

Reconstructing Satellite-Era Southern Ocean Temperature and Salinity Trends within Observational Uncertainty

Matthew T. Luongo^{a,b,*}, Kyle C. Armour^{b,c}, & Gregory C. Johnson^{b,d}

1. Cooperative Institute for Climate, Ocean, & Ecosystem Studies, University of Washington, Seattle, WA, USA
2. School of Oceanography, University of Washington, Seattle, WA, USA
3. Department of Atmospheric & Climate Science, University of Washington, Seattle, WA, USA
4. NOAA Pacific Marine Environmental Laboratory, Seattle, WA, USA

* mluongo@uw.edu

This manuscript is a pre-print submitted to EarthArXiv.

The pre-print has been submitted for review to *Journal of Climate*.

Subsequent versions may have altered content.

Reconstructing Satellite-Era Southern Ocean Temperature and Salinity Trends within Observational Uncertainty

Matthew T. Luongo^{a,b}, Kyle C. Armour^{b, c}, & Gregory C. Johnson^{b,d}

^a *Cooperative Institute for Climate, Ocean, and Ecosystem Studies, University of Washington,
Seattle, WA, USA,*

^b *School of Oceanography, University of Washington, Seattle, WA, USA,*

^c *Department of Atmospheric and Climate Science, University of Washington, Seattle, WA, USA,*

^d *NOAA Pacific Marine Environmental Laboratory, Seattle, WA, USA*

Corresponding author: M.T. Luongo, mluongo@uw.edu

10 ABSTRACT: Southern Ocean (SO) sea surface temperatures (SSTs) have exhibited large-scale
11 cooling over the satellite era (1979-present). Several potential drivers of this cooling have been
12 proposed – including changes in winds, freshwater fluxes, and natural variability – but their relative
13 contributions have been challenging to identify because climate models largely fail to simulate the
14 observed trend. Moreover, observational estimates of SST exhibit substantial uncertainty. In this
15 work we present novel ocean-only simulations individually forced by observationally-informed
16 surface flux trends in heat, momentum, and freshwater from precipitation minus evaporation, ice
17 sheet melt, and sea ice hydrology. We focus not only on SST changes, but also on changes in
18 sea surface salinity (SSS) and subsurface temperature and salinity, because any proposed driver
19 of SST change must be dynamically consistent with available, spatially-varying observations of
20 all fields at once (within observational uncertainties). We show that the response to each surface
21 flux change has a unique temperature and salinity fingerprint, and a linear combination of these
22 responses captures key features of observed SO temperature and salinity trends. We conclude
23 by performing a Monte Carlo analysis to refine this linear estimate, constraining with observed
24 SST, SSS, and ocean heat content to create an estimate where $\sim 83\%$ of the SO area is within
25 observational uncertainty for SST and $\sim 71\%$ for SSS. By considering salinity, regional changes,
26 and observational uncertainty, we provide a holistic approach to understanding observed SO trends
27 and suggest that known changes in winds and freshwater are sufficient to explain much of recent
28 SO change.

29 **1. Introduction**

30 Observational estimates of Southern Ocean (SO) sea surface temperatures (SSTs) reveal a large-
31 scale cooling trend south of the Antarctic Circumpolar Current (ACC) over the satellite era (1979-
32 present), particularly in the Pacific sector of the SO from approximately 150°E to 60°W. While the
33 expected response of SO SSTs to increased greenhouse gas radiative forcing is a weak warming
34 (Manabe et al. 1991) slowed by mean upwelling of unmodified deep waters (Armour et al. 2016),
35 the observed large-scale SO cooling was not predicted and is not well-understood. Indeed, most
36 global climate model (GCM) simulations from the fifth and sixth generations of the Coupled Model
37 Intercomparison Project (CMIP) driven by historical forcings fail to capture the observed SO surface
38 cooling over the satellite era, even when accounting for internal variability by considering spread
39 across large ensembles, suggesting potential systematic model biases (e.g., Wills et al. 2022).

40 Three mechanisms have been proposed to explain the observed SO surface cooling over recent
41 decades. Some studies (Swart and Fyfe 2012; Marshall et al. 2014; Kostov et al. 2018; Blanchard-
42 Wrigglesworth et al. 2021; Hartmann 2022; Chung et al. 2022; Roach et al. 2023; Li et al. 2026)
43 suggest that observed trends in Southern Hemisphere (SH) westerly winds have driven SO cooling.
44 This hypothesis is motivated by the fact that over recent decades both greenhouse gas forcing
45 (Fyfe and Saenko 2006; Fyfe et al. 2007) and Antarctic ozone loss (Polvani et al. 2011; Thompson
46 et al. 2011) have driven an annual-mean strengthening and an austral summer poleward shift of
47 the SH westerlies (Fyfe and Saenko 2006; Swart and Fyfe 2012). This observed SO westerly
48 wind change in turn resembles the positive phase of the Southern Annular Mode (Thompson et al.
49 2000), which causes SO cooling through anomalous northward Ekman transport of cold surface
50 waters (Sen Gupta and England 2006; Spence et al. 2010; Bitz and Polvani 2012; Ferreira et al.
51 2015; Kostov et al. 2017; Doddridge et al. 2019). The response to westerly wind strengthening
52 on decadal timescales, however, is SO surface warming, as relatively warm waters are upwelled
53 from below (Kostov et al. 2017; Ferreira et al. 2015), though this response may be muted by eddy
54 compensation (Hallberg and Gnanadesikan 2006; Bitz and Polvani 2012; Doddridge et al. 2019;
55 Bilgen and Kirtman 2020; Yeager et al. 2023; Kang et al. 2026). It is thus unclear to what extent
56 wind trends have contributed to observed SO cooling.

57 Other studies suggest that observed and inferred changes in freshwater fluxes have driven SO
58 cooling by increasing near-surface stratification, shoaling mixed layers and reducing the upward

59 flux of heat from depth (Gregory 2000). Many of these studies have focused on freshwater fluxes
60 from increased Antarctic ice sheet melt (Bintanja et al. 2013; Swart and Fyfe 2013; Pauling et al.
61 2016; Rye et al. 2020; Dong et al. 2022b; Roach et al. 2023; Swart et al. 2023; Schmidt et al.
62 2023; Kaufman et al. 2025), while other studies point to an increase in SO precipitation minus
63 evaporation ($P - E$, Durack et al. 2012; Purich et al. 2018; Kaufman et al. 2025) or changes in
64 freshwater fluxes due to sea ice formation and transport (Kirkman IV and Bitz 2011; Haumann
65 et al. 2016, 2020). However, unrealistic amounts of freshwater are often required to produce SO
66 cooling of the magnitude observed (e.g., Pauling et al. 2016; Dong et al. 2022b).

67 Finally, other studies suggest that natural internal variability, particularly associated with open-
68 ocean polynyas, has contributed to the observed SO cooling (Zhang et al. 2019; Singh et al. 2019).
69 However, this raises the question of why the CMIP suite of models is unable to readily simulate
70 the observed SO cooling even when accounting for internal variability (Wills et al. 2022).

71 All three of these potential mechanisms – wind forcing, freshwater forcing, and internal variability
72 – may have contributed to observed SO surface cooling over the satellite era. Indeed, multiple
73 mechanisms may be needed at once to explain the observed trends (e.g., Roach et al. 2023).
74 However, it is challenging to quantify their relative importance for several reasons. First, as
75 mentioned above, very few individual ensemble members across CMIP large ensembles show SO
76 cooling at all, let alone the magnitude of cooling suggested by observations (Wills et al. 2022). This
77 observed versus modeled SST trend mismatch could result from GCMs’ misrepresentation of SO
78 historical wind and freshwater forcing. For example, while historical CMIP6 simulations include
79 increased $P - E$ over the SO, they do not represent increased freshwater input from Antarctic ice
80 sheet melt. However, the mismatch could also result from GCM mean-state biases that affect the
81 SO response to forcings. For example, a GCM with a sufficiently biased mean-state stratification
82 may not simulate SO cooling even in response to realistic wind (Kostov et al. 2017) or freshwater
83 fluxes. Second, the proposed mechanisms have been most often evaluated narrowly in the context
84 of explaining SO SST trends alone; it is not obvious whether they are physically consistent with
85 other available SO observations, including trends in sea surface salinity (SSS), subsurface ocean
86 temperature, and subsurface ocean salinity. Observations suggest large-scale trends of SO surface
87 freshening, subsurface warming, and subsurface salinification over the satellite era which also
88 must be understood (Durack and Wijffels 2010; Durack et al. 2012; Swart et al. 2018). Moreover,

89 the proposed mechanisms also need to explain the regional structure of observed trends, rather
90 than only a zonal-mean or area-averaged trend as has been usually considered. And finally, SO
91 temperature and salinity observations have considerable uncertainty, even over the satellite era.
92 Thus, multiple observational products must be used when evaluating the contributions of proposed
93 mechanisms to observed trends.

94 Motivated by both the variety of proposed explanations for the observed SO SST cooling and
95 the considerable uncertainties described above, in this study, we seek to answer two key questions:
96 1) Given a well-constructed ocean modeling set-up and observationally-informed surface forcings,
97 can we recreate observed Southern Ocean temperature and salinity features within observational
98 uncertainty?, and 2) What are the relative contributions of these various forced responses to these
99 features? We discuss observational estimates and uncertainty in Section 2 and present our novel
100 ocean-only GCM simulations in Section 3. In Section 4 we present the SO ocean-only response
101 to observationally-informed forcings from heat, momentum, and freshwater flux changes, and in
102 Section 5 we compare best estimates of our simulations to observations. We discuss implications
103 of these results in Section 6 and we conclude in Section 7.

104 **2. Satellite-Era Trends and Observational Uncertainty**

105 *a. Observational Products*

106 Before the global implementation of the Argo program ($\sim 2004 - 2006$), there are relatively
107 few observations of the SO. Even now, SO observations are relatively sparse, especially in SH
108 winter. Gridded observational estimates of historical SO SST and SSS are thus implicitly shaped
109 by research centers' decisions relating to this data paucity, such as imperfect sampling of extant
110 observations or infilling of missing data (e.g., Lyman and Johnson 2014; Kent and Kennedy 2021).
111 These choices can lead to qualitatively different magnitudes and patterns of satellite-era SO SST
112 trends across observational products (Fig. 1). Analyses of the observed SO SST cooling trend are
113 thus directly shaped by the specific observational product analyzed.

123 With this in mind, we average nine observational estimates (Table 1) of the 1979-2020 annual-
124 mean SO SST trend to create a multi-product average estimate (Figs. 2a and c). We chose individual
125 gridded products based on the following criteria: i) the product must cover the entire period of
126 interest [1979-2020, chosen to match Wills et al. (2022)], ii) the product must be “state-of-the-art”

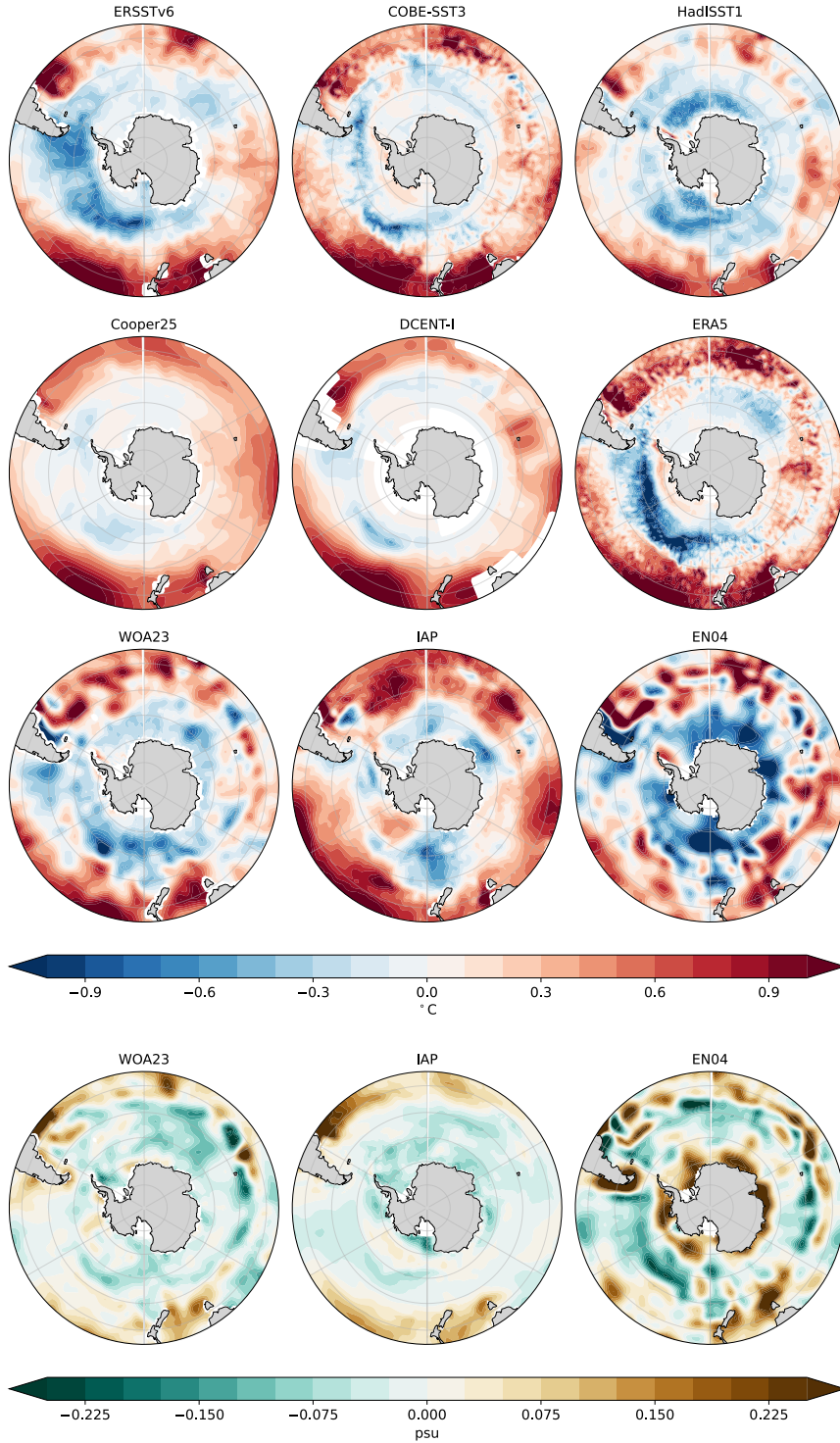


FIG. 1. Observed Southern Ocean 1979-2020 annual-mean sea surface temperature (SST) trend (top three rows) for the nine observational products listed in Table 1. Observed Southern Ocean 1979-2020 annual-mean sea surface salinity (SSS) trend (bottom row) for the three observational products listed in Table 1.

TABLE 1. Observational products considered in this study and the ocean field (SST, SSS, subsurface temperature, or subsurface salinity) they were used to estimate.

Product	Reference	SST	SSS	Subsurf. Temp.	Subsurf. Salt
ERSSTv6	Huang et al. (2025)	✓	×	×	×
COBE-SST3	Ishii et al. (2025)	✓	×	×	×
HadISST1	Rayner et al. (2003)	✓	×	×	×
DCENT-I	Chan et al. (2026)	✓	×	×	×
Cooper25	Cooper et al. (2025)	✓	×	×	×
ERA5	Hersbach et al. (2020)	✓	×	×	×
WOA23	Locarnini et al. (2024), Reagan et al. (2024)	✓	✓	✓	✓
IAP	Cheng et al. (2024)	✓	✓	✓	✓
EN04	Good et al. (2013)	✓	✓	✓	✓

(i.e., the most recent product version at the time of data access), and iii) the product must use some amount of in situ data (i.e., not just satellite data). We bi-cubically interpolate all observational products to the same $1^\circ \times 1^\circ$ grid using the CDO package (Schulzweida 2023). Relaxing these criteria to include older product versions or products that do not cover the whole period of interest does not lead to a qualitatively different SST trend multi-product average (not shown). We may have unintentionally neglected additional observational products that fit these prescribed criteria, but for the sake of defining a single multi-product average estimate of the satellite-era SO SST trend, we consider these nine estimates, which span a suite of analysis methods, sufficient for this study.

We use the same criteria to create a multi-product average estimate for satellite-era trends in SSS¹ (Figs. 2b and d), subsurface potential temperature (Fig. 3a), and subsurface salinity (Fig. 3b). Because there are substantially fewer observational products of SSS and subsurface fields, these trends are estimated from three common products which are a subset of the SST products (Table 1).

b. Major Features of Satellite-Era SO Trends

The first step toward understanding potential causes of satellite-era SO cooling is understanding where this cooling has occurred regionally and the degree to which individual products agree on

¹Practical salinity is a unitless quantity measured with reference to the practical salinity scale of 1978. While we acknowledge that practical salinity “units” are a misnomer (Millero 1993), we use psu throughout this study as i) it is reported by both our ocean-only GCM and salinity observational products and ii) for ease of comparison with previous climate-focused literature on SO SST and SSS changes.

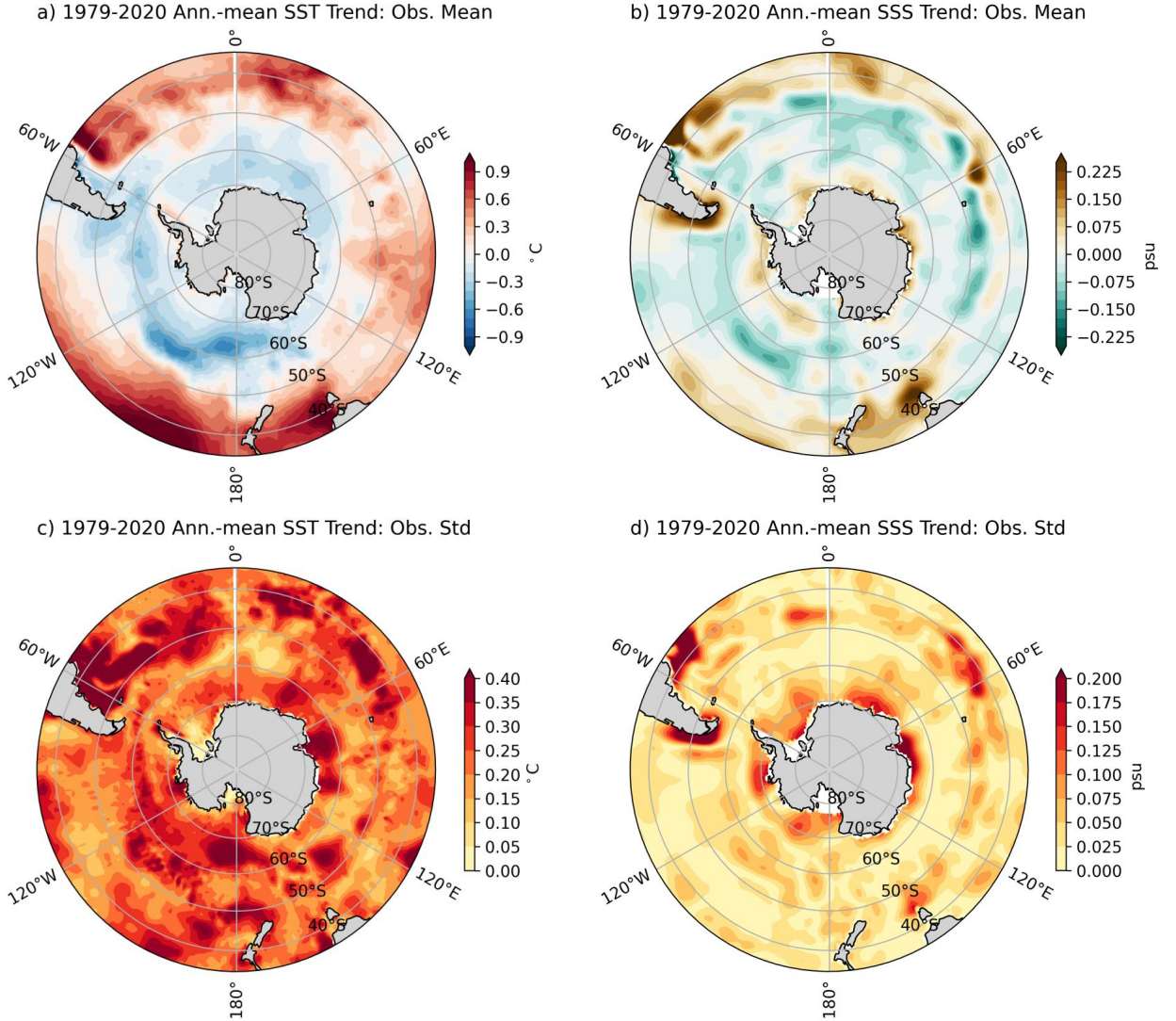


FIG. 2. Observed multi-product Southern Ocean 1979-2020 a) average sea surface temperature (SST) trend, b) average sea surface salinity (SSS) trend, c) SST trend standard deviation, and d) SSS trend standard deviation. Panels a) and c) consider nine observational products (Table 1). Panels b) and d) consider three observational products (Table 1).

those regions (Fig. 1). As mentioned above, any mechanism proposed to explain the observed SO SST cooling should also explain other robust observed changes in SSS and subsurface temperature and salinity.

Our multi-product average observational estimate of the SO SST trend (Fig. 2a) shows zonal cooling throughout the SO, especially south of the Antarctic Circumpolar Current (ACC) from

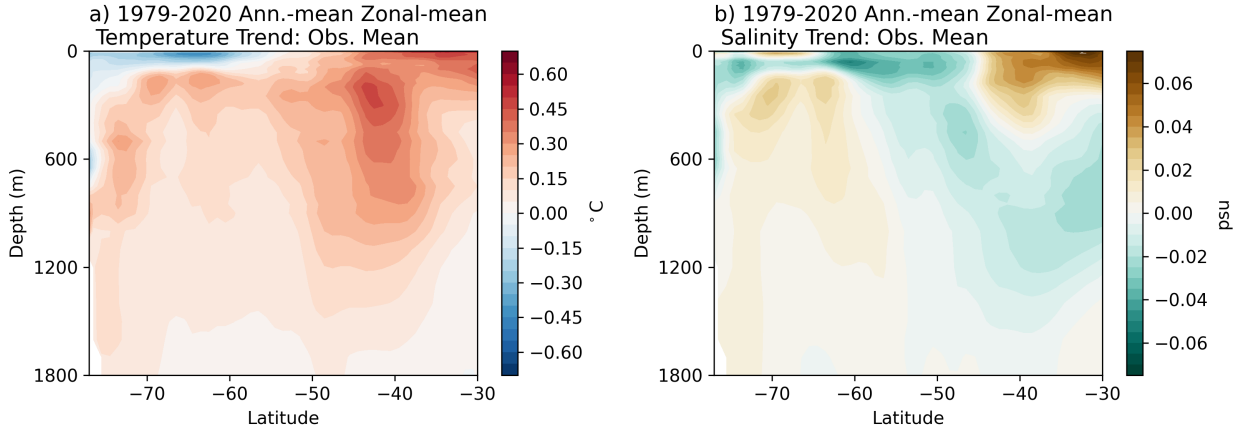


FIG. 3. Observed multi-product average of Southern Ocean 1979-2020 zonal-mean a) subsurface temperature trend and b) subsurface salinity trend. Both temperature and salinity trends consider three observational products (Table 1).

about 50°S to 70°S. However, there is substantial regional structure to this large-scale cooling. The strongest cooling trend occurs in the Pacific sector of the SO north of the Ross, Amundsen, & Bellingshausen Seas between approximately 150°E-60°W. This Pacific cooling trend is substantially larger than the weak cooling between approximately 60°W-60°E and the near-zero SST response between approximately 60°E-150°E. In fact, there is even a weak warming trend in some regions of the SO, such as along the Antarctic peninsula and in the SO Indian sector. Equatorward of 50°S and entering the SH subtropical gyre dynamical regime, the SO exhibits a warming trend that is strongest in the Pacific and weakest in the Indian.

There is substantial spread in the observational products (Fig. 1) that create the multi-product mean observed SST trend over the past several decades (Fig. 2a). Some products show strong, nearly zonally-uniform cooling, others show strong cooling in the Pacific only, and others still show weak cooling with patchy warming. This observational spread leads to a relatively large standard deviation in trends across products (Fig. 2c), the magnitude of which is even larger than the mean estimate in some areas. Cooling in the Pacific around 60°S between 180°-120°W, a small region west of the Drake passage, and a small region north of Queen Maud Land and west of the Weddell Sea are the only locations where all observational products agree on the sign of the SST trend (not shown); all other SO areas feature at least some disagreement among products in the sign of

the trend. Considering SH summer alone (December-February) does not qualitatively change this interpretation or lead to better agreement across observational products (Figs. S1-S2).

The multi-product mean observed historical SO SSS trend (Fig. 2b) shows a widespread freshening throughout the open ocean. While this mean freshening is somewhat patchy, the three SSS estimates generally agree on the sign of this trend (Fig. 1), except in coastal Antarctica, which exhibits both a mean salinification and a high standard deviation (Figs. 2b and d). The zonal-mean temperature trend poleward of 55°S exhibits a surface cooling and freshening and a subsurface warming and salinification (Fig. 3). Equatorward of 55°S there is a deep-reaching warming north of the ACC which has been tied to both mean circulation (Armour et al. 2016) and circulation adjustments (Taylor et al. 2025). In approximately this same region, a freshening signal that plunges downward and northward has been tied to a freshening of the subducting Antarctic Intermediate Waters (AAIW; Durack and Wijffels 2010). Individual observational estimates of SO subsurface temperature and salinity trends largely capture these features (Fig. S3).

3. Ocean-only GCM Simulations

a. Model Set-up & Control Simulation

We use the Massachusetts Institute of Technology General Circulation Model (MITgcm; Marshall et al. 1997a,b) ocean-only GCM (OGCM) in the Estimating the Circulation and Climate of the Ocean version 4 release 4 configuration (ECCOV4r4; Forget et al. 2015). ECCOV4r4 is a dynamically-consistent 1992-2017 ocean and sea ice state estimate that uses the adjoint method to fit the model solution to available observations through forcing adjustments. These simulations have a horizontal resolution of 1° in the zonal direction globally, 1° in the meridional direction in mid latitudes, and 1/3° in the meridional direction at both low and high latitudes. This higher resolution meridional refinement in the tropics and polar regions allows ECCOV4r4 to resolve tropical instability waves and begin permitting high-latitude mesoscale eddies.

Although we do not use adjoint functionality in this work, we take advantage of the fact that the ECCOV4r4 state estimate is a reasonable approximation of the real ocean with a realistic mean-state stratification. As such, we use the 1992 ocean state as initial conditions for our simulations, which can be broadly differentiated into three primary types: 1) a simulation forced by climatological surface fluxes and strong surface restoration (referred to here as Simulation 1); 2) a simulation

198 forced by the full surface fluxes stored from Simulation 1 but with surface restoring turned off
 199 (constituting the control simulation for our study and referred to here as Simulation 2); and 3) a
 200 simulation forced by the same fluxes from Simulation 2, but with additional flux forcings (heat,
 201 momentum, freshwater) applied and an additional radiative damping term to mimic radiative
 202 damping to space with increased warming (constituting the forced simulations for our study and
 203 referred to here as Simulation 3). We discuss these three simulation types in-turn.

204 As in Luongo et al. (2025, 2026), Simulation 1 is forced with monthly climatologies of net air-sea
 205 fluxes of heat, freshwater, shortwave radiation, and zonal and meridional momentum first diagnosed
 206 by Peng et al. (2022) from a 1992-2017 control integration of ECCOv4r4 forced by 6-hourly ERA5
 207 atmospheric reanalysis with bulk formulae forcing. In addition to this climatological flux forcing,
 208 we also restore SST and SSS to Peng et al. (2022)’s monthly climatologies on a 10-day timescale
 209 to prevent model drift. The surface temperature forcing and surface salinity forcing equations in
 210 these OGCM simulations are as follows:

$$F_{\theta} = -\lambda_{\theta}(\theta - \theta^*)C_{\theta} - Q_{net} , \quad (1)$$

$$F_S = -\lambda_S(S - S^*)C_S - (P - E + R) . \quad (2)$$

211 The model’s surface temperature and salinity flux at each point (F_{θ} and F_S , respectively) are affected
 212 by a relaxation flux (first term on the right hand side of Equations (1) and (2) and a climatological
 213 flux (second term on the right hand side). In the case of F_{θ} , the relaxation term is a product of the
 214 relaxation timescale (λ_{θ}), the difference between the model-calculated SST (θ) and the monthly
 215 SST climatology (θ^*), and a constant term (C_{θ}), which is the product of seawater heat capacity,
 216 a reference density, and the width of the first vertical layer. The climatological term is then the
 217 net surface heat flux (Q_{net}), which includes contributions from shortwave and longwave radiation
 218 and latent and sensible heat. For F_S , the relaxation term is a product of the relaxation timescale
 219 (λ_S), the difference between the model calculated SSS (S) and the monthly SSS climatology (S^*),
 220 and a constant term (C_S), which is the width of the first vertical layer normalized by a reference
 221 salinity. The climatological term is then precipitation minus evaporation plus runoff ($P - E + R$).

222 After starting from the 1992 ocean state estimate, we spin up our simulation for 500 years with this
223 climatological flux forcing and surface relaxation to reach a near-steady upper ocean.

224 A major shortcoming of traditional OGCM simulations is that their SST anomalies are strongly
225 damped, either via bulk formulae and/or strong surface relaxation to prevent drift. These forms
226 of damping produce damping rates that are an order of magnitude larger than that of surface
227 temperature anomalies to space through radiative damping processes, which is about $1 \text{ Wm}^{-2}\text{K}^{-1}$
228 globally (Forster et al. 2021). This greatly limits the use of traditional OGCM simulations for
229 studying the long-term climate response to forcings.

230 With this shortcoming in mind, and inspired by a similar modeling set-up used by Marshall et al.
231 (2015) and Armour et al. (2016), we present a novel OGCM methodology to create Simulation
232 2, which experiences very little drift in its control state and allows surface changes in response to
233 anomalous surface forcing. In this set-up, SST and SSS relaxation are turned off (i.e., $\lambda_\theta = \lambda_S = 0$),
234 to allow surface changes. However, to prevent major simulation drift, we add the climatology of
235 those SST and SSS relaxation fluxes derived from years 101-500 of Simulation 1 to the climato-
236 logical heat and freshwater fluxes. A 400-year spin up of this “combined-flux-forced” simulation
237 shows global-mean surface temperature drift of less than 0.05 K (not shown). We select years
238 201-300 of this combined-flux-forced simulation as a 100-year control simulation throughout this
239 work.

245 Because the simulations are initialized with the 1992 ECCOv4r4 state estimate and use monthly
246 climatological fluxes calculated from a reanalysis-forced integration of ECCOv4r4, they produce
247 a realistic SO mean-state stratification that compares much better with observations than do many
248 CMIP GCM simulations (e.g., Farneti et al. 2015). The 100-year average SO mean-state strat-
249 ification of our control simulation largely agrees with the observed 1979-2020 SO mean-state
250 stratification, especially in the open SO (Fig. 4). Our simulations exhibit warmer temperatures
251 than observations (and ECCOv4r4) directly beneath the climatological sea ice region and slightly
252 too fresh subducted AAIW. Both of these biases may be due to the lack of interactive sea ice in
253 our combined-flux-forced simulations— in order to exactly constrain surface fluxes, a necessary
254 limitation of our modeling set-up is that the SO is only impacted by sea ice forcings through
255 climatological surface fluxes. While this OGCM simulation choice has previously been justified

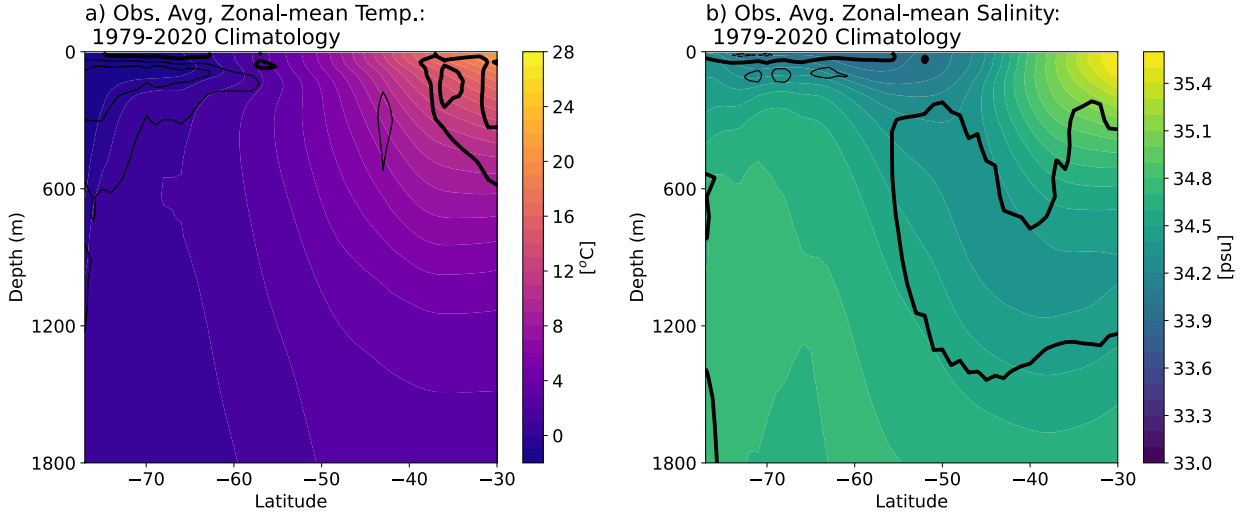


FIG. 4. a) 1979-2020 average observed Southern Ocean zonal-mean temperature (color fill, average of WOA23, IAP, and EN04). OGCM bias relative to these observations as black contours of 1°C with the zero contour thickened. b) 1979-2020 average observed Southern Ocean zonal-mean salinity (color fill, average of WOA23, IAP, and EN04). OGCM bias relative to these observations as black contours of 0.2 psu with the zero contour thickened.

(e.g., Marshall et al. 2015; Armour et al. 2016; Haumann et al. 2020), several centuries of forcing without interactive sea ice may begin to affect the mean state.

In summary, our combined-flux-forced simulations reasonably simulate the observed mean SO while addressing the common OGCM shortcomings of having too strong surface constraints and/or substantial model drift.

b. Forced Simulations

Combined-flux-forced OGCM simulations are useful tools which can approximate the ocean-only response to an anomalous surface forcing on decadal-to-centennial timescales because: i) anomalous fluxes are prescribed exactly rather than calculated online, ii) simulations have very little drift due to the addition of climatological surface relaxation fluxes, and iii) in the absence of strong damping, surface changes due to applied forcings can clearly establish. If forced with changes in heat, freshwater, and momentum fluxes (on top of the background fluxes of Simulation 2, as in the case of our Simulation 3 runs), these combined-flux-forced simulations can approximate how the ocean responds to climate change, absent changes in atmospheric heat transport.

Following Marshall et al. (2015) and Armour et al. (2016), in all forced Simulation 3 runs we parameterize climate feedbacks by introducing an SST damping term to represent heat lost from the surface of the ocean to space via radiation. In practical terms, this parameterization is equivalent to re-introducing the SST relaxation flux term in Equation (1), however we now prescribe λ_θ as a weak, spatially-uniform $1 \text{ Wm}^{-2}\text{K}^{-1}$ and θ^* as the SST climatology from the control simulation (Simulation 2). As a result, the difference between a forced simulation (Simulation 3) and the control simulation (Simulation 2) demonstrates the ocean response to that forcing in the presence of an idealized, spatially-uniform climate feedback with a realistic global magnitude (Murphy et al. 2009). We present these anomalies throughout our study.

As such, we investigate the SO response to observationally-informed estimates of satellite-era surface forcing from heat, freshwater, and momentum fluxes. Specifically we individually force the OGCM with observationally-informed step changes in radiative forcing, momentum, and freshwater from individual changes in $P - E$, ice sheet melt, and changing sea ice hydrology. These individual forcing experiments allow us to understand the intrinsic ocean response to each type of forcing, including the magnitude, pattern, and timing of the response. With these experiments, we can ask, for instance, whether all types of freshwater forcing affect the SO similarly or whether the ocean response to these forcings exhibits a change in character throughout time as it does in response to momentum forcing (e.g., Bitz and Polvani 2012; Ferreira et al. 2015; Kostov et al. 2017). The “fast” (year 2) and “slow” (year 30) temperature responses of the SO to these abrupt forcings are presented in Figs. A1-A2 and described in more detail in Section 4.

c. *Estimating forced trends*

To add a time dimension to our simulations, we calculate the linear transient response of the ocean to these step function forcings following Hasselmann et al. (1993):

$$\Phi(t) = \int_0^t G(t-t') \frac{dF}{dt}(t') dt' , \quad (3)$$

representing the temporal response of some ocean quantity (Φ) to a prescribed forcing (F) as the convolution of the response of that ocean quantity to the step forcing (G , the “climate response function”). The SO linear response to a step function (i.e., impulse / Green’s function) forcing has been used in multiple studies (e.g., Marshall et al. 2014; Armour et al. 2016; Kostov et al. 2018;

297 Rye et al. 2020; Kaufman et al. 2025). In our case, this time dimension now allows us to consider
298 an analogous period to 1979-2020 in our combined-flux-forced simulations.

299 **4. Oceanic Response to Individual Observationally-Informed Forcings**

300 *a. Radiative Forcing*

301 We first simulate the SO response to radiative forcing alone by running a 170-year simulation
302 forced by a globally-uniform 1 Wm^{-2} anomalous radiative forcing. The SO response to this abrupt
303 and sustained radiative forcing (Figs. A1a-b and A2a-b) is similar to that of Armour et al. (2016),
304 who used the same basic OGCM architecture but with a globally-uniform 4 Wm^{-2} forcing. We
305 then convolve (Equation 3) the response to this forcing step change with the median estimate of the
306 1851-2020 global radiative forcing time series (black line in Fig. 5e) derived from historical and
307 SSP2-4.5 emissions scenarios (Dvorak et al. 2022) to estimate the linear time evolution of the SO
308 temperature and salinity response over 1979-2020 (orange and blue lines in Fig. 5e).

313 In response to the past 170 years of radiative forcing, the surface SO both warms by more than half
314 a degree and slightly freshens. Importantly, this response occurs without any changes in freshwater
315 or momentum forcing. The patterns of simulated 1979-2020 annual-mean temperature and salinity
316 trends (Figs. 5a-d) provide important insight into the dynamics that shape this slight warming
317 and freshening. As discussed at length in Armour et al. (2016) for a slightly different period, the
318 simulated 1979-2020 temperature trend features a muted surface warming throughout most of the
319 SO south of the ACC. This muted warming is due to SO mean circulation: unmodified deep waters
320 upwell near Antarctica and take up anomalous heat; those warmed waters are advected equatorward
321 via Ekman transport; and that anomalous heat is then stored at depth on the equatorward flank of
322 the ACC where waters subduct into the interior ocean. However, the Amundsen & Bellingshausen
323 Seas warm more than other sections of the SO, demonstrating that this muted warming is not
324 homogeneous. While this surface warming trend is damped relative to the rest of the global ocean
325 (e.g., north of 45°S), the radiative forcing does not lead to any of the cooling seen in observations
326 (Figs. 2a & 3a).

327 Interestingly, radiative forcing alone slightly freshens the SO surface (Fig. 5b) and contributes
328 to the distinctive subducting AAIW freshening trend seen in observations (c.f. Figs. 5d & 3b).
329 Durack and Wijffels (2010) first noted this observed AAIW freshening trend and, after removing

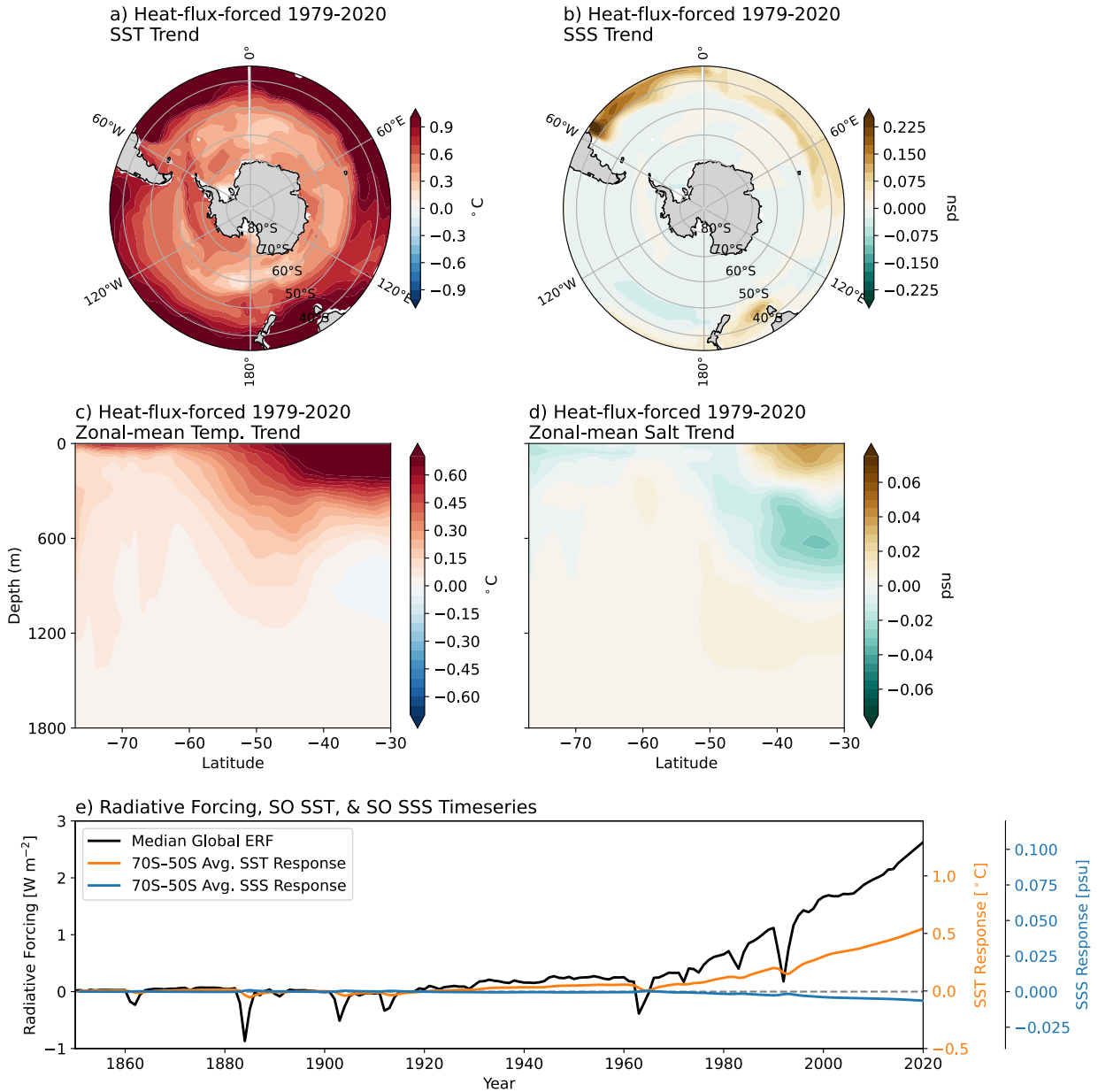


FIG. 5. Simulated 1979-2020 trend in a) SST, b) SSS, c) subsurface zonal-mean temperature, and d) subsurface zonal-mean salinity in response to idealized satellite-era radiative (heat flux) forcing. e) Time series of median global estimated radiative forcing (ERF) from historical + SSP2-4.5 scenario (black line, Dvorak et al. 2022) and simulated historical 70°S-50°S average SST (orange line) and SSS (blue line).

effects of isopycnal heave, showed that it primarily resulted from surface-driven water mass transformation. They hypothesized that the surface water mass changes were linked to observed warming-driven poleward migration of outcropped isopycnals, which could drive a freshening of

AAIW as climatologically fresher waters would now subduct along that isopycnal due to the mean SO SSS latitudinal gradient. They then suggested that this poleward outcrop migration is most likely to be driven by historical surface warming, rather than any change in surface freshwater. Our radiatively-forced-alone results support this conclusion.

The simulated 1979-2020 SO surface trends due to radiative forcing alone show a weak warming and freshening. Thus, the radiatively-forced response provides a scaffolding of sorts with which to understand the observed response (Figs. 2a & b). It allows us to ask, for instance, how observed momentum and freshwater forcing have modulated this weak warming and freshening to obtain the observed weak cooling and stronger freshening.

b. Momentum forcing

Atmospheric reanalyses show a robust strengthening of the SH westerlies over recent decades (Fig. S4a and Swart and Fyfe 2012). Quantifying wind changes over 1979-2020 with the ERA5 reanalysis (Hersbach et al. 2020), the strengthening is coherent for both annual-mean winds (9.5% increase over 45 – 65°S) and seasonal-mean winds (11.5% increase over 45 – 65°S for October through March and 8.5% for April through September). Additionally, in SH summer (December-February) ERA5 suggests that there has been about a 3-degree poleward shift of the westerly wind core, which has been primarily attributed to ozone depletion (e.g., Polvani et al. 2011).

We perform an OGCM momentum-forced anomaly simulation where the anomaly is a step forcing equal to the monthly pattern and magnitude of the 1979-2020 linear trend per year of ERA5 35°S-70°S zonal and meridional wind stress multiplied by 42 years (Fig. S4a-b). As noted in multiple prior studies focused on the SO response to an increase in Southern Annular Mode (SAM) forcing (e.g., Bitz and Polvani 2012; Ferreira et al. 2015; Armour et al. 2016; Kostov et al. 2017, 2018), the first two years of our momentum step change simulation shows a patchy temperature response near Antarctica and primarily cooling over 40°S-60°S (Fig. A1c). However, after this initial “fast” period, the long-term response of the SO to this imposed momentum anomaly is a relatively strong warming near Antarctica (Fig. A1d). While this “slow” warming response is thought to result from the upwelling of relatively warm, salinity-stratified waters in sea ice regions (Bitz and Polvani 2012; Ferreira et al. 2015), both the amount of initial cooling and the amount of long-term warming depend strongly on model architecture (Kostov et al. 2017). The relatively

362 strong long-term SO warming in response to the applied momentum forcing in our simulations is
363 consistent with the results of Armour et al. (2016), who also found a relatively strong long-term
364 warming response to wind changes using MITgcm². As noted above, our control simulation has a
365 warm bias beneath the climatological sea ice zone (Fig. 4a) which may contribute to the “slow”
366 warming response to momentum forcing.

367 To estimate the impact of wind trends on the SO over 1979-2020, we convolve (Equation 3) the
368 ocean response to this step change with a 42-year linear trend (i.e., the forcing annually increases
369 by the same amount from 1979 until finally reaching the full amount in 2020) and take the annual-
370 mean trend of the result. The SST response to the monthly trends in wind stress (Fig. S5) exhibits
371 a meridional dipole with mostly warming poleward of 60°S and mostly cooling equatorward of
372 60°S. In the open SO, cooling is deep-reaching and creates an analogous, but opposite-signed,
373 temperature response co-located with subduction pathways north of the ACC as in the case of the
374 radiatively-forced simulation (c.f. Figs. 5c and S5c).

375 Because of the strong warming in our OGCM’s slow response, this simulated temperature
376 response to observed momentum anomalies negatively projects onto the observed historical tem-
377 perature trend (Fig. 2a). While this result is perhaps somewhat surprising given that a regression
378 of SST onto the SAM index shows cooling in the Pacific sector of the SO (e.g., Thompson et al.
379 2011; Hartmann 2022), this warming may be inherent to our simulation set-up as mentioned above.
380 With that in mind, recent work by Doddridge et al. (2019) has suggested that the slow SO warming
381 that many GCMs experience in response to momentum forcing is a consequence of their coarse
382 resolution. Higher resolution models, which resolve mesoscale eddies, compensate for this long-
383 term warming through changes in the eddy-driven circulation, resulting in a long-term SO SST
384 response to momentum forcing that more closely resembles the fast response. To circumvent our
385 low-resolution OGCM’s inherently warm long-term response, we devise temperature and salinity
386 fields that can be thought of as an idealized “fast-only” response of the ocean to this same mo-
387 mentum forcing by replacing anomalies in years 3-100 with anomalies taken from year 2 (the fast

²In addition to this primary momentum forcing simulation, we also perform four momentum forcing sensitivity analyses: i) a simulation where the momentum anomaly is the actual monthly pattern of ERA5 SO *zonal* wind stress trends only; ii) a simulation where the momentum anomaly is a 10% increase in monthly climatological SO *zonal* winds; iii) a simulation where December-February zonal and meridional winds are shifted two degrees poleward; and iv) a simulation recreating Marshall et al. (2014) and Armour et al. (2016) where the momentum anomaly is the wind stress field from a +1 SAM index modulated by an annual-cycle maximized in November. While there are slight regional differences among simulations, all broadly show a similar fast response of slight SO cooling and a slow response of strong SO warming. As a result, we are confident that this general two-timescale response pattern is robust with respect to the details of the momentum forcing applied.

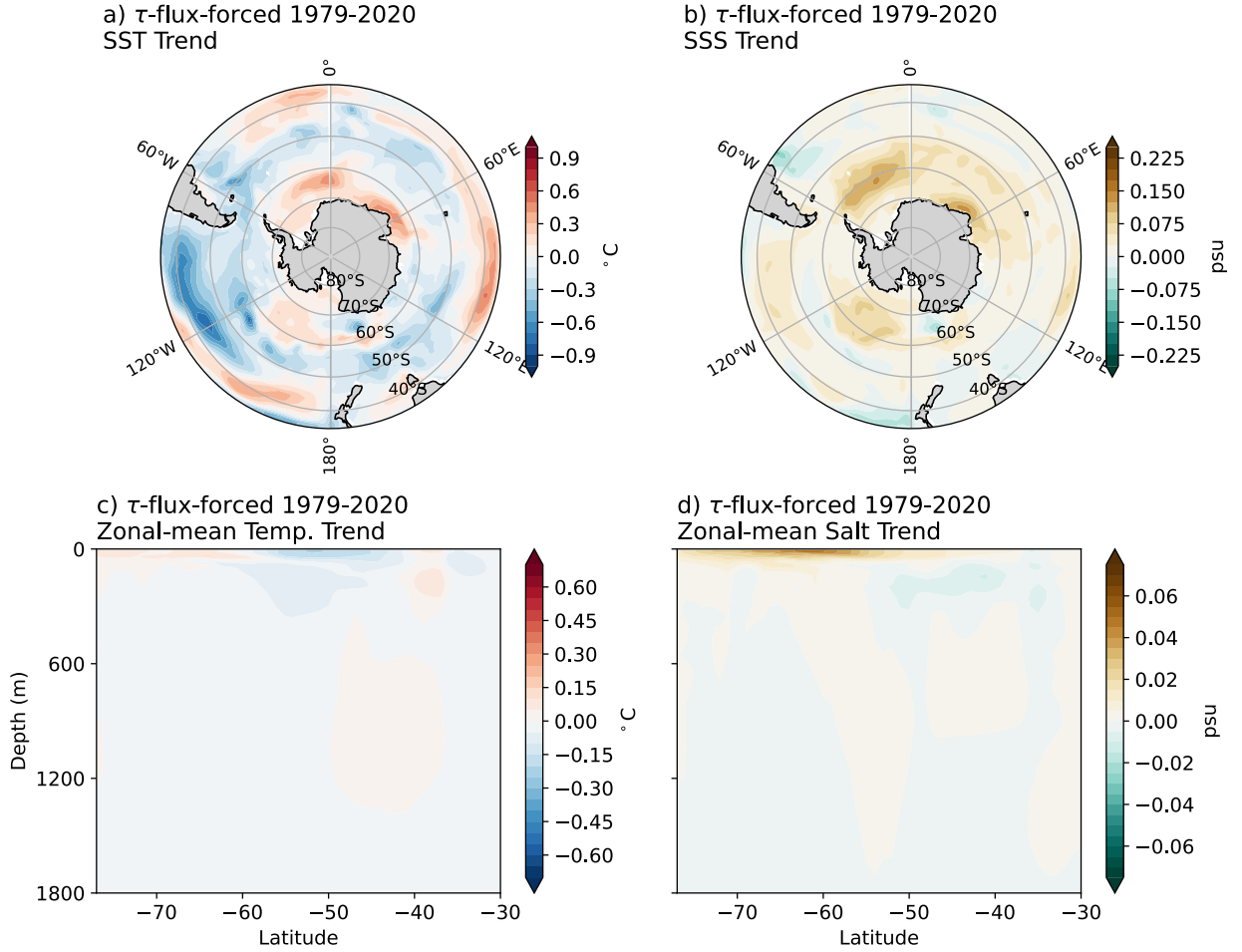


FIG. 6. a) Simulated 1979-2020 trend in a) SST, b) SSS, c) subsurface zonal-mean temperature, and d) subsurface zonal-mean salinity trend in response to idealized fast-only satellite-era momentum flux forcing.

response). We then convolve this modified ocean response with the same 42-year linear trend as above and take the annual-mean trend of this result.

This estimate of the ocean's response to historical momentum trends over 1979-2020 (Fig. 6) features a patchy SST response poleward of 60°S . This response consists of near-coastal cooling in the Amundsen and Bellingshausen Seas and over 80°E - 180° , and warming in the Ross and Weddell Seas and over 0° - 80°E . The SO response equatorward of 60°S is primarily cooling, with the strongest cooling anomalies west of Chile where SST is most sensitive to SAM forcing (e.g., Thompson et al. 2011; Hartmann 2022).

Although the subsurface temperature response is weak (Fig. 6c), this simulation shows the importance of subsurface salinity stratification when considering momentum-forced trends. This change in wind stress forcing leads to a large-scale salinification of the SO surface (Fig. 6b and d) as saltier waters from depth are anomalously upwelled. Near Antarctica, warm anomalies are co-located with salty anomalies, and these salt anomalies are then transported northward to generally salinify the SO. The finding that momentum-driven historical fluxes have likely caused a coherent increase in SO salinity agrees with results from Shi et al. (2020) and Haumann et al. (2020). It additionally suggests that even if historical changes in wind stress have contributed to SO surface cooling, they have likely simultaneously caused a salinity trend that opposes the observed freshening, suggesting winds are unlikely to be the sole driver of historical SO SST changes.

c. *Freshwater forcing*

There have been trends in three distinct sources of freshwater fluxes to the SO over the period of 1979-2020: i) large-scale changes in $P - E$; ii) freshwater input from Antarctic ice sheet melt; and iii) changes in the sea ice hydrologic cycle. These three freshwater sources have all been suggested as potential drivers of, or contributors to, the observed SO surface cooling and freshening. We evaluate the ocean response to each of these sources of freshwater fluxes in observationally-informed freshwater-anomaly-forced OGCM simulations.

Observational products suggest a large-scale increase in SO $P - E$ over recent decades (Durack et al. 2012; Fyfe et al. 2012). We thus perform an OGCM freshwater-forced anomaly simulation where the anomaly is a step forcing equal to the monthly pattern and magnitude of ERA5 $P - E$ trends from 30°-80°S. We convolve (Equation 3) the ocean response to this step change with a 42-year linear trend to estimate the 1979-2020 SO temperature and salinity response to increased $P - E$. Performing a similar simulation with monthly ERA5 $P - E$ trends over only 50°-80°S does not qualitatively change the results (not shown). While $P - E$ fluxes are the largest factor in the SO freshwater flux changes (Pauling et al. 2016), the approximate SO-average 10% increase in P-E from 1979-2020 (Figure S4c) seen in ERA5 is the smallest SO precipitation increase among several reanalysis products (Kaufman et al. 2025). As such we consider this to be a conservative estimate of the freshwater flux to the SO from changes in $P - E$.

Surface mass balance observations suggest an increase in meltwater flux into the SO from the Antarctic ice sheet over recent decades (e.g., Schmidt et al. 2023). While a substantial amount of Antarctic ice sheet melt happens in the subsurface, Pauling et al. (2016) show that simulations forced by surface melt and subsurface melt are qualitatively similar. We thus perform an OGCM simulation wherein we uniformly add an anomalous step increase in surface freshwater flux within 2° of the Antarctic coast. We determine the magnitude of our step forcing by extending Schmidt et al. (2023)’s 1990-2020 time series of satellite-derived Antarctic ice sheet melt to 1979 (conservatively assuming the 1990 value as the value from 1979-1989), fitting a linear trend to that time series (Fig. S4d), and then using the 2020 value of the linear trend solution as our step forcing magnitude. We also add a heat flux due to the latent heat of fusion derived from melting ice in seawater which is commensurate with this anomalous freshwater flux. Because heat is drawn from seawater to melt ice, this flux cools the surface ocean and has been shown to be a major component of the Antarctic coastal heat budget (Moorman et al. 2026). We convolve (Equation 3) this step-forced simulation with a 42-year linear trend to estimate the 1979-2020 SO temperature and salinity response to ice sheet melt increase.³

Finally, analyses suggest an increase in the Antarctic sea ice hydrologic cycle has shaped SO surface freshwater fluxes (Haumann et al. 2016, 2020). Climatologically, freshwater fluxes due to sea ice can be broadly thought of as salt fluxes around coastal Antarctica where sea ice is formed and freshwater fluxes in the open SO where sea ice melts after being transported northward by winds. This corresponds to a net northward transport of freshwater. Haumann et al. (2016) reconstruct sea ice concentrations using satellite observations to suggest that this freshwater transport has increased by $20 \pm 10\%$ from 1982-2008 due to changes in sea ice hydrology in this period when Antarctic sea ice largely expanded (Roach et al. 2020; Blanchard-Wrigglesworth et al. 2021). We thus perform an OGCM simulation wherein the model’s monthly climatological salinity flux is increased by 10% in the region where Haumann et al. (2016) suggests there has been a change in freshwater fluxes due to sea ice, amounting to an anomalous step increase in the sea ice hydrologic cycle. We deem this forcing choice adequate because the vast majority of the model’s annual-mean freshwater forcing in this region is due to sea ice and observational products have suggested relatively muted historical $P - E$ changes over the sea ice region (Bromwich et al. 2011). We specifically choose the

³We also run a simulation where we only add anomalous surface freshwater flux within 2° of the Antarctic coast in the Amundsen & Bellingshausen Seas and a simulation where we add anomalous surface freshwater fluxes within 5° of the Antarctic coast. While there are regional differences in the Amundsen-Bellingshausen-only simulations, the overall two-timescale response pattern is robust between all three forcing geographies.

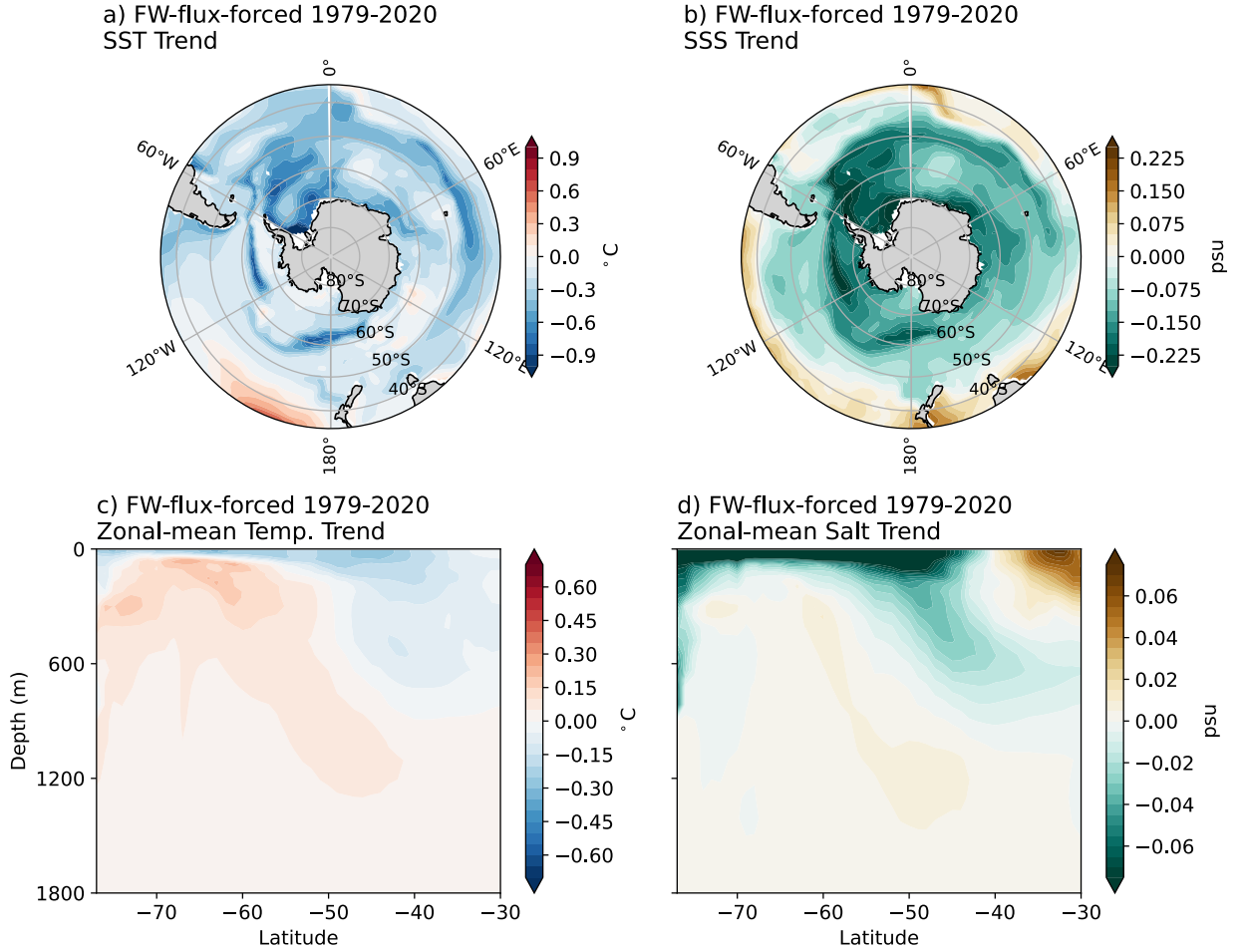


FIG. 7. a) Simulated 1979-2020 trend in a) SST, b) SSS, c) subsurface zonal-mean temperature, and d) subsurface zonal-mean salinity trend in response to idealized satellite-era freshwater flux forcing. All panels show the sum of three simulations individually forced by changes in $P - E$, Antarctic ice sheet melt, and changing sea ice hydrology.

lower end of Haumann et al. (2016)'s estimate to account for the strong decrease in Antarctic sea ice that occurred from 2015 onward which is not included in the 20% estimate. As in the case of the ice sheet melt simulation, we add an estimate of the anomalous heat flux due to latent heat of fusion from this sea ice melting and formation. We convolve (Equation 3) this step-forced response with a with a 42-year linear trend to estimate the 1979-2020 SO temperature and salinity response to sea ice hydrologic cycle changes.

465 Considered (summed) together, these three freshwater forcing simulations – increased $P - E$,
 466 Antarctic ice sheet melt, and an increase in the sea ice hydrological cycle – lead to a large-scale
 467 SO surface cooling (Fig. 7a). This cooling is especially pronounced in two distinct regions of
 468 the Pacific sector of the SO, one north of the Ross Sea and the other north of the Amundsen &
 469 Bellingshausen Seas. There is also substantial cooling in the Weddell Sea and the Indian sector of
 470 the SO over 50°S-40°S. The cooling is weakest, and in some cases very slight warming, along the
 471 coast in the Ross, Amundsen, and Bellingshausen Seas. This broad surface cooling (confined to
 472 a thin surface layer south of 50°S) overlays a subsurface warming (Fig. 7c), similar to observed
 473 subsurface trends poleward of 50°S (Fig. 3a). The salinity response shows a strong surface
 474 freshening atop a subsurface salinification (Figs. 7b & d), again similar to observed subsurface
 475 trends poleward of 50°S (Fig. 3b). Overall the three individual freshwater simulations lead to
 476 roughly similar amounts of surface cooling averaged over the SO (Fig. S6), but $P - E$ creates the
 477 slight coastal warming patches seen in the total response and the ice-sheet-melt-forced cooling
 478 is concentrated more around Antarctica and is slightly weaker in magnitude than the other two
 479 responses. Similarly, the ice-sheet-melt-forced freshwater increase is more concentrated around
 480 Antarctica. While Fig. 7 shows the summed response of the three individually-forced freshwater
 481 responses, the response is quite linear as compared to a simulation where all forcings are applied
 482 together (not shown).

483 **5. Reconstructing Satellite-Era Southern Ocean Temperature and Salinity Trends**

484 *a. Observed Trends as an Unweighted Linear Combination of Forced Responses*

489 We have created an ocean modeling set-up with a reasonable mean state (Section 3) and we
 490 have forced that OGCM with observationally-informed surface fluxes of heat, momentum, and
 491 freshwater to estimate their relative contributions to SO temperature and salinity trends over 1979-
 492 2020 (Section 4). We now consider whether combinations of these OGCM simulations are able
 493 to recreate observed SO temperature and salinity features within the substantial observational
 494 uncertainty (Section 2). To address this question, we begin by hypothesizing that both historical
 495 SST and SSS responses can be recreated as a linear combination of individual temperature and
 496 salinity responses to multiple observationally-informed surface forcings,

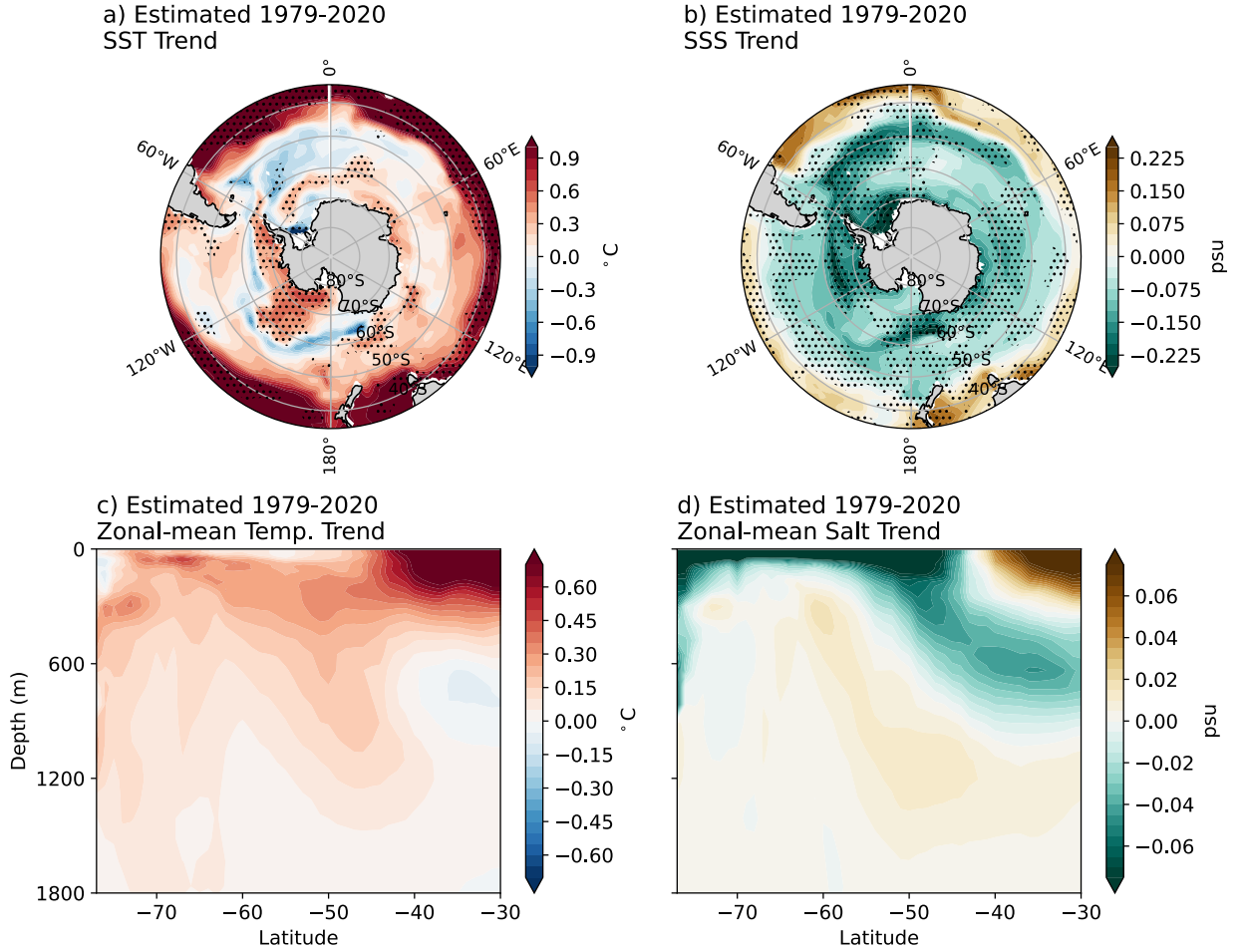


FIG. 8. Linear combination of a) SST, b) SSS, c) subsurface zonal-mean temperature, and d) subsurface zonal-mean salinity 1979-2020 trend according to Equations (4) and (5), where all coefficients are equal to one. Stippling in a) and b) represent locations where the linear combination is outside of two standard deviations of the observed mean trend.

$$SST_{estimate} = \alpha SST_{Qnet} + \beta SST_{P-E,FW} + \gamma SST_{IceSheet,FW} + \delta SST_{SeaIce,FW} + \zeta SST_{\tau} \quad (4)$$

and

$$SSS_{estimate} = \alpha SSS_{Qnet} + \beta SSS_{P-E,FW} + \gamma SSS_{IceSheet,FW} + \delta SSS_{SeaIce,FW} + \zeta SSS_{\tau}, \quad (5)$$

where α , β , γ , δ , and ζ are coefficients shared between Equations (4) & (5) that are unique to and modulate each forced response.

The simplest reasonable combination is the case where all coefficients are equal to one (i.e., $\alpha = \beta = \gamma = \delta = \zeta = 1$: Fig. 8), representing the model's response to our best estimates of observed forcings. Similar to the multi-product estimates of observed temperature and salinity (Fig. 2), this combination shows surface cooling in the Pacific and Atlantic sectors and strong circumpolar freshening throughout the open SO. This response also shows a subsurface warming and salinification near Antarctica, AAIW freshening, and subsurface warming in the ACC band. However, the simulated response features too much warming around coastal Antarctica relative to the observational mean, especially in the Amundsen, Bellingshausen, and Ross Seas and north of the ACC. This excess warming results from the radiative- and momentum-forced simulations.

Nevertheless, the linear combination of responses from observationally-informed estimates of forcings creates temperature and salinity patterns that share key features with the observed patterns. In particular, this response exhibits a cooling and freshening response which is more in-line with observations than most coupled GCMs manage. In addition, the magnitude of temperature and salinity change in this response is largely comparable to observations: 74.5% and 51.6% of the SO area between 35°S and 70°S are within two standard deviations from the multi-product mean estimate of SST and SSS, respectively.

b. Observed Trends as a Weighted Linear Combination of Forced Responses

The above analysis (Fig. 8) illustrates the OGCM estimate of SO temperature and salinity trends over 1979-2020 given best estimates of observationally-informed forcing trends. To allow for uncertainty in both the magnitude of observed forcings and the model's response, we now consider cases where α through ζ are close, but not equal, to one. Inspired by Swart et al. (2018)'s detection and attribution technique, we first build five 1,000,000 member random normal distributions of each coefficient with a mean of 1 and a standard deviation of 0.25 (blue prior distributions in Fig. 9). We then perform a Monte Carlo analysis to refine these prior distributions, looping through 1,000,000 coefficient combinations randomly chosen from the prior distributions to create an estimate of SST trends via Equation (4). For this random combination, we calculate the Z-score of the prediction at each point in space using the mean and standard deviation of the observational

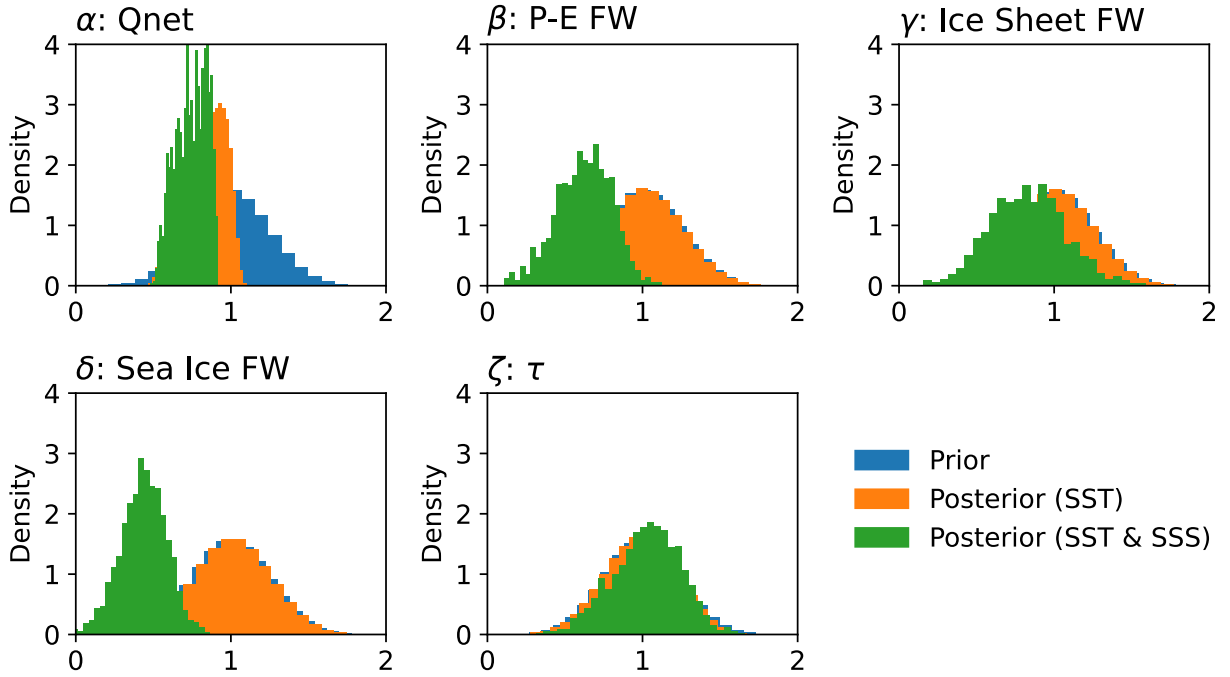


FIG. 9. Distribution of coefficients for linear combinations in Equations (4) and (5). Blue distribution is our prior distribution with a mean of 1 and a standard deviation of 0.25 ($n = 1,000,000$), orange distribution is a posterior distribution after a first Monte Carlo analysis considering SST and ocean heat content observations ($n \approx 495,000$), and green distribution is a posterior distribution after a second Monte Carlo analysis initialized on the orange distribution considering both SST and SSS observations ($n \approx 3,400$).

products and we only keep coefficient combinations where both $> 70\%$ of the ocean area over 35°S - 70°S is within two standard deviations of the observed mean (Fig. 2c) and the 0-2000m average ocean heat content poleward of 30°S is within two standard deviations of the observed subsurface mean (Fig. 3a). We choose to use SO-average ocean heat content here rather than the full structure of subsurface temperature trends for two reasons: i) there is substantial spread in subsurface temperature trends across observational products, even in the zonal average (Fig. S3); and ii) the OGCM exhibits biases in the location of the ACC that produces a bias in the location, but not total amount, of heat storage. The use of ocean heat content can be expected to constrain α (representing the magnitude of net surface heat flux), while having little impact on the other coefficients as momentum and freshwater forcing primarily act to redistribute heat within the SO through changes in circulation or stratification.

543 Considering only the observed SST and ocean heat content trends (and their respective un-
 544 certainties), about 49.5% of the prior coefficient combinations pass our observational constraint
 545 (orange posterior distributions in Fig. 9). The posterior distributions of β , γ , δ , and ζ barely
 546 change, consistent with the fact that using observationally-informed patterns and magnitudes of
 547 momentum and freshwater forcing without scaling (all coefficients set to 1) already produce a re-
 548 sponse that is comparable to observations over much of the SO (Fig. 8). However, the distribution
 549 of α is strongly modulated by the SST and ocean heat content constraint such that the posterior
 550 distribution is left-skewed to values slightly lower than 1. It is perhaps not surprising that α is
 551 modulated most strongly, as we chose a global-mean estimate of radiative forcing as our prior:
 552 though this was an adequate first guess, greenhouse gas forcing is smaller at high latitudes than in
 553 the global mean (e.g., Jeevanjee et al. 2021). While the 70% area threshold is a somewhat arbitrary
 554 benchmark, we chose this value to avoid over-constraining our analysis such that certain areas of
 555 the SO could disagree between our estimate and observations to allow for dynamics not considered
 556 in our analysis (e.g., internal variability). Nevertheless, choosing an 80% area threshold primarily
 557 affects the size rather than the mean of the orange posterior distribution. Similarly, though the
 558 specific coefficient distribution presented in this manuscript is random, performing this analysis
 559 multiple times does not qualitatively change the distributions.

560 Using the mean value of each posterior distribution of coefficients for our linear combination
 561 (Fig. S7) somewhat damps the temperature trends seen in the case where all coefficients are equal
 562 to one (Fig. 8), but the key features are similar. However, by only considering the mean and
 563 uncertainty of observed SST and ocean heat content, we are still left with unrealistically high
 564 levels of freshening throughout the SO: while Fig. S7 improves on Fig. 8 with 82.4% of the area
 565 now within two standard deviations of the observed SST trend, still only 51.4% of SSS is within
 566 observational uncertainty. As a result, although this combination agrees with temperature trends,
 567 we view this linear combination as potentially physically unrealistic.

568 To now account for observed changes in salinity, we perform a second Monte Carlo analysis which
 569 considers SSS. We consider this two step analysis preferable than a single step because the prior for
 570 this second Monte Carlo analysis comes from SST, which we have greater confidence in given the
 571 larger number of observational estimates. As above, we loop through 1,000,000 new coefficient
 572 combinations randomly chosen from the orange posterior distributions to create an estimate of SST

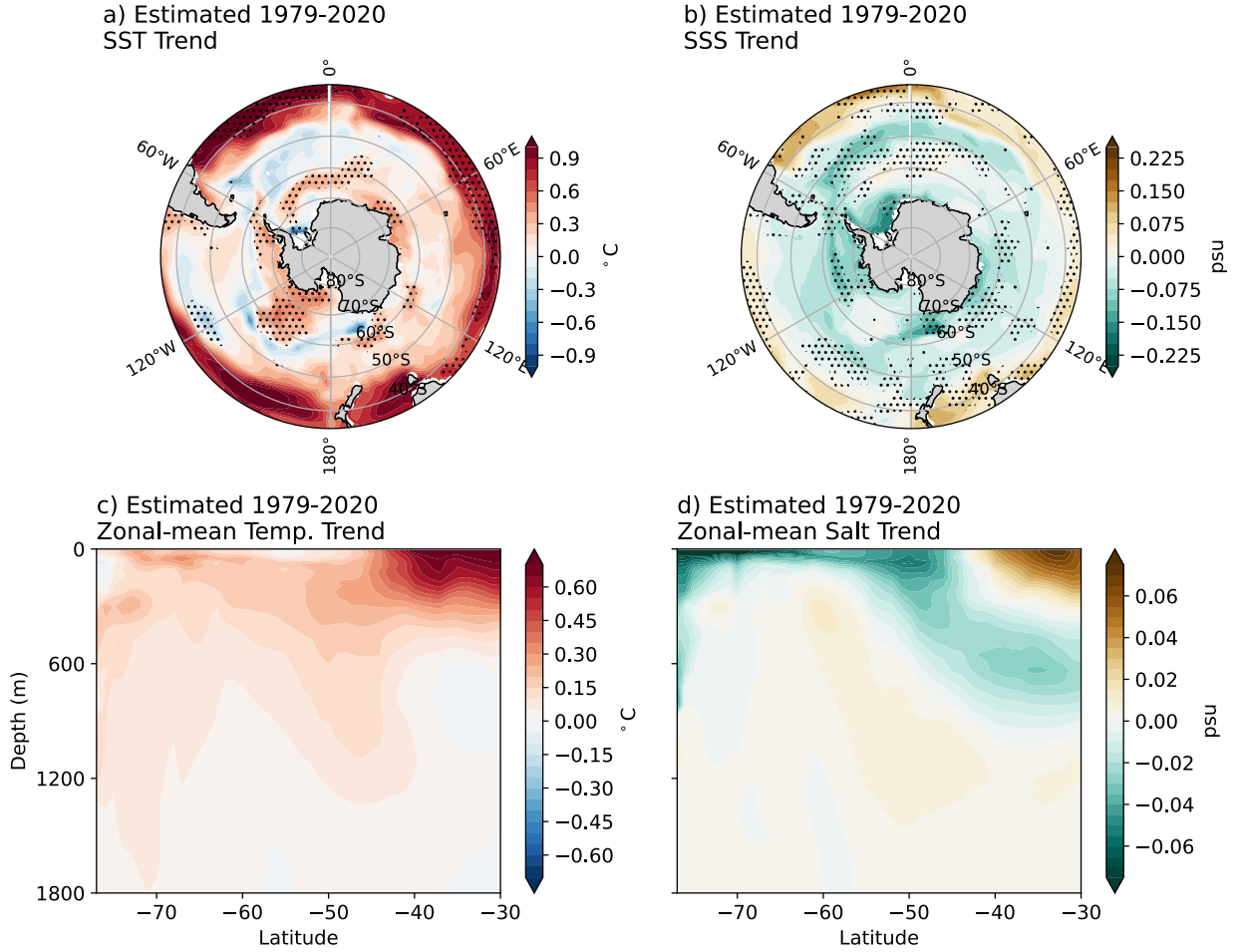


FIG. 10. Linear combination of a) SST, b) SSS, c) subsurface zonal-mean temperature, and d) subsurface zonal-mean salinity 1979-2020 trend according to Equations (4) and (5), where all coefficients are constrained by observed SST, SO-average ocean heat content, and SSS and are the mean of the green posterior distributions in Fig. 9. Stippling in a) and b) represent locations where the linear combination is outside of two standard deviations of the observed mean trend.

and SSS, we calculate the Z-score of each SST and SSS prediction at each point in space using the mean and standard deviation of respective observational products, calculate Z-scores, and then only keep coefficient combinations where $> 70\%$ of the ocean area from 70°S - 35°S is within two standard deviations of the observed mean trends for both SST and SSS.

Requiring both SST and SSS to be within observational uncertainty strongly constrains the analysis. While the final posterior distributions (green posterior distributions in Fig. 9) are more physically plausible than the initial SST-only-derived posteriors, only about 3.4% of the

585 random coefficient combinations pass this stricter observational constraint. Considering observed
586 SSS trends strongly constrains certain coefficient distributions: the magnitudes of all coefficients
587 are reduced relative to the SST-only constraint, with the ice sheet melt and momentum forcing
588 coefficients least modulated.

589 We consider the linear combination using the mean value of coefficients constrained by SST,
590 SSS, and subsurface heat content (green posterior distributions in Fig. 9) as our best estimate
591 of the response to forcings (Fig. 10). As in the case of Fig. S7, this response features cooling
592 throughout various regions of the SO, especially the equatorward sections of the Ross, Amundsen,
593 Bellingshausen, and Weddell Seas, but it now features more realistically patchy salinity trends
594 throughout the SO. Considering SSS does not degrade the quality of the SST estimate: in addition
595 to 71.0% of the SO area now being within SSS observational uncertainty, approximately the same
596 amount (81.7%) of the SO area remains within SST observational uncertainty. Areas outside of
597 observational uncertainty for SST are largely equatorward of the ACC or in climatological sea
598 ice zones, while areas outside of observational uncertainty for SSS are evenly distributed (Figs.
599 10a-b).

600 While these features are encouraging, we note that there is still patchy warming near the coast in
601 our simulated response. Although some observational products show warming in the Amundsen,
602 Bellingshausen, and Ross Seas poleward of the strong cooling (Fig. 1), our simulated warming
603 trend here is larger than the observational-mean temperature trend. This disagreement in the sea
604 ice region reflects the large uncertainty in SST and SSS in these sea ice regions (Figs. 2c-d), and a
605 potential systematic model bias from using an OGCM simulation without coupled feedbacks.

606 Although we have only constrained coefficients to match SST, SSS, and SO-average heat con-
607 tent trends, the spatial patterns of subsurface temperature and salinity trends also broadly match
608 observed trends (c.f. Figs. 10c-d and Fig. 3). In particular, both show zonal-mean surface cooling
609 and subsurface warming near Antarctica and in the ACC band as well as AAIW freshening and
610 subsurface salinification near Antarctica. This suggests that an accurate representation of surface
611 forcings is sufficient to produce reasonable estimates of subsurface changes, even in the absence
612 of changes in atmospheric heat transport or dynamic sea ice.

613 The Monte Carlo analysis leads to several immediate results. First, observationally-informed
614 trends in surface fluxes of heat, momentum, and freshwater appear sufficient to explain much of

615 the SO temperature and salinity changes seen over recent decades – at least within an OGCM with
616 a realistic mean SO state, and despite the many idealizations inherent to our modeling framework.

617 Second, the density functions (Fig. 9) show that while observationally-informed freshwater
618 forcing from trends in $P - E$ and sea ice hydrology cool the SO, they freshen it too much to be
619 considered realistic, and thus are modulated toward lower values when constrained by SSS trends.
620 On the other hand, a wide range of freshwater forcings from ice sheet melt, as the weakest of
621 the three anomalous freshwater forcings in terms of both temperature and salinity responses, are
622 consistent with observed trends. Meanwhile, the momentum forcing distributions do not change
623 much between constraint methods, implying that observationally-informed momentum trends are
624 broadly consistent with observed temperature and salinity trends; this consistency is compelling
625 because we are more confident in wind trends than freshwater trends over this period. We note,
626 however, that part of this agreement is due to our use of the “fast” response to momentum
627 forcing (Section 4b). Performing this same Monte Carlo analysis with the full (including “slow”)
628 response to momentum forcing (Fig. S5), which negatively projects onto the observed mean
629 SST trend, produces values of ζ near zero. Framed another way, the results suggest that given
630 observationally-informed momentum trends, a long-timescale warming response to momentum
631 forcing appears incompatible with observed SO temperature and salinity trends, providing support
632 for the arguments of Doddridge et al. (2019) that the long-timescale warming response may be a
633 feature of low-resolution models rather than of nature.

634 Finally, the radiative forcing coefficient is modulated to even lower values when constraining
635 with SSS trends than when considering only SST and ocean heat content. This result reflects
636 the fact that reducing freshening from β , γ , and δ to match SSS trends inherently means less
637 cooling from freshwater forcing, which otherwise can temper stronger warming from higher α
638 values. Thus, considered together, the most realistic way to agree with both SO temperature and
639 salinity observations is to have both freshwater and momentum forcing that provide some amount
640 of cooling, but also a low radiative forcing which allows that cooling to establish. This is opposed
641 to, for instance, strong freshwater forcing alone (as in the case of Fig. 8 and S7). An important
642 takeaway from this conclusion is that because each forced response has a distinct temperature and
643 salinity fingerprint, considering both temperature and salinity together allows the determination of
644 how each forcing has contributed to observed SO trends.

6. Discussion

a. A wide envelope of uncertainty

We return to the first central question of our study: Given a well-constructed ocean modeling set-up and observationally-informed surface forcings, can we recreate observed Southern Ocean temperature and salinity features within observational uncertainty? Our estimated SO response to idealized historical forcing from heat, freshwater, and momentum fluxes (Fig. 10) exhibits many features common to the observed historical temperature and salinity trends: cooling patches throughout the SO, especially in the Weddell and the Pacific ACC region north of the Ross, Amundsen, and Bellingshausen Seas, a muted warming in the non-cooling regions, subsurface warming near Antarctica, intensified subsurface warming near the ACC, zonally broad surface freshening throughout the open SO, and AAIW freshening above a subsurface salinification. Compared with the many coupled CMIP historical simulations that fail to replicate observed SO trends (e.g., Wills et al. 2022), our best estimate is encouraging. However, the spatial similarity between the estimated SST trend and the multi-product mean observed SST trend near Antarctica is weak in certain regions: while some observational products do suggest warming near the Antarctic coast, especially in the Ross, Amundsen, and Bellingshausen Seas (Fig. 1), our estimated response features too much coastal warming relative to the observed mean.

Nevertheless, our Monte Carlo analysis ensures that our best estimate of the forced response (Fig. 10) is within two standard deviations of the observed mean SST throughout the vast majority of the SO: $\sim 83\%$ of the area is within two standard deviations of the observed mean SST trend and $\sim 71\%$ of the area is within two standard deviations of the observed mean SSS trend. Yet, this agreement also reflects the huge amount of observational uncertainty in historical SST and SSS trends around their mean estimate. That is, our best estimate and the observed mean SST response can look somewhat different while still being statistically consistent. So, our answer to our first central question is that an OGCM driven with observationally-informed surface forcings can recreate observed patterns of SO temperature and salinity trends, but that a critical aspect of this success is the large observational uncertainty.

This suggests that studies that consider only one or a limited set of observational products may produce results that are strongly shaped by that choice. For instance, Wills et al. (2022) largely

674 focus their analysis on ERSSTv5 (a precursor to ERSSTv6), which is an outlier in terms of SO
675 cooling magnitude, and only considered the uncertainty across three observational SST datasets,
676 likely influencing the conclusion that very few model ensembles capture “observed” cooling in this
677 region. Had the Wills et al. (2022) analysis used one of the dynamically-consistent SST estimates
678 [e.g., from Cooper et al. (2025) or Chan et al. (2026), which were not available at the time but show
679 muted SO SST trends], or considered the spread across more datasets as we have done here, it
680 may have reached different conclusions. Thus, we recommend that future studies on the mismatch
681 between observed and CMIP-modeled SO trends explicitly consider this substantial observational
682 uncertainty.

683 In this study, we take a relatively even-handed approach to observations. Rather than picking
684 and choosing among them, we set selection criteria and accept all observations which adhere to
685 those criteria as equally plausible realities. However, we acknowledge that there is some true SO
686 temperature and salinity trend over this period; while we may not know what that truth is, some
687 observational products are closer to that truth than others. Thus, an important next step in further
688 clarifying the drivers of SO changes and the extent to which coupled models and observations
689 disagree over the historical period would be to classify and rank observational products in terms of
690 their specific skill in the SO and only consider those observational products deemed fit for purpose.
691 One possible criteria to start producing this ranking, for instance, might be to favor products which
692 are dynamically-consistent across multiple climate variables (e.g., Cooper et al. 2025; Chan et al.
693 2026) and which show better consistency with the satellite-estimated sea ice record. For example,
694 we also performed our SST-constrained Monte Carlo analysis using the Cooper25 mean SST trend
695 and uncertainty (Fig. S8). Because the uncertainty in this one product is substantially smaller
696 than the uncertainty across the full-suite of products (Fig. 2c), only a small number of coefficient
697 combinations ($n \approx 1100$) create SST trends within uncertainty in over 70% of the SO area. However,
698 the temperature and salinity patterns estimated only using Cooper25 look reasonably similar to
699 Fig. 10, which results from similar coefficient posterior distributions (with the exception of ζ).

700 *b. Dynamical Implications*

701 Using an idealized model is helpful to ascertain cause and effect without the muddying influence
702 of coupled feedbacks. We did not expect our idealized modeling framework to perfectly recreate the

703 observed temperature and salinity trends given that it lacks important features such as changes in
704 atmospheric heat transport and sea ice feedbacks. Rather, we are most interested in understanding
705 the ocean's response to observed forcings, and then evaluating how much of the observed response
706 can be understood through the ocean response alone. With that in mind, there are several dynamical
707 details that our simulations help to clarify for climate-focused studies of SO trends.

708 First, cooling in the Pacific sector of the Southern Ocean is strongly influenced by freshwater
709 forcing (Fig. 7a). Not only is the Pacific sector of the SO the only region where all observational
710 products unanimously agree that there has been cooling, but it has also been proposed as a
711 potentially critical component of an atmospheric teleconnection between observed cooling in
712 the SO and SH subtropical Pacific (Dong et al. 2022a; Kim et al. 2022; Kang et al. 2023).
713 Interestingly, freshwater forcing from changes in precipitation, ice sheet melt, and sea ice hydrology
714 all contribute to cooling in this region (Fig. S6), suggesting that cooling there is a robust response
715 to surface freshwater forcing in any form. While the precise dynamics of this adjustment merit
716 further investigation, we note that changes in surface freshwater alone can drive strong, zonally-
717 asymmetric changes in temperature within the ACC (Fig. 7a) that have otherwise often been
718 primarily considered in terms of wind changes (e.g., Spence et al. 2010).

719 Another important conclusion is that heat-forced changes can shape large-scale salinity features.
720 This conclusion is seen most clearly in maps of subsurface salinity: the observed subducting
721 AAIW freshening signal is captured in simulations forced only by radiative forcing (Fig. 5d),
722 affirming Durack and Wijffels (2010)'s hypothesis based on observations alone. More broadly, this
723 conclusion shows the importance of heat fluxes in shaping the pattern of ocean salinity trends, on top
724 of changes in freshwater fluxes. Due to the magnitude of historical and projected anthropogenic
725 radiative forcing, these effects are important to keep in mind when investigating the causes of
726 observed salinity trends.

727 Finally, it is important to consider both salinity changes and temperature changes in tandem.
728 For instance, while winds largely lead to an SST cooling due to enhanced northward Ekman
729 transport (Fig. 6a), they simultaneously lead to a large-scale salinification of the SO as warm,
730 salty waters are upwelled from depth near Antarctica. Thus, it is not reasonable to only consider
731 wind-driven momentum changes as a possible driver of the historical SO SST mismatch. Even
732 in a high resolution model that may better resolve the wind-driven coastal warming issue (e.g.,

733 Doddridge et al. 2019), salinity is still an important fingerprint for momentum-forced changes.
734 Observationally-informed momentum flux trends only make sense as a driver of SO cooling if they
735 are considered in concert with other forcings that lead to SO freshening, such as freshwater fluxes.
736 As another example, we show that observationally-informed freshwater surface fluxes cool the SO
737 considerably (Fig. 7a) and could explain a substantial fraction of the mean SST cooling trend
738 (Fig. 2a). However, basing our simulations only on SST suggests far too much SO freshening;
739 a more realistic SO freshening suggests a weaker radiative forcing. Importantly, any solution to
740 the question of what has driven the historical observed SO surface cooling and freshening must
741 be physically and dynamically consistent with the full suite of available surface and subsurface
742 observations.

743 Differences between our best estimate of observationally-informed forced trends and observations
744 (c.f. Fig. 10 and Figs 2a-b and 3) also point to potential dynamical implications. For instance, most
745 observational products agree there has been substantial cooling north of Queen Maud Land and
746 west of the Weddell Sea (Fig. 1), but our simulations do not produce substantial cooling here. This
747 region is also nearly exactly where a large polynya formed in the mid-1970s. Internal variability
748 of deep SO convection, as would be driven by this large polynya event, has been implicated as
749 a potential driver of satellite-era SO SST trends: Zhang et al. (2019) show that SSTs cool around
750 Antarctica when simulations are initialized from a convective state akin to the mid-1970s. Because
751 our simulations do not include any internal variability, they are missing this potentially important
752 dynamic. This may then help to explain some of the lack of cooling in this region in our simulations.
753 Meanwhile, the general agreement between our best estimate of observationally-informed forced
754 trends and observations (c.f. Fig. 10 and Figs. 2a-b and 3) suggests that internal variability may
755 have played a smaller role in driving SO trends over most other regions.

756 **7. Conclusions**

757 In this study we use an ocean-only GCM with a relatively realistic mean state to show that
758 observationally-informed surface forcings of heat, momentum, and freshwater can recreate key
759 features of observed satellite-era SO temperature and salinity trends within observational uncer-
760 tainty. Despite the fact that our ocean-only modeling framework does not include several potentially
761 important SO processes, such as coupled sea ice dynamics, atmospheric heat transport, resolved

mesoscale and finer eddies, or internal variability, we show that a simple linear combination of the oceanic response to these forcings can create SO temperature and salinity changes within the envelope of observational uncertainties. This result suggests that the observed SO trends can be largely explained through ocean-only processes given observationally-informed surface forcings.

Our approach of taking linear combinations of the response to individual forcings provides important insights into the drivers of key patterns of observed changes, such as the well-agreed-upon Pacific sector cooling and AAIW freshening. While certain regions of our best estimate of the observationally-informed forced response (Fig. 10a) show SST trends opposite to the mean observed trend (Fig. 2a), especially near the Antarctic coast, the vast majority of the SO in our estimate is within observational uncertainty. This result also reflects the large disagreement between observational products in general (Fig. 1). This uncertainty is especially pronounced in regions with seasonal sea ice coverage.

This work was directly inspired by the variety of studies that have sought to explain historical SO SST cooling. While our results using an idealized modeling framework do not, and cannot, provide a definitive solution to this multi-faceted problem, we conclude with several major takeaways:

1. The true trend in historical SO temperatures and salinity is not perfectly known due to substantial observational estimate disagreement. Future studies on this topic should consider this uncertainty or create a hierarchy of observational estimates.
2. Salinity changes provide a major constraint on mechanisms driving observed SST changes. Thus, while a variety of forcings could create an SST response that resembles observations, only a very specific subset of those responses also match observed SSS change and uncertainty.
3. While zonal-mean changes in the SO have largely been considered in the literature, our results hint at the importance of considering regional, zonally-varying change. For example, it may be more appropriate to ask how models perform relative to observations in the north of the Ross, Amundsen, and Bellingshausen Seas specifically, rather than how they perform relative to a zonal-mean index. Similarly, it may not be appropriate to ask whether a model without decadal variability in deep ocean convection can be expected to cool in regions with observed open ocean polynyas.

4. Directly following from point 3, this work highlights that each forced response has a distinct temperature and salinity fingerprint. These fingerprints may be useful tools to diagnose drivers of regional change.

5. Changes in surface fluxes due to greenhouse gases, winds, and freshwater are all necessary to explain observed SO temperature and salinity trends.

Our results suggest a rethinking of why the Southern Ocean has both cooled and freshened over the historical era. In particular, we test many of the hypotheses proposed throughout previous work using an oceanographic framework and, in doing so, show that a coarse resolution model without coupled processes can recreate SO SST and SSS change within observational uncertainty. However, this agreement is only possible because the observational uncertainty is quite wide. This understanding provides nuance to the larger discussion of observed SO cooling and the observed versus modeled historical SO SST mismatch, suggesting certain prior hypotheses are less likely than others, motivating future work to “rank” observational products in terms of in situ historical observations, and recommending a more holistic approach to climate-focused SO studies that considers both regional changes and salinity.

Acknowledgments. MTL was supported by the Cooperative Institute for Climate, Ocean, & Ecosystem Studies (CICOES) under NOAA Cooperative Agreement NA20OAR4320271, Contribution No. XX. KCA was supported by National Science Foundation (NSF) Award AGS-2203543 and a Calvin Professorship in Oceanography. GCJ was supported in part by NOAA Research. We thank NSF NCAR for providing an exploratory allocation of core hours on the Derecho supercomputer. Without implying their endorsement, we thank Dave Bonan, David Battisti, Jeffery Scott, LuAnne Thompson, and Cecilia Bitz for helpful discussions and suggestions. PMEL Contribution Number 5890.

Data availability statement. MITgcm simulations used in this study will be uploaded to Zenodo upon study publication.

Observational products were last accessed in February 2026 and are available as follows: NOAA ERSSTv6 SST data (Huang et al. 2025) is provided by the NOAA PSL, Boulder, Colorado, USA at <https://psl.noaa.gov>; COBE-SST3 SST data (Ishii et al. 2025) is provided by Japan Meteorological Agency Meteorological Research Institute at <https://climate.mri-jma.g>

819 o.jp/pub/archives/Ishii-et-al_COBE-SST3/; HadISST1 SST data (Rayner et al.
 820 2003) is provided by the UK Met Office Hadley Research Centre at <https://www.metoffice.gov.uk/hadobs/hadisst/data/download.html>; DCENT-I SST data (Chan et al.
 821 2026) is provided at <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/R0G38Q>; Cooper25 SST data (Cooper et al. 2025) is provided at
 822 <https://zenodo.org/records/17714760>; ERA5 SST data (Hersbach et al. 2020) is provided
 823 by the European Center for Medium-Range Weather Forecasts Copernicus Climate Data Store
 824 at <https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels-monthly-means?tab=overview>; WOA23 temperature and salinity data (Locarnini
 825 et al. 2024; Reagan et al. 2024)] is provided by the NOAA National Centers for Environmental
 826 Information at <https://www.ncei.noaa.gov/access/world-ocean-atlas-2023/>; IAP
 827 temperature and salinity data (Cheng et al. 2024) is provided at http://www.ocean.iap.ac.cn/ftp/cheng/CZ16_v3_IAP_Temperature_gridded_1month_netcdf/Monthly/ and
 828 http://www.ocean.iap.ac.cn/ftp/cheng/CZ16_v0_IAP_Salinity_gridded_1month_netcdf/Monthly/ respectively; EN04 data (Good et al. 2013) with the ‘g10’ bias correction
 829 (Gouretski and Reseghetti 2010; Gouretski and Cheng 2020) is provided by the UK Met Office at
 830 <https://www.metoffice.gov.uk/hadobs/en4/>.
 831
 832
 833
 834
 835

836 APPENDIX

837 Fast & Slow Timescales of Forced Responses

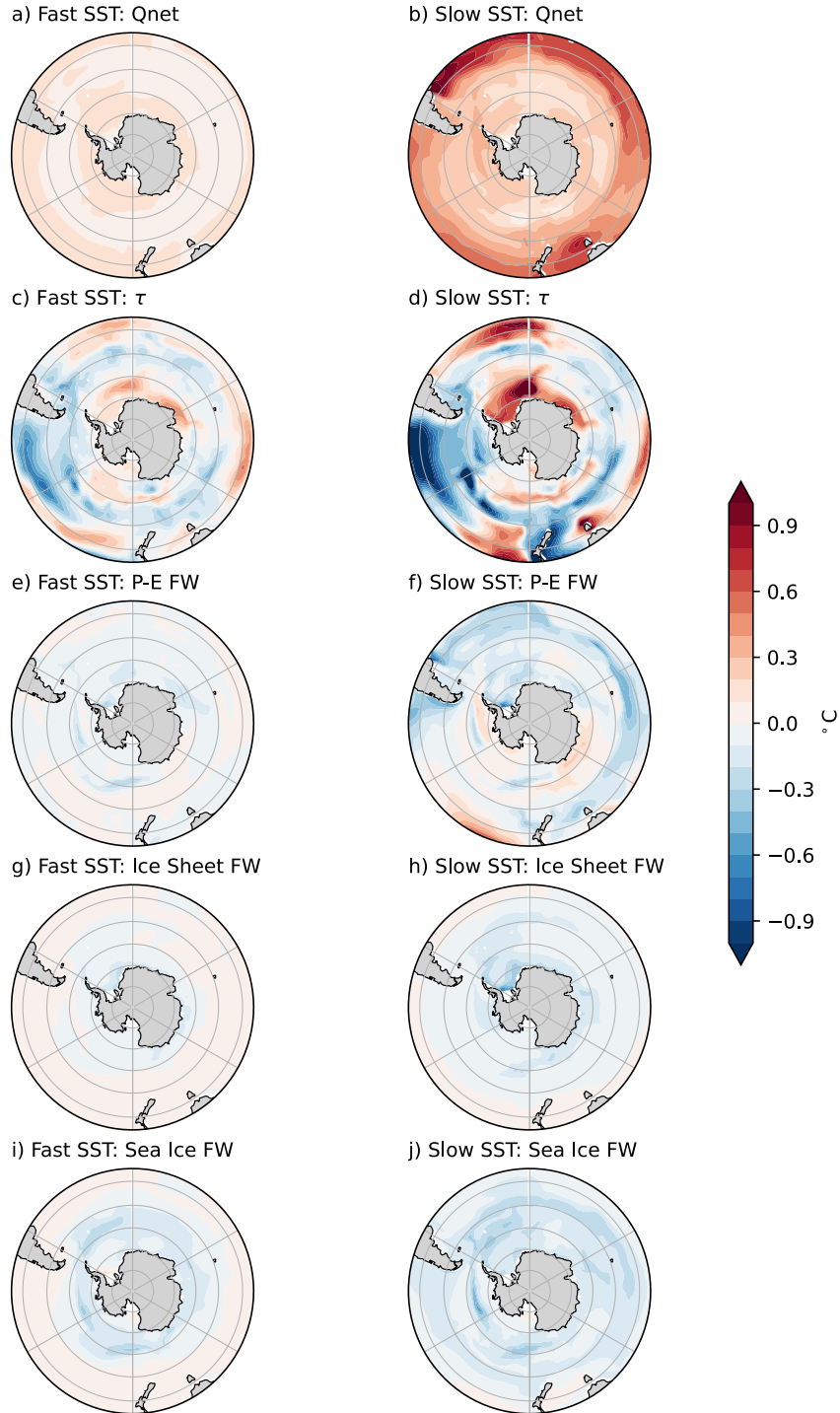


FIG. A1. Left column: “Fast” response (year 2) of SST to step change in forcing from heat (first row),
momentum (second row), $P - E$ freshwater (third row), ice sheet melt freshwater (fourth row), and sea ice
freshwater (fifth row). Right column: “Slow” response (year 30) of SST to step change in forcing.

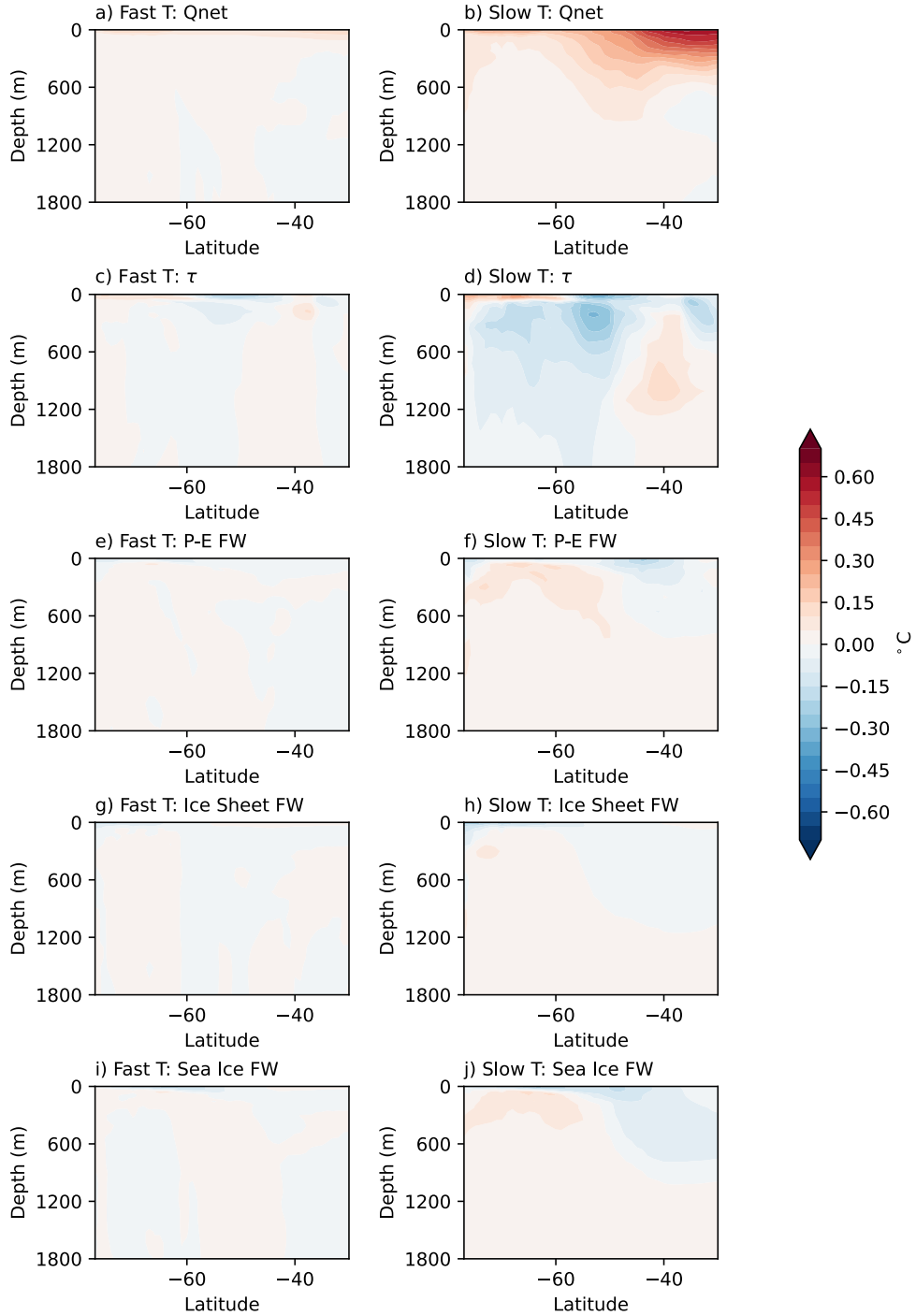


FIG. A2. Left column: “Fast” response (year 2) of zonal-mean SO temperature to step change in forcing from heat (first row), momentum (second row), $P-E$ freshwater (third row), ice sheet melt freshwater (fourth row), and sea ice freshwater (fifth row). Right column: “Slow” response (year 30) of zonal-mean SO temperature to step change in forcing.

References

- Armour, K. C., J. Marshall, J. R. Scott, A. Donohoe, and E. R. Newsom, 2016: Southern Ocean Warming Delayed by Circumpolar Upwelling and Equatorward Transport. *Nature Geoscience*, **9** (7), 549–554.
- Bilgen, S. I., and B. P. Kirtman, 2020: Impact of Ocean Model Resolution on Understanding the Delayed Warming of the Southern Ocean. *Environmental Research Letters*, **15** (11), 114 012.
- Bintanja, R., G. J. van Oldenborgh, S. Drijfhout, B. Wouters, and C. Katsman, 2013: Important Role for Ocean Warming and Increased Ice-Shelf Melt in Antarctic Sea-Ice Expansion. *Nature Geoscience*, **6** (5), 376–379.
- Bitz, C., and L. M. Polvani, 2012: Antarctic Climate Response to Stratospheric Ozone Depletion in a Fine Resolution Ocean Climate Model. *Geophysical Research Letters*, **39** (20).
- Blanchard-Wrigglesworth, E., L. A. Roach, A. Donohoe, and Q. Ding, 2021: Impact of Winds and Southern Ocean SSTs on Antarctic Sea Ice Trends and Variability. *Journal of Climate*, **34** (3), 949–965.
- Bromwich, D. H., J. P. Nicolas, and A. J. Monaghan, 2011: An Assessment of Precipitation Changes over Antarctica and the Southern Ocean since 1989 in Contemporary Global Reanalyses. *Journal of Climate*, **24** (16), 4189–4209.
- Chan, D., and Coauthors, 2026: DCENT-I: A Globally Infilled Extension of the Dynamically Consistent ENsemble of Temperature Dataset. *Geoscience Data Journal*, **13** (2), e70 054.
- Cheng, L., and Coauthors, 2024: IAPv4 Ocean Temperature and Ocean Heat Content Gridded Dataset. *Earth System Science Data Discussions*, **2024**, 1–56.
- Chung, E.-S., and Coauthors, 2022: Antarctic Sea-Ice Expansion and Southern Ocean Cooling Linked to Tropical Variability. *Nature Climate Change*, **12** (5), 461–468.
- Cooper, V. T., G. J. Hakim, and K. C. Armour, 2025: Monthly Sea Surface Temperature, Sea Ice, and Sea Level Pressure over 1850–2023 from Coupled Data Assimilation. *Journal of Climate*, **38** (19), 5461–5490.

- 871 Doddridge, E. W., J. Marshall, H. Song, J.-M. Campin, M. Kelley, and L. Nazarenko, 2019: Eddy
872 Compensation Dampens Southern Ocean Sea Surface Temperature Response to Westerly Wind
873 Trends. *Geophysical Research Letters*, **46** (8), 4365–4377.
- 874 Dong, Y., K. C. Armour, D. S. Battisti, and E. Blanchard-Wrigglesworth, 2022a: Two-Way
875 Teleconnections between the Southern Ocean and the Tropical Pacific via a Dynamic Feedback.
876 *Journal of Climate*, **35** (19), 6267–6282.
- 877 Dong, Y., A. G. Pauling, S. Sadai, and K. C. Armour, 2022b: Antarctic Ice-Sheet Meltwater Re-
878 duces Transient Warming and Climate Sensitivity through the Sea-Surface Temperature Pattern
879 Effect. *Geophysical Research Letters*, **49** (24), e2022GL101 249.
- 880 Durack, P. J., and S. E. Wijffels, 2010: Fifty-year Trends in Global Ocean Salinities and Their
881 Relationship to Broad-Scale Warming. *Journal of Climate*, **23** (16), 4342–4362.
- 882 Durack, P. J., S. E. Wijffels, and R. J. Matear, 2012: Ocean Salinities Reveal Strong Global Water
883 Cycle Intensification during 1950 to 2000. *science*, **336** (6080), 455–458.
- 884 Dvorak, M., K. C. Armour, D. M. Frierson, C. Proistosescu, M. B. Baker, and C. J. Smith, 2022:
885 Estimating the Timing of Geophysical Commitment to 1.5 and 2.0 °C of Global Warming. *Nature*
886 *Climate Change*, **12** (6), 547–552.
- 887 Farneti, R., and Coauthors, 2015: An Assessment of Antarctic Circumpolar Current and Southern
888 Ocean Meridional Overturning Circulation during 1958–2007 in a Suite of Interannual CORE-II
889 Simulations. *Ocean Modelling*, **93**, 84–120.
- 890 Ferreira, D., J. Marshall, C. M. Bitz, S. Solomon, and A. Plumb, 2015: Antarctic Ocean and
891 Sea Ice Response to Ozone Depletion: A Two-Time-Scale Problem. *Journal of Climate*, **28** (3),
892 1206–1226.
- 893 Forget, G., J.-M. Campin, P. Heimbach, C. Hill, R. Ponte, and C. Wunsch, 2015: ECCO version 4:
894 An Integrated Framework for Non-Linear Inverse Modeling and Global Ocean State Estimation.
895 *Geoscientific Model Development*, **8** (10), 3071–3104.
- 896 Forster, P., and Coauthors, 2021: The Earth’s Energy Budget, Climate Feedbacks, and Climate
897 Sensitivity. *Climate Change 2021: The Physical Science Basis. Contribution of Working Group*

I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, V. Masson-Delmotte, P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J. B. R. Matthews, T. K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou, Eds., Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 923–1054, <https://doi.org/10.1017/9781009157896.009>.

Fyfe, J., N. Gillett, and G. Marshall, 2012: Human Influence on Extratropical Southern Hemisphere Summer Precipitation. *Geophysical Research Letters*, **39** (23).

Fyfe, J. C., and O. A. Saenko, 2006: Simulated Changes in the Extratropical Southern Hemisphere Winds and Currents. *Geophysical Research Letters*, **33** (6).

Fyfe, J. C., O. A. Saenko, K. Zickfeld, M. Eby, and A. J. Weaver, 2007: The Role of Poleward-Intensifying Winds on Southern Ocean Warming. *Journal of Climate*, **20** (21), 5391–5400.

Good, S. A., M. J. Martin, and N. A. Rayner, 2013: EN4: Quality Controlled Ocean Temperature and Salinity Profiles and Monthly Objective Analyses with Uncertainty Estimates. *Journal of Geophysical Research: Oceans*, **118** (12), 6704–6716.

Gouretski, V., and L. Cheng, 2020: Correction for Systematic Errors in the Global Dataset of Temperature Profiles from Mechanical Bathythermographs. *Journal of Atmospheric and Oceanic Technology*, **37** (5), 841–855.

Gouretski, V., and F. Reseghetti, 2010: On Depth and Temperature Biases in Bathythermograph Data: Development of a New Correction Scheme Based on Analysis of a Global Ocean Database. *Deep Sea Research Part I: Oceanographic Research Papers*, **57** (6), 812–833.

Gregory, J. M., 2000: Vertical Heat Transports in the Ocean and Their Effect on Time-Dependent Climate Change. *Climate Dynamics*, **16** (7), 501–515.

Hallberg, R., and A. Gnanadesikan, 2006: The Role of Eddies in Determining the Structure and Response of the Wind-Driven Southern Hemisphere Overturning: Results from the Modeling Eddies in the Southern Ocean (MESO) project. *Journal of Physical Oceanography*, **36** (12), 2232–2252.

Hartmann, D. L., 2022: The Antarctic Ozone Hole and the Pattern Effect on Climate Sensitivity. *Proceedings of the National Academy of Sciences*, **119** (35), e2207889 119.

926 Hasselmann, K., R. Sausen, E. Maier-Reimer, and R. Voss, 1993: On the Cold Start Problem
 927 in Transient Simulations with Coupled Atmosphere-Ocean Models. *Climate Dynamics*, **9** (2),
 928 53–61.

929 Haumann, F. A., N. Gruber, and M. Münnich, 2020: Sea-Ice Induced Southern Ocean Subsurface
 930 Warming and Surface Cooling in a Warming Climate. *AGU Advances*, **1** (2), e2019AV000 132.

931 Haumann, F. A., N. Gruber, M. Münnich, I. Frenger, and S. Kern, 2016: Sea-Ice Transport Driving
 932 Southern Ocean Salinity and its Recent Trends. *Nature*, **537** (7618), 89–92.

933 Hersbach, H., and Coauthors, 2020: The ERA5 Global Reanalysis. *Quarterly journal of the royal*
 934 *meteorological society*, **146** (730), 1999–2049.

935 Huang, B., and Coauthors, 2025: Extended Reconstructed Sea Surface Temperature, Version 6
 936 (ERSSTv6). Part I: An Artificial Neural Network Approach. *Journal of Climate*, **38** (4), 1105–
 937 1121.

938 Ishii, M., A. Nishimura, S. Yasui, and S. Hirahara, 2025: Historical High-Resolution Daily SST
 939 Analysis (COBE-SST3) with Consistency to Monthly Land Surface Air Temperature. *Journal*
 940 *of the Meteorological Society of Japan. Ser. II*, **103** (1), 17–44.

941 Jeevanjee, N., J. T. Seeley, D. Paynter, and S. Fueglistaler, 2021: An Analytical Model for Spatially
 942 Varying Clear-Sky CO₂ Forcing. *Journal of Climate*, **34** (23), 9463–9480.

943 Kang, S. M., D. A. Putrasahan, N. G. Brizuela, H. Haak, J. Kröger, J. Marotzke, B. Stevens,
 944 and J.-S. von Storch, 2026: Km-Scale Coupled Simulation and Model–Observation SST Trend
 945 Discrepancy. *Proceedings of the National Academy of Sciences*, **123** (8), e2522161 123.

946 Kang, S. M., Y. Yu, C. Deser, X. Zhang, I.-S. Kang, S.-S. Lee, K. B. Rodgers, and P. Ceppi, 2023:
 947 Global Impacts of Recent Southern Ocean Cooling. *Proceedings of the National Academy of*
 948 *Sciences*, **120** (30), e2300881 120.

949 Kaufman, Z., E. Wilson, A. Purich, R. Beadling, and Y. Li, 2025: The Impact of Underesti-
 950 mated Southern Ocean Freshening on Simulated Historical Sea Surface Temperature Trends.
 951 *Geophysical Research Letters*, **52** (6), e2024GL112 639.

952 Kent, E. C., and J. J. Kennedy, 2021: Historical Estimates of Surface Marine Temperatures. *Annual*
953 *Review of Marine Science*, **13** (1), 283–311.

954 Kim, H., S. M. Kang, J. E. Kay, and S.-P. Xie, 2022: Subtropical Clouds Key to Southern Ocean
955 Teleconnections to the Tropical Pacific. *Proceedings of the National Academy of Sciences*,
956 **119** (34), e2200514 119.

957 Kirkman IV, C. H., and C. M. Bitz, 2011: The Effect of the Sea Ice Freshwater Flux on Southern
958 Ocean Temperatures in CCSM3: Deep-Ocean Warming and Delayed Surface Warming. *Journal*
959 *of Climate*, **24** (9), 2224–2237.

960 Kostov, Y., D. Ferreira, K. C. Armour, and J. Marshall, 2018: Contributions of Greenhouse Gas
961 Forcing and the Southern Annular Mode to Historical Southern Ocean Surface Temperature
962 Trends. *Geophysical Research Letters*, **45** (2), 1086–1097.

963 Kostov, Y., J. Marshall, U. Hausmann, K. C. Armour, D. Ferreira, and M. M. Holland, 2017: Fast
964 and Slow Responses of Southern Ocean Sea Surface Temperature to SAM in Coupled Climate
965 Models. *Climate Dynamics*, **48** (5), 1595–1609.

966 Li, S., W. Liu, L. Zhang, W. J. Seviour, and G. A. Schmidt, 2026: Stratospheric Ozone
967 Depletion Causes Southern Ocean Surface Cooling. *Geophysical Research Letters*, **53** (13),
968 e2025GL120 200.

969 Locarnini, R. A., and Coauthors, 2024: World Ocean Atlas 2023, Volume 1: Temperature. *NOAA*
970 *Atlas NESDIS*, **90**.

971 Luongo, M. T., S.-P. Xie, I. Eisenman, S. Sun, and K. C. Armour, 2026: Explaining the Equa-
972 torial Pacific Thermocline Response to Climate Change with a Model Hierarchy. *Journal of*
973 *Geophysical Research: Oceans*, **131** (7), e2025JC023 559.

974 Luongo, M. T., S.-P. Xie, I. Eisenman, S. Sun, and Q. Peng, 2025: How the Subsurface Tropical
975 Pacific Responds to Subtropical Surface Cooling: Implications for Cross-Equatorial Transport.
976 *Journal of Climate*, **38** (14), 3313–3331.

977 Lyman, J. M., and G. C. Johnson, 2014: Estimating Global Ocean Heat Content Changes in the
978 Upper 1800 m since 1950 and the Influence of Climatology Choice. *Journal of Climate*, **27** (5),
979 1945–1957.

- 980 Manabe, S., R. J. Stouffer, M. J. Spelman, and K. Bryan, 1991: Transient Responses of a Coupled
981 Ocean–Atmosphere Model to Gradual Changes of Atmospheric CO₂. Part I. Annual Mean
982 Response. *Journal of Climate*, **4 (8)**, 785–818.
- 983 Marshall, J., A. Adcroft, C. Hill, L. Perelman, and C. Heisey, 1997a: A Finite-Volume, Incom-
984 pressible Navier Stokes Model for Studies of the Ocean on Parallel Computers. *Journal of*
985 *Geophysical Research: Oceans*, **102 (C3)**, 5753–5766.
- 986 Marshall, J., K. C. Armour, J. R. Scott, Y. Kostov, U. Hausmann, D. Ferreira, T. G. Shepherd,
987 and C. M. Bitz, 2014: The Ocean’s Role in Polar Climate Change: Asymmetric Arctic and
988 Antarctic Responses to Greenhouse Gas and Ozone Forcing. *Philosophical Transactions of the*
989 *Royal Society A: Mathematical, Physical and Engineering Sciences*, **372 (2019)**.
- 990 Marshall, J., C. Hill, L. Perelman, and A. Adcroft, 1997b: Hydrostatic, quasi-hydrostatic, and
991 nonhydrostatic ocean modeling. *Journal of Geophysical Research: Oceans*, **102 (C3)**, 5733–
992 5752.
- 993 Marshall, J., J. R. Scott, K. C. Armour, J.-M. Campin, M. Kelley, and A. Romanou, 2015: The
994 Ocean’s Role in the Transient Response of Climate to Abrupt Greenhouse Gas Forcing. *Climate*
995 *Dynamics*, **44 (7)**, 2287–2299.
- 996 Millero, F. J., 1993: What is PSU? *Oceanography*, **6 (3)**, 67–67.
- 997 Moorman, R., A. F. Thompson, M. K. Youngs, and A. L. Stewart, 2026: The Antarctic Coastal
998 Ocean Heat Budget is Dominated by Heat Loss to Land Ice Melt. *Science Advances*, **12 (9)**,
999 eaec7443.
- 1000 Murphy, D., S. Solomon, R. Portmann, K. Rosenlof, P. Forster, and T. Wong, 2009: An Obser-
1001 vationally Based Energy Balance for the Earth since 1950. *Journal of Geophysical Research:*
1002 *Atmospheres*, **114 (D17)**.
- 1003 Pauling, A. G., C. M. Bitz, I. J. Smith, and P. J. Langhorne, 2016: The Response of the Southern
1004 Ocean and Antarctic Sea Ice to Freshwater from Ice Shelves in an Earth System Model. *Journal*
1005 *of Climate*, **29 (5)**, 1655–1672.

1006 Peng, Q., S.-P. Xie, D. Wang, R. X. Huang, G. Chen, Y. Shu, J.-R. Shi, and W. Liu, 2022: Surface
 1007 Warming–Induced Global Acceleration of Upper Ocean Currents. *Science Advances*, **8** (16),
 1008 eabj8394.

1009 Polvani, L. M., D. W. Waugh, G. J. Correa, and S.-W. Son, 2011: Stratospheric Ozone Deple-
 1010 tion: The Main Driver of Twentieth-Century Atmospheric Circulation Changes in the Southern
 1011 Hemisphere. *Journal of Climate*, **24** (3), 795–812.

1012 Purich, A., M. H. England, W. Cai, A. Sullivan, and P. J. Durack, 2018: Impacts of Broad-Scale
 1013 Surface Freshening of the Southern Ocean in a Coupled Climate Model. *Journal of Climate*,
 1014 **31** (7), 2613–2632.

1015 Rayner, N. A., D. E. Parker, E. Horton, C. K. Folland, L. V. Alexander, D. Rowell, E. C. Kent, and
 1016 A. Kaplan, 2003: Global Analyses of Sea Surface Temperature, Sea Ice, and Night Marine Air
 1017 Temperature since the Late Nineteenth Century. *Journal of Geophysical Research: Atmospheres*,
 1018 **108** (D14).

1019 Reagan, J. R., and Coauthors, 2024: World Ocean Atlas 2023, Volume 2: Salinity. *NOAA Atlas*
 1020 *NESDIS*, **90**.

1021 Roach, L. A., K. D. Mankoff, A. Romanou, E. Blanchard-Wrigglesworth, T. W. Haine, and G. A.
 1022 Schmidt, 2023: Winds and Meltwater Together Lead to Southern Ocean Surface Cooling and
 1023 Sea Ice Expansion. *Geophysical Research Letters*, **50** (24), e2023GL105 948.

1024 Roach, L. A., and Coauthors, 2020: Antarctic Sea Ice Area in CMIP6. *Geophysical Research*
 1025 *Letters*, **47** (9), e2019GL086 729.

1026 Rye, C. D., J. Marshall, M. Kelley, G. Russell, L. S. Nazarenko, Y. Kostov, G. A. Schmidt, and
 1027 J. Hansen, 2020: Antarctic Glacial Melt as a Driver of Recent Southern Ocean Climate Trends.
 1028 *Geophysical Research Letters*, **47** (11), e2019GL086 892.

1029 Schmidt, G. A., and Coauthors, 2023: Anomalous Meltwater from Ice Sheets and Ice Shelves is a
 1030 Historical Forcing. *Geophysical Research Letters*, **50** (24), e2023GL106 530.

1031 Schulzweida, U., 2023: CDO User Guide. Zenodo, URL <https://doi.org/10.5281/zenodo.1002080>
 1032 0, <https://doi.org/10.5281/zenodo.10020800>.

- 1033 Sen Gupta, A., and M. H. England, 2006: Coupled Ocean–Atmosphere–Ice Response to Variations
1034 in the Southern Annular Mode. *Journal of Climate*, **19 (18)**, 4457–4486.
- 1035 Shi, J.-R., L. D. Talley, S.-P. Xie, W. Liu, and S. T. Gille, 2020: Effects of Buoyancy and Wind
1036 Forcing on Southern Ocean Climate Change. *Journal of Climate*, **33 (23)**, 10 003–10 020.
- 1037 Singh, H., L. M. Polvani, and P. J. Rasch, 2019: Antarctic Sea Ice Expansion, Driven by Internal
1038 Variability, in the Presence of Increasing Atmospheric CO₂. *Geophysical Research Letters*,
1039 **46 (24)**, 14 762–14 771.
- 1040 Spence, P., J. C. Fyfe, A. Montenegro, and A. J. Weaver, 2010: Southern Ocean Response to
1041 Strengthening Winds in an Eddy-Permitting Global Climate Model. *Journal of Climate*, **23 (19)**,
1042 5332–5343.
- 1043 Swart, N., and J. Fyfe, 2013: The Influence of Recent Antarctic Ice Sheet Retreat on Simulated
1044 Sea Ice Area Trends. *Geophysical Research Letters*, **40 (16)**, 4328–4332.
- 1045 Swart, N., and J. C. Fyfe, 2012: Observed and Simulated Changes in the Southern Hemisphere
1046 Surface Westerly Wind-Stress. *Geophysical Research Letters*, **39 (16)**.
- 1047 Swart, N. C., S. T. Gille, J. C. Fyfe, and N. P. Gillett, 2018: Recent Southern Ocean Warming and
1048 Freshening Driven by Greenhouse Gas Emissions and Ozone Depletion. *Nature Geoscience*,
1049 **11 (11)**, 836–841.
- 1050 Swart, N. C., and Coauthors, 2023: The Southern Ocean Freshwater Input from Antarctica (SOFIA)
1051 Initiative: Scientific Objectives and Experimental Design. *Geoscientific Model Development*,
1052 **16 (24)**, 7289–7309.
- 1053 Taylor, B. A., J.-R. Shi, S.-P. Xie, L. D. Talley, M. T. Luongo, and Q. Peng, 2025: Warming
1054 Band in Southern Ocean’s Indian Sector: The Role of Remote Atlantic Buoyancy Forcing via
1055 Poleward-Shifting Circulation Response. *Journal of Climate*, **38 (14)**, 3219–3238.
- 1056 Thompson, D. W., S. Solomon, P. J. Kushner, M. H. England, K. M. Grise, and D. J. Karoly, 2011:
1057 Signatures of the Antarctic Ozone Hole in Southern Hemisphere Surface Climate Change. *Nature*
1058 *geoscience*, **4 (11)**, 741–749.

- 1059 Thompson, D. W., J. M. Wallace, and G. C. Hegerl, 2000: Annular Modes in the Extratropical
1060 Circulation. Part II: Trends. *Journal of climate*, **13** (5), 1018–1036.
- 1061 Wills, R. C., Y. Dong, C. Proistosescu, K. C. Armour, and D. S. Battisti, 2022: Systematic Climate
1062 Model Biases in the Large-Scale Patterns of Recent Sea-Surface Temperature and Sea-Level
1063 Pressure Change. *Geophysical Research Letters*, **49** (17), e2022GL100 011.
- 1064 Yeager, S. G., and Coauthors, 2023: Reduced Southern Ocean Warming Enhances Global Skill and
1065 Signal-to-Noise in an Eddy-Resolving Decadal Prediction System. *Npj Climate and Atmospheric
1066 Science*, **6** (1), 107.
- 1067 Zhang, L., T. L. Delworth, W. Cooke, and X. Yang, 2019: Natural Variability of Southern Ocean
1068 Convection as a Driver of Observed Climate Trends. *Nature Climate Change*, **9** (1), 59–65.

**Supporting Information for “Reconstructing Satellite-Era Southern Ocean
Temperature and Salinity Trends within Observational Uncertainty”**

Matthew T. Luongo^{a,b}, Kyle C. Armour^{b,c}, & Gregory C. Johnson^{b,d}

^a *Cooperative Institute for Climate, Ocean, and Ecosystem Studies, University of Washington,
Seattle, WA, USA,*

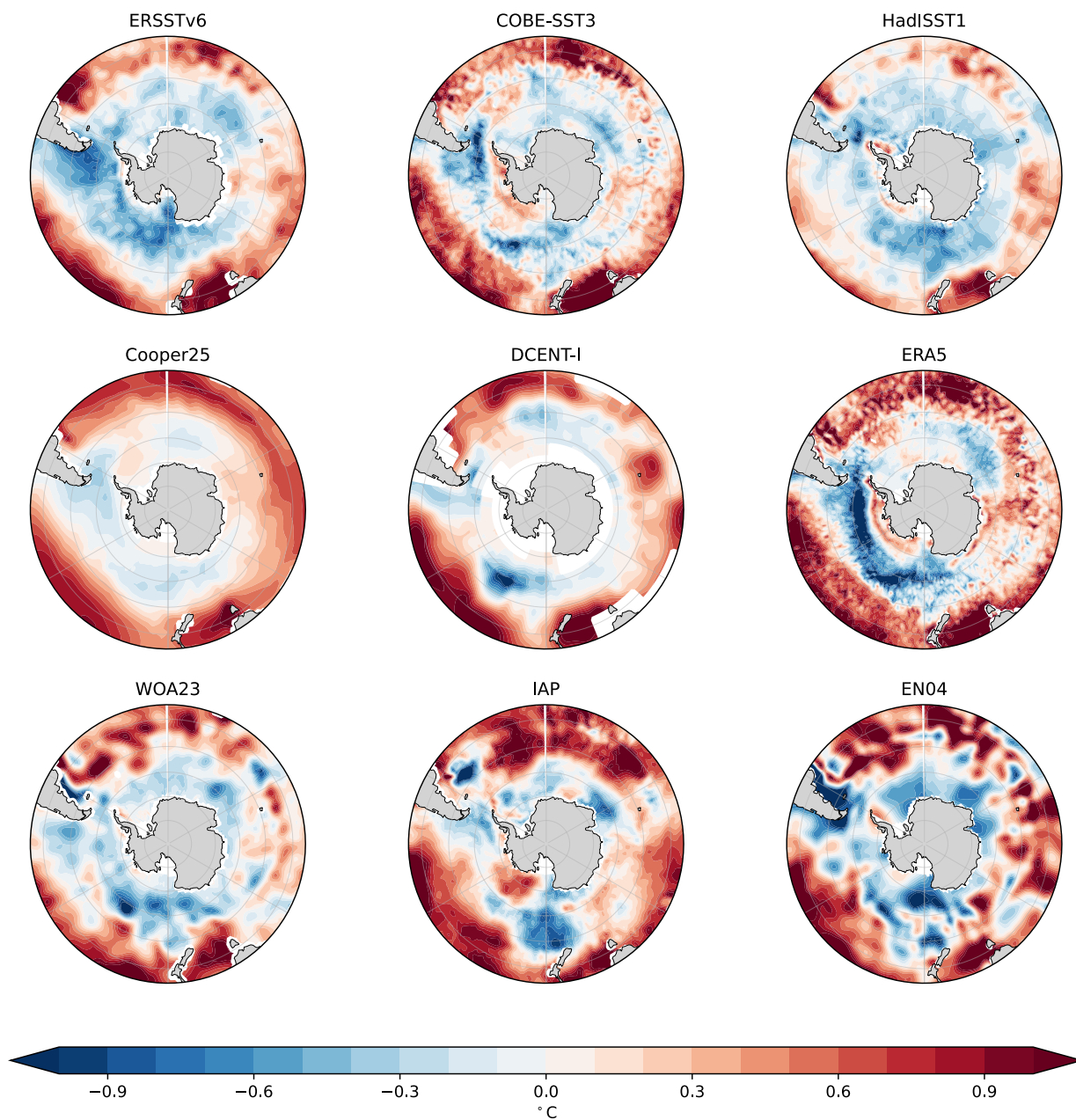
^b *School of Oceanography, University of Washington, Seattle, WA, USA,*

^c *Department of Atmospheric and Climate Science, University of Washington, Seattle, WA, USA,*

^d *NOAA Pacific Marine Environmental Laboratory, Seattle, WA, USA*

Corresponding author: M.T. Luongo, mluongo@uw.edu

10 **1. Supplementary Figures**



11 FIG. S1. Observed Southern Ocean 1979-2020 December-February sea surface temperature (SST) trend for
12 the nine observational products listed in Table 1 of the main text.

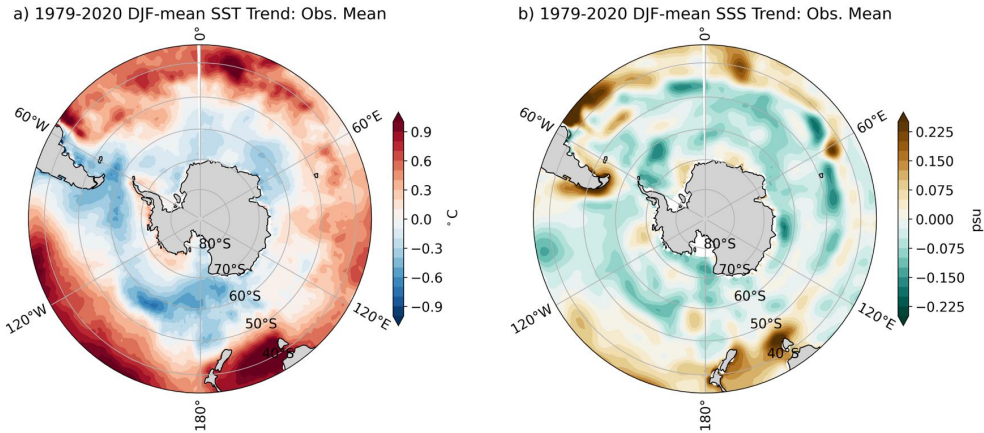


FIG. S2. Observed multi-product Southern Ocean 1979-2020 December-February (1979-2020) a) average sea surface temperature (SST) trend and b) average sea surface salinity (SSS) trend. Panel a) is an average of nine observational products (Table 1 in the main text). Panel b) is an average of three observational products (Table 1 in the main text).

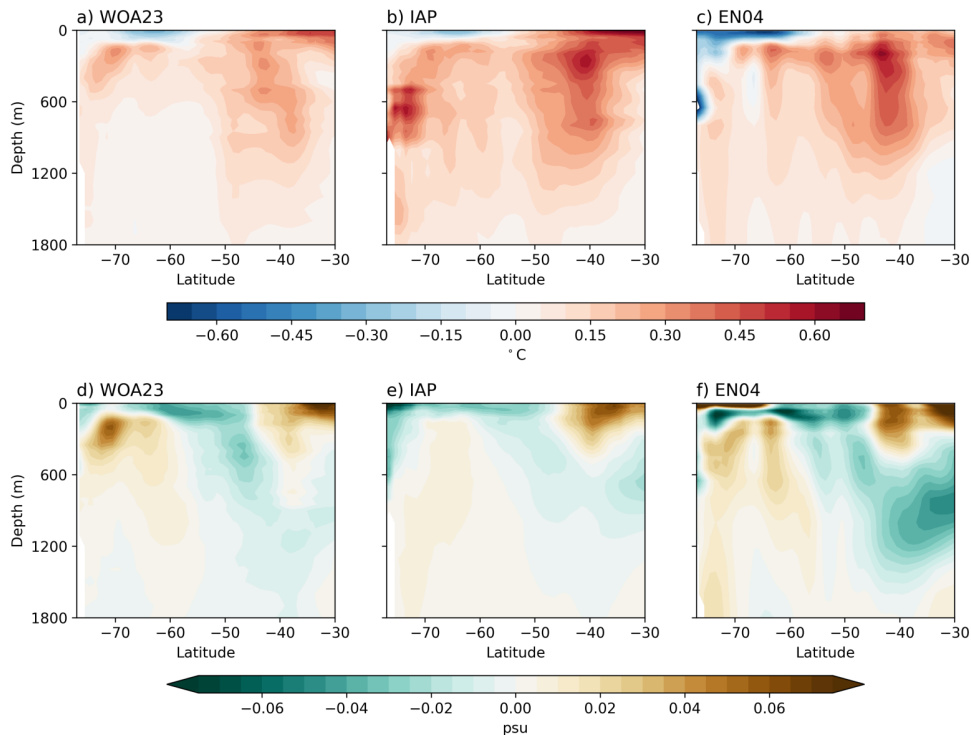


FIG. S3. Observed Southern Ocean 1979-2020 annual-mean trend in zonal-mean subsurface temperature (top row) and zonal-mean subsurface salinity (bottom row) from WOA23 (a,d), IAP (b,e), and EN04 (c,f). Observational products are listed in Table 1 of the main text.

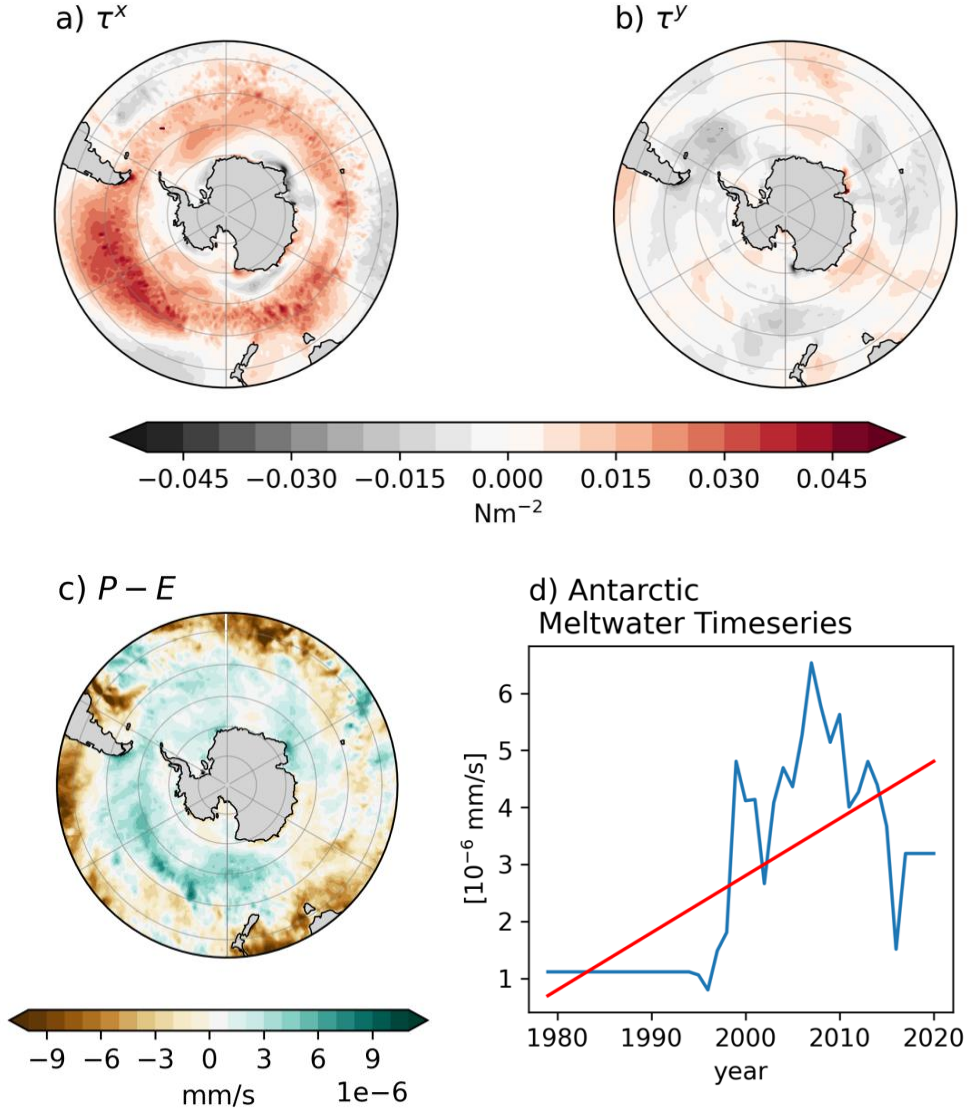


FIG. S4. 1979-2020 annual-mean trends in Southern Ocean surface forcings from a) ERA5 zonal wind stress τ^x , b) ERA5 meridional wind stress τ^y , c) ERA5 precipitation minus evaporation $P - E$, and d) Antarctic ice sheet melt. In panel d) we extend Schmidt et al. (2023)'s Antarctic ice sheet melt time series to 1979, conservatively assuming no change from 1979-1990 (blue line), and take the linear trend of this extended time series (red line) to get the final forcing magnitude for our ice sheet melt perturbation experiments.

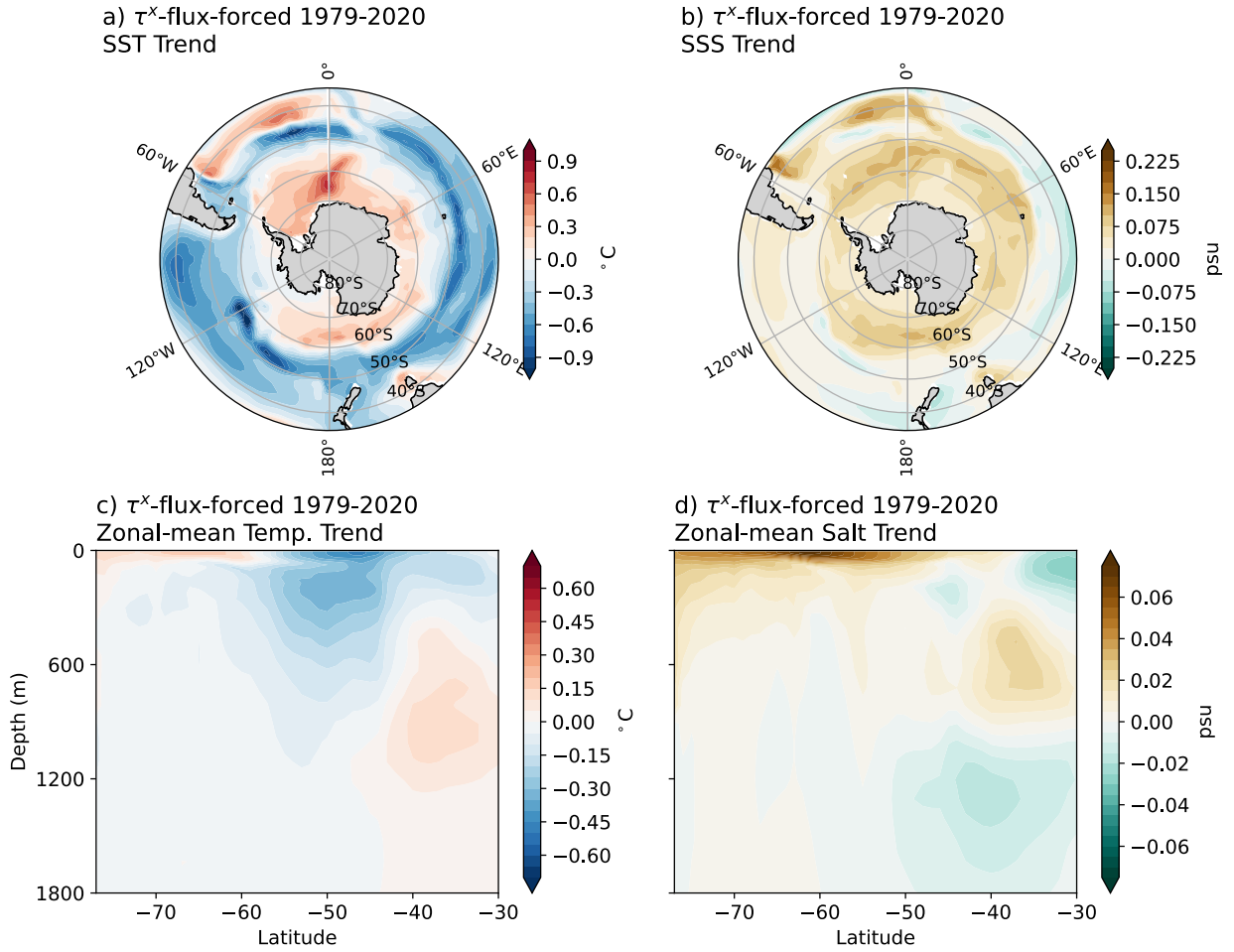


FIG. S5. a) Simulated 1979-2020 trend in a) SST, b) SSS, c) subsurface zonal-mean temperature, and d) subsurface zonal-mean salinity in response to idealized satellite-era momentum flux forcing, including slow response.

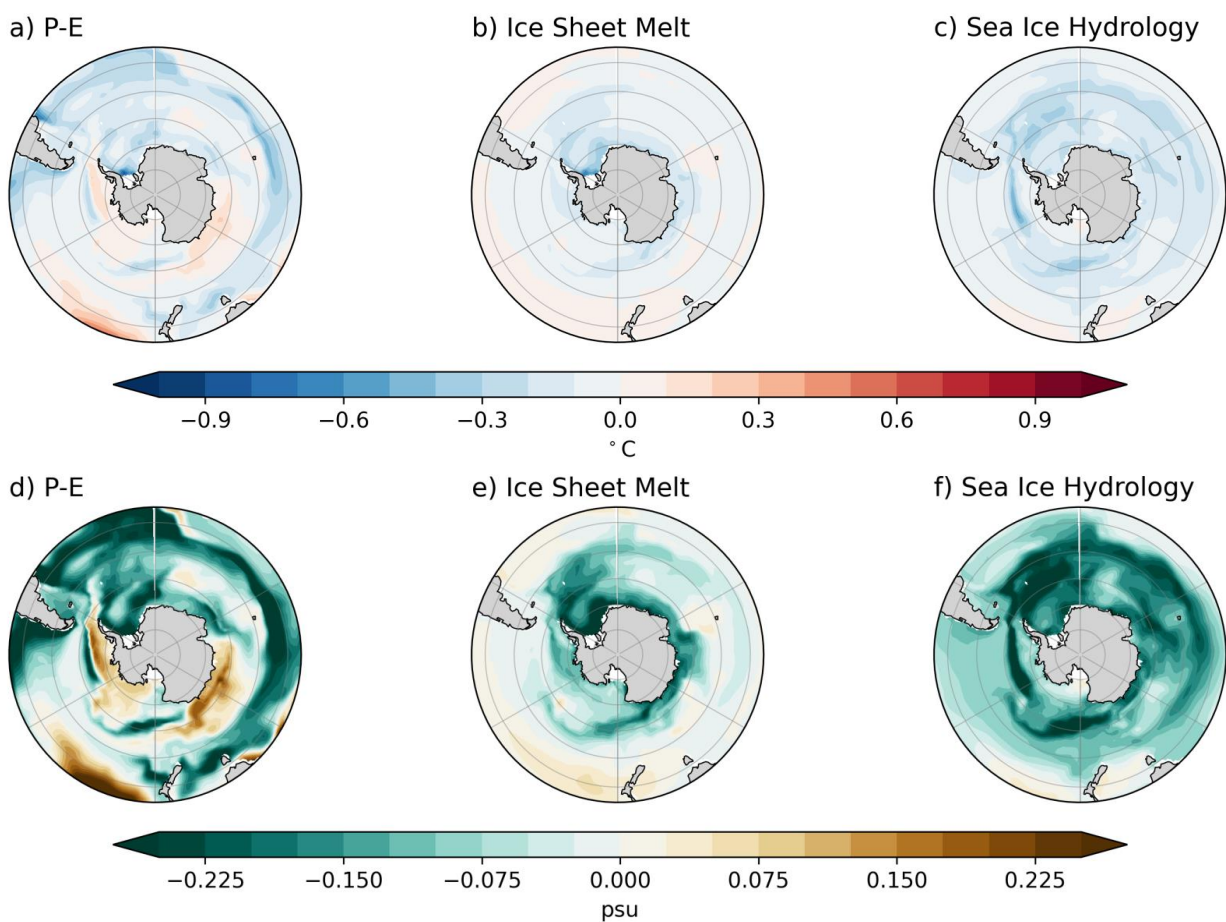


FIG. S6. Simulated 1979-2020 trend in SST (top row) and SSS (bottom row) in response to idealized satellite-era freshwater flux forcing from $P - E$ (a, d), Antarctic ice sheet melt (b, e), and sea ice hydrology (c, f).

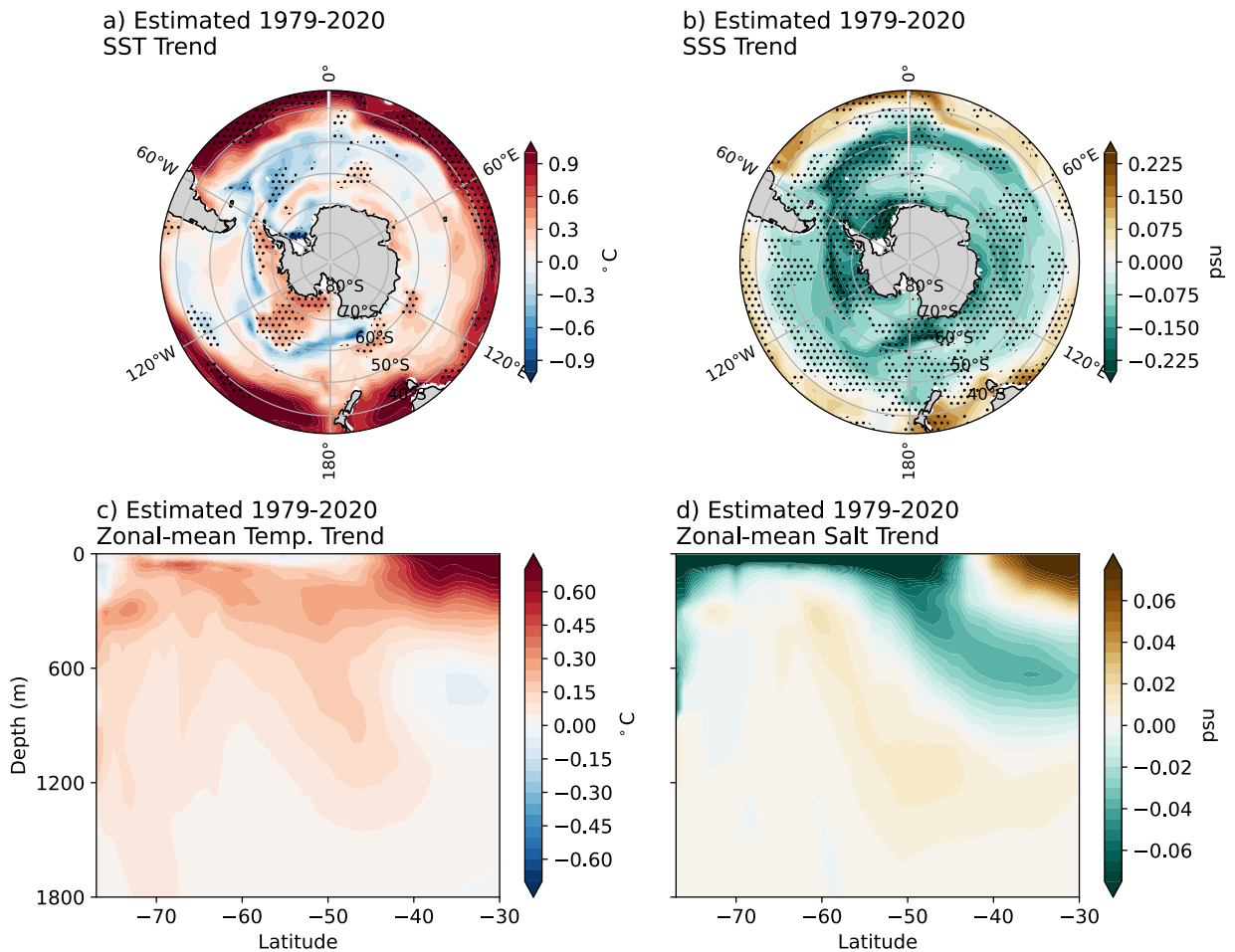


FIG. S7. a) Linear combination of a) SST, b) SSS, c) subsurface zonal-mean temperature, and d) subsurface zonal-mean salinity 1979-2020 trend according to Equations (4) and (5) of the main text. This estimate is constrained by SST-only and all coefficients are the mean of the orange posterior distributions in Fig. 9 of the main text.

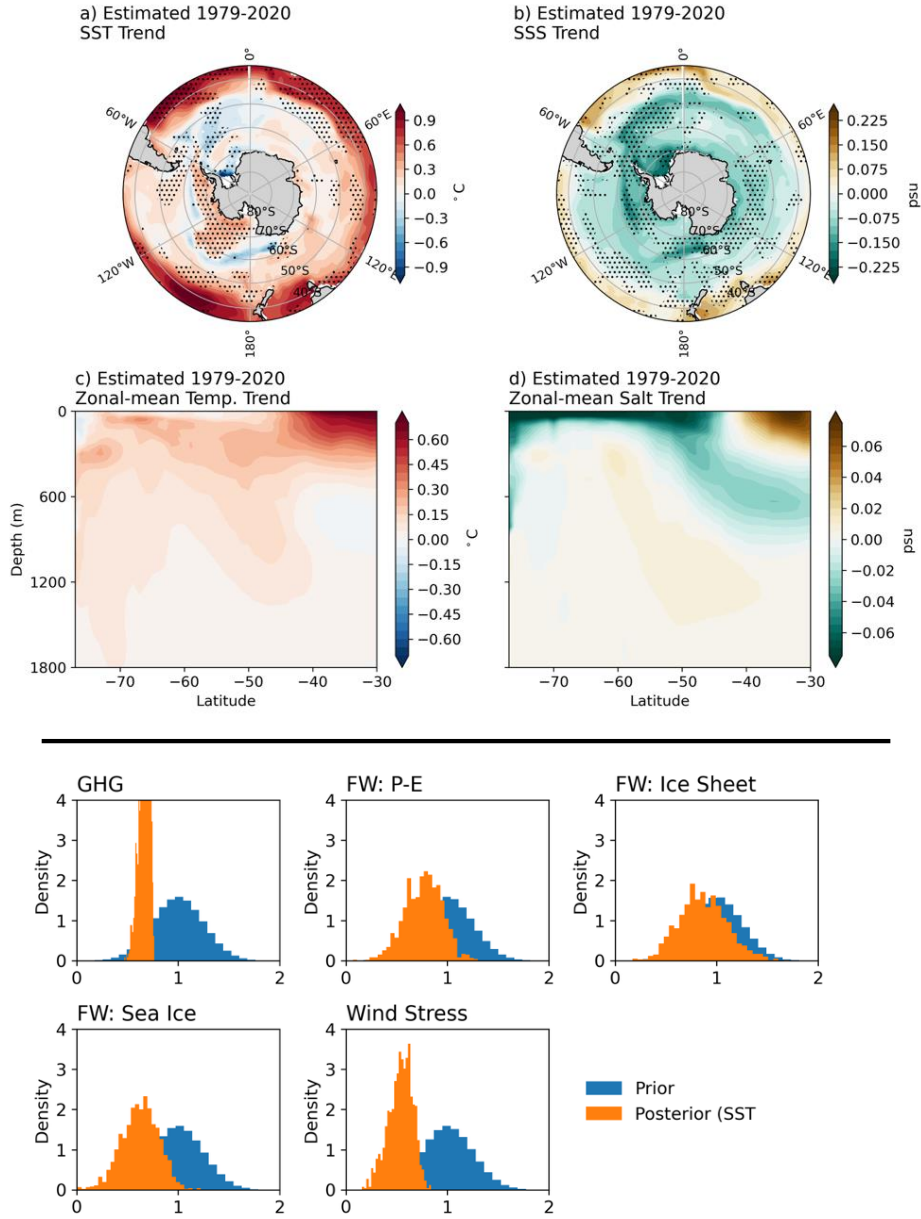


FIG. S8. Top: Linear combination of a) SST, b) SSS, c) subsurface zonal-mean temperature, and d) subsurface zonal-mean salinity 1979-2020 trend according to Equations (4) and (5) of the main text. While Fig. S7 considers the multi-product mean SST trend and uncertainty (Fig. 2a and c of the main text) this estimate is constrained by the mean SST trend and uncertainty from Cooper et al. (2025) only. All coefficients are the mean of the orange posterior distributions below. Bottom: Distribution of coefficients for linear combinations in Equations (4) and (5) of the main text. Blue distribution is our prior distribution with a mean of 1 and a standard deviation of 0.25 ($n = 1,000,000$) and orange distribution is a posterior distribution after a first Monte Carlo analysis considering SST from Cooper et al. (2025) and ocean heat content observations ($n \approx 1,100$).

42 **References**

- 43 Cooper, V. T., G. J. Hakim, and K. C. Armour, 2025: Monthly Sea Surface Temperature, Sea Ice,
44 and Sea Level Pressure over 1850–2023 from Coupled Data Assimilation. *Journal of Climate*,
45 **38 (19)**, 5461–5490.
- 46 Schmidt, G. A., and Coauthors, 2023: Anomalous Meltwater from Ice Sheets and Ice Shelves is a
47 Historical Forcing. *Geophysical Research Letters*, **50 (24)**, e2023GL106 530.