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2 **Asymmetric Responses in the Equatorial Pacific to Wind Forcing in OMIP2**
3 **Experiments: Role of Zonal Currents**

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13 **Key Points:**

- 14 • The asymmetric temperature response to zonal wind-stress forcing in the western Pacific
15 is commonly underestimated by ocean models
- 16 • A generally weaker zonal currents in ocean models than in the observations is a cause of
17 the underestimated asymmetric temperature response
- 18 • The weaker zonal current response in ocean models is linked to a less steep zonal tilt of
19 the thermocline
20

21 Abstract

22 Numerical experiments from phase II of the Ocean Model Intercomparison Project (OMIP2)
23 generally underestimate the asymmetric temperature response to interannual changes in the
24 wind-stress over the equatorial western Pacific subsurface. Despite the knowledge that such a
25 bias may be directly behind the general lack of asymmetry in model-simulated ENSO, its causes
26 remain unknown. Here we report that a weaker response in the zonal currents to wind forcing in
27 these models results in a biased response in the vertical motion which in turn causes weaker
28 asymmetric temperature responses through the contribution of the vertical motion to the
29 advective heating (dynamic heating). This finding underscores the critical importance of
30 accurately modeling the zonal currents—a previously less noticed element in the modeling
31 effort—to better capture the asymmetric responses in the tropical western Pacific to external
32 wind forcing and thereby improving simulations of ENSO by coupled climate models.

33 Plain Language Summary

34 The responses of ocean dynamics to changes in atmospheric forcing plays a crucial role in
35 simulating ENSO in fully-coupled climate models. This study utilizes simulations from stand-
36 alone ocean models to show that ocean models underestimate temperature responses to
37 atmospheric forcing in the western Pacific subsurface. The cause of this response is a weaker
38 response in the zonal (west-east) ocean currents, which in turn leads to a biased response in
39 vertical motion in the equatorial upper ocean and thereby a weaker dynamic heating. The weaker
40 dynamic heating then results in the weakened temperature response. These findings highlight the
41 need for accurately simulating zonal currents to improve simulation of ENSO by climate models,
42 in particular its asymmetry.

43 1 Introduction

44 The El Niño-Southern Oscillation (ENSO) is the major interannual oscillation in the
45 tropical Pacific (McPhaden et al., 2006; Timmermann et al., 2018). It arises from anomalous
46 warming in the eastern tropical Pacific surface, which is amplified by oceanic zonal circulation
47 driven by eastward wind-stress anomalies, a process known as the Bjerknes feedback (Bjerknes,
48 1969; Wyrki, 1975). Accurate simulation of ENSO requires studying how oceanic processes
49 respond to wind-stress (Hua & Yu, 2015).

50 A significant deviation in ENSO simulations by climate models is the temperature
51 asymmetry over the western and eastern Pacific subsurface during El Niño and La Niña phases
52 of ENSO (Zhang et al., 2009; Zhang & Sun, 2014; Zhao & Sun, 2022). This bias largely stems
53 from the inadequate representation of nonlinear dynamic heating (NDH), especially its zonal
54 component (Hayashi & Jin, 2017; Hayashi et al., 2020). Previous studies have primarily focused
55 on investigating the sources of bias in ENSO asymmetry over the surface and subsurface of the
56 eastern equatorial Pacific (An & Jin, 2004; Frauen & Dommenges, 2010; Carre et al., 2014; Zhao
57 & Sun, 2022; Wang et al., 2023), leaving the western equatorial Pacific, particularly its
58 subsurface, relatively underexplored. Since the equatorial undercurrent (EUC) forms in the
59 western equatorial Pacific (Pedlosky, 1987; Pedlosky, 1991; Hu et al., 2015) and theories
60 associated with ENSO cycles, such as recharge oscillator (Jin, 1997) and delayed oscillator
61 (Suarez & Schopf, 1988), are established primarily based on western Pacific, it is crucial to study
62 ENSO asymmetry in this region by investigating the ocean's dynamic responses to zonal wind-
63 stress.

64 Here, to identify origins of the bias in temperature asymmetry related to oceanic dynamic
 65 processes and role of zonal currents in this bias, we utilize outputs from phase II of Ocean Model
 66 Intercomparison Project (OMIP2, Griffies et al., 2016) to diagnose the source of bias in
 67 asymmetric temperature responses to zonal wind-stress anomalies. The structure of this paper is
 68 as follows: Section 2 introduces the datasets and methods used for analysis. Section 3 presents
 69 the results, highlighting predominant ocean dynamic processes that cause the bias in asymmetric
 70 response of temperature in the western equatorial Pacific subsurface and section 4 provides a
 71 summary and discussion of the findings, along with suggestions for future research.

72 **2 Data and Methods**

73 2.1 Datasets

74 We obtained monthly ocean reanalysis variables (potential temperature, zonal,
 75 meridional, and vertical currents, sea surface zonal wind-stress) from the NCEP Global Ocean
 76 Data Assimilation System (GODAS) (Behringer et al., 1998), Simple Ocean Data Assimilation
 77 datasets (SODA, Carton & Giese, 2008) and GECCO versions 2 and 3 (Köhl, 2015; Köhl, 2020)
 78 from the Estimating the Circulation and Climate of the Ocean project. Details of the reanalysis
 79 datasets are provided in Table S1. OMIP2 offers simulation results from 15 Ocean-Sea ice
 80 coupled models, with an analysis period of 1980-2016 to ensure coverage across all datasets.
 81 Details of the ocean models are shown in Table S2. Ocean models from different institutes
 82 worldwide are primarily derived from a few core ocean model frameworks as shown in Table S2,
 83 such as POP, MOM and NEMO. To ensure clarity, we continue using the names of the climate
 84 models to represent their respective ocean components. Notably, positive and negative sign of
 85 vertical currents (zonal wind-stress) correspond to downwelling (eastward) and upwelling
 86 (westward), respectively. Subsurface zonal currents were validated using data from the Tropical
 87 Atmospheric Ocean (TAO) mooring array (2004-2016) (McPhaden, 1995).

88 2.2 Methods

89 The study focuses on investigating the source of bias of asymmetric response of
 90 temperature in ocean models. Monthly mean anomalies were used, with the seasonal cycle and
 91 warming trend removed. Bilinear interpolation was applied to unify the resolution onto a $1^\circ \times 1^\circ$
 92 horizontal grid. The Niño-3 and Niño-4 regions were defined as $5^\circ\text{N}-5^\circ\text{S}$, $150^\circ\text{W}-90^\circ\text{W}$ and
 93 $5^\circ\text{N}-5^\circ\text{S}$, $160^\circ\text{E}-150^\circ\text{W}$, respectively. The western and eastern equatorial Pacific subsurface
 94 regions (referred to as WEPS and EEPS) were (100 m-200 m, $2^\circ\text{S}-2^\circ\text{N}$, $160^\circ\text{E}-150^\circ\text{W}$) and (50
 95 m-150 m, $2^\circ\text{S}-2^\circ\text{N}$, $150^\circ\text{W}-90^\circ\text{W}$), respectively.

96 Heat budget analysis is used to analyze the bias of dynamic heating terms in the
 97 ensemble-averaged model results compared to reanalysis datasets. The heat budget of the ocean
 98 subsurface layer is calculated using the temperature anomaly tendency equation as below (From
 99 Jin et al., 2003):

$$\begin{aligned}
 \frac{\partial T'}{\partial t} &= LDH + NDH + R \\
 LDH &= -u' \frac{\partial \bar{T}}{\partial x} - v' \frac{\partial \bar{T}}{\partial y} - w' \frac{\partial \bar{T}}{\partial z} - \bar{u} \frac{\partial T'}{\partial x} - \bar{v} \frac{\partial T'}{\partial y} - \bar{w} \frac{\partial T'}{\partial z} \\
 NDH &= -u' \frac{\partial T'}{\partial x} - v' \frac{\partial T'}{\partial y} - w' \frac{\partial T'}{\partial z}
 \end{aligned} \tag{1}$$

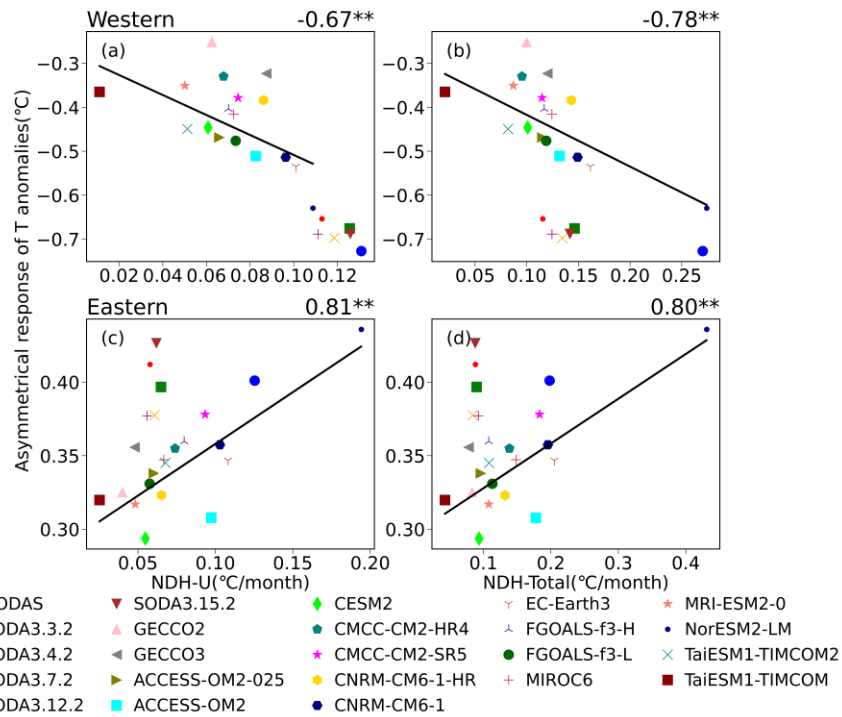
101 Here, $\bar{\theta}$ is the potential temperature, and u , v , and w represent the zonal, meridional, and vertical
102 velocities in the ocean, respectively; the overbar indicates the climatological mean, and the prime
103 denotes anomalies. R represents sub-grid processes of heating and thermodynamic heating. The
104 first and second terms on the right-hand side denote linear dynamic heating (referred to as LDH)
105 and nonlinear dynamic heating (referred to as NDH), respectively, which can be calculated using
106 the central difference approximation.

107 This study also adopts the composite analysis to characterize the asymmetric temperature
108 responses to zonal wind-stress between warm (El Niño) and cold (La Niña) phases of ENSO.
109 Warm (cold) phase of ENSO is defined as averaged temperature anomalies above 0.5°C (below -
110 0.5°C) in the Niño-3 region (Zhang et al., 2009). In this paper, we attribute the asymmetric
111 temperature response to the difference in amplitudes between El Niño and La Niña events over
112 equatorial Pacific subsurface, same as the definition of temperature asymmetry in climate models
113 because OMIP2 uses the same atmospheric forcing data to drive ocean models. We focus only
114 on the one-way responses to isolate biases from ocean dynamics.

115 **3 Results**

116 We first evaluate the performance of standard deviation (STD) and ENSO asymmetry of
117 temperature over Niño-3 (shown in Figure S1a and S1b), confirming that OMIP2 ocean models
118 perform better in eastern equatorial Pacific surface compared to climate models from previous
119 studies (Zhang and Sun, 2014; Zhao and Sun, 2022). As NDH along equatorial Pacific
120 thermocline plays a crucial role in shaping ENSO temperature asymmetry (Hayashi et al., 2020),
121 we then explore Pacific subsurface for the relationship between NDH (unit: $^{\circ}\text{C}/\text{month}$) and
122 asymmetric responses of temperature to zonal wind-stress (unit: $^{\circ}\text{C}$) over WEPS (Figure 1,
123 panels 1a and 1b) in comparison to EEPS (Figure 1, panels 1c and 1d) in stand-alone ocean
124 models. NDH was divided into four components: three-dimensional NDH (referred to as NDH-
125 Total, panels 1a and 1c) and zonal component of NDH (referred to as NDH-U, panels 1b and
126 1d), meridional and vertical component of NDH (referred to as NDH-V and NDH-W,
127 respectively, depicted in Figure S3). As shown in Figs. 1a, 1c and S3, NDH-U is the dominant
128 component of NDH, exhibiting a stronger heating rate than NDH-V and NDH-W. Neither NDH-
129 U nor asymmetric temperature response in ocean models were underestimated compared with
130 ocean reanalysis datasets over WEPS (as shown by the uniquely colored symbols in Figure 1a
131 and Figure S2b), which aligns with the results derived from climate models (Zhao and Sun,
132 2022).

133 Additionally, Figure 1 illustrates that stronger asymmetric responses correlate with
134 stronger positive NDH. NDH generally maintains positive over the equatorial Pacific, which
135 could strengthen (weaken) El Niño (La Niña) events, in turn, leading to positive asymmetric
136 temperature responses over eastern equatorial Pacific surface and subsurface (Jin et al., 2003;
137 Hayashi and Jin, 2017; Figure 1c and 1d). This mechanism, however, seems invalid over WEPS
138 in Figure 1a that stronger positive NDH corresponds to stronger negative asymmetric
139 temperature responses. Thus, the bias of NDH-U may not directly drive the bias in negative
140 asymmetric responses over WEPS in OMIP2 ocean models, warranting further investigation.
141 Using Figure 1 as a starting point, one questions arise: why is asymmetric responses of
142 temperature weaker in most ocean models from OMIP2 in WEPS?



143

144 Figure 1. The relationship between nonlinear dynamic heating (NDH, unit: °C/month) and
 145 asymmetric responses of subsurface temperature anomalies (unit: °C) is examined among ocean
 146 models from OMIP2 over the western equatorial Pacific subsurface (a & b) and eastern
 147 equatorial Pacific subsurface (c & d). The left columns (a & c) depict the relationship with the
 148 zonal component of NDH, while the right columns (b & d) show the relationship with the three-
 149 dimensional NDH. Different symbols in unique colors represent distinct datasets, as indicated in
 150 the legends of the right panel of the figure. A black line represents the regression line, and the
 151 correlation coefficient is displayed in the upper right corner of each subgraph. Statistical
 152 significance is denoted by asterisks (* for 95% confidence level, ** for 99% confidence level),
 153 determined by standard Student’s t-test.

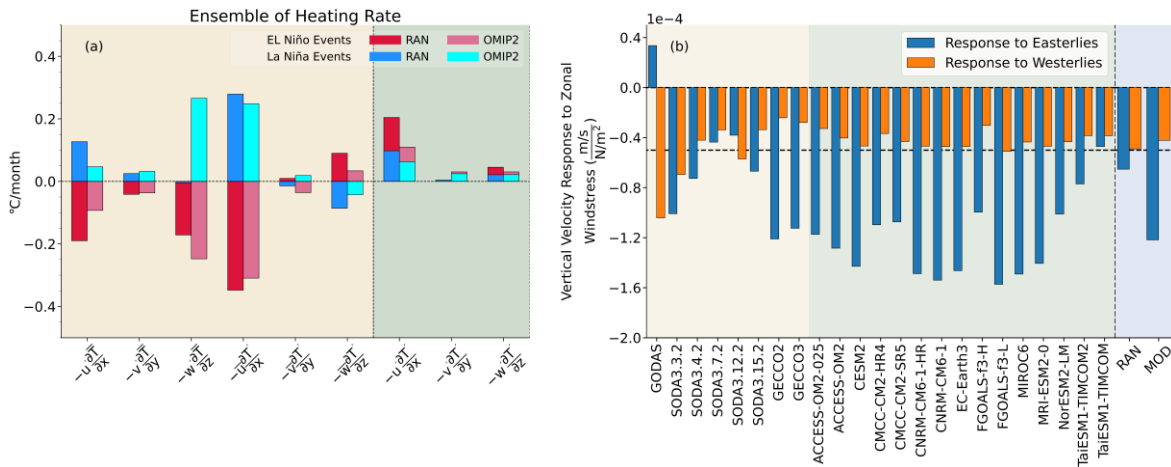
154

155 To address this question, we conduct analysis of the ensemble heating rate of temperature
 156 anomalies during El Niño and La Niña events over WEPS. The terms for LDH and NDH (units:
 157 °C/month) are derived from Eq (1). Figure 2a illustrates that, on the one hand, as depicted in
 158 Figure 1a and Figure S3a, the NDH-U of OMIP2 models exhibits significantly weaker strength
 159 in both phases of ENSO compared to reanalysis datasets. On the other hand, what intrigues us is
 160 that the vertical velocity anomalies-induced LDH (hereafter: LDH-W') in OMIP2 models are
 161 positively stronger during La Niña events than the ensemble of reanalysis datasets, weakening
 162 the asymmetric response of temperature. Additionally, positive NDH-U during La Niña events
 163 that can weaken the negative asymmetric temperature response, is notably weaker than LDH-W'.
 164 Therefore, it is confirmed that NDH-U is not the direct driving factor and stronger LDH-W'
 165 during La Niña events emerges as the predominant factor contributing to the weaker asymmetric
 166 response of temperature in OMIP2 models.

167

168 Hua and Yu (2015) proposed that the oceanic dynamic asymmetric responses to wind-
 stress play a crucial role in ENSO asymmetry of temperature in the western Pacific. Results in

169 Figure 2a reveals the asymmetric heating rate LDH-W' during two phases of ENSO in ocean
 170 reanalysis data, which corresponds to the conclusion from Hua and Yu (2015). LDH-W',
 171 however, is less asymmetric in OMIP2 models and is dominated by vertical velocity anomalies
 172 in Eq (1). Further evaluation is needed to check the asymmetric response of vertical velocity
 173 anomalies. In Figure 2b, the vertical velocity anomalies are regressed against easterly and
 174 westerly anomalies for both reanalysis datasets and OMIP2 datasets. The last two bars represent
 175 the ensemble means of the reanalysis and OMIP2 datasets, respectively. It is evident that the
 176 response of vertical velocity anomalies to easterly anomalies are significantly stronger in the
 177 OMIP2 datasets compared to the reanalysis datasets. This bias then causes the stronger positive
 178 LDH-W' during La Niña phase of ENSO (as illustrated in Figure 2a), consequently resulting in a
 179 weaker composited LDH-W' in the OMIP2 results. These findings suggest that the weaker
 180 negative asymmetric responses of temperature over WEPS in OMIP2 is due to the less
 181 asymmetric LDH-W'. It is primarily exerted by a stronger response of downwelling to easterly
 182 anomalies with greater decline in thermocline than that in reanalysis datasets, which strengthen
 183 the positive LDH-W' during La Niña phase.



184
 185 Figure 2. (a) Ensemble-averaged linear (brown shading) and nonlinear (green shading) heating
 186 rate terms in Eq(1) for temperature anomalies during El Niño and La Niña events over the
 187 western equatorial Pacific subsurface. (b) response (unit: (m/s)/(N/m²)) of vertical velocity
 188 anomalies averaged over western equatorial Pacific subsurface to easterly (blue bars) and
 189 westerly (orange bars) anomalies averaged over (2°S-2°N, 160°E-150°W) for reanalysis datasets
 190 (brown shading) and OMIP2 datasets (green shading), as well as the ensemble mean of
 191 reanalysis (RAN) and OMIP2 (MOD) datasets (blue shading).

192
 193 Considering the Boussinesq approximation with character of ocean's incompressibility in
 194 ocean models, which ignores spatial-temporal density variations, the continuity equation
 195 degrades to:

196

$$-\left(\frac{\partial u'}{\partial x} + \frac{\partial v'}{\partial y}\right) = \frac{\partial w'}{\partial z} \quad (2)$$

197 where u' , v' , and w' represent anomalies in the zonal, meridional, and vertical currents,
 198 respectively. Here, vertical velocity anomalies are the diagnostic variable and derived from zonal

199 and meridional currents through the continuity equation above. Further investigation is needed to
 200 confirm the primary source of the bias in vertical velocity anomalies. We first integrate these
 201 three terms from Eq (2) along depth to obtain vertical velocity induced by the zonal (W_u') and
 202 meridional (W_v') convergence, respectively:

$$\int_z^0 \frac{\partial w'}{\partial z} dz = \int_z^0 \left(-\frac{\partial u'}{\partial x}\right) dz + \int_z^0 \left(-\frac{\partial v'}{\partial y}\right) dz$$

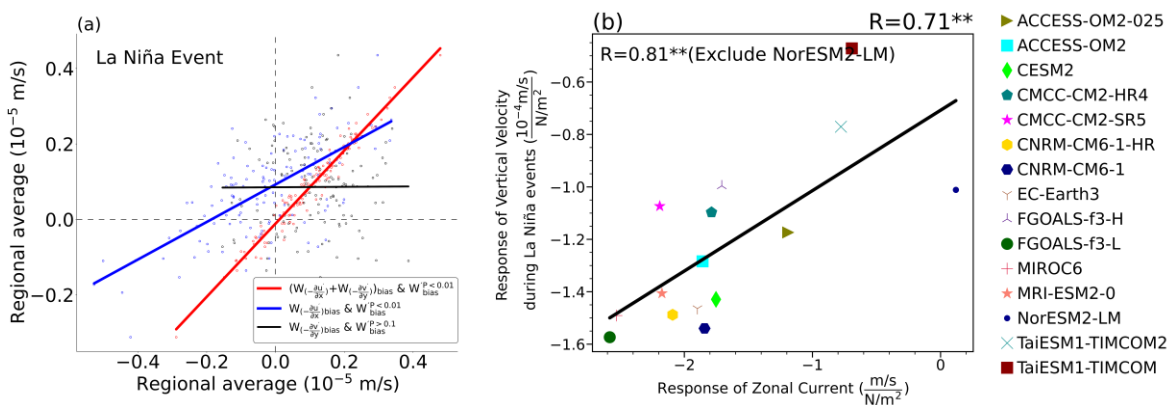
$$203 \quad W_{u'} = \int_z^0 \left(-\frac{\partial u'}{\partial x}\right) dz \quad (3)$$

$$W_{v'} = \int_z^0 \left(-\frac{\partial v'}{\partial y}\right) dz$$

204 then, averaging Eq (3) over WEPS and compare the OMIP2 ensemble mean with the reanalysis
 205 datasets ensemble mean to obtain the bias for each term as shown below:

$$206 \quad \left[\frac{1}{V} \iiint_{WEPS} w' dx dy dz\right]_{bias} = \left[\frac{1}{V} \iiint_{WEPS} W_{u'} dx dy dz\right]_{bias} + \left[\frac{1}{V} \iiint_{WEPS} W_{v'} dx dy dz\right]_{bias} \quad (4)$$

207 where V represents the volume of WEPS. We further divide the right-hand side of Eq (4) into
 208 two components: zonal and meridional components, to evaluate which term predominantly affect
 209 the bias of vertical velocity anomalies. Figure 3a depicts the relationship between vertical bias
 210 and zonal bias, meridional bias, and their combined effect during La Niña events, corresponding
 211 to Figure 2a. Primarily, the vertical bias is predominantly influenced by the combined effect of
 212 zonal and meridional biases, with correlation coefficient of 0.979 between them, as indicated by
 213 the red line in Figure 3a. Furthermore, the relative importance of zonal and meridional biases can
 214 be discerned by comparing the blue and black lines on Figure 3a. It is established that zonal bias,
 215 with a correlation coefficient of 0.700, holds greater significance compared to meridional bias,
 216 which has a correlation coefficient of -0.005. We use Figure 3b to examine the relationship
 217 between response of zonal current anomalies and response of vertical velocity anomalies during
 218 La Niña events, further confirming the crucial role of zonal current anomalies. Thus, the biases
 219 in zonal current anomalies from OMIP2 results serve as the primary source of biases in vertical
 220 current anomalies.

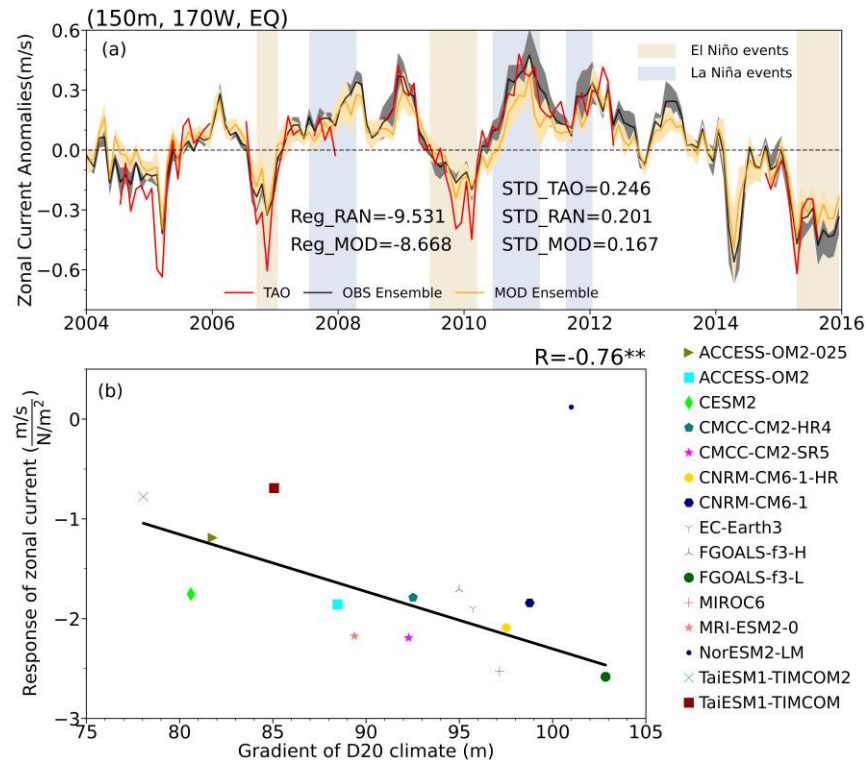


221
 222 Figure 3. (a) Scatterplot depicting the relationship between the bias in vertical velocity anomalies
 223 due to horizontal currents (y-axis) and the overall bias in vertical velocity anomalies (x-axis)
 224 over the western equatorial Pacific subsurface during La Niña events. The biases (difference

225 between OMIP2 datasets and reanalysis ensemble datasets, unit: 10^{-5} m/s) are decomposed into
 226 contributions from horizontal, zonal, and meridional components, quantified by integrating the
 227 continuity equation (Eq. 2) along the depth. The regression lines for each component are shown
 228 in black, blue and red. Statistical significance, indicated in the legend, is determined by the
 229 standard Student's t-test. (b) Scatterplot illustrating the relationship between the response of
 230 zonal current anomalies to zonal wind-stress anomalies (unit: $(\text{m/s})/(\text{N/m}^2)$) and the response of
 231 vertical velocity anomalies during La Niña events to zonal wind-stress anomalies (unit: $(10^{-4}\text{m/s})/(\text{N/m}^2)$)
 232 in model results from OMIP2. The black line is the regression line, with the
 233 correlation coefficient (R) displayed in the upper-right corner. Statistical significance is denoted
 234 by asterisks (* for 95% confidence level, ** for 99% confidence level), determined by standard
 235 Student's t-test.

236

237 Subsequently, this study further explores the potential effect of biases in zonal current
 238 anomalies on mean state of ocean temperature. Figure 4a presents the time series of zonal current
 239 anomalies of observation, reanalysis, and model ensemble mean at a depth of 150 meters, along
 240 the equator at 170°W longitude (150 m, 170°W , EQ) from 2004 to 2015 (the details are shown in
 241 Figure S4). The baseline data is from the monthly TAO mooring array, with reanalysis and
 242 model results truncated to match the same extended time span as TAO. From Figure 4a, it is
 243 evident that the STD of zonal current anomalies is weaker in both the reanalysis (0.206 ± 0.037
 244 m/s) and model results (0.167 ± 0.029 m/s) compared to TAO dataset (0.246 m/s). Notably, these
 245 reanalysis datasets do not assimilate current observations (Behringer et al., 1998, Carton &
 246 Giese, 2008), indicating that ocean currents, although regulated by observed temperature,
 247 salinity, and sea level, are underestimated. Meanwhile, the STD in the reanalysis datasets is
 248 slightly greater than that in the model results (as shown in Figure 4a and S6), confirming that the
 249 underestimation of asymmetric response of temperature arises from the models' inability to
 250 accurately simulate the subsurface zonal currents. The similar signal can also be found associated
 251 with the weaker negative response of zonal current anomalies in ocean models (-8.668
 252 $(\text{m/s})/(\text{N/m}^2)$) compared to that of reanalysis datasets (-9.531 $(\text{m/s})/(\text{N/m}^2)$), as illustrated in the
 253 single-grid analysis in Figure 4a and at the location marked by the "X" in Figure S7.
 254 Furthermore, inspired by Wen et al (2014) which demonstrated the important role of thermocline
 255 variations in modulating ENSO evolutions, Figure 4b illustrates that the thermocline tilt,
 256 represented by gradient of depth of 20°C isotherm and with its bias shown in Figure S5 are
 257 proportional to the response of zonal current anomalies to zonal wind-stress anomalies among
 258 ocean models except NorESM2-LM. Although the ocean component of NorESM2-LM exhibits a
 259 more reasonable magnitude in the zonal current response at the "X" location (170°W , 150m)
 260 indicated in Figures 4a&S4, its spatial distribution over the WEPS region differs significantly
 261 from other datasets (Figure S7). This particular pattern suggests a cancellation of positive and
 262 negative values when averaged over the WEPS region. Seland et al. (2020) suggest that
 263 subsurface ocean biases in this model may be linked to the coarse ocean resolution and
 264 deficiencies in the parameterized processes. The bias of asymmetric temperature response has a
 265 pattern that resembles the bias of mean state of temperature over WEPS and EEPS (Figure S2a
 266 and S2b). This further emphasize the crucial role of rectification effect of ENSO on climate state
 267 of tropical ocean suggested in Sun et al (2014) through thermostat effect (Sun and Liu, 1996).
 268 And Sun and Liu (1996) revealed that responses of zonal currents are essential for modulating
 269 equilibrium of thermostat. Above all, zonal current response is tied to the thermocline mean
 270 state, warranting further study of their dynamical link.



271
 272 Figure 4. (a) The monthly time series of zonal current anomalies (in m/s) at 150 meters depth,
 273 170°W longitude, and the Equator (EQ) for the period from 2004 to 2015 is presented, with the
 274 standard deviation of zonal currents anomalies from TAO, reanalysis and model datasets
 275 displayed in the lower right corner. The ensembled responses of zonal currents from reanalysis
 276 and model datasets at this site are shown in the middle. Data sources include the TAO mooring
 277 array (red), the ensemble-mean of reanalysis datasets (black), and the ensemble mean of OMIP2
 278 models (orange). Gray and orange shading represent ± 1 standard deviation for each dataset,
 279 respectively, illustrating the standard deviation and spread of different patterns. (b) Scatterplots
 280 illustrating the relationship between the gradient of the depth of 20°C isotherm in the mean state
 281 (unit: m) and the response of zonal current anomalies (averaged over 160°E-150°W, 2°S-2°N,
 282 100m-200m) to zonal wind-stress anomalies (averaged over 160°E-150°W, 2°S-2°N). The
 283 gradient is defined as the depth difference between the western Pacific (160°E-150°W, 2°S-2°N)
 284 and the eastern Pacific (150°W-90°W, 2°S-2°N). The black line represents the regression line
 285 (excluding NorESM2-LM), with the correlation coefficient displayed in the upper right corner.
 286 Statistical significance is denoted by asterisks (* for 95% confidence level, ** for 99%
 287 confidence level), determined using the standard Student's t-test.

288 **4 Conclusions and Discussions**

289 In this work, we have identified the prevalent biases in asymmetric responses thermal and
 290 dynamical processes to zonal wind-stress at interannual timescales in stand-alone ocean models
 291 forced by JRA55 from OMIP2 over WEPS, especially the underestimated asymmetric
 292 temperature responses along the mean state of thermocline. Compared with results of reanalysis
 293 datasets, ocean models overestimate the response of vertical velocity anomalies to easterly
 294 anomalies. The resulting stronger linear dynamic heating induced by vertical velocity anomalies
 295 during cold phase of ENSO then lead to a weaker-negative asymmetric temperature responses to

296 external wind forcing. We have further used the continuity equation to diagnose the source of
297 biases in the vertical velocity anomalies. The diagnosis has revealed that it is the bias in the zonal
298 current anomalies that contribute most significantly to this bias over WEPS. Through comparing
299 with TAO dataset and regression analysis, we have further revealed that standard deviation and
300 responses of zonal current anomalies to zonal wind-stress anomalies in OMIP2 models are
301 underestimated. This discrepancy is found to be linked to the weaker thermocline tilt in mean
302 state. In summary, the answer to the question why the asymmetric responses of temperature are
303 weaker in most ocean models from OMIP2 in WEPS may be phrased as follows:

304 The primary reason is the stronger-than-observed response of vertical velocity
305 anomalies to easterly anomalies, driven by biases in zonal current anomalies. This
306 leads to a weaker LDH- W' and diminishes the temperature response to zonal wind
307 stress in OMIP2 models.

308 This study thus links the bias in asymmetric temperature responses to weaker zonal
309 current responses, a factor often overlooked in previous research. The bias of asymmetric
310 temperature responses has a pattern that resembles the bias of mean state of temperature over
311 WEPS and EEPS, underscoring the role of rectification effect of ENSO on mean climate
312 suggested in Sun et al (2014). The deviation of this effect in models' result depends on the bias
313 in zonal current responses over WEPS. The strength of the response of zonal current to changes
314 zonal wind-stress further plays a key role in the mean state of SST in the tropical Pacific Ocean
315 through the dynamical thermostat mechanism (Sun and Liu, 1996).

316 Although existing theories have provided a perspective of describing the dynamics
317 behind the relationship between response of zonal currents anomalies to zonal wind-stress
318 anomalies and zonal tilt of the thermocline, further research is needed to pinpoint the source
319 contributing to the bias in the zonal current response. To improve ocean models' ability to
320 capturing ocean current responses to external forcing, advancements are needed in vertical
321 mixing parameterizations (Fox-Kemper & Menemenlis, 2008). Traditionally, ocean models rely
322 on empirical formulas to parameterize sub-grid processes, but their dependence on fixed
323 parameters limits accuracy. With advances in machine learning, data-driven parameterization
324 using observational or large eddy simulation data has emerged, improving efficiency and
325 enhancing ocean dynamic simulations.

326 In summary, this study raises a crucial role of the zonal currents, in particular, their
327 responses to external forcing in coupled atmosphere-ocean dynamics and modeling ENSO. To
328 enhance the capability in simulating zonal currents in ocean models should be of a step of
329 priority for further improving ENSO simulations by the fully-coupled climate models.

330 **Acknowledgments**

331 This study is jointly supported by National Natural Science Foundation of China (NSFC)
332 (Grants 42130608 and Grants 42250710154) and the National Key Scientific and Technological
333 Infrastructure project 'Earth System Numerical Simulation Facility' (EarthLab). And thanks to
334 ICDC, CEN, University of Hamburg for data support.

335 **Open Research**336 **Data availability statement**

337 The GODAS data are available from (<https://www.psl.noaa.gov/data/gridded/data.godas.html>). The SODA
 338 data are available from (https://www2.atmos.umd.edu/~ocean/index_files). The GECCO2 and GECCO2 data
 339 are available from ([https://icdc.cen.uni-](https://icdc.cen.uni-hamburg.de/thredds/catalog/ftp/thredds/EASYInit/GECCO2/regular_1x1_grid/catalog.html)
 340 [hamburg.de/thredds/catalog/ftp/thredds/EASYInit/GECCO2/regular_1x1_grid/catalog.html](https://icdc.cen.uni-hamburg.de/thredds/catalog/ftp/thredds/EASYInit/GECCO2/regular_1x1_grid/catalog.html)) and
 341 (https://icdc.cen.uni-hamburg.de/thredds/catalog/ftp/thredds/EASYInit/GECCO3/regular_1x1_grid/catalog.html).
 342 The TAO mooring array data are available from (<https://www.pmel.noaa.gov/tao/drupal/disdel/>). The CMIP6
 343 datasets are available from (<https://aims2.llnl.gov/search>). The list of the CMIP6 models analyzed in the study
 344 can be found in Table S1.

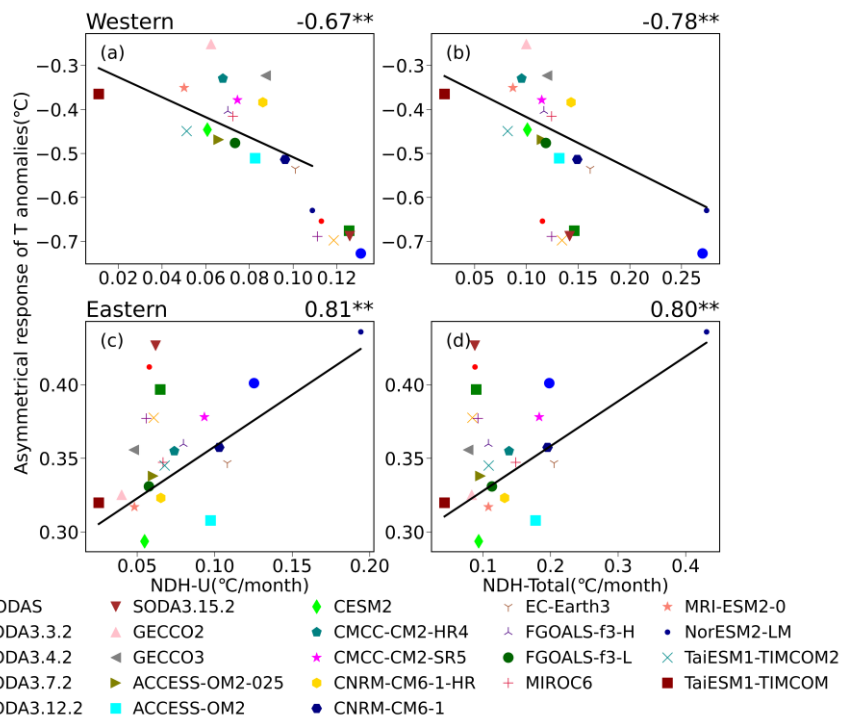
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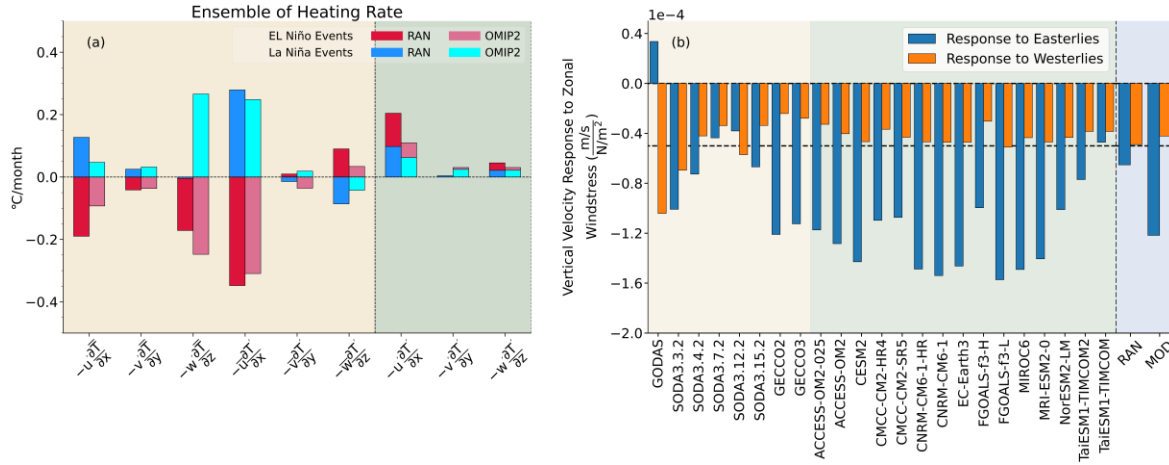
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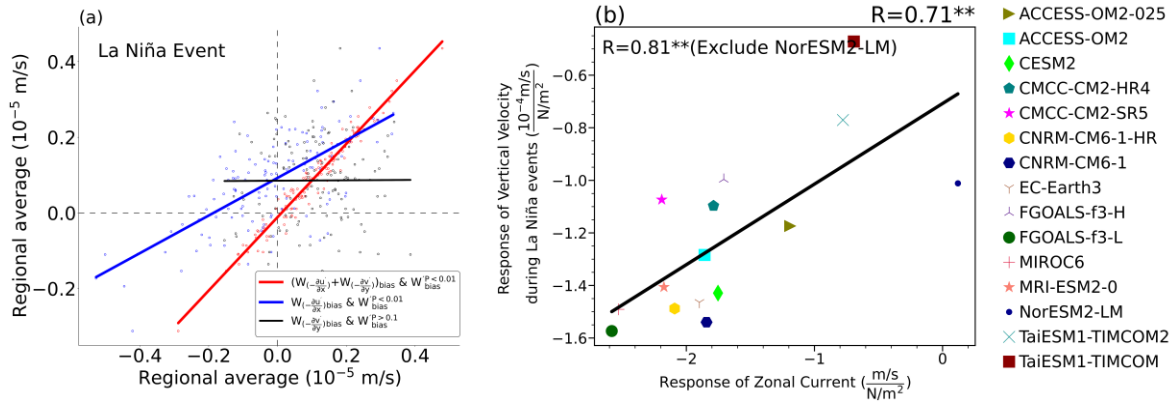
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Figure 1. The relationship between Nonlinear Dynamic Heating (NDH, unit: °C/month) and subsurface asymmetric response of T anomalies (unit: °C) is examined over the western equatorial Pacific subsurface (a & b) and eastern equatorial Pacific subsurface (c & d). The left columns (a & c) depict the relationship with the zonal component of NDH, while the right columns (b & d) show the relationship with the three-dimensional NDH. Different symbols in unique colors represent distinct datasets, as indicated in the legends of the right panel of the figure. A black line represents the regression line, and the correlation coefficient is displayed in the upper right corner of each subgraph. Statistical significance is denoted by asterisks (* for 95% confidence level, ** for 99% confidence level), determined by standard Student's t-test.



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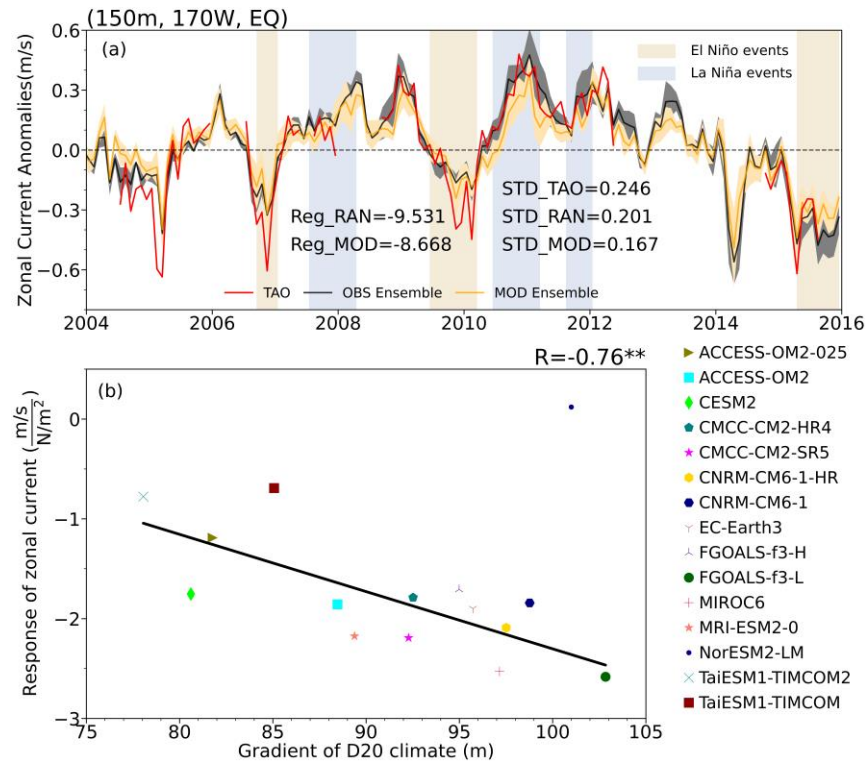
466 **Figure 2.** (a) Ensemble-averaged linear (brown shading) and nonlinear (green shading) heating
 467 rate terms in Eq(1) for temperature anomalies during El Niño and La Niña events over the
 468 western equatorial Pacific subsurface. (b) response (unit: (m/s)/(N/m²)) of vertical velocity
 469 anomalies averaged over western equatorial Pacific subsurface to easterly (blue bars) and
 470 westerly (orange bars) anomalies averaged over (2°S-2°N, 160°E-150°W) for reanalysis datasets
 471 (brown shading) and OMIP2 datasets (green shading), as well as the ensemble mean of
 472 reanalysis (RAN) and OMIP2 (MOD) datasets (blue shading).
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475 **Figure 3.** (a) Scatterplot depicting the relationship between the bias in vertical velocity
 476 anomalies due to horizontal currents (y-axis) and the overall bias in vertical velocity anomalies
 477 (x-axis) over the western equatorial Pacific subsurface during La Niña events. The biases
 478 (difference between OMIP2 datasets and reanalysis ensemble datasets, unit: 10^{-5} m/s) are
 479 decomposed into contributions from horizontal, zonal, and meridional components, quantified by
 480 integrating the continuity equation (Eq. 2) along the depth. The regression lines for each
 481 component are shown in black, blue and red. Statistical significance, indicated in the legend, is
 482 determined by the standard Student's t-test. (b) Scatterplot illustrating the relationship between
 483 the response of zonal current anomalies to zonal wind-stress anomalies (unit: (m/s)/(N/m²)) and
 484 the response of vertical velocity anomalies during La Niña events to zonal wind-stress anomalies
 485 (unit: (10^{-4} m/s)/(N/m²)) in model results from OMIP2. The black line is the regression line, with
 486 the correlation coefficient (R) displayed in the upper-right corner. Statistical significance is
 487 denoted by asterisks (* for 95% confidence level, ** for 99% confidence level), determined by
 488 standard Student's t-test.

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498 **Figure 4.** (a) The monthly time series of zonal current anomalies (in m/s) at 150 meters depth,
 499 170°W longitude, and the Equator (EQ) for the period from 2004 to 2015 is presented, with the
 500 standard deviation of zonal currents anomalies from TAO, reanalysis and model datasets
 501 displayed in the lower right corner. The ensembled responses of zonal currents from reanalysis
 502 and model datasets at this site are shown in the middle. Data sources include the TAO mooring
 503 array (red), the ensemble-mean of reanalysis datasets (black), and the ensemble mean of OMIP2
 504 models (orange). Gray and orange shading represent ± 1 standard deviation for each dataset,
 505 respectively, illustrating the standard deviation and spread of different patterns. (b) Scatterplots
 506 illustrating the relationship between the gradient of the depth of 20°C isotherm in the mean state
 507 (unit: m) and the response of zonal current anomalies (averaged over 160°E-150°W, 2°S-2°N,
 508 100m-200m) to zonal wind-stress anomalies (averaged over 160°E-150°W, 2°S-2°N). The
 509 gradient is defined as the depth difference between the western Pacific (160°E-150°W, 2°S-2°N)
 510 and the eastern Pacific (150°W-90°W, 2°S-2°N). The black line represents the regression line
 511 (excluding NorESM2-LM), with the correlation coefficient displayed in the upper right corner.
 512 Statistical significance is denoted by asterisks (* for 95% confidence level, ** for 99%
 513 confidence level), determined using the standard Student's t-test.

514