

Intraseasonal variations and extreme occurrence in the local sea level along the western coast of India remotely controlled by a basin-scale climate variability

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Abstract

The equatorial Kelvin waves, remotely excited by basin-scale climate modes, and subsequent coastal trapped waves significantly influence the intraseasonal variations, their low-frequency modulations, and the frequency of extreme sea level events along the western coast of India. This study demonstrates that the frequency of extreme events are linked to the phase of the Indian Ocean Dipole mode. The temporal changes in the occurrence frequency of extremes are simulated in an eddy-resolving ocean model consistently with observations. However, a non-eddying model significantly underestimate the occurrence frequency of extreme sea level events, suggesting the importance of coastal trapped wave propagations regulated by the horizontal scale with the Rossby radius of deformation. This result implies that many state-of-the-art climate models with a one-degree ocean horizontal resolution may underestimate future coastal sea level variability and the frequency of extreme events under global warming and potential modulations of major internal climate modes.

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2 **coast of India remotely controlled by a basin-scale climate variability**

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14 **Key Points:**

- 15 • The eddy-resolving model represents the intraseasonal sea level variability along the coast
16 of India explained by coastal trapped waves.
- 17 • The occurrence frequency of extreme intraseasonal sea level anomalies is significantly
18 underestimated in the non-eddy model.
- 19 • Changes in the probability distributions of sea level associated with the Indian Ocean
20 Dipole are simulated in the eddy-resolving model.

21

22 **Abstract**

23 The equatorial Kelvin waves, remotely excited by basin-scale climate modes, and subsequent
24 coastal trapped waves significantly influence the intraseasonal variations, their low-frequency
25 modulations, and the frequency of extreme sea level events along the western coast of India. This
26 study demonstrates that the frequency of extreme events are linked to the phase of the Indian Ocean
27 Dipole mode. The temporal changes in the occurrence frequency of extremes are simulated in an
28 eddy-resolving ocean model consistently with observations. However, a non-eddy model
29 significantly underestimate the occurrence frequency of extreme sea level events, suggesting the
30 importance of coastal trapped wave propagations regulated by the horizontal scale with the Rossby
31 radius of deformation. This result implies that many state-of-the-art climate models with a one-
32 degree ocean horizontal resolution may underestimate future coastal sea level variability and the
33 frequency of extreme events under global warming and potential modulations of major internal
34 climate modes.

35

36 **Plain Language Summary**

37 Sea level variations in the northern Indian Ocean are influenced by ocean waves near the coast,
38 typically in a horizontal scale less than 100 km. It remains unclear whether there is a
39 relationship between extreme events associated with coastal waves and climate variability. Also,
40 if such a relationship exists, it is uncertain how well it is represented in climate simulations,
41 which often have relatively coarse horizontal resolution. To highlight the role of relatively small
42 scale coastal waves, this study compared sea level variations along the western coast of India
43 using two ocean models with coarse and fine horizontal resolutions. We found that the high-
44 resolution model adequately simulates the generation and propagation of coastal waves, and thus
45 successfully simulate sea level variations along western India modulated by large scale climate
46 variability with a 20–150-day time scale. This result suggests that many recent climate
47 simulations may have underestimated the frequency of extreme sea level events in coastal
48 regions.

49

50 **1 Introduction**

51 The warming climate is projected to cause persistent sea level rise worldwide (IPCC 2022a).

52 In addition to the global mean sea level rise owing to thermal expansion, melting of glaciers, etc.,
53 extreme sea level projections associated with changes in atmospheric circulation and river runoff
54 are also required in coastal regions, especially projections of changes in the occurrence of
55 extreme events (IPCC 2022b). Given that many of the state-of-art climate models in the Coupled
56 Model Intercomparison Project Phase 6 (CMIP6) use a relatively coarse horizontal resolution of
57 approximately 100 km (Tsujino et al., 2020), the projections obtained using these models may
58 underestimate influence of oceanic mesoscale and coastal processes. Hence, it remains unclear
59 whether current sea level projections, particularly in coastal regions, adequately capture changes
60 in extreme sea level events (i.e., as indicated by the tails in probability distributions).

61 In the densely populated coastal areas of the northern Indian Ocean, projected sea level rises in
62 the Arabian Sea and the Bay of Bengal (Han et al., 2010; Jyoti et al., 2023) present serious risks,
63 including coastal storm surges and extreme tidal events (e.g., Needham et al., 2015). Sea level
64 variability along the coasts of the northern Indian Ocean is strongly influenced by equatorial
65 waves and their resultant coastal trapped wave (CTW). Clarke and Liu (1994) showed that the
66 interannual sea level anomalies (SLA) along the coasts of the northern Indian Ocean were
67 remotely triggered by equatorial zonal winds. More recently, using linear stratified models
68 (McCreary, 1996), several studies have investigated how wind stress forcing over the Arabian
69 Sea, the southern tip of Sri Lanka, and the equatorial Indian Ocean impacts intraseasonal-to-
70 interannual sea level variations along the coast of India (Suresh et al., 2013, 2016, 2018). Wind
71 variations leading to CTWs can be attributed to semiannual basin-scale wind variability that
72 drives the equatorial jet (Yoshida, 1959; Wyrki, 1973), intraseasonal anomalies associated with
73 the Madden-Julian Oscillation (MJO; Madden & Julian, 1977), and interannual anomalies
74 associated with the Indian Ocean Dipole (IOD) (Saji et al., 1999; Han & Webster, 2002; Aparna
75 et al., 2012).

76 Although previous studies suggested the potential role of CTWs in the Northern Indian Ocean,
77 the extent to which standard climate models reproduce the coastal sea level variations remains
78 unclear. Therefore, using the coastal sea level variability along the west coast of India as an
79 illustrative example, this study undertakes a comparative analysis of multiple simulations derived
80 from the oceanic component utilized in a climate model. Here we show that an eddy-resolving
81 ocean general circulation model (OGCM) is required to accurately represent sea level variations
82 along the western coast of India. In particular, since intraseasonal sea level variations have a

83 relatively pronounced amplitude and consequently lead to extreme events, this study focuses
84 mainly on how the intraseasonal variations in coastal sea level are represented in OGCMs. Even
85 though the non-eddy-resolving OGCM simulation is forced by the same atmospheric boundary
86 conditions as in the eddy-resolving OGCM, the coarse horizontal resolution of the non-eddy-resolving
87 OGCM fails to accurately capture the sea level variability, especially variations originating from
88 the equator through the coastal wave guide in the Bay of Bengal.

89

90 **2 Models, Data, and Methods**

91 This study compares two simulations of CCSR Ocean Component Model (COCO) (Hasumi,
92 2006); the coarse stand-alone OGCM with a nominal 1° horizontal resolution (COCO-LR) and a
93 global high-resolution version with a horizontal resolution of 0.1° (COCO-HR). Also, to highlight
94 the impact of interannual variations in surface wind forcing on the coastal sea level, we also
95 conducted a sensitivity experiment, referred to as “WIND0”. See Text S1 for the details of model
96 setups and validations.

97 In this study, we used the following observational datasets. PCMDI-SST (Hurrell et al., 2008)
98 was used for the monthly sea surface temperature (SST) data for the period 1993–2019 with a
99 horizontal resolution $1^\circ \times 1^\circ$, as in Tsujino et al. (2020). CMEMS sea level products (DUACS
100 DT2014; Pujol et al., 2016) have a daily interval and a horizontal resolution of $0.25^\circ \times 0.25^\circ$ for
101 the period 1993–2019. Drifter-derived monthly climatological surface currents data were also
102 used (Laurindo et al., 2017). To compare sea level anomalies with the satellite altimeter
103 products, we mainly analyzed model outputs after 1993. SLAs relative to global mean was
104 analyzed for both the observation and models.

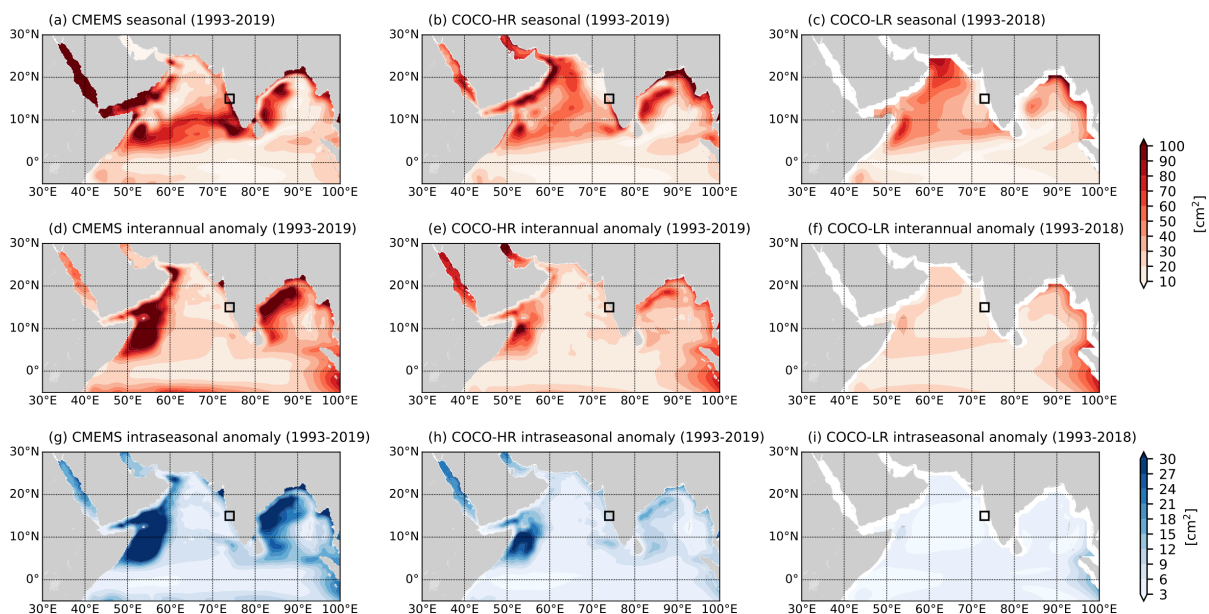
105 To examine SLA propagation in the coastal area, we calculated lag composites of SLA for
106 extreme sea level events. A two-tailed t -test was adapted to the statistical test at 90% confidence
107 level. To estimate the probability density functions (PDFs) of SLA, Kernel Density estimation
108 was applied (Dehand, 1987; Marshall & Molteni, 1993). A Butterworth filter was employed to
109 isolate the intraseasonal variability within the 20-150 day period.

110

111 3 Sea level variance in the Northern Indian Ocean

112 In this section, we briefly validate the COCO-HR model focusing on sea level variability.
 113 COCO-HR showed noticeable improvements in the northern Indian Ocean, especially in regions
 114 where oceanic mesoscale eddies are dominant (Fig. 1). In addition to the seasonal variations
 115 (Fig. 1a-c, Text S2), COCO-HR more accurately captures detrended interannual and
 116 intraseasonal SLAs compared to COCO-LR (Fig. 1d-i). Note that we refer to the 20-150 day
 117 band-passed timeseries of detrended anomalies from the daily climatology as “intraseasonal
 118 anomalies” hereafter. The noticeable variations in the Somalia-Oman upwelling region are well
 119 represented in COCO-HR, aligning closely with observations, although COCO-HR does slightly
 120 underestimate them. This difference can be explained that the intraseasonal variability associated
 121 with mesoscale eddies and its low-frequency modulation are better represented in COCO-HR
 122 under the influence of the Somali Current. Interannual and intraseasonal sea level variability in
 123 the western Bay of Bengal also tends to be better represented in COCO-HR, indicating that the
 124 intraseasonal variability of coastal trapped waves and local mesoscale variability is also well
 125 captured by COCO-HR. These results are also confirmed by the spatially high-passed sea level
 126 anomalies (Text S2). In the following section, we examined sea level variations along the
 127 western coast of India in greater detail.

128



129

130 **Figure 1.** Variances in seasonal sea level anomalies (SLAs) [cm^2] in the northern Indian Ocean
 131 for (a) observations, (b) COCO-HR, and (c) COCO-LR. Black boxes indicate the area where
 132 area-averaged SLAs are calculated in Section 4 (73°E - 75°E , 14°N - 16°N for CMEMS and
 133 COCO-HR, 72°E - 74°E , 14°N - 16°N for COCO-LR). (d)-(f) As in (a)-(c), but for interannual
 134 SLAs. Interannual anomalies are defined as deviations from the climatology for daily-mean
 135 SLAs relative to global-mean. Linear trends are also subtracted. (g)-(i) As in (d)-(f), but for
 136 intraseasonal SLAs, which are defined as the 20-150 day band-passed components of interannual
 137 SLAs. Note that blue colors and different range of color bars from (a)-(f) are used since
 138 variances in intraseasonal SLAs are smaller than those in seasonal or interannual SLAs.
 139

140 **4 SLAs along the western coast of India**

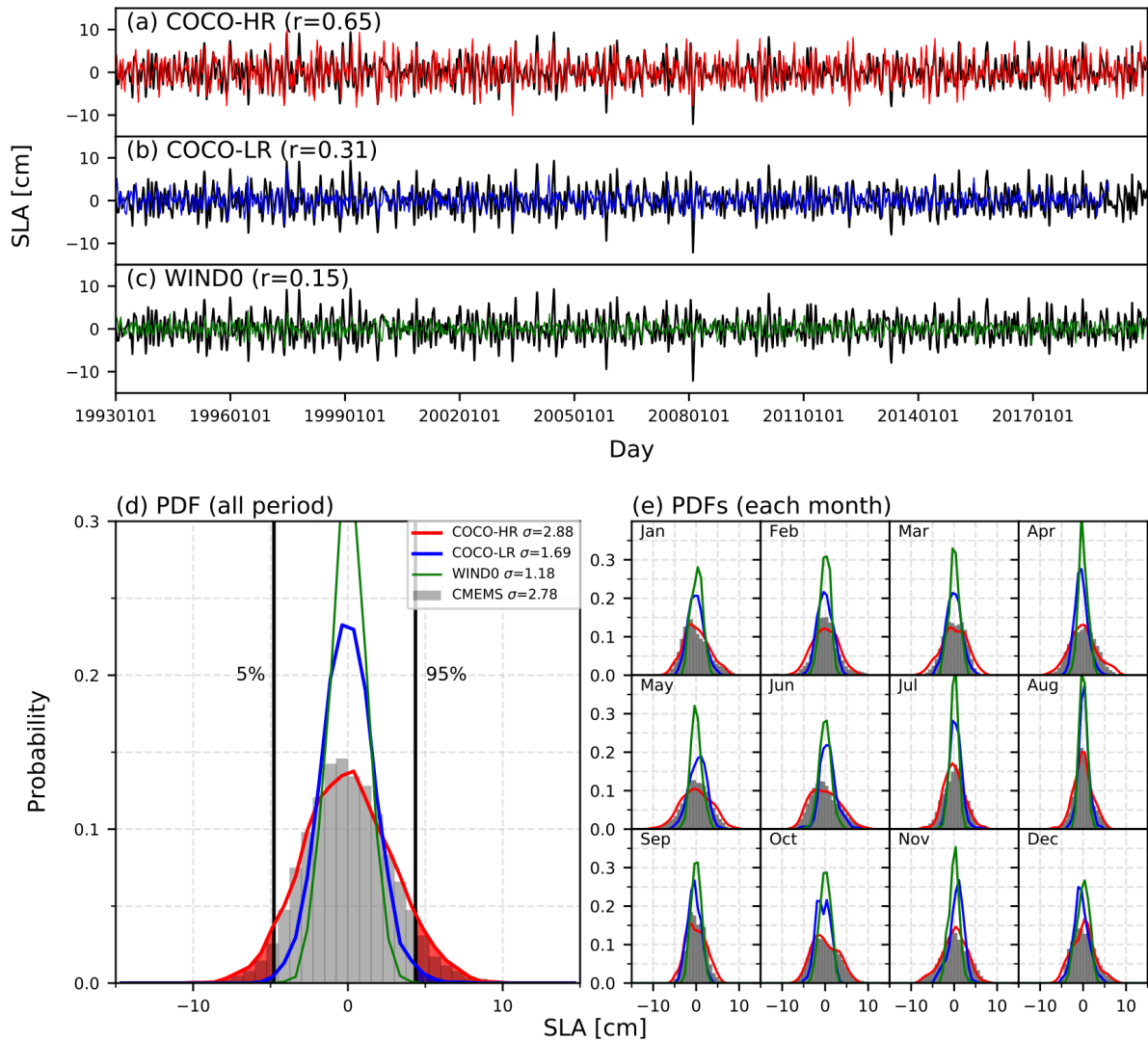
141 **4.1 Intraseasonal sea level variations**

142 In order to investigate sea level variations along the western coast of India, area-averaged sea
 143 level variations are calculated within $2^\circ \times 2^\circ$ boxes at 15°N (black boxes in Fig. 1), ensuring that
 144 multiple data points are included in all the boxes. Note that qualitatively similar results are
 145 obtained if we use $1^\circ \times 1^\circ$ boxes. The comparison indicates that COCO-HR more accurately
 146 represents both seasonal (Text S3) and intraseasonal SSH variations along the west coast of India
 147 (Fig. 2a-c).

148 PDFs for 20-150 day band-passed SLA time series are estimated (Fig. 2d,e). In all months,
 149 COCO-HR reproduces PDFs that are similar to the observational data, with standard deviations
 150 that also match those of the observational data. Conversely, COCO-LR exhibits smaller standard
 151 deviations for each PDF compared to the observations, resulting in underestimation of extreme
 152 SLA events. Indeed, in observations, the thresholds employed for positive (negative) extreme
 153 SLA events, which are defined as events exceeding 95% (5.0%) probability, are estimated to be
 154 4.4 cm (-4.8 cm) (Fig. 2d). For COCO-HR, the occurrence rates of positive (negative) extreme
 155 SLA events are 7.3% (4.7%), which is consistent with the observed rates. For COCO-LR, the
 156 occurrence of positive (negative) SLA events is 0.95% (0.21%), which is considerably smaller
 157 than in the observations. This result means that COCO-LR underestimates the occurrence
 158 frequency of the extreme intraseasonal sea level maxima (minima), and underscores the
 159 importance of using an eddy-resolving ocean model to accurately hindcast coastal sea level

160 variability.

161 The narrower PDFs (i.e., indicating less variance) in WIND0 compared to COCO-HR
162 suggests a reduced occurrence of extreme SLA events. Therefore, dynamical wind forcing
163 anomalies are necessary for simulating intraseasonal SLA along the western coast of India (Fig.
164 2d,e). This result also implies that the contribution of factors other than wind stress forcing, such
165 as buoyancy flux and barotropic/baroclinic instability associated with West Indian Coastal
166 Current (e.g., Varna et al., 2023), is not predominant. The above result remains qualitatively
167 unchanged if the PDFs are calculated for detrended anomalies without 20–150-day bandpass
168 filtering (Fig. S7). Thus, differences in anomalies with periods shorter (longer) than 20 (150)
169 days do not explain the reduction in the standard deviation of PDFs in WIND0. Consequently,
170 the higher frequency of extreme SLA events in COCO-HR can be attributed to interannual-to-
171 decadal changes in the intraseasonal anomalies. Given that the variance in the intraseasonal
172 component is prominent in both the observation and models (Fig. S8) and contribution of the
173 intraseasonal anomalies to the total amplitude of extreme SLA events is largest in the
174 observation and COCO-HR (Fig. S9), we will discuss the processes driving these differences in
175 PDFs of intraseasonal variability in the next section.



176

177 **Figure 2.** Time series of SLAs [cm] along the western coast of India (15°N ; black boxes in
 178 Fig. 1) for CMEMS (black), (a) COCO-HR (red), (b) COCO-LR (blue), and (c) WIND0 (green).
 179 All panels show time series filtered into band-pass (20-150 days) frequency. The correlation
 180 coefficients (r) with CMEMS are shown in panels. (d) Probability density functions (PDFs) of
 181 intraseasonal (20-150 days) sea level anomalies (SLA) [cm] along the western coast of India
 182 (15°N) for observations (CMEMS; black bars), COCO-HR (red lines), COCO-LR (blue lines),
 183 and WIND0 (green lines) for all seasons. PDFs are estimated by kernel density estimation. The
 184 standard deviation (σ) for each month is given in the legend. All PDFs are normalized and the
 185 vertical axis indicates probability (unit less). Vertical black lines indicate the 5% and 95%
 186 anomalies based on CMEMS data. Areas where anomalies exceed the 5 or 95 percentiles for

187 CMEMS are highlighted in red (COCO-HR) and blue (COCO-LR) colors, respectively, with the
188 corresponding percentile values marked in each model. (e) As in (d), but for each month.

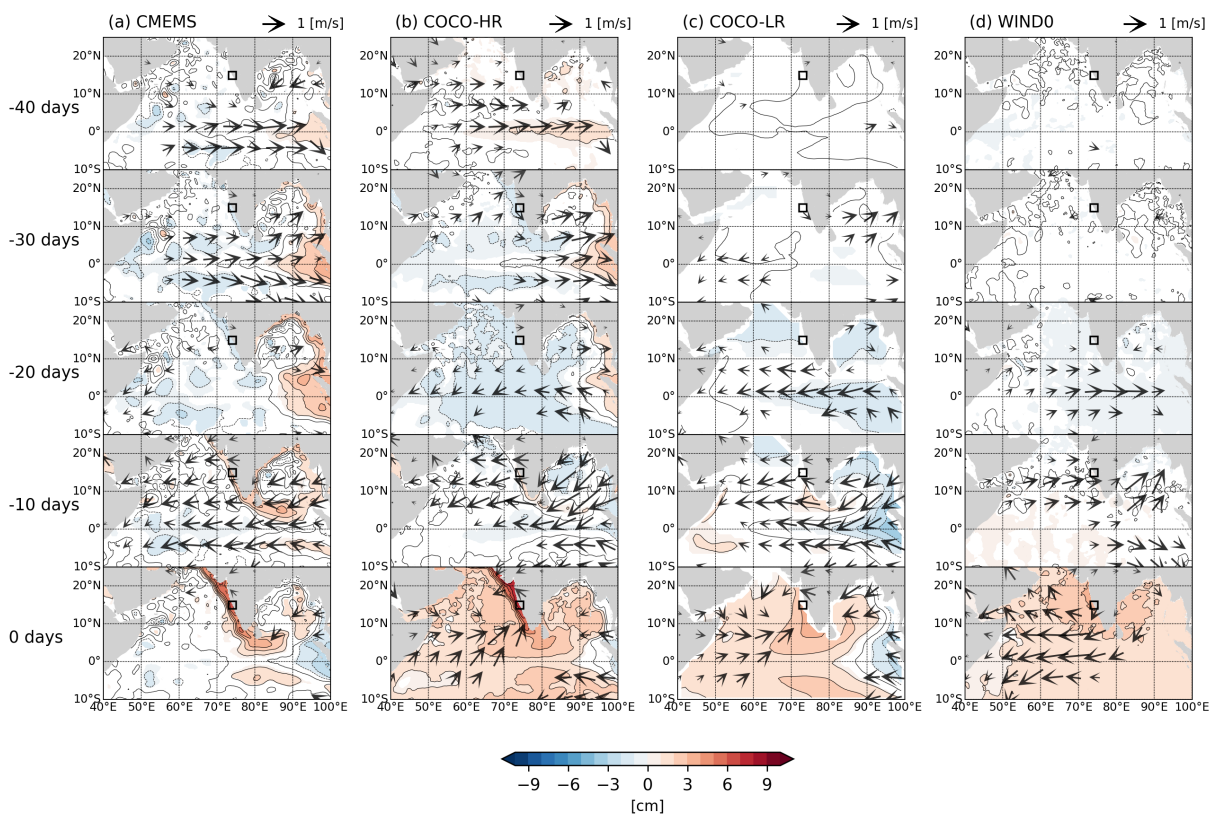
189

190 **4.2 Resolution dependency of the propagation of coastal trapped waves**

191 Regarding the remote impacts of CTWs on the western coast of India, the large intraseasonal
192 SLA variances in COCO-HR may be attributed to the propagation of sea level anomalies. Figure
193 3 shows a lag composite of SLA from 0 to 40 days before the occurrence of intraseasonal SLA
194 exceeds +1 standard deviation at the western coast of India (indicated by red symbols in Fig. S8).
195 Since the composites obtained for the negative anomalies are almost mirror images, we discuss
196 only the results obtained for positive SLA events. In the observations, a significant SLA
197 associated with equatorial Kelvin wave is triggered by westerly wind anomalies in the tropical
198 Indian Ocean 40 days prior. Subsequently, this wave reaches the coast of Sumatra island and
199 then propagates as CTWs along the coast of the Bay of Bengal. These waves pass through the
200 southern tip of India, arrive at the western coast of India, and eventually extend into the northern
201 Arabian Sea (Fig. 3a). Furthermore, SLAs also appear to be radiated from the eastern coast of the
202 Bay of Bengal as westward Rossby waves, and are enhanced by easterly wind anomalies along
203 the southern tip of Sri Lanka.

204 In COCO-HR, similar to the observations, the equatorial Kelvin wave enters the eastern
205 boundary and propagates as CTWs from the Bay of Bengal to the western coast of India (Fig.
206 3b). Westward SLAs also appeared to be radiated from the eastern coast of the Bay of Bengal to
207 the southern coast of India. On the other hand, COCO-LR does not show SLA propagation in the
208 coastal region from the equator to the Bay of Bengal. Instead, positive SLAs appear to develop
209 locally about 10 days prior, before rapidly increasing in the western coast of India. Previous
210 studies proposed that intraseasonal SLA variations along the western coast of India are
211 predominantly influenced by the propagation of the CTWs from the equatorial Indian Ocean
212 (Suresh et al., 2013). Therefore, the results obtained in this study suggest that COCO-HR
213 effectively captures the propagation of CTWs from the equator. However, the propagation of
214 CTWs from the equator is not well captured by COCO-LR due to the coarser horizontal
215 resolution (Text S4), suggesting an exaggerated influence of local wind and/or thermal forcing in
216 the western coast of India.

217 In the WIND0 composites, no SLA propagation originating from the equatorial Kelvin waves is
 218 evident. This is because the wind stress variations with frequency longer than a year are
 219 suppressed in WIND0, and thus interannual modulation of intraseasonal SLAs associated with
 220 the equatorial Kelvin waves are not triggered, consequently, the resultant SLA propagation as
 221 CTWs in the Bay of Bengal are not generated. Whilst, thermal forcing or mesoscale variability
 222 associated with internal oceanic instabilities do not contribute to the intraseasonal SLA
 223 propagation. These results are also supported by the lag-composite analysis of SLA from 0 to 40
 224 days following instances when the SLA exceeds +1 standard deviation at the eastern equatorial
 225 Indian Ocean (Fig. S10). While both COCO-HR and COCO-LR depict the propagation of
 226 equatorial Kelvin waves to the eastern boundary, only the observations and COCO-HR show the
 227 subsequent SLA propagation in the Bay of Bengal.



228
 229 **Figure 3.** Lag-composites of sea level anomalies (SLA) (contour and color) and 10-m wind
 230 (vectors) for area-averaged SLA time series along the western coast of India (black boxes). Data
 231 are shown for (a) CMEMS, (b) COCO-HR, (c) COCO-LR, and (d) WIND0. Colors and vectors
 232 indicate statistically significant SLA and zonal wind anomalies at the 90% confidence level,

233 respectively.

234

235 **4.3 Influence of Indian Ocean Dipole on the probability distribution of coastal SLA along** 236 **the western coast of India**

237 In section 4.2, differences in PDFs of intraseasonal SLA are attributed to the representation of
238 CTWs. This section examines the origin of the CTWs, particularly their association with wind
239 variations in the tropical Indian Ocean. Given that basin-scale wind anomalies in the tropical
240 Indian Ocean are affected by the IOD, it follows that the IOD contributes to interannual low-
241 frequency SLA variations along the western coast of India through CTWs (e.g., Suresh et al.,
242 2018). However, the extent to which interannual wind anomalies associated with the IOD
243 modulate intraseasonal SLA variations, specifically the probability distribution of coastal SLA
244 along the western coast of India, remains unclear. We therefore investigated the relationship
245 between IOD and intraseasonal SLA, and assessed its representation in both COCO-HR and
246 COCO-LR. In this analysis, the dipole mode index (DMI) is defined as the difference between
247 area-averaged monthly-mean SST difference between the western (50°E - 70°E , 10°S - 10°N) and
248 eastern (90°E - 110°E , 10°S - 0°) poles, as defined in previous studies (Saji et al., 1999; Tanizaki et
249 al., 2017). A 3-month running mean is also applied to the DMI. Zonal wind index associated
250 with IOD (U_{eq}) is also defined as the daily-mean zonal wind are-averaged over 70°E - 90°E , 5°S -
251 5°N (Saji et al., 1999) using JRA55-do. Note that the influence of El Niño/Southern Oscillation
252 is less than IOD (figures not shown), which is consistent to the previous studies discussing
253 interannual variations of equatorial thermocline (Rao and Behera, 2005; Yu et al., 2005).

254 Since SST anomalies associated with the IOD typically peak in October (e.g., Saji et al.,
255 1999), we focus on the relationship between the IOD and intraseasonal SLA along the western
256 coast of India during this month. During positive IOD events, equatorial easterly wind anomalies
257 trigger positive (negative) SLAs along the southern tip of Sri Lanka (in the eastern equatorial
258 Indian Ocean) and, subsequently, positive (negative) CTWs along the western coast of India
259 (coastal region of the Bay of Bengal) as observed (Fig. 4a). The IOD affects the interannual
260 modulation of intraseasonal equatorial zonal wind and SLAs along the western coast of India
261 (Fig. 4d). The correlation between the October-mean of intraseasonal SLAs (U_{eq}) and the DMI
262 is 0.68 (-0.62), indicating that the IOD modulates the interannual variations in intraseasonal

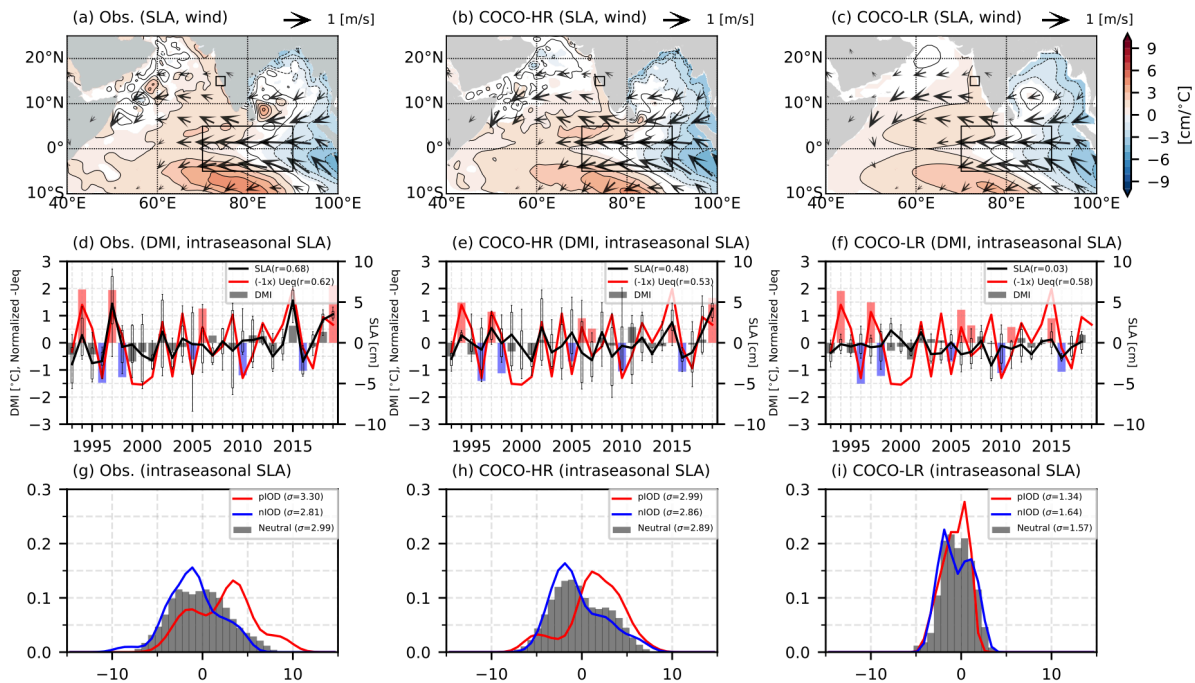
263 equatorial winds and consequently SLA. During the positive IOD phases, the PDF of the
264 intraseasonal SLA shifts positively (Fig. 4g). Conversely, the PDFs during negative IOD and
265 neutral years are less distinct, which may be related to the asymmetry in the IOD, with negative
266 events having a smaller amplitude than positive events (e.g., Nakazato et al., 2021, An et al.,
267 2023).

268 COCO-HR can simulate positive SLAs along the west Indian coast during the positive IOD
269 (Fig. 4b). Also, the relatively strong correlation between intraseasonal SLA and DMI ($r=0.48$)
270 are moderately represented (Fig. 4e), and the PDF shifts positively during positive IOD phases,
271 as observed (Fig. 4h). On the other hand, although the SLA patterns along the west coast of India
272 are similar during the IOD (Fig. 4a-c), intraseasonal SLAs are not correlated with the DMI
273 ($r=0.03$) and the PDF does not shift positively in COCO-LR (Fig. 4f, i).

274 While both COCO-HR and COCO-LR are driven by the same surface forcings, leading to
275 similar large-scale SLA variation patterns in October, there are notable differences at a local
276 scale. This discrepancy is particularly evident when focusing on the local SLA along the western
277 coast of India. COCO-LR underestimates the variability in SLAs associated with intraseasonal
278 variations, and the differences in PDFs of intraseasonal SLAs between the IOD phases are not
279 adequately represented (Fig. 4; Fig. S13). This issue in COCO-LR is likely due to its inability to
280 adequately represent the propagation process of coastal waves originating from the equator, as
281 discussed in the previous section. Therefore, we conclude that interannual wind anomalies
282 associated with the IOD influence the occurrence of extreme SLAs along the western coast of
283 India, and that this effect is represented in the eddy-resolving ocean model. Furthermore, while
284 the non-eddy model can represent the low-frequency SLA patterns associated with the IOD, it
285 lacks the necessary resolution to simulate modulations in extreme intraseasonal SLAs.

286 Although IOD is mainly characterized by interannual variations, IOD also highly correlates
287 with intraseasonal equatorial wind anomalies and we suggest that influences of IOD on MJO
288 could be implicated (Izumo et al., 2010; Suematsu and Miura, 2018). The large-scale equatorial
289 zonal SST gradient associated with IOD may modulate the characteristics of MJO, potentially
290 driving intraseasonal zonal winds in equatorial Indian Ocean.

291



292

293 **Figure 4.** (a) Regressions of October-mean sea level anomalies (SLAs) and 10 m wind
 294 anomalies to September-October-November (SON)-mean dipole mode index (DMI) for CMEMS
 295 and JRA55-do data. Colors and vectors indicate statistically significant regression coefficients
 296 for SLAs and zonal winds at the 90% confidence level, respectively. Black boxes indicate the
 297 area where area-averaged SLAs and zonal equatorial wind (U_{eq}) are calculated, respectively. (d)
 298 Time series of the DMI (bar) and intraseasonal (i.e., bandpassed for 20-150 days) SLA along the
 299 western Indian coast ($15^{\circ}N$; black box in (a)) (black line) and normalized intraseasonal U_{eq}
 300 multiplied by -1 (red line) during October, based on observational data. The correlation between
 301 DMI and October-mean intraseasonal SLA is shown in the legend of each graph. Red (blue) bars
 302 indicate positive (negative) IOD, while gray bars indicate neutral years. Daily intraseasonal
 303 SLAs for a 31-day during October are depicted using box-whisker plots, where boxes span the
 304 25% to 75% ranges in the data, the line indicates the monthly mean, and the whiskers indicate
 305 the 5% to 95% ranges in the data. (g) PDFs for intraseasonal SLAs based on observational data
 306 for October, as in Fig. 2, but for during positive IOD years (red line), negative IOD years (blue
 307 line), and neutral years (gray bars). As in (a), (d), (g), but for (b),(e),(h) COCO-HR and (c),(f),(i)
 308 COCO-LR.

309

310 **5 Summary and discussion**

311 This study showed that the eddy-resolving OGCM (COCO-HR) is capable of reproducing the
312 intraseasonal variability of SLAs along the western coast of India. The results indicate that
313 COCO-HR effectively represents extreme SLA events along the western coast of India.
314 Conversely, the non-eddy model (COCO-LR) significantly underestimate the occurrence
315 frequency of these extreme intraseasonal sea level events. In the COCO-HR model, equatorial
316 Kelvin waves originating in the equatorial ocean reach the eastern boundary and subsequently
317 propagate along the coast of the Bay of Bengal and western India, while COCO-LR fails it due to
318 the coarser horizontal resolution. Furthermore, changes in the PDFs of intraseasonal SLAs
319 associated with the IOD are captured only in the COCO-HR model.

320 This study shows that CTWs are crucial for representing the occurrence of extreme sea level
321 events influenced by basin-scale climate variability, highlighting the importance of representing
322 CTWs in climate models to further improve simulations of coastal sea level extremes. The
323 underestimation of coastal extreme sea level events in the non-eddy OGCM further implies
324 that such extremes may be underestimated in CMIP6 models. For example, the intraseasonal
325 variability along the western coast of India is also underestimated in one of the CMIP6 models
326 (MIROC6) that employs COCO-LR as the ocean component (Fig. S14). Therefore, even when
327 comparisons are made in coupled models, qualitatively similar results can be expected as in this
328 study. Whilst, since evaluating the role of submesoscale eddies is still challenging using global
329 OGCMs, this study should be revisited using OGCMs with the submesoscale-resolving
330 resolution.

331 In the context of recent research on extreme weather events and their links to a warming
332 climate, several studies have emphasized the large-scale drivers of local extreme events (Kawase
333 et al., 2019; Imada et al., 2020). Han et al. (2022) also pointed out the large-scale climate
334 variability drives on local sea level extremes and marine heatwaves in the Indian Ocean. Our
335 results show that the probability of local sea level extremes along the western coast of India is
336 also affected by large-scale wind anomalies associated with the IOD, thus demonstrating a
337 "global-to-local" approach in oceanic contexts. While this study focused on the IOD, future
338 studies should examine the impacts of intraseasonal atmospheric variability, such as the MJO
339 and the Boreal Summer Intraseasonal Oscillation (Wang & Xie, 1997) on coastal SLAs.
340 Consequently, a reassessment of the risk of extreme sea level events, such as storm surges and

341 floods in the coastal areas of the North Indian Ocean, may be needed. This reassessment should
342 focus on the resolution of ocean models to better understand the relationship between changes in
343 local coastal sea level extremes and basin-scale climate variability under global warming.

344

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353

354 **Open Research**

355 The altimeter products were produced and distributed by Copernicus Marine Environment
356 Monitoring Service (CMEMS, 2023). Drifter-derived data was downloaded from
357 https://www.aoml.noaa.gov/ftp/phod/pub/lumpkin/drifter_climatology/. JRA55-do data
358 (<https://esgf-node.llnl.gov/search/input4mips>), PCMDI-SST
359 (https://aims2.llnl.gov/search/input4mips/?institution_id=PCMDI&source_version=1.1.9),
360 COCO-LR outputs ([http://esgf-](http://esgf-node.llnl.gov/search/cmip6/?mip_era=CMIP6&activity_id=OMIP&institution_id=MIROC&source_id=MIROC6&experiment_id=omip2)
361 [node.llnl.gov/search/cmip6/?mip_era=CMIP6&activity_id=OMIP&institution_id=MIROC&source_id=MIROC6&experiment_id=omip2](http://esgf-node.llnl.gov/search/cmip6/?mip_era=CMIP6&activity_id=OMIP&institution_id=MIROC&source_id=MIROC6&experiment_id=omip2)), and MIROC6 historical simulations
362 (https://aims2.llnl.gov/search?project=CMIP6&activeFacets=%7B%22activity_id%22%3A%22CMIP%22%2C%22source_id%22%3A%22MIROC6%22%2C%22experiment_id%22%3A%22historical%22%2C%22variant_label%22%3A%22r1i1p1f1%22%2C%22variable_id%22%3A%22zos%22%7D) are now distributed through the Earth System Grid Federation. The COCO-HR
363 and WIND0 data have been deposited in the Zenodo (Yamagami et al., 2024).

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