Supporting Information for

“Seasonal variation in the correlation between anomalies of sea level and chlorophyll in the Antarctic Circumpolar Current”

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This document provides supplementary information describing the methods used in this study as well as additional figures and tables substantiating statements made in the main article.

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Satellite observations

We used the absolute dynamic topography mapped on $1/4^\circ \times 1/4^\circ$ grid from Collecte Localis Satellites / Archiving, Validation and Interpretation of Satellite Oceanographic

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data (CLS/AVISO). The absolute dynamic topography data spans 10 years from 1998 to 2007 at 7-day interval. The sea surface height (SSH) anomaly fields were then computed from this weekly data by spatially high-pass filtering with a half-power cutoff of 6° in both latitude and longitude.

Near-surface chlorophyll (CHL) concentration product comes from the Sea-Viewing Wide Field-of-View Sensor (SeaWiFS) project during the same period as the SSH anomaly. The Garver-Siegel-Maritorena (GSM) semi-analytical ocean color algorithm [Garver and Siegel, 1997; Maritorena et al., 2002; Siegel et al., 2002] was used to estimate CHL from ocean color measurements made by SeaWiFS. The log-transformed 9-km resolution daily CHL concentration estimates were averaged within the 1/4×1/4 degree grid to match the resolution of the SSH anomaly fields. This daily CHL data was merged to create data with 7-day interval to match the frequency of SSH anomaly fields using a loess filter with a half-power cutoff of 35-days (equivalent to a running mean with approximately a 20-day span) to remove temporal variability in the CHL measurements that are not captured in the SSH anomaly fields. This smoothing in time attenuates variability with wavelengths shorter than approximately 1 month, thus attenuating much of the submesoscale variability. This procedure was based on the detailed analysis of the AVISO SSH fields presented in Appendix A of Chelton et al. [2011]. The resulting CHL (and also SSH) fields can resolve mesoscale features with radii of approximately 50 km [Chelton et al., 2011]. Finally, the high-pass filtering with a spatial loess smoother with a half-power cutoff of 6° in both latitude and longitude was used to compute the anomaly which was transformed back to linear concentrations [Campbell, 1995; Gaube et al., 2013]. The resultant smoothed CHL fields have spatial and temporal resolution comparable with the SSH anomaly fields. The Pearson correlation between anomalies of SSH and CHL (\(\rho_{SSH',CHL'}\)) was computed for each grid box as shown in Figures 1a,b. In addition, we computed \(\rho_{SSH',CHL'}\) in SSH bins, i.e. approximately along streamlines as shown in Figure 2a (see also Frenger [2013]).

Model Simulation

The mechanisms generating observed \(\rho_{SSH',CHL'}\) were examined using the Biogeochemical Elemental Cycling (BEC) model [Moore et al., 2002, 2004, 2013] coupled to the ocean circulation component of the Community Earth System Model (CESM) with a resolution of 0.1° (less than 10 km in zonal direction in the Drake Passage). Prior to this
simulation, the 0.1° physical model has run for 15 years and provides the initial conditions for the physical-biogeochemical coupled simulation. The GLobal Ocean Data Analysis Project (GLODAP) and World Ocean Atlas (WOA) climatology data were used for the initial condition for long-lived pools (e.g. dissolved inorganic carbon, alkalinity and nutrients) while other biogeochemical variables were integrated from the solution of 1° model. The total CHL concentration at any given depth is computed as the sum of CHL of three phytoplankton functional groups whose biomasses are affected by the uptake of varied nutrients including iron, and grazing by zooplankton. The vertical mixing is estimated by the K-Profile Parameterization (KPP) mixing scheme [Large et al., 1994]. This scheme computes the depth of planetary boundary layer or vertical-mixing depth using a Richardson number criterion. This depth is generally shallower than that determined by hydrographic properties (e.g., potential density) because the latter one may include a region below the mixing layer reminiscent of the previous mixing. In this study, we referred to the depth of the mixing layer as the mixed-layer depth (MLD) in the analysis because the vertical mixing for tracers such as iron is subject to the vertical mixing scheme, which is the relevant metric for the budget analysis of iron over the mixing depth. The model simulates the depth attenuation of photosynthetically active radiation (PAR) on the basis of CHL concentration following [Morel and Maritorena, 2001].

Phytoplankton growth rates in the ocean biogeochemistry component of the CESM are computed as

\[ \mu_i = \mu_{i,\text{ref}} \cdot T_f \cdot V_i \cdot L_i \]  

where \( \mu_i \) is the C-specific growth rate (d\(^{-1}\)) for phytoplankton functional type (PFT) \( i \), \( \mu_{i,\text{ref}} \) is the maximum growth rate (referenced to 30°C), and \( T_f \) is the temperature limitation (“Q10”) function; \( V_i \) and \( L_i \) are the nutrient and light response functions, respectively [Geider et al., 1998]. For diatoms (diat), diazotroph (diaz) and “small” phytoplankton (sp), the nutrient response function follows Liebig’s law of the minimum, such that the ultimate limitation term used to compute growth is that of the most limiting nutrient:

\[ V_{\text{diat}} = \min(V_{N_{\text{diat}}}, V_{P_{\text{diat}}}, V_{Fe_{\text{diat}}}, V_{Si_{\text{diat}}}) \]  

\[ V_{\text{diaz}} = \min(V_{P_{\text{diaz}}}, V_{Fe_{\text{diaz}}}) \]  

\[ V_{\text{sp}} = \min(V_{N_{\text{sp}}}, V_{P_{\text{sp}}}, V_{Fe_{\text{sp}}}) \]  

The model was integrated for 5 years archiving 5-day means. The simulated SSH anomalies were computed as the observations; using a high-pass loess smoother with a
half-power cutoff of $6^\circ$ [Chelton and Schlax, 2003]. The procedure for the CHL anomaly computation follows that used in the satellite data but from simulated 5-day mean total CHL concentrations near the surface. For Figures 1 and 2, the solutions were mapped to the same grid as the satellite SSH anomalies using a bilinear interpolation before computing the correlation.

**Evaluation of the Model Simulation**

The eddy-rich 0.1$^\circ$ CESM has an SSH variability that agrees well with that estimated from space. Figure S1(a) shows the standard deviation of SSH in the observation from CLS/AVISO. The model simulation captures not only the observed spatial pattern of elevated SSH variability but also its magnitude, with regions of elevated SSH variability along the Antarctic Circumpolar Current (ACC), Brazil-Malvinas Confluence, Agulhas Current retroflection and East Australian Current (Figure S1(b)). The simulated CHL near the surface agrees with SeaWiFS observations to a somewhat lesser degree than SSH variability. Although the model underestimates the CHL concentration, it generally reproduces enhanced productivity near the shelf regions and islands, as well along the ACC as suggested by satellite observations. The depth of the mixed-layer estimated using potential density ($\Delta \rho = 0.03$ kg m$^{-3}$) in the model is also comparable with that in the observations from Dong et al. [2008] based on Argo float profiles (Figure S2). The non-uniformity of the depth of mixed-layer along the ACC in winter is represented by the model. The simulated iron also captures a large scale iron distribution in observations taken from the dataset by Tagliabue et al. [2012] (Figure S3).

**Robustness of the seasonality in $\rho_{\text{SSH}, \text{CHL}}$**

The $\rho_{\text{SSH}, \text{CHL}}$ was evaluated using 95% confidence interval from Fisher transformation. The seasonality of the $\rho_{\text{SSH}, \text{CHL}}$ characterized by the opposite sign in different seasons remains along the ACC within the 95% confidence interval (Figure S4(a-d)). We also evaluated the robustness of the seasonality of $\rho_{\text{SSH}, \text{CHL}}$ using the rank correlation. As shown in Figure S4(e,f), $\rho_{\text{SSH}, \text{CHL}}$ along the ACC is generally positive in summer but negative in winter similar to Figure 1. Hence the seasonality in $\rho_{\text{SSH}, \text{CHL}}$ is robust.

The $\rho_{\text{SSH}, \text{CHL}}$ in the model has the upper and lower limits of the 95% confidence levels that are similar to Figure 1(c,d) and not shown here. The seasonality of the $\rho_{\text{SSH}, \text{CHL}}$
in the model is also robust as the rank correlation shows the coefficients that seasonally change signs along the ACC (not shown).

The Fe budget averaged over the mixed layer

We analyzed the budget of iron \((Fe(z,t))\) averaged over the mixed layer \(H(t) = \eta(t) - h(t)\), where \(\eta(t)\) is the SSH and \(h(t)\) is the time-varying MLD. The temporal evolution of the iron averaged over the mixed layer \(\langle Fe \rangle \equiv \frac{1}{H(t)} \int_{h(t)}^{\eta(t)} Fe(z,t)dz\) can be written as

\[
\frac{d\langle Fe \rangle}{dt} = \frac{d}{dt} \left[ \frac{1}{H(t)} \int_{h(t)}^{\eta(t)} Fe(z,t)dz + \frac{1}{H(t)} \int_{h(t)}^{\eta(t)} \frac{d}{dt} Fe(z,t)dz \right]
+ \frac{1}{H(t)} \int_{h(t)}^{\eta(t)} \frac{d}{dt} Fe(z,t)dz
\]

\[
= \frac{1}{H(t)} \int_{h(t)}^{\eta(t)} \frac{d}{dt} Fe(z,t)dz
+ \frac{1}{H(t)} \left[ (Fe(\eta(t),t) - \langle Fe \rangle) \frac{d\eta(t)}{dt} - (Fe(h(t),t) - \langle Fe \rangle) \frac{dh(t)}{dt} \right].
\]

The first term in (5) represent the iron tendency averaged over the MLD and the remaining terms are the contribution by entrainment/detrainment.

The \(Fe(z,t)\) tendency in the model is computed as follows:

\[
\frac{d}{dt} Fe(z,t) = -A_h(z,t) - \frac{\partial}{\partial z} (w(z,t)Fe(z,t)) + \frac{\partial}{\partial z} \left( \kappa(z,t) \frac{\partial Fe(z,t)}{\partial z} \right)
+ F(z,t) + B(z,t),
\]

where \(A_h\) is the horizontal advection, \(w\) is the vertical velocity, \(\kappa(z,t)\) is the vertical diffusivity, \(F(z,t)\) is the surface iron flux (nonzero only at the surface) and \(B(z,t)\) is the biological source/sink term. The right-hand-side terms in (6) are computed using the 5-day mean model output, while the left-hand-side term is estimated using a centered difference approximation over 10 days. Using (6), (5) can be written as

\[
\frac{d\langle Fe \rangle}{dt} = \frac{1}{H(t)} \int_{h(t)}^{\eta(t)} \left[ -A_h(z,t) - \frac{\partial}{\partial z} (w(z,t)Fe(z,t)) \right] dz
\]

\[
- \frac{1}{H(t)} \kappa(h(t),t) \frac{\partial Fe(z,t)}{\partial z} \bigg|_{z=h}
\]

\[
+ \frac{1}{H(t)} \int_{h(t)}^{\eta(t)} F(z,t)dz
\]

\[
+ \frac{1}{H(t)} \int_{h(t)}^{\eta(t)} B(z,t)dz
\]

\[
+ \frac{1}{H(t)} \left[ (Fe(\eta(t),t) - \langle Fe \rangle) \frac{d\eta(t)}{dt} - (Fe(h(t),t) - \langle Fe \rangle) \frac{dh(t)}{dt} \right]
\]

(7)

with the surface value of the diffusivity, \(\kappa(\eta(t),t) = 0\). The meaning of each label are as follows: “3D adv: 3-dimensional advection”, “v. mix: vertical mixing”, “s. flux: aeolian
input of dust”, “bio: biological source/sink and scavenging” and “ent: entrainment associated with MLD changes”.

Iron supply by advection

The contribution from advection, including eddy-driven lateral advection via trapping and stirring, potentially plays a role regionally if iron concentrations increase equatorward (i.e., warm anticyclonic features with anomalously high iron concentration and cold cyclonic features with lower iron concentration). The Atlantic Ocean sector has a clear increasing equatorward trend of iron concentration in observations [Mawji et al., 2015], i.e. sufficiently large to make an effect. Yet, in the Indian and Pacific Ocean sectors, small meridional gradients in iron are reported in the spring/summer vertical section of iron from GEOTRACES Intermediate Data Product 2014 [Mawji et al., 2015].

The simulated iron in the model exhibits similar lateral gradient as observations. In summer (January-March, Figure S5(top)), the Indian-Pacific sector has little meridional gradient of surface iron as iron is depleted by active primary production, which makes it unlikely that lateral advection by, e.g., stirring and trapping are driving the iron anomaly in Fig 4a. In the Atlantic sector, however, iron concentration generally increases equatorward. Consistent with in situ observations [Bowie et al., 2002], iron is supplied from the Patagonian Shelf to the northern ACC creating a meridional gradient in the model. With iron concentrations increasing toward the equator, eddy-driven advection as well as vertical mixing, can create iron perturbations associated with eddies.

In winter (July-September), the surface ocean features a higher iron concentration than in summer (Figure S5(bottom)). The primary productivity is more regulated by light availability, nevertheless the wintertime iron distribution shows how closely iron is linked to the vertical mixing, especially in the Indian-Pacific sector. There, deeper vertical mixing enriches the surface ocean with iron as indicated by the fact that higher concentration of iron collocates with the region of relatively deep mixed layers (> 50 m). The MLD in the Indian-Pacific sector is spatially inhomogeneous with larger horizontal iron gradients in winter than in summer. As a result, it is more likely that the eddy-driven advection sets the perturbations in iron, but vertical mixing modulation becomes larger than in summer at the same time. The meridional gradient of Fe in the Atlantic sector shows no seasonality.
Statistics

We constructed distributions of $\langle \text{Fe} \rangle$, $\langle \text{PAR} \rangle$ and the terms in (7) at the locations of anticyclones and cyclones in summer and winter along the ACC. Since not all distributions are normally distributed (e.g. $\langle \text{Fe} \rangle$), the median is used as a representative measure of the distributions. Medians of $\langle \text{Fe} \rangle$ and $\langle \text{PAR} \rangle$ distributions for anticyclones and cyclones in the ACC are first obtained. Then the differences in medians between anticyclones and cyclones are normalized by the median for the entire ACC to measure the relative size of those differences. In Figures 4a,c, we plot the percent value of the median differences. The terms in (7) are normalized by the median of $\langle \text{Fe} \rangle$ along the entire ACC after being multiplied by 10 days, the time interval used in the tendency equation in the model. We then compare the medians of each term to quantify the systematic differences between anticyclones and cyclones in Figures 4b,d in the main article.

The 95% confidence intervals are estimated using a bootstrap test where we randomly subsampled the data ($O(10^6)$) and obtained a median value. By repeating this resampling procedure 100 times, the 95% confidence interval can be estimated from the distribution of medians. Since the 95% confidence intervals are too narrow to be visible, they are not plotted in Figures 3 and 4.

References


Moore, J. K., K. Lindsay, S. C. Doney, M. C. Long, and K. Misumi (2013), Marine ecosystem dynamics and biogeochemical cycling in the Community Earth System Model [CESM1(BGC)]: Comparison of the 1990s with the 2090s under the RCP4.5 and RCP8.5 scenarios, *J. Clim.*, 26(23), 9291–9312, doi:10.1175/JCLI-D-12-00566.1.


Figure S1. Standard deviation of SSH from (a) satellite observation and (b) eddy-resolving CESM. (c) and (d) show the 10-year mean surface CHL estimated by ocean color and 5-year mean surface CHL from CESM, respectively. The white mask in (c) represents missing data.
Figure S2. The depth of the mixed-layer estimated using potential density. The potential density at this level is 0.03 kg m\(^{-3}\) greater than that at the surface. (a,b) are the average for austral summer (January-March) and (c,d) are the average MLD for austral winter (July-September). (a,c) are the MLD from Dong et al. [2008] and (b,d) are from CESM.
Figure S3. Dissolved iron concentration from observations and the model simulation is plotted along 6 transects in the SO. The observational data is taken from Tagliabue et al. [2012]. The colored lines are the linear least squares fit between the observations and the model data (gray dots), while gray lines are the one with a slope of 1. R² values are provided at the right bottom corner of each panel. The colored dots on the map indicate the sampling location corresponding to the same colored line in the 6 panels.
Correlation between SSH' and CHL'

(a) Upper limit, Summer
(b) Upper limit, Winter
(c) Lower limit, Summer
(d) Lower limit, Winter
(e) Rank correlation, Summer
(f) Rank correlation, Winter

Figure S4. (Caption next page.)
**Figure S4.** (Previous page.) The (a,b) upper limit and (c,d) and lower limit of the 95% confidence intervals were estimated using Fisher transformation for the correlation coefficients between anomalies of SSH and CHL from satellite observations. Panels (e,f) are the rank correlation coefficients between anomalies of SSH and CHL from the same satellite observations. The panels (a,c,e) and (b,d,f) shows the correlation coefficients in austral summer (January-March) and winter (July-September), respectively.

**Figure S5.** The shading is the seasonal mean surface iron along the SSH isolines for austral (top) summer and (bottom) winter computed in CESM. Orange, pink, red and dark red contours represent MLD contours of 50 m, 100 m, 150 m and 200 m, respectively.