North Pacific Upper-Ocean Cold Temperature Biases in CMIP6 Simulations and the Role of Regional Vertical Mixing

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ABSTRACT

Substantial model biases are still prominent even in the latest CMIP6 simulations; attributing their causes is defined as one of the three main scientific questions addressed in CMIP6. In this paper, cold temperature biases in the North Pacific subtropics are investigated using simulations from the newly released CMIP6 models, together with other related modeling products. In addition, ocean-only sensitivity experiments are performed to characterize the biases, with a focus on the role of oceanic vertical mixing schemes. Based on the Argo-derived diffusivity, idealized vertical diffusivity fields are designed to mimic the seasonality of vertical mixing in this region, and are employed in ocean-only simulations to test the sensitivity of this cold bias to oceanic vertical mixing. It is demonstrated that the cold temperature biases can be reduced when the mixing strength is enhanced within and beneath the surface boundary layer. Additionally, the temperature simulations are rather sensitive to the parameterization of static instability, and the cold biases can be reduced when the vertical diffusivity for convection is increased. These indicate that the cold temperature biases in the North Pacific can be largely attributed to biases in oceanic vertical mixing within ocean-only simulations, which likely contribute to the even larger biases seen in coupled simulations. This study therefore highlights the need for improved oceanic vertical mixing in order to reduce these persistent cold temperature biases seen across several CMIP models.

1. Introduction

Understanding systematic model biases and reducing uncertainties in climate change modeling remain a great challenge in climate science research. In the past, the Coupled Model Intercomparison Project (CMIP) products have been extensively and intensively used to

address the related scientific questions (Eyring et al. 2016). It is clearly seen that biases are strongly region and model dependent, with different responsible processes involved. Great efforts have been devoted to understanding tropical biases in sea surface temperature (SST) because SST plays an important role in the climate system by controlling the exchanges of energy and mass between the ocean and atmosphere, and also having worldwide impacts through teleconnections from the tropics (Alexander et al. 2002). For example, warm SST biases in the southeastern tropical Pacific tend to induce a stronger El Niño–Southern Oscillation

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(ENSO) signal (Manganello and Huang 2009), whereas the excessive cold-tongue bias tends to weaken the coupling strength and thermocline feedback in ENSO simulations (Xiang et al. 2012; Gao and Zhang 2017). Thus, tropical SST biases can degrade the fidelity of ENSO simulations and will affect the simulations in other regions through the ENSO teleconnection (Ham and Kug 2012). Many previous studies try to identify the causes and mechanisms responsible for tropical biases (Li and Xie 2014; Zuidema et al. 2016; Kang et al. 2017; Thomas and Fedorov 2017; Li et al. 2019). Nevertheless, state-of-the-art climate models still suffer from substantial tropical SST biases, which have persisted for decades in the coupled simulations.

Pronounced model biases are also seen in the North Pacific subtropics (NPS). For example, systematic cold temperature biases exist in the upper ocean. In fact, even ocean-only models, driven by prescribed-atmospheric forcing fields, commonly produce a similar cold bias over the subtropical regions (Griffies et al. 2009), indicating that the contribution from ocean model processes may be significant. Extensively focused efforts have been made to identify the causes of the subtropical cold temperature biases. By analyzing the outputs from the CMIP5 models, for example, Burls et al. (2017) reveal that subtropical SST biases are related to cloud albedo errors, which can cause deficiencies in simulated surface shortwave fluxes.

Understanding the subtropical biases in the North Pacific is important not only in its own right, but also because subtropical biases can play a role in generating tropical biases. For example, Vannière et al. (2014) find that the tropical cold-tongue bias can result from an equatorward advection of subtropical cold SST errors. Subtropical origins of the cold-tongue bias are also investigated by Thomas and Fedorov (2017), who suggest that improving the representation of subtropical cloud albedo may be crucial to the simulation of the cold tongue. Since the cold bias in the subtropics contributes to the equatorial cold bias significantly, understanding the mechanisms responsible for the former may be a key to understanding the latter. It is necessary to investigate the characteristics of temperature biases particularly over the NPS. Previously, many factors have been identified. As will be seen below, atmospheric factors cannot fully explain the formation of the cold temperature biases in the upper ocean of the NPS. Oceanic factors need to be taken into account.

It is widely recognized that one of the largest uncertainties in ocean models is vertical mixing parameterization. Errors in vertical mixing schemes inevitably misrepresent the vertical redistribution of momentum, heat, and so on. Some previous studies have discussed

the relationship between uncertainties in vertical mixing schemes and tropical biases (Zhang and Zebiak 2002; Hazeleger and Haarsma 2005; Harrison and Hallberg 2008; Jochum 2009; Moum et al. 2013; Sasaki et al. 2013; Zhu and Zhang 2018a,b, 2019). But the relationship between the subtropical cold bias and the errors in vertical mixing schemes has been rarely examined although some hints are seen in some previous studies. For example, Furue et al. (2015) and Jia et al. (2015) find that increasing ocean background diffusivity in the subtropics tends to induce a warming over the cold-tongue regions, implying that the intensity of parameterized vertical mixing is underestimated. A similar conclusion is made by Huang et al. (2014). They find that although the simulated surface wind stress is overestimated and net surface heat flux (NHF) is underestimated over the subtropics, the subtropical oceanic mixed layer depth (MLD) is greatly underestimated in most of the CMIP5 models. Therefore, insufficient vertical mixing in the upper ocean may be the potential reason for the underestimated MLD in the subtropics.

In this study, a focus is placed on cold temperature biases in the NPS, which are commonly seen in climate models. Here, the upper-ocean temperature biases are investigated using the simulations from the newly released CMIP6 models (Eyring et al. 2016), together with other related modeling products. In addition, in order to separate the contributions from ocean models, MOM5-based ocean-only simulations are performed, with sensitivities of the biases to oceanic vertical mixing schemes illustrated.

This paper is organized as follows. Section 2 describes the datasets used from CMIP simulations, observational products for model evaluation, and the model configurations for MOM5-based numerical experiments. Section 3 describes the characteristics of subtropical cold biases in the North Pacific, and the possible relationship with vertical mixing schemes is also discussed. Numerical experiments are performed to verify this relationship and the results are presented in sections 4 and 5. Finally, discussions and summaries are given in section 6.

2. Datasets and ocean model used

In this study, historical simulations from 22 CMIP6 models (Table 1) available online (<https://esgf-node.llnl.gov/projects/cmip6/>) are used to characterize the temperature biases in the NPS. Model outputs are taken from the experiment labeled “historical” spanning 1979–2014. In addition, simulations from 41 CMIP5 models (Table 2) spanning 1979–2005 are also used to determine whether the temperature representation in the NPS is improved or not as compared with the current generation

TABLE 1. CMIP6 models used in this study.

Institute	Model	Vertical mixing
Alfred Wegener Institute, Helmholtz Centre for Polar and Marine Research, Germany (AWI)	AWI_CM_1_1_MR	KPP ^a + BL ^b + EVD ^c
Beijing Climate Center, China (BCC)	BCC_CSM2_MR BCC_ESM1	KPP ^a + CAS ^d
Chinese Academy of Meteorological Sciences, China (CAMS)	CAMS_CSM1.0	KPP ^a + BL ^b + CAS ^d
Canadian Centre for Climate Modeling and Analysis, Environment and Climate Change Canada, Canada (CCCma)	CanESM5	TKE ^c + EVD ^c
National Center for Atmospheric Research, Climate and Global Dynamics Laboratory, United States (NCAR)	CESM2 CESM2(WACCM)	KPP ^a + BL ^b + EVD ^c
CNRM (Centre National de Recherches Meteorologiques, France), CERFACS (Centre Européen de Recherche et de Formation Avancée en Calcul Scientifique, France) (CNRM-CERFACS)	CNRM-CM6.1 CNRM-ESM2.1	TKE ^c + EVD ^c
EC-Earth Consortium, Rossby Center, Swedish Meteorological and Hydrological Institute/SMHI, Sweden (EC-Earth-Consortium)	EC-EARTH3 EC-EARTH3-Veg	TKE ^c + EVD ^c
National Oceanic and Atmospheric Administration, Geophysical Fluid Dynamics Laboratory, United States (NOAA GFDL)	GFDL CM4 GFDL ESM4	EPBL ^f + background diffusivity of Henye et al. (1986) + EVD ^c
Goddard Institute for Space Studies, United States (NASA GISS)	GISS-E2.1-G GISS-E2.1-H	KPP ^a KT ^g + CAS ^d
Met Office Hadley Centre, United Kingdom (MOHC)	HadGEM3-GC3.1-LL UKESM1.0-LL	TKE ^c + EVD ^c
Institut Pierre Simon Laplace, France (IPSL)	IPSL-CM6A-LR	TKE ^c + EVD ^c
JAMSTEC (Japan Agency for Marine-Earth Science and Technology), AORI (Atmosphere and Ocean Research Institute, The University of Tokyo), NIES (National Institute for Environmental Studies), and R-CCS (RIKEN Center for Computational Science), Japan (MIROC)	MIROC6 MIROC-ES2L	NK ^h + background diffusivity of Tsujino et al. (2000) + CAS ^d
Nanjing University of Information Science and Technology, China (NUIST)	NESM3	TKE ^c + EVD ^c
Seoul National University, South Korea (SNU)	SAM0-UNICON	KPP ^a + BL ^b + EVD ^c

^a KPP = *k*-profile parameterization (KPP) by [Large et al. \(1994\)](#).

^b BL = Diapycnal mixing associated with internal wave energy dissipation by [Bryan and Lewis \(1979\)](#).

^c EVD = Enhanced vertical diffusion for convection.

^d CAS = Convection adjustment scheme.

^e TKE = Turbulent kinetic energy scheme based on the model of [Gaspar et al. \(1990\)](#).

^f EPBL = Energetically constrained parameterization of the surface boundary layer by [Reichl and Hallberg \(2018\)](#).

^g KT = Surface mixed layer model by [Kraus and Turner \(1967\)](#).

^h NK = Surface mixed layer parameterization by [Noh and Kim \(1999\)](#).

TABLE 2. CMIP5 models used in this study.

ACCESS1.0	ACCESS1.3	CanCM4	CanESM2	CCSM4
CESM1(BGC)	CESM1(CAM5)	CMCC-CESM	CMCC-CM	CMCC-CMS
CNRM-CM5	CNRM-CM5.2	CSIRO-Mk3.6.0	FGOALS-g2	FGOALS-s2
GFDL CM2p1	GFDL CM3	GFDL-ESM2G	GFDL-ESM2M	GISS-E2-H
GISS-E2-H-CC	GISS-E2-R	GISS-E2-R-CC	HadCM3	HadGEM2-AO
HadGEM2-CC	HadGEM2-ES	INM-CM4	IPSL-CM5A-LR	IPSL-CM5A-MR
IPSL-CM5B-LR	MIROC-ESM	MIROC-ESM-CHEM	MIROC4h	MIROC5
MPI-ESM-LR	MPI-ESM-MR	MPI-ESM-P	MRI-CGCM3	MRI-ESM1
NorESM1-M				

of climate models. Model outputs are compared against the EN4 dataset (Good et al. 2013), an objective analysis product of subsurface temperature and salinity. Wind stress and surface heat fluxes are obtained from several observational and reanalysis datasets, including ERA5 (Hans et al. 2018) spanning 1979–2014, the NCEP–DOE Reanalysis 2 (Kanamitsu et al. 2002) spanning 1979–2014, MERRA-2 (Gelaro et al. 2017) spanning 1980–2014, the QuikSCAT Scatterometer Climatology of Ocean Winds (SCOW; Risien and Chelton 2008), and the Woods Hole Oceanographic Institution (WHOI) OAFlux dataset (Yu et al. 2008) spanning 1983–2009, respectively.

The complexity of coupled models makes it difficult to track back the oceanic origins of this cold bias in the North Pacific. One practical way for isolating the oceanic contribution is to perform ocean general circulation model (OGCM) experiments forced by the observed atmospheric forcing fields and examine whether the similar biases emerge in the ocean-only simulation. In the present study, ocean-only simulations are conducted based on the GFDL-MOM5. This ocean model has a nominal 1° horizontal resolution, with latitudinal resolution progressively refined to $1/3^\circ$ equatorward of 30° latitude. It has 50 levels in the vertical with 10-m resolution in the upper 22 levels. More model details can be found in Griffies et al. (2009). MOM5 is initialized using the January temperature and salinity fields from Steele et al. (2001), and is spun up for 295 years (5 repeated cycles) using the JRA55-do (JRA-55 with a “driving ocean” component; Tsujino et al. 2018) forcing fields from 1959 to 2017. After the spinup, in order to characterize the ocean model’s contribution to the bias problem in the coupled models, four ocean-only simulations forced by another cycle of the JRA55-do forcing fields are conducted, in which idealized vertical mixing fields are imposed. In these four experiments, parameterization for upper boundary layer mixing is k -profile parameterization (Large et al. 1994) and that for tidally driven mixing is the scheme of Simmons et al. (2004). In the control run (CTL), background diffusivity is assigned to be $10^{-5} \text{ m}^2 \text{ s}^{-1}$ globally and enhanced

diffusivity for static instability is $0.1 \text{ m}^2 \text{ s}^{-1}$. Three sensitivity tests are conducted, in which background diffusivity and enhanced diffusivity for static instability are changed (Table 3). Model outputs from the last 36 years (the period of 1979–2014) are saved for analysis. In addition, outputs from five available Ocean Model Intercomparison Project (OMIP; Griffies et al. 2016) models are also used in this study (Table 4).

3. The upper-ocean temperature biases in CMIP models and ocean-only simulations

a. CMIP simulations

Figure 1a shows the multimodel mean of upper-ocean (0–100 m) temperature bias with respect to EN4 from CMIP6 models. In general, cold bias over the NPS and warm bias along the northeastern tropical Pacific and the southeastern tropical Atlantic are most significant. The Atlantic coastal warm bias has been well documented in previous studies (Zuidema et al. 2016; Exarchou et al. 2018). In this study, thus, more attention is paid to the cold bias over the NPS. As seen, this cold bias covers a large area of the North Pacific from 10° to 40°N and from 130°E to 120°W , with the maximum reaching -2°C around 25°N . Figure 1b shows the vertical distribution of temperature bias as a function of seasons, which is the horizontally averaged from 20° to 35°N and from 150°E to 160°W (indicated by the black box in Fig. 1a), roughly the region with bias greater than -1.5°C . It reveals that the maximum cold bias is

TABLE 3. Experiments performed using MOM5 forced by prescribed atmospheric fields, with different specifications of vertical mixing schemes.

Expt	Background diffusivity	Enhanced diffusivity for static instability
CTL	$10^{-5} \text{ m}^2 \text{ s}^{-1}$ globally	$0.1 \text{ m}^2 \text{ s}^{-1}$
BD-SC	Prescribed with seasonal cycle over the NPS	$0.1 \text{ m}^2 \text{ s}^{-1}$
EBD	$10^{-4} \text{ m}^2 \text{ s}^{-1}$ over the NPS	$0.1 \text{ m}^2 \text{ s}^{-1}$
EDC	$10^{-5} \text{ m}^2 \text{ s}^{-1}$ globally	$10 \text{ m}^2 \text{ s}^{-1}$

TABLE 4. OMIP models used in this study.

Institute	Model
NCAR	CESM2
CNRM-CERFACS	CNRM-ESM2.1
GFDL	GFDL CM4
IPSL	IPSL-CM6A-LR
MIROC	MIROC6

located at approximately 50 m, rather than at the surface layer. The amplitudes of the upper-ocean cold bias vary with season, being more significant during the second half of the year. Accompanied by the cold bias in the upper ocean of ~ 300 m, a warm bias arises right below. Different from the cold bias, the warm bias is largely independent of season.

Although great efforts have been made to improve model performance over the past decades, it is still frustrating that the biases are so stubborn and improvements in upper-ocean temperature simulation are quite limited from CMIP5 to CMIP6 (Figs. 1c,d). Nevertheless, some models are quite successful in reproducing the upper-ocean temperature over the NPS. For example, Fig. 2 shows the vertical distribution of temperature bias for individual models. It demonstrates that rather than a cold bias, CESM2 and CESM2-

WACCM tend to produce a warm bias during the second half of the year.

b. Ocean-only simulations

These subtropical biases can have various origins, and the processes responsible for them are not well understood. To verify the hypothesis that the cold bias is partly of oceanic origin, we perform ocean-only simulations using MOM5 forced by observed atmospheric fields. Several numerical experiments are conducted to demonstrate whether the similar biases can emerge in the ocean-only simulations.

Figure 3a demonstrates the upper-ocean temperature bias from the MOM5-based ocean-only simulation (CTL run). Note that the NPS cold bias (annually averaged over 20° – 35° N, 150° E– 160° W and 0–100 m) is -1.6° C in the coupled simulation, and is -0.6° C in the ocean-only simulation. While the cold biases in the ocean-only simulations are smaller than those in the coupled simulations, it is obvious that the spatial pattern and seasonal variation are similar. For example, there is also a cold bias in the subtropical and equatorial regions, accompanied by a warm bias in the vicinity of the eastern boundaries. In addition, the seasonality of the cold bias over the NPS is also a prominent feature (Fig. 3b). This CTL run is forced by the JRA55-do forcing fields

FIG. 1. (left) Multimodel mean biases in upper-ocean temperature (averaged over 0–100 m) relative to EN4 for (a) CMIP6 and (c) CMIP5 models. (right) Vertical season sections of temperature biases horizontally averaged in the region 20° – 35° N, 150° E– 160° W [black dashed box in (a) and (c)] for (b) CMIP6 and (d) CMIP5 models.

FIG. 2. Vertical season sections of temperature biases horizontally averaged in the region 20°–35°N, 150°E–160°W for individual CMIP6 models. Seasonality (August–October minus February–April) at 50 m is marked in the lower-left corner of each panel.

(Tsujino et al. 2018). For further verification, results from the available OMIP models are also shown in Fig. 3. These results are very similar to each other, indicating the important roles played by ocean model deficiencies in inducing the NPS cold bias.

4. Atmospheric sources of the NPS cold bias

Formation of the cold bias can be related to the simulated atmospheric states in CMIP6. Figure 4 shows the scatterplots of temperature at 50 m (T50) versus wind stress curl (Fig. 4a) and wind stress amplitude (Fig. 4b) for August–October. It is no surprise that T50 increases with the strengthening of the wind stress curl and amplitude, because more vigorous wind-induced mixing and downward Ekman pumping act to enhance the downward heat transport. However, wind stress in most individual models is generally overestimated, which should lead to a subsurface warm bias rather than the cold bias. Thus, it seems that errors in simulated wind stress cannot account for the subsurface cold bias alone.

Figure 5a shows the relationship between T50 and the net surface heat flux (NHF) for August–October. It seems that the NHF is generally underestimated in most models, compared with the estimate from OAFlux. Note that the previous study by Li et al. (2015) suggested an overestimation of the OAFlux NHF into the ocean. Therefore, three additional reanalysis datasets are also

examined for cross-validation. It is seen that if the NHF estimate from the MERRA2 is considered to be more realistic, the NHF into the ocean might be overestimated in most CMIP6 models. It is interesting to note that the scatterplots of 5-m temperature versus NHF demonstrate a negative correlation (Fig. 5b). That is to say, the models with larger cold bias tend to obtain more heat from atmosphere. Figure 6 shows the underlying mechanism. If the bias in NHF is the dominant source of the cold bias (Fig. 6a), an underestimated NHF would cool the surface layer directly. The upper-ocean stratification would be decreased as a consequence of surface cooling, which would cause an enhanced oceanic vertical mixing and more heat penetration to the subsurface depth, which acts to warm the subsurface layer. Therefore, the NHF and T50 should be negatively correlated. This is inconsistent with the scatterplots shown in Fig. 5a, so we assume that the bias in oceanic vertical mixing is a dominant source of the cold bias. In this case (Fig. 6b), an underestimated oceanic vertical mixing can inhibit the downward heat transport, leading to the subsurface cooling and surface warming. Simultaneously, the SST warming can increase upward turbulent heat fluxes. As such, NHF is decreased, showing a positive relation with T50. This is consistent with the scatterplots in Fig. 5a. Hence, heat redistribution in the upper ocean by oceanic vertical mixing may suffer from great errors.

FIG. 3. As in Fig. 1, but for (a) the MOM5-based ocean-only simulation (driven by JRA55-do atmospheric forcing fields; Tsujino et al. 2018) and (b) OMIP models [driven by the forcing fields from Large and Yeager (2009)].

5. Oceanic sources of the NPS cold bias

a. Oceanic factors associated with vertical background diffusivity

Climate model deficiencies can be partly attributed to those in the oceanic component, including insufficient model resolution, limitations of grid discretization, and

uncertainties in parameterizations for subgrid processes. In this study, uncertainties in the diapycnal mixing scheme are our focus. Vertical mixing may suffer from great errors, leading to biases in heat redistribution in the vertical direction. To verify our hypothesis, vertical eddy diffusivities in the CTL run are demonstrated in Fig. 7. It shows that the values of vertical

FIG. 4. Scatterplots of temperature (at the depth of 50 m) vs (a) wind stress curl and (b) wind stress amplitude. Each dot is the averaged value from August to October over the NPS region (black dashed box in Fig. 1a); the red dots are CMIP6 models and the blue dots are OMIP models (atmospheric variables for MIROC6 are unavailable at the time of writing). The corresponding observations and reanalyses are also demonstrated by the dashed gray lines.

FIG. 5. As in Fig. 4, but for the relationships of NHF with temperature at depth of (a) 50 and (b) 5 m.

eddy diffusivities over the NPS are close to the prescribed background one ($10^{-5} \text{ m}^2 \text{ s}^{-1}$; Fig. 7a), implying that the turbulent downward heat transport at the depth of 50 m is weakly represented in the model. Besides, large cold bias is located just beneath the isoline of $10^{-4.5} \text{ m}^2 \text{ s}^{-1}$ (Fig. 7b). These indicate two possible mechanisms at work. One mechanism seems to be related with the fact that the penetration of boundary layer mixing is not deep enough to warm the subsurface layer. The second mechanism for the cold bias may be related to an excessive downward transport

of heat. The second mechanism seems quite reasonable in consideration of the warm bias below ~ 300 m. Thus, we prefer to examine the second mechanism first.

If the second mechanism dominates, the prescribed vertical diffusivity in the ocean interior (below 200 m) over the NPS is overvalued, bringing more heat from the upper ocean to the deep layers during August–October. Indeed, diffusivities derived from the Argo profiles support this view. Figure 8 shows the Argo-derived diffusivity based on the finescale method (Kunze et al. 2006). Consistent with the previous studies (Li and Xu

FIG. 6. A schematic representing the influences of (a) NHF and (b) oceanic vertical mixing biases on the subsurface cold bias.

FIG. 7. (a) Diffusivity [$\log_{10}(\text{m}^2 \text{s}^{-1})$] at the depth of 50 m from the CTL run and (b) the region-averaged temperature bias (colors; $^{\circ}\text{C}$) and diffusivity [contours; $\log_{10}(\text{m}^2 \text{s}^{-1})$] over the NPS.

2014; Inoue et al. 2017; Whalen et al. 2018), the Argo-derived diffusivity exhibits a clear seasonal cycle, with a reduced vertical diffusivity during the second half of the year. That is to say, the prescribed background diffusivity typically employed in ocean and climate modeling ($\sim 10^{-5} \text{m}^2 \text{s}^{-1}$) is relatively realistic for the first half of the year, but is overvalued for the second half of the year.

It is natural to investigate the consequences when the seasonality of background diffusivity are considered. Then, we perform a numerical experiment (the Background Diffusivity with Seasonal Cycle run, denoted as BD-SC run) in which the background diffusivity is prescribed as

$$\begin{aligned} \text{amp} &= \exp \left[- \left(\frac{\text{lon} - 160^{\circ}\text{E}}{70^{\circ}} \right)^2 \right] \exp \left[- \left(\frac{\text{lat} - 38^{\circ}\text{N}}{20^{\circ}} \right)^2 \right], \\ \text{mag} &= 5 + 0.5 \left[1 - \cos \left(2\pi \frac{\text{day} - 60}{365} \right) \right] \times \text{amp}, \\ \text{Kt} &= 10^{-\text{mag}} \text{m}^2 \text{s}^{-1}, \end{aligned} \quad (1)$$

for the whole water column (Fig. 9), in which “lon” and “lat” are the longitude and latitude of a grid point in the ocean model, and “day” is the model time in days. Note that although vertical changes in the Argo-derived diffusivity are shown in Fig. 8b, the prescribed background

FIG. 8. The diapycnal diffusivity in the ocean interior estimated using the Argo profiles (2-m vertical resolution) based on the finescale method (Kunze et al. 2006). Each estimate is grouped into a 3° square bin according to the calendar month; the periods during January 2006–April 2019 are selected for use. The median value for each group is selected to represent the diffusivity for each calendar month at each bin. Thus, 12 different maps for the diffusivity in the ocean interior are obtained, one for each calendar month. Shown are (a) the difference in base-10 logarithm of diffusivity (Kt; at the depth of 50 m; the mean value from August–October minus that from February–April) and (b) the region-averaged value in 20° – 45°N , 150°E – 160°W (covering the NPS), consistent with the results in Whalen et al. (2018).

FIG. 9. (a) Base-10 logarithm of the prescribed vertical diffusivity [as expressed in Eq. (1)] averaged in August–October. (b) The region-averaged value in 20° – 45° N, 150° E– 160° W.

diffusivity employed in our experiment is independent of depth.

Figure 10 shows the differences in the simulated temperature between the BD-SC run and the CTL run. Contrary to the expectation, the cold bias is increased in the BD-SC run. In essence, reducing background diffusivity acts to weaken the strength of vertical mixing below the surface boundary layer, which tends to inhibit downward heat transport from the surface boundary layer. Less heat supply tends to cool the subsurface layer, and hence this mechanism may be incorrect and the seasonality of background diffusivity is not responsible for the cold bias during August–October. Although the bias problem gets worse in the above experiment, useful information can nevertheless be inferred from Fig. 10. It is related to the subsurface warm bias below 300 m (Figs. 3b,d). As previously studied (Griffies et al.

2015), this warm bias is believed to be the result of coarse model resolution, because coarse-resolution models cannot resolve oceanic mesoscale eddies, which act to transport heat upward and offset the downward heat transport. Here in our study, we show that the misrepresentation of diapycnal mixing can be a source of subsurface warm bias. By introducing the seasonality of diapycnal mixing with an order-of-magnitude reduction during the second half of the year, the subsurface warm bias is somewhat reduced (Fig. 10b).

One shortcoming of the above experiment is the vertical structure of the prescribed background diffusivity. The estimated vertical diffusivity based on the finescale method is regarded as unreliable in the upper ocean due to the potential contamination by sharp pycnoclines (Kunze et al. 2006), and hence the estimates above 400 m are discarded in our study (Fig. 8b). Therefore, although the estimated diffusivity below 400 m exhibits a magnitude of $O(10^{-6}) \text{ m}^2 \text{ s}^{-1}$ in the next half year, the values above 400 m are not known. That means the prescribed depth-independent background diffusivity above 400 m (particularly beneath the surface boundary layer) in the BD-SC run may be unrealistic. In addition, since reducing diffusivity leads to an increase in the cold bias, increasing diffusivity is most likely to relieve this bias tendency. It is hard to justify the rationality of increasing subsurface diffusivity since direct observations are rare. But the budget analyses for heat (Cronin et al. 2015; Lee et al. 2015; Yamaguchi et al. 2019) and dissolved oxygen (Sukigara et al. 2011) demonstrate that this diffusivity is on the order of $10^{-4} \text{ m}^2 \text{ s}^{-1}$ during the warm season. Thus, one more experiment (the Enhanced Background Diffusivity run, denoted the EBD run) is conducted, in which the depth-independent background diffusivity is simply prescribed as

FIG. 10. Temperature difference between the BD-SC run and the CTL run. (a) Global distribution at the depth of 50 m. (b) Vertical distribution over the NPS region.

FIG. 11. (a),(b) As in Fig. 10, but for the temperature difference between the EBD run and the CTL run. (c),(d) Upper-ocean temperature bias relative to EN4.

$$\text{amp} = \exp \left[- \left(\frac{\text{lon} - 160^\circ\text{E}}{70^\circ} \right)^2 \right] \exp \left[- \left(\frac{\text{lat} - 38^\circ\text{N}}{20^\circ} \right)^2 \right],$$

$$Kt = 10^{-5+\text{amp}} \text{ m}^2 \text{ s}^{-1}. \quad (2)$$

Figure 11 shows the temperature difference between the EBD run and the CTL run. Consistent with our expectation, the cold bias during the second half of the year is reduced when background diffusivity is increased, implying the important role played by vertical diffusivity at the base of boundary layer in the simulation of upper-layer temperature over the NPS.

The above two experiments clearly show that increasing background diffusivity below the surface boundary layer can reduce the cold bias at the depth of 50 m, whereas reducing background diffusivity in the ocean interior can reduce the warm bias below 300 m. Thus, it implies that background diffusivity decreases with depth over the NPS. This type of profile has been examined by Jia et al. (2015), in which subsurface warming also occurs around 50 m. However, microstructure observations from Moum and Osborn (1986) show that vertical eddy diffusivity increases with depth, and the diffusivity is about $2 \times 10^{-6} \text{ m}^2 \text{ s}^{-1}$ around 50 m in early summer. Thus, the seasonality simply formulated as in Eq. (1) is more consistent with their

observations. But the microstructure observations are too scarce to be representative. Therefore, we can only conclude that the appearance of this cold bias is sensitive to the background diffusivity, whose realistic representation is still a challenging issue.

b. Influences induced by convective adjustment schemes

In the previous subsection, we have investigated the important role played by background diffusivity. However, questions still remain about its adequate representation in ocean modeling. In this subsection, we will discuss another factor contributing to this bias problem. It is associated with the convective adjustment scheme in OGCMs, whose effects are rarely discussed in ocean related modeling studies.

The hydrostatic approximation of climate models necessitates the use of a parameterization for static instability. In general, there are two types of treatments when static instability occurs: one is through convective adjustment, and the other is to use an enhanced vertical diffusivity (Marshall and Schott 1999). The second way is recommended for use in many models, but the typical value for enhanced diffusivity, which characterizes the time scale of convective mixing, is rather different among different models. For instance, enhanced diffusivity is assigned to be $1 \text{ m}^2 \text{ s}^{-1}$ in CESM2 and GFDL CM4, but is assigned to be $100 \text{ m}^2 \text{ s}^{-1}$ in NEMO-based

FIG. 12. As in Fig. 11, but for the differences between the EDC run and the CTL run.

climate models (Madedec 2016). To test the sensitivity of cold bias in the NPS to the enhanced diffusivity, one experiment is performed, in which the vertical eddy diffusivity is assigned to be $10 \text{ m}^2 \text{ s}^{-1}$ in the regions where the static instability occurs (Enhanced Vertical Diffusivity by Convection, denoted the EDC run). Note that the corresponding value in the CTL run is $0.1 \text{ m}^2 \text{ s}^{-1}$.

Figure 12 shows the temperature difference between the EDC run and the CTL run. The cold bias over the NPS is greatly reduced in the ocean-only simulation when the enhanced diffusivity for static instability is increased. In addition, the cold bias over the North Atlantic is also reduced with similar spatial pattern. However, the simulation in the eastern tropics gets worse; the warm bias is increased, especially in the eastern Atlantic. In the previous section, we have shown that CESM2 and CESM2(WACCM) produce a subsurface warm bias rather than a cold bias. Although there are many reasons for this, we suggest that more attention should be paid to the convective adjustment scheme, as demonstrated in Fig. 13 showing the differences between the CESM2 and the multimodel mean. The warming pattern is similar to that in Fig. 12, implying that the uncertainty in this parameter is an important attribution to subsurface temperature bias. It remains unclear how to parameterize the static instability effects so that the diffusivity can be enhanced in

ocean models. Large-eddy simulations have confirmed the dependence of convection on Earth rotation (Jones and Marshall 1993; Wang 2003). Thus, though globally uniformly prescribed in the present climate models, the enhanced diffusivity should be taken as a function of the Coriolis parameter in order to have a more realistic temperature simulation.

6. Summary and discussion

Realistic simulations of mean climate and its natural variability are critically important to model applications to climate predictions and projections. Unfortunately, model developments over the past decade do not clearly transfer into a significant improvement in upper-ocean temperature simulations. Indeed, the state-of-the-art climate models still suffer from substantial biases, including SST and subsurface thermal structure. Particularly through atmospheric teleconnections, SST biases in the tropical Pacific can have significant impacts on global climate simulations. Recent studies (Burls et al. 2017; Thomas and Fedorov 2017) have revealed the subtropical origins of the tropical SST bias, but the causes of subtropical cold temperature biases have not yet been fully investigated.

In this study, model biases in the subtropics of the North Pacific are investigated using the simulations from the newly released CMIP6 products, together with other

FIG. 13. As in Figs. 12a and 12b, but for the temperature difference between the CESM2 and the multimodel mean.

related modeling products including CMIP5. Our study reveals that the cold bias covers a large area of the North Pacific, with a maximum occurring at approximately 50 m, rather than in the surface layer. The amplitudes of the upper-ocean cold bias vary with season; the cold bias is more significant during the second half of the year. Deficiencies in wind stress and surface heat fluxes may contribute to the generation of these biases. But the correlation between the temperature bias and NHF is positive in the subsurface layer and is negative in the surface layer. Thus, heat redistribution by vertical mixing may suffer from great errors, and uncertainties in the oceanic vertical mixing schemes can make great contributions to this cold bias. Indeed, despite being much weaker, this cold bias also exists in OMIP simulations. Thus, sensitivity of the cold bias to oceanic vertical mixing schemes is illustrated using ocean-only simulations. Based on the Argo-derived diffusivity, idealized vertical diffusivity fields are designed to mimic the vertical mixing in the region. It is demonstrated that this bias problem can be relieved in ocean-only simulations when the mixing strength is enhanced within and beneath the surface boundary layer.

In this study, we have demonstrated that adequate parameterizations of vertical mixing processes beneath the surface ocean boundary layer are critically important to the upper-ocean temperature simulations over the NPS. Unfortunately, direct observations are rare to verify our method with increasing diffusivity at the base of surface boundary layer. Particularly, microstructure observations from Moum and Osborn (1986) demonstrate a weak mixing strength around 50 m, casting doubt on our prescriptions in the ocean-only simulations. Thus, more microstructure observations are clearly needed to give a complete description of the upper-ocean mixing over the NPS. The ocean model solution is sensitive to the enhanced diffusivity for static instability, but its parameterization is rather crude. The enhanced diffusivity characterizes the finite time of convective

plumes, and is influenced by Earth's rotation (Jones and Marshall 1993). In the next study, we will use large eddy simulations to investigate this issue in attempting to better parameterize the rotating convection.

Essentially, increasing the upper-ocean mixing coefficient is beneficial to the downward heat transfer. Therefore, by introducing the Langmuir turbulence and nonbreaking wave mixing, subsurface warming effect is also reported in some previous studies (Fan and Griffies 2014; Wang et al. 2019). It is a promising approach to separate the individual mixing processes from the traditional turbulence closure schemes [e.g., the k -profile parameterization (KPP) scheme]. But questions still remain about how to adjust the empirical parameters in the traditional turbulence closure schemes. As these empirical parameters are carefully tuned to fit the observed oceanic variables (usually including temperature and mixed layer depth) when constructing the vertical mixing schemes (Large et al. 1994; Godfrey and Schiller 1997), so the effects from different mixing processes are implicitly considered in the empirical parameters. When some mixing processes are parameterized individually, the original empirical parameters should be adjusted accordingly. Thus, it is still a question about how to properly evaluate the performances of vertical mixing schemes in the ocean modeling.

The NPS cold bias covers the subtropical gyres, where Subtropical Mode Water (STMW) is formed. As the formation rate of STMW plays an important role in the oceanic uptake of heat and CO_2 (Oka and Qiu 2012), climatic impacts of this cold bias could be significant but are poorly understood. Besides the cold bias over the NPS, systematic biases in other regions are still prominent in the CMIP6 models, including cold bias over the subtropics in the South Pacific and warm bias along the southeastern tropical Atlantic and the northeastern tropical Pacific. In addition, temperature biases can also be related to freshwater flux forcing and salinity effects (e.g., Zhang et al. 2010; Kang et al. 2017; Zhi et al. 2019).

Thus, further research efforts are clearly needed to identify the origins and impacts of these biases. Analyses from this study can provide valuable guidance for identifying and ultimately reducing these model biases, with better parameterizations of vertical mixing processes.

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