Spatiotemporal variability and drivers of $p\text{CO}_2$ and air–sea $\text{CO}_2$ fluxes in the California Current System: an eddy-resolving modeling study

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Abstract

We quantify the CO$_2$ source/sink nature of the California Current System (CalCS) and determine the drivers and processes behind the mean and spatiotemporal variability of the partial pressure of CO$_2$ ($p$CO$_2$) in the surface ocean. To this end, we analyze eddy-resolving, climatological simulations of a coupled physical-ecosystem-biogeochemical ocean model on the basis of the Regional Oceanic Modeling System (ROMS). The model-simulated $p$CO$_2$ agrees very well with in situ observations over the entire domain with virtually no bias, but the model overestimates $p$CO$_2$ in the nearshore 100 km, and underestimates the observed temporal variability.

In the annual mean, the entire CalCS within 800 km of the coast and from $\sim$33$^{\circ}$ N to 46$^{\circ}$ N is essentially neutral with regard to atmospheric CO$_2$. The model simulates an integrated uptake flux of $-0.9$ Tg C yr$^{-1}$, corresponding to a very small average flux density of $-0.05$ mol C m$^{-2}$ yr$^{-1}$, with an uncertainty of the order of $\pm 0.20$ mol C m$^{-2}$ yr$^{-1}$. This near zero flux is a consequence of an almost complete regional compensation between the strong outgassing in the nearshore region (first 100 km), with flux densities of more than 3 mol C m$^{-2}$ yr$^{-1}$ and a weaker, but more widespread uptake flux in the offshore region with an average flux density of $-0.17$ mol C m$^{-2}$ yr$^{-1}$. This pattern is primarily a result of the interaction between upwelling in the nearshore that brings waters with high concentrations of dissolved inorganic carbon (DIC) to the surface, and an intense biological drawdown of this DIC, driven by the nutrients that are upwelled together with the DIC. The biological drawdown occurs too slowly to prevent the escape of a substantial amount of CO$_2$ into the atmosphere, but this is compensated by the biological generation of undersaturated conditions offshore of 100 km, permitting the CalCS to take up most of the escaped CO$_2$. Thus, the biological pump over the entire CalCS is essentially 100 % efficient, making the preformed DIC and nutrient concentrations of the upwelled waters a primary determinant of the overall source/sink nature of the CalCS. The comparison of the standard simulation with one for preindustrial conditions show that the CalCS is taking up anthropogenic CO$_2$ at a rate of...
about $-1 \text{ mol C m}^{-2} \text{ yr}^{-1}$, implying that the region was a small source of CO$_2$ to the atmosphere in preindustrial times.

The air–sea CO$_2$ fluxes vary substantially in time, both on seasonal and sub-seasonal timescales, largely driven by variations in surface ocean $p$CO$_2$. There are important differences among the subregions. Notably, the total variance of the fluxes in the central nearshore CalCS is roughly 4–5 times larger than elsewhere. Most of the variability in $p$CO$_2$ is associated with the seasonal cycle, except in the nearshore, where sub-seasonal variations driven by mesoscale processes dominate. In the regions offshore of 100 km, changes in surface temperature are the main driver, while in the nearshore region, changes in surface temperature, as well as anomalies in DIC and alkalinity (Alk) owing to changes in circulation, biological productivity and air–sea CO$_2$ fluxes dominate. The dominance of eddy-driven variability in the nearshore 100 km leads to a complex spatiotemporal mosaic of surface ocean $p$CO$_2$ and air–sea CO$_2$ fluxes that require a substantial observational effort to determine the source/sink nature of this region reliably.

1 Introduction

The coastal ocean often has not been appropriately taken into account in global carbon budget estimates, despite the fact that the associated carbon fluxes are disproportionately large with respect to the small fraction of the global ocean area that coastal oceans occupy (e.g., Liu et al., 2000; Borges et al., 2005; Chavez et al., 2007; Liu et al., 2010; Regnier et al., 2013). Global ocean models tend to be too coarse to resolve important coastal processes and observational data are often limited in space and time (e.g., Laruelle et al., 2010). Therefore, coastal air–sea CO$_2$ fluxes are currently still relatively poorly quantified, with considerable regional and global uncertainties.

Coastal upwelling regions are particularly dynamic in terms of carbon cycling as they experience extreme temporal and spatial variability in carbon fluxes (e.g., Friederich et al., 2002; Cai et al., 2006; Leinweber et al., 2009; Evans et al., 2011), further adding
to the uncertainty in the coastal carbon budget. As the upwelled water is rich in dissolved inorganic carbon (DIC), its partial pressure of CO$_2$ ($p$CO$_2$) is very high and can often exceed atmospheric levels, hence leading to an outgassing of CO$_2$. At the same time, the upwelled nutrients stimulate phytoplankton productivity, which supports a large fixation and export of organic carbon (e.g., Muller-Karger et al., 2005). This leads to a decrease in surface ocean $p$CO$_2$ and enhances the drawdown of atmospheric CO$_2$ (e.g., Hales et al., 2005, 2012; Chavez and Messié, 2009). These opposing mechanisms and the highly variable ocean circulation with a large amount of mesoscale variability render coastal upwelling systems extremely complex with regard to carbon cycling.

The California Current System (CalCS), one of the four major Eastern Boundary Upwelling Systems (EBUS), exhibits an intricate interplay of physical and biological controls on lateral and air–sea CO$_2$ fluxes. On the one hand, its relatively high level of eddy activity reduces biological productivity to levels below those expected on the basis of its rate of upwelling, leading also to a reduced vertical export of fixed carbon (Gruber et al., 2011; Lachkar and Gruber, 2011). On the other hand, filaments and other meso- and submesoscale structures cause a substantial lateral export of organic carbon (Nagai et al., 2013), thereby leading to a strong decoupling between biological production and vertical carbon export (Plattner et al., 2005).

The CalCS has been the subject of many studies investigating a variety of different aspects ranging from ecosystem vulnerability to global anthropogenic perturbations such as ocean acidification (e.g., Feely et al., 2008; Gruber et al., 2012; Hauri et al., 2013) and the emergence of areas of hypoxic oxygen concentrations (e.g., Chan et al., 2008), to more process-related topics such as the phenology of coastal upwelling (e.g., Bograd et al., 2009) and the impacts of different processes on biological production (e.g., Gruber et al., 2011; Lachkar and Gruber, 2011, 2013). However, only a few studies have so far dealt with the source/sink nature of the CalCS with regard to atmospheric CO$_2$ or quantified the contribution of the CalCS to the global carbon budget (Borges et al., 2005; Cai et al., 2006; Chavez et al., 2007; Hales et al., 2012).

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The published studies have come to rather different conclusions with regard to whether the entire CalCS is a source or a sink of atmospheric CO$_2$. Using a very limited set of observations, Borges et al. (2005) suggested that the whole Californian coast acts as a weak source with a mean flux density of about 0.5 mol C m$^{-2}$ yr$^{-1}$. In contrast, Cai et al. (2006) argued that the whole coast between California and Washington acts as a sink with a mean flux density of $-1$ mol C m$^{-2}$ yr$^{-1}$, with the Oregon coast having a particularly strong sink strength of $-2$ mol C m$^{-2}$ yr$^{-1}$. More recent observations from the Oregon coast support the conclusion of this region being a sink (Hales et al., 2005; Evans et al., 2011), but Evans et al. (2011) also showed that the air–sea CO$_2$ fluxes in this area are highly variable. In particular, they found very high pCO$_2$ with values exceeding 1000 µatm in late summer to early fall, while waters in that area were almost consistently undersaturated with respect to the atmosphere in winter and spring. This led to a small annual uptake with a mean flux density of $-0.3 \pm 6.8$ mol C m$^{-2}$ yr$^{-1}$. A similar small uptake flux was reported for the Santa Monica Bay, using a limited duration, but high frequency time series (Leinweber et al., 2009).

In the first attempt to provide a CalCS-wide estimate without relying on the extrapolation of measurements from one site to the entire region, Chavez et al. (2007) collected all available pCO$_2$ observations from the Lamont–Doherty Earth Observatory (LDEO) database, and inferred an essentially neutral CalCS with an outgassing flux density of 0.03 mol C m$^{-2}$ yr$^{-1}$. This corresponds to a total loss of 0.5 Tg C yr$^{-1}$ to the atmosphere over the entire US West Coast and extending $\sim 300$ km offshore (first three 1° × 1° bins). Using a large set of zonal cruises offshore of Monterey Bay, Pennington et al. (2010) confirmed the nearly balanced air–sea CO$_2$ budget for the central part of the CalCS, but also emphasized the existence of large onshore-offshore gradients in the fluxes.

Most recently, Hales et al. (2012) refined the estimate by Chavez et al. (2007) using the same data but employing a self organizing map approach to extrapolate the observations in time and space. For the same region, i.e., the area of the central North American Pacific continental margin (22–50° N, within 370 km from the coast), they came to a rather different result, i.e., a moderate sink of $-14$ Tg C yr$^{-1}$ for the period
of 1997 to 2005, corresponding to a flux density of $-0.66 \text{molC m}^{-2} \text{yr}^{-1}$. They confirmed the strong onshore-offshore differences in $p\text{CO}_2$ and $\text{CO}_2$ fluxes pointed out by Pennington et al. (2010), both in terms of the annual mean and the level of variability.

While these previous studies document the direction and magnitude of the air–sea $\text{CO}_2$ fluxes in different locations of the CalCS and reveal their subseasonal to interannual variability, their lack of consistent geographic settings, the absence of sufficiently dense and spatially extended observational coverage and their differing temporal coverage hinders the emergence of a synthetic view of the CalCS acting as a source or a sink of atmospheric $\text{CO}_2$. This provides an opportunity for numerical models to complement the observational studies as they can provide a synoptic and more complete view of the spatiotemporal variability of the air–sea $\text{CO}_2$ fluxes. The models further offer the opportunity to investigate the processes underlying the mean fluxes and their variability in considerably greater depth than currently possible with the in situ data.

Here, we use a series of eddy-resolving simulations from a coupled physical-ecosystem-biogeochemical oceanic model on the basis of the Regional Oceanic Modeling System (ROMS) to quantify (i) the climatological mean air–sea $\text{CO}_2$ fluxes and their drivers, (ii) the spatiotemporal variability of these fluxes, and (iii) the key drivers and processes behind the variability of these fluxes, i.e., the drivers and processes affecting surface ocean $p\text{CO}_2$. Our study shows that although the CalCS as a whole acts on average as a very weak carbon sink with respect to the atmosphere, the air–sea $\text{CO}_2$ fluxes are locally large and highly variable in space and time. Furthermore, the present work highlights the fundamental contrasts in the dynamics of the carbon cycle that exist between the nearshore areas dominated by the effects of upwelling and biological production and the regions further offshore where variations induced by temperature play a more prominent role. Finally, our investigation reveals that mesoscale eddies contribute substantially to surface $p\text{CO}_2$ variability in the nearshore central CalCS, making it challenging to derive a synoptic and representative view of the $\text{CO}_2$ fluxes on the basis of the sparse observations currently available.
2 Methods

2.1 Model details

The model used in this study is an eddy-resolving coupled physical-ecosystem-biogeochemical oceanic model of the US West coast based on the ROMS. The model domain covers roughly 2800 km alongshore (30° N–50° N) and 1250 km offshore (Fig. 1), and has a curvilinear, coast-following grid with an average grid spacing of 5 km. The model's vertical grid consists of 32 depth levels with increasing resolution towards the surface and the shallower nearshore regions. The physical model is based on the UCLA-ETH version of ROMS (Marchesiello et al., 2003; Shchepetkin and McWilliams, 2005).

The ecosystem-biogeochemical model is a nitrogen-based Nutrient-Phytoplankton-Zooplankton-Detritus (NPZD) model and includes a single phytoplankton group, implemented to mimic diatom-like behavior. A comprehensive description of the NPZD model can be found in Gruber et al. (2006). We use the same model setup and ecological parameters as Gruber et al. (2011).

An interactive carbon module was additionally implemented in the model and introduces three new state variables: Dissolved inorganic carbon (DIC), alkalinity (Alk) and calcium carbonate (CaCO$_3$) (Gruber et al., 2012; Hauri et al., 2013; Lachkar and Gruber, 2013). All of these state variables are subject to physical transport and mixing, while CaCO$_3$ is furthermore allowed to sink at a constant rate of 20 m day$^{-1}$. The organic carbon cycle is linked to the organic nitrogen cycle with a fixed stoichiometric C:N ratio of 106:16 (Redfield et al., 1963). DIC concentrations are altered by the air–sea CO$_2$ flux, the precipitation and dissolution of CaCO$_3$ and the net community production, which is defined as net primary production (NPP) minus heterotrophic respiration. The Alk concentration is modified by the formation and removal of nitrate as well as the precipitation and dissolution of CaCO$_3$. The precipitation of CaCO$_3$ is linked to NPP via a constant proportionality factor of 0.03, meaning that for each formed mole
of organic carbon, 0.03 mol of CaCO₃ are produced. CaCO₃ dissolves at a rate of 0.0057 day⁻¹ in the water column and 0.002 day⁻¹ in the sediments.

We lowered the production ratio for CaCO₃ from the value of 0.07 used previously by Gruber et al. (2011) and Hauri et al. (2013) to account for the fact that their resulting CaCO₃ to organic carbon export ratio of 0.25 at 100 m depth was substantially larger than expected, while our new value of 0.09 is consistent with the global mean export ratio of about 0.06 to 0.11 (Lee, 2001; Sarmiento et al., 2002; Jin et al., 2006). In addition, we found that lowering the production ratio also yielded model-simulated pCO₂ that compared better to observations.

The surface ocean carbonate chemistry is calculated following the standard OCMIP carbonate chemistry routines¹. For all our simulations, atmospheric pCO₂ (pCO₂air) oscillates seasonally around a mean value of 370 µatm, which corresponds approximately to the atmospheric concentration in the years 2000/2001, with a seasonal amplitude of pCO₂air of 2.9 µatm, which was taken from the NOAA Marine Boundary Layer Reference² for the mean latitude of our domain.

With the partial pressures of CO₂ of atmosphere (pCO₂air) and surface ocean (pCO₂sea), the air–sea CO₂ flux is computed using the standard bulk formula:

\[
F_{\text{CO}_2} = -K_0 \cdot k_w \cdot \left( p_{\text{CO}_2}^{\text{air}} - p_{\text{CO}_2}^{\text{sea}} \right)
\]

(1)

where \( K_0 \) denotes the solubility of CO₂, computed using the temperature- and salinity-dependent formulation of Weiss (1974), and \( k_w \) is the CO₂ gas transfer (piston) velocity. The calculation of the piston velocity for steady (short-term) winds assumes a quadratic dependence on the wind speed (Wanninkhof, 1992), using the coefficient for long-term winds. pCO₂sea is calculated using DIC, Alk, temperature (\( T \)), salinity (\( S \)) and nutrients, employing the first and second dissociation constants of carbonic acid of Millero (1995), with original reference to Mehrbach et al. (1973) and as refitted by Dickson and Millero

²http://www.esrl.noaa.gov/gmd/ccgg/mbl/mbl.html
(1987). Our sign convention is that positive values of $F_{\text{CO}_2}$ denote an outgassing of CO$_2$, while negative values indicate an uptake by the surface ocean.

2.2 Initial and boundary conditions

The model was started from rest and run for 12 yr with monthly climatological forcing. As our model simulations require about 5 yr for the spinup, we use model years 6 to 12 for analysis. The initial and boundary conditions for our runs are as described in Hauri et al. (2013) and Lachkar and Gruber (2013). In particular, the DIC and Alk initial and boundary conditions were derived from the Global Ocean Data Analysis Project (GLODAP; Key et al., 2004). A seasonal cycle was added to Alk in the surface ocean, using the regression approach of Lee et al. (2006) and employing surface ocean $T$ and $S$. Similarly, a seasonal cycle of surface DIC was constructed using the monthly $p\text{CO}_2$ climatology of Takahashi et al. (2006), and monthly surface Alk, $T$ and $S$. The seasonal cycles of DIC and Alk are then modeled to penetrate into the upper thermocline, assuming that these variations are proportional to the seasonal amplitude of $T$ at the different depths.

We slightly modified the upper ocean lateral boundary conditions of DIC inferred from GLODAP (Lee et al., 2006; Takahashi et al., 2006) in order to improve upon our model-simulated $p\text{CO}_2$, DIC and Alk fields relative to observations (see more on model evaluation in Sect. 3). The modification consisted of adjusting the vertical profile of DIC with an offset starting value of $-8$ mmol C m$^{-3}$ at the surface, and then tapering off linearly with density to a depth of 350 m, below which the adjustment is zero. We determined the magnitude of this correction from the model-simulated positive DIC bias of about $10$ mmol C m$^{-3}$ in the first 10 m relative to data collected from a coast-wide survey cruise undertaken from May to June 2007 by Feely et al. (2008). The most likely reason for the bias in our uncorrected boundary conditions is that they were computed from the gridded products of GLODAP and Takahashi et al. (2006), with particularly the former being based on relatively sparse observations in the eastern North Pacific. The magnitude of the correction is small relative to the uncertainties of GLODAP’s DIC
gridded product, with the gridding error alone exceeding 10 mmol C m\(^{-3}\) for the CalCS (Key et al., 2004).

### 2.3 Drivers and processes

We employ two complementary approaches to quantify and understand the causes of the spatial and temporal variability in surface ocean \(p_{\text{CO}_2}\) in Sects. 5 and 6. The first approach focuses on the drivers, i.e., it aims to identify the role of the different state variables, namely DIC, Alk, \(T\) and \(S\), in causing variations in \(p_{\text{CO}_2}\). The second approach goes one step further by focusing on the actual processes, i.e., the processes that alter the state variables, namely air–sea \(\text{CO}_2\) flux, ocean biology, ocean transport and mixing, and the net fluxes of heat and freshwater (FW) at the ocean surface.

To compute the contribution of each driver to the spatial or temporal variability of \(p_{\text{CO}_2}\), we use a first-order Taylor expansion to decompose \(p_{\text{CO}_2}\) into four individual components representing contributions from changes in DIC, Alk, \(T\) and \(S\). We neglect the very small contribution arising from variations in nutrients. Following Lovenduski et al. (2007) and Doney et al. (2009), we separated the DIC and Alk changes into a part driven by FW fluxes and one driven by other processes, and combined the FW flux-induced changes in DIC and Alk with the changes in \(S\) to form a FW flux term, thus:

\[
\Delta p_{\text{CO}_2} \approx \frac{\partial p_{\text{CO}_2}}{\partial \text{DIC}^S} \cdot \Delta \text{DIC}^S + \frac{\partial p_{\text{CO}_2}}{\partial \text{Alk}^S} \cdot \Delta \text{Alk}^S + \frac{\partial p_{\text{CO}_2}}{\partial T} \cdot \Delta T + \frac{\partial p_{\text{CO}_2}}{\partial \text{FW}} \cdot \Delta \text{FW}
\]

(2)

where \(\text{DIC}^S\) and \(\text{Alk}^S\) are the salinity-normalized concentrations of DIC and Alk (normalized to a salinity of 34.78 PSU), and where the partial derivatives describe the sensitivities of \(p_{\text{CO}_2}\) to small changes in DIC, Alk, \(T\) and FW (after Sarmiento and Gruber, 2006, p. 329). We determined the partial derivatives by perturbing each driver by a small amount compared to their respective domain means and recalculating \(p_{\text{CO}_2}\).
with these new values. The Δ-terms are the temporal or spatial anomalies from an annual or domain mean, respectively. The spatial anomalies for each model grid cell were computed as the difference between the in situ $pCO_2$ of each cell and the domain mean $pCO_2$ (i.e., $\Delta pCO_2 = pCO_2(x) - \langle pCO_2 \rangle$), while the temporal anomalies were computed as the difference between the $pCO_2$ at each grid cell and its annual mean (i.e., $\Delta pCO_2 = pCO_2(t) - \overline{pCO_2}$).

This first analysis approach identifies the drivers, but only partially identifies the actual processes causing the changes. In order to identify these processes we ran a series of three sensitivity studies where we consecutively removed the contributions of three main processes (Table 1). In addition, we ran a control simulation (CTRL) with no perturbations to be used as a reference. Due to computational resource limitation, we undertook these simulations at a slightly coarser horizontal resolution of 15 km. These sensitivity simulations were set up to identify the contributions of the air–sea $CO_2$ flux (S1), of biology (S2) and of solubility (S3). The contribution of solubility to $pCO_2$ is essentially driven by changes in surface ocean $T$ and $S$. Upon removal of all these processes, the only process left impacting surface ocean $pCO_2$ is the influence of ocean circulation on the distribution of DIC and Alk. The latter component together with the biological component represent essentially the net effect of ocean biology on the air–sea $CO_2$ fluxes. This is because ocean biology not only induces a downward flux of organic matter, which is usually referred to as the biological pump (Volk and Hoffert, 1985), but is also responsible for a very large part of the vertical gradients in DIC and Alk, which are then transported to the surface by ocean circulation (Gruber and Sarmiento, 2002; Sarmiento and Gruber, 2006).

We thus separate the model-simulated $pCO_2$ from the control run ($pCO_2^{\text{Control}}$) into the following four components:

$$pCO_2^{\text{Control}}_{\text{CTRL}} = pCO_2^{\text{Control}}_{\text{Gas ex.}} + pCO_2^{\text{Biology}}_{\text{CTRL} - \text{S1}} + pCO_2^{\text{Solubility}}_{\text{S1} - \text{S2}} + pCO_2^{\text{Circulation}}_{\text{S2} - \text{S3}} + pCO_2^{\text{Circulation}}_{\text{S3}} \quad (3)$$
where we implicitly make the assumption that the contributions of the different processes are linearly additive. Given the non-linearities of the ocean carbonate system (Sarmiento and Gruber, 2006), this is strictly speaking not the case. However, our experience with a permuted sequence showed little difference, indicating that these non-linearities are not substantial enough to alter our results.

The sensitivity runs were conducted in the following manner: In the first sensitivity study (S1) we set the air–sea CO₂ flux coefficient in the model to zero, thereby preventing any exchange of CO₂ between the surface ocean and the atmosphere. The difference in pCO₂ between this simulation and the control simulation, i.e., CTRL − S1, is thus the impact of the air–sea CO₂ flux on pCO₂. In the second sensitivity study (S2), we started from S1, but additionally set incoming solar radiation in the model to zero, thereby inhibiting phytoplankton growth and hence eliminating biological production of organic and inorganic carbon. The difference S1 − S2 is then the impact of biological production on pCO₂. In the third sensitivity study (S3) we eliminated the impact of solubility, i.e., of surface ocean T and S, by setting the CO₂ solubility to a constant value. This was achieved by setting T and S within the solubility equations to domain mean values of 15°C and 33.1 PSU, respectively. The difference S2 − S3 is then the impact of surface ocean T and S on pCO₂. We end up with a simulation S3 whose only remaining mechanism impacting pCO₂ is circulation acting upon the boundary conditions of DIC and Alk, i.e., transporting and mixing these values from the boundaries into the interior of the domain and then also to the surface, where they impact surface ocean pCO₂.

3 Model evaluation

A thorough model evaluation for sea-surface temperature (SST), chlorophyll, mixed layer depth (MLD), density structure and NPP for the CalCS was presented by Gruber et al. (2011) and Lachkar and Gruber (2011). They found that the model reproduces the annual mean and seasonal patterns of chlorophyll and MLD reasonably well, but
that the model has a cold bias of roughly 1°C compared to satellite data. Further, Gruber et al. (2011) found an underestimation of NPP by the model by about 41% within 1000 km and 30% within 100 km from the coast and between 34° N and 42° N compared to satellite-based estimates from Kahru et al. (2009).

We extend the evaluation by comparing the model’s simulated sea surface $p$CO$_2$ to observations from three different in situ data sources: (i) measurements of the fugacity of CO$_2$ from the Surface Ocean CO$_2$ Atlas (SOCAT Version 2; Pfeil et al., 2013), which spans the time period from 1970 to 2011 and includes more than 220,000 observations within our model domain; (ii) $p$CO$_2$ measurements from the Global Surface $p$CO$_2$ (LDEO) database (Takahashi et al., 2013), spanning the period from 1957 to 2013 for our model domain and consisting of roughly 534,000 measurements; and (iii) $p$CO$_2$ data collected by the Naval Postgraduate School and the Monterey Bay Research Aquarium Institute (MBARI) along the California Cooperative Fisheries Investigations’ (CalCOFI) Line 67 with more than 7000 data points in our domain for the years 1997 through 2001 (Collins et al., 2003). To facilitate the comparison with the model, we first converted all data to $p$CO$_2$, then binned them into 0.5° × 0.5° bins and finally normalized them to the year 2000 assuming a mean annual $p$CO$_2$ increase rate of 1.5 µatmyr$^{-1}$ as used in Takahashi et al. (2006). We then regridded the binned and normalized data to match our ROMS curvilinear grid. If bins from different databases overlapped, we gave preference to the SOCAT database. For the subsequent analysis, we only used bins with at least two observations taken in two different months within a season for the seasonal analysis and bins with at least 2 observations from opposite seasons (DJF and JJA, MAM and SON) for the annual mean analysis. This eliminated a large number of bins, particularly in the nearshore region in winter and spring and offshore of 100 km, leaving us with a total of 2021 binned and averaged observations of surface ocean $p$CO$_2$. We evaluated our model’s performance for 9 subdomains separately, namely a nearshore (0–100 km), a near-offshore (100–400 km) and a far-offshore (400–800 km) subdomain (see contour lines in Fig. 1). The choice of these
specific subdomains is based on the magnitude and offshore extent of upwelling, as well as the distinct meridional differences in the structure of the CalCS.

Figure 2 highlights that the model has reasonable to good skills in reproducing the observed near- to offshore gradient of $pCO_2$ for all seasons, and does particularly well in the summer months when it captures the seasonal upwelling signal near the coast (Fig. 2c). The model also captures the north-south gradients and its seasonal progression, particularly in the offshore regions (Fig. 2a, b and d). Furthermore it reproduces the analysis domain-wide mean $pCO_2$ very well, with an almost negligible negative bias of less than $-0.2 \mu$atm.

A more quantitative assessment of the model’s successes and challenges in reproducing the observed $pCO_2$ is offered by the Taylor diagrams in Fig. 3. The annual mean correlations of the spatial pattern range between about 0.5 and 0.8 and are therefore comparable to those achieved for chlorophyll (Gruber et al., 2011; Lachkar and Gruber, 2011). Also the poorer performance of the model with regard to the seasonal cycle is reminiscent of the generally lower seasonal correlations found for all variables, such as SST, mixed layer depth, and chlorophyll. Much better captured than chlorophyll is the spatial variance of surface ocean $pCO_2$. While the variance of chlorophyll tends to be underestimated everywhere, the model captures it well for $pCO_2$: normalized standard deviations for all regions range between 0.7 and 2.4 with annual means between 0.6 for the nearshore region (Fig. 3c) and around 1.1 for the offshore regions (Fig. 3a and b). There exist substantial seasonal differences in the degree to which the spatial variance is captured. While the model overestimates the $pCO_2$ variance in the far-offshore in all seasons and in spring and fall in the more nearshore regions, it tends to underestimate it in summer and winter in the nearshore and near-offshore regions.

Furthermore, the Taylor diagrams in Fig. 3 reveal substantial regional and temporal differences in the magnitude of the bias in the surface ocean $pCO_2$. The magnitude of over- and underestimation is largest in the nearshore 0–100 km for all seasons with values ranging between $-25 \mu$atm for winter and 46 $\mu$atm for summer. Between 100–400 km offshore, the bias varies between $-24 \mu$atm in winter and 14 $\mu$atm in summer.
Similarly in the 400–800 km offshore region, the biases range between −11 µatm for winter and spring and 9 µatm for fall. In the annual mean, the model has a $p\text{CO}_2$ bias of 10 µatm in the nearshore subdomain, and biases of −4 µatm and less than 1 µatm in the near- and far-offshore subdomains, respectively.

The comparison of our model to the ungridded $p\text{CO}_2$ data from CalCOFI Line 67 (Fig. 4), provides us with more detailed information about our model's performance in simulating the onshore-offshore gradient. In accordance with our results for the whole domain, the model mean $p\text{CO}_2$ of each season has a positive bias with respect to the mean observed $p\text{CO}_2$ in the first 100 km, where the model overestimates $p\text{CO}_2$ by up to 300 µatm (summer), but on average agrees very well with the data offshore of 100 km. For all four seasons, the maximum value of modeled $p\text{CO}_2$ peaks closer to the coast than the observed $p\text{CO}_2$, i.e., in the first 10–20 km, and decreases with increasing distance to the coast. The observed $p\text{CO}_2$ however reaches a maximum on average between 20–50 km offshore. One potential explanation for this is that in our model forcing the typical nearshore wind speed drop-off is underestimated (Capet et al., 2004), which would favor more intense coastal upwelling and elevate nearshore $p\text{CO}_2$ levels.

To further check the model's performance, particularly in the nearshore, we compared the modeled surface ocean $p\text{CO}_2$ with that predicted by the neural network model of Hales et al. (2012) for the 6 subdomains within 400 km of the coast (Table 2). This confirms that in the annual mean, our model's overestimation of $p\text{CO}_2$ is larger in the nearshore 0–100 km than in the near-offshore 100–400 km, consistent with our analysis domain-wide model evaluation with the SOCAT, LDEO and MBARI $p\text{CO}_2$ data. Over all these 6 subdomains however, the model has a nearly negligible bias of −0.3 µatm compared to data from Hales et al. (2012).

In conclusion, our model has very good skills in modeling the domain-wide mean $p\text{CO}_2$ and captures the observed spatial and temporal variability of $p\text{CO}_2$ well. In particular, our regional model, although benefitting from the additional constraints provided by the lateral boundary conditions, tends to simulate the observed $p\text{CO}_2$ considerably
better than any typical global-scale ocean biogeochemistry model, which often have
domain-wide biases of several tens of μatm (e.g., Wanninkhof et al., 2013). However,
the model consistently overestimates $p\text{CO}_2$ in the nearshore 100 km, which we veri-
ified with various independent databases. We believe this overestimation to be mainly
due to deficiencies in our forcing: First, due to the relatively coarse resolution of our
wind forcing ($\frac{1}{4}^\circ \times \frac{1}{4}^\circ$), the wind speed may be overestimated in the nearshore (Capet
et al., 2004). Second, our use of climatological forcing results in a nearly continuous
upwelling along the coast, while in reality, periods of intense upwelling are followed
by relaxation periods, when ocean biology can reduce surface ocean $p\text{CO}_2$. Errors in
our lateral boundary conditions, the model’s too low levels of NPP and biases in the
nutrient distributions may also help explain the nearshore $p\text{CO}_2$ biases.

4 Sources and sinks for atmospheric CO$_2$

4.1 Annual mean fluxes

We model the whole CalCS as a nearly balanced system with regard to atmospheric
CO$_2$, annually taking up only about $-0.9$ TgC yr$^{-1}$ over the analysis domain (0–
800 km and $\sim 33^\circ$N–$46^\circ$N). This corresponds to a tiny average uptake flux density
of $-0.05$ molC m$^{-2}$ yr$^{-1}$ (Table 2). However, this near zero flux hides the presence of
strong regional sources and sinks (Figs. 1b and 5). The whole northern subdomain
acts as a net sink of $-0.46$ molC m$^{-2}$ yr$^{-1}$ (Fig. 5a), while the central and southern sub-
domains are on average sources with flux densities of 0.04 and 0.16 molC m$^{-2}$ yr$^{-1}$,
respectively (Fig. 5b and c). The domain-wide flux density is nearly that associated with
the global oceanic uptake of anthropogenic CO$_2$ from the atmosphere (e.g., Mikaloff
Fletcher et al., 2006; Gruber et al., 2009; Wanninkhof et al., 2013), which one can as-
sume to apply also for the CalCS. Thus the small current uptake flux over the entire
CalCS can be interpreted to be largely a consequence of the anthropogenic pertur-
bation of atmospheric CO$_2$, i.e., nearly all driven by anthropogenic CO$_2$. In the off-
shore direction, the nearshore 100 km is the strongest source, losing CO$_2$ to the atmosphere with a flux density of 0.78 mol C m$^{-2}$ yr$^{-1}$ (Table 2). In contrast, the area between 100–400 km is the most important contributor to the overall sink with a flux density of $-0.47$ mol C m$^{-2}$ yr$^{-1}$. Further offshore of 400 km, the surface ocean is nearly neutral in the annual mean, outgassing on average only 0.05 mol C m$^{-2}$ yr$^{-1}$. Of the individual subdomains, the central nearshore CalCS between Pt. Conception, California, and Cape Blanco, Oregon, is the strongest CO$_2$ source, with an average flux density of 1.11 mol C m$^{-2}$ yr$^{-1}$, whereas the central area between 100–400 km is one of the strongest sink areas with $-0.53$ mol C m$^{-2}$ yr$^{-1}$ (Fig. 5).

We have not undertaken a systematic investigation of the uncertainties associated with our modeled pCO$_2$ and air–sea CO$_2$ fluxes. But some of our sensitivity simulations, where we varied either the boundary conditions or some of the model’s parameters within their uncertainty may provide an indication of the order of magnitude of this error. Altering the model’s DIC boundary conditions by $\pm 10$ mmol C m$^{-3}$, which corresponds to the model’s bias in surface DIC which we established by comparing to data from the Feely et al. (2008) cruise, resulted in a domain-wide pCO$_2$ change of approximately $\pm 5$ µatm, with a corresponding air–sea CO$_2$ flux change of about $\pm 0.2$ mol C m$^{-2}$ yr$^{-1}$. Changing the CaCO$_3$ production ratio from 0.07 to 0.03 and the use of the set of biological parameters of Gruber et al. (2011) instead of those of Gruber et al. (2006) resulted in domain-wide flux changes within the same uncertainty range. Thus, we estimate that the uncertainty associated with our modeled annual mean flux for the whole domain is at least $\pm 0.20$ mol C m$^{-2}$ yr$^{-1}$, corresponding to an integrated flux uncertainty of $\pm 3.6$ Tg C yr$^{-1}$. In the nearshore, our pCO$_2$ bias of around 10 µatm corresponds roughly to an error in the CO$_2$ flux of 0.4 mol C m$^{-2}$ yr$^{-1}$, so that reducing this bias to zero would cause a decrease in our net outgassing in the nearshore 100 km to around 0.4 mol C m$^{-2}$ yr$^{-1}$.

Including this rough estimate of the modeled flux uncertainty, our domain mean flux density of $-0.05 \pm 0.20$ mol C m$^{-2}$ yr$^{-1}$ agrees best with the results of Chavez et al. (2007), who suggested the whole US West Coast to act as a nearly balanced, small
source of 0.03 mol C m\(^{-2}\) yr\(^{-1}\). However, the flux densities of the individual subdomains agree more with the findings of Evans et al. (2011), who showed that the Oregon coast (which is to the largest part included in our northern subdomain) acts as an annual net sink of \(-0.3\) mol C m\(^{-2}\) yr\(^{-1}\), and with the results of Pennington et al. (2010), who found that the central California region is nearly balanced.

In order to compare our air–sea CO\(_2\) fluxes more directly to the most comprehensive assessment to date by Hales et al. (2012), we average our results over only the first 0–400 km. This yields an average uptake flux density of \(-0.17\) mol C m\(^{-2}\) yr\(^{-1}\), which is smaller than their result of \(-0.66\) mol C m\(^{-2}\) yr\(^{-1}\) over the same region. However, given the sizable errors in the estimate by Hales et al. (2012) as well as ours, the two estimates are actually statistically indistinguishable. They both agree that the CalCS is essentially neutral with regard to atmospheric CO\(_2\) or a small sink at best.

4.2 Processes and seasonal variability

The annual mean flux pattern is entirely driven by the modeled distribution of the surface ocean pCO\(_2\), which exhibits strong regional differences (Fig. 1a and Table 2). Variations in the gas transfer velocity, responding to regional differences in wind speed, and differences in the CO\(_2\) solubility are, in comparison, of secondary importance, as they only tend to modulate the magnitude of air–sea CO\(_2\) fluxes without influencing their sign (Eq. 1). Furthermore, the temporal variations in atmospheric pCO\(_2\) are very small (e.g., Komhyr et al., 1985; Conway et al., 1994).

The high outgassing in the nearshore regions is a result of surface ocean pCO\(_2\) exceeding 500 \(\mu\)atm there in the annual mean, while the sink regions have strongly undersaturated pCO\(_2\) values of 320 \(\mu\)atm and lower. The domain wide average pCO\(_2\) is very close to that of the atmospheric CO\(_2\), as expected given the near-zero net air–sea CO\(_2\) flux.

The strongest outgassing occurs in summer (during the upwelling season) in the nearshore central CalCS (Fig. 5b), while further offshore in summer outgassing is sub-
stantially reduced and there is even an uptake in fall. This pattern is also simulated in the northern area, but to a lesser degree (Fig. 5a). Nearly the whole analysis domain acts as a sink for CO$_2$ in winter and spring, except for the central and southern nearshore domains, which are sources from spring until fall (Fig. 5b and c). All of the subdomains experience a sign change in CO$_2$ fluxes during the course of a year, which is consistent with the findings of Hales et al. (2012). This demonstrates that while the net CO$_2$ flux over the entire CalCS is relatively small, the fluxes vary strongly in space and time, in accordance with findings from previous studies (e.g., Hales et al., 2005, 2012; Chavez et al., 2007; Evans et al., 2011).

We next investigate the drivers and mechanisms for this spatiotemporal variability in more quantitative terms, focusing on the contribution of surface ocean $p$CO$_2$ only. This is justified given it being the primary parameter driving the variations in the air–sea CO$_2$ fluxes. We first quantify the drivers and processes causing the spatial variations, and then investigate the temporal variations on both seasonal and sub-seasonal timescales.

5 Spatial variability of annual mean $p$CO$_2$

To highlight the spatial variability of the annual mean surface ocean $p$CO$_2$, we subtract its domain average and consider spatial anomalies only (Fig. 6a). Two distinct features can be identified on this plot, which is very close to that of the air–sea $p$CO$_2$ difference, given that the domain average $p$CO$_2$ differs little from atmospheric $p$CO$_2$: (i) large positive anomalies are found in the upwelling area along the coast of the central CalCS, and (ii) there is a division around 38° N between the northern part of the model domain, which tends to have negative anomalies, and the southern part with positive anomalies.

The analysis of the drivers behind this pattern reveals that it is largely a result of strong spatial gradients in DIC$^s$ and $T$ (Fig. 6b and d), with Alk$^s$ having a smaller role and FW fluxes being unimportant (Fig. 6c and e). The strong north-south gradients induced by DIC$^s$ and $T$ tend to cancel each other substantially, so that the largely un-opposed onshore-offshore gradient of DIC$^s$ becomes a prominent feature of the annual
mean distribution of $p$CO$_2$. An exception to this general pattern is the Southern California Bight, where the contribution of Alk$^s$ is important, tending to oppose the effect of DIC$^s$.

The identification of the processes underlying the spatial pattern in $p$CO$_2$ permits us to better understand the processes behind the gradients, and particularly those of the key driver DIC$^s$ (Fig. 7). This process-based separation reveals that the most important contributions to the spatial gradients of annual mean $p$CO$_2$ are circulation and biological production (Fig. 7a and b), both of which act upon DIC and Alk. Circulation, i.e., the transport of high DIC and Alk from the boundaries into the domain’s interior and then to the surface, leads to high surface ocean $p$CO$_2$ values far exceeding atmospheric $p$CO$_2$ over most of the domain (Fig. 7a). The high DIC in the upwelled waters push surface $p$CO$_2$ up to values around 700 µatm in the upwelling area and between 400–600 µatm further offshore. In the central domain, high $p$CO$_2$ values extend particularly far offshore: Values of 550 µatm can still be found around 400–500 km offshore. This large offshore extent is caused by the intense offshore Ekman and eddy-driven transport in the central CalCS (Nagai et al., 2013), which is not strongly opposed by the biological removal of DIC. The upwelled waters are also enriched in Alk, which acts to reduce the impact of the upwelling of DIC on surface ocean $p$CO$_2$, but this effect is substantially smaller.

The biological fixation of CO$_2$ and the subsequent transport of the fixed carbon to depth opposes the circulation effect and acts to decrease $p$CO$_2$ nearly everywhere by around 160 µatm on average (Fig. 7b). This biologically-induced $p$CO$_2$ drawdown is generally largest in the nearshore region. Yet, unlike physical circulation whose effects are largest in the upwelling area of the central CalCS and decrease with increasing distance to the coast, the biologically-driven $p$CO$_2$ drawdown is highest between 50 and 100 km offshore in the central CalCS and extends farther offshore than the physical circulation-driven maximum. This results in the biological compensation of circulation effects being much weaker in the first 50 km nearshore region of the central CalCS in comparison to the rest of the domain. The spatial decoupling between the area of
maximum upwelling and the region of maximum biological production has been documented in previous studies of the CalCS and was linked to the large upwelling-driven offshore fluxes of nutrients which are not fully utilized in the coastal upwelling zone (Gruber et al., 2011; Lachkar and Gruber, 2011). The combined effects of circulation and biological production, which we will refer to here as the “biological loop”, is hence largest in the first 50–100 km, with values of 500–650 µatm (Fig. 7c). Offshore of 100 km the contribution of the biological loop is nearly homogeneous at around 350 µatm, i.e., below atmospheric CO2.

In contrast to circulation and biology, the contribution by the air–sea CO2 flux is comparatively small, contributing ±30 µatm (Fig. 7d). This pattern is directly tied to the regions where the CalCS acts as a source or sink for atmospheric CO2 (see Fig. 1b). The contribution by the processes affecting the solubility of CO2 is somewhat larger, amounting to spatial gradients in pCO2 of up to ±50 µatm (Fig. 7e). This contribution very closely resembles that associated with the T driver (compare with Fig. 6d). This is because variations in T dominate the variations in the CO2 solubility, while the contribution of FW is very small.

In summary, the net effect of circulation and biological productivity, i.e., the contribution of the biological loop, control to a large extent the distribution of pCO2 with small differences in the spatial pattern between the two opposing tendencies explaining much of the onshore–offshore gradient. This is because these small differences explain the spatial distribution of DIC5, the most important driver for the spatial distribution of pCO2. This also explains the very high pCO2 values found in the 50 km wide coastal strip in the central CalCS as well as the rapid decrease of pCO2 with increasing distance to the coast in that region (see Fig. 1a). The processes affecting solubility, i.e., primarily surface ocean T, explain most of the north-south gradient in surface ocean pCO2, since the combined effect of circulation and biology shows nearly no spatial gradient in the offshore regions, and the air–sea CO2 flux is largely unimportant.
As \( pCO_2 \) and the air–sea CO\(_2\) fluxes vary not only on a spatial scale but show also high temporal variability, we next investigate the drivers and processes behind the seasonal and non-seasonal components of \( pCO_2 \) variability.

6 Temporal \( pCO_2 \) variability

Surface ocean \( pCO_2 \) in the CalCS varies substantially in time with a temporal variance of more than 2000 µatm\(^2\) in most of the nearshore areas, i.e., a standard deviation of up to ±50 µatm (Fig. 8a). The variance tapers off quite quickly with increasing offshore distance with a typical variance of about 400 to 800 µatm\(^2\) in the far offshore region, i.e., a standard deviation of between ±20 to ±30 µatm. A good part of this variance is driven by the seasonal cycle (Fig. 8b), especially in the offshore region, where it accounts for almost all of the variance. In contrast, in the nearshore areas of the central CalCS as well as in a region extending out to 200–300 km, the non-seasonal contribution is very substantial, and often exceeds that of the seasonal cycle (Fig. 8c).

6.1 Seasonal variability

To investigate the seasonality of surface ocean \( pCO_2 \), we subtract the annual mean \( pCO_2 \) from the simulated monthly climatology and consider \( pCO_2 \) seasonal anomalies and their drivers following the same approach used for studying the spatial pattern. To capture the contrasting features of \( pCO_2 \) seasonality between the coastal and open ocean regions, we analyze nearshore-averaged (less than 100 km offshore) and offshore-averaged temporal anomalies separately. In both the nearshore and offshore regions, positive anomalies of \( pCO_2 \) prevail during summer and early fall whereas negative anomalies are observed during the winter and in early spring (black lines in Figs. 9 and 10).

The decomposition of the \( pCO_2 \) seasonal anomalies into individual contributions associated with changes in DIC\(^S\), Alk\(^S\), \( T \) and FW (Fig. 9) shows that the seasonal vari-
ability of $p$CO$_2$ in the two regions is driven by distinctly different combinations, whose relative contributions to the seasonal cycle are relatively similar to that discussed for the spatial pattern. In the offshore region, the seasonal cycle is to a very large extent caused by the seasonality of $T$, i.e., by the seasonal cycle of warming and cooling (Fig. 9a). The $p$CO$_2$ variations driven by DIC$^s$ tend to have an opposing seasonal cycle, thereby flattening the simulated $p$CO$_2$ relative to that purely driven by $T$. In contrast, the $p$CO$_2$ seasonality in the nearshore region is caused by variations in both $T$ and DIC$^s$ – and to a lesser degree variations in Alk$^s$ and in the FW fluxes (Fig. 9b). Here, the DIC$^s$-driven variations are about 4 months out of phase with those of $T$, causing primarily a phase shift of the $p$CO$_2$ seasonality relative to the purely $T$-driven seasonal cycle. The seasonal cycle of the Alk$^s$-driven component is characterized by higher modes, i.e., further modifying the modeled seasonal cycle of $p$CO$_2$.

As was the case for the spatial distribution of $p$CO$_2$, we can gain further insight into the working of the seasonal cycle of $p$CO$_2$ by analyzing the processes causing the seasonal cycle, i.e., to determine the contributions of the air–sea CO$_2$ flux, ocean biology, solubility, and ocean circulation.

In the offshore domain, the processes controlling the CO$_2$ solubility contribute most to the seasonal $p$CO$_2$ variability (Fig. 10a). In this region, circulation and biology tend to nearly perfectly balance each other, whereas the air–sea CO$_2$ flux acts to slightly reduce the overall amplitude of the $p$CO$_2$ seasonal cycle (Fig. 10b). In contrast, in the nearshore area circulation, i.e., essentially upwelling, is the most important driver of $p$CO$_2$ seasonality. Biological production tends to counteract the circulation effect particularly in spring and early summer. Yet, this biological compensation is only partial, especially during winter when biology has little effect on $p$CO$_2$. The seasonal variations in CO$_2$ solubility also play an important role in the nearshore area, but are less prominent than in the offshore region. Finally, similarly to its role in the offshore region, the air–sea CO$_2$ flux acts throughout the year to dampen the seasonal cycle of $p$CO$_2$.

In conclusion, the simulated seasonality of $p$CO$_2$ emerges from the degree of compensation between the solubility-driven $p$CO$_2$ variations associated with the seasonal
cooling and heating of the surface waters and the circulation/biology-driven variations affecting surface ocean DIC and hence $p\text{CO}_2$. In the offshore region, the solubility-driven variations clearly dominate, while circulation/biology can only dampen the seasonality somewhat. In the nearshore regions, the circulation/biology-driven variations are of nearly the same amplitude, but out of phase, leading to a complex seasonal cycle in $p\text{CO}_2$. This is somewhat different, yet overall consistent with our findings with regard to the drivers and processes governing the spatial $p\text{CO}_2$ distribution.

6.2 Mesoscale variability

Our model results show that the non-seasonal component is the dominant variability mode in the first 200–300 km of the central CalCS (Fig. 8c), explaining between 20–70% of the total $p\text{CO}_2$ variability. Most of this is driven by mesoscale variability, which is more intense in the upwelling regions due to stronger baroclinic instabilities. To further investigate the eddy-driven component of our modeled $p\text{CO}_2$ variability, we analyzed the non-seasonal $p\text{CO}_2$ component as a function of time and offshore distance using Hovmöller diagrams (Fig. 11; Hovmöller, 1949): a comparison of the northern and central offshore transects confirms that the activity attributable to mesoscale and non-seasonal processes is much more prominent in the central area (Fig. 11b), which displays year-round strong eddy activity often reaching out up to 200 km offshore, whereas in the north (Fig. 11a) the eddy activity is detectable only on a seasonal timescale, starting in late summer or early fall. In general, for both domains, strong offshore transport occurs most frequently around the middle of the year.

This high variability associated with eddy activity, which is especially pronounced in the nearshore area, leads to relatively short temporal and spatial decorrelation scales, requiring relatively dense sampling in time and space in order to fully capture the true $p\text{CO}_2$ signal. In the open ocean, Jones et al. (2012) showed that $p\text{CO}_2$ can be correlated over distances of several hundred kilometers, but he also pointed out that these scales are much shorter in the coastal ocean, perhaps as short as a few ten kilometers in space and a few days to weeks in time. However, given that our model is forced with
monthly climatologies at the surface and at the lateral boundaries, the fraction of non-seasonal variability is likely underestimated in our simulations. This is because neither long-term variability such as interannual or -decadal variability nor very high frequency variability associated with weather systems are included in our forcing. Furthermore, sub-mesoscale processes like filaments and fronts, which cannot be properly resolved at our model resolution, may further decrease the level of non-seasonal variability in $p\text{CO}_2$. We thus refer to a future study for a more detailed assessment of the required sampling density in order to fully capture the true variability of $p\text{CO}_2$ and the associated air–sea $\text{CO}_2$ fluxes.

7 Discussion

Several questions emerge from our finding that the strong sources and sinks within the CalCS sum up to a nearly balanced system overall with regard to atmospheric $\text{CO}_2$. First, does this nearly complete spatial compensation occur by chance, or are there some underlying mechanisms at play? Second, if such underlying mechanisms exist, how might they control the air–sea $\text{CO}_2$ balance under future climate change? Third, what is the contribution of the oceanic uptake of anthropogenic $\text{CO}_2$ to the overall source/sink balance? Fourth, how do the air–sea $\text{CO}_2$ fluxes within the CalCS compare to fluxes elsewhere, and in particular, how do these results fit into the global picture?

Our analysis of the mechanisms underlying the annual mean air–sea $\text{CO}_2$ fluxes reveal that the near complete spatial compensation is a result of ocean productivity very closely compensating for the effect of ocean circulation on the air–sea $\text{CO}_2$ flux. This latter compensation is not fortuitous, as these two processes are fundamentally linked to each other. This is because they represent the two components of the biological loop, i.e., the downward component largely caused by the downward export of organic matter, and the upward component driven by the upward mixing and transport of the DIC-and Alk-rich deeper waters to the surface (Gruber and Sarmiento, 2002; Sarmiento and Gruber, 2006). As the upward component tends to control also the supply of the
limiting nutrient to the near surface ocean, and hence also determines to a large degree the magnitude of biological productivity, the upward and downward components of the biological loop are strongly coupled with each other. The degree of nutrient use efficiency, i.e., the degree to which the upward supplied limiting nutrient is biologically taken up and exported downward again, is a good indicator of the strength of this linkage (Sarmiento and Gruber, 2006). In the CalCS, where nitrate tends to be the limiting nutrient (Eppley and Peterson, 1979), the nitrate use efficiency turns out to be very high, as evidenced by the complete consumption of nitrate in the offshore region. This implies also a very high efficiency of the biological pump, and hence a tendency for an overall near complete compensation between the effects of biology and circulation. This does not occur regionally: in the very nearshore, the nutrient use efficiency is relatively low, allowing a part of the upwelled DIC to escape into the atmosphere. However, as these waters “age” while they are being transported further offshore, the biological pump operates so efficiently that all nitrate is fully utilized, creating the conditions for some of the escaped CO$_2$ to be taken up again by the surface ocean.

However, the efficiency of the biological pump might change in the future under climate change-driven perturbations such as upwelling-favorable wind intensification and increased stratification. For example, Lachkar and Gruber (2013) show that increasing upwelling-favorable winds results in a decrease in the biological pump efficiency, and hence an increase in the CO$_2$ outgassing. This is because the large increase in outgassing associated with the upwelling intensification outweighs the effects of the concurrent increase in productivity on surface pCO$_2$.

It is important to recognize that the anthropogenic perturbation of atmospheric CO$_2$ has perturbed the air–sea CO$_2$ fluxes in the CalCS. By comparing our simulations to one we had set atmospheric CO$_2$ to a preindustrial value of 270 µatm (Gruber et al., 2012; Hauri et al., 2013), we estimate the domain mean uptake flux of anthropogenic CO$_2$ in the CalCS to be about $-1$ mol C m$^{-2}$ yr$^{-1}$, which is very close to the global mean (e.g., Mikaloff Fletcher et al., 2006; Gruber et al., 2009; Wanninkhof et al.,...
This implies that the entire CalCS in preindustrial times was a small net source of CO$_2$ to the atmosphere.

The different processes controlling surface ocean $p$CO$_2$ operate in the CalCS in a manner that is similar to how they impact surface ocean $p$CO$_2$ on the global scale, as also there the interaction of ocean circulation and biology is a primary determinant of the spatial distribution of the air–sea CO$_2$ fluxes (e.g., Gruber and Sarmiento, 2002; Toggweiler et al., 2003; Sarmiento and Gruber, 2006; Gruber et al., 2009). Globally, circulation in the absence of biology tends to increase $p$CO$_2$ everywhere, with the efficiency of the biological pump ultimately determining how strong the opposing effect of biology ends up being, i.e., whether a particular region becomes a source or a sink with regard to the biological loop. As the CalCS tends to be a region of relatively high nutrient utilization, the compensation between circulation and biology is nearly complete, helping to explain the relatively small net fluxes if integrated over the whole analysis domain. The high degree of nutrient utilization and the implied high efficiency of the biological pump in the CalCS suggests that this region operates more like the temperate to subpolar North Atlantic, where the biologically-induced fluxes are overall small, and very unlike the North Pacific, where a low nutrient utilization leads to a substantial net outgassing of CO$_2$ associated with the biological loop (Gruber et al., 2009). We expect also the Canary Current System to operate very similarly to the CalCS given the observed complete nutrient utilization there. In contrast, we expect the Humboldt Current System, where nitrate is often not very efficiently used due to iron limitation, to have a strong net outgassing caused by the inefficient biological pump. While we do not expect large differences in the different EBUS with regard to the solubility-driven component, the CalCS and the North Atlantic differ strongly in this respect, as the strong CO$_2$ uptake in the North Atlantic is largely driven by its strong cooling.
8 Summary and outlook

We used a series of eddy-resolving simulations of the CalCS (i) to assess the climatological mean air–sea CO$_2$ fluxes and their spatiotemporal variability and (ii) to determine the drivers and processes behind the variability of these fluxes and ultimately surface ocean $p$CO$_2$.

Our model results demonstrate that the CalCS is essentially balanced in terms of air–sea CO$_2$ fluxes, with a very small net uptake flux density of $-0.05 \pm 0.20$ mol C m$^{-2}$ yr$^{-1}$. The fluxes vary strongly locally and on a seasonal timescale, with the nearshore 100 km losing a substantial amount of CO$_2$ to the atmosphere, which is largely compensated by biologically-driven uptake in the regions offshore of 100 km. We interpret this strong spatial compensation to be the result of a nearly 100% efficient biological pump, as indicated by the complete utilization of the upwelled limiting nutrient, nitrate. The CalCS acts also as a substantial sink for anthropogenic CO$_2$, taking up approximately $-1$ mol C m$^{-2}$ yr$^{-1}$, implying that the CalCS was a weak source of CO$_2$ to the atmosphere in preindustrial times.

Nearly all of the variability in air–sea CO$_2$ fluxes is caused by surface ocean $p$CO$_2$, whose seasonal variability dominates over most of the offshore areas, while in the nearshore 100 km most of the variability is determined by subseasonal, mesoscale activity. The variability in the nearshore is mostly associated with circulation and biological production, which affect DIC, Alk and $T$, while air–sea CO$_2$ fluxes, solubility and FW fluxes play a minor role. Offshore of 100 km on the other hand, changes in $T$ are the most important drivers of $p$CO$_2$ variability.

One of the main caveats of our model study is that we neither include the high frequency forcing associated with weather-related events, nor longer-term interannual variability. We aim to address this issue in a future study by adding such forcing to our model. We also plan to include an analysis of spatial and temporal decorrelation length scales in order to assess the required sampling density for accurately determining the source/sink nature of the CalCS.
Although we made through our model-based study substantial progress in determining the source/sink nature of the CalCS and the mechanisms underlying it, it would be highly desirable to verify this with observations. Clearly, the current network is largely inadequate for this purpose, and would have to be substantially strengthened. Furthermore, accurate quantification of the net air–sea CO$_2$ fluxes in the CalCS is also becoming increasingly important in the context of studies that aim to verify the emissions of anthropogenic CO$_2$ in California through measurements of atmospheric CO$_2$. This is because the large and highly variable air–sea CO$_2$ fluxes leave a substantial imprint on atmospheric CO$_2$, which has to be well quantified before the emissions can be inferred. Together with the observations, the models need to be further developed and refined, as they permit to put the observations into a spatiotemporal context, and help assess the relevant processes.

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References


**Table 1.** Calculation of the contributions of air–sea CO$_2$ flux, biological production, CO$_2$ solubility and circulation to the total $p$CO$_2$ from the control simulation.

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<td>“Pure circulation”: $p$CO$_2$ if only circulation existed</td>
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Table 2. Regional variability of surface $pCO_2$ and air–sea CO$_2$ fluxes in the CalCS. $\Delta pCO_2$ is $pCO_{2\text{sea}} - pCO_{2\text{air}}$ (370 µatm) and Hales et al. (2012) $pCO_2$ bias refers to $pCO_2$ from our study minus $pCO_2$ from Hales et al. (2012).

<table>
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<tr>
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<tr>
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<td>n/a</td>
<td>$-0.05 \pm 0.20$</td>
<td>$-0.9 \pm 3.6$</td>
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Fig. 1. Annual mean surface $p$CO$_2$ (a) and air–sea CO$_2$ flux (b) as simulated in the CalCS. Positive air–sea fluxes denote an outgassing of CO$_2$. The superimposed black lines indicate the nine subdomains, where the northern (N), central (C) and southern (S) subdomains are all split into a nearshore (0–100 km), a near-offshore (100–400 km) and a far-offshore (400–800 km) subdomain. The white line in panel (a) indicates the approximate location of the MBARI/CalCOFI Line 67.
Fig. 2. Seasonally averaged modeled (left column) and observed (right column) surface $pCO_2$ for winter (a; DJF), spring (b; MAM), summer (c; JJA) and fall (d; SON). Observations are $pCO_2$ computed from the Surface Ocean CO$_2$ Atlas (SOCAT Version 2; Pfeil et al., 2013), the Global Surface $pCO_2$ database (Takahashi et al., 2013) and the MBARI/CalCOFI Line 67 (Collins et al., 2003). The data were first binned to 0.5° × 0.5° bins to compute a climatology, normalized to the year 2000 and then regridded to match the ROMS grid. The right column shows all the bins, independent of the number of observations in them.
Variability and drivers of $\text{pCO}_2$ and air–sea $\text{CO}_2$ fluxes in the CalCS

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Fig. 3. Taylor diagram (Taylor, 2001) of modeled vs. observed $\text{pCO}_2$ for the far-offshore (a), near-offshore (b) and nearshore (c) subdomains. Observations are from the Surface Ocean $\text{CO}_2$ Atlas (SOCAT Version 2; Pfeil et al., 2013), the Global Surface $\text{pCO}_2$ database (Takahashi et al., 2013) and the MBARI/CalCOFI Line 67 (Collins et al., 2003). The distance to the origin point (dashed lines) indicates the modeled field's standard deviations, normalized to the standard deviation of observations (i.e., a value of 1 would mean a perfect agreement with the observed spatial variability). The Spearman correlation coefficient for the model vs. the observations is represented by the angle between the model point and vertical axis. The distance from the observation reference point (black dot) to the model point indicates that model field's central pattern root mean square. The color code indicates the bias of the modeled vs. the observed $\text{pCO}_2$: positive values mean the model overestimates $\text{pCO}_2$ and vice versa.
Fig. 4. Seasonally averaged $p$CO$_2$ from our model (green line) and from MBARI/CalCOFI Line 67 (blue line) as a function of distance offshore. The gray shaded area represents the range of observed $p$CO$_2$ within each season. The dashed black line indicates our model’s annual mean atmospheric $p$CO$_2$ of 370 µatm.
Fig. 5. Seasonally averaged air–sea CO₂ flux for the northern (a), central (b) and southern (c) subdomains in the nearshore, near-offshore and far-offshore. Positive values denote an outgassing of CO₂, negative values an uptake by the surface ocean.
Fig. 6. Spatial $pCO_2$ anomalies computed as the difference between in situ and domain mean $pCO_2$. Panel (a) shows total $pCO_2$ anomalies in the control simulation and panels (b–e) show the contributions of the four drivers DIC$^S$, Alk$^S$, $T$ and FW to the total.
Fig. 7. Contributions of ocean circulation (a), biological production (b), air–sea CO$_2$ flux (d) and CO$_2$ solubility (e) to annual mean $p$CO$_2$ as simulated in the control simulation. Panel (c) represents the contribution of the biological loop, i.e., the sum of (a) and (b) (indicated by the green line). Positive contributions are displayed as solid lines, negative contributions as dashed lines.
Fig. 8. Total $pCO_2$ variance (a) computed from 2-day output spanning seven consecutive model years, and seasonal $pCO_2$ variance (b) derived from a fitted mean over the same seven years. Panel (c) shows the fraction of the total $pCO_2$ attributable to non-seasonal variability.
Fig. 9. Monthly mean $p$CO$_2$ anomalies for the offshore (a) and the nearshore (b) domains: the colored lines represent the contributions of the four drivers DIC$^8$, Alk$^8$, $T$ and FW to monthly mean $p$CO$_2$ anomalies from the control simulation (black line).
Fig. 10. Monthly mean $p$CO$_2$ anomalies for the offshore (a) and the nearshore (b) domains: the colored lines represent the contributions of ocean circulation, biological production, CO$_2$ solubility and air–sea CO$_2$ flux to monthly mean $p$CO$_2$ anomalies from the control simulation (black line).
Fig. 11. Hovmöller diagrams (Hovmöller, 1949) representing non-seasonal $pCO_2$ anomalies as a function of distance offshore, based on 2-day output spanning seven consecutive model years. The anomalies were computed as the difference between the total $pCO_2$ over the seven analysis years and a seasonal fitted mean over the same seven years, and were smoothed with 40-day running mean. Panel (a) shows a transect at around $44^\circ$N, while panel (b) depicts a transect at around $36^\circ$N. The transects run roughly along the midlines of the northern and central subdomains, respectively. We do not show any transects for the southern subdomain, as any activity attributable to mesoscale eddies was negligible compared to the other two subdomains.