Intraseasonal sea level variability along the western coast of India simulated by an eddy-resolving ocean general circulation model

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Key Points:

- Reproducibility of sea level variability is compared along the western coast of India using eddy-resolving and non-eddying ocean models.
- The eddy-resolving model captures coastal Kelvin waves arising from Indian Ocean dipole and consequent intraseasonal sea level variations.
- The non-eddying model may miss over 81% of the extreme sea level events compared to observations.

Abstract

Future sea level rise under global warming poses serious risks of extreme sea level events in coastal regions worldwide. Numerous state-of-the-art climate models, with their relatively coarse horizontal resolution, may not adequately resolve coastal wave dynamics, leading to uncertainties in coastal sea level variability representation. This study compared eddy-resolving and non-eddying ocean models in reproducing sea level variability, focusing on the probability distribution along the western coast of India. The eddy-resolving model can simulate intraseasonal sea level variations associated with coastal waves driven by equatorial wind anomalies. The non-eddying model fails to capture over 81% of observed extreme sea level events, as shown in the probability distribution for intraseasonal time series. Although capable of simulating Indian Ocean Dipole-related low-frequency sea level anomalies, the non-eddying model does not replicate their connection to intraseasonal extreme events. The results suggest that climate model projections may underestimate future changes in extreme sea level events.

Plain Language Summary

Sea level variations in the northern Indian Ocean are influenced by ocean waves near the coast, typically in a horizontal scale of approximately 100 km. It is not clear if these coastal waves and their movement are accurate represented in climate simulations, which typically have a relatively coarse horizontal resolution. This study compared sea level variations along the western coast of India using two ocean models with coarse and fine horizontal resolutions. We found that the high-resolution model adequately simulates the generation and propagation of coastal waves, and thus successfully simulate sea level variations with a 20–150-day time scale along western India. This result suggests that many recent climate simulations may have underestimated the frequency of extreme sea level events in coastal regions.

1 Introduction

Global warming is projected to cause persistent sea level rise worldwide (IPCC 2022a). In addition to the global mean sea level rise owing to thermal expansion, melting of glaciers, etc., extreme sea level projections associated with changes in atmospheric circulation and river runoff are also required in coastal regions, especially projections of changes in the occurrence of extreme events (IPCC 2022b). Given that many of the state-of-art climate models in the Coupled Model Intercomparison Project Phase 6 (CMIP6) use a relatively coarse horizontal resolution of approximately 100 km, the projections obtained using these models may underestimate influence of oceanic mesoscale structures and coastal phenomena. Hence, it remains unclear whether current sea level projections, particularly in coastal regions, adequately capture changes in extreme sea level events (i.e., as indicated by the tails in probability distributions).

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

Although previous studies suggested the potential role of coastal Kelvin waves in the Northern Indian Ocean, the extent to which standard climate models reproduce the coastal sea level variations remains unclear. Therefore, using the coastal sea level variability along western India as an illustrative example, this study undertakes a comparative analysis of multiple simulations derived from the oceanic component utilized in a climate model. Here we show that an eddy-resolving ocean general circulation model (OGCM) is required to accurately represent sea level variations along the western coast of India. In particular, since intraseasonal sea level variations have a relatively pronounced amplitude and consequently lead to extreme events, this study focuses mainly on how the intraseasonal variations in coastal sea level are represented in OGCMs. Even though the non-eddying OGCM simulation is forced by the same atmospheric boundary conditions as in the eddy-resolving OGCM, the coarse horizontal resolution of the non-eddying OGCM fails to accurately capture the sea level variability, especially variations originating from the equator through the coastal wave guide in the Bay of Bengal.

2 Models, Data, and Methods

This study compares two simulations of CCSR Ocean Component Model (COCO) (Hasumi, 2006), which serves as the sea ice-ocean component of the sixth version of the Model for Interdisciplinary Research on Climate (MIROC6; Tatebe et al., 2019) that was developed cooperatively by the Japanese climate modeling community. The configurations of the coarse stand-alone OGCM used in the present study are exactly the same as the global OGCM component of MIROC6. The model employs a nominal 1° horizontal resolution in a tripolar coordinate system, and there are 63 vertical levels, including the lowermost layer that incorporates bottom boundary layer parameterization (Nakano & Suginohara, 2002). This simulation is referred to as "COCO-LR" hereafter. We also used a global high-resolution version of COCO, which has horizontal resolution of 0.1° (hereafter referred to as COCO-HR). Using the phase 2 protocol of the Ocean Model Intercomparison Project (OMIP2; Tsujino et al., 2020), an endorsed Multi-Model Intercomparison Project (MIP) of CMIP6, both models were initialized using observed temperature and salinity data from the World Ocean Atlas 2013 version 2 (Locarnini et al., 2013; Zweng et al., 2013). The models were driven by JRA55-do 3-hourly surface forcings (Tsujino et al., 2020) from 1958 to 2019 for COCO-HR and to 2018 for COCO-LR (Komuro, 2019). In the COCO-HR model, regardless of the existence of sea ice, sea surface salinity (SSS) above the latitudes of 60°N and below 60°S was weakly relaxed to observational data with a 10-day restoring timescale to avoid model drift. Similarly, temperature and salinity at depths greater than 1500 m were also restored to observed values with a 5-year timescale. Note that COCO-HR improved the representation of the mean state in the Indian Ocean (see Text S1 for details).

To highlight the impact of interannual variations in surface wind forcing on the coastal sea level along the western coast of India, we also conducted a sensitivity experiment, hereafter referred to as "WIND0". In this experiment, we used only the 3-hourly climatological mean of surface wind data for calculating surface wind stresses in COCO-HR. Thus, the surface wind stresses (i.e., dynamical forcing) in WIND0 incorporate only climatological mean variations, excluding low-frequency variations that occur over periods longer than 1 year. Other surface forcings in WIND0, such as surface heat flux, freshwater flux, and river runoff (i.e., thermodynamical forcing), are the same as those in COCO-HR.

In this study, we used the following observational datasets. PCMDI-SST (Hurrell et al., 2008) was used for the monthly sea surface temperature (SST) data for the period 1993–2019 with a horizontal resolution 1°×1°, as in Tsujino et al. (2020). CMEMS sea level products (DUACS DT2014; Pujol et al., 2016) have a daily interval and a horizontal resolution of 0.25°×0.25° for the period 1993–2019. Drifter-derived monthly climatological surface currents data were also used (Laurindo et al., 2017). To compare sea level anomalies with the satellite altimeter products, we mainly analyzed model outputs after 1993.

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

3 Sea level variance in the Northern Indian Ocean

In this section, we briefly validate the COCO-HR model focusing on sea level variability. COCO-HR showed noticeable improvements in the northern Indian Ocean, especially in regions where oceanic mesoscale eddies are dominant (Fig. 1). Regarding seasonal variability, observational data showed large-amplitude sea level variance in the Arabian Sea and the Bay of Bengal (Fig. 1a). These patterns are explained by the seasonal dynamics of the Lakshadweep High/Low in the southern Arabian Sea (Vinayachandran et al., 2007) and coastal wave guide effect in the Bay of Bengal (Clarke & Liu, 1994). The general structure of this seasonal sea level variability is well represented in the COCO-HR model, both in terms of spatial pattern and amplitude (Fig. 1b). Although the COCO-LR model showed a similar pattern, the overall amplitude was smaller than that in COCO-HR (Fig. 1c), suggesting that the coarse resolution model underestimates the seasonal sea level variability in the northern Indian Ocean.

In addition, COCO-HR more accurately captures detrended interannual SLAs compared to COCO-LR (Fig. 1d-f). The noticeable interannual variations in the Somalia-Oman upwelling region are well represented in COCO-HR, aligning closely with observations, although COCO-

HR does slightly underestimate them. This difference is presumably because the interannual variability of the mesoscale variability associated with the Somali Current is well represented in COCO-HR. Interannual sea level variability in the western Bay of Bengal also tends to be better represented in COCO-HR, indicating that the interannual variability of coastal trapped waves and local mesoscale variability is also well captured by COCO-HR. In the following section, we examined sea level variations along the western coast of India in greater detail.

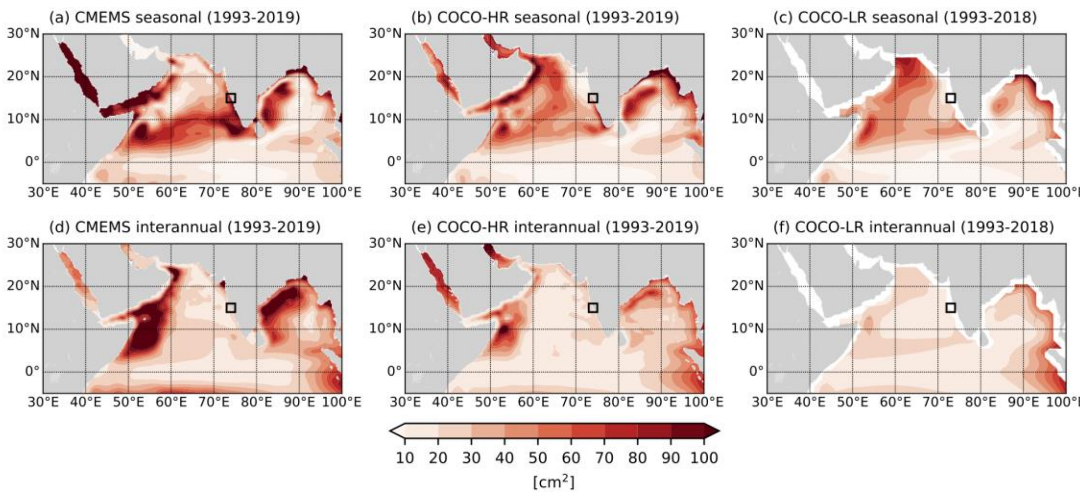

Figure 1. Variances in seasonal sea level anomalies (SLAs) [cm^2] in the northern Indian Ocean for (a) observations, (b) COCO-HR, and (c) COCO-LR. (d)-(f) As in (a)-(c), but for interannual SLAs. Interannual anomalies are defined as detrended anomalies from the climatology.

4 SLAs along the western coast of India

4.1 Intraseasonal sea level variations

In order to investigate sea level variations along the western coast of India, area-averaged sea level variations are calculated within 2°×2° boxes at 15°N (black boxes in Fig. 1). Note that qualitatively similar results are obtained if we use 1°×1° boxes. The comparison indicates that COCO-HR more accurately represents both seasonal (Text S2) and intraseasonal SSH variations along the west coast of India.

PDFs for 20-150 day band-passed SLA time series are estimated (Fig. 2). Note that we refer to the 20-150 day band-passed timeseries of detrended anomalies from the daily climatology as “intraseasonal anomalies” hereafter. In all months, COCO-HR reproduces PDFs that are similar to the observational data, with standard deviations that also match those of the observational data. Conversely, COCO-LR exhibits smaller standard deviations for each PDF compared to the observations, resulting in underestimation of extreme SLA events. Indeed, in the observational data, the thresholds employed for positive (negative) extreme SLA events, i.e., events exceeding 95% (5.0%) probability, are estimated to be 4.4 cm (-4.8 cm) (Fig. 2a). For COCO-HR, the occurrence rates of positive (negative) extreme SLA events are 7.3% (4.7%), which is consistent with the observed rates. For COCO-LR, the occurrence of positive (negative) SLA events is 0.95% (0.21%), which is considerably smaller than in the observations. This result means that COCO-LR misses 81% (96%) of the extreme intraseasonal sea level maxima (minima), and underscores the importance of using an eddy-resolving ocean model to accurately hindcast coastal sea level variability.

The narrower PDFs (i.e., indicating less variance) in WIND0 compared to COCO-HR suggests a reduced occurrence of extreme SLA events. Therefore, dynamical wind forcing anomalies are necessary for simulating intraseasonal SLA along the western coast of India (Fig. 2b-m). This result also implies that the contribution of factors other than wind stress forcing, such as buoyancy flux and baroclinic instability associated with West Indian Coastal Current (e.g., Varna et al., 2023), is not predominant. The above result remains qualitatively unchanged if the PDFs are calculated for detrended anomalies without 20–150-day bandpass filtering (Fig. S5). Thus, differences in anomalies with periods shorter (longer) than 20 (150) days do not explain the reduction in the standard deviation of PDFs in WIND0. Consequently, the higher frequency of extreme SLA events in COCO-HR can be attributed to interannual-to-decadal changes in the intraseasonal amnomalies. Given that the variance in the intraseasonal component is prominent in both the observation and models (Fig. S6), compared to the total variance, we will discuss the processes driving these differences in PDFs of intraseasonal variability in the next section.

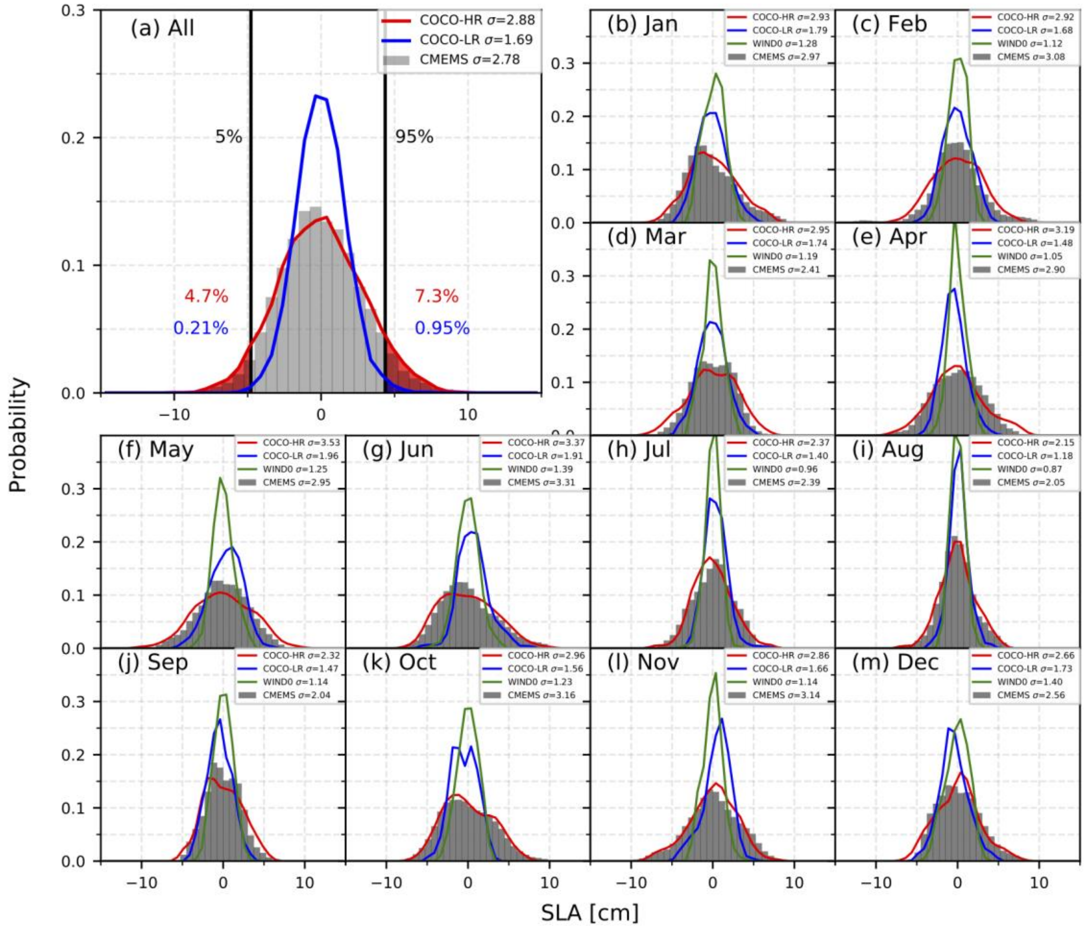

Figure 2. Probability density functions (PDFs) of intraseasonal (20-150 days) sea level anomalies (SLA) [cm] along the western coast of India (15°N) for observations (CMEMS; black bars), COCO-HR (red lines), COCO LR (blue lines), and WIND0 (green lines) for (a) all seasons and (b)-(m) each month. PDFs are estimated by kernel density estimation. The standard deviation (σ) for each month is given in the legend accompanying each graph. All PDFs are normalized and the vertical axis indicates probability (unit less). In (a), vertical black lines indicate the 5% and 95% anomalies based on CMEMS data. Areas where anomalies exceed the 5 or 95 percentiles for CMEMS are highlighted in red (COCO-HR) and blue (COCO-LR) colors, respectively, with the corresponding percentile values marked in each model.

4.2 Resolution dependency of the propagation of coastal Kelvin waves

Regarding the remote impacts of coastal Kelvin waves on the western coast of India, the large intraseasonal SLA variances in COCO-HR may be attributed to the propagation of sea level anomalies. Figure 3 shows a lag composite of SLA from 0 to 40 days before the occurrence of intraseasonal SLA exceeds +1 standard deviation at the western coast of India (indicated by red symbols in Fig. S6). Since the composites obtained for the negative anomalies are almost mirror images, we discuss only the results obtained for positive SLA events. In the observations, a significant SLA associated with equatorial Kelvin wave is triggered by westerly wind anomalies in the tropical Indian Ocean 40 days prior. Subsequently, this wave reaches the coast of Sumatra island and then propagates as coastal Kelvin waves along the coast of the Bay of Bengal. These waves pass through the southern tip of India, arrive at the western coast of India, and eventually extend into the northern Arabian Sea (Fig. 3a). Furthermore, SLAs also appear to be radiated from the eastern coast of the Bay of Bengal as westward Rossby waves, and are enhanced by easterly wind anomalies along the southern tip of Sri Lanka.

In COCO-HR, similar to the observations, the equatorial Kelvin wave enters the eastern boundary and propagates as coastal Kelvin waves from the Bay of Bengal to the western coast of India (Fig. 3b). Westward SLAs also appeared to be radiated from the eastern coast of the Bay of Bengal to the southern coast of India. On the other hand, COCO-LR does not show SLA propagation in the coastal region from the equator to the Bay of Bengal. Instead, positive SLAs appear to develop locally about 10 days prior, before rapidly increasing in the western coast of India. Previous studies proposed that intraseasonal SLA variations along the western coast of India are predominantly influenced by the propagation of the coastal Kelvin waves from the equatorial Indian Ocean (Suresh et al., 2013). Therefore, the results obtained in this study suggest that COCO-HR effectively captures the propagation of coastal Kelvin waves from the equator. However, the propagation of Kelvin waves from the equator is not well captured by COCO-LR due to the coarser horizontal resolution (Text S3), suggesting an exaggerated influence of local wind and/or thermal forcing in the western coast of India.

In the WIND0 composites, no SLA propagation originating from the equatorial Kelvin waves is evident. This is because the suppressed wind stress anomalies do not trigger intraseasonal anomalies of the equatorial Kelvin waves and, consequently, the coastal Kelvin waves in the Bay of Bengal. These results are also supported by the lag-composite analysis of SLA from 0 to 40 days following instances when the SLA exceeds +1 standard deviation at the eastern equatorial Indian Ocean (Fig. S7). While both COCO-HR and COCO-LR depict the propagation of equatorial Kelvin waves to the eastern boundary, only the observations and COCO-HR show the subsequent SLA propagation in the Bay of Bengal.

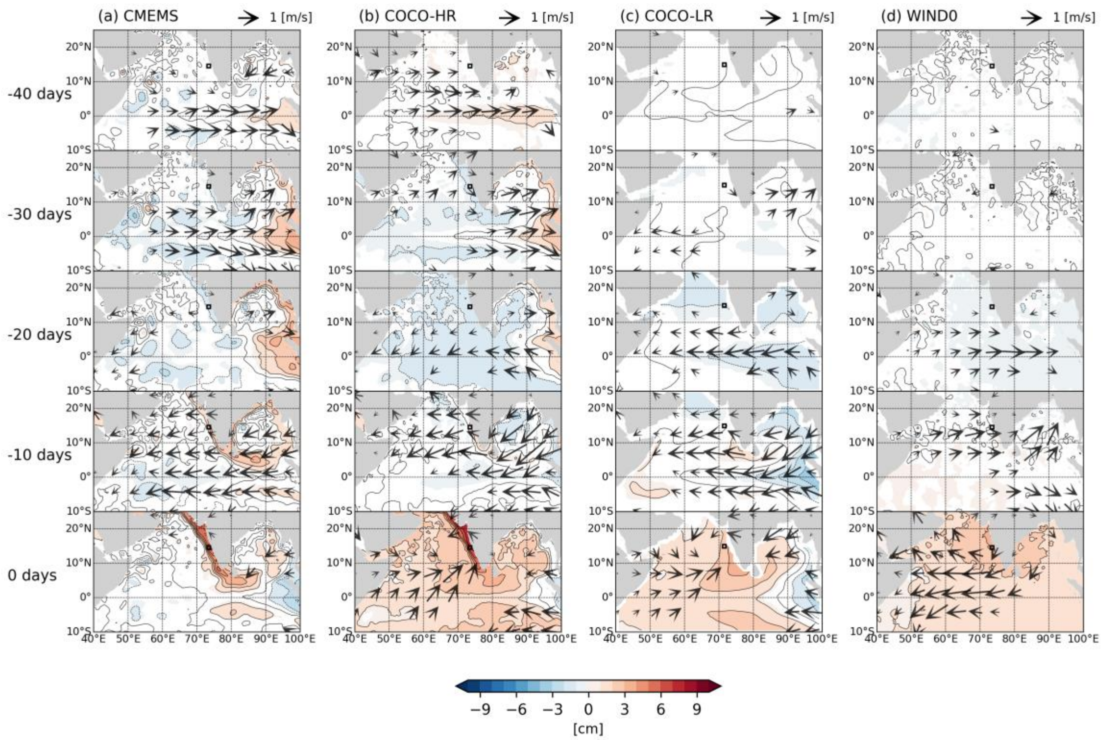

Figure 3. Lag-composites of sea level anomalies (SLA) (contour and color) and 10-m wind (vectors) for area-averaged SLA time series along the western coast of India (black boxes). Data are shown for (a) CMEMS, (b) COCO-HR, (c) COCO-LR, and (d) WIND0. Colors and vectors indicate statistically significant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

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

In section 4.2, differences in PDFs of intraseasonal SLA are attributed to the representation of coastal Kelvin waves. This section examines the origin of the coastal Kelvin waves, particularly their association with wind variations in the tropical Indian Ocean. Given that basin-scale wind anomalies in the tropical Indian Ocean are affected by the IOD, it follows that the IOD contributes to interannual low-frequency SLA variations along the western coast of India through coastal Kelvin waves (e.g., Suresh et al., 2018). However, the extent to which interannual wind anomalies associated with the IOD modulate intraseasonal SLA variations, specifically the probability distribution of coastal SLA along the western coast of India, remains unclear. We therefore investigated the relationship between IOD and intraseasonal SLA, and assessed its representation in both COCO-HR and COCO-LR. In this analysis, the dipole mode index (DMI) is defined as the difference between area-averaged monthly-mean SST difference between the western (50°E-70°E, 10°S-10°N) and eastern (90°E-110°E, 10°S-0°) poles, as defined in previous studies (Saji et al., 1999; Tanizaki et al., 2017). A 3-month running mean is also applied to the DMI.

Since SST anomalies associated with the IOD typically peak in October (e.g., Saji et al., 1999), we focus on the relationship between the IOD and intraseasonal SLA along the western coast of India during this month. During positive IOD events, equatorial easterly wind anomalies trigger positive (negative) SLAs along the southern tip of Sri Lanka (in the eastern equatorial Indian Ocean) and, subsequently, positive (negative) coastal Kelvin waves along the western coast of India (coastal region of the Bay of Bengal) as observed (Fig. 4a). The SLAs associated with the IOD affects the interannual modulation of intraseasonal SLAs along the western coast of India (Fig. 4d). The correlation between the October-mean of intraseasonal SLAs and the DMI is 0.68, indicating that the IOD modulates the interannual variations in intraseasonal SLA. During the positive IOD phases, the PDF of the intraseasonal SLA shifts positively (Fig. 4g). Conversely, the PDFs during negative IOD and neutral years are less distinct, which may be attributed to the asymmetry in the IOD, with negative events having a smaller amplitude than positive events (e.g., Nakazato et al., 2021, An et al., 2023).

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

While both COCO-HR and COCO-LR are driven by the same surface forcings, leading to similar large-scale SLA variation patterns in October, there are notable differences at a local scale. This discrepancy is particularly evident when focusing on the local SLA along the western coast of India, where COCO-LR fails to represent the interannual variations. Additionally, COCO-LR underestimates the variability in SLAs associated with intraseasonal variations, and the differences in PDFs between the IOD phases are not adequately represented (Fig. 4; Fig. S9). This issue in COCO-LR is likely due to its inability to adequately represent the propagation process of coastal waves originating from the equator, as discussed in the previous section. Therefore, we conclude that interannual wind anomalies associated with the IOD influence the occurrence of extreme SLAs along the western coast of India, and that this effect is represented in the eddy-resolving ocean model. Furthermore, while the non-eddying model can represent the low-frequency SLA patterns associated with the IOD, it lacks the necessary resolution to simulate modulations in extreme intraseasonal SLAs.

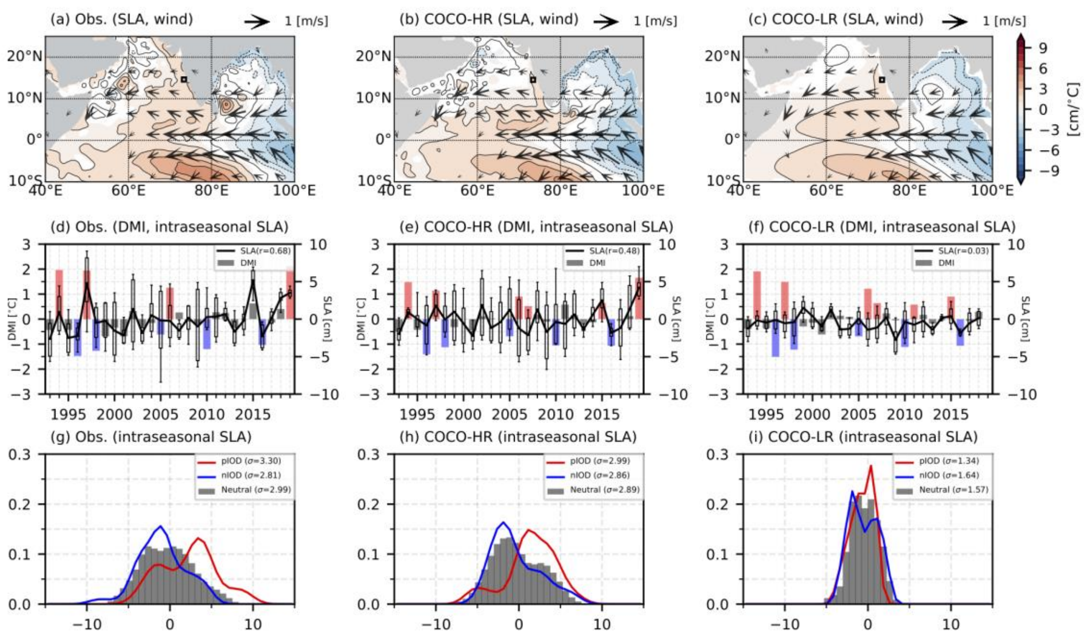

Figure 4. (a) Regressions of October-mean sea level anomalies (SLAs) and 10 m wind anomalies to September-October-November (SON)-mean dipole mode index (DMI) for CMEMS and JRA55-do data. Colors and vectors indicate statistically significant regression coefficients for SLAs and zonal winds at the 90% confidence level, respectively. (d) Time series of the DMI (bar) and intraseasonal SLA (i.e., bandpassed for 20-150 days) (line) during October along the western Indian coast (15°N; black box in (a)), based on observational data. The correlation between DMI and October-mean intraseasonal SLA is shown in the legend of each graph. Red (blue) bars indicate positive (negative) IOD, while gray bars indicate neutral years. Daily intraseasonal SLAs for a 31-day period, October, are depicted using box-whisker plots, where boxes span the 25% to 75% ranges in the data, the line indicates the monthly mean, and the

whiskers indicate the 5% to 95% ranges in the data. (g) PDFs for intraseasonal SLAs based on observational data for October, as in Fig. 2, but for during positive IOD years (red line), negative IOD years (blue line), and neutral years (gray bars). (b),(e),(h) As in (a), (d), (g), but for COCO-HR. (c),(f),(i) As in (a),(d),(g), but for COCO-LR.

5 Summary and discussion

This study showed that only the eddy-resolving OGCM (COCO-HR) is capable of reproducing the intraseasonal variability of SLAs along the western coast of India. The results indicate that COCO-HR effectively represents extreme SLA events along the western coast of India. Conversely, the non-eddying model (COCO-LR) fails to capture more than 81% of these extreme intraseasonal sea level events. In the COCO-HR model, equatorial Kelvin waves originating in the equatorial ocean enter the eastern boundary and subsequently propagate along the coast of the Bay of Bengal and western India, while COCO-LR fails it due to the coarser horizontal resolution. Furthermore, changes in the PDFs of intraseasonal SLAs associated with the IOD are captured only in the COCO-HR model. This suggests that basin-scale wind anomalies in the equatorial Indian Ocean can modulate the occurrence of extreme SLA events along the western coast of India.

The underestimation of coastal extreme sea level events in the non-eddying OGCM further implies that such extremes may be underestimated in CMIP6 models. In the context of recent research on extreme weather events and their links to a warming climate, several studies have emphasized the large-scale drivers of local extreme events (Kawase et al., 2019; Imada et al., 2020). Our results show that the probability of local sea level extremes along the western coast of India is also affected by large-scale wind anomalies associated with the IOD, thus demonstrating a "global-to-local" approach in oceanic cntexts. While this study focused on the IOD, future studies should examine the impacts of intraseasonal atmospheric variability, such as the MJO and the Boreal Summer Intraseasonal Oscillation (Wang & Xie, 1997) on coastal SLAs. Consequently, a reassessment of the risk of extreme sea level events, such as storm surges and floods in the coastal areas of the North Indian Ocean, may be needed. This reassessment should focus on the resolution of ocean models to better understand the relationship between changes in local coastal sea level extremes and basin-scale climate variability under global warming.

Acknowledgments

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Open Research

The altimeter products were produced and distributed by Copernicus Marine Environment Monitoring Service (https://doi.org/10.48670/moi-00148). Drifter-derived data was downloaded from https://www.aoml.noaa.gov/ftp/phod/pub/lumpkin/drifter_climatology/. JRA55-do data (https://esgf-node.llnl.gov/search/input4mips), PCMDI-SST (https://aims2.llnl.gov/search/input4mips/?institution_id=PCMDI&source_version=1.1.9), and COCO-LR outputs (http://esgf-node.llnl.gov/search/cmip6/?mip_era=CMIP6&activity_id=OMIP&institution_id=MIROC&source_id=MIROC6&experiment_id=omip2) are now distributed through the Earth System Grid Federation. The COCO-HR and WIND0 data have been deposited in the Zenodo (https://doi.org/10.5281/zenodo.10633562).

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