Supporting Information for
Muted Tropical Pacific Carbon Response to the 2023 El Niño

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Section S1. Data and model evaluation

Climatological fields for both the model and observations are calculated over the period from January 1982 to December 2024, except for observational products with shorter temporal coverage. Interannual anomalies are derived through a three-step procedure. First, the long-term trend is removed using a quadratic polynomial fit of the form $ax^2 + bx + c$, fitted over 1982–2024. Second, the climatological monthly mean is subtracted to remove the seasonal cycle. Finally, a 3-month running mean is applied to suppress high-frequency variability. Throughout this study, positive CO_2 flux values denote CO_2 outgassing from the ocean to the atmosphere.

MOM6-COBALT2 simulations of air-sea CO_2 fluxes and sea surface pCO_2 are evaluated through comparison with observation-based data products, including SOCAT monthly gridded dataset (Bakker et al., 2016) and multiple independent data products (see Table S1). The simulated sea surface pCO_2 exhibits strong coherence with SOCAT-based data reconstructions in both spatial patterns and temporal variability (Fig. S1). In particular, the model realistically reproduces the spatial distribution of oceanic pCO_2 in the tropical Pacific, with higher values in the equatorial and central–eastern Pacific and lower values in the western Pacific (Fig. S1a-b). On temporal scales, the model also captures both the long-term trend and the dominant interannual variability, characterized by decreases in oceanic pCO_2 during El Niño events and increases during La Niña events (Fig. S1c). This agreement indicates that the model successfully captures the large-scale features of tropical Pacific carbon variability associated with ENSO-driven air–sea CO_2 exchange.

To further assess the physical fidelity of the MOM6 model, we compare simulated and observed climatological annual-mean fields of key physical variables, including sea surface temperature (SST), sea surface salinity (SSS), and mixed layer depth (MLD) (Fig. S2). SST observations are obtained from the Optimum Interpolation Sea Surface Temperature (OISST; Huang et al. (2021a)) product, SSS from the Optimum Interpolation analysis of Aquarius sea surface salinity (OISSS; Melnichenko et al. (2016)), and MLD estimates from Argo float profiles (Holte et al., 2017). Overall, the model successfully captures the major large-scale features of the mean state, including the warm SST in the western basin and the relatively cooler conditions in the eastern basin, as well as the low-SSS band associated with the ITCZ, supporting a physically consistent background state suitable for diagnosing interannual anomalies.

Model performance at individual locations is further evaluated using in situ observations from the Tropical Atmosphere Ocean (TAO) array (McPhaden et al., 1998; Sutton et al., 2014), obtained from the NOAA Pacific Marine Environmental Laboratory. We

analyze time series of observed data from five equatorial TAO mooring sites (Fig. S4). The model simulation successfully reproduced the observed variations in SSS and SST in the equatorial Pacific, with a significant rise in SST and decrease in SSS corresponding to the 2023 El Niño. pCO_2 simulations are moderately lower than observations, but demonstrate good consistency in temporal variation.

In Fig. S3, we evaluate the climatological annual-mean distributions of key biogeochemical tracers against GLODAP observations, including dissolved inorganic carbon (DIC), total alkalinity (Alk), phosphate (PO_4), and nitrate (NO_3). The model reproduces realistic basin-scale magnitudes and spatial patterns of these tracers at climatological states, including the dilution associated with the ITCZ band. The close match with observations confirms the model's ability to accurately represent key CO_2-related biogeochemical variables.

Finally, we evaluate the model's ability to represent the spatial–temporal evolution of ENSO-related anomalies during the 2023 extreme El Niño by comparing simulated anomalies of SST, SSS, chlorophyll, and sea surface height (SSH) with observations (Figs. S5–S6). The model successfully reproduces the observed progression of large-scale anomaly patterns, including the rapid warming of the central and eastern equatorial Pacific, the associated freshening signals, and the basin-wide sea level response. In particular, both the magnitude and timing of SST and SSH anomalies are well captured, demonstrating that the model realistically represents the key physical processes governing the development and decay of the event. Chlorophyll anomalies are also broadly consistent with observations, although their amplitude is partially overestimated in the equatorial region. Overall, these evaluations confirm that MOM6-COBALT2 provides a credible representation of the 2023 El Niño evolution, supporting its use for investigating the mechanisms underlying the muted tropical Pacific CO_2 flux response. A companion simulation with nearly identical physics has previously been validated and applied to study CO_2 flux variability in the tropical Pacific (Liao et al., 2020).

To further evaluate the ability of data-driven products and numerical models to reproduce the carbon response to the 2023 El Niño, we analysed the relationship between SST and air–sea CO_2 flux (FCO_2) in the equatorial Pacific over the period 1982–2024 (Friedlingstein et al. (2025); Fig. S11). A detailed description of the datasets is provided in Table S1. For each dataset, a linear regression was performed with respect to the Niño3.4 index. To quantify how well each dataset captures deviations from the conventional SST–FCO_2 coupling, the departure of the 2023 value from the fitted regression was characterized using both the residual (r) and the standardized residual (z), where z represents the number of standard deviations by which the 2023 observation departs from the expected linear relationship. Overall, model simulations outperform

	Dataset	Data type	Reference
1	SJTU-AViT	Obs-based product	Zhang et al. (2025)
2	VLIZ-SOMFFN	Obs-based product	Landschützer et al. (2020)
3	JENA-MLS	Obs-based product	Rödenbeck et al. (2022)
4	JMA-MLR	Obs-based product	Iida et al. (2015)
5	CSIR-ML6	Obs-based product	Gregor et al. (2019)
6	UExP-FNN-U	Obs-based product	Ford et al. (2024)
7	LDEO-HPD	Obs-based product	Bennington et al. (2022)
8	NIES-ML3	Obs-based product	Zeng (2022)
9	CMEMS-LSCE-FFNN	Obs-based product	Chau et al. (2024)
10	OceanSODA-ETHZv2	Obs-based product	Gregor and Gruber (2021)
11	FESOM	Model simulation	Gürses et al. (2023)
12	IPSL	Model simulation	Aumont et al. (2015)
13	PRINCETON	Model simulation	Liao et al. (2020)
14	CESM	Model simulation	Doney et al. (2009)
15	CNRM	Model simulation	Séférian et al. (2019); Berthet et al. (2019)
16	ACCESS	Model simulation	Law et al. (2017)
17	PLANKTOM	Model simulation	Wright et al. (2021)
18	MRI	Model simulation	Tsujino et al. (2020)
19	MPI	Model simulation	Lacroix et al. (2021)
20	NORESM	Model simulation	Schwinger et al. (2016)

Table S1. Description of observation-based data products and model simulations used for MOM6 validation.

data-driven products in reproducing the anomalous carbon signal associated with the 2023 El Niño event. In half of the machine learning based data products, the standard residual in 2023 exceeded 1, while 6 out of 10 model simulations reported a similar phenomenon. To assess the robustness of the results, tropical Pacific FCO_2 time series are derived using both linearly and quadratically detrended data (Fig. S21). The close agreement between the two approaches confirms the stability of the inferred variability.

Section S2 MOM6-COBALT2 model setup

In this work, we employ the coupled ocean–sea ice–biogeochemistry modeling framework developed at the Geophysical Fluid Dynamics Laboratory (GFDL). The physical circulation is represented by the Modular Ocean Model version 6 (MOM6) in combination with the Sea Ice Simulator version 2 (SIS2). We adopt the OM4p5 configuration,

which has a nominal 0.5° horizontal grid spacing and applies eddy parameterizations (see Adcroft et al. (2019) for further details). Biogeochemistry is simulated with the Carbon, Ocean Biogeochemistry, and Lower Trophics module version 2 (COBALT2), which explicitly resolves 33 tracers. These tracers encompass the major nutrients (nitrate, phosphate, silicate, and iron), dissolved oxygen, carbonate system variables, three functional groups of phytoplankton, three zooplankton size classes, three pools of dissolved organic matter, and a single detrital pool (Stock et al., 2020). A comprehensive description of the trophic interactions and global carbon cycling represented by COBALT2 can be found in Stock et al. (2020).

The ocean model is driven by the Japanese 55-year atmospheric reanalysis forcing dataset (JRA55-do v1.5; Tsuji et al. (2018)) and by atmospheric deposition fluxes of iron, lithogenic material, phosphate, and reactive nitrogen (NO_3, NH_4) from the GFDL-ESM4 simulations. The coupled system is spun up from rest for 81 years using a repeated cycle of 1959 JRA55-do v1.5 forcing. The imposed atmospheric CO_2 is taken from the Global Carbon Budget dataset (Friedlingstein et al., 2025), which merges Mauna Loa and South Pole observations into a globally averaged monthly time series. Initial fields of temperature, salinity, nutrients (nitrate, phosphate, silicate), and oxygen are derived from the World Ocean Atlas 2013 (Locarnini et al., 2013; Zweng et al., 2013; Garcia et al., 2013a,b). DIC and Alk initial conditions are based on GLODAPv2 (Lauvset et al., 2022), with DIC adjusted for anthropogenic carbon accumulation to represent conditions in 1959 following the data-based estimates of Khatiwala et al. (2013). Remaining COBALT tracers (e.g., ammonium, calcium carbonate) are initialized from a preindustrial GFDL-ESM2M–COBALT simulation (Stock et al., 2014).

Section S3 Air-sea CO_2 flux decomposition

The air-sea CO_2 flux is computed from the air-sea pCO_2 gradient and a gas transfer coefficient determined by wind speed and temperature:

$$\mathrm{FCO_2} = k_w \alpha (p\mathrm{CO_{2w}} - p\mathrm{CO_{2a}}) = K \Delta p\mathrm{CO_2} \tag{S1}$$

where $p\mathrm{CO_{2w}}$ and $p\mathrm{CO_{2a}}$ denote the partial pressures of CO2 in sea surface and the atmosphere, respectively. The term α is the solubility of CO_2, computed as a function of temperature and salinity following the formulation of Weiss and Price (1980), and k_w is the gas transfer velocity, calculated using a quadratic wind-speed parameterization (Wanninkhof et al., 2013). The implementation of both coefficients follows the approach described by Najjar and Orr (1998). Positive values of FCO_2 indicate net outgassing

of CO_2 from the ocean to the atmosphere. For simplicity, the product $k_w\alpha$ is combined into a single bulk gas transfer coefficient, K. The term ΔpCO_2 represents the air–sea difference in CO2 partial pressure, defined as $pCO_{2w} - pCO_{2a}$.

To calculate the variation in air-sea CO_2 flux, the Reynolds average is applied to K and ΔpCO_2. By removing the seasonality and quadratic trend, it yields the following decomposition of K and ΔpCO_2:

$$K = \overline{K} + K' \tag{S2}$$

$$\Delta pCO_2 = \overline{\Delta pCO_2} + \Delta pCO_2' \tag{S3}$$

where $\overline{K}$ and $\overline{\Delta pCO_2}$ represents long-term mean K and ΔpCO_2, and K' and ΔpCO_2 represents the interannual flucuations. Based on this simplification, air-sea CO_2 flux can be represented as:

$$\begin{aligned} FCO_2 &= K\Delta pCO_2 = (\overline{K} + K')(\overline{\Delta pCO_2} + \Delta pCO_2') \\ &= \overline{K}\,\overline{\Delta pCO_2} + K'\,\overline{\Delta pCO_2} + \overline{K}\,\Delta pCO_2' + K'\,\Delta pCO_2' \end{aligned} \tag{S4}$$

which derives the long-term mean air-sea CO_2 flux:

$$\overline{FCO_2} = \langle FCO_2 \rangle = \langle \overline{K}\ \ \overline{\Delta pCO_2} \rangle + \langle K'\,\overline{\Delta pCO_2} \rangle + \langle \overline{K}\,\Delta pCO_2' \rangle + \langle K'\,\Delta pCO_2' \rangle \tag{S5}$$

where angle brackets are used to denote the average. Assuming the interannual anomaly is randomly distributed, and we have:

$$\begin{aligned} \langle K'\,\overline{\Delta pCO_2} \rangle &= 0 \cdot \overline{\Delta pCO_2} = 0 \\ \langle \overline{K}\,\Delta pCO_2' \rangle &= \overline{K} \cdot 0 = 0 \\ \langle \overline{K}\ \ \overline{\Delta pCO_2} \rangle &= \overline{K}\ \ \overline{\Delta pCO_2} \\ \langle K'\,\Delta pCO_2' \rangle &= \langle K'\,\Delta pCO_2' \rangle \end{aligned} \tag{S6}$$

Thus, the interannual variation of air-sea CO_2 flux can be calculated as:

$$\begin{aligned} FCO_2' &= FCO_2 - \overline{FCO_2} \\ &= \overline{K}\,\overline{\Delta pCO_2} + K'\,\overline{\Delta pCO_2} + \overline{K}\,\Delta pCO_2' + K'\,\Delta pCO_2' \\ &\quad - \langle \overline{K}\ \ \overline{\Delta pCO_2} \rangle - \langle K'\,\overline{\Delta pCO_2} \rangle - \langle \overline{K}\,\Delta pCO_2' \rangle - \langle K'\,\Delta pCO_2' \rangle \\ &= \underbrace{K'\overline{\Delta pCO_2}}_{FCO_2-GT} + \underbrace{\overline{K}\Delta pCO_2'}_{FCO_2-BGC} + RES \end{aligned} \tag{S7}$$

where RES represents the small residual of the cross terms ($K'\,\Delta p\mathrm{CO}_2' - \langle K'\,\Delta p\mathrm{CO}_2' \rangle$). The variation in CO_2 flux is thus separated into two components, the wind-driven term and the $p\mathrm{CO}_2$ driven term.

Section S4 Ocean $p\mathrm{CO}_2$ decomposition

The variability of oceanic partial pressure of CO_2 ($p\mathrm{CO}_2$) can be decomposed into contributions from changes in DIC, alkalinity (Alk), temperature (T), and salinity (S), following the linear approximation proposed by Takahashi et al. (1993) and Le Quéré et al. (2000). The change in oceanic $p\mathrm{CO}_2$, denoted as $\Delta pCO_{2,w}$, can be expressed as:

$$\Delta p\mathrm{CO}_{2w} \approx \underbrace{\frac{\partial p\mathrm{CO}_{2w}}{\partial T}\Delta T}_{p\mathrm{CO}_2-T} + \underbrace{\frac{\partial p\mathrm{CO}_{2w}}{\partial \mathrm{DIC}}\Delta\mathrm{DIC} + \frac{\partial p\mathrm{CO}_{2w}}{\partial \mathrm{Alk}}\Delta\mathrm{Alk} + \frac{\partial p\mathrm{CO}_{2w}}{\partial \mathrm{S}}\Delta\mathrm{S}}_{p\mathrm{CO}_2-\mathrm{NONT}} \tag{S8}$$

Where $\Delta\mathrm{pCO}_{2w}$ denotes the ocean $p\mathrm{CO}_2$. Among the four main factors, the ΔT term is identified as the thermal component ($p\mathrm{CO}_2 - T$), and the $p\mathrm{CO}_2$ change derived from the other tracers (ΔDIC, ΔAlk, and ΔS) forms the non-thermal component ($p\mathrm{CO}_2 - T$).

Taking the total time derivative of Eq. (S8), a tracer-based decomposition of ocean $p\mathrm{CO}_2$ budget is represented as:

$$\partial_t p\mathrm{CO}_{2w} \approx \frac{\partial p\mathrm{CO}_{2w}}{\partial \mathrm{T}}\,\partial_t\mathrm{T} + \frac{\partial p\mathrm{CO}_{2w}}{\partial \mathrm{DIC}}\,\partial_t\mathrm{DIC} + \frac{\partial p\mathrm{CO}_{2w}}{\partial \mathrm{Alk}}\,\partial_t\mathrm{Alk} + \frac{\partial p\mathrm{CO}_{2w}}{\partial \mathrm{S}}\,\partial_t\mathrm{S} \tag{S9}$$

To further investigate the sources of variability in each tracer (DIC, Alk, T, and S), their temporal evolution is attributed to several key oceanic processes, including horizontal and vertical transport, biological activity, air–sea gas exchange, and surface forcing (Liao et al., 2024; Sun et al., 2025). The general tracer budgets for the scalar quantities can be written as:

$$\begin{aligned}
\partial_t\mathrm{T} &\approx \mathrm{T}_H + \mathrm{T}_V + \mathrm{T}_Q \\
\partial_t\mathrm{DIC} &\approx \mathrm{DIC}_H + \mathrm{DIC}_V + \mathrm{DIC}_{FCO_2} + \mathrm{DIC}_{Bio} + \mathrm{DIC}_{FW} \\
\partial_t\mathrm{Alk} &\approx \mathrm{Alk}_H + \mathrm{Alk}_V + \mathrm{Alk}_{Bio} + \mathrm{Alk}_{FW} \\
\partial_t\mathrm{S} &\approx \mathrm{S}_H + \mathrm{S}_V + \mathrm{S}_{FW}
\end{aligned} \tag{S10}$$

where the H terms represent contributions of horizontal transport processes, the V terms indicate vertical advection, FCO_2 in the DIC equation accounts for variations due to air-sea gas exchange, the Bio terms encapsulate the effects of biological processes, and the Q term in the temperature equations reflects the impact of surface heat flux. The FW terms represent the effects of freshwater inputs from rainfall, rivers, and sea ice, which modulate DIC/Alk/S through dilution and concentration processes.

Substituting the tracer tendency equations in Eq. S10 into Eq. S9 yields

$$\begin{aligned}\partial_t pCO_{2w} \approx & \frac{\partial pCO_{2w}}{\partial T}(T_H + T_V + T_Q) \\ & + \frac{\partial pCO_{2w}}{\partial DIC}(DIC_H + DIC_V + DIC_{FCO_2} + DIC_{Bio} + DIC_{FW}) \\ & + \frac{\partial pCO_{2w}}{\partial Alk}(Alk_H + Alk_V + Alk_{Bio} + Alk_{FW}) \\ & + \frac{\partial pCO_{2w}}{\partial S}(S_H + S_V + S_{FW}).\end{aligned} \tag{S11}$$

Time tendency of pCO_{2w} is referred to as the pCO_2 response. To isolate and quantify the non-thermal mechanisms driving changes in ocean pCO_{2w} ($\partial_t pCO_{2w-nonT}$), Eq. S11 can be regrouped into process-level budgets:

$$\begin{aligned}\partial_t pCO_{2w-nonT} \approx & \underbrace{\left(\frac{\partial pCO_{2w}}{\partial DIC} DIC_H + \frac{\partial pCO_{2w}}{\partial Alk} Alk_H + \frac{\partial pCO_{2w}}{\partial S} S_H\right)}_{H_{circ}} \\ & + \underbrace{\left(\frac{\partial pCO_{2w}}{\partial DIC} DIC_V + \frac{\partial pCO_{2w}}{\partial Alk} Alk_V + \frac{\partial pCO_{2w}}{\partial S} S_V\right)}_{V_{circ}} \\ & + \underbrace{\left(\frac{\partial pCO_{2w}}{\partial DIC} DIC_{FW} + \frac{\partial pCO_{2w}}{\partial Alk} Alk_{FW} + \frac{\partial pCO_{2w}}{\partial S} S_{FW}\right)}_{FW} \\ & + \underbrace{\left(\frac{\partial pCO_{2w}}{\partial DIC} DIC_{Bio} + \frac{\partial pCO_{2w}}{\partial Alk} Alk_{Bio}\right)}_{Bio} + \underbrace{\left(\frac{\partial pCO_{2w}}{\partial DIC} DIC_{FCO_2}\right)}_{Flux\ response}\end{aligned} \tag{S12}$$

where the non-thermal changes in ocean surface pCO_{2w} (left-hand side) are decomposed into contributions from individual processes (right-hand side): horizontal transport (H_{circ}), vertical advection (V_{circ}), freshwater fluxes (FW), biological uptake (Bio), thermal effects (Thermal), and its flux response (Flux response).

Similar to Eq. S12, the thermal-induced temporal change in pCO_{2w} ($\partial_t pCO_{2w-T}$) can be represented as:

$$\begin{aligned}\partial_t pCO_{2w-T} \approx & \frac{\partial pCO_{2w}}{\partial T}(T_H + T_V + T_Q) \\ = & \underbrace{\left(\frac{\partial pCO_{2w}}{\partial T} T_H\right)}_{T_{Hcirc}} + \underbrace{\left(\frac{\partial pCO_{2w}}{\partial T} T_V\right)}_{T_{Vcirc}} + \underbrace{\left(\frac{\partial pCO_{2w}}{\partial T} T_Q\right)}_{T_{flux}}\end{aligned} \tag{S13}$$

where the pCO_{2w-T} tendency is attributed to three processes: horizontal and vertical transport of temperature (T_{Hcirc}, T_{Vcirc}), and surface heat flux (T_{flux}).

This decomposition framework (Eqs. S12 and S13) allows a quantitative assessment of the contribution of each physical and biogeochemical process to surface ocean pCO_2 variability. In the following sections, it is applied to evaluate the dominant drivers of the carbon anomaly observed during the 2023 El Niño.

The coefficients used for the pCO_{2w} dependence on DIC, alkalinity, salinity, and temperature are approximated by the following equations (Lovenduski et al., 2007; Sarmiento and Gruber, 2013):

$$\begin{aligned}\frac{\partial pCO_{2w}}{\partial DIC} &\approx \frac{\overline{pCO_{2w}}}{\overline{DIC}} \frac{3 \times \overline{Alk} \times \overline{DIC} - 2 \times \overline{DIC}^2}{(2 \times \overline{DIC} - \overline{Alk})(\overline{Alk} - \overline{DIC})} \\ \frac{\partial pCO_{2w}}{\partial Alk} &\approx -\frac{\overline{pCO_{2w}}}{\overline{Alk}} \frac{\overline{Alk}^2}{(2 \times \overline{DIC} - \overline{Alk})(\overline{Alk} - \overline{DIC})} \\ \frac{\partial pCO_{2w}}{\partial T} &\approx \overline{pCO_{2w}} \times 0.0423 \\ \frac{\partial pCO_{2w}}{\partial S} &\approx \frac{\overline{pCO_{2w}}}{\overline{S}}\end{aligned} \tag{S14}$$

Here, overbars denote the annual mean values for the period 1982–2024, and the coefficients are assumed to be time invariant. The coefficients associated with DIC and salinity are positive, indicating that increases in DIC or salinity lead to increases in pCO_{2w}. In contrast, the coefficient for alkalinity is negative, implying that higher alkalinity reduces pCO_{2w}. Although variations in DIC and alkalinity often exert opposing influences on pCO_{2w}, the effect of DIC typically dominates because of its larger sensitivity coefficient.

All terms in Eqs. S12 and S13 are evaluated within the mixed layer. The mixed layer depth is defined as the depth at which seawater density exceeds the surface density by 0.01 kg m^{-3}.

Section S5 Figures. S1-S21

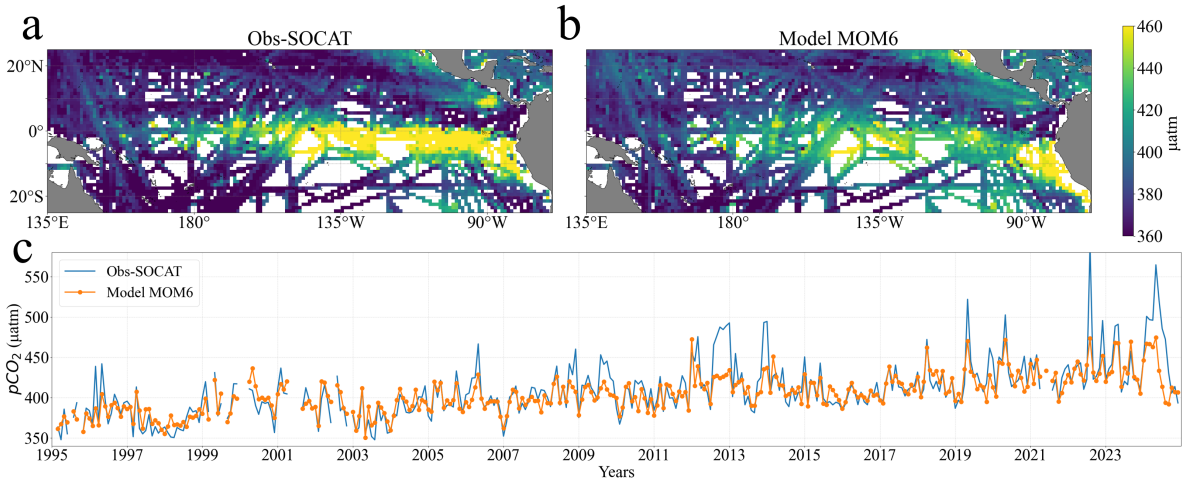


Figure S1. Comparison of climatological mean sea surface pCO_2 from (a) SOCAT observations (Bakker et al., 2016) and (b) MOM6-COBALT2 simulations, both calculated using only the spatial and temporal sampling of available SOCAT observations during 1995–2024. (c) Time series of basin-mean pCO_2, derived from SOCAT observation points within the tropical Pacific (160°E–285°E, 15°S–15°N), with the model sampled at the same locations and times.

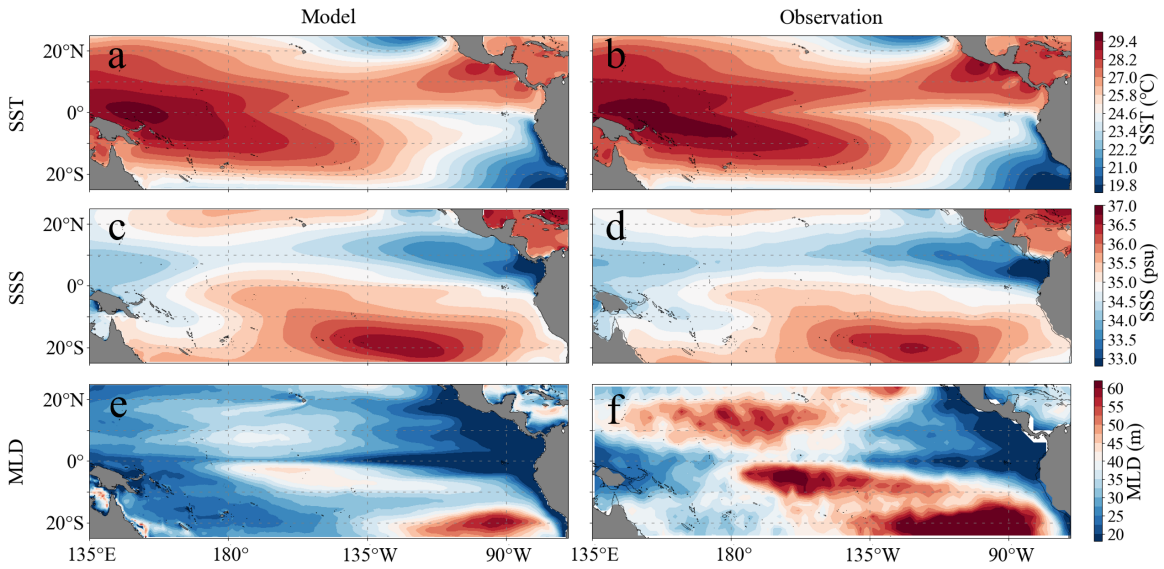


Figure S2. Comparison of climatological mean fields in the tropical Pacific between MOM6-COBALT2 simulations (left column) and observations (right column): SST (a, b), SSS (c, d), and MLD (e, f). Observed SST is from OISST v2 (Huang et al., 2021a), SSS from OISSS (Melnichenko et al., 2016), and mixed layer depth from Argo profiles (Holte et al., 2017). The climatological means of each variable are calculated over the full temporal coverage of the corresponding dataset: 1982–2024 for SST, 2011–2024 for SSS, and 2000–2024 for MLD.

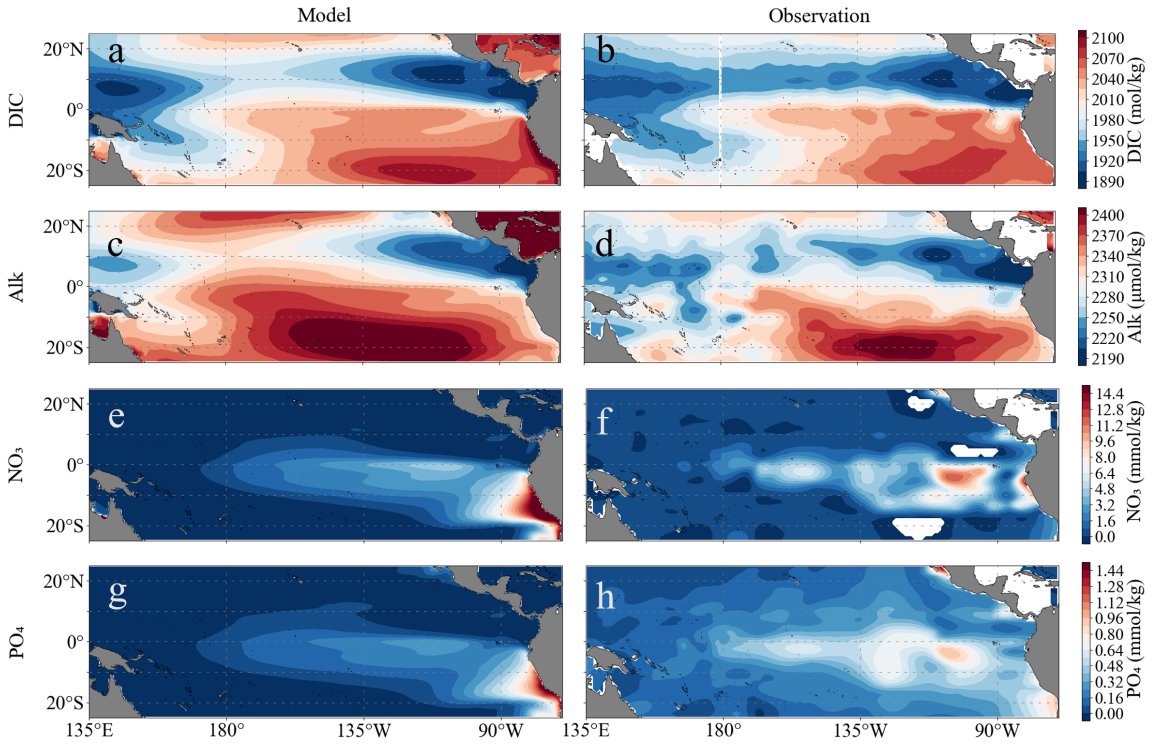


Figure S3. Comparison of climatological mean fields in the tropical Pacific between MOM6-COBALT2 simulations (left column) and observations (right column): DIC (a, b), Alk (c, d), PO_4 (e, f), and NO_3 (g, h). Observational fields of DIC, Alk, PO_4, and NO_3 are from the WOA 2023 data product. Model climatologies represent the mean over 1982–2024.

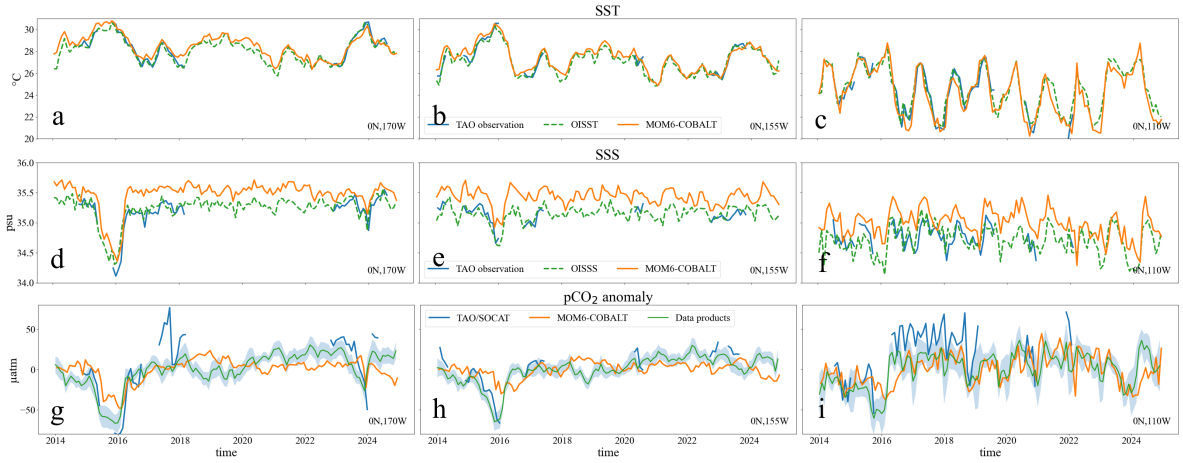


Figure S4. Comparison of interannual variability at three TAO mooring stations in the tropical Pacific between MOM6–COBALT2 simulations and observations: SST (a–c), SSS (d–f), and sea-surface pCO_2 anomalies (g–i). Each row corresponds to a different mooring location, as indicated in the individual panels. Observations are derived from TAO measurements and observation-based products. Both the observation-based products and MOM6–COBALT2 simulations are interpolated to the TAO locations. Observed SST data product is from OISST v2 (Huang et al., 2021a), SSS data product is from OISSS (Melnichenko et al., 2016), and pCO_2 anomalies are from an ensemble of ten observation-based products (see details in Table S1).

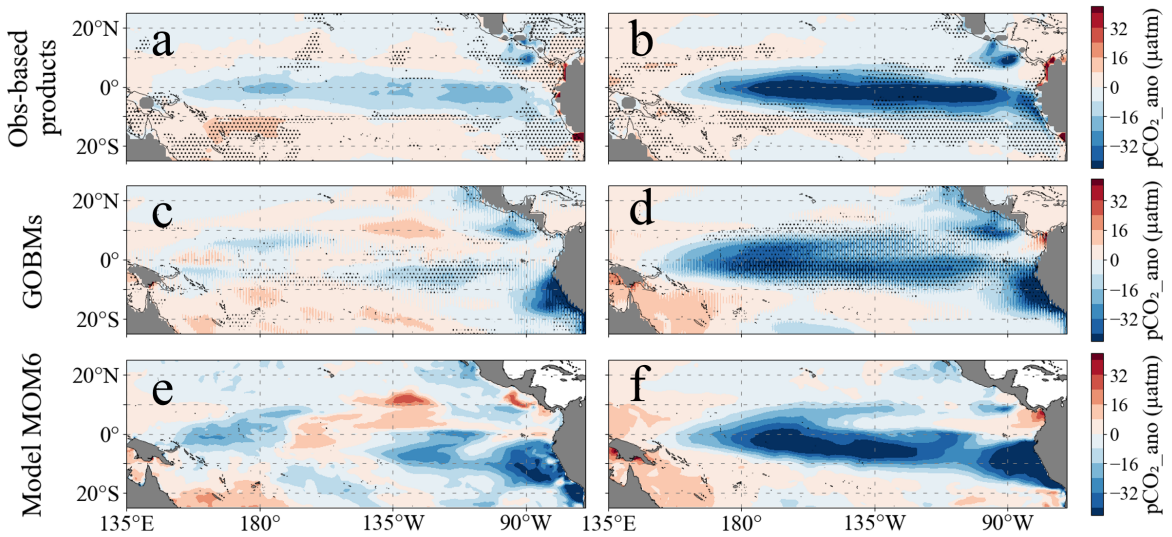


Figure S5. Distribution of pCO_2 anomalies during the December–February (DJF) of 1997, 2015, and 2023 events from the ensemble mean of (a-b) ten observation-based fCO_2 products, (c-d)ten GOBMs, and (e-f)MOM6–COBALT2 simulations. Stippling indicates regions where the inter-product spread (0.2 standard deviation) exceeds the magnitude of the ensemble-mean anomaly. Dataset details are provided in the Methods and Section S1.

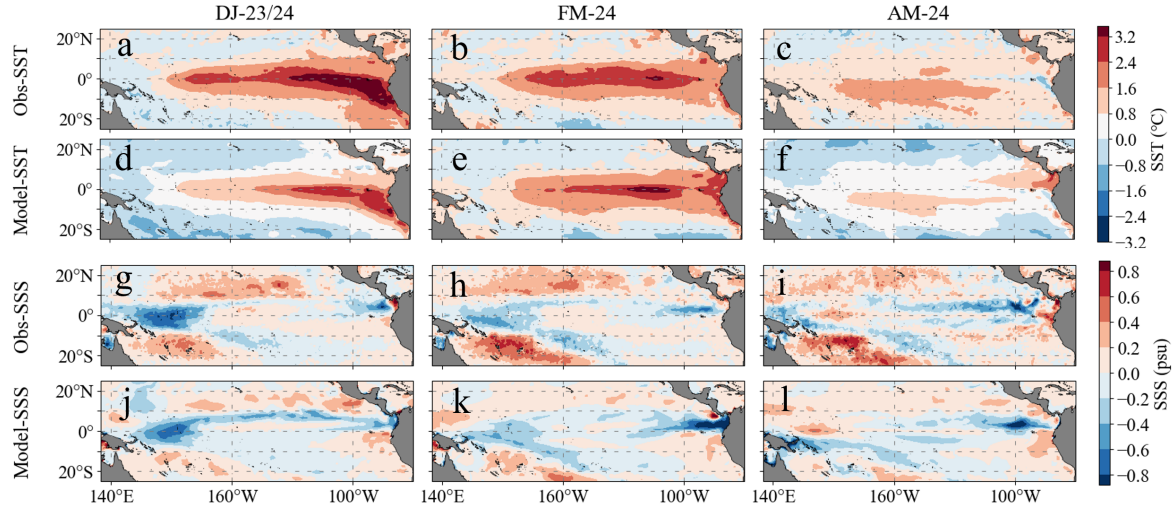


Figure S6. Comparison of observed and modeled seasonal evolution of interannual anomalies during the 2023 El Niño for SST (a–f) and SSS (g–l). Observed fields are shown in panels (a–c) and (g–i) from OISST (Huang et al., 2021b) and OISSS (Melnichenko et al., 2016), and corresponding MOM6-COBALT2 simulations in panels (d–f) and (j–l). Columns represent seasonal means for December–January 2023/24 (DJ-23/24), February–March 2024 (FM-24), and April–May 2024 (AM-24), respectively.

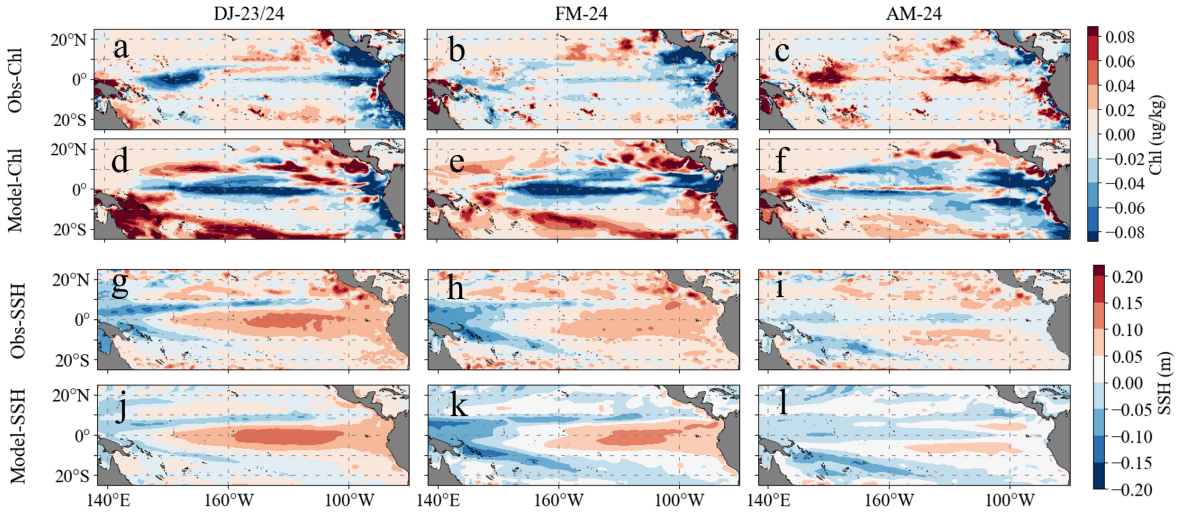


Figure S7. Comparison of observed and modeled seasonal evolution of interannual anomalies during the 2023 El Niño for chlorophyll (a–f) and SSH (g–l). Observed fields are shown in panels (a–c) and (g–i) from OC-CCI and satellite altimetry, respectively, and corresponding MOM6-COBALT2 simulations in panels (d–f) and (j–l). Columns represent seasonal means for December–January 2023/24 (DJ-23/24), February–March 2024 (FM-24), and April–May 2024 (AM-24), respectively. The OC-CCI chlorophyll is from Sathyendranath et al. (2019) and the AVISO SSH is from Ducet et al. (2000).

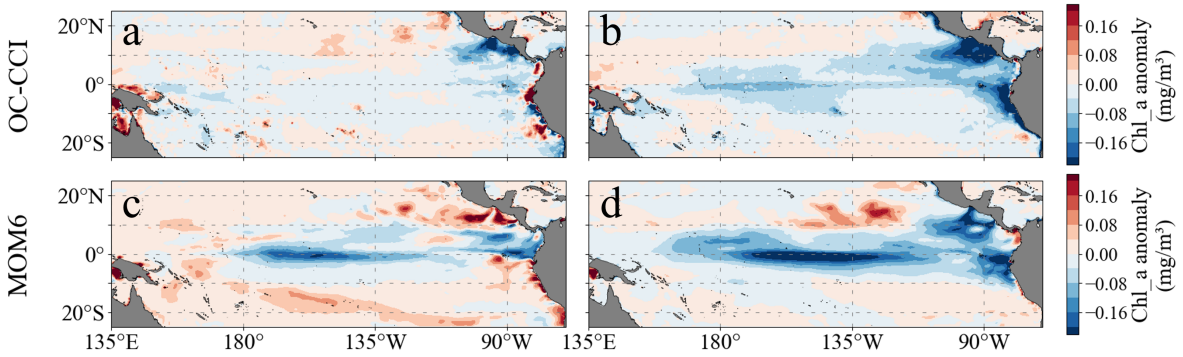


Figure S8. Spatial distribution of chlorophyll-*a* (Chl-*a*) anomalies in the tropical Pacific. The left panels show anomalies during the 2023 El Niño, while the right panels present the composite mean anomalies of the 1997 and 2015 events averaged over December–February. Panels (a,b) are derived from OC-CCI observations (Sathyendranath et al., 2019), and panels (c,d) show results from MOM6 simulations.

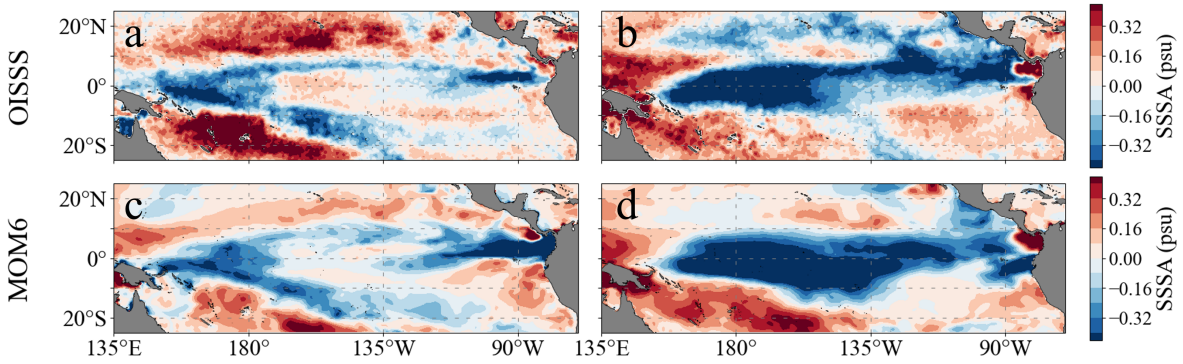


Figure S9. Spatial distribution of SSS anomalies in the tropical Pacific. Left panels show anomalies during the 2023 El Niño, while right panels show the composite mean anomalies for the 1997 and 2015 events averaged over December–February. (a,b) are derived from OISSS observations (Melnichenko et al., 2016), while (c,d) are MOM6 simulations.

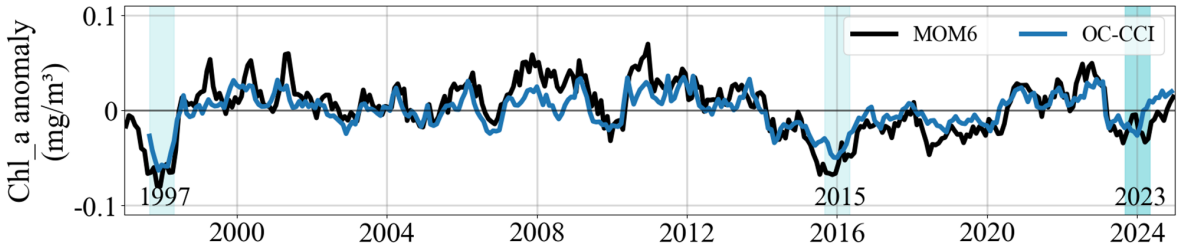


Figure S10. Time series of tropical Pacific (160°E-185°E, 15°S-15°N) chlorophyll-*a* anomalies from 1995 to 2024, based on MOM6 simulations and OC-CCI observations.

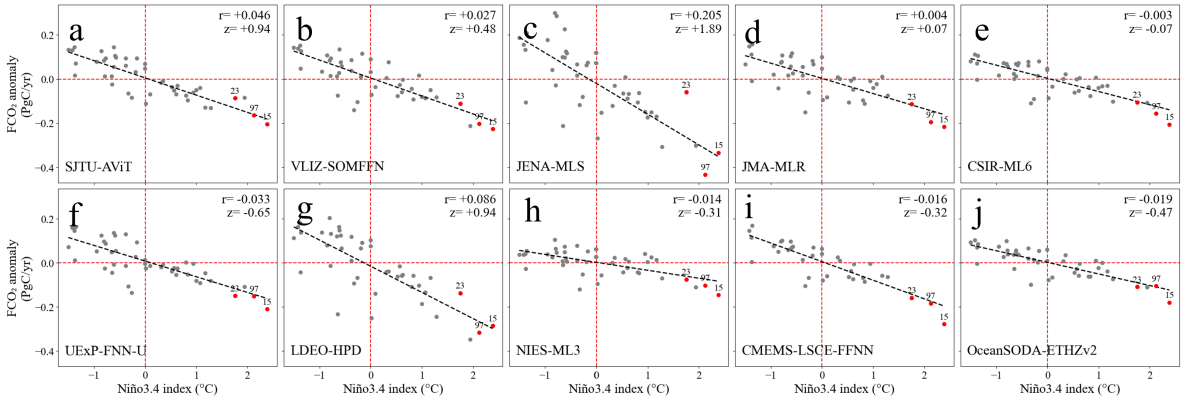


Figure S11. Scatter diagrams of the tropical Pacific Sep-Mar FCO_2 and the Niño 3.4 index during 1980–2025, based on data-driven observational products. The black dashed line denotes the linear regression between the Niño 3.4 index and the regionally integrated FCO_2 anomaly, both calculated for September–March and integrated over 160°E–285°E and 15°S–15°N. Strong El Niño years (1997, 2015, and 2023) are labeled red. r and z scores represent the bias of the 2023 event from the historical SST-FCO_2 relationship. All data products are quadratically detrended. See data product details in Table S1.

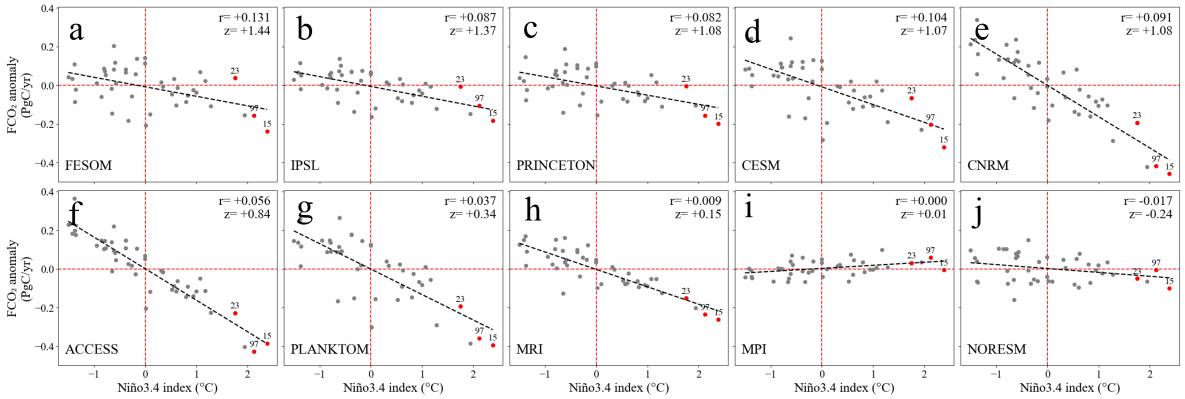


Figure S12. Scatter diagrams of the tropical Pacific Sep–Mar FCO_2 and the Niño 3.4 index during 1980–2025, based on model simulations. The black dashed line denotes the linear regression between the Niño 3.4 index and the regionally integrated FCO_2 anomaly, both calculated for September–March and integrated over 160°E–285°E and 15°S–15°N. Strong El Niño years (1997, 2015, and 2023) are labeled red. r and z scores represent the bias of the 2023 event from the historical SST-FCO_2 relationship. All model simulations are quadratically detrended. See model details in Table S1.

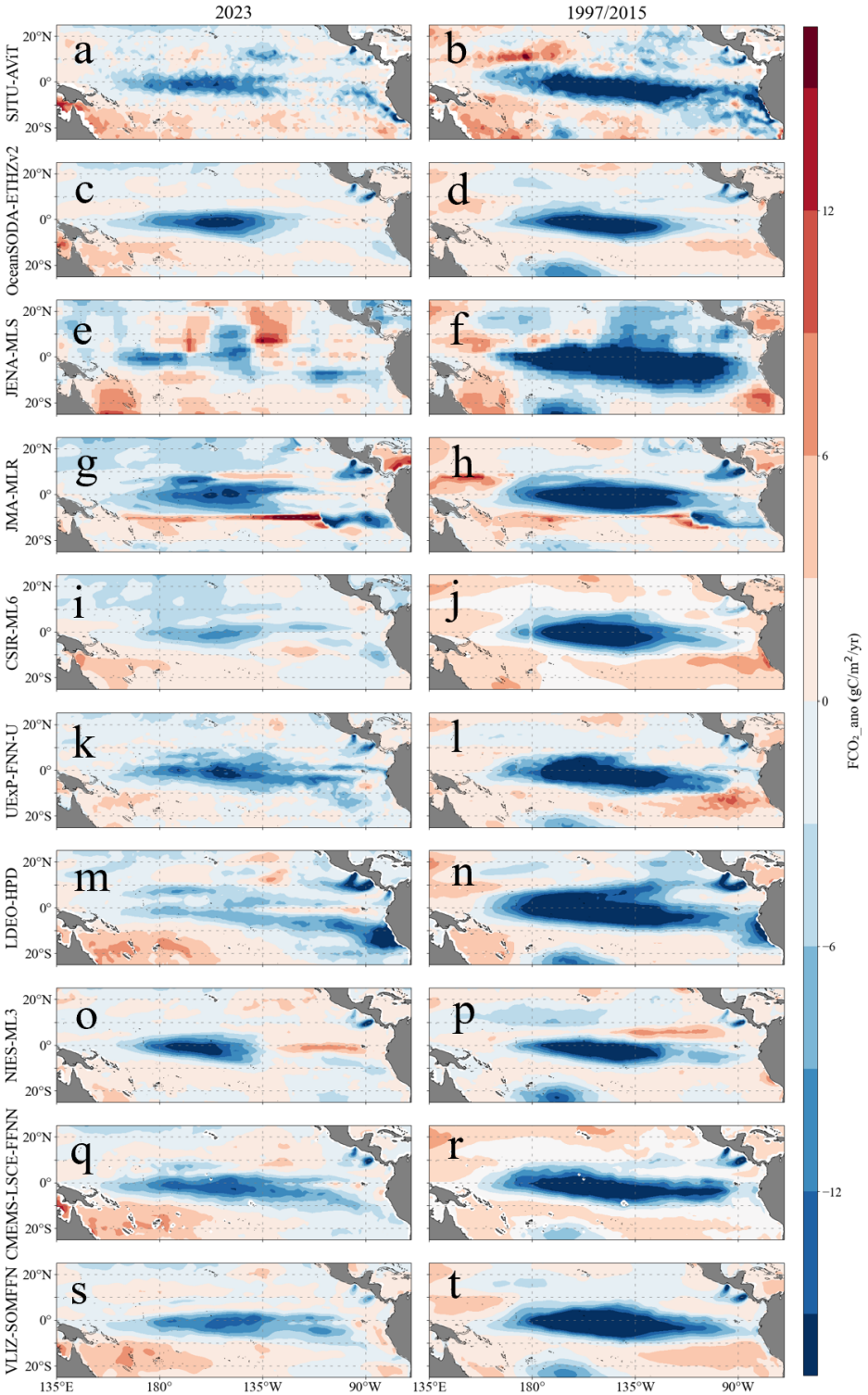


Figure S13. Spatial distribution of air–sea CO_2 flux (FCO_2) anomalies relative to the climatological mean (1980-2024), derived from data-driven products. Left panels show anomalies during the 2023 El Niño event, while right panels display the composite mean anomalies for the 1997 and 2015 El Niño events averaged over December–February.

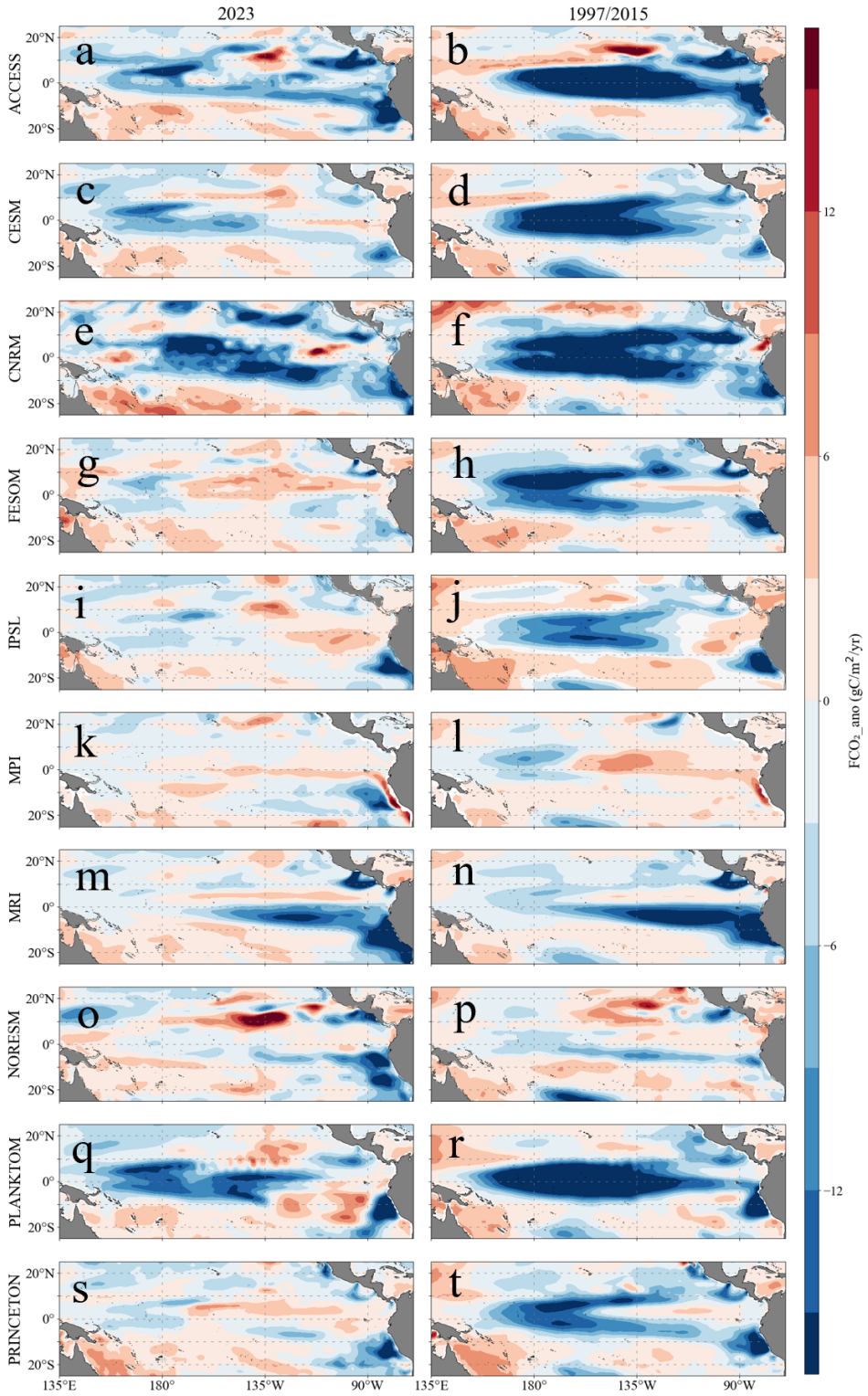


Figure S14. Spatial distribution of air–sea CO_2 flux (FCO_2) anomalies relative to the climatological mean (1980-2024), derived from model simulations. Left panels show anomalies during the 2023 El Niño event, while right panels display the composite mean anomalies for the 1997 and 2015 El Niño events averaged over December–February.

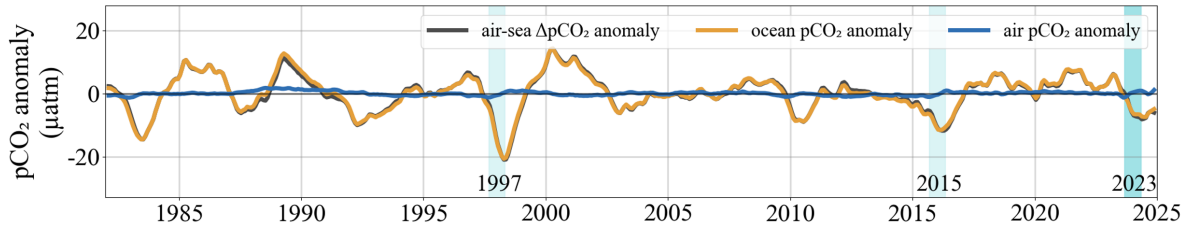


Figure S15. Temporal evolution of air–sea ΔpCO_2, oceanic pCO_2, and atmospheric pCO_2 anomalies averaged over the tropical Pacific (160°E–285°E, 15°S–15°N) for 1982–2025. Vertical shaded regions denote major El Niño events.

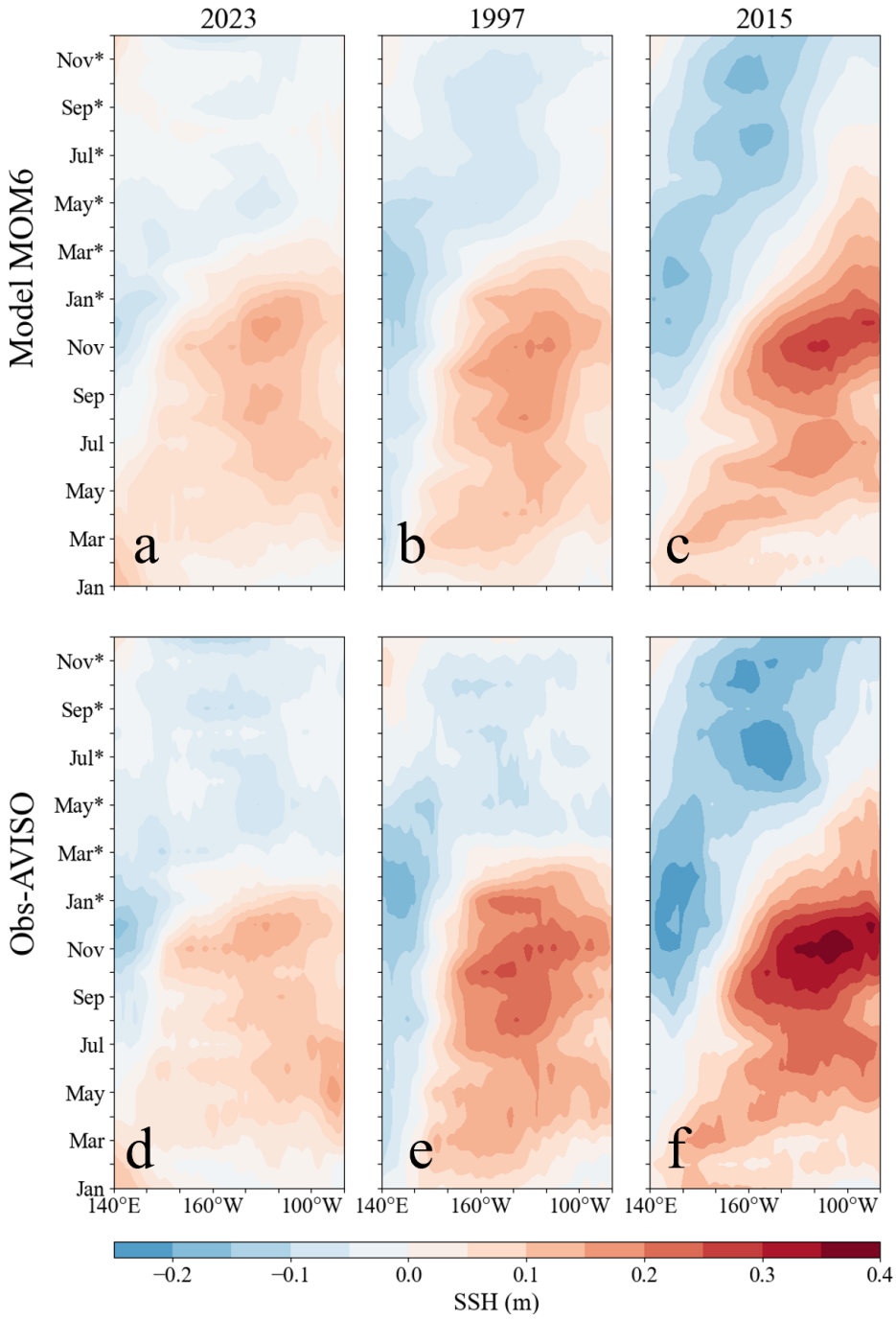


Figure S16. Hovmöller diagrams showing the longitude–time evolution of equatorial SSH anomalies (140°E–80°W, averaged over 2°S–2°N) during the (a) 2023, (b) 1997, and (c) 2015 El Niño events from MOM6-COBALT2 simulations, and the corresponding (d–f) AVISO observations (Ducet et al., 2000). The time axis spans January of the El Niño onset year to December of the following year (e.g., Jan 2023–Dec 2024 for the 2023 event). Months marked with "*" denote the second year of the event, while months without "*" correspond to the onset year.

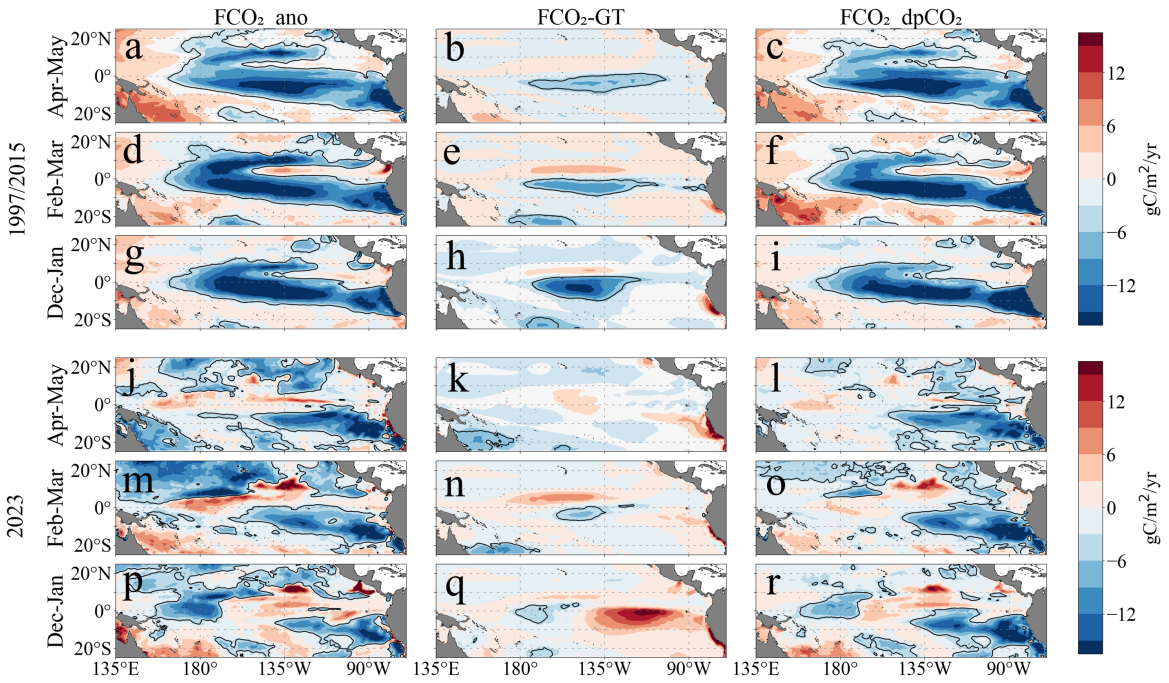


Figure S17. Spatial distribution of FCO_2 and its decompositions (FCO_2-GT, FCO_2-ΔpCO_2) during the 2023 El Niño and other comparable events (1997/2015). Contours denote -5 $gC/m^2/yr$ FCO_2 anomaly.

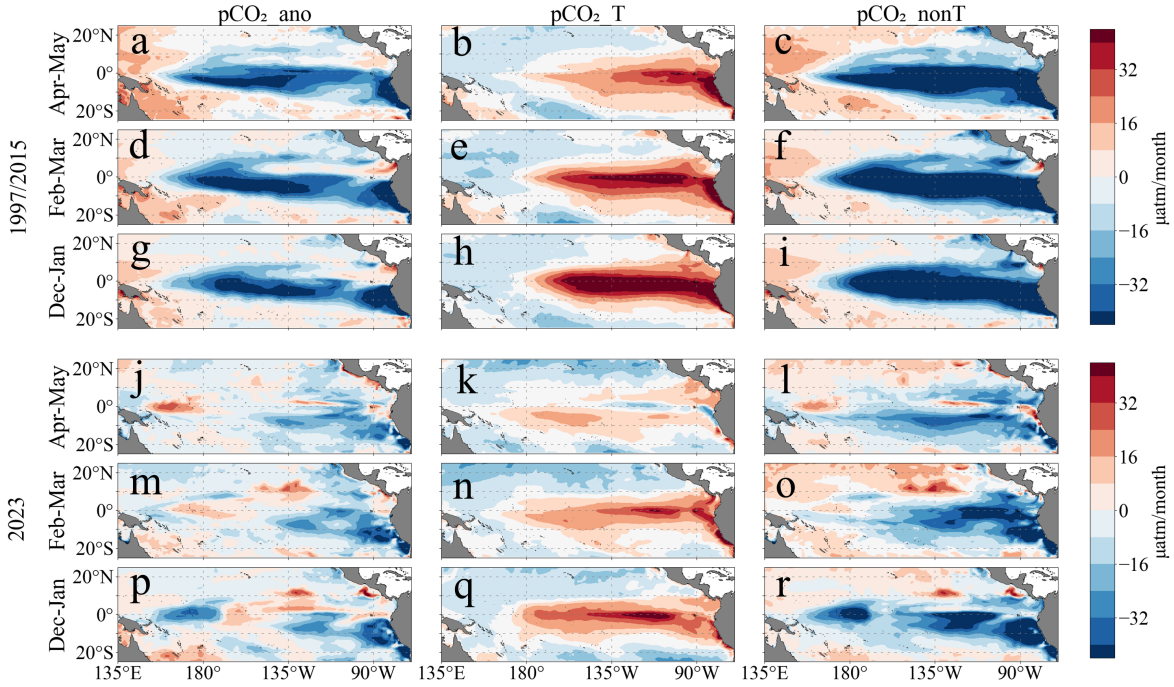


Figure S18. Spatial distribution of surface ocean pCO_2 and its thermal (pCO_2–T) and non-thermal (pCO_2–nonT) components during the 2023 El Niño, compared with the 1997 and 2015 El Niño events.

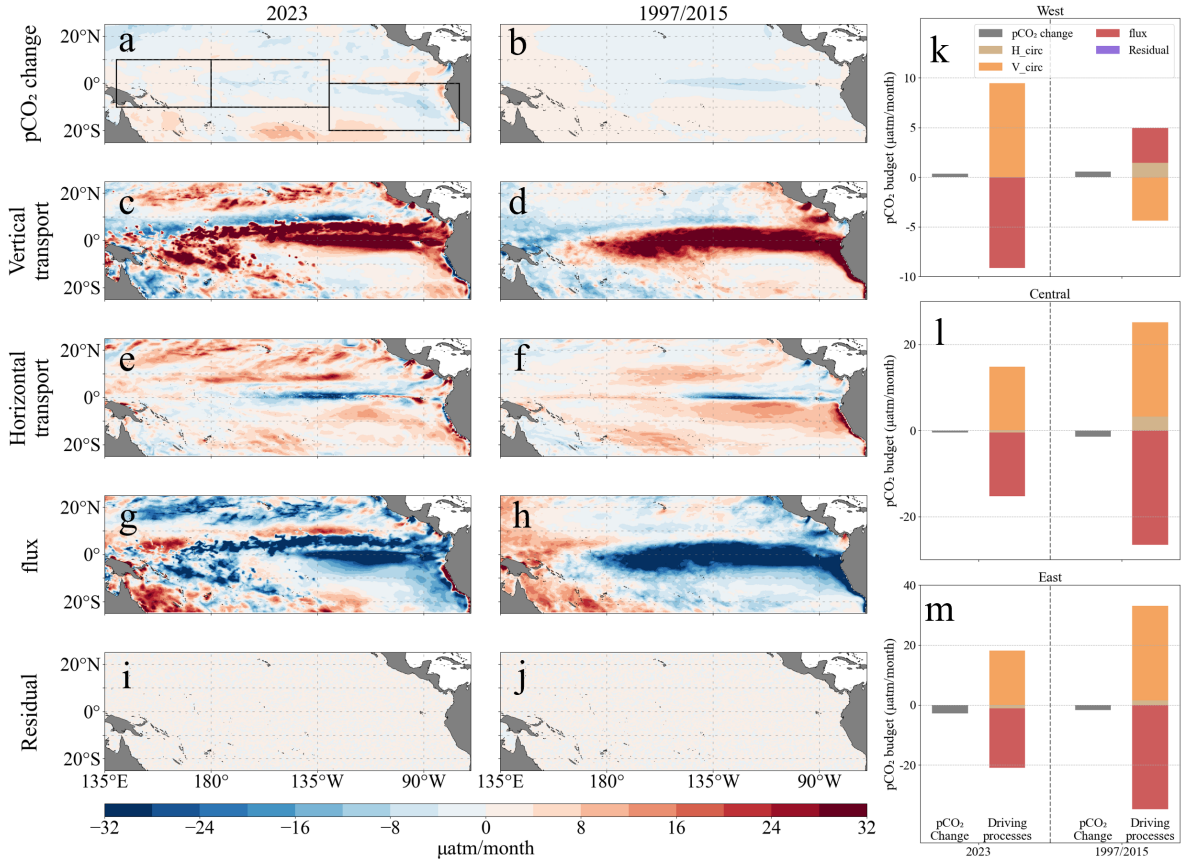


Figure S19. Thermal-driven ocean pCO_2 anomaly budget in the tropical Pacific during the 2023 El Niño and comparable extreme events (1997/2015), based on Eq. S13. (a, b) Spatial distribution of thermal pCO_2 change for 2023 and 1997/2015, respectively. (c–j) Contributions of individual processes to pCO_2 variability. (k–m) Regional pCO_2 budget comparisons between 2023 and 1997/2015 for the western, central, and eastern tropical Pacific, as indicated in (a). The western basin is defined as 140°E–180°E, 10°S–10°N, the central basin as 180°W–130°W, 10°S–10°N, and the eastern basin as 130°W–70°W, 20°S–0°N. All anomalies are computed as the December–February mean of monthly anomalies from MOM6-COBALT2.

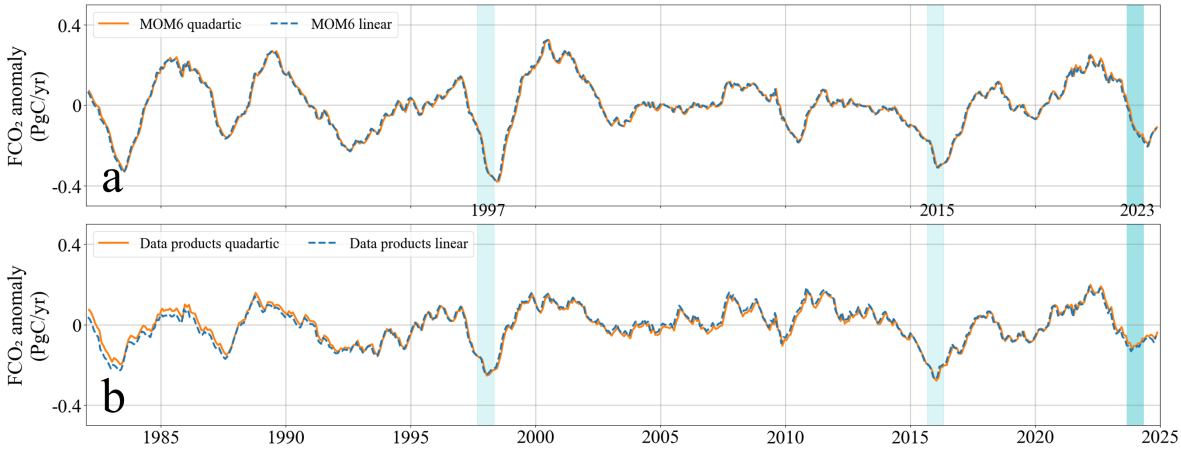


Figure S20. Time series of tropical Pacific FCO_2 anomalies derived from (a) MOM6 simulations and (b) observational data products. The anomalies are integrated over the tropical Pacific (160°E–285°E, 15°S–15°N) for the period 1982–2025. Orange lines denote linearly detrended anomalies, while blue dashed lines indicate quadratically detrended results.

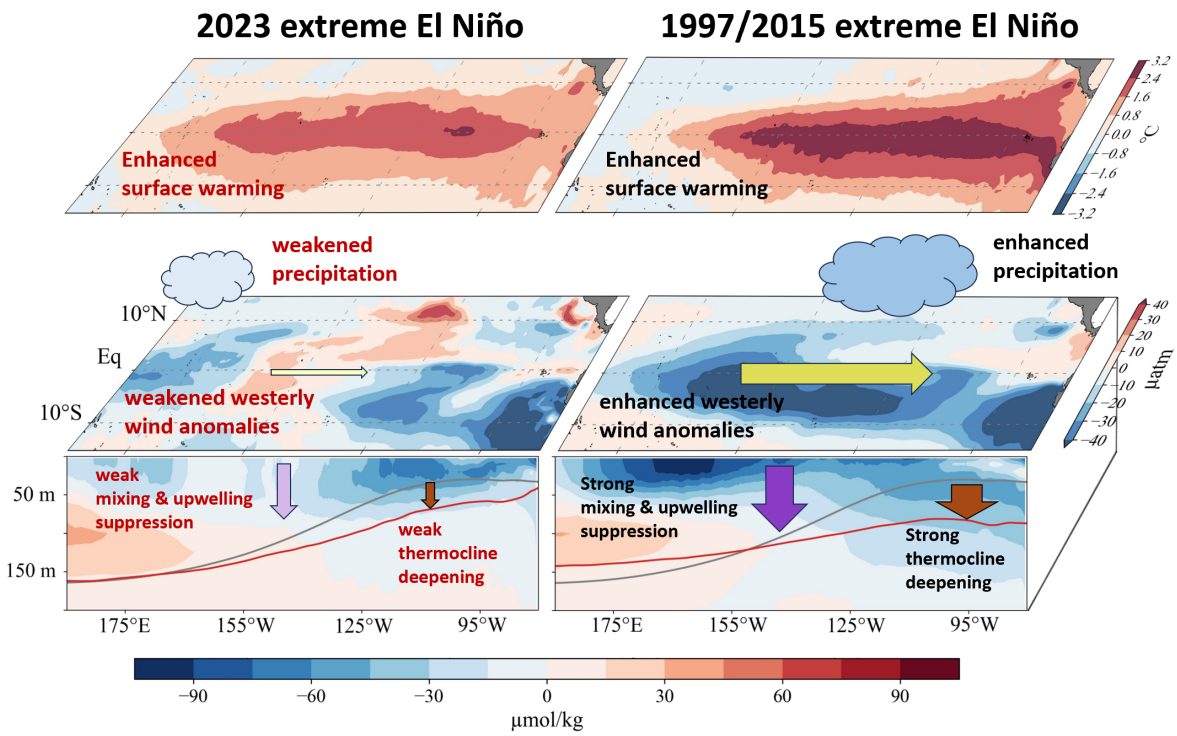


Figure S21. Schematic comparison of the mechanisms driving the tropical Pacific carbon cycle response during the 2023 El Niño and other comparable strong El Niño events. The map panels show SST (upper) and sea surface pCO_2 (lower) anomalies, while the vertical sections illustrate DIC concentration anomalies and thermocline depth relative to climatology. Arrows indicate the key processes involved, including changes in precipitation patterns, wind anomalies, freshwater flux, vertical mixing and upwelling, and thermocline adjustments.

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