispheres (Cabré et al., 2016; Mongwe et al., 2018; Nevison et al., 2016), and the same limitation appears to be pertinent in our study.

In the subtropical biomes, on the other hand, the GOBMs consistently simulate a pCO$_2$ seasonal cycle that is larger than what is seen in the pCO$_2$ products (**Table 5**). For NH-STSS the amplitude averaged across the GOBMs is 80% larger than for that averaged across the pCO$_2$ products, for NH-STPS it is 26% larger, and for SH-STPS it is 34% larger. This occurs with phasing that is largely consistent between the GOBMs and pCO$_2$ products. As seen in **Fig. 4** (second column), this discrepancy in the amplitude of pCO$_2$ variations does not reflect biases in the seasonal amplitude of SST variations, as the thermodynamic boundary conditions for forcing the GOBMs result in SSTs that have relatively strong fidelity to observations when averaged over biome scales. Rather, the discrepancy in the amplitude of the pCO$_2$ seasonal amplitude indicates that surface DIC (**Fig. 4**, second column) as the main driver of the nonthermal component of pCO$_2$ seasonality is not providing sufficient counterbalance to the realistic thermal component of seasonal forcing (i.e., the seasonal amplitude seems to be too small in GOBMs). For the subtropical biomes it is worth noting that the OCIM model (**Fig. 4**, thin line) has an even larger pCO$_2$ seasonal amplitude than the GOBMs. The OCIM model has a realistic SST seasonal evolution (not shown), but simulates only circulation- and surface flux-driven DIC variations without including a contribution of the biological drawdown of DIC. The OCIM pCO$_2$ and DIC seasonal cycle amplitude discrepancies relative to the GOBMs provide an estimate of the contribution of the biological pump to DIC and pCO$_2$ seasonality.

The fact that the DIC seasonal amplitude is weaker for the GOBMs relative to the pCO$_2$ products means that the nonthermal component of pCO$_2$ seasonality is smaller. Over the subtropical regions, this will serve to enhance the thermal dominance of seasonal pCO$_2$ variations and in the subpolar and circumpolar regions this will reduce the nonthermal dominance of seasonal pCO$_2$ variations. This provides a means to alter the phasing of pCO$_2$ variations, although the degree to which this occurs will be modulated by the background mean state of DIC and TA (Fassbender et al., 2018). In all biomes, the DIC seasonal amplitude for GOBMs lies between that of the abiotic OCIM model and that of the pCO$_2$/TA products, suggesting that for the GOBMs there may be as-yet undetermined shortcomings in the representation of the seasonal processes that increase DIC (entrainment) and decrease DIC (net biological consumption of DIC).

Comparing the decadal changes (**Fig. 4**, right column) with the climatologies over 2014-2018 (left column), we see again that the decadal changes in pCO$_2$ to first order amplify the climatological seasonal cycle in the Northern Hemisphere as well as for SH-STSS, consistent with what was identified in the Hovmöller diagrams in **Fig. 2**. Importantly, the pCO$_2$ products show significantly less internal disagreement for the climatological seasonal cycle (left column of **Fig. 4** and **Table 5**) than the GOBMs. Yet, for the decadal changes (right column of **Fig. 4**), the spread across the GOBMs and across the pCO_2 products is similar (one standard deviation for the biome averaged seasonal amplitude changes are roughly between 1 and 10 ppm, **Table 5**). While this is of the same order of magnitude as for their seasonal amplitude for the pCO_2 products, GOBMs show significantly less internal disagreement for the decadal change than for the seasonal amplitude. This indicates that the processes responsible for the increase in seasonal pCO_2 amplitude are relatively well represented in GOBMs We hypothesize here that the pertinent process in the GOBMs is the invasion flux of C_{ant} dominating pCO_2 seasonality modulations associated with climate-driven changes in the state of the ocean, a hypothesis to which we will return in the **Attribution** section. The best agreement for decadal changes in the pCO_2 seasonal amplitude occurs in the subtropical biomes, consistent with **Fig. 2**. For NH-STSS, the GOBMs show a mean net increase in the seasonal amplitude of 10.7 μatm and the pCO_2 products of 9.8 μatm, with the difference in their increase being less than 10%. For NH-STPS, the mean net increase in the seasonal amplitude for the GOBMs and pCO_2 products are the same at 6.3 μatm. For SH-STPS the increase for GOBMs is 2.7 μatm, which is approximately half of the mean pCO_2 product increase of 5.3 μatm. It can also be seen in **Table 5** that the relatively consistent ranges of change over the subtropical biomes between GOBMs and pCO_2 products are approximately within each other's uncertainty range.

3.2. Attribution

Having evaluated the seasonal cycle of pCO_2 in terms of its phasing and amplitude, as well as related discrepancies between the pCO_2 products and the GOBMs, we now turn our attention to attribution of the drivers. We have already inferred from the biome-aggregated analyses in **Fig. 4** that DIC should be explored as having a potential first-order role in modulating the differences between pCO_2 products and GOBMs in the pCO_2 seasonal cycle by serving as the main nonthermal driver.

3.2.1 Spatial patterns of the seasonal cycle in surface DIC concentrations

The spatial patterns for the surface DIC seasonal cycle amplitude (winter minus summer, climatology over 2014-2018) for the pCO_2/TA products is shown in **Fig. 5a** (average across JMAMLR, CMEMS-LSCE-FFNN, and OceanSODA-ETHZ) as well as for the GOBMs in **Fig. 5b**. We see a good agreement between the amplitude of the surface DIC seasonal cycle from pCO_2/TA products and the GOBMs for the overall patterns with maximum values seen in the Northern Hemisphere subpolar domains. For the pCO_2/TA products we also see a zonally-oriented local surface DIC maximum across 40°S-45°S that can be distinguished from a local minimum over the Antarctic Circumpolar Current (ACC) region between 50°S-60°S, with this feature being more weakly present in the GOBMs. The differences in the seasonal amplitude of DIC (GOBMs minus pCO_2 products) in **Fig. 5c** indicates a negative bias of the GOBMs that is relatively consistent over large scales, and that is particularly pronounced at northern high latitudes .

The zonal average of the amplitude of the seasonal cycle (winter minus summer) in DIC is shown in **Fig. 5d**. Additionally the amplitude of the surface ocean DIC seasonal variability for the two three-dimensional DIC climatologies, namely MOBO-DIC and NNGv2LDEO are also shown. The MOBO-DIC product tends to have a seasonal amplitude that is somewhat larger than the surface DIC products over most latitudes, except over the Southern Ocean and north of 50°N. NNGv2LDEO is also larger than the GOBMs over most latitudes, also with an exception to the north of 50°N but not over the Southern Ocean.

The same collection of products considered as zonal means in **Fig. 5d** are shown as biome averages in **Fig. S4**, along with the OCMIP product. This further illustrates that there is a discrepancy between the weaker DIC seasonal amplitude of GOBMs relative to not only the pCO_2/TA products but also to MOBO-DIC and NNGv2LDEO, although the seasonal DIC amplitude of MOBO-DIC is smaller than that of all other observation-based products (and thus closer to the GOBMs) in the high latitude biomes (NA-SPSS, NP-SPSS, and SH-SS). Interestingly, for both large permanently stratified biomes (NS-STPS and SH-STPS) the late summer seasonal minimum in DIC concentrations for the MOBO-DIC and NNGv2LDEO products precedes that of the pCO_2/TA products.

3.2.2 pCO_2 seasonality differences between observational products and GOBMs

To systematically attribute discrepancies in the pCO_2 seasonal cycle between GOBMs and pCO_2 products to their drivers, we begin with an analysis of the relative importance of the thermal and nonthermal drivers of pCO_2 seasonal variability following the framework of Fassbender et al. (2022) (see the **Supplementary Materials** for a description). For this approach, in contrast to the widely applied deconvolution method of Takahashi et al. (1993, 2022), monthly pCO_2 deviations in a given year are considered relative to the pCO_2 value calculated from annual mean values of SST, SSS, DIC, TA, PO_4 and SiO_4 rather than relative to a direct mean of the monthly pCO_2 values, which could obscure seasonally asymmetric pCO_2 responses to its drivers.

Within this analysis we consider for each grid point the absolute value of the differences between the winter and summer seasonal averages over 2014-2018. The difference between the thermal and nonthermal pCO_2 amplitudes is shown for the observational products (**Fig. 6a**) and for the GOBMs (**Fig. 6b**). For both panels, positive values (red) indicate that the thermal pCO_2 component dominates the seasonal cycle amplitude and negative values (blue) indicate that the nonthermal component dominates for this climatological diagnostic.

We see consistency between the pCO_2 products (**Fig. 6a**) and the GOBMs (**Fig. 6b**) in that the thermal pCO_2 component is dominant over the subtropics, with this dominance being even stronger for the GOBMs. Over the northern subpolar gyres and the Southern Hemisphere circumpolar regions there is a pronounced disagreement between the pCO_2 products and the GOBMs. Specifically, for the pCO_2 products the nonthermal pCO_2 component is dominant in these biomes, while the GOBMs exhibit a relatively strong thermal component in these regions. These discrepancies between the pCO_2 products and GOBMs are also shown for each GOBM and pCO_2 product separately in **Fig. 6c**, revealing the relatively strong agreement between the pCO_2 products and the disparity between the GOBMs that was also in evidence in **Fig. 4** for pCO_2 itself averaged over biome scales.

As we have identified in **Figs. 4** and **5**, there is a systematic discrepancy between GOBMs and pCO_2 products, with GOBMs indicating a weaker climatological seasonal cycle in DIC variations, which is consistent with a more pronounced dominance of the thermal component of pCO_2 seasonality highlighted in **Fig. 6**. Next, we evaluate whether the nonthermal pCO_2 component discrepancy between GOBMs and pCO_2 products can be explained by the smaller DIC seasonal variability in the GOBMs.

We consider the drivers of the climatological pCO_2 seasonal cycle during 2014-2018 over the six aggregated biomes in **Fig. 7**. The left column shows pCO_2 climatologies for the pCO_2 products (blue) and the GOBMs (green). This serves as a reminder that over the NA-SPSS, NP-SPSS and SH-SS domains, there are fundamental discrepancies between the GOBMs and the pCO_2 products in their representation of both the phase and amplitude of pCO_2 seasonality, while in NH-STSS, NH-STPS, and SH-STPS regions the amplitude of the seasonal cycle of pCO_2 is consistently larger in GOBMs. In order to understand the cause of these discrepancies, a decomposition of the month-to-month changes in pCO_2 into its main drivers (SST, SSS, DIC, and TA) is presented in the second and third column of **Fig. 7**. For the pCO_2 products (**Fig. 7**, second column) the SST term dominates over the DIC term in the subtropics, while the DIC contribution is dominant in the subpolar biomes of the Northern Hemisphere and high latitude regions of the Southern Hemisphere. For each of these six biomes, we see that the GOBMs have a smaller DIC contribution (third column of **Fig.7**) when compared to the pCO_2 products (second column of **Fig. 7**).

It is worth noting for the observational pCO_2 products (second column in **Fig. 7**) that although the effect of the spring bloom in NA-SPSS is marked by a short DIC-driven minimum in the pCO_2 tendency in April, for NP-SPSS the DIC-driven pCO_2 tendency is sustained from April through July (emphasis on the blue DIC tendency line in each case). For the GOBMs (third column in **Fig. 7**) there is no sustained dominance of the DIC contribution relative to SST over most of the seasonal cycle for NA-SPSS and NP-SPSS. For both of these biomes the GOBMs simulate weak phytoplankton blooms in late spring as indicated by the DIC tendency term for both cases, with the discrepancies in amplitude being larger than discrepancies in phase. This results in an SST dominance of the pCO_2 tendency through the summer months, thereby driving pCO_2 to peak 6-7 months earlier than that of the pCO_2 products for each of the two biomes. This represents the impact of the weaker representation of the seasonal amplitude of surface DIC variations for the GOBMs.

In the fourth column of **Fig. 7**, the difference between the GOBM contributions (third column) and the pCO_2 product contributions (second column) allows us to identify DIC discrepancies as the underlying term that leads to the principal different tendencies in pCO_2 seasonal amplitude over biome scales. In other words, over these aggregated scales the most important driver that causes the disagreement between the pCO_2 seasonal cycle of the GOBMs and the pCO_2 products lies in the processes that control DIC seasonality. It is important to emphasize that the GOBMs provide a distinct advantage over coupled ESMs in studying disagreements between modeled and observation-based pCO_2 seasonality, because their climatological seasonal evolution of SST is effectively imposed from observations. This allowed us to identify and understand the potential magnitude of pCO_2 seasonality biases that are imposed by a seeming systematic bias with GOBMs to underestimate the importance of DIC seasonality. It is worth recalling here that the DIC from the pCO_2/TA products is more consistent with the independent products (MOBO-DIC and NNGv2LDEO) than with the GOBMs (**Fig. 5d**), lending credence to the discrepancies highlighted in **Fig. 7**.

A candidate mechanism that could potentially account for why the GOBMs have smaller seasonal surface DIC variability than the DIC products could be in the modeled seasonal variability of biological drawdown of surface DIC. However, in addressing this question we are faced with the caveat that seasonal variability in biological drawdown of surface DIC over global scales is poorly constrained by observations. To shed light on this question, we consider in **Fig. 8** the relationship between climatological (2014-2018) surface salinity-normalized DIC (nDIC) variations and mixed layer depth (MLD) averaged over the six biomes. The MLD product is derived from Argo observations, described above. **Fig. 8** shows that MLD variations averaged across the GOBMs are smaller throughout the seasonal cycle than they are for the observational product. Additionally, during summer months when the

MLD becomes minimum, strong nDIC reductions are more pronounced in the observations than in the GOBMs. This suggests that the surface summer DIC drawdown, likely associated with biological drawdown of DIC, is underestimated in GOBMs. This could reflect a spurious exhaustion of nutrients by early summer in GOBMs. Investigating these questions further is not possible with the tools available through RECCAP2. However, given their importance for pCO$_2$, it is strongly advised that process understanding of the potential shortcomings of models in this regard be further investigated.

3.2.3. Attribution for decadal increases in pCO$_2$ seasonality

Here we adopt the framework of Fassbender et al. (2022) to address both mechanistically and quantitatively the drivers of enhanced pCO$_2$ seasonal amplitude. Specifically, this method allows one to deconvolve the relative importance of these drivers, namely the transient invasion flux of anthropogenic carbon (denoted as the C_{ant} contribution) and other drivers (denoted collectively as climate contribution). As the attribution methodology of Fassbender et al. (2022) requires not only surface pCO$_2$ but also surface DIC and TA concentrations (in addition to SST, SSS, PO_4, and SiO_4), we focus here on the three RECCAP2 pCO$_2$ products that include the necessary quantities, specifically JMAMLR, OceanSODA-ETHZ, and CMEMS-LSCE-FFNN, as well as the GOBMs listed in **Table 3**. For the observation-based products, monthly climatological PO_4 and SiO_4 fields were taken from World Ocean Atlas 2018 (Garcia et al., 2019).

We begin the analysis for this section on decadal changes in pCO$_2$ and CO_2 flux seasonality with a descriptive assessment of seasonal asymmetries in the changes in seasonal amplitude between 1985-1989 and 2014-2018 in **Fig. 9**. pCO$_2$ anomalies are shown relative to the annual mean value computed from annual means of SST, SSS, DIC, TA, and nutrients (pCO$_{2\ AM}$) for both observationally-based products and GOBMS, following the method described in Fassbender et al. (2022). Calculations are performed separately for each year and then averaged over the time intervals 1985-1889 and 2014-2018. This provides an estimate of the annual mean if pCO$_2$ were to respond linearly to its individual drivers over the seasonal cycle, making it possible to identify seasonally asymmetric changes in pCO_2 that are obscured when computing a mean of monthly pCO_2 values over an annual cycle.

We first consider the case of the subtropics as approximately 15°N-40°N and 15°S-40°S, where summer anomalies of pCO_2 for 1985-1989 (**Fig. 9a**) and 2014-2018 (**Fig. 9b**) are larger for the GOBMs than for the pCO_2 products, reflecting discrepancies in the amplitude of DIC seasonality between the GOBMs and observation-based products discussed previously (**Fig. 5d**). Importantly, between 25°N-40°N and 25°S-40°S the summer anomalies are larger than the winter anomalies over both time intervals. For the difference between the 2014-2018 and 1985-1989 intervals (**Fig. 9c**), we see that over the Northern Hemisphere subtropical latitudes the summer changes are larger than the winter changes. In other words, notable asymmetry can be identified over the Northern Hemisphere subtropics with larger increases in summer highs than decreases in winter lows. North of 45°N there are relatively symmetric changes in summer and winter for the observation-based products and the GOBMs, but the changes for the two product classes are of reverse sign (see next paragraph) and larger for the pCO_2 products. The changes for the Southern Hemisphere are less pronounced, with some degree of asymmetry over 10°S-25°S where for the observation-based products the winter lows decrease more than the summer highs increase. There is no discernable asymmetry over the Southern Ocean.

The disagreement between the GOBMs and pCO_2 products, both for seasonal pCO_2 anomalies (**Fig. 9a,b**) and their changes (**Fig. 9c**), is largest in the northern subpolar latitudes (45°N-60°N). For both the 1985-1989 and 2014-2018 climatologies, the pCO_2 products show relatively strong positive pCO_2 anomalies in winter, and relatively strong negative pCO_2 anomalies in summer, reflecting the interplay between winter convective mixing and warm-season export production in this region where nonthermal pCO_2 effects are dominant. In contrast, over the same region the anomalies for pCO_2 in GOBMs are relatively small in both winter and summer, reflecting the near balance between thermal and nonthermal pCO_2 cycles. Although it is not explicitly shown here, it is important to keep in mind that **Fig. 2** and **Fig. 4** revealed that there are discrepancies in the phenology or phasing of seasonal variations between the GOBMs and pCO_2 products, such that the results with the GOBMs are sensitive to the specific definition of the seasonal cycle amplitude with pCO_2 products showing indeed the largest seasonal change in winter and summer for 45°N-60°N, while GOBMs show the largest change in early spring and late summer/early autumn (**Fig. 2** and **Fig. 4**). For the Southern Hemisphere region between 45°S and 60°S, the GOBMs and pCO_2 products are much more similar than they are over the Northern Hemisphere subpolar regions over both 1985-1989 and 2014-2018, with relatively modest decadal changes for the northern subpolar regions where nonthermal pCO_2 drivers are larger than thermal pCO_2 drivers for the pCO_2 products.

The corresponding asymmetries in zonally-integrated seasonal CO_2 fluxes, shown in **Fig. 9d-9f**, are quite different from what was seen for surface pCO_2 anomalies. For both time periods 1985-1989 and 2014-2018, seasonal CO_2 fluxes are larger over the subtropics in winter (ingassing) than in summer (outgassing), which indicates that seasonal wind speed asymmetries more than compensate the summer-skewed pCO_2 seasonal asymmetry over the same latitude range (Fassbender et al., 2022). This is consistent with the winter CO_2 fluxes showing local extrema for ingassing near 40°N and 40°S where westerly winds exhibit meridional maxima. This feature is also found in the 1985-1989 to 2014-2018 decadal change. For the Northern Hemisphere subpolar regions spanning 45°N-60°N, the seasonal amplification in CO_2 fluxes between 1985-1989 and 2014-2018 shows enhanced ingassing during summer for the pCO_2 products, whereas the GOBMs show enhanced winter uptake over these latitudes. For the circumpolar regions of the Southern Hemisphere spanning 45°S-60°S, both the GOBMs and the pCO_2 products broadly exhibit enhanced ingassing in summer (JFM) and winter (JAS) seasons relative to the 1985-1989 period.

We next turn our attention in **Fig. 10** to deconvolve the role of C_{ant} invasion and climate perturbations (e.g., changes to the ocean physical or biogeochemical state caused by anthropogenic climate change) in driving multi-decadal changes in pCO_2 seasonality between 1985-1989 and 2014-2018. The changes in the subtropics are qualitatively similar in the pCO_2 products and GOBMs (top and model rows of **Fig. 10**), with the changes in the total seasonal cycle amplitude (**Fig. 10a**) dominated by the C_{ant} invasion impact on the thermal component with a small climate-driven increase in the thermal pCO_2 component (**Fig. 10b**).

However, for the subpolar regions of the Northern Hemisphere and the Southern Ocean, the pCO_2 products show that the nonthermal pCO_2 component changes driven by climate perturbations (**Fig. 10c**) are sufficiently large to dominate the total response in these regions (**Fig. 10a**), a feature that is not seen (or considerably weaker) for the GOBMs. C_{ant}-induced declines in carbonate buffering in the high latitudes also work to slightly amplify the total nonthermal pCO_2 seasonal cycle changes in both the pCO_2 products and GOBMs (red lines in right column).

For the total change in the GOBM pCO_2 values (**Fig. 10d**), the impact of climate perturbations is relatively minor so that the change in pCO_2 seasonality is largely dominated by the invasion flux of C_{ant}. For the thermal component of pCO_2 changes in the GOBMs, both the subtropical and subpolar latitudes of the Northern Hemisphere indicate dominance of the effect of transient C_{ant} invasion, with the Southern Ocean posing one region where this is neutralized by climate perturbations. For the nonthermal component of pCO_2 changes in the GOBMs, the impact of C_{ant} invasion is relatively minor, so that the changes are dominated by climate perturbations, which are also small. In summary, for the GOBMs, increases in the total pCO_2 seasonal cycle amplitude are dominated by the direct influence of C_{ant} on the thermal pCO_2 component seasonal cycle amplitude through the enhanced temperature sensitivity associated with elevated ocean pCO_2 values.

3.3. Estimating Irreducible Uncertainty in Seasonal Cycle Amplitude Changes

We now turn our attention to the emergence of decadal changes in pCO_2 seasonality, with applications at the gridoint, zonal mean, and biome scales.

3.3.1 Natural variability uncertainty in detecting forced changes in pCO_2 seasonal amplitude

As was emphasized in the study of Landschützer et al. (2018), natural variability in the seasonal amplitude of pCO_2 variations can obscure detection of anthropogenic trends, an effect that can be termed natural variability uncertainty. For sea surface pCO_2, the signal (**Fig. 11a**) and the signal-to-noise ratio (SNR) (**Fig. 11b**) are calculated for a single LE, to illustrate patterns of emergence. We choose here the CESM2 model (Danabasoglu et al., 2020) for which the phasing of the pCO_2 seasonal cycle over the Northern Hemisphere subpolar biomes has the best correspondence with the observation-based products out of the LE simulations described in **Table 4** or the CMIP6 models shown in **Table. 6**.

According to the CESM2-LE, the pCO_2 seasonality increases are most emergent ($|SNR|>1$) (**Fig. 11b**) at the grid point level over much of the subtropical Northern Hemisphere, as well as over a band spanning the subtropical convergence regions of the Southern Hemisphere. Large parts of the North Atlantic subpolar gyre exhibit a decrease in the amplitude of seasonal pCO_2 variations. This analysis is indicative of pCO_2 seasonality changes over the Southern Ocean being non-emergent above the noise level of natural variability at the grid point level over our three-decade interval. In particular, pCO_2 seasonality changes in the Antarctic Circumpolar Current region spanning 50°S-60°S are non-emergent, along with some parts of the Southern Hemisphere subtropics.

We next consider the emergence characteristics for the underlying thermal and nonthermal drivers of pCO_2 seasonality as represented by the large ensemble model. We see that the forced decadal change (ensemble mean) for the thermal component (**Fig. 11c**) and nonthermal component (**Fig. 11e**) are both considerably larger than the decadal change for the full pCO_2 field itself (**Fig. 11a**). For the resultant signal-to-noise ratio, we see that the patterns for the thermal component (**Fig. 11d**) and the nonthermal component (**Fig. 11f**) are spatially offset from each other, and when considered together help to account for the relatively restricted regions over which there is local grid point emergence, predominantly over the thermally dominated subtropical domain, for the pCO_2 seasonal cycle. From these analyses, we can see that within the subtropics, the emergent regions for total pCO_2 SNR ($|SNR|>1$ in **Fig. 11a**) correspond to the regions where the ensemble mean nonthermal component (**Fig. 11e**) is small.

3.3.2 Interpretation of results of attribution analysis

Having visualized the patterns of emergence for pCO$_2$ seasonality changes in **Fig, 11** we redirect out attention to the last row of **Fig. 10** (panels **10g-10i**), where the same set of 50 large ensemble members with the CESM2-LE are applied to interpret the zonal mean changes in the pCO$_2$ products (first row of **Fig. 10**). The shading for the LE results represents natural variability uncertainty (one standard deviation about the 50-ensemble-member mean), while the shading for the pCO$_2$ products **(Figs. 10a-10c)** can be interpreted to represent mapping uncertainty. These forms of uncertainty are distinct, but can be used together to assess the degree to which the C_{ant} and climate-driven signals for the pCO$_2$ products are detectable. We consider the means of the pCO$_2$ products in **Figs. 10a-10c** to be "best estimates" of the decadal changes. Superimposing the envelope of natural variability from the LE analysis (**Figs. 10g-10i**) onto the pCO$_2$ product means would suggest that the C_{ant} and climate driven signals are emergent when they and their associated natural variability are separated from zero for their decadal change.

Under this framework, we interpret the C_{ant} component of the pCO$_2$ product changes to be detectable for all regions and pCO$_2$ components (pCO$_2$, pCO$_{2\ T}$, and pCO$_{2\ NT}$). What is more surprising and compelling with the pCO$_2$ products is the fact that the climate driven changes over the Northern subpolar domains, with much of this signal found in the nonthermal component, cannot be explained by natural variability according to our CESM2-LE results. Further attribution of this climate-driven signal (mixing versus biology, for example) is beyond the scope of this study, but at the very least this underscores the importance of sustained seasonally-resolving observations in high latitude regions to better constrain and understand this behavior.

Taken together, the attribution analysis in **Fig. 10** and the analyses of pCO$_2$ and CO$_2$ flux seasonal asymmetries in **Fig. 9** indicate that, over the broad areal extent of the subtropics, the pCO$_2$ seasonal amplitude increases with an asymmetric larger increase in summer are in large part due to the C_{ant} impact on the thermal driver of seasonal amplitude. Through the effect of stronger wind speeds in winter than summer, the seasonal CO_2 flux asymmetry becomes even larger and of opposite sign over the subtropics, with large increases in winter ingassing. Over the broad expanse of the subtropics, the agreement between the $p$$CO_2$ products and GOBMs, together with the clear emergence indicated by the LE, gives us reasonable confidence for both the driver (C_{ant}) and the asymmetry of $p$$CO_2$ seasonality changes and elevated winter CO_2 uptake. However, for the high northern latitudes, $p$$CO_2$ products and GOBMs disagree on the drivers of the changing $p$$CO_2$ seasonality. Here, the products indicate that a rather large climate forcing is responsible for $p$$CO_2$ seasonal cycle changes.

3.3.3 Emergence of forced trends with biome aggregation

We next address the degree to which biome aggregation improves the emergence of $p$$CO_2$ seasonality trends between 1985-1989 and 2014-2018. To this aim, we use multiple LE simulations with five different ESMs (detailed in **Table 4**), and apply them to interpret the decadal changes in $p$$CO_2$ seasonal variations represented by the $p$$CO_2$ products. However, before considering multi-decadal trends we consider first in **Fig. 12a** an analysis for the six aggregated biomes of the simulated seasonal amplitude of $p$$CO_2$ variations for a climatology over 2014-2018, both for $p$$CO_2$ products and LEs, with uncertainty ranges indicated for each case. For the observation-based $p$$CO_2$ products, the uncertainty shown represents the uncertainty across the nine $p$$CO_2$ products themselves, which is reflecting the spread across methods (mapping uncertainty) in representing gridded $p$$CO_2$. For an individual LE, the uncertainty represents the range of natural variability represented by the collection of individual ensemble members for that specific LE. We see that for all six aggregated biomes, at most, two of the five LEs have a climatological seasonal amplitude (defined as the absolute value of JFM-JAS) where the first quartile range (25%-75%, solid bar) overlaps with the first-to-third quartile range of the $p$$CO_2$ products. Over four of the six biomes (NP-SPSS, NH-STPS, SH-STPS, and SH-SS) CESM2-LE overlaps with the $p$$CO_2$ products, thereby indicating correspondence. We also see that inter-model differences in seasonal amplitude (ensemble median) are much larger than the ensemble spread (natural variability) for the individual ESMs. Overall, the analysis in **Fig. 12a** indicates that the representation of the climatological seasonal amplitude of pCO_2 in LEs is partly inconsistent with the pCO_2 products, mirroring what was found for GOBMs in the first part of the **Results** section of this study.

On the other hand, the decadal changes in the amplitude of seasonal pCO_2 variations between 1985-1989 and 2014-2018 (**Fig. 12b**) reveal a much better agreement (relative to **Fig. 12a**) between the median of the observational products and the ensemble spread of the individual LEs. Most importantly, with one exception over the three subtropical biomes (NH-STSS, NH-STPS, SH-STPS) and for each LE within these regions, the range of outcomes for modeled pCO_2 seasonality changes (the range indicated by the whiskers) does not intersect with a zero trend or go negative. Thus in the subtropics the biome-aggregated changes in the seasonal amplitude of pCO_2 are predominantly emergent, with SH-SS also being largely emergent. For the NP-SPSS biome, the median decadal change calculated for each LE indicates an increase in pCO_2 seasonal amplitude, although one of the LEs is not emergent while two other LEs are near the one standard deviation threshold for emergence. This is indicative of the NP-SPSS being moderately emergent under aggregation.

For the NA-SPSS biome the decadal changes in pCO_2 seasonal amplitude are quite distinct from the other regions, in that all LEs are at least moderately emergent, but that they have divergent signs in their simulated decadal changes. Three of the LEs (CESM1, CESM2, and ESM2M) exhibit a decrease in pCO_2 seasonal amplitude, while two of the LEs (CanESM2 and CanESM5) exhibit an increase. Under the caveat that we have imposed a somewhat restrictive definition of the seasonal cycle that is optimally suited for the pCO_2 products (see **Fig. 2** and **Fig. 4**), the at least moderately emergent decrease in pCO_2 seasonal amplitude for three LEs is distinctive for the NA-SPSS biomes. The study of Goris et al. (2022) suggests that such behavior may be expected from the disparate responses of the Atlantic Meridional Overturning Circulation (AMOC) for the LEs. However, further exploration of this point should be done while taking into consideration the sensitivity of the models to the definition of the seasonal cycle. It is interesting that one of the pCO_2 products does show zero net change between 1985-1989 and 2014-2018.

The fact that the distribution of multi-decadal trends for individual LEs overlaps with the 25%-75% (bar) range for the observation-based pCO_2 products gives us a degree of confidence that the biome-aggregated changes can be considered emergent or detectable over this 30-year period. It should be noted, however, that the Northern Hemisphere biomes tend to be faced with a triple-whammy of elevated uncertainty, given the relatively high degree of disaccord between pCO_2 products (mapping uncertainty), the relatively elevated level of natural variability uncertainty, and the offset of the medians of the different LEs (model structural uncertainty). The LEs nevertheless bring great value to the parsing of uncertainty in that they allow us to distinguish between internal variability uncertainty and model structural uncertainty. Qualitatively they are of similar amplitude for the decadal changes (**Fig. 12b**), but the model structural uncertainty is much larger for the 2014-2018 climatology (**Fig. 12a**).

The Southern Ocean (SH-SS) region is characterized by relatively weak trends **(Fig. 12b**), yet due its relatively weak natural variability is also predominantly emergent at the biome scale despite being non-emergent at the gridpoint scale (**Fig. 11b**). The reason for there being both weak natural variability and a weak decadal trend over the Southern Ocean is due to the combined effects of the tendency of models to have a relatively weak dominance of thermal over nonthermal seasonality drivers over the Southern Ocean, and that the relatively small amplitude of seasonal SST variations over the Southern Ocean. Taken together, this limits the ability of the invasion flux of C_{ant} to boost pCO_2 seasonality amplitude between the 1980s and 2010s.

4 Discussion

The unprecedented collection of pCO_2 products and model simulations available through the RECCAP2 project has provided an opportunity for not only synthesizing but also understanding the changing seasonal cycle in sea surface pCO_2. The use of new observation-based pCO_2/TA products that include DIC and TA in addition to pCO_2 has made it possible to address the following scientific questions: (i) what are the underlying causes of discrepancies in pCO_2 seasonal variability between GOBMs and observation-based products? (ii) what are the drivers of decadal-timescales trends towards increasing pCO_2 seasonality?, and (iii) are there asymmetries in the growth of pCO_2 and CO_2 flux seasonal variations over multi-decadal timescales that could give rise to a feedback mechanism consistent with the mechanism identified in the modeling study of Fassbender et al. (2022)?

One of the main findings of this study is that there are systematic discrepancies in the climatological seasonal amplitude of surface DIC variations between GOBMs and observation-based pCO_2/TA products over very large spatial scales (**Fig. 5c**) that are primarily responsible for compromising the climatological seasonal cycle of pCO_2. More specifically, simulated DIC seasonal variability is systematically smaller for GOBMs than for DIC seasonal variability in the pCO_2/TA products. The climatological seasonal amplitude of DIC variations can be impacted by both the seasonal amplitude of net biological removal of DIC from the surface layer and the seasonal process of entrainment associated with destratification. Although it is beyond the scope of this study to parse these processes, important information can be inferred from previous studies. Models have previously been shown to prematurely exhaust limiting nutrients in summer (Goris et al., 2018), and such behavior could impact the seasonal amplitude of surface DIC variations

From the biome-averaged time series shown in **Fig. 4**, we have seen that there are some important discrepancies in phasing of the climatological seasonal cycle for pCO_2 between GOBMs and pCO_2 products over biome scales. We have opted here to focus largely on a definition of seasonal cycle amplitude as the difference between winter and summer, defined as JFM-JAS (JAS-JFM) for the Northern (Southern) Hemisphere, as this was deemed to capture the main characteristics of pCO_2 seasonality over large scales, based on the pCO_2 products, as shown in the Hovmöller diagrams in **Fig. 2**. Although our main story of seasonality changes in pCO_2 is not strongly sensitive to this definition for the pCO_2 products or the GOBMs (**Fig. 3**), the presence of phasing differences between pCO_2 products and GOBMs in high latitudes influences the seasonal amplitude calculated according to this definition. We recommend further investigation of such phasing differences to better understand the underlying reasons for this discrepancy.

We emphasized earlier that for our purposes of a synthesis, the GOBMs potentially offer an important advantage over coupled ESMs for our seasonality study and associated attribution analysis. This is due to the fact that the SSTs of the GOBMs are constrained to correspond closely to observations through the imposition of a negative feedback in surface heat fluxes by virtue of using observed surface air temperatures (Large and Yeager, 2009). However, there is no analogous data-constraint applied for the DIC seasonal evolution, other than an indirect and much weaker effective restoring of sea surface $p\mathrm{CO}_2$ to atmospheric $p\mathrm{CO}_2$ over a one-year timescale (an order of magnitude less than for SST). As the SSTs of the GOBMs effectively track the observed seasonal cycle with fidelity, our attention in this study was drawn to the dominant role of DIC seasonality discrepancies in distorting $p\mathrm{CO}_2$ seasonality for the GOBMs relative to the observation-based products.

Nevertheless, as a complementary exercise to the evaluation of GOBMs in **Fig. 4**, we consider here an analogous analysis of a collection of the 11 CMIP6 ESMs listed in **Table 6**. The ESMs are evaluated for their climatological seasonal cycle in $p\mathrm{CO}_2$, SST, and DIC, as well as for decadal changes in $p\mathrm{CO}_2$. For this case, we have considered changes between 1985-1989 and 2010-2014 (an interval four years shorter than in **Fig. 4**) to be consistent with the fact that the historical period in CMIP6 ends in 2014. In general terms there is no fundamental difference between both classes of models. Despite the absence of observational constraints, the simulated SST seasonal cycle in ESMs is in good agreement with observations (dotted lines in central column of **Fig. 13**), although the model spread is significantly larger as expected. The DIC seasonality of the ESMs is very similar to that of the GOBMs (weaker in models than in observation-based $p\mathrm{CO}_2$ products) and the overall $p\mathrm{CO}_2$ changes are very consistent between fully-coupled ESMs and GOBMs (right column of **Fig. 4** and **Fig. 13**). This serves to further underscore our main finding that there is a pervasive discrepancy between ocean carbon cycle models and $p\mathrm{CO}_2$ products, not limited to the RECCAP2 GOBMs, with a seasonal variability in models that is too weak relative to $p\mathrm{CO}_2$ products. Interpretation of projected future seasonal changes in ESMs should therefore take into account the systematic model uncertainties highlighted in this study. As we have seen in **Fig. 12**, a future extension of this analysis for coupled models could benefit from the inclusion of LEs, which offer a means to deconvolve for models the effects of structural uncertainty from natural variability uncertainty.

Our attribution analysis indicates that in the subtropics the GOBMs and pCO_2 products are qualitatively consistent in both the degree of seasonal asymmetry in decadal pCO_2 changes and CO_2 flux changes (**Fig. 9**), as well as for the mechanistic drivers (**Fig. 10**). This reflects the fact that both the GOBMs and pCO_2 products are dominated by the thermal pCO_2 component in the subtropics, albeit with the degree of dominance of the thermal pCO_2 component being exaggerated by the GOBMs. The fact that the Northern Hemisphere subtropics have a larger response than the Southern Hemisphere subtropics is expected given that the seasonal cycle in SST is larger in the north than in the south, and thereby the thermal component of seasonality to be larger in the north than in the south. Thus, C_{ant} invasion will preferentially boost the amplitude of pCO_2 seasonality in the subtropics of the Northern Hemisphere relative to the Southern Hemisphere, due to the higher amplitude SST variability to the north.

An important implication of our attribution analysis is that the decadal changes in seasonal pCO_2 and CO_2 flux amplitudes are qualitatively consistent with the existence of a negative climate feedback over the historical period spanning 1985-2018. Consistent with what was found by Fassbender et al. (2022) using future projections with an LE simulation, the seasonal asymmetry in CO_2 fluxes identified here for the historical period is by inference in large part due to seasonal asymmetries in wind speeds and thereby piston velocities, rather than in pCO_2 itself. It is our hope that the analysis provided here will motivate future work to quantify the strength of this feedback over the historical period, as doing so was beyond the scope of this study.

Two studies that evaluated the early generation of prognostic ocean biogeochemistry models for their representation of pCO_2 seasonality against observations were McKinley et al. (2006) for the case of the North Pacific and Tjiputra et al. (2012) for the case of the North Atlantic. Although an explicit comparison of the models applied by McKinley et al. (2006) and

Tjiputra et al. (2012) with the RECCAP2 GOBMs is beyond the scope of this study, it is important to ask, "how far have we come?". The message from this study is that the new suite of pCO$_2$/TA products that provide time-varying surface DIC products that have become available provide invaluable tools for identifying and attributing potential model biases over global scales. Moving forward, we recommend that efforts be devoted to understanding how complexity in physical and biogeochemical process representation in models is reflected in pCO$_2$ seasonality. For the case of the biogeochemical components of models, one opportunity would be to evaluate with the same circulation state a climatology of pCO$_2$ seasonality using different complexity of biogeochemical models, analogous to what was explored by Galbraith et al. (2015) with the BLING and TOPAZ biogeochemical models, or by Karakus et al. (2022). Moreover, it could be beneficial to link the simulated strength of key circulation metrics (e.g. Atlantic Meridional Overturning Circulation for the North Atlantic) to the pCO$_2$ seasonality of the GOBMs. In a study with several coupled climate models, Goris et al. (2022) were able to show that the representation of a model's pCO$_2$ seasonality in the North Atlantic is strongly linked to the simulated strength of the Gulf Stream volume transport. In order to address the question of how missing physical processes may impact biogeochemistry and pCO$_2$ seasonality, it would be beneficial to explore independently the impact of mesoscale turbulence with ocean eddies (Lévy et al., 1998) and shear-induced turbulence associated with near-inertial oscillations, ocean swells, and wind stirring (Jochum et al., 2013; Keerthi et al., 2021; Rodgers et al., 2014) through perturbation studies with individual models. Such efforts would be beneficial in identifying the processes that contribute to the discrepancies identified in this RECCAP2 synthesis effort.

5 Conclusions

In this study, we have presented as a contribution to the RECCAP2 effort a synthesis of how the seasonal cycle in sea surface pCO$_2$ and air-sea CO$_2$ fluxes has changed over the last three decades (1985-2018). Our main findings include:

For a 2014-2018 climatology, we identified a systematic discrepancy in the seasonal amplitude of surface DIC variations between the GOBMs, which are too weak, and the surface DIC products, such that the $p\mathrm{CO_2}$ seasonal cycle in subtropical biomes is spuriously large, and both the amplitude and phase of seasonal $p\mathrm{CO_2}$ variations are spuriously modulated in subpolar and Southern Ocean biomes. Similar biases are found in ESMs as submitted to CMIP6. When averaged over aggregated biomes, both $p\mathrm{CO_2}$ products and GOBMs represent consistent increases in the seasonal amplitude of $p\mathrm{CO_2}$ and CO_2 fluxes between 1985-1989 and 2014-2018.

Decadal increases in $p\mathrm{CO_2}$ seasonal amplitude in subtropical biomes are shown to be dominated process-wise by the invasion flux of anthropogenic carbon (C_{ant}) for both the $p\mathrm{CO_2}$ products and GOBMs. For $p\mathrm{CO_2}$ seasonality changes over subpolar and circumpolar biomes, GOBMs see this change as being dominated by C_{ant} invasion, but for $p\mathrm{CO_2}$ products it is dominated rather by modulations of the climate state, which can be associated with changes in SST seasonality or in perturbations occurring in mixing or biological processes. Our analysis of LE simulations indicates that the climate-driven signal found in the subpolar biomes of the Northern Hemisphere (bold blue line in **Fig. 10a**) is likely too large to be explained by natural variability, as estimated from the amplitude of natural variability in the LE (width of blue shading in **Fig. 10g**). Considered together, the subtropical biomes exhibit decadal increases in CO_2 flux seasonality that are larger during winter than summer, consistent with the mechanism identified by Fassbender et al. (2022) whereby increased seasonal cycles may be promoting a negative feedback in the climate system.

We have also identified and quantified two distinct sources of uncertainty that can impact the detection of anthropogenic trends in $p\mathrm{CO_2}$ seasonal amplitude. The first type is mapping uncertainty (**Fig. 3a** and **Fig. 3c**), which is in essence a reducible form of uncertainty. The second type is natural variability uncertainty (**Fig. 11** and **Fig. 12**), which we identified with the LE simulations, with this being an irreducible form of uncertainty. For both cases, we identified that there are large regions of the global domain where the forced anthropogenic signal does not rise above the one standard deviation (noise) level at the gridpoint scale. Even for the idealized case of a perfectly-resolving observational system where mapping error disappears, one would still need to quantify the degree of confidence one has that a local measured decadal change represents forced changes in the presence of natural variability. We tend in the subtropics to find unanimous agreement at the gridpoint scale across pCO_2 products and GOBMs on the dominant mechanism of enhanced pCO_2 seasonality, namely the C_{ant}-driven boost to the thermally component of pCO_2 seasonality.

Thus our synthesis provides evidence that the seasonal pCO_2 amplitude has significantly increased globally, and for many regions, this increase has already emerged from the noise with biome aggregation. This highlights the importance of including seasonal changes when considering long-term acidification trends, as we will likely cross critical thresholds in some seasons, before such thresholds are crossed in the annual mean (Burger et al., 2020; Henson et al., 2017; Kwiatkowski and Orr, 2018; McNeil and Sasse, 2016). For similar reasons, we recommend that modeling resources be devoted to identifying missing processes and implementing representations or parameterizations of the pertinent missing processes in ocean biogeochemical models.

Our conclusions rest on the growing availability of pCO_2 products that include associated time-varying DIC and TA products, with this representing a significant advance for scientific inquiry into the mechanisms controlling the ocean uptake of anthropogenic carbon. The fact that the three pCO_2/TA products (considered here as surface DIC products) that exist to date (JMAMLR, OceanSODA-ETHZ, and CMEMS-LSCE-FFNN) indicate consistent patterns of seasonal variability over large scales, which are also consistent with depth-resolving three-dimensional monthly DIC climatologies (MOBO-DIC and NNGv2LDEO) over large scales, should boost community confidence in the scientific utility of these products. We therefore strongly recommend to the pCO_2 product providers to provide DIC and TA along with sea surface pCO_2 and air-sea CO_2 fluxes. In parallel, we recommend a rigorous skill-assessment of the mapping methods that transform from SOCAT measurements to globally-gridded pCO_2 products, for example by using LEs with ESMs as a synthetic testbed similar to the work presented by Gloege et al. (2021).

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OPEN RESEARCH

All of the RECCAP2 data will be made available in a public repository before publication.

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Names	Aggregated seasonality biomes	RECCAP2 biomes
North Atlantic subpolar seasonally stratified	NA-SPSS	NA-SPSS
North Pacific subpolar seasonally stratified	NP-SPSS	NP-SPSS
Northern Hemisphere subtropical seasonally stratified	NH-STSS	NA-STSS+NP-STSS
Northern Hemisphere subtropical permanently stratified	NH-STPS	NA-STPS + NP-STPS
Southern Hemisphere subtropical permanently stratified	SH-STPS	SA-STPS + SP-STPS + Southern Indian Ocean
Southern Hemisphere seasonally stratified (subpolar and subtropical combined)	SH-SS	SO-STSS + SO-SPSS

Table 1: The six aggregated biomes used in this study. The full names are given in the left column, the abbreviated names used throughout this study in the central column, and the original RECCAP2 biomes from which they are constructed are listed in the right column. Our six aggregated biomes are shown in the central panel of **Fig. 1**. As has been noted in the Methods section, spatial and temporal data coverage of data products and models might further constrain the area of the aggregated biomes used for our analysis.

Product name	References	Duration and Remarks
CSIRML6	Gregor et al., 2019	1985-2018
CMEMS-LSCE-FFNN	Chau et al., 2022	1985-2018; DIC and TA available
JMAMLR	Iida et al., 2021	1985-2019; DIC and TA available
Jena-MLS	Rödenbeck et al., 2013, 2022	1985-2018
NIES-ML3	Zeng et al., 2022	1980-2020
OceanSODA-ETHZ	Gregor and Gruber, 2021	1985-2018; DIC and TA available
SOMFFN	Landschützer et al., 2016	1982-2019
UOEX_WAT20	Watson et al., 2020	1985-2019
spco2_LDEO_HPD	Gloege et al., 2022	1985-2018

Table 2: pCO_2 data products used for this study. The products are described more completely in the global RECCAP2 analysis of DeVries submitted to Global Biogeochemical Cycles. Note that the CMEMS-LSCE-FFNN, JMAMLR, and OceanSODA-ETHZ products include associated surface DIC and TA fields that are used in this study.

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Model Name	References	Remarks
CCSM	Doney et al., 2009	Covers only 1985-2017, For 2014-2018 climatologies an exception is made for this model
CESM-ETHZ	Doney et al., 2009; Lindsay et al., 2014; Yang and Gruber, 2016	
CNRM-ESM2-1	Berthet et al., 2019; Séférian et al., 2016, 2019	
EC-Earth3	Döscher et al., 2022	
FESOM-REcoM-LR	Hauck et al., 2020	No phosphate available, WOA2018 used for attribution analysis
MOM6-COBALT-PRINCETON	Liao et al., 2020; Stock et al., 2020	
MRI-ESM2-1	Nakano et al., 2011; Urakawa et al., 2020	
NorESM-OC1.2	Schwinger et al., 2016	
ORCA025-GEOMAR	Chien et al., 2022; Kriest and Oschlies, 2015; Madec et al., 2017	No silicate available, silicate from WOA2018 used for attribution analysis
IPSL-NEMO-PISCES	Aumont et al., 2015; Friedlingstein et al., 2022	

PlankTOM12	(Le Quéré et al., 2010; Wright et al., 2021)	No silicate available, WOA2018 used for attribution analysis
Assimilation Model	**References**	**Remarks**
OCIM v2021	(DeVries, 2014, 2022)	Abiotic model with data assimilated circulation; Used for some analyses but never included in ensemble means for GOBMs

Table 3: Global Ocean Biogeochemical Models (GOBMs) and an assimilation model used for this study. Model names are given in the first column, references are given in the second column, and comments pertinent to the application of the products are given in the third column. The CCSM model differs from the others in that output only extends to 2017 rather than to the RECCAP2 protocol end-year of 2018.

Earth System Model	References	Comments
CESM2 (CMIP6)	Rodgers et al., 2021	50 members
CanESM2 (CMIP5)	Kirchmeier-Young et al., 2017	50 members
CanESM5 (CMIP6)	Swart et al., 2019b	24 members
CESM1 (CMIP5)	Kay et al., 2015	34 members
ESM2M (CMIP5)	Rodgers et al., 2015	30 members
MPI-GE (CMIP5)	Maher et al., 2019	100 members

Table 4: Large Ensemble Simulations used in the analysis in **Fig. 12**.

	GOBMs		***p*CO_2 products**	
Region	*p*CO_2 amplitude	*p*CO_2 amplitude change	*p*CO_2 amplitude	*p*CO_2 amplitude change
NA-SPSS	-18.5 +/- 18.5	-2.1 +/- 9.9	46.0 +/- 4.9	5.9 +/- 6.1
NP-SPSS	-34.1 +/- 29.3	-8.3 +/- 6.0	17.1 +/- 4.3	2.8 +/- 7.7
NH-STSS	-67.8 +/- 16.2	-10.7 +/- 3.2	-37.2 +/- 1.7	-9.8 +/- 3.9
NH-STPS	-42.0 +/- 6.7	-6.3 +/- 1.1	-33.2 +/- 2.4	-6.3 +/- 2.8
SH-STPS	-39.5 +/- 10.7	-2.7 +/- 2.0	-29.4 +/- 3.2	-5.3 +/- 2.7
SH-SS	-5.8 +/- 14.7	0.6 +/- 1.4	11.4 +/- 2.4	1.0 +/- 2.5

Table 5: Seasonal amplitude (winter-minus-summer) of biome averaged *p*CO_2 for GOBMs and *p*CO_2 products for the period 2014-2018. Seasons are defined as the three month periods JFM and JAS. Change represents the difference between 1985-1989 and 2014-2018,

Model Name	ESM reference	Data reference
ACCESS-ESM1-5	Law et al., 2017	Ziehn et al., 2019
CanESM5	Swart et al., 2019b	Swart et al., 2019a
CESM2	Lauritzen et al., 2018	Danabasoglu, 2019
CMCC-ESM2	Lovato et al., 2022	Lovato et al., 2021
CNRM-ESM2-1	Séférian et al., 2019	Séférian, 2018
GFDL-ESM4	Dunne et al., 2020	Krasting et al., 2018
IPSL-CM6A-LR	Boucher et al., 2020	Boucher et al., 2018
MIROC-ES2L	Hajima et al., 2020	Hajima et al., 2019
MRI-ESM2-0	Yukimoto et al., 2019b	Yukimoto et al., 2019a
NorESM2-MM	Seland et al., 2020	Bentsen et al., 2019
UKESM-0-LL	Sellar et al., 2019	Tang et al., 2019

Table 6: CMIP6 models evaluated against $p\mathrm{CO_2}$ products in **Fig. 13**.

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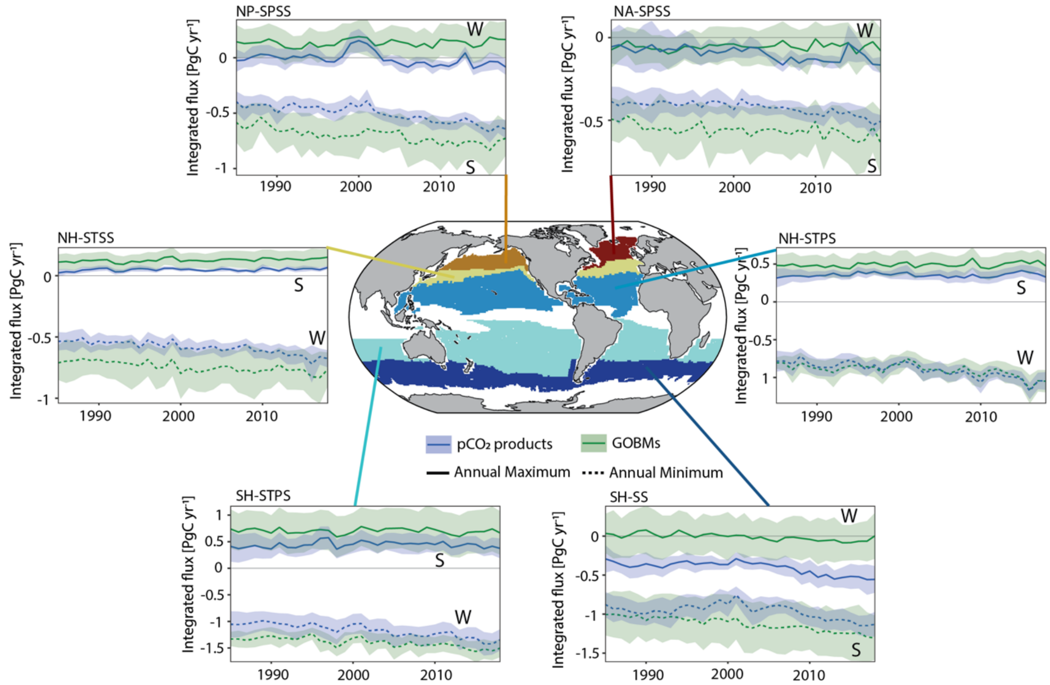

Fig. 1: Central panel showing biomes used for this study (see **Table 1** for details): North Atlantic subpolar seasonally stratified (NA-SPSS), North Pacific subpolar seasonally stratified (NP-SPSS), Northern Hemisphere subtropical seasonally stratified (NH-STSS), Northern Hemisphere subtropical permanently stratified (NH-STPS), Southern Hemisphere subtropical permanently stratified (SH-STPS), and Southern Hemisphere seasonally stratified, incorporating the subpolar and subtropical components (SH-SS). Surrounding panels show time series plots of biome-integrated sea-air CO_2 fluxes (annual maximum and minimum values irrespective of the month of occurrence). $p$$CO_2$ products (blue) and GOBMs (green) are shown for both the ensemble mean (bold) and for one standard deviation (shaded). Positive (negative) values indicate outgassing (ingassing) of CO_2. The regions in white in the central panel are not included in this analysis., in each panel, winter is designated by W, and summer by S, in order to distinguish the seasonal phasing between the subtropical and subpolar/Southern Ocean biomes.

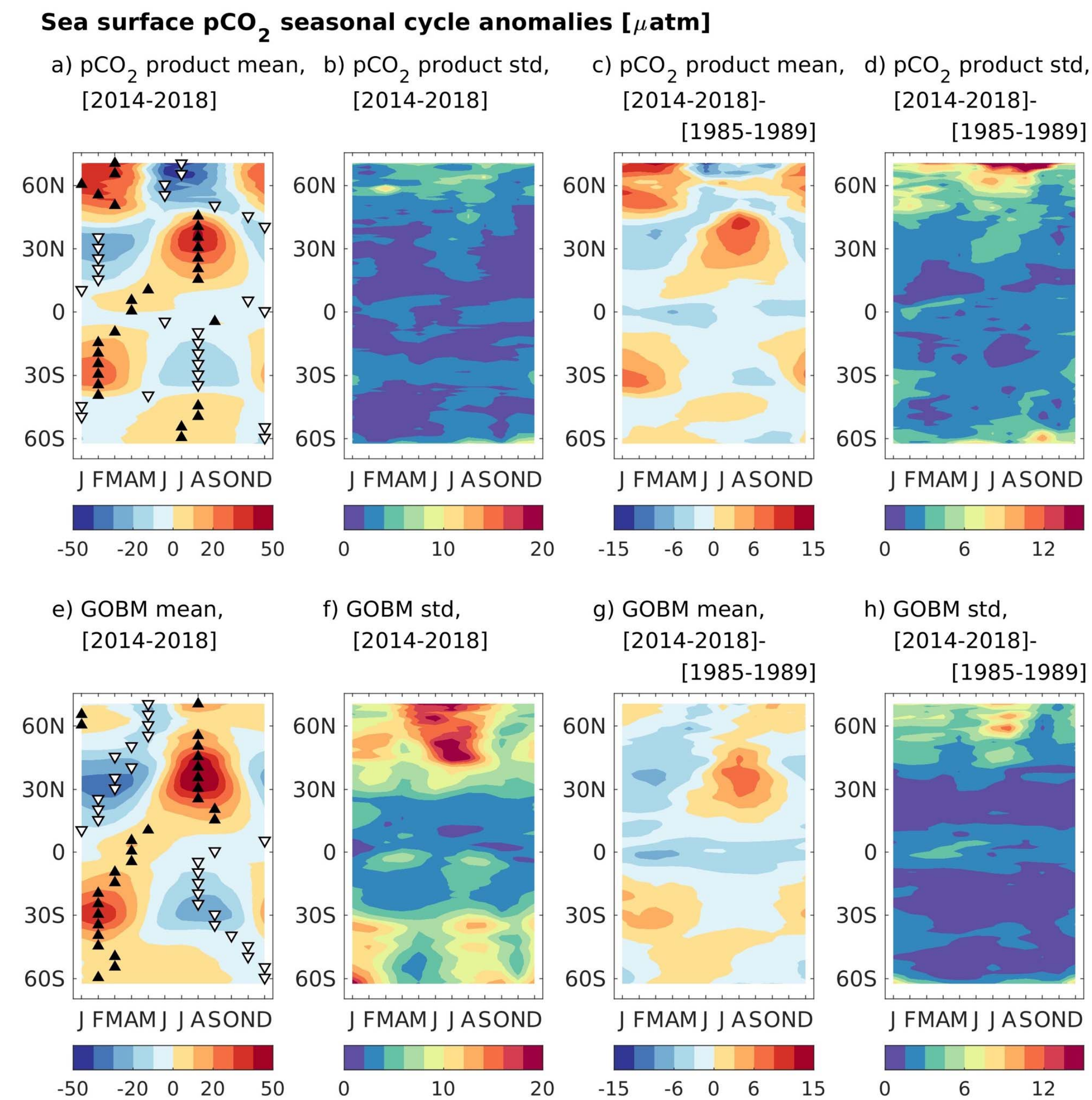

Fig. 2: Hovmöller diagrams of zonally-averaged climatological (2014-2018) pCO_2 anomalies for pCO_2 products (a) and GOBMs (e), and corresponding standard deviations (b, f); multi-decadal change in pCO_2 climatology between 1985-1989 and 2014-2018 for pCO_2 products (c) and GOBMs (g) and corresponding standard deviation (d, h). The seasonal maxima (black triangles) and minima (white triangles) are highlighted in panels a and e. Anomalies were calculated, grid-point by grid-point, by first fitting a quadratic polynomial through the full monthly time series over the period 1985-2018 and removing this trend from the data. Then, mean pCO_2 values over 1985-1989 and 2014-2018 were calculated for each month as a deviation from the detrended mean pCO_2 over the whole five year period.

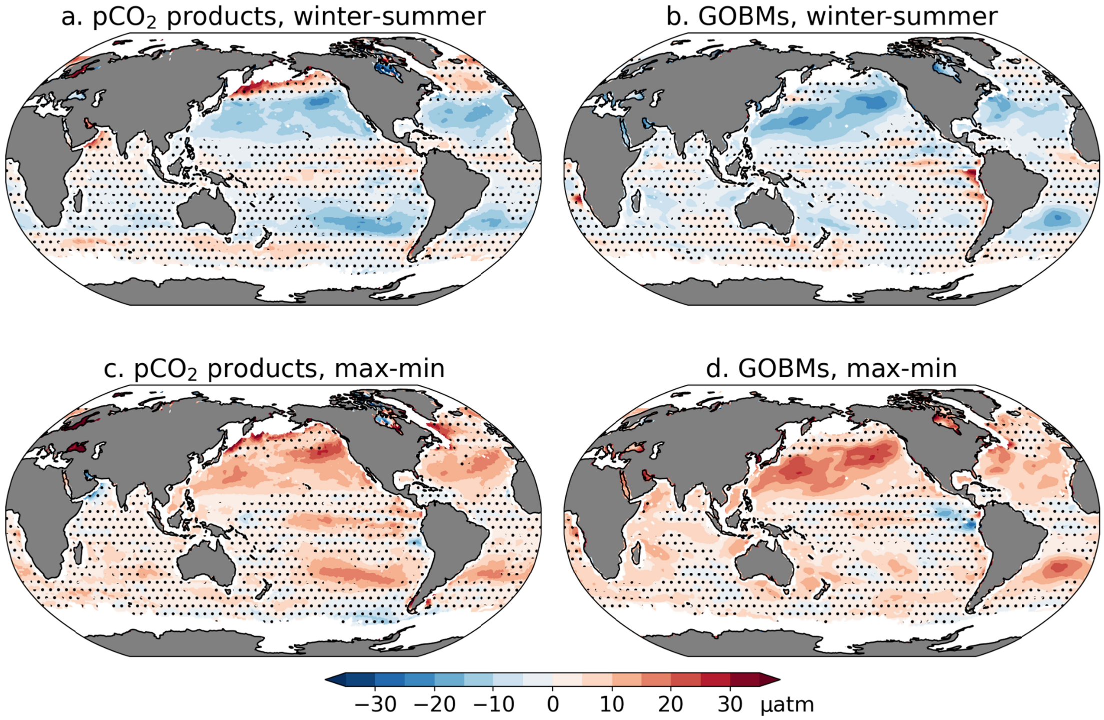

Fig. 3: Multi-decadal changes in the $p\mathrm{CO_2}$ seasonal amplitude between the two five-year periods 1985-1989 and 2014-2018, for (a,c) $p\mathrm{CO_2}$ products and (b,d) GOBMs. For panels a and b, seasonal amplitude is calculated as a winter-minus-summer difference, where winter and summer are defined as JFM and JAS (JAS and JFM) for the Northern (Southern) Hemisphere, respectively. For panels c and d seasonal amplitude is calculated as maximum-minus-minimum. Dotted regions indicate where the spread of the ensemble members (STD=1 level) is larger than the ensemble mean multi-decadal change. For this analysis, the nine $p\mathrm{CO_2}$ products listed in **Table 2** and the 11 GOBMs in **Table 3** (excluding OCIM) are used. The sensitivity to the choice of five-year versus 10-year versus 15-year averaging for characterizing decadal changes is displayed in **Fig. S3**.

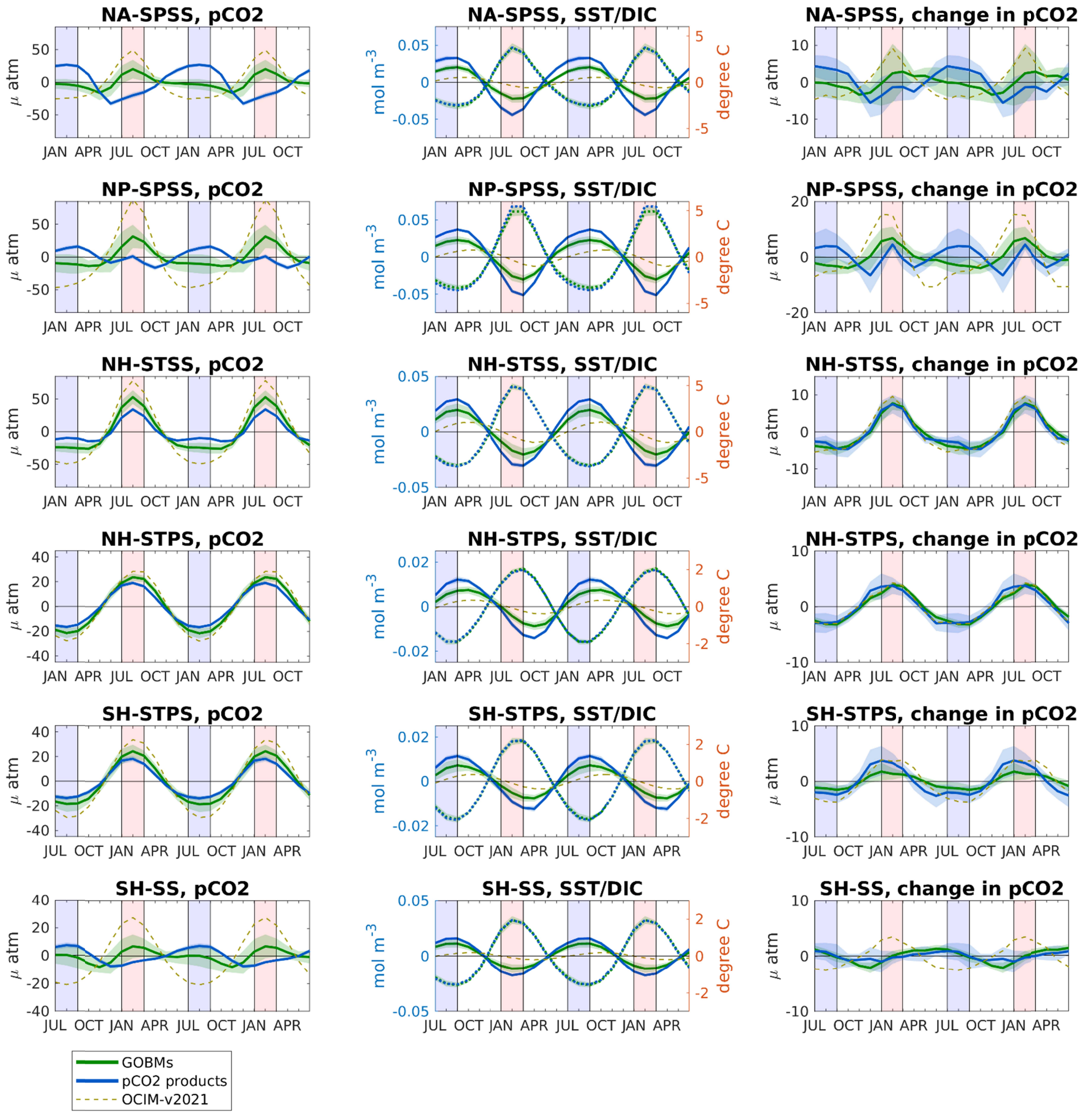

Fig. 4: Climatological seasonal cycle anomalies for 2014-2018 for pCO_2 (left column), SST (center column, dashed) and DIC (center column, solid), and change in pCO_2 seasonale cycle anomalies between 1985-1989 and 2014-2018 (right column) over the six aggregated biomes for GOBMs (green), pCO_2 products (blue), and for OCIM (brown, dashed). The biome names as defined in **Table 1** and **Fig. 1** are given in each panel title. Ensemble means for GOBMs and pCO_2 products are shown as thick lines while the shading indicates the standard deviation around the mean. Note the different scales of the left and right columns, and that the Southern Hemisphere sub-plots begin with the month of July.

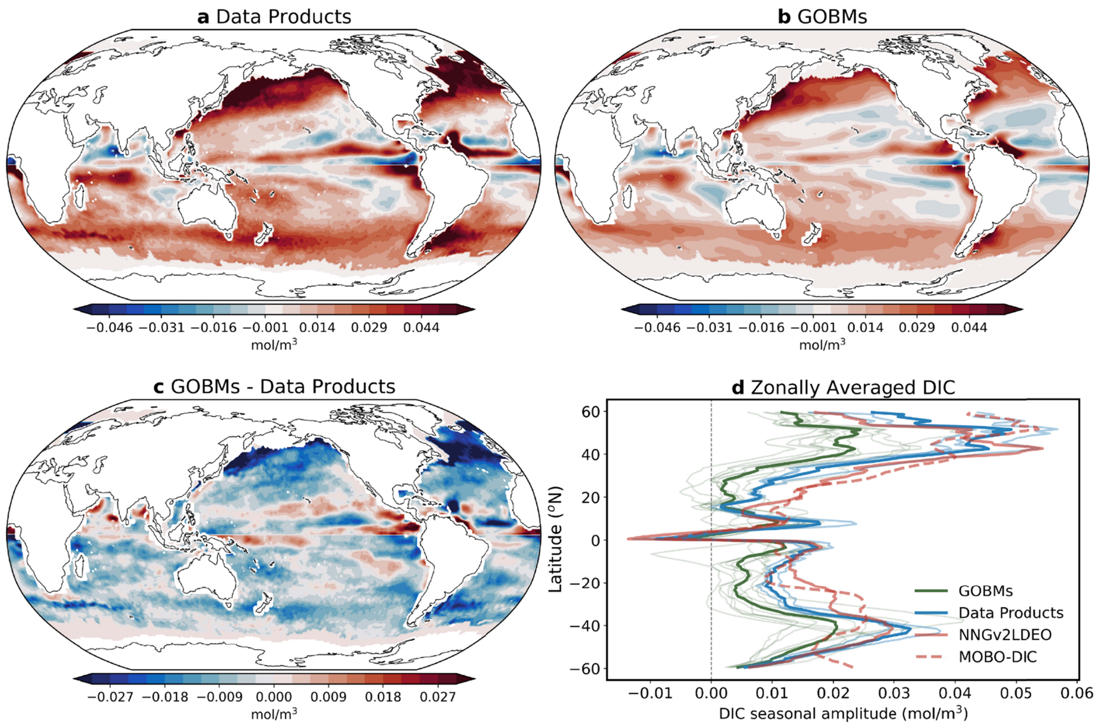

Fig. 5: Climatological seasonal amplitudes in surface DIC concentrations over 2014-2018 considered as winter-minus-summer (JFM-JAS for the Northern Hemisphere and JAS-JFM for the Southern Hemisphere) for (a) the average of three *p*CO_2/TA (DIC) products (JMAMLR, CMEMS-LSCE-FFNN, and OceanSODA-ETHZ), (b) the average across 11 GOBMs, and (c) the difference between (b) and (a), where negative (positive) values indicate that GOBMs under-represent (over-represent) the climatological seasonal amplitude of DIC variability. (d) shows latitudinal averages for GOBMs (green) and data products (blue), where bold lines represent product averages, and light lines indicate individual products. Also shown in (d) are MOBO-DIC (red dashed) and NNGv2LDEO (red solid). The MOBO-DIC climatology corresponds to the period 2004 through 2017 and NNGv2LDEO to 1995.

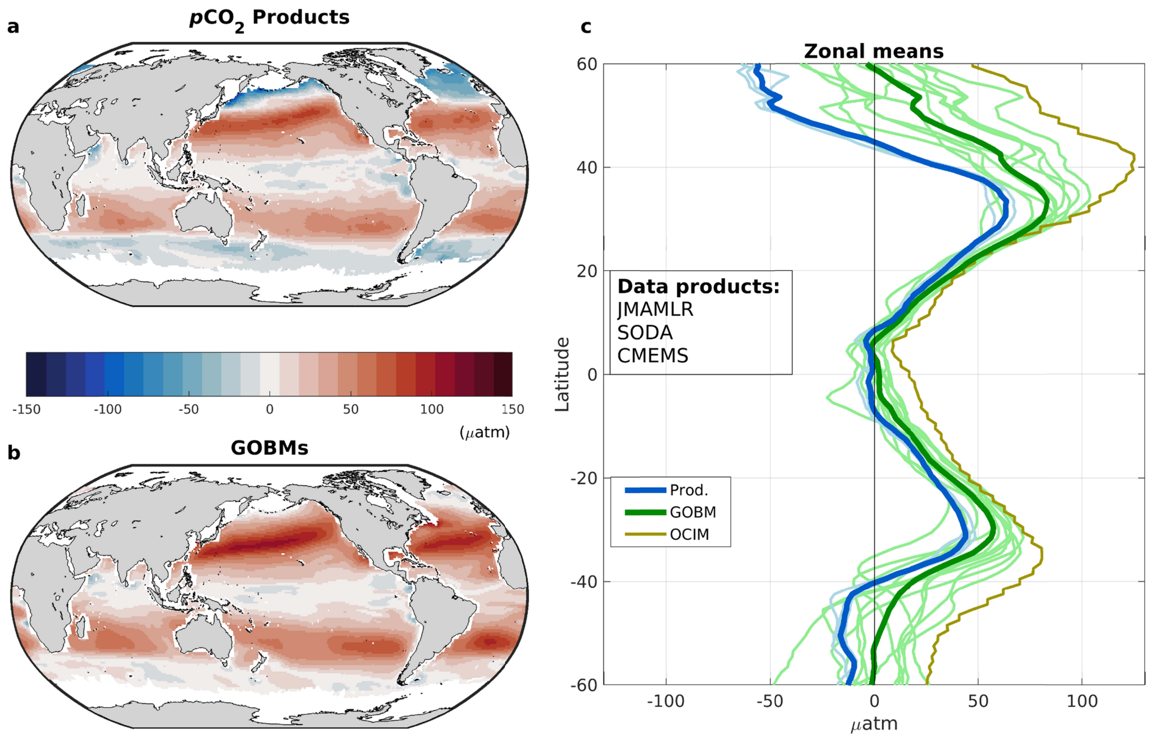

Fig. 6: Ensemble mean difference between the thermal and nonthermal pCO_2 component of its seasonal cycle amplitude (ΔA) for (**a**) the three pCO_2 products that include associated DIC and TA products (JMAMLR, OceanSODA-ETHZ, and CMEMS-LSCE-FFNN and (**b**) 11 GOBMs. (**c**) Zonal mean of ΔA values for GOBMs and pCO_2 products with bold lines showing the ensemble mean values. The olive-colored line shows the abiotic OCIM model, which is not included in the model ensemble mean. pCO_2 component seasonal cycle amplitudes were computed as the absolute value of the difference between the winter minus summer seasonal averages over 2014-2018. For each case the separation into thermal and nonthermal components follows the approach of *Fassbender et al.* (2022), where a carbon system calculator (CO2SYS) is used to quantify the thermal component, and thereby the nonthermal component via difference from the full pCO_2 annual cycle. Seasons are defined as JFM and JAS.

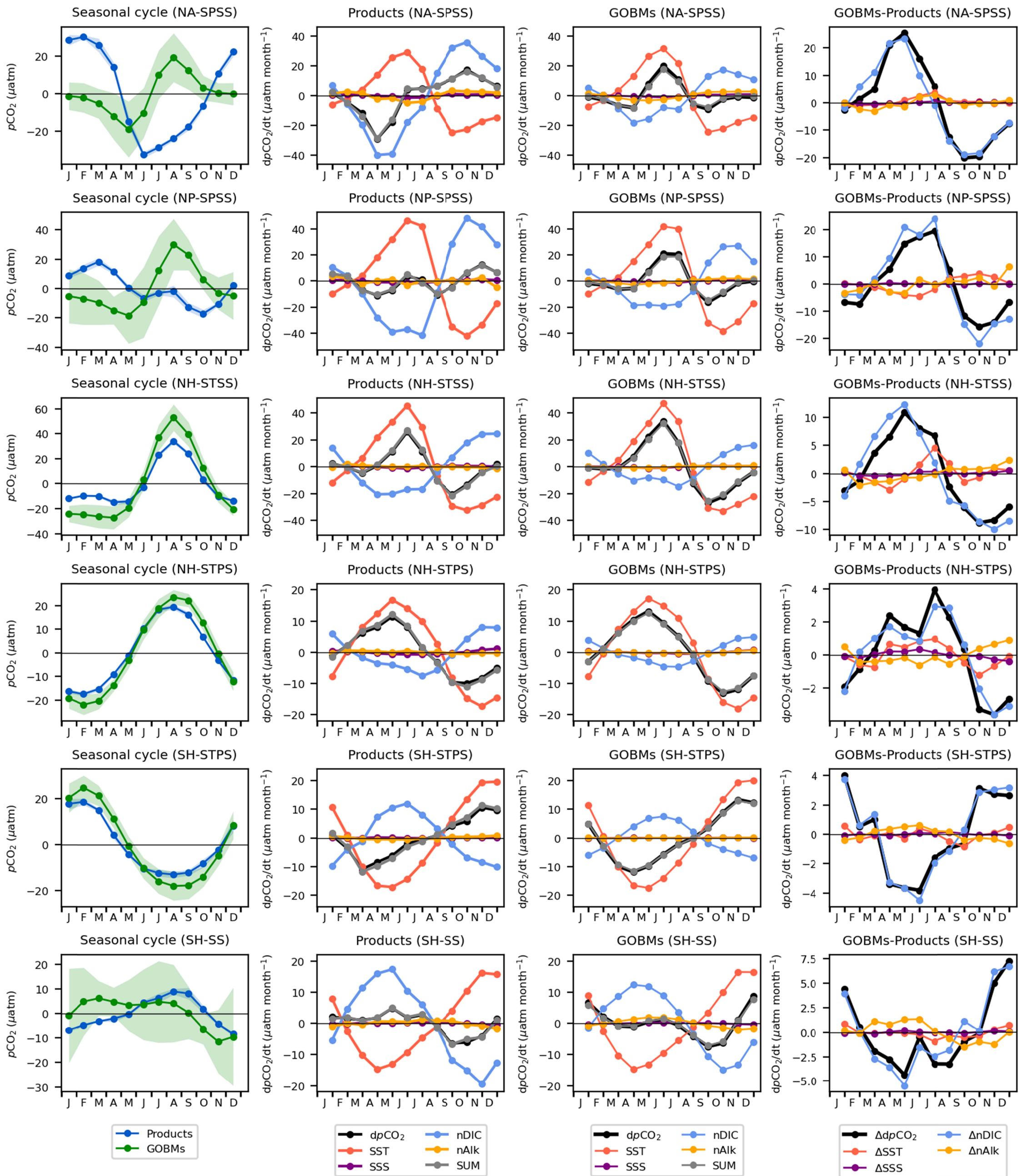

Fig. 7: Decomposition of the seasonality drivers for pCO_2 products and GOBMs (one standard deviation shading for GOBMs) for all six biomes. The 2014-2018 climatological seasonal cycle of pCO_2 (left column) is decomposed into month-to-month changes due to two physical (SST (orange) and SSS (purple)) and two biogeochemical (salinity-normalized DIC (nDIC, blue) and salinity-normalized TA (nAlk, yellow)) drivers (2nd and 3rd column). The

observational products are the three products that include DIC and TA, namely JMAMLR, OceanSODA-ETHZ, and CMEMS-LSCE-FFNN. Calculations are performed first individually on each product or GOBM, and subsequently averaged to arrive at a mean respectively for the observation-based products and GOBMs. The differences in the drivers between the $p\mathrm{CO_2}$ products and the GOBMs are shown in the right column - note the differences in scale. The drivers are identified via Taylor Series decomposition using PYCO2SYS to calculate the coefficients for DIC and TA, and using constant values for SST and SSS ($d\ln p\mathrm{CO_2}/dT=0.0423°C^{-1}$ and $d\ln p\mathrm{CO_2}/d\ln S=1$) as in *Sarmiento and Gruber* (2006). For $p\mathrm{CO_2}$ itself (left column) the monthly dots are positioned mid-month, mid-way between tick marks. For tendencies (columns two and three) dots are located at the end of the month, so on tick marks. SUM in columns two and three represents the sum of the four underlying tendencies.

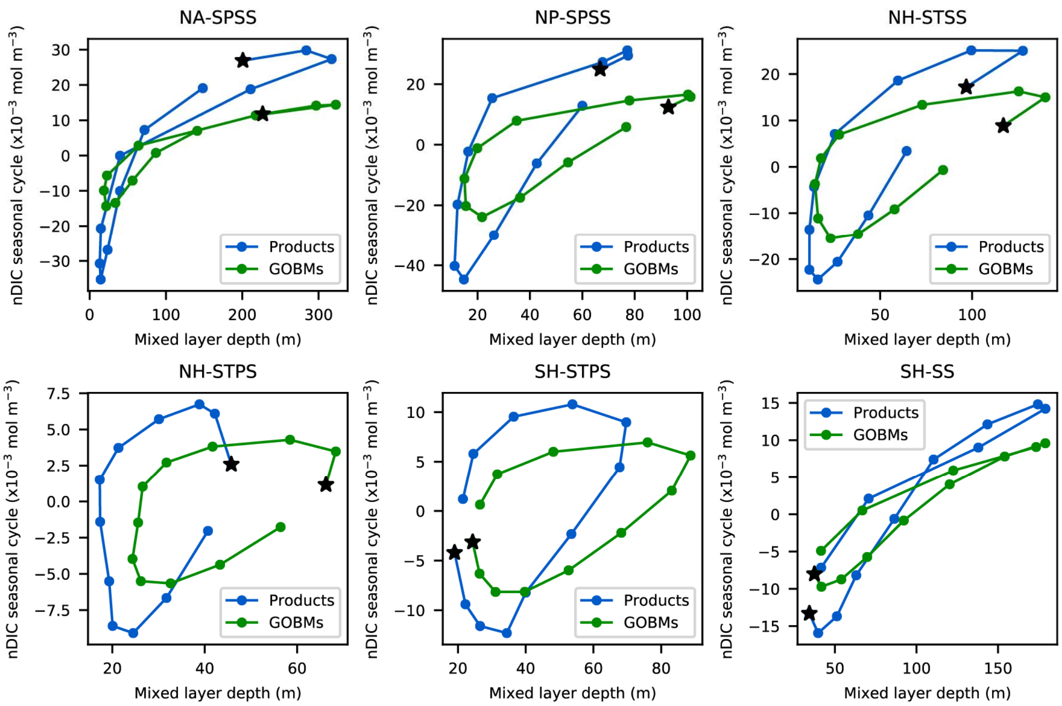

Fig. 8: Seasonal evolution of the relationship between MLD and anomalies of nDIC over the six biomes for a climatology over 2014-2018 for observation-based products (blue) and GOBMs (green). The stars indicate January. The pCO$_2$ products that include DIC and TA, namely JMAMLR, OceanSODA-ETHZ, and CMEMS-LSCE-FFNN, are considered along with the full suite of 11 GOBMs. Observationally-based MLDs have been derived for this study from the gridded Argo-derived temperature and salinity product of *Roemmich and Gilson* (2009) using a density threshold criterion (*Holte and Talley*, 2009) using the years 2014-2018, for consistency with the nDIC fields.

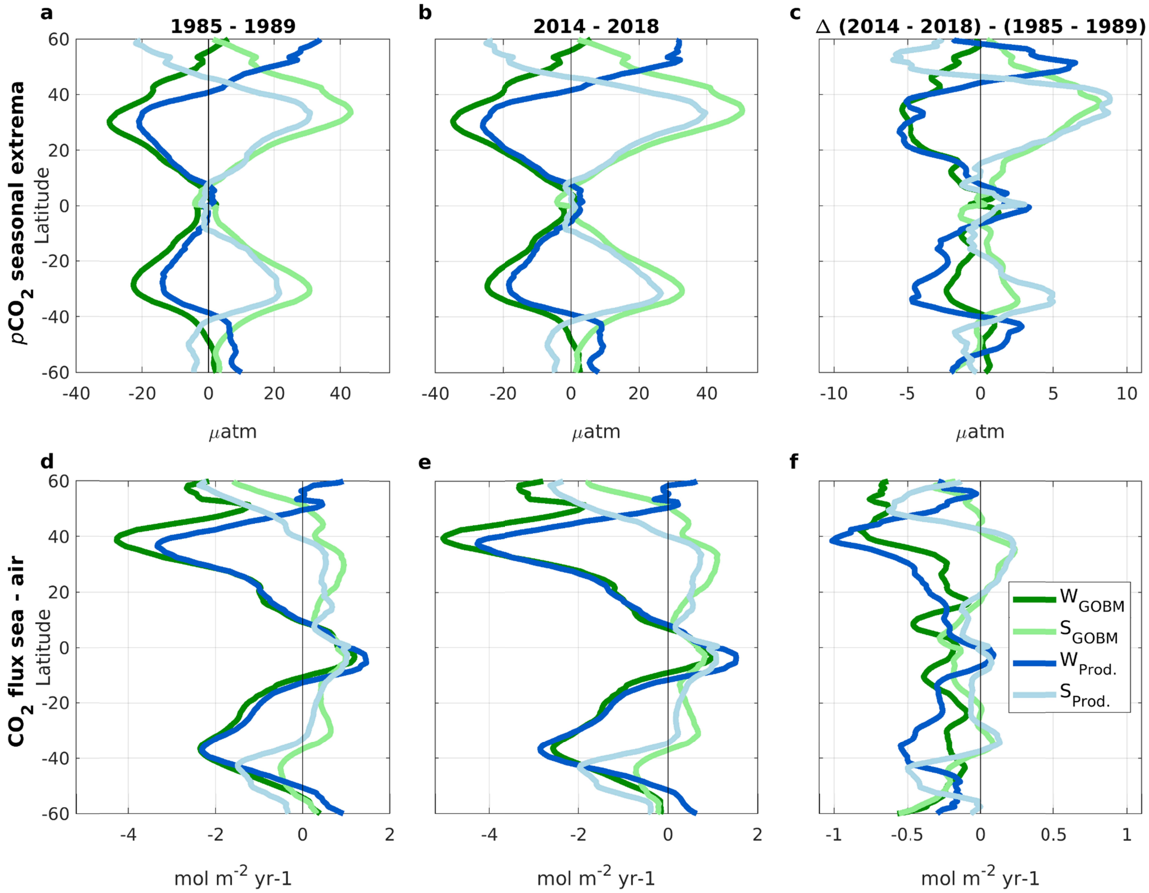

Fig. 9: Mean summer (S) and winter (W) (**a-c**) surface pCO$_2$ anomalies and (**d-f**) CO$_2$ sea-to-air flux. Results for the 1985-1989 period, 2014-2018 period, and the difference between periods (Δ) are shown in separate columns. Sea pCO$_2$, seasonal anomalies are calculated relative to the annual mean computed from annual means of temperature, salinity, dissolved inorganic carbon, total alkalinity, and nutrients for each year (pCO$_{2\ AM}$). Different magnitudes in the multi-decadal changes for each season (panel c) reflect asymmetry in the pCO$_2$ seasonal cycle change. Ensemble mean GOBM changes are shown in green hues (11 models listed in **Table 3**, excluding OCIM). Ensemble mean pCO$_2$ product (Prod.) changes are shown in blue hues (same pCO$_2$ products as in **Fig. 6**). Seasons are defined as JFM and JAS.

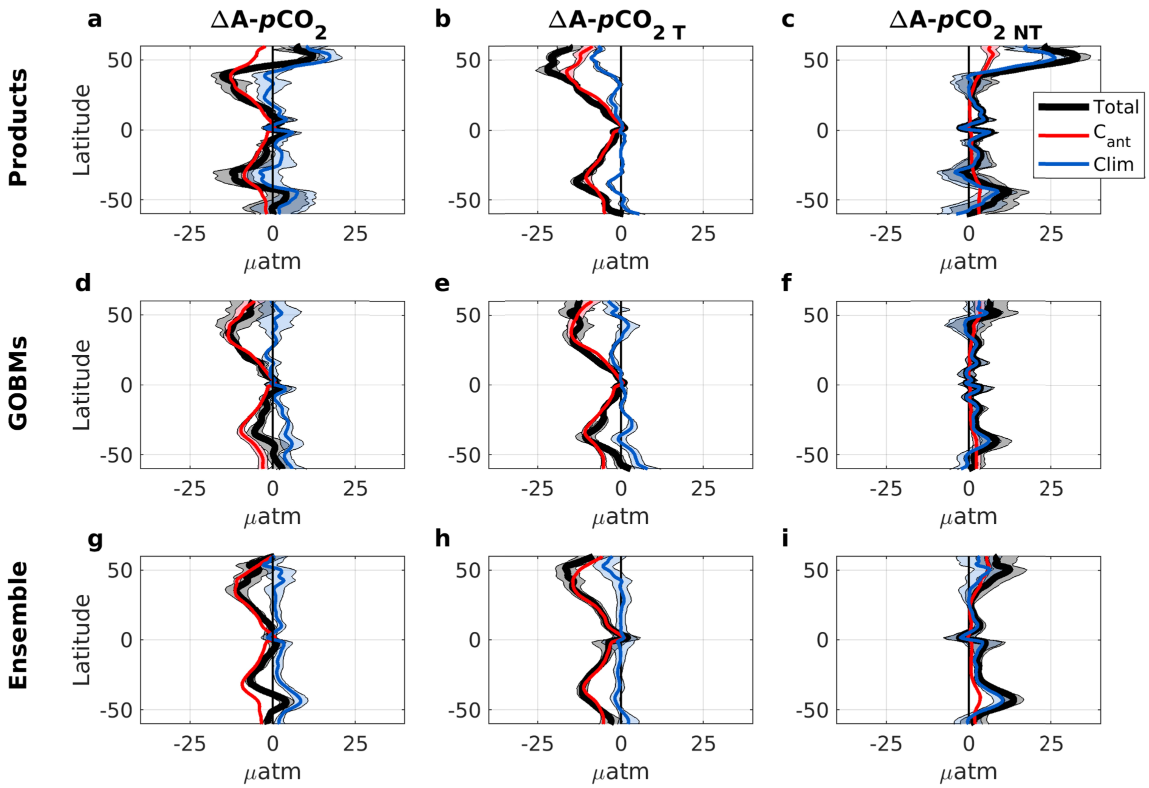

Fig. 10: Mean change in the seasonal cycle amplitude (winter minus summer) of pCO_2 and its thermal (T) and nonthermal (NT) components from the period 1985-1989 to the period 2014-2018. Changes are broken down into the total change and the portion of the change attributed to the accumulation of anthropogenic carbon (C_{ant}) versus climate (Clim: changes to the ocean physical or biogeochemical state caused by anthropogenic climate change). The top, middle, and bottom rows show the ensemble mean results for the three pCO_2 products, the eleven GOBMs listed in **Table 3**, and the CESM2 large ensemble, respectively. Shading reflects the standard deviation across the pCO_2 products, GOBMs, and ensemble members. Seasons are defined as JFM and JAS.

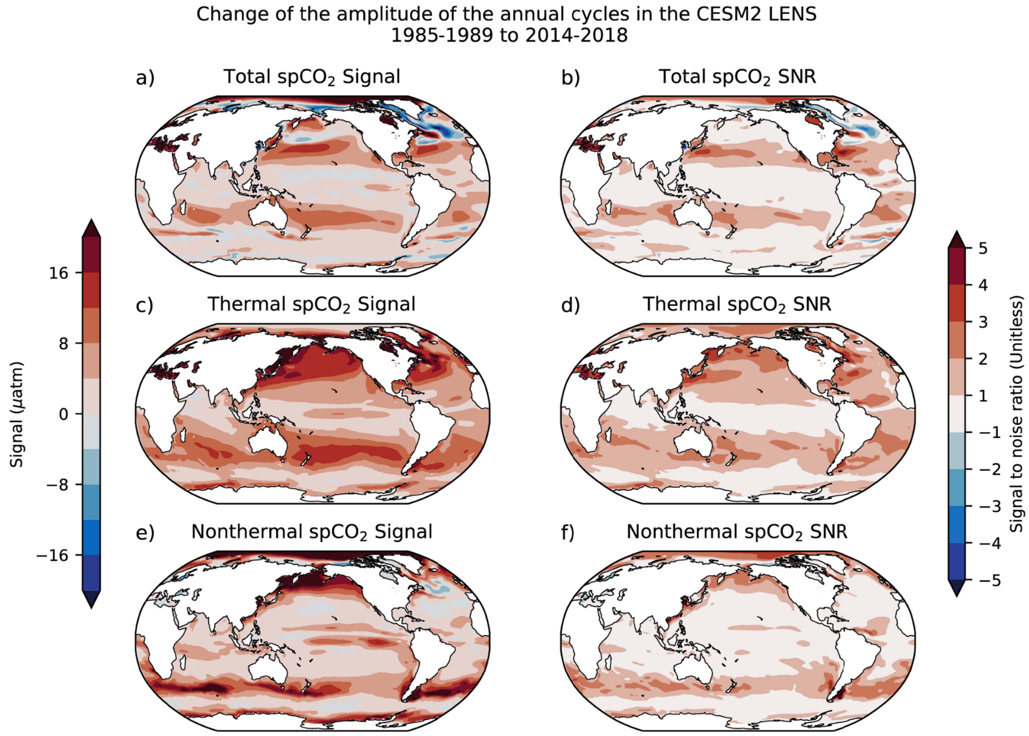

Fig. 11: Multi-decadal changes in pCO_2 seasonality between 1985-1989 and 2014-2018 (left column) and signal-to-noise ratio (SNR) maps for pCO_2 seasonality changes between 1985-1989 and 2014-2018 (right column). For each case, the seasonal amplitude is defined as the absolute value of the difference between JFM and JAS averages of pCO_2 in the model, such that negative values indicate decreasing amplitude. (a) the full decadal change in pCO_2 seasonal amplitude, (b) the SNR for the full pCO_2 signal, (c) the absolute value of the change in the thermal component of pCO_2 seasonal amplitude, (d) the SNR for the thermal component change, (e) the absolute value of the change in the nonthermal component, and (f) the SNR for the nonthermal component. All fields are from the CESM2 large ensemble (50 members). For each ensemble member, the change in the amplitude of the annual cycle was measured by (i) detrending the 1985-2018 time series by subtracting a quadratic polynomial fit, (ii) calculating the annual cycle strength as the absolute value of the JFM-JAS difference in pCO_2 for each year, (iii) averaging the five yearly values for each period, and (iv) subtracting the average over the earlier period from the average over the later period. For the full pCO_2 seasonal cycle, (i) the signal is defined as the ensemble mean change, and (ii) the

noise as the ensemble standard deviation, and (iii) the SNR indicates the confidence levels for emergence. This is done analogously for the thermal component of seasonality changes for (iv) the signal, (v) the noise, and (vi) the confidence intervals for emergence. Likewise for the nonthermal component, (vii) the signal, (viii) the noise, and (ix) the confidence intervals for emergence. Absolute magnitudes are chosen to emphasize the strength of the signal, so that the thermal and nonthermal fields in the left column do not necessarily sum to the total $p\mathrm{CO_2}$ signal. The decomposition of the thermal and nonthermal components of the $p\mathrm{CO_2}$ seasonal cycle is described in the Appendix.

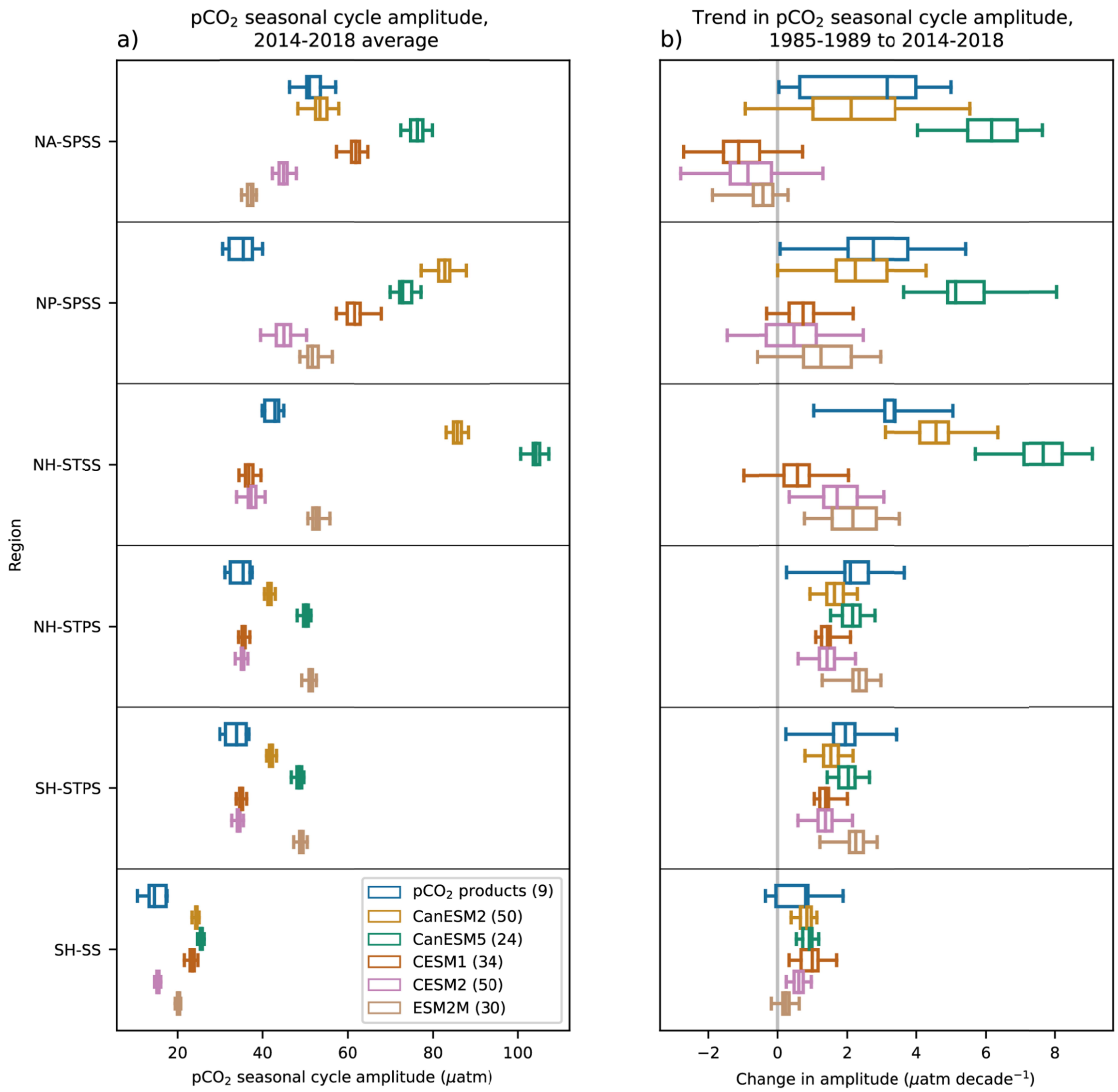

Fig. 12: Box plots of the absolute amplitude of the sea surface pCO_2 seasonal cycle for the period 2014-2018 (left) and the change in the amplitude of the pCO_2 seasonal cycle between 1985-1989 and 2014-2018 (right) based on pCO_2 products (blue) and five large ensemble experiments. For the large ensemble experiments, the number of ensemble members used for each model is shown in parentheses in the legend. The seasonal cycle amplitude is calculated as the absolute value of biome-averaged winter-minus-summer differences (JFM-JAS and JAS-JFM for the Northern and Southern Hemisphere, respectively). The boxes show the values between the first quartile (25%) and the third quartile (75%) with a line at the median (50%), with the whiskers indicating the minimum and maximum values. Note that for the pCO_2 products, the uncertainty range reflects uncertainty between the available nine

observational pCO_2 products, whereas the uncertainty range for the large ensemble simulations indicates natural climate variability as simulated by each model. For each ensemble member and data product, the change of the amplitude of the seasonal cycle for each region was measured by (i) detrending the 1985-2018 time series by subtracting a quadratic polynomial fit, (ii) calculating the seasonal cycle amplitude as the winter-minus-summer pCO_2 values for each year, (iii) averaging the five yearly values for each period, (iv) subtracting the earlier period average from the latter, and (v) calculating the spatial mean with latitude weighting. The amplitude of the seasonal cycle in 1985-1989 was obtained in step (iii). For each biome the sequencing of the colors is identical to the sequencing in the legend.

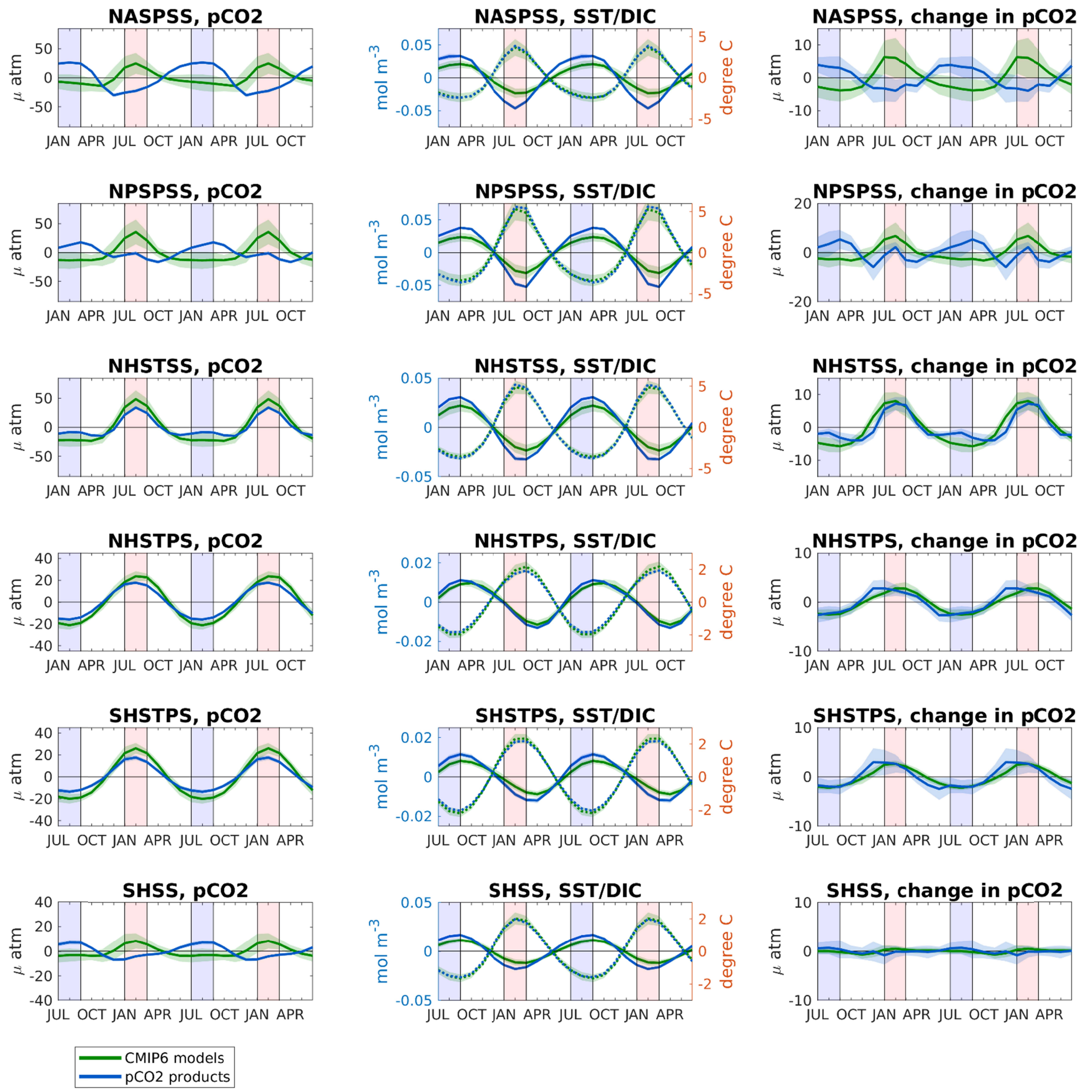

Fig. 13: Same as **Fig. 4** but with CMIP6 models as listed in **Table 6.** Note that the climatologies for pCO_2 (left column) and both DIC and SST (middle column) are taken over the years 2010-2014 (last five years of the CMIP6 historical simulations) and that the change in pCO_2 seasonality (right column) is calculated as the difference between 2010-2014 and 1985-1989.

Seasonal variability of the surface ocean carbon cycle: a synthesis

Supplementary Materials

Draft: April 3rd 2023

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† principal scientific contribution

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Surface DIC products associated with pCO$_2$ products

Here we provide more details on the pCO$_2$/TA products that provide time-varying surface DIC. These have been provided for CMEMS-LSCE, OceanSODA-ETHZ, and JMAMLR.

For CMEMS-LSCE, surface ocean DIC is calculated by using the CO2SYS speciation software (Lewis & Wallace, 1998; Van Heuven et al., 2011) given the reconstructions of pCO$_2$ and TA, nutrient concentrations (silicate, nitrate, phosphate), physical variables (SST and SSS), and dissociation constants. Total dissociation constants follow the best practices of (Dickson, 2010), wherein K_1 and K_2 are from Lueker et al. (2000). K_{HSO4} is from Dickson et al. (1990), and the formulation of boron to salinity ratio is from Uppstrom (1974). Details of the algorithms and derivations are documented in Chau et al. (2022). TA is derived from LIAR (Carter et al., 2018) - an approach of multiple linear regressions.

For OceanSODA-ETHZ, TA is (equivalent to the sea surface pCO$_2$) estimated using ensembles of two-step cluster-regression approaches, using K-means clustering for the first step, and a combination of neural networks, gradient-boosted trees and support vector regression for the second step (Gregor & Gruber, 2021). K_1 and K_2 are from the Dickson and Millero (1987) refit of Mehrbach et al. (1973), as these constants had the lowest error for the pCO$_2$-TA pairing (Raimondi et al., 2019). The K_{HSO4} and boron-salinity ratios are consistent with the CMEMS-LSCE approach.

For the JMAMLR product, salinity-normalized DIC (nDIC) is calculated by coupling each set of pCO$_2$, SST and SSS in SOCATv2019 (Bakker et al., 2016) with monthly fields of surface ocean TA expressed as a function of sea surface dynamic height (SSDH) and SSS that was built on GLODAPv2.2019 (Olsen et al., 2019; Takatani et al., 2014). The dissociation constants used are those recommended in the best practices of Dickson (2010). They are then fitted by multiple linear regressions for respective ocean domains with explanatory variables such as SST, SSS, SSDH, chlorophyll, mixed layer depth and year of measurements to account for the trend of DIC increase due to anthropogenic CO_2 uptake. Monthly fields of surface ocean nDIC are derived by combining these empirical expressions of nDIC with data sets of these explanatory variables derived from satellite measurements and an ocean data assimilation (Iida et al., 2021).

Three Dimensional DIC climatologies

Here we provide a brief overview of the three-dimensional DIC climatologies used to assess GOBM representation of vertical gradients in DIC. The two climatologies described below are MOBO-DIC and NNGv2LDEO, and they are both independent of the surface DIC products that are directly associated with the surface $p\mathrm{CO_2}$ products described above.

An interior DIC climatology DP is provided from the Mapped Observation-Based Oceanic DIC (MOBO-DIC) product by Keppler et al. (2020a; 2020b). MOBO-DIC is a machine-learning-based approach, and is built on the same 2-step neural network method that has been used previously to reconstruct surface ocean $p\mathrm{CO_2}$ for the SOM-FFN product by Landschützer et al. (2016) and adjusted to resolve DIC fields in the interior ocean. This two-step cluster-regression approach first divides the ocean into clusters using self-organizing maps (SOM), and then runs a feed-forward network (FFN) in each of the SOM-clusters. During the FFN step, this version of MOBO-DIC uses mapped observation-based temperature and salinity fields from the Argo program (Roemmich & Gilson, 2009) together with climatological nutrient and oxygen fields from the World Ocean Atlas (WOA18; *(Garcia et al., 2019)*) to obtain the statistical relationships between these predictor data and interior ocean DIC measurements from the GLODAPv2019 database (Olsen et al., 2019). These relationships are then applied to reconstruct gap-filled maps of the interior oceanic DIC. The differences between MOBO-DIC and the original SOM-FFN approach include that the target variable to be mapped is DIC (compared to $p\mathrm{CO_2}$ in SOM-FFN), the fields have an additional dimension (depth), and different predictors are used due to data availability and different processes in the water column relative to the surface. In addition, this version of MOBO-DIC only resolves a monthly climatology (compared to monthly resolution in SOM-FFN). As a result of these differences, the structure of the networks differs in MOBO-DIC, with fewer clusters in the SOM-step, and fewer neurons in the FFN step. More information on the method is provided in Keppler et all (2020a). This MOBO-DIC monthly climatology is at 1° horizontal resolution on 28 depth levels (2.5-2000 m), and is based on data from 2004 through 2017.

We also use the NNGv2LDEO monthly climatology of interior DIC by Broullón et al. (2020). This DIC product is based on a two-layer FFN neural network, that utilizes physical and biogeochemical predictor data from the World Ocean Atlas (WOA13; Garcia et al., 2013; Locarnini et al., 2013; Zweng et al., 2019), as well as information on the depth, horizontal location, and year of the measurement, to reconstruct gap-filled maps of the interior oceanic DIC. The relationship from predictors and DIC measurements is established through a combination of observation-based DIC measurements from GLDAPv2.2019 (Olsen et al., 2019) and DIC obtained from pCO2 from the Lamont Doherty Earth Observatory (LDEO) database (Takahashi et al., 2017), combined with TA from the NNGv2 neural network of Broullón et al. (2019). These NNGv2LDEO DIC fields are at 1° horizontal resolution, on 102 depth levels (0–5500 m), where the upper 1500 m resolve a monthly climatology and below 1500 m it is at annual resolution; the data are centered around the year 1995.

Attribution of discrepancies in the pCO$_2$ seasonal cycle phase and amplitude

In the main text section describing climatological pCO$_2$ seasonal cycle drivers, we applied the method of Fassbender et al. (2022), which is a modified version of the framework originally developed by Takahashi et al. (1993; 2002), where for each grid point local temperature and pCO$_2$ are used as follows to define the thermal (pCO$_{2\ T}$) and nonthermal (pCO$_{2\ NT}$) components of pCO$_2$ seasonal variability:

$$pCO_{2\,T} = pCO_{2\,am} * exp[0.0423\,(T_{mm} - T_{am})] \quad (1)$$

$$pCO_{2\,NT} = pCO_{2\,mm} * exp[0.0423\,(T_{am} - T_{mm})] \quad (2)$$

Within this approach the subscripts *am* and *mm* represent annual means and monthly means, respectively. However, one of the limitations of the method of Takahashi et al. (1993; 2002) is that the two components in (1) and (2) do not sum to reproduce the full pCO$_2$ seasonal cycle (e.g., $pCO_{2\,mm} \neq pCO_{2\,T} + pCO_{2\,NT} - pCO_{2\,am}$). This is because the thermal sensitivity of pCO_2 (expressed with a factor of 0.0423/°K in the equations above) in fact varies slightly with background chemistry (Wanninkhof et al., 1999).

In this study, we use the alternative approach of Fassbender et al. (2022), where an important focus of the analysis is to identify asymmetries in seasonal pCO_2 variations. For this case, rather than working with an annual mean pCO_2 to characterize asymmetries, one defines a neutral pCO_2 with respect to the annual cycle as being the pCO_2 one would obtain using annual means of its drivers (T, S, DIC, TA, PO_4, and SiO_4), which reflects the mean pCO_2 if pCO_2 were to respond linearly to the seasonal variability of its drivers. With this in mind, $pCO_{2\,AM}$ is given by:

$$pCO_{2\,AM} = f\left(\overline{T}, \overline{S}, \overline{DIC}, \overline{TA}, \overline{PO_4}, \overline{SIO_4}\right) \quad (3)$$

where the function f() represents a carbon system calculator. The time-varying (monthly mean) thermally-driven pCO_2 component can be identified using the same approach but by using monthly varying output temperature for the carbonate system calculator:

$$pCO_{2\,T\,FASS} = f\left(T_{mm}, \overline{S}, \overline{DIC}, \overline{TA}, \overline{PO_4}, \overline{SIO_4}\right) \quad (4)$$

The thermal pCO_2 component seasonal cycle anomaly is then determined as:

$$pCO_{2\,T_{anom}} = pCO_{2\,T\,FASS} - pCO_{2\,AM} \quad (5)$$

making it possible to calculate the nonthermal component by difference:

$$pCO_{2\,NT\,FASS} = pCO_2 - pCO_{2\,T_{anom}} \quad (6)$$

These definitions for thermal- and nonthermal decomposition in Equations (5)-(6), which are applied in **Fig. 6**, will prove to be important to our attribution of decadal changes in pCO_2 seasonality, to identify whether decadal changes project differently onto summer and winter.

Attribution of decadal changes in the pCO_2 seasonal cycle

The goal of the attribution analysis is to isolate the direct (C_{ant}) and indirect (climate change; Clim) influences of C_{ant} on pCO$_2$ seasonal cycle changes between the time periods of interest via offline calculations. Due to the short duration over which this method is applied relative to what it was originally designed for (i.e., >100-year time scales), both the C_{ant} and Clim components of the total pCO$_2$ seasonal cycle change may contain non-trivial interference from natural variability, which we attempt to constrain with the CESM2 LE analysis in **Sections 3.3.1** and **3.3.2**. Here we provide further description of the method of Fassbender et al. (2022) to facilitate understanding of the attribution analysis for decadal changes; however, readers are encouraged to review the original publication for complete methodological details.

To perform the attribution analysis, we focus on isolating the direct and indirect impacts of C_{ant} on thermal and nonthermal pCO$_2$ component seasonal cycle changes. Since these calculations are performed offline, the method requires an initial step of reconstructing the model pCO$_2$ values. A Taylor series decomposition was used previously in **Section 3.2.2** to compare discrepancies between the GOBM and pCO$_2$ product seasonal pCO$_2$ variability resulting from each of its drivers. A similar approach is used here for attribution following the method of Fassbender et al. (2022).

Changes in surface ocean pCO$_2$ with time can be expressed as the sum of temporal changes in the various pCO$_2$ drivers multiplied by the sensitivity of pCO$_2$ to that driver:

$$\frac{dpCO_2}{dt} = \left(\frac{\partial pCO_2}{\partial DIC}\right)\left(\frac{\partial DIC}{\partial t}\right) + \left(\frac{\partial pCO_2}{\partial TA}\right)\left(\frac{\partial TA}{\partial t}\right) + \left(\frac{\partial pCO_2}{\partial SSS}\right)\left(\frac{\partial SSS}{\partial t}\right) + \left(\frac{\partial pCO_2}{\partial SST}\right)\left(\frac{\partial SST}{\partial t}\right) \quad (7)$$

The first three terms on the right-hand side reflect the nonthermal pCO$_2$ drivers and the last term on the right-hand side reflects the thermal pCO$_2$ driver. For the thermal sensitivity, we use a carbonate system calculator, as described in the preceding section, to isolate the monthly thermal pCO$_2$ component anomalies (pCO$_{2\ \mathrm{Tanom}}$) relative to pCO$_{2\ \mathrm{AM}}$ at each grid point during each year of 1985-1989 and 2014-2018. For the remaining sensitivity terms, we rely on familiar relative sensitivity terms including the Revelle Factor (RF; (Bolin & Eriksson, 1959;

Broecker et al., 1979)), Alkalinity Factor (AF; (Takahashi et al., 1993)), and Salinity Factor (Takahashi et al., 1993), which all take the same form, with an example for the AF given here:

$$AF = \left(\frac{\Delta pCO_2}{\overline{\overline{pCO_2}}}\right) \times \left(\frac{\Delta TA}{\overline{\overline{TA}}}\right)^{-1} \quad (8)$$

Where ΔpCO_2 reflects the change imposed by a small TA perturbation (ΔTA) to initial TA and pCO_2 values with all other parameters held constant. The RF is provided as direct output from the carbonate system calculator while the AF and SF are calculated using the carbonate system calculator by independently imposing small TA and salinity perturbations (±0.01 μmol/kg TA and ±0.0001, respectively) for each grid point and month.

Monthly anomalies (Δ) in DIC, TA and SSS, relative to their annual mean values, can then be multiplied by their corresponding relative sensitivity factors to estimate the relative change in pCO_2. These relative changes in pCO_2 are then summed and multiplied by $pCO_{2\ AM}$ to estimate the corresponding monthly nonthermal pCO_2 component anomalies ($pCO_{2\ NT}$) relative to $pCO_{2\ AM}$ at each grid point during each year of 1985-1989 and 2014-2018, as follows:

$$pCO_{2\,NT_{anom}} = pCO_{2\,AM} \times \left(\left[RF \times \left(\frac{\Delta DIC}{\overline{\overline{DIC}}}\right)\right] + \left[AF \times \left(\frac{\Delta TA}{\overline{\overline{TA}}}\right)\right] + \left[SF \times \left(\frac{\Delta SSS}{\overline{\overline{SSS}}}\right)\right]\right) \quad (9)$$

Summing the thermal and nonthermal component anomalies with $pCO_{2\ AM}$ yields the total pCO_2 value consistent with the model pCO_2 output for the time periods of interest. The offline reconstruction of the model pCO_2 field is important in later methodological steps when we difference a suite of calculated values that are subject to the same offline estimation uncertainties.

To isolate the influence of C_{ant} and Clim on $pCO_{2\ NT}$, we perform the same calculations outlined above but use the climatological monthly mean RF and AF values from the 1985-1989 period in each year of the 2014-2018 calculations. This holds the sensitivity of pCO_2 to the nonthermal carbonate system drivers constant at the 1980s level, providing an estimate of the indirect impact of C_{ant} (i.e., Clim) on the nonthermal pCO_2 component ($pCO_{2\ NTanom\text{-}Clim}$).

The difference between pCO_2 $_{NTanom}$ and pCO_2 $_{NTanom-Clim}$ yields an estimate of the direct impact of C_{ant} on the nonthermal pCO_2 component.

$$pCO_{2\,NT_{anom}-C_{ant}} = pCO_{2\,NT_{anom}} - pCO_{2\,NT_{anom}-Clim} \quad (10)$$

Similarly, to isolate the influence of C_{ant} and Clim on $pCO_{2\ T}$, we use the same carbonate system calculator approach described in the previous section but apply the climatological $pCO_{2\ AM}$ value from the 1985-1989 period ($pCO_{2\ AM80s}$) in each year of the 2014-2018 calculations as input values rather than annual mean DIC.

$$pCO_{2\,T\,FASS80s} = f\left(SST_{mm}, \overline{SSS}, pCO_{2\,AM80s}, \overline{TA}, \overline{PO_4}, \overline{SIO_4}\right) \quad (11)$$

This holds the thermal sensitivity of pCO_2 constant at the 1980s level providing an estimate of the indirect impact of C_{ant} (i.e., Clim) on the thermal pCO_2 component ($pCO_{2\ Tanom-Clim}$). We then subtract $pCO_{2\ AM80s}$ to yield the thermal term anomalies for each year of the 2014-2018 period.

$$pCO_{2\,T_{anom}-Clim} = pCO_{2\,T\,FASS80s} - pCO_{2\,AM80s} \quad (12)$$

The difference between $pCO_{2\ Tanom}$ and $pCO_{2\ Tanom-Clim}$ yields an estimate of the direct impact of C_{ant} on the thermal pCO_2 component.

$$pCO_{2\,T_{anom}-C_{ant}} = pCO_{2\,T_{anom}} - pCO_{2\,T_{anom}-Clim} \quad (13)$$

Summing the thermal and nonthermal anomalies derived using time-varying and constant sensitivity terms with $pCO_{2\ AM}$ yields the total pCO_2 and $pCO_{2\ Clim}$ values, respectively, which can be differenced to isolate the C_{ant} contribution:

$$pCO_{2\,C_{ant}} = pCO_2 - pCO_{2\,Clim} \quad (14)$$

With the Clim and C_{ant} components of total pCO_2 differentiated relative to the 1980s reference period, we can assess attribution for the changes in seasonal cycle characteristics in the thermal, nonthermal, and full pCO_2 values for the 2014-2018 period.

Fig. S1: Time series of the net amplitude (annual maximum minus minimum) of monthly CO_2 fluxes spatially integrated over the six aggregated biomes shown in **Fig. 1**. The GOBMs (green) and $p$$CO_2$ products (blue) are shown for their product-mean (bold line) and 1-std of their spread amongst individual products (shaded).

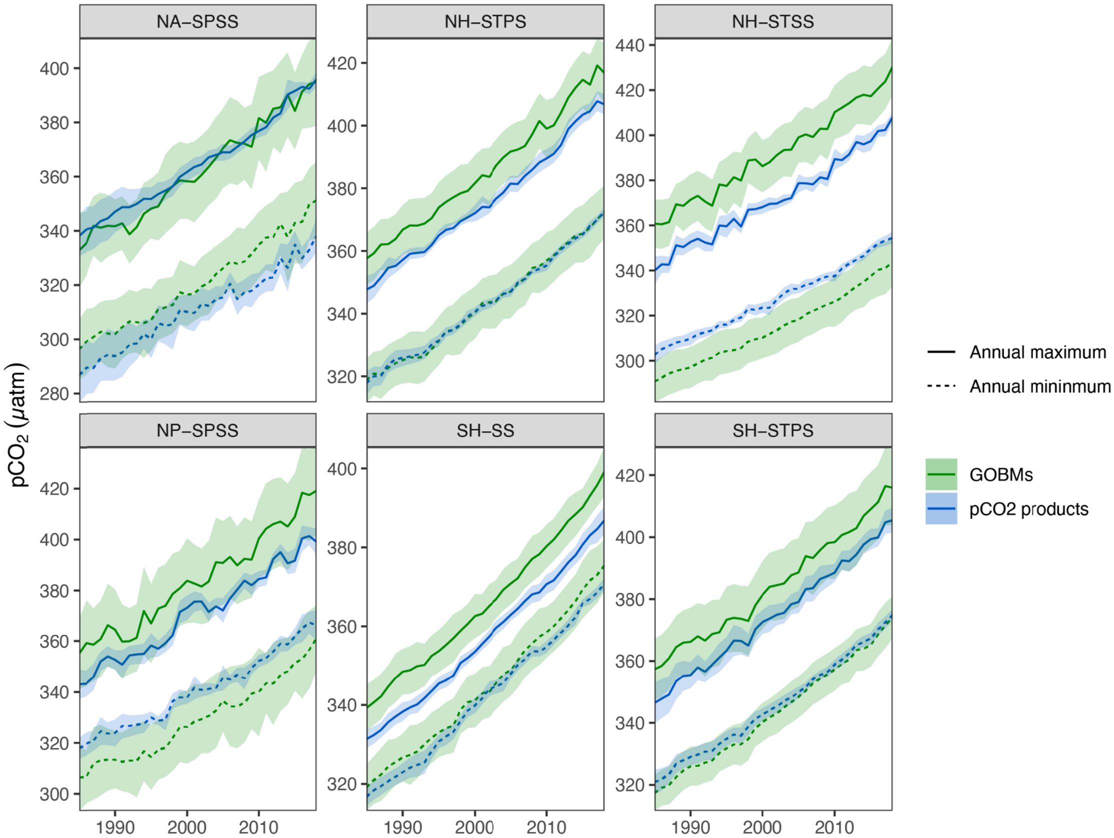

Fig. S2: Time series of pCO_2 averaged over biomes showing annual maximum and annual minimum values, both for GOBMs and for pCO_2 products. Lines indicate the mean and shading indicates the one standard deviation range for each ensemble of estimates.

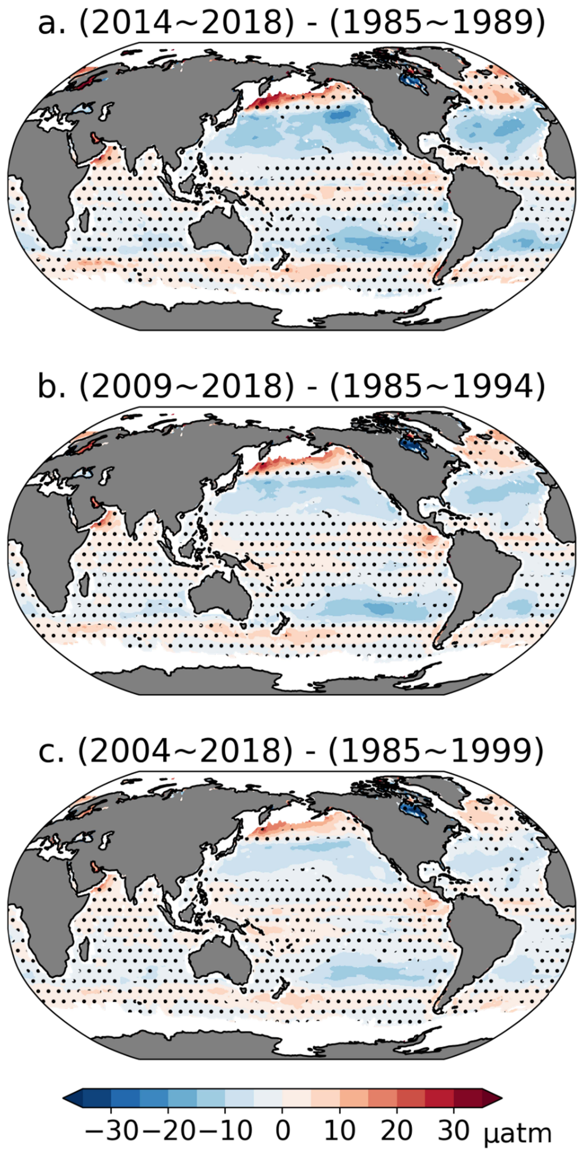

Fig. S3: Evaluation of the sensitivity of the decadal changes in pCO_2 seasonal amplitude for the pCO_2 products using (a) five-year climatologies, (b) 10-year climatologies, and (c) 15-year climatologies. Panel (a) is the same field shown in **Fig. 3a**.

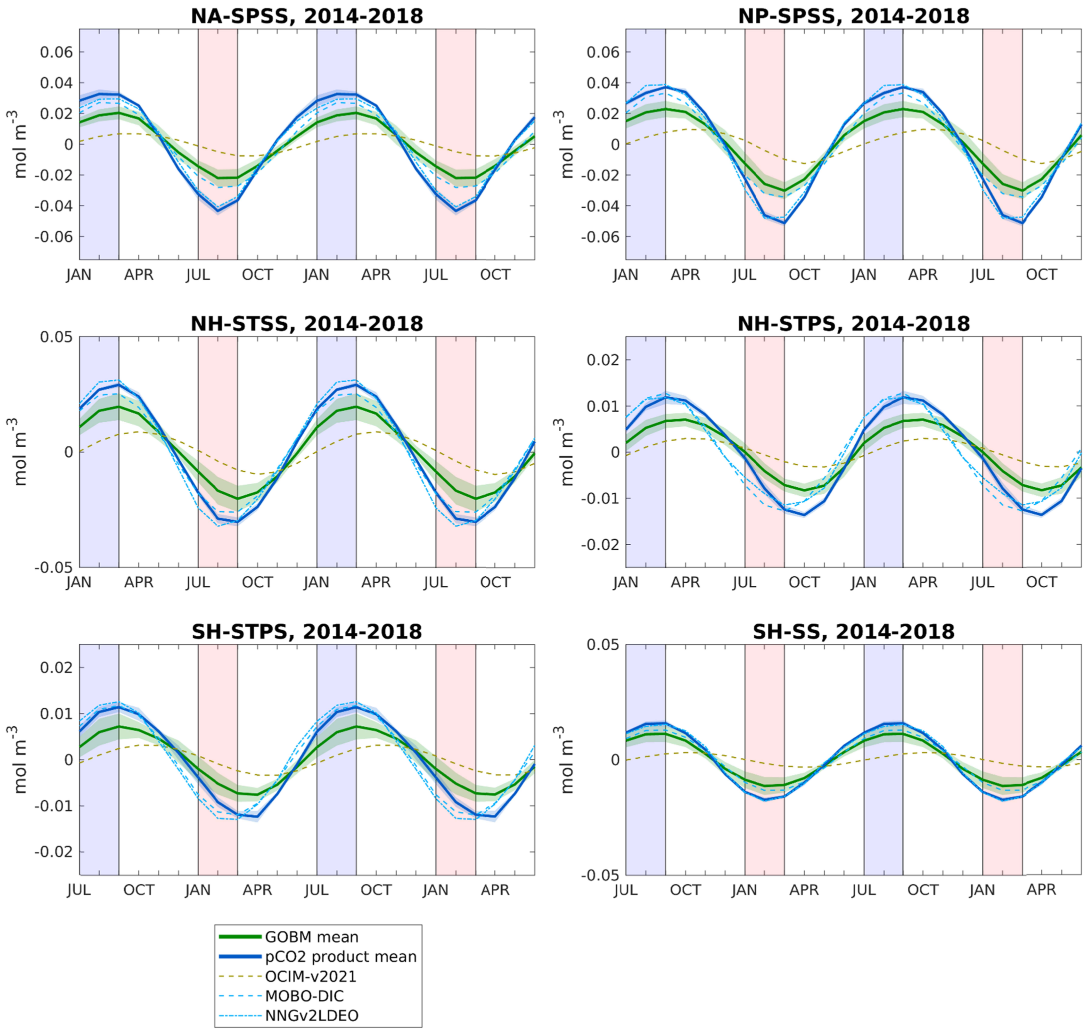

Fig. S4: Climatological seasonal cycle anomalies for 2014-2018 DIC over the six aggregated biomes for GOBMs (green), pCO_2 products (blue), for OCIM (brown, dashed), and for the two DIC-climatologies MOBO-DIC (lightblue, dashed) and NNGv2LDEO (lightblue, dash-dotted). The biome names as defined in **Table 1** and **Fig. 1** are given in each panel title. Ensemble means for GOBMs and pCO_2 products are shown as thick lines while the shading indicates the standard deviation around the mean. Note that the DIC climatologies are referenced to time periods 2004 through 2017 for MOBO-DIC and 1995 for NNGv2LDEO different from the averaging period used for GOBMs and pCO_2 products (2014-2018). Also note that, due to differences in spatial data coverage, the inclusion of MOBO-DIC and NNGv2LDEO entails that the areas.

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