Response of Mixed Layer Depth Variability to Ocean Eddies and Atmospheric Noise in the Southern Ocean

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Ocean Eddies and Atmospheric Noise Drive Mixed Layer Depth Variability in the Southern Ocean

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Key Points:

11	• Simulations that account for ocean eddies show a significantly deeper average mixed
12	layer depth (MLD) compared to those that do not account for eddy effects.
13	• In regions with strong eddy activities, reduced atmospheric noise in simulations
14	results in higher MLD variability, driven more by increased ocean current variabil-
15	ity than by reduced atmospheric influence.
16	• Atmospheric noise suppresses ocean's natural variability, particularly diminish-
17	ing the ocean's inherent influence on MLD variations during ocean-atmosphere
18	coupling.

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19 Abstract

We investigate the impact of atmospheric noise and model resolution on the relationship 20 between oceanic currents, SST, and mixed layer depth (MLD) in the Southern Ocean, 21 using global climate simulations and interactive ensemble experiments with the NCAR 22 Community Climate System Model version 4.0, at both low (LR) and high spatial res-23 olution (HR) in the ocean. Atmospheric noise is the variability from internal atmospheric 24 dynamics, independent of low-frequency changes or anomalies in boundary conditions 25 or atmospheric composition. The interactive ensemble coupling approach reduces atmo-26 spheric noise at the air-sea interface, enabling us to isolate its impact by comparing in-27 teractive ensemble simulations to directly coupled (control) runs. We assess the impor-28 tance of ocean mesoscale currents by contrasting LR and HR simulations. The HR sim-29 ulations that resolves ocean eddies shows deeper MLD compared to the non-eddy-resolving 30 simulations, which is most likely due to excessive re-stratification by the parameterized 31 eddies in the non-eddy-resolving simulations. In the HR simulations, reduced atmospheric 32 noise amplifies mesoscale ocean currents in the interactive ensemble, which leads to in-33 creased SST and MLD variance in the Antarctic Circumpolar Current and Western Bound-34 ary Current regions. Furthermore, wind stress feedback interacting with ocean eddies 35 modulates Ekman transport in eddy-resolving simulations, whereas in non-eddy-resolving 36 simulations, Ekman transport is solely driven by atmospheric noise. This study addresses 37 38 a gap in understanding the importance of oceanic intrinsic variability in driving MLD variability and demonstrating that atmospheric noise suppresses ocean's natural vari-30 ability during atmosphere-ocean coupling. 40

41 Plain Language Summary

This paper investigates how ocean currents and atmospheric noise affect the South-42 ern Ocean's mixed layer depth (MLD) variability. The mixed layer is the ocean's upper 43 layer where temperature and salinity are relatively constant. The study uses computer 44 simulations to analyze the impact of ocean currents and atmospheric noise on MLD vari-45 ability. The results show that ocean currents significantly impact MLD variability, and 46 the atmospheric noise suppresses the intrinsic oceanic variability in driving the MLD vari-47 ations during the atmosphere-ocean coupling. The study also highlights the importance 48 of eddy-resolving simulations in capturing the impact of ocean mesoscale currents on MLD 49 variability. The findings of this study can help us better understand the complex inter-50 actions between the ocean and atmosphere in the Southern Ocean and improve our abil-51 ity to predict future changes in the ocean and climate. 52

53 1 Introduction

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1.1 Ocean Mixed Layer Variability and Ocean Eddies

The ocean mixed layer plays a vital role in modulating exchanges of heat, fresh-55 water, and gases such as oxygen and carbon dioxide between the atmosphere and the ocean. 56 Consequently, changes in mixed layer depth (MLD) can have profound implications for 57 climate modeling, affecting exchange rates between the atmosphere, upper ocean, and 58 deep ocean. The entrainment of carbon-rich, oxygen-poor waters into the mixed layer 59 drives the interannual variability of air-sea oxygen and carbon dioxide fluxes in the South-60 ern Ocean (Verdy et al., 2007). Additionally, MLD can modulate air-sea interaction by 61 changing the effective heat capacity of the upper ocean: a shallower MLD results in lower 62 heat capacity and increased sensitivity of sea surface temperature (SST) to surface heat 63 flux. At the same time, a deeper MLD leads to higher heat capacity and reduced SST sensitivity (Tozuka & Cronin, 2014). Therefore, the contribution of surface heat fluxes 65 to surface frontogenesis and frontolysis depends on their gradients and the distribution 66 of MLD (Tozuka et al., 2018; Gao et al., 2023). 67

The Southern Ocean is an integral part of the global overturning circulation since 68 the upwelling in the Southern Ocean is a vital branch of the circulation (Speer et al., 2000; 69 Marshall & Speer, 2012). The formation of the deep winter mixed layer has been linked 70 to the intermediate water masses, Subantarctic Mode Water (SAMW) and Antarctic In-71 termediate Water (AAIW), in the Southern Ocean (McCartney, 1977; Rintoul, 2002; Sallée 72 et al., 2006; J. Holte & Talley, 2009; Lee et al., 2011; J. W. Holte et al., 2012). These 73 intermediate water masses control the ventilation of the thermocline of the subtropical 74 gyres in the Southern Hemisphere and contribute to the changes in heat, carbon, and 75 productivity globally (Sloyan & Rintoul, 2001; Sarmiento et al., 2004; Sallée et al., 2012). 76 Therefore, it is essential that we understand the MLD variability in the Southern Ocean. 77

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1.2 Atmospheric Noise and Interactive Ensembles

Atmospheric noise is defined here as the variability due to internal atmospheric dynamics independent of low-frequency variability or anomalies in boundary conditions (e.g., SST anomalies, soil moisture, snow cover, sea-ice) or in atmospheric composition (i.e., aerosols). For conceptual simplicity, the atmospheric forcing can be separated into signal and noise components: (1) SST-driven atmospheric variability, which is referred to as "signal", and (2) the stochastic internal dynamics that is not directly driven by Sea Surface Temperature Anomalies, which is referred to as "atmospheric noise".

SST-driven atmospheric variability (the "signal") refers to atmospheric response 86 to mesoscale SST anomalies (Small et al., 2008). For example, Kirtman et al. (2012) demon-87 strates that the correlation between the upward turbulent heat fluxes and SST anoma-88 lies in the Southern Ocean is positive in simulations that resolve mesoscale eddies, which 89 implies that the atmosphere dampens SST variability. As a result, ocean eddy ampli-90 tude is enhanced when mesoscale SST-driven atmospheric processes are absent in the 91 air-sea coupling (Kirtman et al., 2017). Gao et al. (2022) shows that mesoscale currents 92 induce SST anomalies that are subsequently dampened by atmospheric heat flexes. SST 93 anomalies also impact near-surface wind, cloud properties, and rainfall in the Southern 94 Ocean by affecting turbulence in the atmospheric boundary layer (Frenger et al., 2013). 95

The role of the oceanic signal can be isolated using the interactive ensemble cou-96 pling strategy, which reduces the atmospheric noise at the air-sea interface. Barsugli & 97 Battisti (1998) provides a stochastically forced conceptual model which shows the inter-98 action between the atmosphere and ocean in midlatitudes amplifies variance within both 99 systems and attenuates the energy exchange between them. The paper also mentions that 100 a principal consequence of this air-sea thermal coupling is the mitigation of thermal damp-101 ing in midlatitude regions. Additionally, the article states that this study serves as a foun-102 dational framework for future explorations using the interactive ensemble design. The 103 interactive ensemble approach introduced an ensemble of atmospheric models coupled 104 to one ocean model to isolate the impact of internal atmospheric variability (Kirtman 105 & Shukla, 2002). Many previous studies have proven its utility for quantifying how mesoscale 106 air-sea coupling affects climate predictability (Wu & Kirtman, 2005; Lopez & Kirtman, 107 2014; Kirtman et al., 2017; Bishop et al., 2017). For example, Kirtman et al. (2017) demon-108 strated that the ocean mesoscale activity increases model-estimated climate predictabil-109 ity by increasing the dependency of atmospheric internal dynamics on the SST-driven 110 signal. 111

These studies suggest that neglecting mesoscale air-sea coupling can lead to inaccurate representation of ocean mesoscale variability, and potential biases in long-term climate modeling. This study will explore the importance of two main processes for mesoscale variability in MLD: 1) mesoscale oceanic currents, by comparing eddy-resolving to noneddy-resolving ocean models; and 2) internal atmospheric noise at the air-sea interface, by using the interactive ensemble coupling technique.

Experiments	Ocean	Atmosphere	ensemble size
LRC	1°lat x 1°lon	0.5 °	1
LRIE	1 lat ° x $1^{\circ} lon$	0.5 $^{\circ}$	1 ocean, 10 atmosphere
HRC	$0.1^{\circ}lat \ge 0.1^{\circ}lon$	0.5 $^{\circ}$	4
HRIE	0.1° lat x 0.1° lon	0.5 $^{\circ}$	1 ocean, 10 atmosphere

Table 1. Global climate model configuration and experiments. Adapted from Kirtman et al.(2017)

¹¹⁸ 2 Data and Methodology

2.1 Model Experiments and Data

The global climate simulations are based on the NCAR Community Climate Sys-120 tem Model version 4.0 Gent et al. (2011). The atmospheric component is based on the 121 Community Atmospheric Model version 4 and the oceanic part – the Parallel Ocean Pro-122 gram version 2 (Smith et al., 2010)). Kirtman & Shukla (2002) and Kirtman et al. (2017) 123 describe the interactive ensemble coupling strategy and details of the experiments used 124 in this study, so here we only provide brief descriptions. We analyze four experiments: 125 two control experiments and two interactive ensembles, at both low- and high spatial res-126 olution in the ocean (Table 1). The standard low-resolution (LRC experiment is a 255-127 year present-day climate simulation, where the first 40 years are considered spin-up. The 128 LRC experiments use a 1° atmospheric model coupled to ocean and sea ice models with 129 a zonal resolution of 1.2° and meridional resolution that varies from 0.27° at the equa-130 tor to the 0.54° in the mid-latitudes. The high-resolution (HR) experiments are based 131 on a 4-member ensemble where each ensemble also uses a present-day forcing. The HR 132 experiments use a 0.5° atmospheric model coupled to 0.1° ocean and sea ice models. We 133 analyze the monthly data between 35 °S to 60 °S to include most of the Southern Ocean 134 while avoiding the region with sea ice. We also selected 30-year-long data from year 121 135 to 150 in each experiment for comparison. We plot an altimetry-derived geographical 136 position of the Subantarctic Front (SAF) and Polar Front (PF) in each figure (Park & 137 Durand, 2019). 138

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2.2 Interactive Ensemble Technique

The intention of the interactive ensemble coupling strategy is to suppress the at-140 mospheric noise at the sea surface. Multiple realizations (ensemble members) of the at-141 mospheric component are coupled to a single realization of the ocean component. The 142 ensemble-mean fluxes of heat, momentum, and freshwater from atmospheric ensemble 143 members are used to force the ocean component, while each atmospheric ensemble mem-144 ber has the same SST forcing produced by the ocean component. This coupling tech-145 nique is to have the ensemble mean of the atmospheric models continuously interact with 146 the ocean model as the coupled system evolves (Kirtman & Shukla, 2002). 147

To estimate the coupling strength and identify processes that drive the SST variability, Kirtman et al. (2005), Kirtman et al. (2017) and Zhang & Kirtman (2019) applied SST variance ratio test based on the Hasselmann (1976) hypothesis. Here we provide a brief description of this conceptual model following their examples.

In the control experiment, in which one atmospheric model is coupled to one ocean model, we assume that an oceanic variable O (such as SST) and an atmospheric variable A at time "n+1" are determined by their values at the previous time:

$$A^{n+1} = \alpha O^n + \mu A^n + N \tag{1}$$

$$O^{n+1} = \beta A^n + \delta O^n + P \tag{2}$$

where μ and δ represent the memory of the previous state, and α and β are the coupling coefficients that are bounded between 0 and 1. N and P stand for the uncoupled internal noise in atmospheric and ocean components, respectively, which is assumed to be Gaussian and white. Ocean noise represents the effects of internal ocean dynamics, which include mesoscale advection.

In the interactive ensemble, multiple atmospheric models (ensemble members) are coupled to one ocean model. Assuming M is the number of atmospheric models that are coupled with one ocean model, the equations 1 can be generalized into a set of equations representing the atmospheric interactive ensembles:

$$A_1^{n+1} = \alpha O^n + \gamma A_1^n + N_1, \tag{3}$$

$$A_2^{n+1} = \alpha O^n + \gamma A_2^n + N_2, \tag{4}$$

... (5)

$$A_M^{n+1} = \alpha O^n + \gamma A_M^n + N_M, \tag{6}$$

$$O^{n+1} = \frac{\beta}{M} \sum_{k=1}^{M} A_k^n + \delta O^n + P,$$
(7)

where the atmospheric models are represented by $A_1^n, A_2^n, ..., A_M^n$ with internal noise $N_1, N_2, ..., N_M$.

The ratio between variance in the control and IE simulations can serve to quantify the impact of atmospheric noise and interpret the interactive ensemble. Taking Oin the above theoretical model to be SST, the variance ratio can be diagnosed in terms of the coupling strength and the amplitude of atmospheric and oceanic noise forcing:

$$\frac{Variance(SST_{IE})}{Variance(SST_{CTRL})} = \frac{\beta^2 \sigma_N^2 / M + \sigma_P^2}{\beta^2 \sigma_N^2 + \sigma_P^2}$$
(8)

where σ_N^2 and σ_P^2 is the variance of the internal atmospheric and oceanic noise, re-170 spectively. Following the example of Kirtman et al. (2017) and Zhang & Kirtman (2019), 171 who applied the variance ratio test solely to SST, we broaden the application of their 172 theoretical model to include additional oceanic variables, such as MLD and current speed. 173 The variance ratio test applies to terms like MLD and currents since MLD is implicitly 174 coupled to the atmosphere and currents are directly coupled via the wind stress. For ex-175 ample, we can quantify the impact of atmospheric noise and ocean noise on the MLD 176 variability, by analyzing the ratio of the MLD variance in the IE to that in the control 177 experiment: 178

$$\frac{Variance(MLD_{IE})}{Variance(MLD_{CTRL})} = \frac{\beta^2 \sigma_N^2 / M + \sigma_P^2}{\beta^2 \sigma_N^2 + \sigma_P^2}$$
(9)

where σ_N^2 and σ_P^2 is the variance of internal atmospheric and oceanic noise, respectively.

For LRIE and HRIE, there are M = 10 atmosphere components coupled to 1 ocean component (Table 1). Suppose the SST or MLD variance ratio is between 0.1 and 1.0. In that case, the ocean noise (internal ocean dynamics), coupled feedback, non-linearity,

or a combination of these three elements can play a role, and the variability is only par-183 tially forced by the atmospheric noise. If the SST or MLD variance ratio exceeds 1.0, 184 the reduction of atmospheric noise in the interactive ensemble enhances the oceanic vari-185 ance compared to the control experiment. We will conclude that, in this case, unstable 186 coupling and non-linearity are essential, which means that a linear conceptual model can-187 not be used to explain the variability. In this case, the non-linear climate system can be 188 chaotic in which the noise is "state-dependent", and the unstable coupled feedback af-189 fects the variability (Kirtman et al., 2017). Similarly, we can analyze the variance ra-190 tio of other oceanic variables, such as the surface current speed and Ekman transport. 191

¹⁹² 3 Results

In this section, we first discuss the relationship between SST, MLD variability, and ocean currents by the eddy-resolving and non-eddy-resolving simulations. Hereafter, we use the terms "mesoscale ocean currents" and "ocean eddies" interchangeably, referring to ocean currents that occur at spatial scales of around 10 to 100 kilometers and temporal scales of days to months. We then explore the importance of atmospheric noise in SST and MLD variability by comparing the control simulations to the interactive ensemble.

3.1 Importance of ocean currents in SST variability

In high-resolution (HR) experiments, the variance of sea surface temperature (SST) 201 is notably higher, particularly in Antarctic Circumpolar Current (ACC) regions and west-202 ern boundary current regions, such as the Agulhas Current areas, when compared to the 203 results of low-resolution (LR) experiments. There are several reasons why the HR ex-204 periments produce significantly higher and more realistic SST variability compare to the 205 LR experiments: 1) heat advection by ocean eddies creates SSTA in regions with strong 206 oceanic currents, which demonstrates that resolving Southern Ocean eddies is critical 207 for getting the SST variability right; 2) MLD variability modulates the relationship be-208 tween SSTA and the eddy advection of heat. The MLD in the HR experiment is deeper 209 than in LRC and exhibits higher variance in general, which further enhances the impor-210 tance of oceanic advection in SST variability. These effects improve the difference in SSTA 211 variance between LR and HR experiments. Besides, these effects possibly increase the 212 HRIE/HRC variance ratio by enhancing the importance of ocean dynamics compared 213 to atmospheric noise. 214

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3.2 Importance of ocean currents in MLD

We first discuss the relationship between MLD and SST. The climatological an-216 nual cycle has not been removed from these values, and the Variations are heavily in-217 fluenced by seasonal variability. The variations of the MLD are negatively correlated with 218 SST in most of the regions in the Southern Ocean (Fig.1 a-b), which means that cooler 219 SST corresponds to deeper MLD. This is a relationship we can expect in seasonal vari-220 ations in MLD, which deepens in winter and shoals in summer. However, this simple one-221 dimensional relationship breaks down in regions with strong oceanic currents, such as 222 the Antarctic Circumpolar Current (ACC) and Western Boundary Currents (WBC, Fig.1 223 b). This breakdown is more pronounced in the HRC simulation than in LRC, largely 224 because of fast time-mean oceanic currents (Fig.1) and stronger mesoscale variability (Fig.2 225 e-f) in HRC. The surface Eddy Kinetic Energy (EKE) is calculated as $EKE = 1/2(U'^2 +$ 226 $V^{\prime 2}$)^{1/2}, where U' and V' are the velocity departure from the 30-year-mean surface cur-227 rent speed. Note that most of the variability in velocities comes from mesoscale currents, 228 although the seasonal anomalies in current speed will also contribute to EKE. 229



Figure 1. The correlation coefficient between the SST and MLD in a) LRC and b) HRC. The time-mean surface current speed in c) LRC and d) HRC, from year 121 to 150. Polar Front (PF, orange line) and Subantarctic Front (SAF, magenta line).

The weak relation between SST and MLD in the ACC region suggests that a onedimensional atmospheric forced mixed layer model Kraus et al. (1967) does not apply in the regions of strong advection. This conclusion is in agreement with the findings of Gao et al. (2023) who concluded that the buoyancy advection shear by oceanic currents generally counteracts the atmospheric buoyancy forcing in driving the mixed layer variability.

The time-mean MLD in HRC is significantly deeper than that in LRC in most Southernn (Fig. 2). This is consistent with Lee et al. (2011), who discovered that the winter MLD in eddy-permitting ocean simulations aligns closely with observed data, while the winter MLD in coarse-resolution ocean models tends to be too shallow. The most significant disparities were identified within the Agulhas Current system, where a higher

surface heat loss over the Agulhas Return Current and a deeper mixed layer were ob-241 served in eddy-permitting simulations. In this study, we also find significant differences 242 between the HRC and LRC experiments in ACC and WBC regions, including the Ag-243 ulhas Current system, part of the Brazil Current, and the Brazil-Malvinas Confluence 244 (Fig.2a-b). In addition to the mean current strength, the difference between the HRC 245 and LRC experiments is also dependent on EKE: the MLD in the HRC simulation is shal-246 lower in regions of higher EKE (WBC and ACC regions) and deeper in the other areas 247 (Fig.2e-f).248

249 It is unclear if we can explain the deepening of the MLD in HRC by the action of mesoscale eddies alone. On average, eddies are assumed to re-stratify the base of the mixed 250 layer (Fox-Kemper et al., 2008; Fox-Kemper & Ferrari, 2008). At the same time, Gao 251 et al. (2022) demonstrates that mesoscale buoyancy advection can also deepen the mixed 252 layer, counteracting the atmospheric forcing. Additionally, mesoscale eddies are param-253 eterized with the Gent & Mcwilliams (1990) scheme (hereafter "GM") in the non-eddy-254 resolving LRC and LRIE experiments and the model used by Lee et al. (2011). There-255 fore, it is possible that the GM parameterization overestimates the re-stratifying effects 256 of mesoscale buoyancy advection. It is also worth noting that, in most of the Southern 257 Ocean, the SST in HRC is significantly warmer than that in LRC Kirtman et al. (2012) 258 and cannot explain the deeper MLD in HRC. Therefore, it is sensible to assume the im-259 portance of ocean buoyancy advection in driving the MLD variability. 260

The reduction of atmospheric noise in LRIE relative to LRC mostly leads to deep-261 ening of MLD north of the SAF and to shoaling of MLD south of the SAF (Fig.2a). There-262 fore, the southerly slope of MLD is generally reduced due to atmospheric noise. The time-263 mean MLD in HRIE is, in contrast, shallower than in the HRC experiment in most re-264 gions of the Southern Ocean, except the Agulhas Current region, part of the Brazil Cur-265 rent, and the Brazil–Malvinas Confluence region (Fig.2b). Gao et al. (2023) concludes 266 that the atmospheric forcing and mixing induce MLD variability, while the oceanic ad-267 vection of buoyancy essentially balances these atmospheric effects. With the reduction 268 of atmospheric forcing, the strong buoyancy advection in ACC and WBC regions can 269 become unbalanced and lead to the deepening of MLD. 270

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3.3 Importance of atmospheric noise in SST variability

The response of SST variability to the reduction in the atmospheric noise in the 272 interactive ensemble simulations differs between HR and LR simulations. Here SST anoma-273 lies (SSTAs) are defined as the departure from the monthly climatology. The absence 274 of eddies in LRC leads to the lower SSTA variance (Fig.4) than in HRC, which is not 275 surprising given weaker buoyancy advection in the LR case. Consistent with this result, 276 the variance ratio (Fig.3) is also lower than in the HR simulations, which suggests that 277 SSTA are primarily caused by the anomalies in the atmospheric forcing, which are sig-278 nificantly reduced in LRIE. The following analysis suggests that the importance of at-279 mospheric noise is overestimated in the LR simulations. 280

The noise reduction in HRIE relative to HRC enhances the SST variability in the 281 ACC and WBC regions, where SSTA variance ratio exceeds 1.0 (Fig.3). This result is 282 consistent with the findings in Kirtman et al. (2017). The results suggests that the SST 283 variability in these regions is attributed to the intrinsic ocean dynamics, unstable cou-284 pled feedback and nonlinear dynamics. This is consistent with Gao et al. (2022) who found 285 that the SSTA variability in the Southern Ocean in the regions with fast oceanic cur-286 rents is driven by the intrinsic ocean dynamics rather than the atmospheric forcing. In 287 other regions, the variance ratio is mostly between 0.5 and 1.0, which suggests the SSTA 288 variability is partially driven by atmospheric noise and partially by coupled feedback, 289 ocean eddies or non-linearity, or a combination of the three. In addition, the SSTA vari-290 ance ratio can exceed 2.0 in the regions south of 60S, and these values may be exagger-291

ated by biases in the Antarctic sea ice and excessive westerly winds in CCSM4 (Kirtman et al., 2017). The enhanced SST variance in the interactive ensemble simulations
is consistent with the increase in the upper-ocean currents, which is discussed in the next
section.

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3.4 Importance of atmospheric noise in MLD variability

The air-sea interaction over Southern Ocean eddies can produce substantial MLD 297 variability, which is underestimated in the non-eddy-resolving ocean models (Fig.5). MLD 298 anomalies (MLDAs) are defined as the departure from the monthly climatology. Gao et 299 al. (2023) suggests that oceanic mesoscale currents compensate the atmosphere-induced 300 variations in MLD: while the atmospheric forcing and oceanic vertical mixing induce the 301 MLD variability, the oceanic advection of buoyancy counteracts these atmospheric ef-302 fects. The anomalies in atmospheric fluxes result either from intrinsic atmospheric vari-303 ability or from an SST-forced response. The analysis of this section will help to estimate 304 the relative importance of these two processes because the IE reduces the former, inter-305 nal source for variability. 306

In both the HRIE and LRIE experiments, the MLDA variance is suppressed in most 307 regions because of the reduced atmospheric noise (Fig.6). The changes are nevertheless 308 dramatically different between the LR and HR simulations. In the LR experiments, the 309 MLDA variance ratio is below 0.5 in most of the Southern Ocean (Fig.6a), which sug-310 gests that MLDA variability is partially forced by the atmosphere noise, and partially 311 results from the coupled feedback, non-linearity and ocean noise. In contrast, in the HR 312 experiments, the MLDA variance ratio is not only overall higher, but exceeds 1.0 in the 313 ACC and WBC regions (Fig.6b). 314

In the ACC and WBC regions, the MLDA variance in HRIE is enhanced due to 315 the reduced atmospheric noise. The SSTA variance is also enhanced there (Fig.3), how-316 ever, the correlation between the SST and MLD anomalies is low in these regions (Fig.1), 317 which means that the increased SST variance cannot explain the increase in MLD vari-318 ance. We can, however, explain the increased MLDA variance with our findings in Gao 319 et al. (2023). There, we concluded that while the atmospheric forcing and oceanic ver-320 tical mixing induce MLD variability, the oceanic advection of buoyancy counteracts these 321 atmospheric effects. Results of Gao et al. (2023) further show that when mesoscale anoma-322 lies are removed from the surface fluxes of heat and momentum, the MLD variability can 323 increase, and this effect is most pronounced in local winter. These conclusions suggest 324 that when the atmospheric stochastic forcing is suppressed in HRIE, the oceanic advec-325 tion can become partially unbalanced and enhance MLD variance. 326

More variance ratio test on the surface current speed. In the LR experiment (Fig.7a), 327 the surface current variance ratio is mostly between 0.1 and 1.0, which suggests a com-328 bination of the atmospheric noise and internal dynamics drives surface present variabil-329 ity. In the HR experiments, in contrast, the current speed variance ratio is larger than 330 1.0 in most of the Southern Ocean (Fig.7b). This means the speed variance in HRIE in-331 creases due to the reduced atmospheric noise. The increase is especially pronounced in 332 the Southern Indian and Atlantic sectors of the Southern Ocean, indicating the critical 333 role of unstable coupling and nonlinearity. In contrast, the ratio is less than 1.0 in the 334 Pacific sector (Fig.7). This pattern is similar to the MLDA variance ratio, which is also 335 lower in the Pacific sector of the Southern Ocean (Fig.6). The similarity suggests the im-336 portance of ocean advection in MLD variance. The current speed and EKE are not as 337 strong in the Southern Pacific sector (Fig.1 and Fig.2), and the ocean-atmosphere in-338 teractions have more considerable relative importance. 339

Compared to the SSTA variance ratio, HR experiments exhibit smaller regions where the MLDA variance ratio exceeds 1.0. This difference indicates that atmospheric noise plays a bigger role in driving MLD variability than SST variability. Atmospheric noise, ³⁴³ such as wind and air temperature variations, can significantly impact Mixed Layer Depth
(MLD) more than Sea Surface Temperature (SST) due to the direct and immediate im³⁴⁵ pact of wind stirring. This process mixes the ocean's surface layer to varying depths, lead³⁴⁶ ing to significant MLD variability. While SST is also affected by atmospheric conditions,
the high heat capacity of the ocean means that a larger amount of heat exchange is re³⁴⁸ quired to alter its temperature significantly. Therefore, atmospheric noise tends to drive
³⁴⁹ more variability in MLD than SST.

This heightened variability reflects a non-linear and unstable coupling. Essentially, this means that the relationship between the different forces (ocean currents, atmospheric noise, etc.) is not straightforward. Instead, these forces interact in complex, unpredictable ways, which is in nature of 'non-linearity.' 'Unstable coupling' indicates that the relationship between these elements isn't stable or consistent and can change rapidly.

This variability could be due to the increased Mixed Layer Depth (MLD), induced by the rise in atmospheric noise and atmosphere-driven mixing (Fig.6). As the MLD increases, the inertia (or resistance to change) in the upper ocean also increases. This could then lead to a decrease in ocean current variability. The state-dependence of atmospheric noise and the chaotic nature of the system could offer possible explanations for these observed phenomena.

This difference is, however, reversed in the LR simulations. The atmospheric noise mainly drives the SST variability in the LR experiments whereas the MLDA variance is due to a combination of the atmospheric noise, oceanic dynamics, and coupled feedbacks. Weaker oceanic currents and air-sea feedback onto SSTA in the LR simulations explain this.

366 3.5 Ocean Eddies Modulating Ekman Transport

To get further insight into the amplification of ocean currents in the absence of atmospheric noise, we investigate the response of Ekman transport to atmospheric forcing. The Ekman transport velocity (unit: m^2/s) in the u and v directions are calculated as below:

$$U_{Ekman} = \frac{\tau^y}{\rho_0 f},\tag{10}$$

$$V_{Ekman} = \frac{-\tau^x}{\rho_0 f} \tag{11}$$

(12)

where τ^y and τ^x is the meridional and zonal wind stress at the sea surface, respectively. ρ_0 is the reference density (1025 kg/m^3) and f is the Coriolis parameter. We next calculate the variance in the magnitude of the Ekman transport $\sqrt{U_{Ekman}^2 + V_{Ekman}^2}$ and the variance ratio.

Fig.8 emphasizes the role of wind stress feedback and Southern Ocean eddies in shap-375 ing Ekman transport in our eddy-resolving experiments: the figure displays the influ-376 ence of eddies on Ekman transport, as illustrated through the contrast between LR and 377 HR experiments. Importantly, the figure shows a decrease in Ekman variance in response 378 to reduced atmospheric noise, a trend that is more significant in HRIE than in LRIE. 379 Fig.8 shows the impact of mesoscale currents on Ekman transport by comparing the LR 380 and HR experiments. In LR experiment, the variance ratio is below 0.1, which indicates 381 atmospheric noise alone drives the variability of the Ekman current speed. In HR ex-382 periment, the variance ratio is between 0.1 and 0.5, which suggests the Ekman transport 383 variance is partially forced by the atmosphere noise, and partially by coupled feedback 384

and internal variability. For example, the presence of ocean eddies can modify South-385 ern Ocean winds at the air-sea interface, which in turn alter the Ekman transport (Small 386 et al., 2008; Frenger et al., 2013; Perlin et al., 2020). Mesoscale variability can also have 387 an impact on wind stress through surface current speed correction: surface ocean cur-388 rents modulate turbulent air-sea exchanges by changing the velocuty shear between the 389 atmosphere and oceanic surface. Current speed correction to the wind stress acts as a 390 "top drag" (Dewar & Flierl, 1987; Duhaut & Straub, 2006; Gaube et al., 2015), since the 391 enhanced Ekman pumping leads to relaxation of the thermocline. Importantly, the sen-392 sitivity of Ekman currents to atmospheric noise cannot explain amplification of surface 393 currents in the HRIE simulations. 394

³⁹⁵ 4 Summary and Discussion

The objective of this study is explore the impact of atmospheric noise and model 396 resolution on the relationship between oceanic currents, SST and MLD variability. This 397 study utilizes the interactive ensemble coupling method, which reduces the atmospheric 398 in both low- and high-resolution simulations. We analyzed the MLD variability and ex-399 amined a variance ratio between the IE and control experiments, which allowed us to 400 estimate the relative importance of the atmospheric noise in the MLD variability. Based 401 on the analysis in Gao et al. (2022) and Gao et al. (2023), we expect variance based on 402 monthly means to be a good measure of mesoscale anomalies. The impact of the strong 403 oceanic currents, fronts and eddies were further assessed by comparing the eddy-resolving 404 (HR) experiments to non-eddy-resolving (LR) experiments. 405

The strong negative correlation between SST and MLD breaks down in regions with 406 strong large-scale currents and mesoscale activity, namely within the ACC fronts and 407 in the WBC regions. The time-mean MLD is also significantly deeper in the presence 408 of eddies even though SST in HR is warmer than in LR (Kirtman et al., 2012). Simi-409 larly, Lee et al. (2011) found the winter MLD in coarse-resolution coupled ocean model 410 is too shallow. The MLD difference also depends on EKE: the MLD in HR simulations 411 is shallower in regions of higher EKE and deeper elsewhere. These results suggest a cru-412 cial role of mesoscale ocean currents in driving SST and MLD anomalies. Eddies are widely 413 assumed to re-stratify the ocean, but our results indicate that the GM parameterization 414 may overestimate the re-stratifying role of ocean eddies. Gao et al. (2023) further demon-415 strates that the effects of eddies on MLD are more complex, and the corresponding buoy-416 ancy advection can even de-stratify the ocean below the mixed layer and deepen the MLD. 417

The results further demonstrate that SST variability is mainly driven by oceanic 418 processes rather than atmospheric noise in the ACC and WBC regions. This result is 419 consistent with Gao et al. (2022): the SST variability is driven by intrinsic ocean dynam-420 ics instead of atmospheric forcing. In such "quiet" regions of the Southern Ocean as the 421 Pacific sector, the role of the atmosphere is more significant, and the SST variability is 422 jointly driven by atmospheric noise and oceanic internal dynamics. Significantly, the re-423 duction of the atmospheric noise in HRIE even enhances the SST variability in the ACC 424 and WBC regions. However, it is still unclear why the SST variability is enhanced in these 425 regions, and this topic deserves further investigation. 426

The atmospheric noise and the Southern Ocean eddies both control MLD variabil-427 ity. The differences between MLD variance ratio in LR and HR experiments demonstrate 428 the importance of intrinsic ocean dynamics, especially in the ACC and WBC regions. 429 Compared to the SST variability, however, the atmospheric forcing plays a more signif-430 icant role in driving MLD variability in the HR experiments than in the LR runs. This 431 result is consistent with Gao et al. (2023): in the Southern Ocean, SST variability is mainly 432 driven by the intrinsic oceanic dynamic, while the MLD variability is caused by both at-433 mospheric forcing and oceanic dynamics. Consistent with previous studies such as Zhang 434 & Kirtman (2019), the atmospheric noise suppresses the upper-oceanic variability, and 435

the upper-ocean mesoscale variability in MLD, SST, and surface currents intensify in HRIE. 436 Given a weak correlation between SST and MLD anomalies in these regions, it is nat-437 ural to assume that the increase in SST and MLD variance in the absence of atmospheric 438 noise are both caused by stronger oceanic currents. Gao et al. (2023) concludes that while 439 the atmospheric forcing and oceanic vertical mixing induce MLD variability, the oceanic 440 advection of buoyancy counteracts these atmospheric effects. Consistent with this find-441 ing, when the atmospheric stochastic forcing is suppressed in HRIE, the oceanic advec-442 tion becomes unbalanced and can thus act to enhance MLD variance. Schneider et al. 443 (2023) points out that ocean dynamics plays a minimal role in SO decadal variability 444 in non-eddy-resolving models, which supports our conclusion that ocean mesoscale dy-445 namics have a large role in SO variability. It is still, however, unclear why the variance 446 in oceanic currents increase in HRIE, and this question deserves further investigation. 447

The suppression of surface currents by atmospheric noise cannot be explained by 448 changes in the Ekman currents alone. The variance in the Ekman transport is decreased 449 in HRIE and LRIE simulations, but the reduction is different between the LR and HR 450 simulations for several reasons. The Ekman transport is modulated by the wind stress 451 feedback over ocean eddies (SST anomalies) in the HR experiments, while the Ekman 452 transport is driven solely by atmospheric noise in the LR experiments. wind speed af-453 fected by SST anomalies, which created wind stress feedback to the ocean (Seo et al. (2016)). 454 In the eddy-resolving experiments, the presence of ocean eddies can modify winds at the 455 air-sea interface, which in turn alters the Ekman transport in the Southern Ocean (Small 456 et al., 2008; Frenger et al., 2013; Perlin et al., 2020). The eddies also have an impact on 457 the wind stress through surface current speed correction (Dewar & Flierl, 1987; O'Neill 458 et al., 2003; Duhaut & Straub, 2006; Gaube et al., 2015). In other words, ocean eddies 459 affect Ekman transport by modifying the wind forcing over the sea surface. Neglecting 460 the eddy-wind coupling in non-eddy-resolving experiments may lead to imbalance in the 461 zonal-mean steady-state circulation, since eddy-induced circulation compensates for the 462 Ekman transport in the eddy-resolving models in the Southern Ocean (Abernathey et 463 al., 2011; Marshall & Speer, 2012). 464

By examining the eddy-resolving and non-eddy-resolving experiments, we found 465 that the air-sea interaction at mesoscale can cause significant differences in the variabil-466 ity of SST, MLD ocean currents, and Ekman transport. By comparing the interactive 467 ensemble and control experiments, we conclude that non-eddy-resolving ocean models 468 oftentimes overestimate the role of atmospheric noise and overlook the importance of ocean 469 dynamics. In eddy-resolving ocean models, the ocean eddies, air-sea coupled feedback 470 and non-linearity become more important to the mixed layer dynamics. We can further 471 assess the eddy-induced effects on atmospere-ocean coupling by using experiments with 472 multiple ocean ensemble members coupled to one atmospheric component. Although run-473 ning 10s global ocean models simultaneously is an ambitious task, we believe this is pos-474 sible in the near future considering the fast development of computational power nowa-475 days. 476

477 5 Open Research

The numerical model and data are available upon request. The Python code and jupyter notebook used to produce the results of this study are shared through the GitHub repository at https://github.com/yugaophd/SO_CCSM4.

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Figure 2. Time-mean MLD in a) LRC and b)₋₁₇-HRC, from year 121 to 150. Polar Front (PF, orange line) and Subantarctic Front (SAF, magenta line).



Figure 3. a) SSTA variance ratio of LRIE to LRC and b) SSTA variance ratio of HRIE to HRC. SSTA are the departures from the monthly SST climatology. Polar Front (PF, blue line) and Subantarctic Front (SAF, orange line).



Figure 4. The variance of MLDA in a) LRC, b) HRC from year 121 to 150. SSTA anomalies (SSTAs) are defined as departures from the monthly climatology. Polar ront (PF, orange line) and Subantarctic Front (SAF, magenta line).



Figure 5. Variance of MLDA in a) LRC, b) HRC from year 121 to 150. MLD anomalies are defined as departures from the monthly climatology. Polar ront (PF, orange line) and Subantarctic Front (SAF, magenta line).



Figure 6. a) MLD variance ratio of LRIE to LRC and b) MLD variance ratio of HRIE to HRC. MLD anomalies are defined as departures from the monthly climatology. Polar Front (PF, blue line) and Subantarctic Front (SAF, orange line).



Figure 7. Surface current speed variance ratio in a) HRC and b) LRC, from year 121 to 150. Polar Front (PF, orange line) and Subantarctic Front (SAF, magenta line).



Figure 8. a) Ekman transport variance ratio of LRIE to LRC and b) Ekman transport variance ratio of HRIE to HRC. Polar Front (PF, blue line) and Subantarctic Front (SAF, orange line).