OCEAN BIOGEOCHEMICAL RESPONSES TO FORCINGS ON WEEKLY TO CENTENNIAL TIMESCALES

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To my parents Carmen and Antonio.
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0.2 Abstract

Anthropogenic carbon emissions are altering the Earth’s climate and oceans. Sea-water is a major sink for carbon dioxide (CO$_2$), and the strength of this sink - about one third of human emissions - depends largely on the oceanic carbon cycle. This cycle is controlled by complex interactions between oceanic currents, mixing, temperature, primary productivity and carbonate chemistry. The intricacy of the carbon cycle poses a challenge for determining the present and future partitioning of carbon between the atmospheric, oceanic and terrestrial reservoirs. Observational, theoretical and numerical modeling efforts have been undergoing to elucidate the present-day processes that increase/decrease the carbon dioxide content in the ocean. These efforts have made it possible to estimate the Earth’s carbon budget and have informed policy makers about the urgency of reducing carbon emissions and protecting marine ecosystems. Yet, the future impacts of climate change on the carbon cycle need to be further refined to improve the accuracy of climate and marine ecosystem projections. In this context, this thesis contributes to the understanding of two components of the carbon cycle at different spatiotemporal scales. In Part I, the mechanisms of the future changes in seasonal and interannual variability of the global ocean’s partial pressure of CO$_2$ (pCO$_2$) are examined. In Part II, an offline high-resolution advection-diffusion model is developed and coupled to a marine ecosystem model based on the Marine Biogeochemistry Library (MARBL). This model is used to study the local effects of tropical cyclones on the biological activity of the Kuroshio region.

In Part I, several fully coupled atmosphere-ocean-biogeochemistry models from the Coupled Model Intercomparison Project 5 (CMIP5), under the high emission scenario pathway 8.5 (RCP8.5), are used to answer the following questions: (1) what changes will the future temporal variability of the oceanic partial pressure of CO$_2$ (pCO$_2$) experience?, and (2) what are the mechanisms driving those changes? These questions are answered for two different time-scales: the annual seasonal cycle (Chapter 2) and interannual scales (Chapter 3).
The global simulations reveal that the seasonal amplitude (climatological maximum-minus-minimum) of upper ocean pCO$_2$ will increase by a factor of 1.5 to 3 times by 2080-2100 compared to 2006-2026 for the RCP8.5 emission scenario. The global interannual variability of the sea-surface pCO$_2$ (calculated as $1\sigma$) will increase by $\sim 64 \pm 20\%$ by 2045-2095 relative to the beginning of the industrial revolution. To unravel the mechanisms behind the amplification we use a complete analytical Taylor expansion of pCO$_2$ variability in terms of its four drivers: dissolved inorganic carbon (DIC), total alkalinity (TA), temperature (T) and salinity (S). The linear approximation allows a separation of the effect of the buffering capacity of the ocean, from the drivers induced by physical and biological phenomena. This study shows that a decrease in buffering capacity is the main cause of pCO$_2$ variability amplification, but not the only one. In regions dominated by T, the amplification is a consequence of mean CO$_2$ build up. Further, a decrease in DIC variability counteracts the seasonal and interannual amplifications. The intra-model differences in pCO$_2$ variability are also characterized. For example, in the equatorial Pacific, at interannual scales, some models feature an amplification of the pCO$_2$ variability dominated by T, while others show a decrease in pCO$_2$ variability dominated by DIC.

In Part II of this thesis, an offline marine ecosystem model is described (Chapter 3). The model is forced with ocean currents from the high-resolution Community Earth System Model 1.2.2., which features several nutrients, phytoplankton groups, zooplankton, dissolved organic matter and particulate matter. In Chapter 4, the following questions are studied: (1) How do tropical cyclones (TCs) affect nutrients and primary productivity on the Kuroshio region? and (2) what are some factors that control the magnitude of the TC-induced anomalies? Surface chlorophyll blooms due to TCs have been widely detected with satellite observations. But the phytoplankton’s response at depth is still not well understood. The results of this chapter show that a TC encountering a cyclonic-eddy largely promotes upwelling of nutrients and subsequent increase in subsurface primary productivity. However, the impact at the surface is negligible. Initially, the TC induces a negative chlorophyll anomaly, due to vertical advection of water from below the euphotic zone. About a week after the TC, an increase in new primary productivity is observed. This suggests that satellites may
be missing these TC-induced subsurface anomalies, which could be a mechanism to sustain life in regions with deep nutriclines.
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Since the industrial revolution the carbon dioxide (CO$_2$) anthropogenic emissions have risen continuously. It is estimated that 555 ± 85 Pg of carbon were released between 1750-2011 into the atmosphere (IPCC, 2014).

As first noted by Tyndall (1861), a fraction of the Earth’s infrared radiation is absorbed and scattered by the atmospheric CO$_2$. This energy makes the atmosphere’s molecules -including CO$_2$ itself- vibrate and produce heat, thus creating a greenhouse-like effect. Thereby, -as first predicted by Arrhenius (1896)- the anthropogenic CO$_2$ emissions have increased the atmospheric temperature by more than 1°C since 1880 (IPCC, 2014). Global warming also affects the oceans; a review by Chao and Feng (2018) highlights that since 1880 the sea level has risen by $\approx$ 20 cm, its temperature has increased at $>0.1$°C per decade, and the Arctic sea ice has decreased while the Antarctic sea ice has overall increased with some abnormal years of extreme low ice coverage. It is widely known - with different levels of confidence - that climate change will likely cause more flooding and draughts (Giorgi et al., 2018), and may alter the intensity of weather events, such as tropical storms (Chu et al., 2020). These changes will mainly affect vulnerable communities ill prepared for natural disasters.

Global warming is in part mitigated by the ocean, because a large portion of anthropogenic CO$_2$
dissociates in sea water. However, the ocean uptake of CO$_2$ has caused the sea water pH to decline by 0.1 units below the pre-industrial levels (IPCC, 2014). The drop in pH - or ocean acidification - has harmful consequences for calcifying organisms, hence referred as "the other CO$_2$ problem" (Doney et al., 2009b). In summary, human carbon emissions have a series of negative consequences for ecosystems and human life. To develop effective policies that tackle these global issues, it is pressing to improve the accuracy of present and future carbon budgets and climate projections.

An important component of the global carbon inventory is the ocean-atmosphere flux of CO$_2$, which partially controls the atmospheric levels of CO$_2$. Between 2008-2017, the ocean absorbed $\approx 2.4 \pm 0.5$ GtC yr$^{-1}$ (Le Quéré et al., 2018), and this number could be even higher ($2.9 \pm 0.5$ GtC yr$^{-1}$) according to a recent study (Watson et al., 2020). Still, the exact amount of oceanic uptake remains unknown in part due to sparsity of data and in part due to the large spatiotemporal variability of the ocean-atmosphere CO$_2$ flux. This flux is determined by the solubility of CO$_2$ in water, the gas transfer coefficient (dependent on wind speed), and the partial pressure of CO$_2$ (pCO$_2$) difference between the atmosphere and ocean. The direction of the flux depends exclusively on the difference of partial pressures, and since the atmosphere is fairly well equilibrated, the flux is mostly determined by the ocean’s pCO$_2$.

In this context, understanding the mechanisms modulating the ocean’s pCO$_2$ variability at different timescales and their future evolution is of importance to improve the accuracy of carbon budgets and the projections of the seawater carbonate chemistry.

The variability of oceanic pCO$_2$ is highly complex compared to the atmospheric one. It depends on intertwined physical, biological and chemical processes that alter the solubility and CO$_2$ concentration of the water. Oceanic CO$_2$ concentration depends on the total dissolved inorganic carbon (DIC), total alkalinity (TA), temperature (T) and salinity (S) and the solubility depends solely on T and S (at surface pressure). Hence, any process altering one of these components, has the potential to change the pCO$_2$. Temperature and salinity are controlled by precipitation, solar radiation and physical mixing, diffusion and advection of water. The DIC and TA, also depend on the oceanic currents and mixing, but they are further affected by biological processes, such as photosynthesis,
respiration and calcification. To add intricacy, the magnitude of the DIC effect on pCO\textsubscript{2} depends on the carbonate chemistry of the water.

All these mechanisms are sensitive to future changes, such as increased temperatures, enhanced ocean stratification and changes on circulation that could imprint on the carbon cycle by altering the spatial gradients of carbon, biological productivity and CO\textsubscript{2} solubility.

In the next section 1.1, I describe the main controlling factors of the ocean’s pCO\textsubscript{2} and their future response to climate change. In the final section 1.2, I give a detailed outline of this thesis.

1.1 Drivers of the ocean’s pCO\textsubscript{2}

The Carbonate System

When CO\textsubscript{2} gas enters the water it can remain as aqueous CO\textsubscript{2} (CO\textsubscript{2}(aq)) or it can react with water molecules to form carbonic acid H\textsubscript{2}CO\textsubscript{3}. Both forms - carbonic acid and aqueous carbon dioxide - are chemically identical, and referred to as [CO\textsubscript{2}] = [CO\textsubscript{2}(aq)] + [H\textsubscript{2}CO\textsubscript{3}] (Zeebe and Wolf-Gladrow, 2001). However, the carbonic acid can further dissociate into bicarbonate (HCO\textsubscript{3}\textsuperscript{−}) and carbonate (CO\textsubscript{3}\textsuperscript{2−}) ions mediated the dissociation constants - \(\kappa\textsubscript{1}\) and \(\kappa\textsubscript{2}\) - which depend on temperature and salinity.

\[
\text{CO}_2(aq) + H_2O \xrightleftharpoons{\kappa_1} HCO_3^- + H^+ \xrightleftharpoons{\kappa_2} CO_3^{2-} + 2H^+ \tag{1.1}
\]

Thus, it is useful to quantify the total dissolved inorganic carbon (DIC) as the sum of three carbonate species: aqueous CO\textsubscript{2}, bicarbonate (H\textsubscript{2}CO\textsubscript{3}) and carbonate (CO\textsubscript{3}\textsuperscript{2−}) ions. Another important quantity is the total alkalinity (TA), which is defined as the charge unbalance -or excess of bases- for the non-conservative ions.

\[
\begin{align*}
\text{DIC} &= [CO_2^{aq.}] + [CO_3^{2-}] + [HCO_3^-] \tag{1.2} \\
\text{TA} &= [HCO_3^-] + 2[CO_3^{2-}] + [B(OH)_4^-] - [H^+] + [OH^-]
\end{align*}
\]
In the alkalinity formulation usually the minor ions are disregarded. Only borate is kept, and it is considered proportional to salinity (Dickson et al., 2007).

The variables DIC, TA, pCO₂, pH, [HCO₃⁻] and [CO₃²⁻] plus T and S, determine the carbonate chemistry of the water. These variables are related through the Equations (1.1 and 1.3). Hence, knowing two carbonate parameters -plus T and S- is necessary to completely characterize the water’s carbonate chemistry. Ocean models frequently use DIC and TA, because they do not depend on pressure or temperature (Zeebe, 2012).

Any process altering DIC, TA, T and S will produce an effect on ocean pCO₂; from the large scale ocean circulation redistributing DIC from the surface to the deep ocean, to small scale eddies producing local changes in temperature and photosynthesis; the upshot of these mechanisms on pCO₂ depends on the spatiotemporal scale considered and their future impact is sensitive to climate change. In what follows I describe some of the mechanisms behind these variations and their future projections.

**Oceanic Buffering Capacity**

The processes represented by Eq. 1.1 give the ocean the capacity to buffer CO₂. The term "buffering capacity" was first introduced by Revelle and Suess (1956), and it indicates how much the pCO₂ changes by a given change in DIC (see Eq. 1.3). At current ocean chemical conditions, most of the DIC is in HCO₃⁻ form (89% at typical surface seawater conditions), about 10.5% is found as CO₃²⁻ and only 0.5% remains as CO₂ (see Figure 1.1); therefore the buffering capacity is largely controlled by the CO₃²⁻ capable of transforming CO₂ into bicarbonate, via the reaction:

$$CO₂ + H₂O + CO₃²⁻ \rightarrow 2HCO₃⁻$$  \hspace{1cm} (1.3)

In mathematical form, the buffering capacity is inversely related to the Revelle factor: R = ∂ln(pCO₂)/∂lnDIC. The greater the buffering capacity, the greater the pCO₂’s ability to resist changes in DIC. In the same fashion as the Revelle factor, it can be calculated the sensitiv-
Figure 1.1: 1985-2018 mean values of carbonate parameters. a) Bicarbonate ion (\(\text{HCO}_3^-\)), b) Carbonate ion (\(\text{CO}_3^{2-}\)) and c) Revelle Factor. The data corresponds to the observation-based neuronal-network interpolation from Gregor and Gruber (2020).

Future projections: As the ocean absorbs anthropogenic CO\(_2\), the ocean’s carbonate ion concentration will decrease. Hence, the ocean’s ability to absorb CO\(_2\) will diminish (Sabine et al., 2004), creating a positive feedback. Increasing pCO\(_2\) sensitivity to DIC and T is one of the main topics described in this thesis.

**Temperature:**

Usually, the pCO\(_2\) sensitivity to temperature is referred to a constant value, \(\partial \ln(\text{pCO}_2)/\partial T = 0.0423^\circ\text{C}^{-1}\) estimated by Takahashi et al. (1993). In other words, pCO\(_2\) changes by \(\approx 4\%\) for a 1 \(\circ\) C variation. The pCO\(_2\) depends on temperature directly through the solubility constant, but also indirectly through the dissociation constants for carbonate and bicarbonate ions (see Eq. (1.1)). The dissociation constants tend to increase with salinity and warmer temperature. As a result, CO\(_2\) is more dissociated in sea-water than in freshwater. An estimated 2/3 of the temperature dependence is due to the solubility sensitivity, and 1/3 due to the dissociation constants (Sarmiento...
and Gruber, 2006). About 70% of the salinity effect on pCO₂ is through the dissociation constants. The T sensitivity is further discussed in Chapter 2. Moreover, its explicit calculation can be found in the Appendix A. The explicit formulation gives similar values to 0.0423°C⁻¹ with minor regional variations.

Future projections: Based on the above calculations, 1°C of warming increases ocean pCO₂ by 10 - 20 ppm. Thereby, one could presuppose a large increase on pCO₂ due to global warming, resulting in a diminished ocean CO₂ sink and a positive global warming feedback (Houghton, 2007). However, the indirect effect of global warming on pCO₂ is far more complex, because temperature affects the ocean stratification, currents and biological activity.

**Ocean circulation and mixing:**

The ocean’s large scale overturning circulation of the upper 1000m facilitates the capture of anthropogenic CO₂ by subduction in the subtropics. This circulation redistributes nutrients and DIC, generating large vertical gradients of carbon. About 38000 Pg of carbon are stored in the ocean, but only 700-1000 PgC reside in the surface (Houghton, 2007). Nutrients are also more abundant in the intermediate and deep waters than in the surface. As a consequence, in some regions, vertical advection determines the surface’s photosynthesis and the CO₂ exchange with the atmosphere. This is the case in the equatorial Pacific, where the carbon, nutrients and cold temperatures are brought back to the surface by upwelling. In this region, the surface pCO₂ increases due to the advected DIC, since the DIC increase overpowers the increased primary productivity (due to nutrients) and the effect of reduced temperature on solubility.

Future projections: The interaction between ocean circulation and climate is highly complex. Changes in global temperature affect the ocean stratification, winds patterns and heat fluxes. Thus,
how the future global warming will alter advection and mixing of oceanic carbon, still remains a
source of debate. As an example, models project a weakening of the wind driven shallow over-
turning circulation, which would diminish upward mixing and upwelling of carbon; thus, enhancing
the oceanic CO$_2$ sink. However, it is not clear whether increasing anthropogenic carbon emissions
could revert the sink strength in the long term (DeVries et al., 2017). In the equatorial Pacific, the
ocean-atmosphere CO$_2$ flux varies at interannual timescales owing to El Niño Southern Oscillation.
However, the response of El Niño’s amplitude and frequency to global warming is not clear. This
response depends on the Walker circulation projected changes, which remain undetermined (Zhao
and Allen, 2019). Besides ocean circulation, other physical processes such as eddies and turbulent
vertical mixing can alter the pCO$_2$. The penetration of these processes below the mixed layer depth
determines how much CO$_2$ is mixed. A recent study found an increase of ocean stratification in re-
cent decades (1960-2018), which could have implications for marine productivity and carbon uptake
(Li et al., 2020). Enhanced stratification could sequester more CO$_2$ at the sea surface and prevent
the entrainment of nutrients from below the mixed layer depth. Both processes would diminish the
surface ocean’s uptake and limit the carbon export to the deeper ocean, creating a global warming
positive feedback.

**Biological activity:**

Mainly three biological processes alter the carbon dioxide content in the ocean: photosynthesis,
respiration and calcification. Photosynthesis decreases pCO$_2$ by converting DIC into organic mat-
ter and enhances alkalinity by consuming negative ions in the form of nutrients. In contrast,
biological respiration increases CO$_2$. Phytoplankton - organisms capable of photosynthesis- only
constitute 1-2% of the total planetary carbon biomass, but contribute to 40% of annual carbon
fixation (Falkowski, 1994). The phytoplankton’s carbon biomass is mostly consumed and reminer-
alized in the ocean’s surface, leaving 11-27% for export to the deep ocean, where it gets buried
into sediments (Henson et al., 2011, Bach et al., 2019, Basu and Mackey, 2018). The carbon ex-
port process is known as the biological carbon pump and it controls 70% of the pre-industrial DIC transfer from the surface to the deep ocean (Sarmiento and Gruber, 2006). The precipitation of calcium carbonate (CaCO$_3$) decreases DIC and TA, and increases CO$_2$, by the following reaction: $\text{Ca}^2+ + 2\text{HCO}_3^- \rightarrow \text{CaCO}_3 + \text{CO}_2 + \text{H}_2\text{O}$. Aragonite and calcite -two forms of CaCO$_3$ - dissolution reduces oceanic CO$_2$. However, calcifying phytoplankton also photosynthesize and respire. Thus, when these organisms are dissolved there is a double and opposite effect on CO$_2$. The net effect on CO$_2$ will depend on the organisms’ rates of photosynthesis, respiration and calcification. As examples, the coral reef flats are a source of CO$_2$ to the atmosphere, because their calcification and respiration rates are larger than the photosynthesis rate (Gattuso et al., 1995). The later is also the case in warm geological periods where the coccolithophores abundance increased CO$_2$ (Balch et al., 1992). However, on geological time scales, the CO$_2$ released due to calcification is compensated by sediment burial of CaCO$_3$ (Zeebe, 2012).

Future projections: As a consequence of oceanic warming, the global net primary productivity (NPP) is projected to decrease in the future, according to the Coupled Intercomparison Model Project phase 5 (CMIP5) models (Bopp et al., 2013) and to a lessen extent in CMIP6 (Kwiatkowski et al., 2020). The decrease in productivity is most pronounced in the tropics and the North Atlantic as a result of ocean stratification, warmer temperatures and acidification. In higher latitudes, the simulations show an increase in NPP due to reduced light and temperature limitations. However, local changes on the biological pump may depend largely on the ecosystem’s structure. For example, large size phytoplankton such as diatoms, could flourish under high CO$_2$ conditions, but smaller phytoplankton could adapt better to low nutrient conditions (Basu and Mackey, 2018). Other calcifying organisms - such as pteropods, coccolithophores and corals- will likely be negatively impacted by a decrease of CaCO$_3$ saturation (Zeebe et al., 2008, Doney et al., 2009a). Thus, the fate of the biological carbon pump remains uncertain.
1.2 Dissertation Outline

This thesis is divided in two parts, focusing on physical and biogeochemical processes that govern the ocean’s carbon cycle variability at different spatiotemporal scales. In the first part, the present-day carbonate chemistry drivers of the global ocean’s pCO$_2$ seasonal and interannual variability and their future amplification are examined. In the second part of this thesis, an offline marine ecosystem model is developed to understand the local effects of tropical cyclones on the ecosystem at the Kuroshio region between 20°N-36°N and 120°E-140°E. In Part I, a series of fully coupled ocean-atmosphere-biogeochemical models from CMIP5 are used to study the present drivers of pCO$_2$ variability (DIC, TA, T and S) and its future amplification in seasonal (Chapter 2) and interannual (Chapter 3) timescales. The global models are re-gridded into 1°x1° resolution and are analyzed for the historical (1850-2006) and future (2006-2100) Representative Concentration Pathway 8.5 (RCP8.5) scenarios. Chapter 2, published as Gallego et al. (2018), further contributes to the current knowledge of the pCO$_2$ seasonality, by characterizing the present drivers of the pCO$_2$ annual cycle in CMIP5 models and estimating its projected amplification by the end of the century. To elucidate the drivers of the future changes on pCO$_2$ variability, an analytical Taylor expansion of pCO$_2$ in terms of DIC, TA, T and S is used. The series expansion allows to disentangle - at first order - changes in the background carbonate chemistry from those caused by physical and biological mechanisms. This study revealed differences in the regional driving mechanisms of the seasonal pCO$_2$ amplification. For example, the pCO$_2$ seasonal cycle is dominated by temperature in the subtropical gyres and DIC in the polar regions. In the subtropical gyres, the increase in pCO$_2$ seasonality is moderate when compared to polar regions. The subtropical amplification is due to a large increase in mean pCO$_2$ that enhances the T contribution. Polar regions experience a lower increase on mean pCO$_2$, but a large increase on DIC sensitivity, both mechanisms amplify the regional DIC-driven pCO$_2$ seasonality.

Chapter 3, published as Gallego et al. (2020), focuses on the present interannual variability of pCO$_2$ and its future changes induced by anthropogenic CO$_2$ emissions. The results of this
thesis, show an overall increase in interannual variability as it would be expected, since the ocean becomes more sensitive to DIC. However, the models largely differ in the mechanisms controlling the variability, specially in the equatorial Pacific. The disagreement among models is a consequence of intra-model differences on the mechanisms driving the changes. Furthermore, a decrease on DIC interannual variability could cause a decrease on pCO₂ interannual changes in the eastern equatorial Pacific. The amplification of interannual variability is smaller than it would be if only the mean carbonate chemistry - Revelle factor and mean pCO₂ were to change.

In Part II of this thesis, an advection-diffusion offline marine ecosystem model is developed to study the effect of tropical cyclones on primary productivity. In daily to weekly time scales, mesoscale phenomena can locally enhance vertical upwelling and in turn increase the nutrients availability at surface. Certain storms’ characteristics and oceanic pre-storm conditions can induce large phytoplankton blooms. The contribution of these storm-induced blooms to annual primary productivity and carbon export depends on the regional number of storms and the bloom’s intensity. Most of these phytoplankton increases have been detected with satellite data, but these observations are limited to the sea surface. Thus, in Chapter 3 an Offline Marine Ecosystem Model (OMEM) is developed to resolve the physical dynamics of tropical cyclones in the ocean and to elucidate the effects on nutrients, phytoplankton and zooplankton. The model is forced with high-resolution zonal and meridional oceanic velocities from the Community Earth System Model (CESM) version 1.2.2. In Chapter 4 I show preliminary results showing an enhancement of nutrients and chlorophyll in the euphotic zone as a consequence of a tropical cyclone.
PART I

PRESENT AND FUTURE VARIABILITY OF OCEANIC $\text{pCO}_2$
Drivers of future seasonal changes in oceanic pCO$_2$

2.1 Abstract

Recent observation-based results show that the seasonal amplitude of surface ocean partial pressure of CO$_2$ (pCO$_2$) has been increasing on average at a rate of 2–3 µatm per decade (Landschützer et al., 2018). Future increases in pCO$_2$ seasonality are expected, as marine CO$_2$ concentration ([CO$_2$]) will increase in response to increasing anthropogenic carbon emissions (McNeil and Sasse, 2016). Here we use seven different global coupled atmosphere-ocean-carbon cycle-ecosystem model simulations conducted as part of the Coupled Model Intercomparison Project Phase 5 (CMIP5) to study future projections of the pCO$_2$ annual cycle amplitude and to elucidate the causes of its amplification. We find that for the RCP8.5 emission scenario the seasonal amplitude (climatological maximum minus minimum) of upper ocean pCO$_2$ will increase by a factor of 1.5 to 3 over the next 60-80 years. To understand the drivers and mechanisms that control the pCO$_2$ seasonal amplification we develop a complete analytical Taylor expansion of pCO$_2$ seasonality in terms of its four drivers: dissolved inorganic carbon (DIC), total alkalinity (TA), temperature ($T$), and salinity ($S$). Using this linear approximation we show that the DIC and $T$ terms are the dominant contributors to
the total change in pCO$_2$ seasonality. To first order, their future intensification can be traced back to a doubling of the annual mean pCO$_2$, which enhances DIC and alters the ocean carbonate chemistry. Regional differences in the projected seasonal cycle amplitude are generated by spatially varying sensitivity terms. The subtropical and equatorial regions (40°S–40°N) will experience a 30-80 µatm increase in seasonal cycle amplitude almost exclusively due to a larger background CO$_2$ concentration that amplifies the T seasonal effect on solubility. This mechanism is further reinforced by an overall increase in the seasonal cycle of T as a result of stronger ocean stratification and a projected shoaling of mean mixed layer depths. The Southern Ocean will experience a seasonal cycle amplification of ≈ 90-120 µatm in response to the mean pCO$_2$-driven change in the mean DIC contribution and to a lesser extent to the T contribution. However, a decrease in the DIC seasonal cycle amplitude somewhat counteracts this regional amplification mechanism.

2.2 Introduction

Owing to its buffering capacity, the ocean has absorbed nearly half of the anthropogenic CO$_2$ produced by fossil fuel burning and cement production since the industrial revolution (Sabine et al., 2004). While the ocean’s absorption of CO$_2$ lowers the atmospheric concentration, it also increases the ocean’s CO$_2$ concentration ([CO$_2$]) and in turn lowers its buffering capacity. This leads to a reduction in the oceanic uptake of CO$_2$ and an intensification of the pCO$_2$ seasonal cycle (from now on referred to as $\delta$pCO$_2$) (McNeil and Sasse, 2016, Völker et al., 2002). In a recent key observational study by Landschützer et al. (2018), it was demonstrated that the $\delta$pCO$_2$ amplitude has increased at a rate of $\approx$2-3 $\mu$atm per decade, from 1982 to 2015.

The pCO$_2$ already experiences large seasonal fluctuations, which in some regions can reach up to 60% above and below the annual mean pCO$_2$, (Takahashi et al., 2002). An intensification of the $\delta$pCO$_2$ amplitude could produce increased [H$^+$] seasonality (Kwiatkowski and Orr, 2018, Hagens and Middelburg, 2016, Fassbender et al., 2017) and aragonite undersaturation events (Hauri et al., 2015, Sasse et al., 2015, Shaw et al., 2013), exposing marine life to harmful seawater conditions, earlier than expected if considering only annual mean values. Moreover, a projected amplification of $\delta$pCO$_2$ might increase the net CO$_2$ uptake in some regions, such as the Southern Ocean, thereby further accelerating the decrease of the buffering capacity in that region (Hauck and Völker, 2015).

The pCO$_2$ seasonal amplitude is controlled mainly by the seasonal changes in temperature (T) and biological activity together with upwelling changes that alter dissolved inorganic carbon (DIC) concentrations. Usually, DIC and T changes work in opposite directions (Sarmiento and Gruber, 2006, Takahashi et al., 2002, Fay and McKinley, 2017). In subtropical regions higher pCO$_2$ values occur in summer when solubility decreases. In subpolar regions, pCO$_2$ increases in winter when waters upwell that are rich in DIC and when respiration of organic matter takes place. Decreased subpolar pCO$_2$ occurs in summer when the primary productivity is higher and the upwelling diminishes (see Fig. 2.1). Therefore, we find close relationships between $\delta$pCO$_2$ and the ocean’s [CO$_2$] that controls the chemical reactions and with the mean pCO$_2$ that moderates the exchange with the atmosphere.
Both factors are related by the solubility constant that depends on temperature and salinity.

Furthermore, the regional differences in the influence of temperature and DIC on δpCO₂ are modulated by the ocean’s buffering capacity. As the ocean captures CO₂, its ability to convert it into HCO₃⁻ and CO₃²⁻ -buffering capacity- decreases, and the pCO₂ sensitivity to any change in DIC increases. In the same way, a larger background aqueous [CO₂] enhances the effect of temperature on pCO₂’s solubility.

To quantify the capacity to buffer changes in DIC, we can introduce the sensitivity factor γDIC, which is inversely related to the buffering capacity, defined as γDIC = ∂ln(pCO₂)/∂DIC, (Egleston et al., 2010). Other sensitivity factors are related to the total alkalinity (γTA), salinity (γS) and temperature (γT) changes, and are defined in a similar way as ∂ln(pCO₂)/∂TA, ∂ln(pCO₂)/∂S and
\( \partial \ln(p\text{CO}_2) / \partial T \) respectively. It is important to note that the pCO\(_2\) is highly sensitive to temperature due to two factors: first through solubility changes that account for 2/3 of the present day temperature impact, and second, through the dissociation constants that control the carbon system reactions (Sarmiento and Gruber, 2006).

While the mechanisms controlling the seasonal cycle of pCO\(_2\) at present day are well documented, the future evolution of these drivers has not been fully elucidated. Current literature suggests that the seasonal amplification is a consequence of an increase in the T and DIC contributions to \( \delta \text{pCO}_2 \) (Landschützer et al., 2018) and an increased sensitivity of the ocean to these variables (Fassbender et al., 2017).

The aim of this chapter is to provide an in-depth analysis of the mechanisms controlling the future strength of \( \delta \text{pCO}_2 \) and its regional differences using 7 CMIP5 global earth system models. Our analysis focuses on the 21\(^{st}\) century evolution using the Representative Concentration Pathway 8.5 (RCP8.5) scenario. We give a comprehensive analysis of the projected evolution of the DIC, TA, T and S contributions to pCO\(_2\) seasonality. To achieve this goal, we derive explicit analytical expressions for pCO\(_2\) sensitivities in terms of \( \gamma_{\text{DIC}} \), \( \gamma_{\text{TA}} \), \( \gamma_T \) and \( \gamma_S \), thereby extending previous work done by Egleston et al. (2010).

### 2.3 Methodology

#### 2.3.1 CMIP5 Models

For our analysis, pCO\(_2\), DIC, TA, pH, T and S monthly-mean output variables covering the period from 2006-2100 were obtained from future climate change simulations conducted with 7 fully coupled earth system models that participated in the Coupled Model Intercomparison Project, Phase 5 (CMIP5). The following models were selected based on data availability: CanESM2, CESM1-BGC, GFDL-ESM2M, MPI-ESM-LR, MPI-ESM-MR, HadGEM2-ES and HadGEM2-CC (See supplementary material of Hauri et al. (2015)). For the purpose of this paper, we used the Representative
Concentration Pathway 8.5 (RCP8.5) future climate change simulations (IPCC, 2013). The ocean’s surface data sets were regrided onto a 1°x1° grid using Climate Data Operators (CDO). The Arctic Ocean and the region poleward of 70°S are removed from the analyses, because observational data for model validation are scarce.

2.3.2 Analysis of $\delta pCO_2$

To elucidate the underlying dynamical, thermodynamical, biological and chemical processes controlling $\delta pCO_2$ we calculated a first order Taylor series expansion of $\delta pCO_2$ in terms of its four drivers, DIC, TA, T and S. While T and S are controlled only by physics, DIC and TA are controlled by physical, chemical and biological processes. Throughout this paper we use salinity-normalized DIC and TA using a mean salinity of 35 psu. This effectively removes the concentration/dilution fresh water effect, following the procedure of Lovenduski et al. (2007). The salinity normalized variables are referred to as DIC$_s$ and TA$_s$, corresponding to DIC-S$_0$/S and TA-S$_0$/S respectively. The freshwater effect on DIC and TA is now included in the S term, renamed as S$_{fw}$. For the Taylor series expansion, each variable ($X$=DIC, TA, T and S) is decomposed into $X = \bar{X} + \delta X$. The term $\bar{X}$ represents the 21 years-long mean and $\delta X$ denotes the seasonal cycle (calculated as the monthly mean deviation from the 21 years average). The Taylor expansion is then computed for each model, for an initial (2006-2026) and final (2080-2100) periods. We use multi-decade means and eventually multi-model ensemble means to remove effects of interannual variability. The full first-order series expansion is given by:

$$\delta pCO_2 \approx \frac{\partial pCO_2}{\partial DIC} \bigg|_{\bar{T}_S} \delta DIC + \frac{\partial pCO_2}{\partial TA} \bigg|_{\bar{T}_S} \delta TA + \frac{\partial pCO_2}{\partial T} \bigg|_{\bar{DIC}_S} \delta T + \frac{\partial pCO_2}{\partial S} \bigg|_{\bar{DIC}_S,\bar{TA}_S} \delta S_{fw}$$ (2.1)

Each term of the right hand side of Eq. (2.1) represents the contribution from one of the four drivers of $\delta pCO_2$. The analytical expressions for the derivatives (without the salinity normalization)
are given by:

\[
\frac{\partial pCO_2}{\partial TA} |_{TA, DIC, T, S} = \frac{-\Delta K_c}{\text{DIC} \cdot \Theta - \Delta K_c} \tag{2.2}
\]

\[
\frac{\partial pCO_2}{\partial DIC} |_{TA, DIC, T, S} = \frac{\Theta}{\text{DIC} \cdot \Theta - \Delta K_c} \tag{2.2}
\]

\[
\frac{\partial pCO_2}{\partial T} |_{TA, DIC, T, S} = \frac{1}{\text{DIC} \cdot \Theta - \Delta K_c} \left[ TA_c \cdot \left( \frac{\partial \Delta K_c}{\partial T} + \frac{\partial [B(OH)_4^-]}{\partial T} + \frac{\partial [OH^-]}{\partial T} \right) - \Theta \cdot \frac{\partial (\text{DIC} - [CO_2])}{\partial T} \right] - \frac{pCO_2}{K_0(T, S)} \cdot \frac{\partial K_0(T, S)}{\partial T} \tag{2.2}
\]

\[
\frac{\partial pCO_2}{\partial S} |_{TA, DIC, T, S} = \frac{1}{\text{DIC} \cdot \Theta - \Delta K_c} \left[ \Delta K_c \cdot \left( \frac{\partial \Delta K_c}{\partial S} + \frac{\partial [B(OH)_4^-]}{\partial S} + \frac{\partial [OH^-]}{\partial S} \right) - \Theta \cdot \frac{\partial (\text{DIC} - [CO_2])}{\partial S} \right] - \frac{pCO_2}{K_0(T, S)} \cdot \frac{\partial K_0(T, S)}{\partial S} \tag{2.2}
\]

where \( \Theta = [\text{HCO}_3^-] + 4[\text{CO}_3^-] + \frac{[B(OH)_4^-][\text{H}^+]}{([\text{K}_b + [\text{H}^+]])} + [\text{H}^+] + [\text{OH}^-] \) and \( \Delta K_c = [\text{HCO}_3^-] + 2[\text{CO}_3^-] \). The explicit \( T \) and \( S \) partial derivatives are given in the Appendix (A). The first two derivatives coincide with the results of Egleston et al. (2010) and Hagens and Middelburg (2016), with the exception of the sign of \([OH^-]\) in Egleston et al. (2010) term \( S \). To verify this approach we compared the sum of the Taylor expansion terms with the full simulated range of \( \delta pCO_2 \) from the model’s output. The Taylor expansion reproduces well the full seasonal cycle amplitude of the original climate model simulations (see Fig. 2.2). The analytical expressions for temperature and salinity presented in here are – to our knowledge – the first ones of their kind. Previously the calculation of these terms was based on the approximation given by Takahashi et al. (1993) or on numerical calculations.

To gain more insights into the processes causing the amplification of \( \delta pCO_2 \) we introduce a method based on a second Taylor series expansion described below. Eq. (2.1) can be rewritten using the expressions for the sensitivities \( \gamma \) determined by the relation \( \frac{1}{pCO_2} \frac{\partial pCO_2}{\partial X} = \gamma X \). These sensitivities have been historically used to represent the percentage of change in \( pCO_2 \) per unit of DIC, TA, T or S. With this notation, Eq. (2.1) can be expressed in the following way:

\[
\delta pCO_2 \approx pCO_2 \cdot \left( \gamma_{DIC} \cdot \delta DIC + \gamma_{TA} \cdot \delta TA + \gamma_T \cdot \delta T + \gamma_{Sfw} \cdot \delta S_{fw} \right) \tag{2.3}
\]
Figure 2.2: Taylor’s expansion method evaluation. We compared the pCO₂ seasonal cycle amplitude calculated from model output with the Taylor expansion reconstruction in a) 2006-2026 and b) 2080-2100. Different colors indicate latitudinal ranges of zonal means, for the Atlantic (triangles), Pacific (circles) and Indian (stars) ocean basins. Large symbols represent the ensemble mean, and small symbols are the result for each model separately.
Each term in Eq. (2.3) consists of three parts: $p\text{CO}_2$, the sensitivity $\gamma_X$ and the corresponding seasonal cycle $\delta X$. To understand which component is the main driver for $\delta p\text{CO}_2$ changes, we perform a second Taylor expansion of the end of the century’s $\delta p\text{CO}_2$ around the initial state of the system in 2006-2026.

To maximize mathematical clarity we will introduce some definitions: first, we introduce the symbol $\Delta$ to indicate the difference between the period 2080-2100 and 2006-2026. Therefore, the total future change in $\delta p\text{CO}_2$ is now referred to as $\Delta \delta p\text{CO}_2$. In the same manner, the total change in sensitivities and seasonal cycles are written as $\Delta \gamma_{\text{DIC}_s}, \Delta \gamma_{\text{TA}_s}, \Delta \gamma_{\text{T}}$ and $\Delta \delta \text{DIC}_s, \Delta \delta \text{TA}_s, \Delta \delta \text{T}, \Delta \delta \text{S}_{fw}$ respectively. Finally, we introduce the vector $\vec{X}$ formed by the four variables $\text{DIC}_s$, $\text{TA}_s$, $\text{T}$ and $\text{S}_{fw}$, as: $\{X_0, X_1, X_2, X_3 \} = \{\text{DIC}_s, \text{TA}_s, \text{T}, \text{S} \}$. With this notation, we can write an expansion of Eq. (2.3) of the final state of the system by 2080-2100 named $\vec{X}^f$ around the initial state $\vec{X}^i = \{\text{DIC}_s^i, \text{TA}_s^i, \text{T}^i, \text{S}_{fw}^i \}$ by 2006-2026 as:

\[
\Delta \delta p\text{CO}_2 = \Delta p\text{CO}_2 \sum_{k=0}^{3} \gamma_k^i \cdot \delta X_k^i \\
+ p\text{CO}_2^i \sum_{k=0}^{3} \Delta \gamma_k \cdot \delta X_k^i \\
+ p\text{CO}_2^i \sum_{k=0}^{3} \gamma_k^i \cdot \Delta \delta X_k \\
+ \Delta p\text{CO}_2 \sum_{k=0}^{3} \Delta \gamma_k \cdot \delta X_k^i \quad \text{(2nd order terms)} \\
+ \Delta p\text{CO}_2 \sum_{k=0}^{3} \gamma_k^i \cdot \Delta \delta X_k \\
+ p\text{CO}_2^i \sum_{k=0}^{3} \Delta \gamma_k \cdot \Delta \delta X_k
\]  

(2.4)

where the first, second and third terms represent the contributions to $\Delta \delta p\text{CO}_2$ due to changes in the mean $p\text{CO}_2$ ($\Delta p\text{CO}_2$), the $p\text{CO}_2$ sensitivities ($\Delta \gamma_k$) and the seasonal cycles ($\Delta \delta X_k$) respectively; the fourth to sixth rows are the second order terms. This method is similar to the one used by
2.4 Results and discussion

2.4.1 δpCO$_2$ amplification

Figure 2.3, (a) shows the ensemble mean δpCO$_2$ amplitude (calculated as climatological maximum-minus-minimum) for the initial period 2006-2026. The values range from ≈98 µatm for the high latitudes ($40^\circ$S-$70^\circ$S, $40^\circ$N-$60^\circ$N) to ≈60 µatm between $40^\circ$S-$40^\circ$N. The ensemble mean initial seasonal amplitude range is in good agreement with observational estimates calculated for the reference year 2005 (Takahashi et al., 2014b), and for the 1982-2015 period (Landschützer et al., 2017). The agreement between models and observations is remarkably good in the equatorial regions, but the initial amplitude is slightly overestimated in the mid and high latitudes (see Fig. 2.4). The higher amplitude in models than observations is expected, as the initial period 2006-2026 already experienced an amplification compared to previous years. Moreover, Tjiputra et al. (2014) found that the ocean’s pCO$_2$ historical trend is larger in models than observations when it is estimated in large scale areas of the ocean. However, they found that models’ pCO$_2$ trends agree with observations when the trends are subsampled to the locations where the observations were taken, and therefore they do a good job reproducing well-known time series. Moreover, differences are expected as Pilcher et al. (2015) suggested that CMIP5 models perform well in reproducing the seasonal cycle timing, but still show considerable errors in reproducing the seasonal amplitude of pCO$_2$ due to differences in the mechanisms represented in each model, especially in subpolar biomes.
Figure 2.3: RCP8.5 ensemble mean pCO$_2$ seasonal cycle amplitude. Amplitude is calculated as climatology maximum-minus-minimum; for a) initial (2006-2026) and b) final (2080-2100) periods. Initial and final climatologies were calculated as the monthly deviation from the respective 21 years period mean. c) and d) show the ratio and difference between the δpCO$_2$ amplitudes for 2080-2100 and 2006-2026 respectively. e) - h) show the zonal mean of a) - d) respectively, with the individual models shown as colored lines and the ensemble mean overlaid in black. Gray shading represents one standard deviation across the models.
Figure 2.4: Drivers of present-day pCO$_2$ seasonality, in observations and models. Column a) shows the pCO$_2$ seasonal amplitude calculated as summer minus winter for each hemisphere respectively. b) and c) show the thermal and non-thermal contributions to pCO$_2$ seasonality respectively. First row shows CMIP5 models ensemble mean for the 2006-2026 period under the RCP8.5 scenario. Second row shows the estimates from Takahashi et al. (2014b) dataset for a reference year 2005, with summer-minus-winter thermal and non-thermal contributions calculated as Takahashi et al. (2002). Third rows show the same components for the Landschützer et al. (2017) pCO$_2$ data-set, and the thermal and non-thermal estimations, for the period 1982-2015 [Peter Landschützer, personal communication].
By 2080-2100 the annual cycle amplitude attains values of \( \approx 197 \ \mu \text{atm} \) and \( \approx 101 \ \mu \text{atm} \) in the high and mid-low latitudes respectively (Fig. 2.3,(b)). These seasonal variations correspond to 20\% and 18\% of annual \( \text{pCO}_2 \) for the initial and final periods respectively. Figure 2.3, (c), shows that the global ocean \( \delta \text{pCO}_2 \) will intensify by a factor of 1.5 to 3 times for the 2080-2100 period relative to the 2006-2026 reference period. Figure 2.3, (d), shows the difference in amplitude \( (\Delta \delta \text{pCO}_2) \); this pattern differs from the ratio, because the ratio emphasizes the amplification in areas where the initial amplitude is lower than \( \approx 10 \ \mu \text{atm} \). McNeil and Sasse (2016) used observations and a neural-network-clustering algorithm to project that by year 2100, the \( \delta \text{pCO}_2 \) amplitude in some regions could be up to ten times larger than it was in year 2000. Our mean amplification factor estimation agrees with the mean threefold amplification found for most of the ocean by McNeil and Sasse (2016). However the high values in this previous study can not be reproduced here - mainly because we consider 21 years average ratios instead of single year ratios, which are strongly affected by interannual variability. Using observations, Landschützer et al. (2018) found an increase of 2.2 \( \mu \text{atm} \) per decade, which is smaller than our findings of a total 42 \( \mu \text{atm} \) increase by the end of the century between 40\(^o\)S-40\(^o\)N, and a global-mean change of 81 \( \mu \text{atm} \) on the high latitudes. This difference is again possibly due the higher mean \( \text{pCO}_2 \) values in models than observations.

The global ocean mean amplification factor of \( \delta \text{pCO}_2 \) roughly coincides with a doubling of \( \overline{\text{pCO}_2} \) (Fig. 2.5). The direct relationship between these two is explained in section 2.4.5. Figure 2.3 (e-h) shows the zonal mean panels of (a-d); In general, towards the end of the century the \( \text{pCO}_2 \) amplifies more in high latitudes, but so does the standard deviation uncertainty among models. This regional pattern agrees with the observation-based findings of Landschützer et al. (2018) which show that high latitudes have already experienced a larger amplification than mid-low latitudes from 1982 to 2015. Furthermore, the same pattern is projected by CMIP5 models for the seasonal amplification of \( [\text{H}^+] \) by the end of the century (Kwiatkowski and Orr, 2018). This is expected from the near-linear relation between \( \text{pCO}_2 \) and \( [\text{H}^+] \). These regional differences in amplification for \( \text{pCO}_2 \) can be explained in terms of the relative magnitudes and the phases between the DIC, TA, T and S contributions, which are explained in subsequent sections.
Figure 2.5: RCP8.5 ensemble mean $\overline{pCO_2}$: by a) 2006-2026 and b) 2080-2100. c) Difference between 2080-2100 and 2006-2026. The North Atlantic and subpolar gyres, show the largest difference between initial and final periods. The scale is different in each plot to enhance regional features.
2.4.2 Present and future drivers of $\delta$\(p\)CO$_2$

To understand the driving factors of $\delta$\(p\)CO$_2$ and its spatiotemporal differences, we split $\delta$\(p\)CO$_2$ into the four different contributions from DIC$_s$, TA$_s$, T and S$_{fw}$ for the initial and final periods, following Eq. (2.1). The results are shown in Fig. 2.6. For most of the ocean, the ensemble mean estimated contributions from DIC$_s$ and T to the present-day $\delta$\(p\)CO$_2$ are in good agreement with the data-based estimates of Takahashi et al. (2014b) and Landschützer et al. (2017), particularly in the equatorial regions (see Fig. 2.4). However our T and DIC contributions are slightly larger in mid and high latitudes, for the same reasons the pCO$_2$ seasonal amplitude is overestimated (see Section 3.1). Also, differences arise between our DIC$_s$ contribution and the observation-based so called "non-thermal" contribution, because the non-thermal contribution also includes the total alkalinity and salinity effects. Nonetheless, between 40ºS-40ºN our ensemble mean shows that $\delta$\(p\)CO$_2$ is dominated by changes in temperature that control CO$_2$ solubility, which decreases in summer enhancing pCO$_2$, in agreement with observations. The Southern Ocean is controlled by DIC, that responds to changes in upwelling and phytoplankton blooms. Both mechanisms act together to decrease (increase) DIC in summer (winter) (Sarmiento and Gruber, 2006).
Figure 2.6: RCP8.5 ensemble mean seasonal cycle ($\delta pCO_2$) and its Taylor decomposition. Colored lines indicate the contributions of DIC ($s$, blue), TA$_s$ (pink), T (red) and $S_{fw}$ (green) to $\delta pCO_2$ reconstructed from its Taylor decomposition (Eq. 2.1) (dashed black). $\delta pCO_2$ calculated from monthly pCO$_2$ (solid yellow) is shown for comparison with the Taylor expansion. Column (a) shows the period 2006-2026 and column (b) shows the period 2080-2100. Each row represents the global zonal average for a different latitudinal band. Temperature dominates all latitudes except the Southern Ocean. In the 40°-60°N band, T contribution is largely compensated by DIC. The TA$_s$ and $S_{fw}$ effects are rather small in all latitudes.
The models show that the $\delta p\text{CO}_2$ in the 40°N to 60°N band is controlled by T, which disagrees with the above mentioned observations that show a non-temperature dominance in this band. The difference between models and observations is apparent in two regions: the North Atlantic basin and the North Western Pacific; specifically near the Oyashio Current, and the outflows from the Okhotsk Seas (see Fig. 2.4). Most models show a T dominance in the North Atlantic basin; only CESM1-BGC and GFDL-ESM2M show a DIC dominance (see Fig. 2.7). The North Atlantic is one of the major sinks of anthropogenic CO$_2$, however some models fail to estimate its uptake capacity. Goris et al. (2018) found that models with an efficient carbon sequestration present a DIC-dominated pCO$_2$ seasonal cycle in the North Atlantic, but models with low anthropogenic uptake show a T dominance in this region. In the North-Western Pacific, Mckinley et al. (2006) found that coarse models are not able to capture the intricate oceanographic features of this area, and therefore the pCO$_2$ seasonality is not well captured.
Figure 2.7: Individual models’ pCO$_2$ present and future seasonal amplitude. Simulated, pCO$_2$ seasonal amplitude calculated as climatological summer minus winter for each hemisphere respectively for column a) 2006-2026 and b) 2080-2100 periods calculated as in Fig. 2.13; each row is the result for a different model. Column c) shows the difference between column b) and a).
Towards the end of the century (Fig. 2.6, right column), the amplification of $\delta p\text{CO}_2$ is caused by an increase in the $\text{DIC}_s$ and $T$ contributions, and to a lesser extent due to $\text{TA}_s$ and $S_{fw}$. Only in the high latitudes the $\text{TA}_s$ contribution reinforces the $\text{DIC}_s$ effect. The $\delta \text{DIC}_s$ and $\delta T$ relative phase and magnitude play an important role in causing regional differences of future $\delta p\text{CO}_2$. For example, between $40^\circ$-60$^\circ$, we find a lower amplification factor than at $30^\circ$-40$^\circ$ in both hemispheres (Fig. 2.3, (c)), contrary to what we expected from the general observed larger amplification at higher latitudes. In this band of lower amplification, the warm water from subtropical regions meets the nutrient rich water from the subpolar regions, but the $\text{DIC}_s$ and $T$ effects are almost 6 months out of phase, and therefore their cancellation is larger than in the $30^\circ$-40$^\circ$ latitude band; where for example, in the North Atlantic, there is 9 month phase-difference between both contributions. A clear illustration of this phase effect is found Fig. 2.8.

In the Southern Ocean there is a shift in the maximum $\delta p\text{CO}_2$ occurring from August-September to March-April (Fig. 2.6, last row). This shift is generated because the $T$ contribution gains importance over $\text{DIC}_s$, due to a reduction of $\delta \text{DIC}_s$ magnitude at the same time that $\delta T$ increases (Fig. 2.10). In the Equatorial Pacific region (Fig. 2.10), $T$ dominates over $\text{DIC}_s$ but both contributions are small due to their low seasonality. Therefore, this region will experience a low amplification in $\delta p\text{CO}_2$. In this region some models underestimate the $p\text{CO}_2$ trend (Tjiputra et al., 2014), and therefore the seasonal amplification might be underestimated too. In the following sections we conduct further analysis by decomposing each contribution as the result of three factors: the mean $p\text{CO}_2$ ($\bar{p}\text{CO}_2$), the regional $p\text{CO}_2$ sensitivities ($\gamma_{\text{DIC}}$, $\gamma_{\text{TA}}$, $\gamma_T$ and $\gamma_{S_{fw}}$) and the seasonal cycles ($\delta \text{DIC}_s$, $\delta \text{TA}_s$, $\delta T$ and $\delta S_{fw}$) as determined in Eq. (2.3).

2.4.3 Future $p\text{CO}_2$ sensitivities

The $\gamma_{\text{DIC}}$ and $\gamma_{\text{TA}}$ are projected to increase by the end of the century due to a lower ocean buffering capacity produced by increasing temperature and larger background concentrations of $\text{DIC}$ (Fassbender et al., 2017). This agrees with our results shown in Fig. 2.9, which shows that all regions will
Figure 2.8: $\delta pCO_2$ climatology and its contributions from T and DIC a) Ensemble mean of zonal average for the North Atlantic $\delta pCO_2$ climatology and b) DIC contribution in color with overlying black contours of T contribution for 2006-2026 period. c) and d) same as a) and b) but for the 2080-2100 period.
experience an increase in $\gamma_{\text{DIC}}$ and $\gamma_{\text{TA}}$. Lower buffer factors (higher sensitivities factors) are found in regions where DIC and TA have similar values, and they will decrease (increase) as the DIC/TA ratio in the oceans increases (Egleston et al., 2010). The alkalinity sensitivity is negative, as pCO$_2$ decreases with increasing alkalinity, but we show here the negative of $\gamma_{\text{TA}}$ for better comparison. $\gamma_{\text{TA}}$ will increase (with negative values) more than the DIC sensitivity. However seasonal changes in open-ocean TA$_s$ are small, and therefore the total contribution of alkalinity in our analysis is negligible compared to the DIC$_s$ and T contributions. $\gamma_{\text{Sfw}}$ decreases everywhere except in the Western Pacific Warm Pool. In this region $\gamma_{\text{Sfw}}$ increases probably due to future changes in precipitation that enhance the fresh-water effect. In Fig. 2.9, the sensitivities ($\gamma$) are expressed as a percentage change of pCO$_2$ per unit of DIC, TA, T and S respectively. This follows the approach of Takahashi et al. (1993), however in their paper the authors compute the Revelle factor, which is related to $\gamma_{\text{DIC}}$ as $R = \text{DIC} \cdot \gamma_{\text{DIC}}$. To illustrate the meaning of the sensitivities, we will focus on the subtropical North Pacific in the 15°N-40°N latitudinal band. In this region $\gamma_{\text{DIC}}$ indicates an average 0.6% change in pCO$_2$ per unit of DIC in 2006-2026. Therefore, for a $\delta$DIC$_s$ seasonal cycle amplitude of 40 $\mu$mol/kg$^{-1}$ and $\overline{\text{pCO}_2} \approx 400$ µatm, the total $\delta$pcO$_2$ amplitude equals 96 µatm. Following the same reasoning, by 2080-2100, $\gamma_{\text{DIC}}$ increases to 0.7% and $\delta$DIC$_s$ decreases to 30 $\mu$mol/kg$^{-1}$; therefore, for a $\overline{\text{pCO}_2}$ equal to 800 µatm, the $\delta$pcO$_2$ amplitude due to $\delta$DIC amounts to 168 µatm. The temperature sensitivity has been experimentally determined by Takahashi et al. (1993); who found a value of 0.0423, meaning that pCO$_2$ changes by about 4% for every °C. This value agrees with our global mean ensemble estimate of 0.0428. However, our analytical expression of $\gamma_T$ shows that this value varies regionally and, by reasons unknown to us, it might decrease in the future to a global mean value of 0.0415, (Fig. 2.9, row (c), third column). The T sensitivity is larger in colder regions and lower in the warmer tropics; however, colder regions will experience a larger reduction on $\gamma_T$, which locally prevents a larger amplification of the T contribution to $\delta$pcO$_2$. In the next section we show that the T seasonality is projected to increase in high latitudes, strengthening the T contribution.
Figure 2.9: RCP8.5 ensemble mean pCO₂ sensitivities: for DICₙ (row a), TAₙ (row b), T (row c) and Sfw (row d). Row b) shows the negative of γ_TA. The first and second columns show the sensitivities by 2006-2026 and 2080-2100 respectively. The third column shows the difference between 2080-2100 and 2006-2026 sensitivities. High latitudes show the largest difference between initial and final periods. While DICₙ and TAₙ sensitivities increase, the T and Sfw sensitivities decreases, except in the Western Pacific Warm Pool, where γSfw increases.
2.4.4 Future $\delta$DIC$_s$, $\delta$TA$_s$, $\delta$T and $\delta$S$_{fw}$.

Towards the end of the century, the global mean amplitude of $\delta$DIC$_s$ is projected to decrease by $\approx$26-28% in the high latitudes (Fig. 2.10, (a)), according to all the CMIP5 earth system model simulations used here. In the mid-low latitudinal band there is no agreement between models; while some show an increase others project a decrease in amplitude. As suggested by Landschützer et al. (2018), the larger decrease in the Southern Ocean may be the result of changes in the shallow overturning circulation that prevent CO$_2$ accumulation in this region. This reduction may be counteracted by the predicted increase in productivity owing to a suppression of light and temperature limitations (Steinacher et al., 2010, Bopp et al., 2013).

According to the CMIP5 models, most of the ocean is projected to experience a slight increase in $\delta$T, as shown in Fig. 2.10, column (b). All models show a slight increase in $\delta$T, only one model showed a slightly decrease in the southern region, and two models showed a decrease in the equatorial region during October to December. It is important to note that Fig. 2.10 shows the seasonal values, with the mean T removed. Therefore, when considering the positive T trends, the absolute summer values show an increase and the absolute winter values a decrease. This agrees with the results of Alexander et al. (2018); who showed that models project a seasonal intensification of T, with larger warm extremes and reduced cold extremes. The authors attributed the T seasonality intensification to an increased oceanic stratification and an overall shoaling of the mixed layer depth, which confines seasonal changes in a reduced volume of water, producing larger changes at the surface. They also showed that the intensification trends are stronger in summer than winter, as the mixed layer depth is shallower in summer. Moreover, ice covered regions will experience the largest increase in T seasonality due the loss of sea ice, because the ice melting/freezing moderates the surface water temperature seasonality (Carton et al., 2015).

The TA seasonality is also projected to increase in the high latitudes according to all models, except CESM1-BGC which shows a decrease. For $\delta$S (see Fig. 2.11) there is no agreement among the different CMIP5 models, except in the Southern Ocean where all the models show a slightly
decrease. Kwiatkowski and Orr (2018) demonstrated that the seasonality of the drivers is important to determine future changes in [H+] seasonality. In the same fashion, our results show that the four \( \delta pCO_2 \) drivers present changes in seasonality, and in particular \( \delta DIC_s \) and \( \delta T \) changes are important to explain future projections of the \( \delta pCO_2 \) amplitude. The increase in \( \delta T \) enhances the \( \delta pCO_2 \) amplification, and the reduction of \( \delta DIC_s \) in the Southern Ocean locally prevents a larger amplification.

### 2.4.5 Regional dominant factors

To identify the main cause of the \( \delta pCO_2 \) amplification we use the Taylor series expansion method. With this method we consider the system’s final state (\( \delta pCO_2 \) by 2080-2100) as a perturbation of the initial state (\( \delta pCO_2 \) by 2006-2026), as shown in Eq. (2.4). The expansion is done in three groups of variables: the seasonal cycles of \( DIC_s \), \( TA_s \), \( T \) and \( S \) (\( \delta X \) ), the sensitivities of \( pCO_2 \) to the same four variables (\( \gamma_X \)), and the mean \( pCO_2 \) (\( \bar{pCO}_2 \)). Therefore, each term of the expansion represents how much of the total \( \delta pCO_2 \) change (indicated by \( \Delta \delta pCO_2 \) and calculated as 2080-2100 value minus 2006-2026 value) is due the change in each of these factors. We also add the second order terms that come from their combination. The results are shown in Fig. 2.12, (a) and they indicate that the leading cause of the \( \delta pCO_2 \) amplification is the change in \( pCO_2 \) (\( \Delta pCO_2 \)), which confirms previous findings by Landschützer et al. (2018).

It is important to note that our linear Taylor expansion approach neglects one aspect of the highly non linear carbonante chemistry of the ocean: it assumes \( \bar{pCO}_2 \) and the sensitivities as independent variables, and therefore does not include the positive feedback between larger \( \bar{pCO}_2 \) and increasing \( \gamma_{DIC} \) (decreasing buffering capacity). Hence in the following, we use changes in \( \bar{pCO}_2 \) and changes in seawater carbonate chemistry synonymously, overall resulting in an enhanced response of \( \delta pCO_2 \) to seasonal changes in DIC, TA, T and S.

Considering regional differences, we note that the amplification increases as we move poleward in spite of decreasing \( \Delta \bar{pCO}_2 \) (see Fig. 2.3 and 2.5 ). This characteristic geographical pattern of
stronger high latitude amplification is the result of larger present-day sensitivities (\( \gamma_{\text{DIC}}, \gamma_T \)) and seasonal amplitudes (\( \delta_{\text{DIC}}, \delta_T \)) in the high latitudes that amplify the effect of \( \Delta p\text{CO}_2 \) even when its value is small compared to other regions (see Eq. (2.4), first row term). Some exceptions can be found south of Greenland and near the subtropical gyres, where \( \Delta p\text{CO}_2 \) reaches higher values and therefore they also present large amplification. We also found spatial differences on smaller scales; for example, the western Equatorial Pacific presents lower initial \( \delta p\text{CO}_2 \) and amplification than the eastern Equatorial Pacific (see Fig. 2.3). This is because the eastern side of the basin has larger DIC and T contributions than the western side (see Fig. 2.13), as consequence of the upwelling of cold, CO\(_2\)-rich waters in the east, which lower the buffering capacity and induce larger \( \delta p\text{CO}_2 \) amplitude due the seasonal effects of productivity and solubility (Valsala et al., 2014).

To further disentangle which of the two main drivers (DIC or T) is most affected by \( \Delta p\text{CO}_2 \), we decomposed the DIC and T contributions in their sensitivity, seasonal cycle and \( p\text{CO}_2 \) components. Figure 2.12, (b), shows the total DIC and T components together with the \( \Delta p\text{CO}_2 \) and seasonal cycles effects on them. The effects from the sensitivities are not depicted, as they only play a minor role. Only the \( \Delta \gamma_{\text{DIC}} \) term gains importance in the Southern Ocean (not shown). In most of the ocean, the \( \Delta p\text{CO}_2 \) effect on T contribution is the leading cause of amplification. This effect is the result of seasonal solubility changes acting over a larger [CO\(_2\)] (Gorgues et al., 2010). In the northern high latitudes, an increase on \( \delta T \) reinforces the amplification. In general, the \( \Delta \delta T \) contribution gains importance as we move poleward in both hemispheres and therefore the second order terms originating from \( \Delta p\text{CO}_2 \cdot \Delta \delta T \) also reinforce the amplification. Interestingly, in the high latitudes, the amplification through second order terms is as important as the change in the seasonality of the drivers.

The Southern Ocean is an exception to the T dominance; in this region the \( \Delta p\text{CO}_2 \) effect on the DIC contribution dominates, and the regional amplification is reinforced by low values of the mean buffering capacity (high \( \gamma_{\text{DIC}} \)). This result agrees with the findings of Hauck and Völker (2015). In this area the amplification is counteracted by a reduction in \( \delta \text{DIC} \).
2.5 Conclusions

In this study, I used output from 7 CMIP5 global models, subjected to the RCP8.5 radiative forcing scenarios, to provide a comprehensive analysis of the characteristics and drivers of the intensification of the seasonal cycle of pCO$_2$ between present (2006-2026) and future (2080-2100) conditions. By 2080-2100 the $\delta$pCO$_2$ is projected to be 1.5-3 times larger compared to 2006-2026. The future amplification in the earth-system models and the possible causes of it, are consistent with observation-based amplification for the period from 1982 to 2015 (Landschützer et al., 2018). However, the models slightly overestimate the present day amplification, probably due the larger pCO$_2$ trends in models than observations (Tjiputra et al., 2014).

The models confirm the well-established mechanisms controlling present-day $\delta$pCO$_2$ (Takahashi et al., 2002, Sarmiento and Gruber, 2006, Fay and McKinley, 2017). DIC$_s$ and T contributions are the main counteracting terms dominating the seasonal evolution of $\delta$pCO$_2$. Furthermore, the models show that under future conditions the controlling mechanisms remain unchanged. This result confirms the findings of Landschützer et al. (2018) that identified the same regional controlling mechanism for the past 30 years. The relative role of the DIC and T terms is regionally dependent. High latitudes and upwelling regions, such as the California Current system and the coast of Chile, are dominated by DIC$_s$ and the temperate low latitudes are driven by T. Only in the North Atlantic and North-Western Pacific the models show a dominance of thermal effects over non-thermal effects, which is in disagreement with observations. This further illustrates the urgent need for models to accurately represent regional oceanographic features to accurately reproduce the $\delta$pCO$_2$ characteristics.

In agreement with Landschützer et al. (2018), also the model projections towards the end of this century demonstrate that the global amplification of $\delta$pCO$_2$ is due to the overall longterm increase of anthropogenic CO$_2$. A higher oceanic background CO$_2$ concentration enhances the effect of T-driven solubility changes on $\delta$pCO$_2$ and alters the seawater carbonate chemistry, also enhancing the DIC seasonality effect. The spatial differences of $\delta$pCO$_2$ amplification, however, are determined by
the regional sensitivities and seasonality of pCO$_2$ drivers. For example, polar regions show larger sensitivity to DIC and T and larger seasonal cycles of DIC and T. Therefore, these areas present a strong enhancement of δpCO$_2$, in spite of smaller changes in mean pCO$_2$.

Moreover, the pCO$_2$ seasonal cycle amplitude depends on the relative magnitude and phase of the contributions. The multi-model ensemble mean reproduces the highly effective compensation of DIC$_s$ and T contributions when they are six months out of phase, confirming previous studies (Takahashi et al., 2002, Landschützer et al., 2018). The compensation of DIC and T prevents a larger amplification of δpCO$_2$, even when both contributions are largely amplified.

The amplification of the TA and S contributions have a small impact on δpCO$_2$ in most regions, except in the high latitudes where the TA contribution complements the DIC one, enhancing the non-thermal effect in this region.

The use of earth system models allows us to state the importance of including future changes on the T and DIC seasonalties for future δpCO$_2$ projections. The T seasonality is projected to increase in most of the ocean basins, thereby reinforcing the δpCO$_2$ amplification. The δT increase is consistent with an increase in stratification that will confine the seasonal changes in net heat fluxes to a shallower mixed layer (Alexander et al., 2018). The DIC$_s$ seasonality decreases in some cold areas and its reduction prevents a larger amplification. For the sensitivities, while γDIC increases, γT decreases. The later phenomenon needs further study.

The increasing amplitude of δpCO$_2$ might have implications for the net air-sea flux of CO$_2$, in particular in regions where there is an imbalance between winter and summer values (Gorgues et al., 2010). Examples of such behavior can be found in the Southern Ocean (between 50°S-60°S) (Takahashi et al., 2014a) and in the latitude band from 20°-40° in both hemispheres (Landschützer et al., 2014). Moreover, seasonal events of high pCO$_2$ could have an impact on acidification and aragonite undersaturation events (Sasse et al., 2015) and hypercapnia conditions (McNeil and Sasse, 2016). Therefore, understanding the drivers of future δpCO$_2$ may help to better assess the response of marine ecosystems to future changes in carbonate chemistry. Finally, our complete analytical expansion of δpCO$_2$ in terms of all its 4 variables provides a practical tool to accurately and quickly
diagnose temperature and salinity sensitivities from observational or modelling datasets.
Figure 2.10: RCP8.5 ensemble zonal mean seasonal cycles: a) δDIC, and b) δT, for different latitudinal bands. Blue lines represent the 2006-2026 period, depicted for comparison with the 2080-2100 period shown by red lines. Different panels represent different latitudinal sections. Black arrows point out that while T seasonal cycle is projected to increase in most of the ocean, global DIC is projected to decrease. The shading represents one standard deviation across the models. It is important to note that the scale is different for some of the latitudinal bands.
Figure 2.11: RCP8.5 ensemble zonal mean seasonal cycles: a) $\delta T_A$ and b) $\delta S$, for different latitudinal bands. Blue lines represent the 2006-2026 period, depicted for comparison with the 2080-2100 period shown by red lines. Different panels represent different latitudinal sections. $\delta T_A$ is projected to slightly increase in all the bands, while $\delta S$ is projected to slightly decrease. The shading represents one standard deviation across the models.
Figure 2.12: Contribution of seasonalities, sensitivities, and mean pCO₂ changes to δpCO₂. a) Time series for the terms of Eq.(2.4) for different latitudinal bands. The Δ symbol represents the total century change, calculated as 2080-2100 value -minus- 2006-2026 value. The total change in seasonal pCO₂ (ΔδpCO₂) is depicted as dashed black. This change is decomposed into changes in seasonalities (ΔδX, purple), sensitivities (ΔγX, green), mean pCO₂ (ΔpCO₂, red) and second order terms (blue) summed over the four variables that control pCO₂ (DIC, TA, T and S). For comparison with the expansion, ΔδpCO₂ is calculated from model output (yellow). Column b) shows the total change of DIC (dashed red) and T (dashed blue) contributions. Also shown, are two components of the total change on these contributions; the ΔδpCO₂ effect on the DIC (solid orange) and T (solid blue) contributions, and the ΔδDIC (yellow) and ΔδT (light blue) effects. In column a), the δpCO₂ change follows the ΔδpCO₂ effect. Column b) shows that actually, the leading cause of amplification is the ΔδpCO₂ effect on the T contribution. It is important note the different scale between column a) and b). Also, the scale was reduced in the 15°S-15°N region to highlight its features.
Figure 2.13: Simulated, ensemble-mean pCO$_2$ seasonal amplitude calculated as summer minus winter for each hemisphere respectively (a). b) to e) show DIC$_s$, T, TA$_s$ and S contributions to the pCO$_2$ summer-minus-winter amplitude. First and second rows represent respectively the 2006-2026 and 2080-2100 periods. Third row shows the difference between second and first rows. The amplitude was calculated from the climatology for periods 2006-2026 and 2080-2100.
Anthropogenic Intensification of Surface Ocean Interannual pCO$_2$ Variability

3.1 Abstract

We use several global coupled atmosphere-ocean-biogeochemistry models from the Coupled Model Intercomparison Project (CMIP5) to show that the global interannual variability of the sea surface pCO$_2$ (calculated as 1σ) will increase by $\approx 64 \pm 20\%$ by 2040-2090 relative to the beginning of the industrial revolution under the RCP8.5 scenario. All models agree that the increase in variability is a consequence of a larger background pCO$_2$ and a lower buffering capacity that enhance the response of pCO$_2$ to the fluctuations of surface temperature (T) and dissolved inorganic carbon (DIC). The most skillful group of models under present-day conditions shows a future global decrease in DIC fluctuations that will weaken the pCO$_2$ interannual variability (IAV). The remaining uncertainties in the projected evolution of pCO$_2$ variability regionally highlight the need for continuous carbon monitoring programs which will contribute to a better understanding of the oceanic carbon sink’s response to increased greenhouse gas emissions.

3.2 Introduction

On average, the ocean absorbs $2.4 \pm 0.5$ Pg of carbon each year, (Le Quéré et al., 2018), but the efficiency of the oceanic carbon sink varies on interannual time-scales. Efforts have been made to estimate the present-day year-to-year variations of CO$_2$ uptake in observations and models (Dong et al., 2017), however there is little agreement. Moreover, numerous studies use different variability metrics which makes it difficult to compare the estimates. Values for the interannual variability calculated as $1\sigma$ of the CO$_2$ flux anomalies range from $\pm 0.14$ PgC yr$^{-1}$ for a 1982-2007 diagnostic model (Park et al., 2010), $\pm 0.29$ for the 1985-2017 observations (Le Quéré et al., 2018), $\pm 0.31$ PgC yr$^{-1}$ for a 1992-2009 data-based estimation (Rödenbeck et al., 2015) to $\pm 0.40$ PgC yr$^{-1}$ for a 1979-1997 simulation (Le Quéré et al., 2000).

The ocean-atmosphere flux of CO$_2$ (FCO$_2$) is determined by the difference between ocean and atmospheric pCO$_2$, and further modulated by solubility, regional wind speed and sea ice coverage. Globally, most of the open ocean’s FCO$_2$ interannual variability is driven by the fluctuations in oceanic pCO$_2$ (see Figure 3.1) (Landschützer et al., 2016, 2019b, Rödenbeck et al., 2015, Li et al., 2019), however in some regions wind speed variations can also have an important impact (Doney et al., 2009b, Wanninkhof and Triñanes, 2017).

The ocean’s pCO$_2$ interannual variability (from now on referred as IAV) is generated by large scale atmosphere-ocean interactions and specific climate modes, such as the El Niño Southern Oscillation (ENSO) in the equatorial Pacific, the Pacific Decadal Oscillation (PDO) in the North Pacific, the Southern Annular Mode (SAM) in the Southern Ocean, and the North Atlantic Oscillation (NAO). These climatic phenomena induce changes in physical parameters (e.g. temperature, salinity, ocean currents, mixing) which in turn influence ocean biology and carbonate chemistry, thereby altering the ocean’s ability to sequester CO$_2$ (Doney et al., 2009b, Feely et al., 2002, Chatterjee et al., 2017, Sutton et al., 2017, McKinley et al., 2004, Friedrich et al., 2006, Landschützer et al., 2019b).

The on-going decline of the ocean’s buffering capacity due to increasing atmospheric CO$_2$ con-
Figure 3.1: pCO$_2$ and FCO$_2$ time series from 1982 to 2019. Depicted is the atmospheric partial pressure of CO$_2$ (red), the oceanic pCO$_2$ (blue) and the ocean-atmosphere flux of CO$_2$ (FCO$_2$) (black). The time-series represents the area mean between 0°-10°N and 270°W-280°W. The figure illustrates the relation between the partial pressures, and the flux. Negative FCO$_2$ values are marked by vertical grey lines, and indicate a net flux into the ocean. The data corresponds to the observation-based neuronal-network interpolation from Landschützer et al. (2020).

centrations is well documented in the literature (Bates et al., 2014, Fassbender et al., 2017, Sabine et al., 2004, Egleston et al., 2010), and recently, the corresponding implications for the seasonal cycle amplitude of pCO$_2$ have been elucidated (McNeil and Sasse, 2016, Landschützer et al., 2018, Gallego et al., 2018, Fassbender et al., 2018). To determine the effect of anthropogenic CO$_2$ on the seasonal cycle of the ocean’s pCO$_2$ it is necessary to distinguish the influences of carbonate chemistry dynamics from those directly related to biophysical mechanisms. This can been done using a Taylor series expansion of pCO$_2$ in terms of the physical and chemical main drivers (McNeil and
Sasse, 2016, Landschützer et al., 2018, Gallego et al., 2018, Fassbender et al., 2018) and through idealized simulations (Hauck and Völker, 2015, Gorgues et al., 2010). These studies concluded that the trends in carbonate chemistry are responsible for the increased seasonal amplitude of pCO$_2$ and hydrogen ion concentrations (Kwiatkowski and Orr, 2018). Yet, the impact of the decreasing ocean’s buffering capacity on the interannual variability of pCO$_2$ has not been documented.

The large interannual variability induced by ocean-atmosphere interactions makes it difficult to detect long-term trends in the ocean’s carbon sink (McKinley et al., 2017, Li et al., 2019, Chatterjee et al., 2017, Sutton et al., 2017), in particular on regional scales. However, some studies have shown that it is possible to use models and data-assimilation techniques to predict the carbon sink up to some extent (Séférian et al., 2018, Li et al., 2019). To further improve these predictions, we need to use carbon monitoring programs as well as mechanistic studies to understand the vulnerability of pCO$_2$ interannual variability to increasing greenhouse gas emissions (McKinley et al., 2017, Gruber et al., 2019).

The aim of this chapter is to quantify how well CMIP5 models capture the mechanisms of present-day sea surface pCO$_2$ IAV when compared to data-based estimates, and from there, elucidate the causes of future changes in the variability of the carbon cycle in response to anthropogenic emissions of CO$_2$.

### 3.3 Methodology

**Models**

For our analysis, the surface pCO$_2$, DIC, TA, pH, T and S monthly-mean output variables covering the period 1861-2005 were obtained from historical simulations, and the period 2006-2100 from climate change simulations forced with the Representative Concentration Pathway 8.5 (RCP8.5) greenhouse gas emission scenarios (IPCC, 2013). The pH is necessary to calculate the hydrogen ion concentration [H$^+$], although it can also be numerically calculated from TA, DIC, T and S.
We selected 16 fully coupled earth system models that participated in the Coupled Model Intercomparison Project, Phase 5 (CMIP5) to analyze the standard deviation of $pCO_2$. However, we removed from the analysis the models CMCC-CESM and GISS-E2-H-CC based on (Dong et al., 2016) and the large difference between their patterns of $pCO_2$ standard deviation (STD) from those of other models and observations (see Figure 3.4 and 3.5 compared to the observational estimate from Figure 3.9). Out of the sixteen, we selected six models for a more comprehensive analysis of the causes driving $pCO_2$ variability; these models were selected based on data availability: CanESM2, CESM1-BGC, GFDL-ESM2G, MPI-ESM-LR, HadGEM2-ES and HadGEM2-CC (See supplementary material of (Hauri et al., 2015)). The ocean’s surface data sets were regrided onto a $1^\circ \times 1^\circ$ grid using Climate Data Operators (CDO). The Arctic Ocean and the region poleward of $70^\circ$S are removed from the analyses, because observational data for model validation are scarce.

Analysis

Commonly, the interannual anomalies are defined as deviations of monthly mean values from a long-term mean monthly climatology, or by using a running 12 month filter on detrended monthly values, (Landschützer et al., 2019b, Rödenbeck et al., 2015). However, for CMIP5 models, the future seasonal cycle of $pCO_2$ is expected to increase (Gallego et al., 2018), therefore removing a mean climatology for the 1861-2100 period would result in an overestimation of IAV amplification (IAVA). On the other hand, a 12 month running filter would remove important sub-annual information associated with the coupling between the seasonal and interannual time-scales, such as Combination modes which play a key role for ENSO dynamics, (Stuecker et al., 2015). Finally, removing a linear trend from a 200-year-long time series poses its own difficulties. To avoid these issues, we calculate the monthly anomalies for each year as the monthly deviation from a 11-year running climatology centered on that year. For example, for the year 1935 we desasonalize the monthly values by subtracting the mean climatology from 1930 to 1940; for the year 1936 we use the climatology from 1931-1941 and so on. From now on, the monthly deviations (or anomalies) are denoted by $pCO_2'$.
Figure 3.2: Time series (1866-2095) of pCO$_2$ as a) 11 years running climatology and b) monthly anomaly (calculated as the deviation from the climatology), for 13 different CMIP5 models, under RCP8.5 scenario. Overlaid in black is the anomalies from the observation-based estimations of (Landschützer et al., 2017) and the running climatology as $\overline{pCO_2}$. Figure 3.2 shows the time series of $\overline{pCO_2}$ and $pCO'_2$ obtained with this method. The size of the running window is arbitrary but is chosen to minimize the loss of data points at the end of the time series. We compared windows of 11, 21 and 31 years and the values for the mean $\overline{pCO_2}$ and the STD of $pCO'_2$ are similar (see Figure 3.3).

To elucidate the underlying physical and chemical processes controlling the $pCO_2$ interannual anomalies (from now $pCO'_2$) we calculated a first-order Taylor series expansion of $pCO'_2$ in terms of its four controlling factors, DIC, TA, T and S, following the method of (Takahashi et al., 1993, Lovenduski et al., 2007, Doney et al., 2009b).

To remove the freshwater concentration/dilution effect we use salinity-normalized DIC and TA using a mean salinity of 35 psu, referred as DIC$_s$ and TA$_s$ (Lovenduski et al., 2007). The freshwater effect is now included in the $S_{fw}$ term. For the Taylor series expansion, each variable ($X = DIC_s$, TA$_s$, T and $S_{fw}$) is decomposed as $X = \overline{X} + X'$. The term $\overline{X}$ represents the averaged seasonal cycle calculated for an 11-year running window at each grid point. The term $X'$ are the monthly anomalies, calculated as the deviation from the climatology. The full first-order series expansion is given by:

$$pCO_2' \approx \frac{\partial pCO_2}{\partial DIC} \overline{DIC'} + \frac{\partial pCO_2}{\partial TA} \overline{TA'} + \frac{\partial pCO_2}{\partial T} \overline{T'} + \frac{\partial pCO_2}{\partial S} \overline{S_{fw}'},$$  \hspace{1cm} (3.1)
where the derivatives are evaluated on the running climatologies. The analytical derivation of Eq. (3.1) is given in the Appendix A. Equation (3.1) can be rewritten as:

\[
pCO_2' \approx \left( \gamma_{DIC} \cdot DIC' + \gamma_{TA} \cdot TA' + \gamma_T \cdot T' + \gamma_S \cdot S' \right)
\] (3.2)

where, for notation purposes, each derivative is re-defined as: \( \gamma_X = \frac{1}{pCO_2} \cdot \frac{dpCO_2}{dX} \), and we will refer to them as the pCO\(_2\) sensitivity to X. It is important to make the distinction between different quantities that measure the oceanic buffering capacity. The DIC sensitivity (\( \gamma_{DIC} \)) is a similar concept to the Revelle factor (RF), and they are related by \( RF = \frac{\gamma_{DIC}}{DIC} \). Our definition of \( \gamma_{DIC} \) is the inverse of the one given by (Egleston et al., 2010). The three different quantities RF, \( \gamma_{DIC} \) and \( 1/\gamma_{DIC} \) characterize how much the pCO\(_2\) changes by a given change in DIC, but they differ in their spatial distribution in the oceans.
In what follows, we use the method of (Doney et al., 2009b) to determine how much each term (from DIC, TA, T and S) contributes to the variability of pCO$_2$ (measured as the root-mean-square (RMS) of pCO$_2$). First, Equation (3.2) is multiplied by pCO$_2$', and then averaged, obtaining the following equation:

\[
\langle (pCO_2')^2 \rangle \approx \bar{pCO_2} \cdot \gamma_{DIC} \langle DIC' \cdot pCO_2' \rangle + \bar{pCO_2} \cdot \gamma_{TA} \langle TA' \cdot pCO_2' \rangle + \bar{pCO_2} \cdot \gamma_T \langle T' \cdot pCO_2' \rangle + \bar{pCO_2} \cdot \gamma_S \langle S_{fw}' \cdot pCO_2' \rangle,
\]

(3.3)

where $\langle ... \rangle$ represents a temporal averaging operator. Introducing the following notation:

\[
\beta_X \equiv \frac{\langle \bar{pCO_2} \cdot \gamma_X \cdot X' \cdot pCO_2' \rangle}{\langle (pCO_2')^2 \rangle}.
\]

(3.4)

Then, we can divide Eq. (3.3) by $\langle (pCO_2')^2 \rangle$ to give the relationship $\sum X \beta_X \approx 1$, where $X = \{DIC, TA, T, S\}$, as introduced by (Doney et al., 2009b). Thus, if we multiply Eq.(3.4) by the RMS of the anomalies (defined as $\sqrt{\langle (pCO_2')^2 \rangle}$), then the $\beta_X$ coefficients can be interpreted as the fraction of the total RMS of the pCO$_2$ that each variable contributes. In our numerical calculations the sum of the $\beta$’s differs slightly from one due the approximation used for the Taylor expansion, and the anomalies averaged being slightly different from zero.

### 3.4 Results

The increase in IAV of surface pCO$_2'$ is illustrated with the running standard deviation of the monthly anomalies from 1871 to 2090 (Figure 3.6). The ensemble mean (14 CMIP5 models) of the globally averaged STD of pCO$_2$ increases from $7 \pm 1.2 \mu$atm to $11.8 \pm 2.8 \mu$atm by the end of the 21st century. Detailed global maps for the periods 1866-1917 and 2045-2095 STD are found in Figures 3.4 and 3.5.
Figure 3.4: pCO$_2$’s interannual anomalies, shown as a) 1866-1916 and b) 2045-2095 standard deviations. c) shows the 2045-2095 STD divided by 1866-1916 STD. Each row shows a different CMIP5 model. These models present large biases in variability patterns according to (Dong et al., 2016)
Figure 3.5: Same as Figure 3.4 but for different models.
For the pCO$_2$, a present day comparison shows that the 1987-2012 ensemble STD is 8.6 $\mu\text{atm}$ and is larger than the observation-based estimates of $\approx 4.4 \mu\text{atm}$ (Landschützer et al., 2019a) (excluding the Arctic region).

The disagreement between models and the data-based results of Landschützer et al. (2019a) may be due to several reasons. First, the data-based estimations are an interpolation of the Surface Ocean CO$_2$ Atlas (SOCAT) dataset (Bakker et al., 2016, Sabine et al., 2013) which may be biased due to under-sampling, and interpolation methods may cause a lower RMS in higher latitudes with limited observational coverage (Landschützer et al., 2019b, Rödenbeck et al., 2015, Sutton et al., 2017, 2014). In another example of under-sampling related bias, it was found that the observed 1970-2011 pCO$_2$ anomalies show a larger standard deviation than the CMIP5 models, but they were of equal magnitude when the models were subsampled to the measurements, (Tjiputra et al., 2014). Secondly, it is important to notice that we use fully-coupled ocean-atmosphere models, therefore they generate their own internally driven climate variability and the amplitude and timing may not match with observational records. This is further analyzed in the next section. Third, the neural-network-based reconstruction approach used for the observations may smooth away important sub-annual variations (Gruber et al., 2019). To test this hypothesis, we apply a 12-month running mean to filter out sub-annual variability in the models’ anomalies. When we apply the filter, we find a global mean STD of $\approx 4.5 \mu\text{atm}$, very similar to the unfiltered anomalies of Landschützer et al. (2019a) (see Figure 3.6 and Figure 3.3 (b)). However, the sub-annual variations captured in the models are specially important in regions with high variability. In the Southern Ocean, the pCO$_2$ interannual variability is highly coupled to the seasonal cycle. Gregor et al. (2018) found that winter wind stress explains decadal variability and summer drivers explains interannual variability in this region. Moreover, Stuecker et al. (2015) suggests that ENSO should not be studied only on interannual time-scales, since is strongly coupled to the seasonal cycle which lead to the generation of variability on timescales of 9 and 15-18 months. Given these considerations, we decided to conduct our study with unfiltered anomalies, recognizing that the background level of natural variability from this approach may differ from the observation-based reconstructions of Landschützer et al.
Drivers of present-day sea surface pCO$_2$ interannual variability

The drivers of the present-day (1987-2010) pCO$_2$'s IAV are analyzed in Fig. (3.7) and Fig. (3.9). We compare the root mean square (RMS) of simulated pCO$_2$ and the respective contributions of T, DIC, TA and S for the 1987-2010 period with the reconstruction of Landschützer et al. (2019a). For the observation-based dataset we only calculate the thermal and non-thermal components using observed sea-surface temperatures (TA and DIC are not available). The non-thermal component comprises the combined contribution of DIC, TA and S (Takahashi et al., 2002). The thermal and non-thermal contributions calculated for the CMIP5 models can be found in Figure (3.8); these follow the DIC and T patterns respectively.

The spatiotemporal-patterns and drivers of the present-day pCO$_2$'s IAV have been largely documented in the literature and are well captured in the estimate of Landschützer et al. (2019a) shown...
in and Fig. (3.8), and further analyzed in Landschützer et al. (2019b). Studies agree that most of the global pCO$_2$ IAV is generated in the equatorial Pacific (Doney et al., 2009b, Rödenbeck et al., 2015, McKinley et al., 2017) and the equatorial belt may account for 40% of the total temporal standard deviation of the global ocean, (Rödenbeck et al., 2014). Previous studies also agree that the pCO$_2$’s IAV is controlled by non-thermal changes in the high latitudes (Resplandy et al., 2015, Verdy et al., 2007) and in the equatorial Pacific, where during El Niño years the reorganization of oceanic currents reduce the upwelling or DIC-rich waters causing negative pCO$_2$ anomalies (Feely et al., 2006, Valsala et al., 2014, Sutton et al., 2014, Cosca et al., 2003, Long et al., 2013, Feely et al., 1999). In contrast, in the subtropical gyres the variability is controlled by thermal changes (Doney et al., 2009b, Landschützer et al., 2019b, Rödenbeck et al., 2015).

Thus, for analysis purposes, we separate the models into two groups according to the following characteristics: 1) the location of the maximum pCO$_2$ variability and 2) the pattern of thermal and non-thermal dominance of the pCO$_2$ IAV. The models CanESM2, CESM1-BGC and GFDL-ESM2G (from now on referred to as Group I) show the largest pCO$_2$ variability in the equatorial Pacific and a DIC-dominance in the equatorial belt and the high latitudes. These models are in good agreement with the observational estimates, (see Figure 3.9, second row). The models HadGEM2-CC/ES and MPIESM-MR (from now on referred to as Group II) have an overall poorer performance compared to Group I. For Group II, the strongest fluctuations occur in the high latitudes, especially in the Southern Ocean and North Atlantic, and the pCO$_2$ IAV is dominated by temperature in the equatorial Pacific. However, this group agrees with observations on the DIC-dominance in the high latitudes, (Figure 3.9, third row).

The low equatorial variability in the Group II models may be a consequence of the CO$_2$ flux variability that exhibits a much shorter period variation than ENSO time-scales, thus ENSO does not play a dominant role on the IAV (Dong et al., 2016). Jin et al. (2019) performed a similar analysis of the IAV drivers in the equatorial Pacific region. The authors found that for CanESM2, CESM1-BGC and GFDL-ESM2G (Group I) the pCO$_2$ anomalies caused by El Niño are negative due to a redistribution of oceanic currents and reduced upwelling of DIC-rich waters; while for MPI-
ESM-IR and HadGEM-ES/CC (Group II) the pCO$_2$ anomalies are positive as a consequence of the anomalous eastward advection of warmer waters. Group II fails to represent the DIC dominance because of an underestimated reduction in upwelling during El Niño years and weak mean vertical gradients of DIC.

Some other interesting differences and similarities between the models and the observations-based estimate are worth mentioning. For example, in the equatorial Atlantic the HadGEM2-CC/ES and GFDL-ESM2G models (from Group II and Group I respectively) show a negative temperature contribution (Wang et al., 2015), disagreeing with the Landschützer et al. (2019b) estimate. In the sub-polar North Atlantic the observations show a non-thermal dominance north of 40°N, whereas in the models the DIC dominance extends to 25-30°N. Only the HadGEM2-CC/ES model shows a relatively important alkalinity contribution in the North Atlantic and North Pacific that counteracts the positive DIC contribution. Salinity has a minor effect everywhere, with a small positive effect in the western Pacific associated with rainfall changes due ENSO (see Figure 3.7).

**Future sea surface pCO$_2$ interannual variability**

We further investigate the future spatio-temporal characteristics of the pCO$_2$ IAV. The sea surface pCO$_2$ IAV, calculated as the RMS-value of the interannual pCO$_2$ anomalies, is amplified in most of the ocean by the end of the 21st century, as shown in Figure (3.10, a), (see Figure 3.11 for each individual model). Yet, the magnitude of the IAV amplification (IAVA) exhibits large regional differences, and even decreases in the equatorial Pacific for some models. Here, we analyze the causes of IAVA and its spatial heterogeneity by separating the analysis into the two groups of models mentioned in the previous section. For Group I the pCO$_2$ IAV increases everywhere except in the equatorial Pacific (see Figure 3.10a, upper row); Group II shows higher values of IAVA than Group I globally (see Figure 3.10a, bottom row).

To determine how much of the pCO$_2$ IAVA is due to carbonate chemistry dynamics and how much is explained by physical and biological processes, we calculate the RMS of pCO$_2'$ for the final
Figure 3.7: Mechanisms driving the 1987-2010 interannual variability of surface ocean pCO$_2$. First row shows the a) (Landschützer et al., 2017) estimate of the root mean square (RMS) of pCO$_2$ interannual anomalies, and its b) thermal and c) non-thermal contributions. Panels on the second to seventh rows show the different CMIP5 models a) root mean square (RMS) of pCO$_2$ interannual anomalies and its contributions from d) temperature (T), e) salinity normalized dissolved inorganic carbon (DIC$_s$), f) salinity normalized total alkalinity (TA$_s$) and g) salinity including fresh water effect ($S_{fw}$). For the observations, we calculate a thermal and non-thermal terms following (Takahashi et al., 2002) method because there is not enough DIC, TA and S data available. The non-thermal component comprises the combined effects of DIC, TA and S. See the methodology section in the main article for details.
Figure 3.8: 1987-2010 values of root mean square (RMS) for a) pCO$_2$ anomalies and the b) thermal and c) non-thermal contributions to pCO$_2$’s RMS. The contributions are defined as the regression coefficients between the components (either thermal or non-thermal) and the pCO$_2$ anomaly, following the method of (Doney et al., 2009b). The thermal and non-thermal components are calculated as (Takahashi et al., 2002).

The first row shows the observation-based results of (Landschützer et al., 2017). The anomalies where calculated with the method of (Landschützer et al., 2018), to compare with their results. The data was first filtered with a 12 month mean, and then detrended with a quadratic polynomial.
Figure 3.9: Mechanisms driving the 1987-2012 interannual variability of surface ocean pCO$_2$. First row shows the a) (Landschützer et al., 2019a) estimate of the root mean square (RMS) of pCO$_2$ interannual anomalies, and its b) thermal and c) non-thermal contributions. The models were grouped according to their behavior (see main text) in Group I (CanESM2, CESM1-BGC and GFDL-ESM2G) and Group II (HadGEM2-CC, HadGEM-ES and MPI-ESM-LR) respectively. We first did an analysis of the RMS of the pCO$_2$ and its DIC, TA, T and S contributions for each individual model, and then we calculated the ensemble mean of Group I and Group II. The panels in the second and third rows show the ensemble mean of the Group I and II respectively, for the a) root mean square (RMS) of pCO$_2$ interannual anomalies and its contributions from d) temperature (T), e) dissolved inorganic carbon that has been salinity normalized (DIC$_s$), f) salinity normalized total alkalinity (TA$_s$) and g) salinity including fresh water effect (S$_{fw}$). For the observations, we calculate a thermal and non-thermal terms following (Takahashi et al., 2002) method because there is not enough DIC, TA and S data available. The non-thermal component comprises the combined effects of DIC, TA and S. Following the method of (Doney et al., 2009b), each map of the contributions is calculated as the $\beta$ coefficient of Eq. (3.4) normalized by the RMS of the pCO$_2$. In the panels, yellow-redish colors indicate a positive contribution to the RMS of pCO$_2$ interannual anomalies and blue colors represent a negative contribution. Each model is depicted individually in the Supplement material Figure 3.7.
period as if only the background carbonate chemistry - represented by $p\text{CO}_2$ and the sensitivities ($\gamma_T$ and $\gamma_{\text{DIC}}$)- increase, but maintaining the historical values of the anomalies given by $T'$ and DIC$_s'$ (see Eq. (3.2)). The latter anomalies are the result of physical and biological variations. In both groups of models, the case in which only the carbonate chemistry is changed shows a global mean IAVA twice as large as the case in which DIC$_s'$ and T' are also allowed to vary (compare in Figure 3.10b with 3.10a). The large increase in $p\text{CO}_2$ and $\gamma_{\text{DIC}}$ is similar for both groups of models and generates an overall amplification (Figure 3.12a,b). It is important to mention that the separation between $p\text{CO}_2$ and $\gamma_{\text{DIC}}$ is a mathematical construct rather than two separate phenomena. Ultimately, the change in $p\text{CO}_2 \cdot \gamma_{\text{DIC}}$ is what determines the increase in the DIC contribution, while the T contribution increases almost exclusively due to the increase in $p\text{CO}_2$ since $\gamma_T$ remains almost unchanged (not shown).

The damping of the pCO$_2$ IAVA (Figure 3.10 (a)) is due to a decrease of the DIC' interannual variability (see Fig. 3.13). As shown in Figure 3.12 (c), the simulations differ in DIC' creating a large spread in the projected IAVA. The most striking difference between the groups of models is the location of the maximum DICs' STD. In the first group of models, the maximum of the DIC' standard deviation is located in the low latitudes, in contrast to Group II for which the maximum variability occurs in high latitudes.

Another important difference, is the future change on DIC IAV in the equatorial band. For Group I, the DIC STD largely decreases in this region, whereas for the models HadGEM2-CC/ES the STD increases. For the MPI-ESM-LR model, the STD slightly increases, but this model (as well as HadGEM2-CC/ES) is dominated by T in this region (see Figure 3.9). In high latitudes, for groups I and II the future DIC STD decreases but the sensitivity increases the most, resulting in a large amplification of pCO$_2$ variability. The high latitudes’ strong sensitivity has been well documented in previous studies (Bates et al., 2014, Egleston et al., 2010, Fassbender et al., 2017).

In summary, of the two groups of models, the Group II simulates a larger increase in the sensitivity and a smaller reduction on DIC', therefore result in a larger pCO$_2$ IAVA than Group I. Interestingly, the $T'$ anomalies remain of similar magnitude during both periods of time, but as
Figure 3.10: Causes of increasing sea surface $\text{pCO}_2'$ variability. Total change (measured as 2045-2095 minus 1870-1920 values) of a) the RMS of $\text{pCO}_2'$, b) RMS of $\text{pCO}_2'$ when only the value of $\text{pCO}_2$, $\gamma_{\text{DIC}}$, and $\gamma_T$ vary, but we keep the historical (1870-1920) value of the $\text{DIC}_s'$ and $T'$ interannual anomalies. First we compute the total change for each model and subsequently take the ensemble mean of Group I (CanESM2, CESM1-BGC and GFDL-ESM2G) (top row) and Group II (HadGEM-CC/ES and MPI-ESM-LR) (bottom row). Each individual model is depicted on Fig. 3.11. Panel b) highlights that the RMS of $\text{pCO}_2$ increases due carbonate chemistry changes. However, the interannual variability of DIC and T generates differences between column a) and b) that depend on the models’ physical and biological dynamics.
Figure 3.11: Causes of increasing pCO$_2'$ variability. Total change (measured as 2045-2095 minus 1870-1920 values) of a) the RMS of pCO$_2'$ and b) RMS of pCO$_2'$ when only the value of pCO$_2'$, $\gamma$DIC, and $\gamma_T$ vary, but we keep constant the 1870-1920 value of the DIC$_s'$ and T' interannual anomalies. Each row represents a different model.
Figure 3.12: Changes in carbonate chemistry and interannual variability of surface DIC$'$ and T$'$. Percentage change (measured as 2045-2095 minus 1870-1920 values) of a) $\Delta pCO_2$ and b) $\Delta \gamma_{DIC}$. A 100% change indicates a doubling in magnitude. c) and d) show the ensemble mean of the zonally averaged standard deviation of DIC$'$ and T$'$ respectively. The top row shows the ensemble mean for models in Group I and the bottom for Group II.

$[CO_2]$ increases, the overall T contribution is more amplified than the DIC contribution (see Figure 3.14).

The intra-model differences of future DIC$'$ and T$'$ IAV arise from the models’ biophysical mechanisms, or due to possible future changes in the main modes of ocean-atmosphere variability, such as ENSO, NAO, SAM and PDO. An in-depth analysis of these causes is beyond the scope of this paper, but we discuss some possible explanations discussed in the current literature. One of the reasons for the diminished DIC$'$ variability may be related to the fact that models simulate a weaker Walker circulation in response to global warming (Vecchi et al., 2006, Zhao and Allen, 2019). A weaker Walker circulation would weaken the upwelling of DIC-rich waters during La Niña conditions.

(Keller et al., 2015) studied ENSO variability in the CESM1-BGC model for the 850-2100 period, the authors found that the warmest period had the lowest variance in ENSO, and that the air-sea CO$_2$ flux response was the lowest. The latter result agrees with our finding that the pCO$_2$ variability decreases in the eastern equatorial Pacific for this model. However, unresolved large equatorial model biases with magnitude similar to the projected future warming (Cai et al., 2015,
Figure 3.13: Standard deviation of DIC$_4$ anomalies, for each CMIP5 model. The blue lines indicate the 1870-1920 STD, and red line the 2045-2095 period. The arrows highlights areas of increase (pointing to the right) or decrease (pointing to the left).
Timmermann et al., 2018) suggest that our model-based projections of future pCO₂ variability in the eastern equatorial could still be subject to larger uncertainties, which at this stage are difficult to quantify.

Another possible explanation for the diminished DIC′ variability is the projected shoaling of the winter mixed layer depth, associated with a reduced heat loss during the cold season. The mixed layer shoaling will cause less mixing of deep rich DIC waters to the surface on both, seasonal and interannual timescales. In the winter deep convection regions the future shoaling of the MLD may be underestimated by models, because they show a shallower than observed present-day mixed layer depth (Downes et al., 2009, Sallée et al., 2013). Simulations show that a decrease in mixed layer depth will also reduce the input of macronutrients and therefore reduce primary productivity (Bopp et al., 2013). However, in higher latitudes, such as the Southern Ocean, a reduction in light and temperature limitations stimulate primary productivity (Steinacher et al., 2010) which could counteract the decrease of the DIC′ variability.

The total reduction of the DIC′ STD may be a combination of these factors; for example, even if ENSO’s magnitude and frequency increase, a reduction of the MLD may confine the ocean uptake of CO₂ to the surface, thereby reducing the DIC vertical gradient. As a result, frequent upwelling events would have a smaller impact on DIC′ IAV.

3.5 Summary and Conclusions

The ocean surface pCO₂ responds to climate modes of variability that alter the ocean’s circulation and biogeochemical conditions on interannual time-scales (Resplandy et al., 2015). The CMIP5 models present a larger present-day pCO₂ IAV than the observation-based estimates of Landschützer et al. (2019a). The difference can be partly attributed to the presence of near-annual variations that are less present in the Landschützer et al. (2019a) dataset, but that have a large impact on the dynamics of the simulated monthly anomalies of pCO₂.

Two opposing mechanisms control the simulated future changes in pCO₂ IAV. The first is the
result of the changing ocean’s carbonate chemistry; a higher background CO$_2$ concentration and increased oceanic sensitivity to naturally occurring DIC and T fluctuations amplify the pCO$_2$ IAV. The second opposing mechanism is a reduction of the interannual fluctuations in DIC that counteract the pCO$_2$ IAVA. In other words, although changes in DIC$'$ will be smaller compared to present-day, the ocean will be much more sensitive to them and to T$'$, resulting in an overall increase of pCO$_2$ variability in most of the global ocean. However, this result is based on fully-coupled ocean models with biases in mean state and variability. Beyond improving future earth system models in this regard, it is paramount to maintain extended carbonate chemistry observational networks that will help monitoring the interannual changes in DIC and pCO$_2$.

The response of the pCO$_2$ variability to greenhouse gases varies with latitude; most models show that the high latitudes with large pCO$_2$ IAV are also the ones that will be exposed to larger variance amplification, because the buffering capacity decreases faster in these regions (Egleston et al., 2010, Fassbender et al., 2017). The mid-latitudes variability will be mildly amplified by a larger pool of CO$_2$ that magnifies the response to T variability. In the equatorial Pacific the models show a larger
discrepancy; the models that agree with present-day observations - in terms of pCO$_2$ dynamics-, project a decrease in equatorial variability due to a large reduction of the DIC'. On the other hand, the HadGEM2-CC/ES and MPI-ESM-LR models show a small increase in equatorial variability, because their local pCO$_2$ IAV is dominated by T instead of DIC.

Further study is required to detect how the pCO$_2$ IAVA will influence the regional and global CO$_2$ flux variability. Dong et al. (2016) found no increase in FCO$_2$ IAV in the CMIP5 models, however, the authors compared the STD of the FCO$_2$ anomalies between pre-industrial and present day levels, while we compared the end of the century levels with those at the onset of the industrial revolution. The increase in IAV is gradual and remains small at the beginning of the 21st. Therefore, longer time series are needed to detect the emerging forced amplification.

Changes of surface ocean pCO$_2$ on interannual time scales affect the source/sink nature of the ocean, and they may generate acidification and hypercapnia episodes on interannual time-scales in the most vulnerable regions (McNeil and Sasse, 2016, Sasse et al., 2015). In the mean time, future projections rely on ocean models as the current datasets are sparse and lack time continuity. The models' differences and similarities highlight the large gap in knowledge about the complex physical and biological factors modulated by ocean-atmosphere interactions that control the interannual variability, but also confirm the undeniable consequences of the changing background carbonate chemistry.
PART II

APPLICATION OF AN OFFLINE ECOSYSTEM MODEL: TROPICAL CYCLONES IMPACT ON PRIMARY PRODUCTIVITY:
4.1 Introduction

Ocean circulation models numerically solve - with different degrees of complexity - the equations of motion of a fluid on a rotating sphere, developed by Navier and Stokes independently in the 1800s. Since the first global numerical models (Bryan, 1969, Bryan and Cox, 1972, Semtner, 1995), rapid advancement in resolution and efficiency has made it possible to fully couple ocean, atmosphere, and biogeochemistry in the last generation. One important advancement is the incorporation of the marine ecosystems’ equations that describe nutrients-phytoplankton-zooplankton interactions. These equations are based on prey-predator oscillatory equations (Lotka, 1920, Volterra, 1926), and further intricacy has been added by incorporating nutrients (Fashman et al., 1990, Sarmiento et al., 1993), detritus (Riley, 1947, Edwards, 2001), acclimation of phytoplankton’s growth rate to environmental conditions (Geider et al., 1998), phytoplankton functional types (Moore et al., 2002a, b), and predation of zooplankton (Daewel et al., 2014). These models provide a valuable tool for understanding the ecosystem responses to different forcings. Because, except for a few research stations, sustained time series of nutrients, phytoplankton, and zooplankton observations are sparse.
Long-term data is necessary to understand possible changes in the ecosystem (Benway et al., 2019).

Currently, it is possible to run high-resolution models of the global ocean-atmosphere-land coupled system. However, high-resolution runs remain time-wise expensive and are solved in supercomputers, which have the additional cost of a large carbon footprint (Stevens et al., 2020, Loft, 2020). Moreover, adding a marine ecosystem to fully-coupled high-resolution models can introduce as many as 50 passive tracers, adding a high extra cost.

One convenient and less expensive framework is offline models, which use ocean currents and mixing coefficients from an external online parent model to solve prognostically an advection-diffusion equation for tracers. In other words, offline models do not resolve the momentum equations. Offline models have been successfully used to study ocean ventilation with chlorofluorocarbon (Gupta and England, 2004, Valsala et al., 2007), chlorophyll interannual variability (Dutkiewics et al., 2001), CO$_2$ flux variability (McKinley et al., 2004), the cycle of mercury (Zhang, 2014), coastal transport (Gillibrand and Herzfeld, 2016) and recently an offline version of the Regional Ocean Modeling System (ROMS) was developed for passive tracers (Thyng et al., 2021).

Offline schemes save computational time by increasing the integration time step by one order of magnitude when compared to online models (Hill et al., 2004). Saving time allows performing multiple runs. An additional advantage is their ability to simulate the effects of mesoscale and submesoscale dynamics with a coarser resolution than the parent model (Lévy et al., 2012). Thus, it is possible to exploit their versatility for long-term simulations of tracers that require a long time to equilibrate, such as radiocarbons (Khatiwala et al., 2005) or for short-term phenomena that require high-resolution.

High-resolution simulations capture mesoscale activity, which is fundamental to represent ocean mixing, heat exchange, and biogeochemical dynamics. In particular, mesoscale dynamics such as eddies and storms can drive significant changes in biogeochemical properties as have been documented by satellite images since the early 2000’s (Grower et al., 1980, Lévy et al., 2018). One of these features is the impact of tropical cyclones on marine productivity.

This chapter describes an Offline Marine Ecosystem Model (OMEM), the first offline model to
include a complex ecosystem with 40 tracers. However, this is a preliminary version of the model, and several improvements are further needed, such as a method to resolve bottom topographic boundaries and a positive definite upwind scheme to ensure the tracers’ positivity. Nonetheless, this preliminary version successfully resolves the eddies and tropical cyclones (TCs) present in the parent model high-resolution (0.1 degrees) daily velocity fields. Small et al. (2014) describes the parent model corresponding to the Community Earth System Model 1.2.2 (CESM1.2.2) (without an ecosystem implemented). The tropical cyclones featured in the model are characterized in the study of Chu et al. (2020). OMEM is based on a simplified version of the CESM Parallel Ocean Programming (POP2) component. The ecosystem model is based on the Marine Biogeochemistry Library (MARBL). At the end of this chapter, the model issues, limitations, and differences with MARBL are discussed. The offline model is designed to be forced with currents, temperature, and short wave radiation from the CESM1.2.2 global high-resolution model. The initial and boundary conditions for the tracers are obtained from a CESM2 low-resolution run (Rodgers et al., 2021). However, the code can be adapted to be forced with other parent models or real datasets.

OMEM provides an ecosystem to physical ocean models, and it can be used in a wide range of applications. For example, the ecosystem parameters can be manipulated to understand the model sensitivity to different ecosystem relations. It could also be adapted for larger runs, to study changes in global primary productivity and particulate carbon export. In Chapter 5 the model is tested on a study case to examine the effect of tropical cyclones on primary productivity in the northwestern Pacific Ocean.

4.2 Model description

The offline model consists of physical and marine ecosystem components forced with ocean currents, temperature and radiation from a parent model. The physical component includes an advection-diffusion scheme forced by zonal and meridional velocities. The ecosystem model is based on the MARBL model, which is an improved version of the CESM Biogeochemical Elemental Cycling
(BEC) code. BEC is well documented by Moore et al. (2002a,b, 2004). OMEM features nutrients, phytoplankton, zooplankton, dissolved organic matter and particulate matter, further described in Section 4.2.2. All the tracers require an initial condition and a climatology for the domain’s open boundaries. The offline model also features inputs for surface deposition of dust, iron, nitrate and ammonia, and interior sources of hydrothermal and sedimentary iron.

In this thesis, the initial and open boundary conditions, as well as the surface and interior fluxes, are obtained from a historical climatology (1950-1960) of the low resolution (1 degree) run of the Community Earth System Model 2 (CESM2) (Rodgers et al., 2021). One year of daily velocities, temperature and short wave radiation are borrowed from the parent model CESM1.2.2 (Small et al., 2014), which runs under present-day fixed CO\textsubscript{2} concentration of 367 ppm. The online simulations of CESM2 and CESM1.2.2 were run on the Aleph supercomputer from the Institute for Basic Science (IBS) Center for Climate Physics (ICCP) in Busan, Korea. The offline model is run on a personal computer, with a 2.3 GHz 8-Core Intel Core i9 processor, and it takes 4.5 days to run 1 simulation year, with a time step of 400 s. The model limitations, including time-cost, are discussed at the end of this chapter.

Input data

The input data must be provided on a rectilinear grid. OMEM uses the high-resolution physical inputs from CESM1.2.2, which does not have an ecosystem. On the other hand, the initial and boundary conditions are obtained from the low-resolution CESM2, which does not feature mesoscale activity. Thus, by combing the data of these two models, we can add an ecosystem to the high-resolution model offline. The ocean-land mask is determined by the parent model (high resolution data); thus, the tracer initial and boundary conditions must be interpolated into the parent model’s grid. This process is achieved in three steps. First, the tracer is interpolated into the parent model’s grid. Second, an interpolation method is used to fill the tracer’s land points. Third, the tracer is masked with the parent model’s mask. The horizontal interpolation is done with the operator
Figure 4.1: Model region. a) Shows the CESM’s initial conditions regrided into a $0.1^\circ \times 0.1^\circ$ rectilinear grid. The masked elements are then filled with an interpolation method (from Climate Data Operators) and finally masked with the high resolution CESM1.2 mask, as shown in panel b).

"remapbil" from the Climate Data Operators (CDO), this method performs a bilinear interpolation. Then, a linear vertical interpolation for 3D tracers is done with the operator "intlevel". The land points are filled with the operator "setmisstonn", which sets the missing land value to the nearest neighbor. The filling process is necessary to avoid ocean points in land areas for the tracers (Fig. 4.1). The data borrowed from the parent model are distributed in 60 vertical levels. In the offline model, 37 levels are selected out of the 60 levels. Then, the data is interpolated in depth at levels that range from 5m to 5375 m. The top levels (from 5 to 175m) are equispaced by 10m, the subsequent levels spacing ($\Delta z$) increases up to 500m.

4.2.1 Physical model

The offline advection-diffusion component is based on the Parallel Ocean Program (POP2) (Smith et al., 2010). The tracer’s evolution is determined by the following equation in the flux-form:

$$
\frac{\partial T}{\partial t} + \frac{\partial (U \cdot T)}{\partial x} + \frac{\partial (V \cdot T)}{\partial y} + \frac{\partial (W \cdot T)}{\partial z} = A_h \left( \frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2} \right) + A_v \left( \frac{\partial^2 T}{\partial z^2} \right) + S
$$

(4.1)
Where T is the tracer, and U, V, W are the zonal, meridional and vertical velocities respectively. The coordinates x and y are the zonal and meridional directions respectively, and z is the vertical coordinate being positive upwards. The parameters are described in Table 4.2. $A_h$ and $A_v$ are the horizontal and vertical diffusivity coefficients set to constant values of $A_h = 2 \cdot 10^7 \text{cm}^2/\text{s}$ and $A_v = 0.25 \text{cm}^2/\text{s}$ respectively. The horizontal diffusivity is in accordance with values suggested by Wallcraft et al. (2005), and the vertical diffusivity value is obtained from CESM2. The "S" term represents the biological sources and sinks terms. The input velocities units are cm/s. The vertical velocity is calculated using the continuity equation, as follows:

$$\frac{\partial U}{\partial x} + \frac{\partial V}{\partial y} + \frac{\partial W}{\partial z} = 0 \quad (4.2)$$

Equation (4.2) is integrated downwards, starting at the surface. This integration returns the value of W at the bottom wall of each grid-cell, as follows:

$$W_{k+1} = W_k - \Delta z_k \cdot \left[ \frac{uE_k - uW_k}{\Delta x} + \frac{vN_k - vS_k}{\Delta y} \right] \quad (4.3)$$

Where $uE$ and $uW$ are the zonal velocities at the east and west faces of the cell, defined by:

$uE = 0.5 \cdot (U_{j,i} + U_{j-1,i})$ and $uW = 0.5 \cdot (U_{j,i-1} + U_{j-1,i-1})$. In the same fashion, $vN$ and $vS$ correspond to the north and south meridional velocities.

There are two options for the W top boundary condition. One option is $W_{\text{top}} = 0$, and the other one is to obtain the value of W at surface from the parent model. CESM 1.2.2 features a variable free surface approximation for the top boundary condition, that returns a non-zero W. In this work, the surface value of W is borrowed from CESM 1.2.2 because it gives more realistic values of W for tropical cyclones.
<table>
<thead>
<tr>
<th>Field</th>
<th>Long Name</th>
<th>Input File Units</th>
<th>Model Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>UVEL_2</td>
<td>Zonal velocity</td>
<td>cm/s</td>
<td>cm/s</td>
</tr>
<tr>
<td>VVEL_2</td>
<td>Meridional velocity</td>
<td>cm/s</td>
<td>cm/s</td>
</tr>
<tr>
<td>WVEL_2</td>
<td>Vertical velocity</td>
<td>cm/s</td>
<td>cm/s</td>
</tr>
<tr>
<td>QSW</td>
<td>Shortwave radiation</td>
<td>W/m²</td>
<td>W/m²</td>
</tr>
<tr>
<td>TEMP</td>
<td>Temperature</td>
<td>°C</td>
<td>°C</td>
</tr>
</tbody>
</table>

aWVEL is calculated from the continuity eq., only the top boundary layer is obtained from the parent model

Table 4.1: Input fields from parent model CESM1.2.2. Names shown as they appear in input files.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Long Name</th>
<th>Default Value</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>dt</td>
<td>time step</td>
<td>400</td>
<td>s</td>
</tr>
<tr>
<td>dx</td>
<td>spacing in the x direction</td>
<td>dy*cosine(latitude)</td>
<td>cm</td>
</tr>
<tr>
<td>dy</td>
<td>spacing in the y direction</td>
<td>1100000</td>
<td>cm</td>
</tr>
<tr>
<td>dz</td>
<td>vertical spacing</td>
<td>1000 (at surface)</td>
<td>cm</td>
</tr>
<tr>
<td>hordiff</td>
<td>horizontal diffusivity</td>
<td>2 · 10⁷</td>
<td>cm²/s</td>
</tr>
<tr>
<td>kvmix</td>
<td>vertical diffusivity</td>
<td>0.25</td>
<td>cm²/s</td>
</tr>
<tr>
<td>τin</td>
<td>open boundary nudging inward time-scale</td>
<td>5·86400</td>
<td>s</td>
</tr>
<tr>
<td>τout</td>
<td>open boundary nudging outward time-scale</td>
<td>300·86400</td>
<td>s</td>
</tr>
</tbody>
</table>

Table 4.2: Model parameters
Mixing scheme

Most offline models borrow the vertical mixing coefficients from the parent model, except for example the model of Valsala et al. (2007) where a KPP parametrization (Large et al., 1994) is implemented. Another offline scheme is the "matrix method" where the advection-diffusion equation is not solved but a matrix with the transport representation is used (Khatiwala et al., 2005). Lévy et al. (2012) showed that in cases where the parent model has high resolution, the submesoscale turbulent processes \( \approx O(1\text{km}) \) are well captured in a degraded field \( \approx O(10\text{km}) \). Thus, their offline model obtained similar results to the high resolution run without the need of an explicit vertical mixing parametrization. OMEM features two possible vertical mixing schemes: an explicit Laplacian scheme with constant diffusivity of 0.25 cm\(^2\)/s and an implicit KPP scheme (Large et al., 1994) that uses vertical mixing coefficients from the CESM2 climatology. The KPP scheme is not implemented in this thesis.

Time-stepping

At the first integration time step, the tracer is advanced on time with a forward step. In subsequent time-steps, the leapfrog method is used for advection, and the forward method for diffusion. Defining the "previous", "current" and "next" steps as \( n-1 \), \( n \) and \( n+1 \), the equation (4.1) evolves as follows:

\[
T^1 = T^0 + \Delta t \cdot \left[ -L^0(T^0) + D_H(T^0) + D_V(T^0) + S^0 \right] \quad \text{for} \quad n = 0 \quad (4.4)
\]

\[
T^{n+1} = T^{n-1} + 2 \cdot \Delta t \cdot \left[ -L^n(T^n) + D_H(T^{n-1}) + D_V(T^{n-1}) + S^n \right] \quad \text{for} \quad n > 0
\]

where \( L^n \) is the advection operator evaluated at time step "n", and \( D_H \) and \( D_V \) are the horizontal and vertical diffusion operators respectively, which are evaluated on the tracer at the previous time-step \( (n-1) \). \( S \) represents the biological sources and sinks. The "\( S^n \)" term is evaluated at \( 0.5 \cdot (T^n + T^{n-1}) \), following the POP2 guidelines.
Spatial Discretization

OMEM is discretized on a B-grid (Figure 4.2), where T is located in the center of each cell, and U and V are located in the corners of the cell at the same depth than the tracer. W is situated at the T lat-lon position, but in the top and bottom faces of the cell. A second order centered advection scheme is used for zonal, meridional and vertical advection.

Thus, if we define T[j,lon] by the indices $T\_j, \_i$, then, for a given vertical level, the zonal advection and diffusion are discretized as:

\[
\frac{\partial (U \cdot T)}{\partial x} = \frac{1}{\Delta x_{j,i}} \cdot [u_E \cdot \frac{(T^n_{j,i+1} + T^n_{j,i})}{2} - u_W \cdot \frac{(T^n_{j,i-1} + T^n_{j,i})}{2}]
\]  

(4.5)

\[
A_h \cdot \frac{\partial^2 T}{\partial^2 x} = \frac{1}{\Delta x^2_{j,i}} \cdot [A_h \cdot (T^{n-1}_{j,i+1} - T^{n-1}_{j,i}) - A_h \cdot (T^{n-1}_{j,i} - T^{n-1}_{j,i-1})]
\]  

(4.6)

Where $u_E$ and $u_W$ are the zonal velocities at the east and west faces of the cell, defined by: $u_E = 0.5 \cdot (U_{j,i} + U_{j-1,i})$ and $u_W = 0.5 \cdot (U_{j,i-1} + U_{j-1,i-1})$.

The meridional advection and diffusion terms are obtained in the same fashion for a given vertical level "k" as:

\[
\frac{\partial W \cdot T}{\partial z} = \frac{1}{\Delta z_k} \cdot [W_k \cdot 0.5 \cdot (T^n_{k-1} + T^n_k) - W_{k+1} \cdot 0.5 \cdot (T^n_{k+1} + T^n_k)]
\]  

(4.7)

\[
A_v \cdot \frac{\partial^2 T}{\partial^2 z} = \frac{1}{\Delta z^2_k} \cdot A_v \cdot [(T^{n-1}_{k-1} - T^{n-1}_k) - (T^{n-1}_{k-1} - T^{n-1}_{k+1})]
\]

Land-Ocean Boundary conditions

At the ocean-land boundaries, the no-flux condition is applied. In the diffusion operator, the ocean-land boundary condition is computed as: $\frac{\partial}{\partial x}T = \frac{\partial}{\partial y}T = 0$ and $U = 0$ or $V = 0$, depending on the normal direction to the land cell. These conditions are imposed via a masking process, with a zonal
and meridional masks. These masks are created by multiplying the tracer’s mask by itself, but shifted in one grid point. More precisely, the boundary mask at the cell’s east wall is given by:

\[ mask_{\text{zonal}}[k, j, i] = mask[k, j, i] \cdot mask[k, j, i + 1] \]  

(4.8)

Top and Bottom Boundary conditions

At the last water column cell, i.e. at the ocean floor, a stagnant layer condition is applied. The condition consists in \( T \neq 0 \) and \( U = V = W = 0 \). In this layer, the diffusivity is different from 0. The stagnant layer is imposed by multiplying the advection components with a mask that is equal to zero at the column’s last grid cell. For the vertical diffusivity, the top and bottom boundary conditions are:

\[ A_v \cdot \frac{\partial T}{\partial z} = Q_T \quad \text{at} \quad z = 0 \]

\[ A_v \cdot \frac{\partial T}{\partial z} = 0 \quad \text{at} \quad z = -H \]  

(4.9)
where $Q_T$ is the ocean-atmosphere flux. The surface fluxes $Q_T$ are in nmol/cm$^2$/s; thus, when used in the vertical diffusion term they will be divided by $dz$, giving units of nmol/cm$^3$/s. These units are equivalent to the tracer concentration units (nmol/m$^3$/s). Currently, only nitrogen, phosphate, silicate and iron have a surface flux different from zero.

**Open Boundary conditions**

The model implements an open boundary condition (OBC) scheme. There are many different OBCs in the literature (Marchesiello et al., 2001, Stevens, 1990). In this work, I use a modified version of the scheme described by Chen et al. (2013). When the normal velocity to the domain’s boundary points inwards, the model uses a nudging term with a time scale of $\tau_{in} = 5$ days. An outward radiation term is applied when the velocity normal to the boundary points outward, with a time scale of $\tau_{out} = 400$ days. The OBCs are given by:

\[
\frac{\partial T}{\partial t} = \frac{1}{\tau_{in}}(T_b - T), \text{ for inward propagation}
\]

\[
\frac{\partial T}{\partial t} + V_n \frac{\partial T}{\partial n} = \frac{1}{\tau_{out}}(T_b - T), \text{ for outward propagation}
\]  

(4.10)

where $T_b$ is the prescribed value at the boundary, and it is obtained from a CESM2 monthly climatology from 1950-1960.

**Sponge Layer**

A sponge layer is implemented in the north, south, east and west boundaries of the domain. The horizontal diffusion coefficient is gradually increased in the 10 outer most points by a cosine function; from $2 \cdot 10^7$ cm$^2$/s at the inner most point, to $3 \cdot 10^7$ cm$^2$/s at edge, as recommended by Marchesiello et al. (2001).
Restoring term

A restoring term is applied to the nutrients, to avoid some numerical issues generated by topography such as narrow passages. The restoring term has the functional form of $-1/\lambda \cdot (T^n - T_{\text{climatology}})$. This term is added on the right hand side of Eq. (4.1). The value of $\lambda$ is 2 years for surface and interior ocean, except in some coastal areas and narrow passages, where the value is increased to 50 days.

4.2.2 Ecosystem model

The ecosystem component of OMEM is largely based on MARBL’s code which is available at GitHub [https://github.com/marbl-ecosys/MARBL](https://github.com/marbl-ecosys/MARBL). MARBL is based on the Biogeochemical Elemental Cycling model; however, several improvements are made in MARBL not yet documented in the literature. In what follows, the ecosystem component is described. The external forcings required by the ecosystem module are the temperature and short wave radiation (for the units, see Table 4.1). In addition, atmospheric depositions and internal sources of iron can be added (see Table 4.4).

A complete list of the 40 ecosystem variables can be found in Table 4.3. The ecosystem model consists of 6 different primary nutrients; nitrate ($\text{NO}_3$), ammonia ($\text{NH}_4$), phosphate ($\text{PO}_4$), silicate ($\text{SiO}_2$), and two iron components: unbounded iron (Fe) and ligand iron (Lig). It has four phytoplankton species; a generic small phytoplankton class, diatoms capable of silicate, diazotrophs capable of fixating nitrate into ammonia, and an implicit subclass of small phytoplankton capable of calcification (coccolithophores). There is one zooplankton class. The small phytoplankton and diatoms are limited by N, Fe, PO$_4$ and temperature and light. The diatoms can further be limited by silicon. The diazotrophs are only limited by Fe and PO$_4$, and are capable of nitrogen fixation. The model also incorporates pools for particulate (large) and dissolved (small) detrital matter. The zooplankton group grazes the three groups of phytoplankton and the large detrital pool. Both pools are remineralized with a temperature-dependent function. The phytoplankton and zooplankton growth rates and the detritus remineralization depend on temperature. The model has variable cell quotas for silicate (Si:C), iron (Fe:C), phosphorus (P:C), and calcium carbonate content.
\[(\text{CaCO}_3:\text{C})\]. The nitrate quota is fixed to \( Q = 0.137 \). The model represents dissolved organic matter which can remineralize at depth and separate into labile and recalcitrant pools. The dissolved organic matter can be carbon (DOC), nitrogen (DON), or phosphorus (DOP), and the same three classes but refractory (DOCr, DONr, DOPr). Particulate matter also is represented and consists of soft and hard pools of Particulate Inorganic Carbon (PIC), Particulate Silicate (\( \text{PSiO}_2 \)), Particulate Dust (Pdust), Particulate Organic Carbon (POC), Particulate Iron (PFe) and Particulate Organic Phosphorus (POP). The particulate material sinks to the ocean floor, and a flux of material represents it. The flux exported out of a grid cell is then vertically exported into the next grid cell. Thus, the particulated tracers are not advected-diffused. The tendencies for the ecosystem equations are of the form Sources - Sinks. The following section describes the main functional form of the represented processes - sources and sinks - in the model.

**Photosynthesis**

The phytoplankton’s photosynthesis depends on the available radiation and temperature. At the top layer, the photosynthetically available radiation (PAR) is calculated as 0.45 times the short wave radiation. At subsequent depth levels, PAR is calculated as the previous level dampened by the amount of chlorophyll present at the grid cell in an exponential formulation. Thus, PAR at depth level \( k \) is:

\[
\text{PAR}_k = \text{PAR}_{k-1} \cdot \exp(-\kappa \cdot \text{Chl}_k^{0.3536} \cdot \Delta z_k)
\]  

where \( \Delta z \) is the grid cell height, and \( \kappa \) is a parameter dependent on the amount of chlorophyll (Chl). There is a minimum threshold for Chl set to 0.02 mg/m\(^3\), to account for the clear water absorption.

**Nutrient Uptake**

The uptake by phytoplankton groups has the Michaelis - Menten form. If a given nutrient "N" has two forms (for example nitrogen has the forms of ammonia (N1) and nitrate (N2)) then, the uptake
<table>
<thead>
<tr>
<th>Model Index</th>
<th>Component</th>
<th>Long Name</th>
<th>Input Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>PO₄</td>
<td>Dissolved Inorganic Phosphate</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>1</td>
<td>NO₃</td>
<td>Dissolved Inorganic Nitrate</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>2</td>
<td>SiO₃</td>
<td>Dissolved Inorganic Silicate</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>3</td>
<td>NH₄</td>
<td>Dissolved Inorganic Ammonia</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>4</td>
<td>Fe</td>
<td>Dissolved Inorganic Iron</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>5</td>
<td>Lig</td>
<td>Iron Binding Ligand</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>6</td>
<td>DOC</td>
<td>Dissolved Organic Carbon</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>7</td>
<td>DON</td>
<td>Dissolved Organic Nitrogen</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>8</td>
<td>DOP</td>
<td>Dissolved Organic Phosphorus</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>9</td>
<td>DOPr</td>
<td>Refractory DOP</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>10</td>
<td>DONr</td>
<td>Refractory DON</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>11</td>
<td>DOCr</td>
<td>Refractory DOC</td>
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</tr>
<tr>
<td>12</td>
<td>zooC</td>
<td>Zooplankton Carbon</td>
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</tr>
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<td>spC</td>
<td>Small Phytoplankton Carbon</td>
<td>mmol/m³</td>
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<tr>
<td>14</td>
<td>spP</td>
<td>Small Phytoplankton Phosphorus</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>15</td>
<td>spChl</td>
<td>Small Phytoplankton Chlorophyll</td>
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</tr>
<tr>
<td>16</td>
<td>spFe</td>
<td>Small Phytoplankton Iron</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>17</td>
<td>spCaCO₃</td>
<td>Small Phytoplankton Calcium Carbonate</td>
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</tr>
<tr>
<td>18</td>
<td>diatC</td>
<td>Diatoms Carbon</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>19</td>
<td>diatChl</td>
<td>Diatoms Chlorophyll</td>
<td>µmol/m³</td>
</tr>
<tr>
<td>20</td>
<td>diatSi</td>
<td>Diatoms Silicate</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>21</td>
<td>diatFe</td>
<td>Diatoms Iron</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>22</td>
<td>diatP</td>
<td>Diatoms Phosphorus</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>23</td>
<td>diazC</td>
<td>Diazotrophs Carbon</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>24</td>
<td>diazChl</td>
<td>Diazotrophs Chlorophyll</td>
<td>µmol/m³</td>
</tr>
<tr>
<td>25</td>
<td>diazFe</td>
<td>Diazotrophs Iron</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>26</td>
<td>diazP</td>
<td>Diazotrophs Phosphorus</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>27</td>
<td>PIC soft</td>
<td>Particulate Inorganic Carbon (soft matter)</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>28</td>
<td>PIC hard</td>
<td>Particulate Inorganic Carbon (hard matter)</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>29</td>
<td>PSiO₂ soft</td>
<td>Particulate Inorganic Silicon (soft matter)</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>30</td>
<td>PSiO₂ hard</td>
<td>Particulate Inorganic Silicon (hard matter)</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>31</td>
<td>PDUST soft</td>
<td>Sinking Dust (soft)</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>32</td>
<td>PDUST hard</td>
<td>Sinking Dust (hard)</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>33</td>
<td>POC soft</td>
<td>Particulate Organic Carbon (soft)</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>34</td>
<td>POC hard</td>
<td>Particulate Organic Carbon (hard)</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>35</td>
<td>PFe soft</td>
<td>Particulate Iron (soft)</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>36</td>
<td>PFe hard</td>
<td>Particulate Iron (hard)</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>37</td>
<td>POP soft</td>
<td>Particulate Organic Phosphorus (soft)</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>38</td>
<td>POP hard</td>
<td>Particulate Organic Phosphorus (hard)</td>
<td>mmol/m³</td>
</tr>
<tr>
<td>39</td>
<td>QA dust deficit</td>
<td>Dust deficit</td>
<td>mmol/m³</td>
</tr>
</tbody>
</table>

Note that $\text{mmol/m}^3 = \mu\text{mol/L} = \text{nmol/cm}^3$, the input initial conditions are in $\mu\text{mol/L}$. The units were obtained from the file marbl-ecosys-MARBL-e0d512d/src/default_settings.yaml, the code was downloaded from https://zenodo.org/record/2541008#.YDR0gs9KAhJ

Table 4.3: Ecosystem’s variables. The names are the same as in MARBL
<table>
<thead>
<tr>
<th>Surface and Interior Fluxes a</th>
<th>Long Name</th>
<th>Input Units</th>
<th>File</th>
<th>Conversion factor</th>
<th>Model Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>DSTSF</td>
<td>Iron dust flux b c</td>
<td>kg/m²/s</td>
<td>DSTSF</td>
<td>6.2668·10⁴</td>
<td>nmol/cm²/s</td>
</tr>
<tr>
<td>Dust deposition d</td>
<td>kg/m²/s</td>
<td>DSTSF</td>
<td>0.1</td>
<td></td>
<td>g/cm²/s</td>
</tr>
<tr>
<td>NHy</td>
<td>Ammonia deposition e</td>
<td>kgN/m²/s</td>
<td>NHy</td>
<td>7.1429·10⁶</td>
<td>nmol/cm²/s</td>
</tr>
<tr>
<td>NOx</td>
<td>Nitrate deposition f</td>
<td>kgN/m²/s</td>
<td>NOx</td>
<td>7.1429·10⁶</td>
<td>nmol/cm²/s</td>
</tr>
<tr>
<td>FEDESFLUXIN</td>
<td>Iron flux from sediment deposition (interior) g</td>
<td>μmolFe/m²/day</td>
<td>FEDESFLUXIN</td>
<td>1.1574·10⁻⁶</td>
<td>nmolFe/cm²/s</td>
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<tr>
<td>FEDESFLUXIN</td>
<td>Iron flux from vents (interior) h</td>
<td>μmolFe/m²/day</td>
<td>FEDESFLUXIN</td>
<td>1.1574·10⁻⁶</td>
<td>nmolFe/cm²/s</td>
</tr>
</tbody>
</table>

a Model units obtained from https://marbl.readthedocs.io/en/latest/usr-guide/GCM-interface/GCM_requirements/forcing_fields.html; Input File does not contain units, but the conversion factor and file units are explained at https://www.cesm.ucar.edu/models/cesm1.0/pop2/doc/users/POPecosys_main.html and https://github.com/ESCOMP/POP2-CESM/blob/master/bld/namelist_files/namelist_defaults_pop.xml.

b file: solFe_scenario_current_gx1v6_8gmol cesm1v93_20161114.nc
c 3.5% iron per dust weight
d file: dst79gnx_gx1v6_090416.nc
e file: ndep_ocn_1850-2000_w_nhx_emis_gx1v6_c180926.nc
f file: ndep_ocn_1850-2000vw_nhx_emis_gx1v6_c180926.nc
g file: fesedfluxTot_gx1v6_cesm2_2018_c180618.nc
h file: feventflux_gx1v6_5gmol cesm1_97_2017.nc

Table 4.4: Surface and interior fluxes of nutrients. Fields as named in CESM2.
of the nutrient N1 is given by:

\[ V_{N1} = \frac{N1/K_{N1}}{1 + N1/K_{N1} + N2/K_{N2}} \]  

(4.12)

Thus, the uptake of the six nutrients is calculated, and the one with the lowest uptake is considered the limiting nutrient. In a similar fashion temperature and light can limit the growth.

**Cellular Acclimation**

Acclimation, or how the cell changes, can also modify the growth depending on the environmental conditions (Geider et al., 1998). When acclimation occurs, the cell quota Chl:C adapts to the lack of nutrients and lack/excess of light (excess light can damage the cell). Temperature affects nutrient uptake, photosynthesis, and respiration. MARBL offers three different functional forms to account for this effect (including the classical Arrhenius formulation). Here it is used the exponential form of CESM.

\[ F(T) = 1.7^{\frac{T - T_{ref}}{10}} \]  

(4.13)

Where the reference temperature is 30°C. The value 1.7 is sometimes referred to as \( Q_{10} \), and its value may vary in other models.

**Losses**

The phytoplankton and zooplankton tendencies have a mortality term. Phytoplankton can also aggregate and sink.

**Grazing:**

The zooplankton grazing of phytoplankton has two possible forms, Michaelis-Menten (M-M) or Sigmoidal. These functional forms are similar, but differ in the exponent "a":

\[ grazing = \mu_{max} \cdot F(T) \cdot zooC \cdot \frac{P_{phyto}^a}{P_{phyto}^a + k_{graze} \cdot P_{phyto}^a} \]  

(4.14)
The exponent "a" is 1 for M-M and 2 for Sigmoidal. The offline model implements the sigmoidal form as in MARBL. The function F(T) is described by Eq. (4.13). When zooplankton grazes the phytoplankton only a portion of the carbon is transferred from the autotrophs to the zooplankton, and the rest is re-routed to the POC, DOC and DIC pools, representing fecal pellet production and sloppy feeding. Then, the grazed carbon is converted to N, P, Fe, and Si using cellular quotas.

**Nitrogen fixation and nitrification**

Diazotrophs are capable of nitrogen fixation, converting nitrogen into ammonia. The three classes of phytoplankton consume nitrate and ammonia. Different mechanisms such as phytoplankton and zooplankton mortality, grazing of phytoplankton, and excretion of nitrogen by diazotrophs return the nitrogen exclusively to the ammonia pool. Moreover, a fraction of the dissolved inorganic carbon (DOC) and particulated organic nitrogen (PON) is added to ammonia. The process of transferring ammonia back into nitrate is nitrification and only occurs under low light conditions.

**Remineralization**

The dissolved organic matter is separated into labile and refractory pools, highlighting the different timescales for remineralization of these two pools. Refractory remineralization is increased in the top layer from photodegradation due to UV light. The refractory matter resides in the ocean on longer timescales than the labile matter, which can be rapidly remineralized, and it is produced by abiotic processes (Osterholz et al., 2015). In the model, the labile matter is transformed into recalcitrant by a parametrization which depends on the available radiation. Moore et al. (2004) gives further details.

**Export flux**

Of particular interest for the carbon cycle is the export and sinking of POC. This mechanism is described by Armstrong et al. (2002). The authors found most of the POC remineralization
occurring in the upper 1000m, and below that, POC gets exported in proportion to the ballast material presented in the water. The ballast material is essential since it helps determine the density of the seawater and how likely the parcel of water will sink. In the model, the ballast material is represented by the particulated dust, iron, and silicate. Hard POC is the POC flux qualitatively associated with a ballast material, and soft POC is the excess POC available for remineralization. A fraction of the hard subclass also is remineralized. Temperature affects POC and SiO$_2$ length scale of remineralization. At depths below 1100m, an iron flux from sediments is added. Finally, at the bottom cell of the water column, all the material is remineralized.

4.3 Physical Model Analysis

4.3.1 Tracer conservation

We perform an initial physics-only test to evaluate the conservation of tracer in the domain. In this run, a random nutrient (nitrate) is initialized and advected -diffused. The ecosystem source-sink term is not activated. The model performance at simulating the advection-diffusion of a tracer is compared with the CESM2 data; to this aim, we chose nitrate (NO$_3$) as the initial conditions of the simulated tracer. The seasonal cycle for ten years is illustrated in Figure 4.3; the offline tracer simulation has a lower seasonality than CESM2; this is expected since the offline model in this experiment only features physical processes and is missing the seasonal signal induced by biological processes. However, others have found that offline models present issues at simulating seasonal variations (Ribbe and Tomczak, 1997), and this needs to be further investigated. Nevertheless, the seasonality timing is in good agreement; the offline models’ seasonal cycle is driven by seasonal changes in the velocity fields and the open boundary conditions given by climatological values borrowed from the parent model’s nitrate.

Time wise, the model remains expensive since the time-step could not be increased over 800s, to avoid violating the Courant–Friedrichs–Lewy condition (CFL). The CFL condition states that the
model velocity should be smaller than the grid-velocity, which is given by the grid’s spacing divided by the integration time-step. CFL condition implies that the Courant number (\(C = \frac{U \cdot \Delta t}{\Delta x}\)) should be less than a \(C_{\text{max}}\). For a three dimensional case, the CFL condition becomes

\[
C = \Delta t \cdot \sum_{i=1}^{3} \frac{U_i}{\Delta x_i} \leq C_{\text{max}} \tag{4.15}
\]

Courant numbers above one often lead to numerically unstable behavior. In this model, the large vertical velocities induced by the tropical cyclones create large Courant numbers; thus, the time step should not be increased above 800s. Moreover, when introducing the ecosystem model, the time step needs to be further reduced to 400s due to the ecosystem’s fast response, which can generate large derivatives. Thus, a varying time-step procedure could be implemented in the future. Others have stated that offline models are not subjected to CFL conditions because of the lack of momentum equations (Valsala et al., 2007, Hill et al., 2004); however OMEM did present numerical instabilities for CFL numbers above one.
4.4 Limitations

The model’s technical limitations are discussed in this section; for the ecosystem’s performance, refer to Chapter 5.

A disadvantage of the offline model is that the runs take 4.5 days for one year of simulation. The time step of 400 s is in accordance with the literature. For example, Thi (2005) implemented a dt=200s for a phytoplankton competition model. The choice of a small integration time step is necessary to resolve the strong vertical upwelling generated by TCs and the fast reactions from the ecosystem. The model integration could be sped up by parallelizing the code in multiple processors, but it is not yet implemented.

Other limitations come from the simplicity of our advection-diffusion scheme, which does not correctly resolve abrupt topography, such as steep slopes and narrow passages. General Circulation Models (GCMs) represent straits and narrow passages with a partial bottom layer, where differences in density can induce overflows and entrainment, and water can flow in between topographic features. In our model at the bottom cell of the water column, advection is not implemented. This was chosen due to significant errors given by the accumulation of tracer at the bottom cells, and it should be improved in the future. Still, some numerical instabilities appear at ocean-land boundaries, but they dissipate fast towards the interior and vanish with time. In the offline model, a restoring term is used to minimize these features, a technique that is also used in CESM.

Center differenced schemes are known to produce zig-zag patterns at $2\Delta x$ spacing, which may contain negative values. In a previous model’s version, the tracers with strong vertical gradients (phytoplankton and zooplankton groups) induced small vertical oscillations with negative values. Negative values are undesired in ecosystem models for obvious reasons; however, they are a common problem (Thi, 2005). These oscillations can be removed with upwinding schemes or increased diffusion (Tang et al., 2018). A good alternative is the positive definite advection scheme MUSCL (Leer, 1977, Levy et al., 2001). In the present work, the upwind scheme is not implemented; thus, we opted for increased vertical diffusivity $\alpha_v = 200 \text{ cm}^2/\text{s}$, below depth-level 20 only for phytoplankton.
and zooplankton variables. For the nutrients and dissolved organic matter, we keep the vertical diffusivity at \(0.25 \text{ cm}^2/\text{s}\). This increase in diffusivity eliminates the oscillations but does not affect the plankton populations since they are zero below 200 m. The remaining small negative values are removed by imposing a non-negative condition for tracers. A non-negative condition can cause conservation violations; therefore, these conditions will be removed with an upwind scheme in future work. We tested the model with and without the non-negative condition and the difference is only short-lived fluctuations on tracer conservation.

Our ecosystem model has some differences from MARBL. For example, we do not include dissolved inorganic carbon, alkalinity, and oxygen. However, this should not affect the ecosystem’s dynamics since DIC and TA are modified by biological activity, but they do not directly alter the ecosystem components. Other differences with MARBL are the lack of denitrification, lack of oxygen-dependent remineralization, and POC dissolution does not increase under low \(O_2\).
5.1 Introduction

Tropical cyclones (TCs) can enhance surface ocean chlorophyll by increasing vertical mixing and upwelling, bringing nutrient-rich deep waters to the surface (Liu et al., 2019, Shibano et al., 2011, Zhang et al., 2021). In some regions, the ocean’s surface is well supplied with light but depleted of nutrients necessary for photosynthesis; thereby, TCs provide an opportunity for phytoplankton to flourish (Lévy et al., 2018, Calil et al., 2011). Phytoplankton blooms induced by TCs have been observed in coastal areas (McKinnon et al., 2003, Hung and Gong, 2011), open oceans (Honda et al., 2018, Lin et al., 2003, Wang et al., 2021), and even in oceanic "desert areas" where productivity is naturally low (Babin et al., 2003, Kuttippurath et al., 2021).

There are many well-documented cases of large blooms induced by TCs (Liu et al., 2009, Wang and Zhao, 2008, Lee et al., 2020, Lü et al., 2020, Wang et al., 2021), but others have found that only a small percentage of TCs are capable of significantly increasing surface chlorophyll (Sun et al., 2010, Lin, 2012, Menkes et al., 2016, Chai et al., 2021); thereby, single-cases of extreme
blooms may not represent the norm. For example, Menkes et al. (2016) analyzed more than 1000 global TCs, out of which only \( \approx 10\% \) produced a bloom. Pan et al. (2017) found a more significant bloom rate in the South China Sea; using a numerical model, the authors determined that out of 109 TCs, half of them produced a surface bloom. Yet, the necessary conditions for a bloom seem to be more complex than previously thought. Favorable storms are those of long duration (Sun et al., 2010, 2014) and slow translational speed - irrespective of their intensity- (Huang et al., 2017, Chacko, 2019, Kuttippurath et al., 2021); pre-existing oceanic conditions, such as a shallow nutricline (Zhao et al., 2008, 2017, Chacko, 2019), absence of warm eddies (Lin, 2012) and presence of cold eddies (Lü et al., 2020, Lee et al., 2020) on the storm path also increase the chances of TC-induced blooms. The latter indicates that although warm eddies may strengthen TCs (Liu et al., 2009) they impede deepwater entrainment (Lin, 2012). The relative importance of the different parameters involved in developing blooms is still unknown. For example, Zhao et al. (2017) found significant chlorophyll anomalies produced by a fast-weak TC passing over a favorable pre-storm shallow nutricline; contrarily, super-typhoon Maemi - the strongest ever to hit South Korea- did not cause a bloom because of the presence of a warm eddy (Lin, 2012).

The estimated effect of TCs on annual primary productivity (PP) remains uncertain; for example, this value ranges from 2\% to 30\% for the South China Sea (Zhao et al., 2008, Lin et al., 2003, Sun et al., 2010) and in the Australian North West Shelf was found to be 10\% (Condie et al., 2009).

Compared to other regions, the subtropical northwestern Pacific has the largest amount of TCs per year, with a yearly average of 16.5 (Pun et al., 2011) accounting for 30\% of global TCs (D’Asaro et al., 2011). TCs feed on warm waters; thus, they can intensify when they cross the Kuroshio current that brings warm water from the tropics to the subtropics (Wu et al., 2008). Nevertheless, despite the region’s TC abundance, the TCs contribute to 1-7\% of local annual PP (Wang et al., 2019). This low contribution is the result of a deep nutricline and the presence of warm eddies in the region (Lin, 2012). Nonetheless, large blooms occasionally develop under the right conditions; as an example, a pre-storm cyclone produced a 5-times increase in local surface chlorophyll (Lee et al., 2020).
However, recent studies with Argo floats highlight that surface chlorophyll spikes in the north-western Pacific are not necessarily an indicator of biological processes, but rather the aftermath of the uplift of sub-surface deep chlorophyll maxima, re-distributing the water-column primary productivity without changing its depth-integrated value (Qiu et al., 2021, Chai et al., 2021). On the other hand, using in-situ data, Ye et al. (2013) found a TC-induced subsurface bloom between 20-100m in the South China Sea, with no significant increase at the surface. These findings suggest that satellites may overestimate or underestimate the impact of TCs on annual primary productivity, depending on the bloom’s characteristics. Thus, a mechanistic understanding of the TC-driven blooms in the surface and subsurface is necessary to estimate the impact of TCs on this region’s productivity.

In this study, we use an offline simulation of a complex ecosystem model to quantify the impact of two TCs on the Kuroshio region’s ecosystem and elucidate the responses of different nutrients and phytoplankton groups through the water column. A similar study conducted by Pan et al. (2017) used a regional model to study the bloom genesis in the South China Sea. They found half of the blooms occurring at the surface, and only less than 1% were subsurface blooms. The question remains whether the dynamics are similar for the Kuroshio region with a much deeper nutricline.

In particular, we aim to answer the following questions: 1) How does the ecosystem change during a TC event? 2) Are the upper layer’s chlorophyll changes the result of biological activity or sub-surface physical processes? 3) What causes phytoplankton blooms in the region?

To answer these questions, we use the offline marine ecosystem model described in Chapter 4, consisting of an offline advection-diffusion equation coupled with a marine ecosystem model based on the Marine Biogeochemistry Library (MARBL) code. The simulation features tropical cyclones, described by Chu et al. (2020). We select two subsequent TCs that interacted with the same cyclonic-eddy for in-depth analysis; their characteristics and influence on the cold-core eddy are described, as well as their physical impact on the ecosystem’s primary productivity. At the end of the chapter, the ecosystem model’s limitations and the future expansion of this preliminary work are described.
5.2 Methods

For this study, an offline model is used, which is described on Chapter 4. The model is forced with one year of daily oceanic currents, short-wave radiation and temperature obtained from a global 0.1-degree resolution run from the Community Earth System Model version 1.2.2 (CESM1.2.2) (Chu et al., 2020, Huang et al., 2021). The ecosystem’s initial conditions and open boundary conditions were provided by a global CESM2’s run on a 1 degree resolution grid; we use the historical monthly climatology for 1950-1960. The simulation features 13 tropical cyclones in the offline model’s domain; two of them are analyzed in this study. The domain used for this study is depicted in Figure 5.1. The offline model was run for 195 days as spin-up, and the next 260 days are used as output. This time is not long enough to reach equilibrium, and a longer run is needed in the future. In this preliminary study we are mainly interested in the transient response of the ecosystem to weekly forcings; thus, the main conclusions and dynamics found in this work should not change considerably for longer runs.

5.3 Results and Discussion

5.3.1 Comparison with CESM2

First, we compare the annual mean and seasonal cycle between the offline model and CESM2. It is important to note that the CESM2’s climatologies were obtained from a 1950-1960 historical run, while the offline simulation is forced with velocities from a very different high-resolution simulation with constant CO$_2$ value. Therefore, we do not expect a perfect match, but we compare their ecosystem’s variables’ magnitudes to detect possible issues.

On the western edge of the north subtropical gyre is situated the Kuroshio current (see Fig. 5.1); thus, it has a shallower thermocline and nutricline at its western side, compared to the eastern side (Mei et al., 2015). This characteristic generates a higher nutrient availability and lower
Figure 5.1: Mean surface currents. Annual mean sea surface horizontal currents’ speed (colors) and direction (black arrows). The large values (yellow color) correspond to the Kuroshio current. A long-lived cyclonic eddy is also observed at 130°E, 26°N.
temperatures on the western side, while the Kuroshio current and the eastern side are considered oligotrophic. Oligotrophic regions feature low levels of nutrients and biological activity. Interestingly higher trophic levels are abundant in the Kuroshio current despite the low nutrient availability, a contradiction that has led to the term "the Kuroshio paradox" (Saito, 2019). The paradox is caused by the Kuroshio’s warm temperatures that stimulate cellular growth, being suitable for the spawning and nursing of fish. Moreover, recent studies have found that turbulent mixing (Kobari et al., 2020) is an essential regional mechanism to deliver nutrients from a nutrient-replete sub-surface current, located between 200-800m (Chen et al., 2021). A similar undercurrent is found underneath the Gulf stream, which is the Atlantic’s western boundary current.

Figure 5.2 shows the integrated value of different nutrients for the water column’s upper 100m. The ammonia is in somewhat good agreement between CESM2 and the offline model, but nitrate, phosphate, and silicate are larger in the offline run. For example, OMEM indicates larger values coming from the north at 130° N due to the influence of open boundary conditions. CESM2 and the offline model simulate a larger abundance of nutrients in the Kuroshio current than in its eastern side. However, the offline model is less depleted on the eastern side than CESM2. This discrepancy could be due to the offline model’s underestimation of diatoms and diazotrophs (Figure 5.3), which are both limited by phosphate and diatoms are also limited by silicate. In terms of planktonic distributions, Kanayama et al. (2020) found that the phytoplankton community of the Kuroshio region is dominated by pico (0.2-2 µm) and nano (2-20 µm) phytoplankton. However, diatoms are abundant under replete nutrient conditions (Law et al., 2011); thus, larger concentrations are found in the East China Sea than in the open ocean. On the other hand, nitrogen fixation is low in the open ocean because diazotrophs need coastal inputs of phosphate (Shiozaki et al., 2010) to survive.

The offline model reproduces small phytoplankton and zooplankton well but features low concentrations of diatoms and diazotrophs compared to CESM2. The phytoplankton groups are susceptible to changes in the uptake constants, and the underestimation of these groups could be a consequence of the adjustment of biological parameters. For the present model run, the uptake constants of diazotrophs and diatoms were lowered to avoid overconsumption of nitrate. However, the adjustment
decreases the diazotrophs and diatoms’ growth rates. The ecosystem’s parameters from the offline model, such as uptake constants, grazing, and mortality, are fixed values from MARBL and may not be the most suitable for the Kuroshio region. For this run, we tested new constants, which may not be the best match. These values will be optimized in future work.

In the time series (Figure 5.2, column c), the initial spike on nutrients is due to the positivity condition imposed on them, i.e., that the values can not be negative. This condition can produce spikes on total tracer conservation, and in the future, we expect to remove the condition by using a positive-definite advection scheme.
Figure 5.2: Ecosystem model’s performance. Comparison between the offline model results and the reference values of the CESM2 1950-1960 climatology. Each row represents a different tracer as named on Table 4.3. a) Mean top 100m value for CESM2, b) mean top 100m value for the offline model, c) time series of the variables integrated over the domain’s area and upper 100m, for CESM2 (blue) and offline (orange).
Figure 5.3: Ecosystem model’s performance. Same as Figure 5.2, but for phytoplankton and zooplankton carbon.
5.3.2 Tropical cyclone impacts on primary productivity

Tropical storms can generate intense oceanic vertical velocities and mixing along their tracks. These short pulses of vertical upwelling generate low-temperature anomalies that can last days to weeks and usually penetrate deep below the mixed layer depth (Price, 1981, Jaimes and Shay, 2015, Chu et al., 2020). These disturbances also affect the marine ecosystem, but the strength of the anomalies depends mainly on the TC characteristics and the oceanic conditions beneath the surface. This study analyzes the impacts of two tropical cyclones on the nutrients, phytoplankton, and zooplankton.

**TC 382 and TC 390 characteristics**

The two tropical cyclones selected for in-depth analysis are TC 382, which crossed the domain during days 196 to 199, and TC 390 that circulated thirty days later (days 227-230) over a similar path as TC 382. The storms' tracks, as well as the sea surface height anomalies (SSHA) before, during, and after the TCs, are depicted in Figure 5.4. The SSH anomalies are calculated with respect to the annual mean; thus, they have a small seasonal signal. To quantify the TCs' induced upwelling, we look at the vertical velocities induced during the TCs.

TC 382 caused more prominent SSH negative anomalies and induced larger vertical velocities than TC 390. The TC-eddy encounters are discussed in the next section. Figure 5.5 depicts the characteristics of the TCs. TCs’ 382 maximum wind speed decreased along the track while moving northwards, but its translational speed increased. TC 390 also experienced a negative trend in maximum wind speed, and its translation speed decreased between days 227 and 231. By day 232, while transiting between South Korea and Japan, its translation speed increased. In the area of interest, between 22°N and 27°N, TC 382 sustained a translation speed between 3-4m/s, while TC 390 moved faster at 4-5 m/s.

The vertical velocities induced by TC 382 were larger than those of TC 390. At its location on day 196 (see Figure 5.4, dashed circle), TC 382 reached a W average value of 0.063 cm/s between 100-180m; at that same depth TC 390's W was 0.011 cm/s. For both TCs, the velocity
slowly decayed with increasing depth. Along the track, TC 382 reached a maximum $W$ of 0.071 cm/s while TC 390’s maximum was 0.049 cm/s. The larger induced velocities of TC 382 may be a consequence of the lower translation speed. Slower storms have a longer residence time, creating stronger perturbations in the ocean. Moreover, depending on the storm size and speed, TCs can create near-inertial oscillations that interact with the thermocline near-inertial waves amplifying the perturbation (Price, 1981, Tsai et al., 2008).

**TCs-eddy interaction**

Cyclonic and anticyclonic eddies are abundant in the Kuroshio region. When a tropical cyclone encounters a cyclonic cold-core eddy, the upwelling of nutrients is enhanced. The increase is because the near-inertial oscillations produced by TCs interact with cyclonic eddies (Jaimes and Shay, 2009), propagating outward from the core (Lee and Niiler, 1998), enhancing the upwelling of deeper waters (Liu and Tang, 2018).
Interestingly, both TCs interacted with the same cyclonic-eddy. Figure 5.4 (first row) shows the timeline of events for the TC-eddy encounters. The eddies are identified with the sea surface height anomalies (SSHA). Negative SSHA indicates the presence of cyclonic eddies characterized by a cold-core. Contrarily, positive SSHA indicates an anticyclonic/warm-core eddy. However, this is not always the case; less frequently it can be found cyclonic warm-core eddies and anti-cyclonic cold core eddies (Sun et al., 2018). However, in this study we focus on one cyclonic eddy present in the TCs path (see Figure 5.4), which is a cold-core eddy (temperature not shown).

During simulation day 196, the TC 382 encountered a cyclonic eddy on its path. After the interaction, the negative SSHA was intensified. About a month later, TC 390 encountered that same eddy; after this second interaction, the eddy was less intensified. Why did TC 382 enhance the negative SSHA more than TC 390? Both TCs had a very similar maximum wind speed during the encounter, corresponding to 48.07 m/s and 48.7 m/s for TC 382 and TC 390, respectively. However, TC 382 was slower than TC 390, with a translation speed of 3.4 m/s vs. 4.2 m/s respectively (see Figure 5.5). Sun et al. (2014) studied fifteen interactions between TCs and cyclonic eddies. They found that slower TCs had a larger impact on cyclonic eddies than faster ones. The authors found that a key parameter was the forcing time, which is a parameter that depends on the interaction’s duration (which is longer for slower translation speeds), the interaction area, and the maximum
wind speed (Sun et al., 2010) (not calculated here). At the surface, the wind-forced response lasts about 12 hours; thus, slower moving TCs would have longer interactions with eddies (Morozov and Velarde, 2008). TCs generate near inertial oscillations, which displace downwards as internal waves. The downward propagation of the storm-induced near-inertial waves can last for many days (Qi et al., 1995).

Figure 5.4 also reveals that the vertical velocities were larger for TC 382 than TC 390. On the other hand, TCs feed on warm waters. Thereby, cold-core eddies tend to weaken the TCs due to the negative SST feedback (Wu et al., 2007, Liu et al., 2009). Figure 5.5 shows a weakening of the maximum wind speed halfway through the interaction with the eddy. The weakening is more pronounced for TC 382; this agrees with the results of Wu et al. (2007), who found that slower translation speeds allow the TC to interact longer with the eddy, creating a more vigorous response on the TC intensity. Two questions beyond the scope of this thesis remain: which one - the TC or the eddy - exerts a larger influence on the other? Moreover, if the TC strengthens the cyclonic-eddy, does it create stronger negative feedback on itself?

**Subsurface chlorophyll bloom**

In the offline simulation, most tropical cyclones did not have a significant influence on chlorophyll concentration. However, TC 382 produced a subsurface enhancement of chlorophyll concentration (Figure 5.6). The subsurface concentration was 0.2 mg/m$^3$ during days -10 to 10 relative to TC arrival, but ten days after the TC, the concentration increased to 0.6 mg/m$^3$. At the surface, a slight increase from 0.03 mg/m$^3$ to 0.05 mg/m$^3$ was observed during the TC, and it decayed fast in the following days. These values were calculated on a circle of radius 100km centered at the TC strongest impact location (see the dashed circle of Fig. 5.4).

Chai et al. (2021), Qiu et al. (2021) found a surface bloom during TCs in this region solely due to vertical mixing of subsurface-chlorophyll maxima, with no increase in total water-column chlorophyll. Thus, the authors suggest that there was no net change in depth-integrated net primary
productivity. In this study, the phytoplankton enhancement did have a local impact on total primary productivity.

During days -10 to 10 since TC 382 arrival the total integrated carbon in the upper 100m of a circle of radius 100km was 3.2-10^{12} mmol C (averaged over time). After the TC (days 10-30), it increased to 4.7-10^{12} mmol C, which accounts for a 46% increase.

Before and during TC 382 (days -10 to 10 since TC arrival) the total integrated carbon in the upper 100m of a circle of radius 100km was 3.2-10^{12} mmol C (averaged over time). After the TC (days 10-30), it increased to 4.7-10^{12} mmol C, which accounts for a 46% increase.

Figure 5.7 shows that the different planktonic groups had varied responses at depth. Small phytoplankton carbon increased by 50% mostly between 20-40m, diatoms increased by 11% at 20-60m, and diazotrophs decreased by 20% due to a significant decrease below 60m. The zooplankton carbon increased only by 5%. Although a slight increase, zooplankton may play an important role in the export of carbon due to fecal pellets and carbon transfer to higher trophic levels. The phytoplankton anomalies decay timescale depend on the mortality and grazing parameters. Natural oscillations between phytoplankton and zooplankton occur at time-scales of days to weeks. These different responses of planktonic groups are analyzed in the next section. It is important to consider that the results presented here may vary depending on the dominant group. In the offline model, small phytoplankton largely dominates over the two other groups, and it may out-compete them during TCs.

A low success rate of TCs to induce blooms in the region has been previously found by Wang et al. (2019), who found a 1-7% contribution of TCs to annual productivity. However, the authors did not identify sub-surface processes. The main reason for the low regional impact of TCs compared to other regions is the deeper nutricline. For example, Mei et al. (2015) found a ten times larger increase in surface chlorophyll in the East China Sea than in the tropical northwestern Pacific due to differences in nutricline depth. Pan et al. (2017) found a high success rate of surface TC-induced blooms in the South China Sea, while there was a low success rate on sub-surface blooms. The difference between their study and ours is that the South China Sea has nitrate values above 10
mmol/m³ between 100-200m, while in at the east side of the Kuroshio current, those values are found between 400-600m (comparing with the same World Ocean Atlas dataset (not shown).

In what follows, we investigate the conditions that generated the bloom, its characteristics, and the responses of different nutrients and phytoplankton groups.

**Effect of TC 382 and TC 390 on the ecosystem**

Figure 5.8 shows that TC 382 and TC 390 enhance the nitrate, silicate, and iron in the upper 120m; but, ammonia and phosphate decrease in the subsurface (20-75m). These values are calculated on a circle centered at the location of TC 382 on day 196 (see Fig. 5.4). The different nutrients’ responses depend on their vertical gradients before the storm’s arrival. Nitrate, silicate, and iron are nutrients that increase with depth below 20m. Instead, ammonia is produced by diazotrophs; thus, it has a
Figure 5.7: Primary productivity anomalies induced by TCs. Profiles of mean carbon concentration of a) small phytoplankton, b) diatoms and c) diazotrophs, before TC 382 arrival at days -20 to 0 (dashed blue), during the TC at days 0-10 (red), and post-TC 10-20 (black). The area mean is taken over a circle of radius 100 km, centered at the TC location on day 196.
sub-surface maximum between 20-70m where diazotrophs are abundant, and it is depleted in the rest of the water column. Phosphate features a shallow layer of high concentration between 20-50m and a deeper layer of lower values between 50-100m. The layer with lower values corresponds to the diazotrophs and diatoms chlorophyll maxima depth. Liu et al. (2009) used an advection-diffusion model for passive tracers to elucidate how different nutrients responded to Hurricane Katrina in the Gulf of Mexico. The authors found that the nitrate was largely enhanced compared to phosphate due to vertical upwelling, and silicate was the least enhanced. However, their model did not provide an ecosystem, so only physical mechanisms affected the nutrients. In our study, nitrate and silicate are more enhanced than phosphate because the biological processes create a layer of depleted PO$_4$ between 50-100 m. Thereby, when this layer is uplifted, it creates a negative anomaly. This negative anomaly could be a limiting factor for phytoplankton, but this requires further analysis. During and after the TC, the redistribution of phytoplankton and nutrients can cause changes in the ecosystem composition. For example, Law et al. (2011) observed in the Tasman Sea an increase in phosphate and silicate after a TC, but surprisingly there was no increase in nitrate due to its deeper nutricline. These conditions promoted the growth of diazotrophs and nitrogen fixation.

All the tracers show a slight downwelling pattern before the TC arrival, produced by the negative vertical velocity created at the exterior wall surrounding the TCs (see Figure 5.4). The negative vertical velocities generate a slight downwelling; thus, at the selected location before the TC 382 center arrives, the downwelling signal of the outer TC-wall is observed.

Figure 5.9 shows that with the TC’s arrival, all the planktonic groups’ carbon concentrations decrease due to the vertical upwelling of water from below the euphotic zone (≈ 100m). After 2-8 days, diatoms’ and diazotrophs’ carbon shows an increment. Only 8-15 days later, the small phytoplankton reaches a peak. Zooplankton follows with a 10-days lag. The phytoplankton and zooplankton exhibit natural oscillations due to grazing and mortality cycles. Thus, the anomalies were calculated with respect to a 20-day average previous to the TC arrival. The initial decrease on phytoplankton and subsequent increase have also been found with Argo floats (Kuttippurath et al., 2021, Chai et al., 2021, Chacko, 2017) and numerical models (Chakraborty et al., 2018).
Surprisingly, although nitrate was increased after both storms (TC 382 and TC 390) with a similar maximum value, only TC 382 produced a significant increase in phytoplankton carbon (Figure 5.9). After TC 382, the nutrients and phytoplankton values remained higher and lower, respectively, than pre-TC 382 conditions. Thereby, when TC 390 arrived, these pre-storm tracers concentrations made an apparent larger increase in nutrients and no increase in phytoplankton.

Two conditions made the anomalies of TC 382 last longer than those of TC 390. First, TC 382 transited at a slower speed than TC 390. Zhao et al. (2008) showed that faster storms tend to produce smaller anomalies. Chakraborty et al. (2018) also found that weak-lingering storms can have a larger impact than short-intense ones. Second, a cyclonic eddy was present at that location, which was reinforced by TC 382. It is known that cyclonic eddies can sustain the upwelling of nutrients; this TC-eddy effect is analyzed in the next section.

Another possible explanation for the lack of bloom after TC 390 is that the iron increase was lower because it was still depleted from the last bloom generated by TC 382. Moreover, the more vigorous upwelling of TC 382 largely depleted the zooplankton, allowing the phytoplankton groups to bloom. However, during TC 390, the surface zooplankton values were still high and may not have permitted the phytoplankton to bloom. The zooplankton’s role in the bloom could be measured with in-situ data. The larger light availability for phytoplankton, when uplifted into the surface, may also play a role (Chakraborty et al., 2018) since the TC 382 induced upwelling reached shallower layers than TC 390, but this effect is not addressed in the present study.

**Effect of TC-cyclonic-eddy interactions**

To elucidate the effect of the cold-core eddy on the TC-induced anomalies, we compare the anomalies induced by the TCs in the area where the cyclonic eddy was located with those at a location where both TCs passed but no cyclonic-eddy was present. These locations are marked on Figure 5.4, as a dashed circle (eddy location) and a solid line circle (no-eddy location). Figure 5.10 shows that the anomalies for nitrate, small phytoplankton carbon, and zooplankton carbon are larger in
Figure 5.8: TCs impact on nutrients. Hovmöller diagrams of depth vs. time of the ecosystem variables, as mean values (first column) and anomalies (second column) of a) nitrate (NO$_3^-$), b) ammonia (NH$_4^+$), c) phosphate (PO$_4^{3-}$), d) silicate (SiO$_3^{2-}$) and e) iron (Fe). The horizontal axis represents the time since TC's arrival (at day 0). The anomalies are calculated as daily data minus the time mean of days -20 to 0 before the TC landing. Values are averaged on a 100km radius circle, around the TC 382 location (see Figure 5.4, dashed circle).
Figure 5.9: TCs impact on the ecosystem. Hovmöller diagrams of depth vs. time of the ecosystem variables, as mean values (first column) and anomalies (second column) of a) small phytoplankton carbon, b) diatoms carbon, c) diazotrophs carbon and d) zooplankton C. The horizontal axis represents the time since TC’s arrival (at day 0). The anomalies are calculated as daily data minus the time mean of days -20 to 0 before the TC 382 arrival. Values are averaged on a 100km radius circle, around the TC 382 location (see Figure 5.4).
the location where the cold-core eddy was present and they last longer. Only at 65m depth, the phytoplankton and zooplankton anomalies were positive at the non-eddy location and negative for the eddy-location. This difference is due to the effect of the plankton-depleted water entrainment from below the euphotic zone. Zheng et al. (2008), showed that pre-TC cyclonic features are a good predictor for stronger TC-induced temperature anomalies. Xu et al. (2017) found that out of 46 TCs, the largest blooms induced near Taiwan were in the presence of cyclonic eddies. This phenomenon has also been observed in the South China Sea (Liu and Tang, 2018). Long-lived cyclonic eddies cause a weaker stratification and uplift deeper water; thus, these eddies facilitate the TC-induced entrainment. These features support a large part of the primary productivity in the oligotrophic ocean (McGillicuddy et al., 2003). However, the presence of a cyclonic feature is not enough because the TCs characteristics influence the nature of the encounter (Wu et al., 2007). In our study, TC 382 with a slower translation speed produced a more significant effect on the eddy, agreeing with the findings of other authors (Liu et al., 2020, Xu et al., 2017).

5.4 Conclusions

In the northwestern Pacific, the surface ocean’s chlorophyll response to tropical cyclones is weak, but extreme blooms have been observed. Thus, the chlorophyll responses are varied, and the total effect of TCs on primary productivity is difficult to estimate. Moreover, the conditions favoring the blooms are diverse, and whether the surface chlorophyll increase represents new primary production - or merely advection of sub-surface chlorophyll-, is not clear. Here, using an ecosystem model we obtained deeper insights into the TC-ecosystem’s dynamics.

Our findings suggest that the sub-surface genesis of blooms may be more common in regions with deeper nutriclines, while surface blooms dominate in regions with shallow nutriclines. These sub-surface blooms have not been well studied since satellites cannot detect them, but they may be important to sustain life in oligotrophic regions. Only one sub-surface bloom has been ever observed (Ye et al., 2013). However, our study’s lack of surface blooms may also be a model feature, which
Figure 5.10: Primary productivity anomalies induced by TC-cyclonic-eddy interaction. Time series of nitrate (first row), small phytoplankton carbon (second row) and zooplankton carbon (third row), at a) 5 m depth, b) 35m, and c) 65m. The time series represent two different locations, one where a cold-core eddy was present (red) and one where no eddy was present (blue). The total values are averaged over a circle of radius 150 km at the circled locations depicted in Figure 5.4.
needs further investigation. For example, we could run the same model in a region with a shallow nutricline to evaluate if the model reproduces the surface’s blooms.

This study observed a water-column integrated increase in the carbon of 46% for the small phytoplankton group compared to the 20 days previous to the storm arrival, mostly between 20-40 m. To less extent, diatoms’ carbon increased temporarily by 11%, especially between 20-60 m. On the other hand, total diazotrophs carbon decreased by 20% due to a large depletion below 60 m. These results reveal that a TC can alter the ecosystem’s composition; species of phytoplankton that live in the shallower layers may be more favored by TC-induced nutrient entrainment, while entrainment from below the euphotic zone depletes variants that prefer deeper regions. However, our model largely underestimates diazotrophs and diatoms, and the numerical experiments need to be repeated with different nutrient-uptake and mortality parameters for robustness.

Nevertheless, others authors have observed ecosystem shifts sparked by extreme wind events. A common finding is a clear dominance of diatoms after storms (Son et al., 2007, Angles et al., 2015, Chen et al., 2009) or in seasonal blooms (Fujiki et al., 2014) because replete nutrient conditions favor larger size phytoplankton. In addition, the ecosystem shifts are important for the carbon export, which can increase when larger organisms flourish (Moore et al., 2004). Therefore, it is necessary to expand observational studies to measure the response of different phytoplankton populations during these events.

Regarding the physical mechanisms that favored the phytoplankton, the slower moving TC induced the longer-lasting anomalies in the nutrients. TC 390 produced a sharp but short-lived increase in nutrients. Only TC 382 generated an enhancement on phytoplankton carbon. Whether the duration of the nutrient anomalies is critical for blooms development requires further study.

Another favorable condition for the chlorophyll increase was the pre-storm presence of a cyclonic eddy. Given the deep nutricline of the Kuroshio region, an important mechanism to increase the success rate of TCs is the presence of cyclonic eddies on their path (Sasai et al., 2019).

The present study is preliminary; longer numerical runs are necessary to understand the total impact of regional TCs at an annual time scale. Nonetheless, these results suggest that estimations of
mesoscale phenomena impacts on primary productivity should account for the response of different phytoplankton groups and address processes below the surface, such as sub-surface blooms and dilution caused by entrainment.

5.4.1 Future scope

The mechanisms revealed in this study are important to understand the future response of the ecosystem to tropical cyclones and mesoscale eddies. Greenhouse warming is expected to decrease TC frequencies and increase TC intensity, leading to more frequent intense storms (Knutson et al., 2010, Murakami et al., 2020). Chu et al. (2020) studied the TCs generated by the CESM1.2.2 high-resolution model under present and future CO$_2$ scenarios. The authors found a global decrease in TC’s density under high CO$_2$, but locally there was increased density of TCs in the Kuroshio region. They also found a global shortening of duration and larger translation speed. Thus, short-lived and faster storms could reduce the impact of TCs on primary productivity. However, the future of the ecosystem’s response to TCs also depends on the projected changes in pre-storm oceanic characteristics. Increased global temperatures are already enhancing the ocean’s stratification (Li et al., 2020), and if the trend continues, it could affect the timing and magnitude of seasonal phytoplankton blooms (Gittings et al., 2019). A shallower mixed layer depth could decrease the effect of TCs, but with enhanced stratification, they may become a key process to bring nutrients to the upper layers.

A future increase in cyclonic (anti-cyclonic) eddy activity could further increase(decrease) the TCs’ impact, but projected changes in eddy activity are diverse in the region of interest (Martinez-Moreno et al., 2021). Moreover, sub-surface blooms like this study may become more common in stratified oceans where the upwelling is limited.

Thus, there are still many unknowns regarding the future of TC influences on regional ecosystems. In the future, we will run the offline model with the velocity fields corresponding to doubling CO$_2$ (734 ppm) and quadrupling CO$_2$ (1468 ppm) experiments, as documented by Chu et al. (2020). This would allow me to elucidate the ecosystem’s response under high CO$_2$ scenarios to topical cy-
clones, and mesoscale activity in general. This work can be expanded to analyze the 100 years of present day CO\textsubscript{2} condition run as an initial step.

Moreover, the model developed here could be forced with real tropical cyclones data for comparisons. However, some authors have found that the offline model’s advection scheme and grid-discretization should be related to the parent model’s ones in order to work. Thus, whether our model would work with other datasets is not clear yet.

5.4.2 Ecosystem model limitations

The offline simulation successfully reproduces mesoscale dynamics at 10km resolution. It simulates the impact of eddies and tropical cyclones in the redistribution of marine tracers between the ocean interior and the upper layers. However, the model presents some important limitations that need to be further addressed. The numerical limitations due to the advection scheme used are discussed in Chapter 4. Here we discuss the ecosystem component of the model.

First, the mean distribution of the tracers in the region is somewhat in disagreement with the parent CESM2 model. For example, the seasonal cycle’s amplitude of the nutrients is lower than in CESM2. This discrepancy needs to be elucidated, but a possible explanation is the choice of ecosystem parameters. Minor adjustments on these parameters can create significant differences. For example, changing the nitrate uptake rate on one phytoplankton group can generate large shifts in the planktomic distribution of species and nutrients. Diazotrophs and diatoms are underestimated in the offline model, these values can be improved by adapting their nutrient-uptake and mortality rates. Moreover, OMEM includes variable stoichiometric ratios that add further complexity to the model. The variable ratios may also contribute to discrepancies in phytoplankton abundances when compared to MARBL. For example, if a nutrient is overestimated, it can alter the stoichiometric ratios, at a difference with the BEC model in which the stoichiometry was fixed.

Second, the results are subjected to open boundary conditions, initial conditions, and restoring terms; I will explore these dependencies further.
Third, some processes that are important for TC-ecosystem interactions are not included in the model. For example, the dilution effect of increased rainfall during storms, coastal runoff (Zheng et al., 2008, Zhao et al., 2017) and riverine discharges (Chen et al., 2009). However, we consider the coastal processes to be minor in the open ocean.

Fourth, the dissolved inorganic carbon (DIC) and alkalinity tracers are not included in the model. These tracers should be included to study the impact of TCs on carbon export since TCs potentiate the upwelling of carbon (Mahadevan et al., 2011) counteracting the effect of biological productivity. The geochemical component of MARBL can be added later on if required.

Finally, one caveat of offline models is the assumption that the ecosystem does not influence the oceanic physical variables - currents, temperature, and salinity -. The latter is not always the case; some studies have shown how the chlorophyll content can influence the heat balance in the equatorial Pacific (Lewis et al., 1990, Timmermann and Jin, 2002, Heinemann et al., 2011). However, when the focal point is the ecosystem’s dynamics, the perturbations in the temperature and currents caused by the ecosystem may be considered negligible compared to those caused by winds, solar radiation, and geostrophic ocean circulation.
In this thesis, the responses of the ocean’s biogeochemical responses to different forcings were studied using global coupled models and developing an offline marine ecosystem model. Numerical models are a valuable tool to understand how changes in physics, biology, and chemistry can have implications for the ecosystem and the ocean-atmosphere exchange of CO$_2$.

The first part of this manuscript analyzed the mechanisms driving the seasonal and interannual variability of pCO$_2$ and their future changes on global CMIP5 models. The results showed that the models agree better with observations at seasonal than interannual timescales for present-day variability. Then, the response of pCO$_2$ variability to anthropogenic CO$_2$ emissions was examined, and the carbonate chemistry influence on these changes was confirmed in agreement with previous observation-based results of Landschützer et al. (2018), Fassbender et al. (2018).

The projected pCO$_2$ seasonal amplification (Gallego et al., 2018) could amplify the seasonal cycle of hydrogen ion concentration (Kwiatkowski et al., 2020, Burger et al., 2020) with possible consequences on the marine ecosystem (Thomas et al., 2020, Jarrold et al., 2020).

The future interannual amplification Gallego et al. (2020) shows the importance of reproducing the mechanisms for DIC variability in the equatorial Pacific region. The discrepancy at interannual timescales with observations is a possible consequence of biases in El Niño Southern Oscillation-
induced changes, such as the excess zonal advection of warm waters that can overcome the DIC contribution (Jin et al., 2019). This mismatch highlights the importance of evaluating models on how well they reproduce variability and its mechanisms.

The second part of this thesis reinforced the idea that mesoscale weekly forcings such as tropical cyclones can significantly impact the ocean’s primary productivity below the surface. Although the results are preliminary, they showed that TCs can decrease and increase nutrients, phytoplankton, and zooplankton depending on their vertical gradients, and after the storm subsurface blooms can develop. Thus, this study is another example that models can be a helpful tool to highlight areas where data collection efforts would be valuable.
A.1 Taylor’s Expansion of pCO$_2$

We construct the full pCO$_2$ Taylor expansion decomposition starting with the carbonate chemistry definitions of DIC and TA as in Egleston et al. (2010):

\[
\text{DIC} = [CO_2] + \frac{K_1[CO_2]}{[H^+]} + \frac{K_1K_2[CO_2]}{[H^+]^2} \tag{A.1}
\]

\[
\text{TA} = \frac{K_1[CO_2]}{[H^+]} + 2 \frac{K_1K_2[CO_2]}{[H^+]^2} + \frac{B_{tot}K_b}{(K_b + [H^+])} - [H^+] + \frac{K_w}{[H^+]} \tag{A.2}
\]

Where $K_1$ and $K_2$ are defined as Millero et al. (2006), $K_w$ as Millero (1995) and $K_b$ according to Dickson (1990). From Eq.(A.1) we can obtain $[H^+]$ and from Eq.(A.2) we get $[CO_2]$ respectively as:

\[
[H^+] = \frac{K_1[CO_2] + \sqrt{K_1^2[CO_2]^2 + 4K_1K_2[CO_2](DIC - [CO_2])}}{2(DIC - [CO_2])} \tag{A.3}
\]

\[
[CO_2] = \frac{[H^+]^2}{K_1[H^+] + 2K_1K_2} \left( TA - \frac{B_{tot}K_b}{(K_b + [H^+])} + [H^+] - \frac{K_w}{[H^+]} \right) \tag{A.4}
\]
For $[H^+]$ the positive solution was chosen; the negative root gives a result far from real values. From Eq.(A.3) and Eq.(A.4) we can make a Taylor’s expansion of $[H^+]$ and $[CO_2]$ respectively as:

$$
\delta[H^+] = \frac{\partial[H^+]}{\partial DIC} \delta DIC + \frac{\partial[H^+]}{\partial [CO_2]} \delta [CO_2] + \frac{\partial[H^+]}{\partial T} \delta T + \frac{\partial[H^+]}{\partial S} \delta S
$$

(A.5)

$$
\delta[CO_2] = \frac{\partial[CO_2]}{\partial TA} \delta TA + \frac{\partial[CO_2]}{\partial [H^+]} \delta [H^+] + \frac{\partial[CO_2]}{\partial T} \delta T + \frac{\partial[CO_2]}{\partial S} \delta S
$$

(A.6)

The overbars indicate the mean values of the variables in which the derivatives are evaluated.

Finally, we insert $\delta[H^+]$ from Eq.(A.5) into Eq.(A.6), to get $[CO_2]$ in terms of DIC, TA, T and S:

$$
\delta[CO_2] = \left[1 - \frac{\partial[CO_2]}{\partial [H^+]} \frac{\partial[H^+]}{\partial DIC} \frac{\partial DIC}{\partial [CO_2]} \frac{\partial [CO_2]}{\partial T} \frac{\partial T}{\partial S} \frac{\partial S}{\partial [CO_2]} \right]^{-1} \left[ \frac{\partial[CO_2]}{\partial TA} \delta TA \right.

+ \left[ \frac{\partial[CO_2]}{\partial [H^+]} \frac{\partial[H^+]}{\partial DIC} \frac{\partial DIC}{\partial [CO_2]} \frac{\partial [CO_2]}{\partial T} \frac{\partial T}{\partial S} \frac{\partial S}{\partial [CO_2]} \right] \delta TA

+ \left[ \frac{\partial[CO_2]}{\partial [H^+]} \frac{\partial[H^+]}{\partial DIC} \frac{\partial DIC}{\partial [CO_2]} \frac{\partial [CO_2]}{\partial T} \frac{\partial T}{\partial S} \frac{\partial S}{\partial [CO_2]} \right] \delta T

+ \left[ \frac{\partial[CO_2]}{\partial [H^+]} \frac{\partial[H^+]}{\partial DIC} \frac{\partial DIC}{\partial [CO_2]} \frac{\partial [CO_2]}{\partial T} \frac{\partial T}{\partial S} \frac{\partial S}{\partial [CO_2]} \right] \delta S

\right] \delta TA

(A.7)

Comparing the terms from Eq.(A.7) to the desired Taylor’s expansion:

$$
\delta pCO_2 \approx \frac{\partial pCO_2}{\partial DIC} \delta DIC + \frac{\partial pCO_2}{\partial TA} \delta TA + \frac{\partial pCO_2}{\partial T} \delta T + \frac{\partial pCO_2}{\partial S} \delta S
$$

(A.8)
We can identify the derivatives from Eq. (A.8), as follows:

\[
\frac{\partial pCO_2}{\partial TA} = \frac{\partial pCO_2}{\partial DIC \cdot T - T_Ac},
\]

\[
\frac{\partial pCO_2}{\partial DIC} = \frac{\partial pCO_2}{\partial DIC \cdot T - T_Ac},
\]

\[
\frac{\partial pCO_2}{\partial T} = \frac{\partial pCO_2}{\partial DIC \cdot T - T_Ac} \left[ T_Ac \left( \frac{\partial Alk_c}{\partial T} + \frac{\partial [B(OH)\text{]}_\text{at}}{\partial T} + \frac{\partial [OH^-]}{\partial T} \right) - \Theta \cdot \frac{\partial (DIC - [CO_2])}{\partial T} \right] - \frac{\partial pCO_2}{\partial K_0(T,S)} \frac{\partial K_0(T,S)}{\partial T}
\]

\[
\frac{\partial pCO_2}{\partial S} = \frac{\partial pCO_2}{\partial DIC \cdot T - T_Ac} \left[ T_Ac \left( \frac{\partial TA}{\partial S} + \frac{\partial [B(OH)\text{]}_\text{at}}{\partial S} + \frac{\partial [OH^-]}{\partial S} \right) - \Theta \cdot \frac{\partial (DIC - [CO_2])}{\partial S} \right] - \frac{\partial pCO_2}{\partial K_0(T,S)} \frac{\partial K_0(T,S)}{\partial S}
\]

where \( \Theta = [HCO_3^-] + 4[CO_3^{2-}] + \frac{[B(OH)\text{]}_\text{at}[H^+]}{k_b + [H^+]} + [H^+] + [OH^-] \) and \( \text{Alk}_c = [HCO_3^-] + 2[CO_3^{2-}] \). Below are some details of the specific concentrations derivatives.

\[
\frac{\partial \text{Alk}_c}{\partial T,S} = \frac{[CO_2]}{[H^+]^2} \frac{\partial [H^+]}{\partial T,S} + \frac{2k_1}{\partial T,S} + \frac{2k_2}{\partial T,S},
\]

\[
\frac{\partial (DIC - [CO_2])}{\partial T,S} = \frac{[CO_2]}{[H^+]^2} \left( k_1 \frac{[H^+]}{\partial T,S} + k_1 \frac{[H^+]}{\partial T,S} + k_2 \frac{[H^+]}{\partial T,S} \right)
\]

\[
\frac{\partial [B(OH)\text{]}_\text{at}}{\partial T} = \frac{B_{tot}[H^+]}{[k_b + [H^+]^2]} \frac{\partial k_b}{\partial T}
\]

\[
\frac{\partial [B(OH)\text{]}_\text{at}}{\partial S} = \frac{B_{tot}[H^+]}{[k_b + [H^+]^2]} \frac{\partial k_b}{\partial S} + \frac{k_b}{\partial S} \frac{\partial B_{tot}}{\partial S}
\]

\[
\frac{\partial [OH^-]}{\partial T,S} = \frac{1}{[H^+]} \frac{\partial k_w}{\partial T,S}
\]

To calculate the terms in Eq. (A.1), it is necessary to use DIC, TA, T and S are required but also the hydrogen ion concentration \([H^+]\). The later concentration can be calculated numerically from TA, DIC, T and S by solving a polynomial. However, since the CIMP5 models output pH, we decided to use the simulated values.
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