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Key Points:

- Enhanced CO₂ sink in the Southern Indian Ocean, with weakened CO₂ sources in the Arabian Sea, Bay of Bengal, and Equatorial Indian Ocean
- Between the 2010s and the 1980s, the CO₂ flux amplitude decreased in the Arabian Sea but increased in other sub-regions of the Indian Ocean
- Below the equator, evolving air-sea pCO₂, gradients drive CO₂ flux changes, while wind sensitivity additionally contributes above the equator

Supporting Information:

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

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Climate Change Induced Seasonal Amplification of the Indian Ocean CO₂ Sink

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Abstract This study investigates changes in the mean and seasonal states of oceanic carbon uptake across the Indian Ocean (IO) using an improved, high-resolution, observationally constrained long-term (1980–2019) surface ocean pCO₂ data product. The Arabian Sea shows a ~14% decline in CO₂ flux amplitude along with reduced mean source strength. In contrast, the Equatorial IO exhibits the largest increase in seasonal amplitude (~48%), followed by the Southern IO (~23%), while the Bay of Bengal shows only a modest change (~7%). Despite these differences, mean source strength decreases in both the Bay of Bengal and Equatorial IO, whereas the Southern IO shows an enhanced carbon sink. Amplitude changes in the Arabian Sea and Bay of Bengal are driven by shifts in flux sensitivity to wind speed and evolving seasonality of the ocean-atmosphere pCO₂ gradient, whereas in the Equatorial and Southern regions, they are primarily controlled by the evolving pCO₂ gradient alone.

Plain Language Summary Global warming is reshaping not only the average ocean carbon uptake but also how this exchange varies during the year. In the Indian Ocean (IO), earlier studies focused on average CO₂ flux changes, but not on their amplitude (the difference between maximum and minimum values in a year). This study uses long-term (1980–2019), high-resolution sea surface pCO₂ data product to estimate CO₂ fluxes in the IO. It shows that CO₂ outgassing has decreased in the Arabian Sea (AS), Bay of Bengal (BoB), and Equatorial Indian Ocean (EIO), while CO₂ absorption has increased in the Southern Indian Ocean (SIO). The amplitude of CO₂ flux decreases only in the AS but increases in other regions, with the largest increase in the EIO, followed by the SIO. In these regions, this increase is mainly due to larger differences in CO₂ between the ocean and the atmosphere. In the AS and BoB, changes are also influenced by how sensitive the flux is to the same wind speed. Overall, the study shows that warming affects not just how much CO₂ is exchanged, but also when and how strongly it occurs during the year.

1. Introduction

The Industrial Era has driven a rapid rise in atmospheric carbon dioxide (CO₂), which has significantly impacted the marine ecosystem (Doney et al., 2020; Friedlingstein et al., 2022). According to the Global Carbon Budget 2024 (Friedlingstein et al., 2024), the ocean absorbs almost 26% of the total emitted atmospheric CO₂ between 2014 and 2023. However, since 2016, the ability of the ocean to absorb atmospheric CO₂ has become almost stagnant (Friedlingstein et al., 2024). This stagnation of the ocean's sink capacity is primarily attributed to increased interannual climate variability (Friedlingstein et al., 2024). The alterations in the ocean's ability to absorb atmospheric CO₂ bring major changes in the inorganic carbonate system of the surface ocean (Sarmiento, 2013). These changes involve an increase in surface dissolved inorganic carbon (DIC), the partial pressure of CO₂ (pCO₂), and a reduction in the concentration of carbonate ions and the pH (Doney et al., 2009; Orr et al., 2005).

Although substantial efforts were made to evaluate alterations in the inorganic carbon system through observations and numerical models, there are relatively few studies to explore the changes in their seasonal cycle (amplitude and/or phase) from a climate change perspective (Fassbender et al., 2018; Kwiatkowski & Orr, 2018; Lerner et al., 2021; McNeil & Sasse, 2016). Seasonal amplification of ocean surface pCO₂ and the associated air-sea CO₂ flux over long timescales increases variability in the regional ocean carbon cycle, with the potential to

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alter regional carbon budgets and weaken the ocean's efficiency as a long-term carbon sink (Arroyo et al., 2026; Fassbender et al., 2022). During warmer seasons, enhanced ocean surface $p\text{CO}_2$ generally promotes stronger CO_2 outgassing to the atmosphere, whereas cooler seasons typically favor greater oceanic CO_2 uptake, thereby amplifying the seasonal air-sea CO_2 exchange. For instance, Lerner et al. (2021) reported an amplification of the seasonal CO_2 flux amplitude in sub-regions of the Pacific and Atlantic oceans. Persistent amplification of these seasonal contrasts can accelerate ocean acidification, contribute to higher atmospheric CO_2 concentrations, and disrupt marine ecosystems by reducing calcification, shifting species distributions, and lowering biodiversity and productivity (Kwiatkowski & Orr, 2018; Leung et al., 2022). Although many ecosystems recover from normal seasonal variability within months to a few years, repeated climate-driven seasonal extremes can delay recovery for decades, particularly in sensitive marine environments. Thus, it underscores the importance of studying long-term climate-induced changes in the seasonal variability of surface $p\text{CO}_2$ and the associated CO_2 flux.

The Indian Ocean (IO) is exposed to severe anthropogenic stress, as $\sim 30\%$ of the world's population resides around the coastal regions of the IO (Doyle, 2018; Kumar et al., 2024; Sarma et al., 2023; Wafar et al., 2011). The Northern Indian Ocean (NIO) is influenced by high freshwater flux from the Himalayan rivers, season-reversing winds, and significant aerosol deposition that primarily regulates the ocean carbon chemistry seasonality in this region (Chakraborty et al., 2021; Joshi et al., 2021, 2025; Joshi & Warrior, 2022; Sarma et al., 2018, 2020; Sridevi & Sarma, 2021). During June–August, strong wind speeds induce intense upwelling in the AS, resulting in maximum CO_2 outgassing (positive CO_2 flux) during this period (Sarma et al., 1998, 2023). The BoB shows high CO_2 outgassing from March–May due to low mixing (weaker winds), while from June–August BoB behaves as a strong sink (negative CO_2 flux), primarily due to stratification and high freshwater flux (Joshi et al., 2021; Sarma et al., 2018). Similarly, positive flux is observed during Jan–May (Jan–March), and a sink during July–September (April–December) in the EIO (SIO) (Sarma et al., 2023). Climate change is known to weaken winds, reducing vertical mixing (DeMello & PrasannaKumar, 2018). Similarly, long-term atmospheric warming melts the Himalayan glaciers, resulting in higher freshwater flux (Sridevi & Sarma, 2021). Hence, we hypothesize that climate change will affect the seasonal cycle (amplitude and/or phase) of CO_2 flux in the IO region.

Long-term (1980–2019) simulations from a regional high-resolution numerical model reveal a climate-change-induced increase in ocean acidification across the IO, with a mean rate of pH decrease of 0.015 dec^{-1} (Chakraborty et al., 2024). Using a machine learning–based approach, it was reported that total alkalinity increased significantly between 1993 and 2020 in three sub-regions of the NIO, while trends in the northern part of the basin appear to be suppressed by substantial dust deposition (Joshi et al., 2025).

Apart from the aforementioned studies, there are a few Coupled Model Intercomparison Project Phase 6 (CMIP6) based studies that report increasing ocean acidification in the IO region until the end of the 21st century (Akhiljith et al., 2019; Sunanda et al., 2023). Despite considerable efforts to assess the regional climate change-induced impacts on ocean biogeochemistry using high-resolution numerical models or Earth System Models (ESMs) from CMIP6, no study to date has examined the long-term evolution of seasonal variability in CO_2 fluxes and surface $p\text{CO}_2$ in the IO. Moreover, the scarcity of sustained in situ observation, particularly across the IO, poses a major challenge for understanding the long-term changes in the seasonal variability of carbonate variables.

The high-resolution regional models are reported to provide improved insights into the regional analysis of CO_2 fluxes and the associated changes in surface $p\text{CO}_2$ (Sarma et al., 2023). This improvement can be attributed to enhanced representation of mesoscale processes (Guo & Timmermans, 2024; Li et al., 2025), multi-element cycling, and mass exchanges between the ocean, land, and atmosphere, thereby improving the accuracy of regional predictions (Ghoshal et al., 2025). Hence, in this study, we utilize a data product that integrates outputs from a high-resolution ($1/12^\circ$) coupled ocean–ecosystem model with available observations to provide an improved estimate of surface $p\text{CO}_2$ in the Indian Ocean (Ghoshal et al., 2025).

Earlier studies report that the mean sink strength in IO is decreasing (Sarma et al., 2023), but changes in the seasonal cycle and its drivers have not yet been explored in IO. Long-term increase or decrease in monthly CO_2 flux anomalies (leading to changes in amplitude and/or phase) may accelerate or decelerate the sink or source strength of the IO. We also investigate the potential drivers responsible for these variations. To the best of our knowledge, this is the first comprehensive analysis of its kind carried out for the IO.

2. Data and Methodology

2.1. Data Sources

2.1.1. Surface Partial Pressure of CO₂

This study employs a machine-learning (ML)-based data product that integrates outputs from a regional, high-resolution coupled ocean-ecosystem model (INCOIS-BIO-ROMS (IBR); Chakraborty et al. (2024)), together with available observations to correct biases in simulated surface pCO₂ (pCO₂^{sea}) over the period 1980–2019. The ML model predicts spatio-temporal deviations (pCO₂^{obs} – pCO₂^{model}) which are then added back to pCO₂^{sea} (a) interannually (pCIBR_INT) and (b) climatologically (pCIBR_CLIM). As pCIBR_CLIM reduces the RMSE by approximately 40% relative to the original model output (Ghoshal et al., 2025), it is used for all subsequent analyses.

2.1.2. Data Required to Estimate CO₂ Flux

The SST, SSS, and atmospheric pCO₂ (pCO₂^{air}) required to calculate CO₂ flux are taken from the IBR (Chakraborty et al., 2024). Since the surface pCO₂ is related to IBR outputs, using the required IBR data maintains dynamical consistency among all the required variables. The IBR is forced using winds from the Japanese 55-year Reanalysis Driving Ocean (JRA55-do) (see (Chakraborty et al., 2024)). Hence, the same winds are used to calculate CO₂ flux in this study.

2.2. Methodology

The analyses are conducted for four distinct sub-regions of the IO, defined according to the RECCAP (Regional Carbon Cycle Assessment and Processes) regional framework and consistent with previous studies (Ghoshal et al., 2025; Sarma et al., 2023): the Arabian Sea (AS; 30°–78°E and 0°–30°N), the Bay of Bengal (BoB; 78°–110°E and 0°–24°N), the Equatorial Indian Ocean (EIO; 30°–120°E and 18°S–0°), and the Southern Indian Ocean (SIO; 30°–120°E and 30°–18°S) (Figure S1 in Supporting Information S1).

2.2.1. Seasonal Smoothing

To calculate the long-term evolution of the seasonal cycle, the original time series was smoothed using a locally fitted polynomial-harmonic model (Landschützer et al., 2018). Each timestamp t_i was converted into fractional years τ_i , defined as

$$\tau_i = Y_i + \frac{t_i - t_{\text{start}}(Y_i)}{t_{\text{start}}(Y_i + 1) - t_{\text{start}}(Y_i)}, \quad (1)$$

where $Y_i = \text{year}(t_i)$. For each target year Y , the model was fitted to all data within a 3-year moving window.

Within each window, the smoothed signal was represented using a centered cubic polynomial combined with the first four seasonal harmonics:

$$\hat{y}(\tau) = \sum_{j=0}^3 a_j (\tau - \bar{\tau})^j + \sum_{k=1}^4 [b_k \sin(2\pi k\tau) + c_k \cos(2\pi k\tau)], \quad (2)$$

where the polynomial is centered using $(\tau - \bar{\tau})$ as implemented in the model. The coefficients $\{a_j, b_k, c_k\}$ were estimated by nonlinear least squares:

$$\{a_j, b_k, c_k\} = \arg \min_{\theta} \sum_{\tau_i \in \mathcal{W}(Y)} [y_i - \hat{y}(\tau_i; \theta)]^2. \quad (3)$$

This smoothing was applied to all the state variables required to calculate the CO₂ fluxes throughout the IO region.

2.2.2. Air-Sea CO₂ Flux

The air-sea CO₂ flux is calculated using the following equation (Wanninkhof, 2014):

$$\text{Flux} = k_w \times K_H^{\text{CO}_2} \times (\text{pCO}_2^{\text{sea}} - \text{pCO}_2^{\text{air}}) \quad (4)$$

Here, $K_H^{\text{CO}_2}$ is solubility of CO₂. $K_H^{\text{CO}_2}$ is estimated as a function of SST and SSS (Wanninkhof, 2014). In the above equation, k_w is the gas transfer velocity, and it has been calculated using the following equation (Sweeney et al., 2007):

$$k_w = 0.251 \times (Sc/660)^{-0.5} \times (WS^2) \quad (5)$$

Here, Sc is the Schmidt number. The WS^2 is the square of average 10 m high winds (ms^{-1}), also known as the second moment of the wind speed (Sarmiento, 2013; Sweeney et al., 2007).

2.2.3. Drivers of the CO₂ Flux Seasonality

From Equations 4 and 5, it is evident that SST, SSS, WS, and ΔpCO_2 (i.e., $(\text{pCO}_2^{\text{sea}} - \text{pCO}_2^{\text{air}})$) are the primary drivers of the CO₂ flux. In this section, we only consider the impact of SST and SSS on the CO₂ flux through solubility and the piston velocity, while its impact on the seasonality of surface pCO₂ (and by extension ΔpCO_2) is described separately in the next section (Lerner et al., 2021). Similarly, the impact of WS is considered only through piston velocity, as this method cannot capture the wind-driven transport processes that affect the CO₂ flux (Lerner et al., 2021). Using a Taylor series expansion, we evaluate the impact of these drivers on the seasonality of CO₂ flux as follows.

$$\begin{aligned} \delta\text{CO}_2 \text{ flux} = & \frac{\partial\text{CO}_2 \text{ flux}}{\partial\text{SST}}\delta\text{SST} + \frac{\partial\text{CO}_2 \text{ flux}}{\partial\text{SSS}}\delta\text{SSS} \\ & + \frac{\partial\text{CO}_2 \text{ flux}}{\partial\text{WS}}\delta\text{WS} + \frac{\partial\text{CO}_2 \text{ flux}}{\partial\Delta\text{pCO}_2}\delta\Delta\text{pCO}_2 \\ & + \text{higher-order terms (H.O.T)} \end{aligned} \quad (6)$$

In Equation 6, δCO_2 flux refers to the CO₂ flux anomaly calculated by subtracting the mean flux of a given period from the monthly climatology of that period. For example, we calculate the flux anomaly for the 1980s (1980–1989) by creating a monthly climatology for the first decade and subtracting the 1980s mean flux from it. Similarly, on the right-hand side of Equation 6, the δ refers to the anomalies of each of the drivers that are calculated following the same method. The partial derivatives are calculated in two steps. Firstly, the CO₂ flux is recalculated by providing a small perturbation (0.01% (De Verneil et al., 2022; Orr et al., 2018) of the annual mean value) to the driver of our interest. Secondly, we estimate the difference between the perturbed and unperturbed flux. To evaluate the impact of each driver, we perturb the driver of interest while allowing the other drivers to evolve as usual.

We estimate the impact of drivers on the CO₂ flux separately for the 1980s (1980–1989) and the 2010s (2010–2019) decades. Further, to analyze the impact of each of the drivers on the changes (between the 2010s and 1980s) in CO₂ flux anomalies ($\Delta\delta\text{CO}_2$), we use the following equation (Lerner et al., 2021):

$$\Delta\delta\text{CO}_2 \text{ flux} = \sum_i \Delta \left(\frac{\partial\text{CO}_2 \text{ flux}}{\partial X_i} \right) \delta X_i + \sum_i \frac{\partial\text{CO}_2 \text{ flux}}{\partial X_i} \Delta\delta X_i + \text{higher-order terms (H.O.T)} \quad (7)$$

where $X_i \in \{\text{WS}, \Delta\text{pCO}_2, \text{SST}, \text{SSS}\}$. Each of these variables impacts the monthly anomalies of CO₂ flux in two ways. First, the change in the anomalies of each of these variables itself, and second, the change in the sensitivity of CO₂ flux to each of these variables. The first term in the right-hand side of Equation 7 refers to the changes in CO₂ flux due to the change in CO₂ flux sensitivity or reaction to the driver X_i . The second term represents the change in CO₂ flux due to the change in the monthly anomaly of X_i . This analysis enables us to determine whether the changes in the δCO_2 flux are due to the sensitivity of CO₂ flux to the driver or the changes in the anomalies of

the driver itself. This sensitivity of δCO_2 flux to the driver is represented as X_{i_sen} , while the change in δCO_2 flux due to the change in driver anomalies (δX_i) is represented as X_{i_driver} . The H.O.T. consists of cross-product terms ($\delta X_i \delta X_j$) and squared single-variable terms (δX_i^2). Although these terms are generally smaller than the first-order contributions, they may become non-negligible when multiple controlling variables interact simultaneously, as is often the case for air-sea CO_2 flux.

2.2.4. Drivers of Surface pCO_2 Seasonality

We split the surface pCO_2 into its thermal and non-thermal components. The thermal component highlights the impact of SST seasonality on the seasonal variability of the surface pCO_2 . The non-thermal component highlights the impact of other bio-physical drivers, such as DIC, SSS, and alkalinity (Landschützer et al., 2018; Müller et al., 2025). We estimate each of these components as follows (Takahashi et al., 1993, 2002)

$$\text{Thermal} = \text{pCO}_{2\text{AM}} \times \exp[0.0423 (\text{SST}_{\text{MM}} - \text{SST}_{\text{AM}})] \quad (8)$$

$$\text{Non-thermal} = \text{pCO}_{2\text{MM}} \times \exp[0.0423 (\text{SST}_{\text{AM}} - \text{SST}_{\text{MM}})] \quad (9)$$

where AM denotes Annual Mean and MM denotes Monthly Mean.

Similar to the CO_2 flux, we construct a climatology of the pCO_2 and its thermal and non-thermal components for the 1980s and the 2010s periods. Then, we remove the annual mean to construct the anomalies of pCO_2 (δpCO_2) and its components in the 1980s and 2010s, respectively.

3. Results and Discussion

3.1. Trends in Mean and Annual Amplitude of CO_2 Fluxes

Before examining the evolution of CO_2 flux amplitude, we examine the trends in mean CO_2 flux across the four sub-regions of the IO from 1980 to 2019 (Figure 1). The mean CO_2 flux in each of the sub-regions is observed to have substantial interannual variability (Figure 1). A clear negative trend is evident in each sub-region of the IO. However, the negative trend in the AS, BoB, and EIO implies a reduction in the source strength (positive CO_2 flux denotes outgassing of CO_2 from the ocean and vice versa). On the contrary, the negative trend in SIO implies increasing sink strength ($-0.003 \pm 0.001 \text{ PgC yr}^{-1}$). The rate of decreasing source strength in the AS ($-0.004 \pm 0.001 \text{ PgC yr}^{-1}$) and EIO regions is similar ($-0.004 \pm 0.002 \text{ PgC yr}^{-1}$), whereas the weakest rate is observed in the BoB region ($-0.002 \pm 0.000 \text{ PgC yr}^{-1}$). The decrease in mean source strength between the 2010s (2010–2019) and the 1980s (1980–1989) is highest in the BoB (~47%), followed by AS (~17%) and EIO (~13%). The increase in mean sink strength between the 2010s and the 1980s in the SIO is seen to be by ~10%. The differences in the 1980s flux magnitudes result in different percentage changes despite similar rates of change, particularly between the AS and EIO. Thus, from Figure 1, it is evident that there is a reduction between oceanic and atmospheric CO_2 levels in AS, BoB, and EIO. In contrast, as the atmospheric CO_2 increases, SIO absorbs more atmospheric CO_2 .

Globally, it is reported that from 1980 to 2019, the rising atmospheric CO_2 increased the sink strength of the ocean (Gruber et al., 2023). However, the AS, which is known to be a perennial source of atmospheric CO_2 (De Verneil et al., 2022; Sarma et al., 1998), along with BoB and EIO, shows a decreasing source strength (Figure 1a). Although this decrease in source strength to north of 18°S , and increase in sink strength in the south of 18°S , is reported in the earlier numerical and empirical model-based study (Sarma et al., 2023), there are no studies explaining the changes in CO_2 flux amplitude. This reduced source strength was attributed to ocean warming, resulting in increased stratification and reduced upwelling intensity (Sarma et al., 2023).

The decreasing CO_2 source strength in the AS, BoB, and EIO, along with increasing sink strength of the SIO, indicates a positive response (removal of atmospheric CO_2) from the IO toward the increased anthropogenic climate change-induced rise in atmospheric CO_2 . However, the increased sinking of atmospheric CO_2 will lead to an increase in ocean acidification in the future, which may (McNeil & Sasse, 2016; Orr et al., 2005) or may not (Alvarez-Fernandez et al., 2018; Clark et al., 2020) have an adverse impact on the ocean ecosystem. However, even if accelerating ocean acidification may not affect ocean phytoplankton due to nutrient limitation (especially in oligotrophic regions), it may still shallow the aragonite saturation depth (Sridevi & Sarma, 2024).

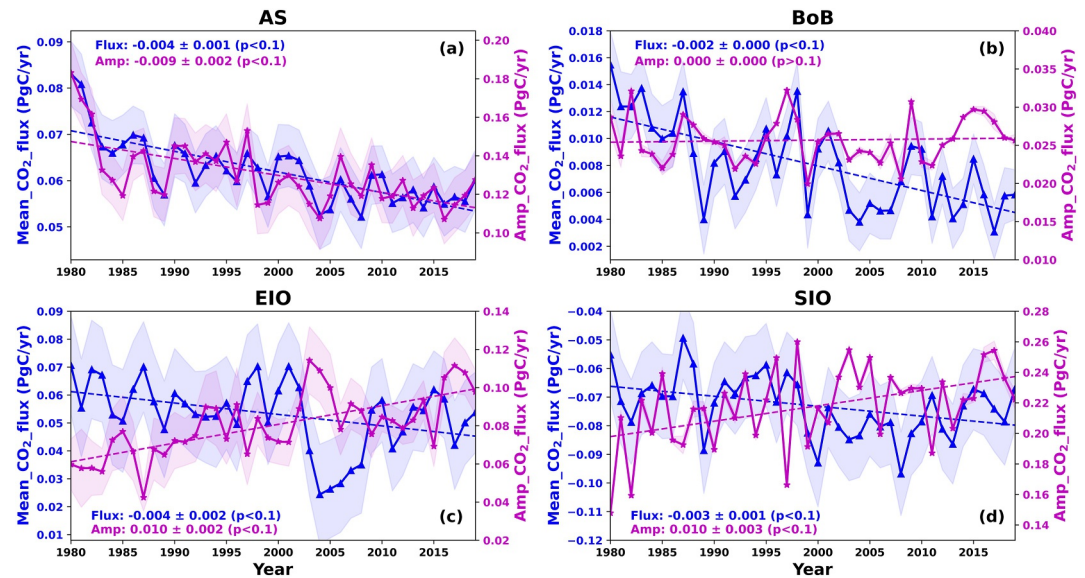


Figure 1. Trends in the mean CO₂ flux (blue) and the amplitude of CO₂ flux (difference between the months showing maximum and minimum; magenta) across the four sub-regions (AS, BoB, EIO, and SIO) of the IO region. The dashed line represents the linear trend (for each mean flux (blue) and amplitude (magenta), while the shades represent the uncertainty in mean CO₂ flux (blue) and the amplitude of CO₂ flux (magenta), respectively. The positive mean CO₂ flux indicates outgassing of CO₂, while a negative mean flux indicates sinking. The *p*-value (*p*) less than 0.1 indicates more than 90% significance, and vice versa. The uncertainties shown in Figure 1 correspond to the model uncertainty associated with the observationally constrained surface ocean pCO₂ data product used in this study.

Further, we analyze the impact of increasing atmospheric CO₂ on the annual CO₂ flux amplitude (the difference between the months with maximum and minimum CO₂ flux) in each sub-region of the IO. The trend of the CO₂ flux amplitude varies over each sub-region (Figure S1 in Supporting Information S1). Each sub-region of the IO exhibits strong interannual variability in the amplitude of the CO₂ flux (Figure 1). In the AS, the amplitude of the CO₂ flux decreased significantly from 1980 to 2019 (Figure S1 in Supporting Information S1), at a rate of $-0.009 \pm 0.002 \text{ PgC yr}^{-1} \text{ dec}^{-1}$ (Figure 1a). On the contrary, the CO₂ flux amplitude increases from 1980 to 2019 in the BoB, EIO, and SIO regions (Figure 1 and Figure S1 in Supporting Information S1). The rate at which these CO₂ flux amplitudes increase is similar in the EIO ($0.010 \pm 0.002 \text{ PgC yr}^{-1} \text{ dec}^{-1}$) and the SIO ($0.010 \pm 0.003 \text{ PgC yr}^{-1} \text{ dec}^{-1}$) region (Figures 1b and 1d). In contrast, no significant trend in the CO₂ flux amplitude was observed in the BoB ($0.000 \pm 0.000 \text{ PgC yr}^{-1} \text{ dec}^{-1}$) region (Figure 1c).

The strong interannual variability in CO₂ flux amplitudes may be associated with climatic modes (e.g., ENSO and IOD). However, an explicit assessment of the influence of these climatic modes on CO₂ flux amplitudes would require a dedicated analysis and is beyond the scope of the present study. We examine the amplification or attenuation of seasonal CO₂ flux amplitudes between the two end-member states by constructing climatologies for the 1980s (1980–1989) and the 2010s (2010–2019). We acknowledge that the selected decades could potentially be influenced by changes in the intensity and frequency of these climatic modes (Coquereau et al., 2025; Wang et al., 2024). To assess whether the selected end-member decades are systematically biased toward a particular phase of ENSO or IOD, we calculate the decadal-mean of the Relative Oceanic Niño Index (RONI (L'Heureux et al., 2024)) and Dipole Moment Index (DMI (Saji et al., 1999)). The decadal mean RONI values are 0.075 for the 1980s and -0.103 for the 2010s, while the corresponding DMI values are 0.02 and 0.13, respectively. These values suggest that neither end-member decade is systematically dominated by a particular phase of ENSO or IOD. Therefore, the selected 1980s and 2010s climatologies are not expected to have a systematic climatic-mode bias that would substantially affect their comparison.

Since our aim is to quantify the net long-term climate-induced change in the monthly anomalies of CO₂ flux over the study period (1980–2019), we compared climatologies of the first (1980s) and last (2010s) decades, which represent the initial and final climate states of the total study period. The intervening decades (1990s and 2000s) were excluded not because they are not important, but because they represent transitional periods between the two

end-member states (Figure 1). Including all decades would primarily show the gradual evolution toward the final state, without highlighting the long-term impact of climate change on the flux amplitude.

3.2. Drivers Controlling the Long-Term Changes in the CO₂ Flux Seasonality

In this section, we identify the primary drivers of CO₂ flux seasonality and its long-term changes. Before proceeding with the analysis, it is important to recognize that long-term climate change can modify the amplitude, the phase, or both, of the seasonal cycle of air-sea CO₂ flux. The left column of Figure 2 compares the monthly CO₂ flux anomalies between the 1980s and 2010s for each IO sub-region and indicates negligible phase shifts, which are further confirmed by the high correlations (AS: 0.99, BoB: 0.97, EIO: 0.98, and SIO: 0.99). This shows that long-term climate change primarily affects seasonal amplitude (amplification/attenuation), consistent with earlier findings in the Atlantic and Pacific regions (Lerner et al., 2021).

The δCO_2 in Figure 2a shows that in the AS, the monthly anomalies have decreased in the 2010s compared to the 1980s. Thus, the attenuation of the flux amplitude by $\sim 14\%$ (Table S1 in Supporting Information S1) indicates a reduction in source strength (Section 3.1) in almost all climatological months of the 2010s decade. Figure 2b shows the magnitude (black dashed-dotted line) by which these monthly flux anomalies have decreased in the AS. In Figure 2a, we see that the flux anomalies are negative in all months except June to September. Hence, in Figure 2b, positive anomaly changes ($\Delta\delta\text{CO}_2$ flux) are shown for the months having negative flux anomalies and vice versa. These decreases in flux anomalies in the AS are observed to be the highest during June to August, driven by the decrease in the WS_{sen} and ΔpCO_2 -driver (Figure 2b).

Contrary to the AS, the EIO and SIO show increases in monthly flux anomalies, thereby amplifying flux amplitude. Highest amplification by $\sim 48\%$ is observed in the EIO region (Table S1 in Supporting Information S1). In the BoB, the highest positive flux anomaly is observed in June for the 1980s and May for the 2010s (Figure 2c). The high negative anomalies in BoB are observed in December and January, which remain unchanged between the two decades. However, the changes in monthly flux anomalies in the BoB are negligible ($\sim 7\%$). Climate change-induced global warming is melting the Himalayan glaciers, which may reduce SSS in the BoB (Goes et al., 2020; Sridevi & Sarma, 2021). This reduction in SSS lowers the surface pCO₂ (Joshi & Warrior, 2022; Sridevi & Sarma, 2021), thereby increasing the CO₂ gradient between the atmosphere and the ocean. Thus, increasing the wind sensitivity in this region that ultimately drives the increased δCO_2 flux (Figure 2d). The changes in ΔpCO_2 anomalies themselves have an impact on the δCO_2 flux, but it is weaker than the changes in wind sensitivity (Figure 2d).

The EIO shows a reduced source strength (with respect to the 1980s) during the SW monsoon period, while an increased source strength in the remaining months. This decrease in source strength in the SW monsoon season is primarily driven by the increase in ΔpCO_2 -driver in the EIO. However, in the EIO, an increase in ΔpCO_2 anomalies impacts the increase δCO_2 flux in the SW monsoon season. This could be attributed to warming-induced weakening of advection of high sub-surface pCO₂ waters to the surface (DeMello & Prasanna Kumar, 2018; Roxy et al., 2015), especially in the western EIO.

Although similar amplification is observed in the SIO, the difference in amplitudes is small compared to the amplitude itself, as shown in Figures 2g and 2h. Thus, the percentage change in amplitude amplification is lower than EIO (Table S1 in Supporting Information S1). Similar to the EIO, ΔpCO_2 -driver majorly drives the enhancement of anomalies in the SIO region (Figure 2h). The contribution of the H.O.T (dotted blue line in Figure 2). is generally small compared with the primary driver contributions but becomes non-negligible during March–April and July–August in the AS, April in the BoB, and February in the SIO. In the EIO, the H.O.T. remains non-negligible throughout the year and consistently represents a secondary contribution relative to the first-order terms. The approximate percentage contributions of all terms across sub-regions and months are shown in Tables S2–S5 of Supporting Information S1. These results indicate that higher-order nonlinear interactions provide a secondary but non-negligible contribution to the seasonal amplitude of CO₂ flux anomalies, with the first-order terms remaining the dominant controls, consistent with Lerner et al. (2021).

3.3. Drivers Controlling the Long-Term Changes in the Surface pCO₂ Seasonality

In this section, we quantify changes in seasonality (amplitude and/or phase) of pCO₂ and its drivers in each sub-region of the IO (using the Method discussed in Section 2.2.4). Figure 3 represents the δpCO_2 in each sub-region

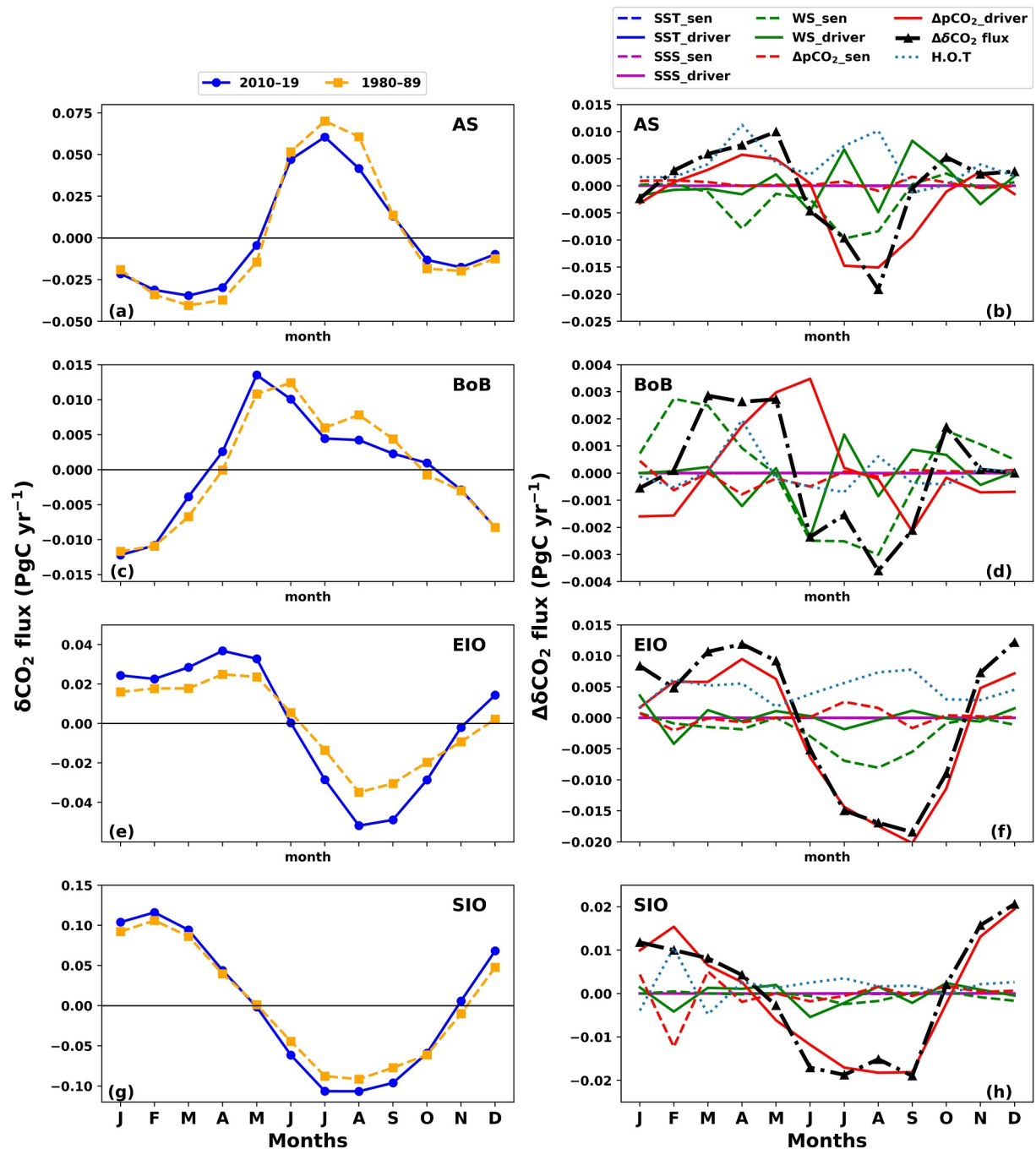


Figure 2. For each of the sub-regions of IO (AS, BoB, EIO, and SIO), the figure shows the CO₂ flux anomalies for the 1980s (1980–1989, yellow) and the 2010s (2010–2019, blue) decades of the study period in the left column. The right column illustrates the contributions of changes in sensitivities (dashed lines) and drivers (solid lines) to the changes in flux anomalies (black dashed-dotted line) between the two decades (2010s and 1980s) driven by SST (blue), SSS (magenta), WS (green), and ΔpCO_2 (red). The higher-order terms (H.O.T) are shown in the right columns (dotted light blue).

of IO (black lines) along with its thermal (red lines) and non-thermal (blue lines) components for the 1980s (dashed lines) and the 2010s (solid lines).

Although in the AS, from Figures 1a and 2a, we observe attenuation of the CO₂ flux amplitude, the pCO₂ amplitude in the AS shows amplification between the 2010s and 1980s (Figure 3a). The δpCO_2 lines in Figure 3a between the 1980s (dashed black line) and the 2010s (solid black line) show a shift in their maxima. In the 1980s, the maxima of δpCO_2 occurred between June and September, whereas in the 2010s they shifted to March and

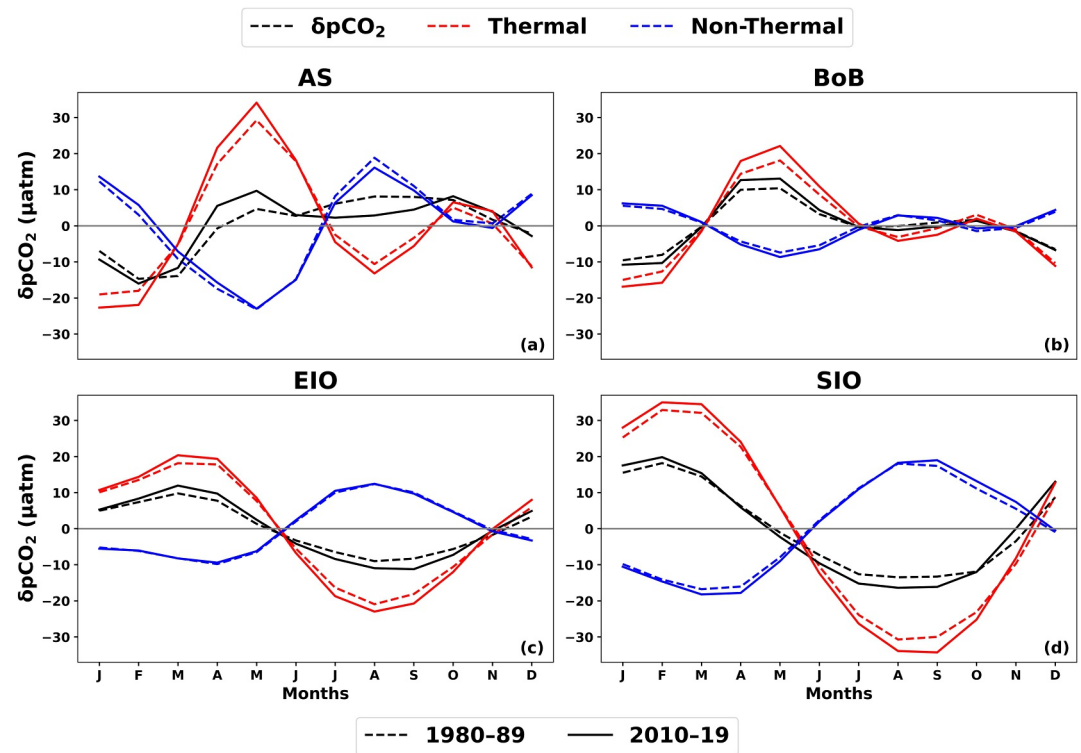


Figure 3. For each of the sub-regions of IO (AS, BoB, EIO, and SIO), the figure shows the $p\text{CO}_2$ anomalies (black) along with their drivers (Thermal (red) and Non-thermal (blue)) for the 1980s (1980–1989) and the 2010s (2010–2019). The dashed lines represent the 1980s, and the solid lines represent the 2010s.

May. No such shift in maxima or minima of $\delta p\text{CO}_2$ is found in the other three sub-regions of the IO (Figure 3b–3d).

In the AS, the $\delta p\text{CO}_2$ increases between March and May, driven primarily by the thermal component (Figure 3a). On the other hand, the $\delta p\text{CO}_2$ decreases in the June to August period owing to both an increase in thermal anomalies and a reduction in non-thermal anomalies (Figure 3a). The increased warming-induced stratification reduces the $\delta p\text{CO}_2$ by reducing the anomalies in the non-thermal component (that includes the impact of the biological pump) of $p\text{CO}_2$ (Figure 3a). Reduced ventilation means there is less gas exchange between the ocean and the atmosphere. Thus, in the AS, as shown in Figure 2b, it results in reduced sensitivity of CO_2 flux to similar WS anomalies (WS_{sen}) in the SW monsoon season.

In BoB and SIO, the increase in $\delta p\text{CO}_2$ is primarily driven by the increase in the thermal anomalies, whereas it is slightly opposed by small changes in non-thermal anomalies (Figures 3b and 3d). However, in EIO, the increase in $\delta p\text{CO}_2$ is only driven by thermal anomalies, while non-thermal anomalies have a negligible impact (Figure 3c).

This suggests that an increase in SST due to global warming leads to higher $p\text{CO}_2$ anomalies. Since in SIO, the $\Delta\delta\text{CO}_2$ flux is primarily driven by $\Delta p\text{CO}_2_{\text{driver}}$ (Figure 2h), this suggests that increasing global warming will continue to increase the CO_2 flux amplitude in this region. Overall, we observe an increase in the amplitude of surface $p\text{CO}_2$ throughout all the sub-regions of the IO (Table S1 in Supporting Information S1). The highest amplification is observed in the EIO (~23%), and the lowest in the AS (~13%).

3.4. Summary and Conclusions

This study examines regional changes in the seasonality (primarily in amplitude, as phase changes are negligible) of CO_2 flux and $p\text{CO}_2$ using a long-term, high-resolution surface $p\text{CO}_2$ data product for the Indian Ocean. In the AS (Figures 2a and 3a), we observed a decrease in the δCO_2 flux and $\delta p\text{CO}_2$ primarily during the June to August period. This decrease in monthly flux anomalies indicates a reduced (from the 1980s) outgassing of CO_2 from the ocean to the atmosphere throughout the year in the AS. Figure 2b showed that the reduction in the $\Delta p\text{CO}_2$

anomalies ($\Delta p\text{CO}_2$ _driver) between the two decades aided in reducing the flux anomalies. The changes in the anomalies of $\Delta p\text{CO}_2$ are primarily driven by the changes in the anomalies of surface $p\text{CO}_2$. Similarly, the source strength of the remaining sub-regions of the IO (except SIO) is observed to be decreasing (Figures 1b–1d). In both the EIO and SIO, the δCO_2 flux is observed to significantly increase (Figures 2e and 2g), primarily driven by changes in $\Delta p\text{CO}_2$ _driver. These $p\text{CO}_2$ anomalies increase primarily due to an increase in its thermal component (Figures 3c and 3d). In the BoB, the changes in δCO_2 flux remain negligible (Figures 1b and 2c).

This study highlights the importance of analyzing the variability of CO_2 flux amplitude on a regional scale (as it may differ across regions, as seen in the AS compared to other sub-regions of IO) across the world ocean. In this study, we use a high-resolution data product developed by integrating model outputs with available observations, providing an enhanced understanding of regional carbonate dynamics, particularly in regions with sparse observational data. We acknowledge that the results may be further refined as additional observations become available. Nevertheless, given the current scarcity of carbonate observations in the IO and the biases in stand-alone regional models and other observation-based reconstructed data products, the findings of this study remain highly relevant and significant.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

The long-term, high-resolution, improved surface $p\text{CO}_2$ datasets (pCIBR_Clim) produced for the IO region can be accessed from Ghoshal et al. (2025b). The other ocean state variables used in this study to estimate air-sea CO_2 fluxes are also available from Ghoshal et al. (2025b). The RONI index (L'Heureux et al., 2024) is taken from https://www.cpc.ncep.noaa.gov/products/analysis_monitoring/enso/roni/. We downloaded Dipole Moment Index (DMI) data (Saji et al., 1999) from <https://www.jamstec.go.jp/virtualearth/general/en/index.html>. The JRA55-do version-1.5.0 (covering 1958–2020) is downloaded from Tsujino et al. (2020). The codes used for this study are available at Joshi (2026).

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