Making the Case for High-Resolution Regional Ocean Reanalyses
An Example with the Red Sea

Sivareddy Sanikommu, Sabique Langodan, Hari Prasad Dasari, Peng Zhan, George Krokos, Yasser O. Abualnaja, Khaled Asfahani, and Ibrahim Hoteit

ABSTRACT: Coastal oceans host 40% of the world population and amount to $1.5 trillion of the global economy. Studying, managing, and developing the coastal regions require decades-long information about their environment. Long-term ocean measurements are, however, lacking for most coastal regions and often global reanalyses are used instead. These are, however, coarse in nature and tuned for the global circulations. The Red Sea (RS) is a narrow basin connected to the Indian Ocean through the Bab-al-Mandab Strait. Despite being the busiest commercial crossroad and hosting the world’s third largest coral reef system, the RS lacks long-term observations. A recent increase in population and an unprecedented acceleration in governmental and industrial developments further emphasized the need for long-term datasets to support its development and the sustainability of its habitats, and to understand its response to a changing climate. Toward this end, we have generated a 20-yr high-resolution reanalysis for the RS (RSRA) using a state-of-the-art ensemble data assimilation system incorporating available observations. Compared to global reanalyses, RSRA provides a markedly better description of the RS general and mesoscale circulation features, their variability, and trends. In particular, RSRA accurately captures the three-layer summer transport through the Bab-al-Mandab, simulated as two-layer transport by some global reanalyses. It further reproduces the seasonal anomalies, whereas global reanalyses misidentify some seasons as anomalous. Global reanalyses further overestimate the interannual variations in salinity, misrepresent the trend in temperature, and underestimate the trend in sea level. Our study clearly emphasizes the importance of generating dedicated high-resolution regional ocean reanalyses.

KEYWORDS: Data assimilation; Ensembles; Model comparison; Ocean models; Reanalysis data; Regional models

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The oceans cover 70% of our planet and are invaluable assets for humans with an estimated economical value of at least $24 trillion (Hoegh-Guldberg 2015). A major portion of these assets lies in the coastal oceans, the hotspots for developments and livelihood. Coastal oceans host a large (~40%) percentage of the global population and are the main economic engines to most of the surrounding countries. They contributed $1.5 trillion to the global economy in 2010, and this is estimated to grow to $3 trillion by 2030 (OECD 2016). To meet these demands and better prepare for sustainable growth, a better understanding of the changes the coastal oceans undergo at various spatiotemporal scales is needed. This can only be possible through the availability of long-term datasets.

Global ocean reanalyses, typically generated by combining available observational information with global ocean general circulation models (OGCM) using data assimilation, are often used for investigating different regional, and even coastal, oceans circulation and climate studies and applications since tuned high-resolution reanalyses are usually not available (e.g., Balaguru et al. 2014; Forget et al. 2015; Li et al. 2017; Periáñez 2020; Albert and Bhaskaran 2020). A wealth of global reanalysis products is available with the differences in their quality depending on the investigated region and period (e.g., Carton et al. 2019; Uotila et al. 2019; Rao et al. 2019; De Souza et al. 2021). Those differences may be due to various factors including the used OGCM and its configuration (Balmaseda et al. 2015; Chassignet and Xu 2021), the driving atmospheric forcing (Haine et al. 2009), the assimilated observations (Balmaseda et al. 2007; Oke et al. 2015; Sanikommu et al. 2017; Fujii et al. 2019; Sanikommu et al. 2019), and of course the characteristics of the assimilation method (e.g., Edwards et al. 2015; Sanikommu et al. 2020).

Global reanalyses may not be robust and/or sufficient to describe local ocean features, as they are tuned to reproduce the global ocean circulation. Moreover, with the current computational resources, global reanalyses cannot be generated on high-resolution grids with advanced assimilation methods, e.g., ensemble Kalman filters that provide flow-dependent prior errors useful for efficient extraction of the information from the observations (Edwards et al. 2015; Hoteit et al. 2018).

The Red Sea (RS), a narrow basin surrounded by deserts, is a key resource for local governments for producing potable water and to diversify their economy through tourism, desert agriculture, fisheries, logistical industries, etc. (Carvalho et al. 2019; Hoteit et al. 2021). It has also recently become an investment corridor with the launching of megaprojects along its shores, including the new futuristic city of the Kingdom of Saudi Arabia (KSA), NEOM, and the ambitious Red Sea Project (Fig. 1a). The RS hosts the third largest coral reef system in the world and supports unique species that thrive under extreme warm and
saline conditions (Carvalho et al. 2019). The RS surface circulation is dominated by energetic mesoscale eddies (e.g., Zhan et al. 2014, 2016) under the influence of along-axis winds and coastal topography (Quadfasel and Baudner 1993; Zhan et al. 2018), baroclinic instabilities (Zhan et al. 2014, 2016), strong buoyancy forcing (Chen et al. 2014; Zhan et al. 2018), and cross-basin winds (Zhai and Bower 2013; Zhan et al. 2018). The RS deep and intermediate layers are renewed through hypersaline discharges from the northern basin including the Gulfs of Suez and Aqaba (e.g., Plähn et al. 2002; Papadopoulos et al. 2015; Sofianos and Johns 2015, 2017; Yao and Hoteit 2018; Krokos et al. 2022). At its southern end, it discharges hypersaline water at deep layers and receives freshwaters at the surface from the Indian Ocean through the narrow strait of Bab-al-Mandab (BAM) (Yao et al. 2014a,b; Sofianos and Johns 2015). The water exchange and associated overturning cells exhibit significant seasonal to interannual variations (Yao et al. 2014a,b; Xie et al. 2019). The RS basin is further experiencing alarming rates of sea level and sea surface temperature rise in connection with the global climate (Raitos et al. 2011; Chaidez et al. 2017; Krokos et al. 2019; Shaltout 2019).

Studying and managing the RS has been mostly based on information available from very sparse observations and global ocean reanalyses, despite their potential limitations at describing the basin local characteristics. For instance, results from an 8-km-resolution Hybrid Coordinate Ocean Model (HYCOM)-based global ocean reanalysis have been used to characterize oceanic features in the northern basin (Eladawy et al. 2017), and for predicting the potential impact of an oil spill in the south (Periáñez 2020). Agulles et al. (2019) analyzed the 8-km-resolution Global Ocean Reanalysis and Simulation (GLORYS) data to explore the long-term evolution of the Red Sea temperature. The same product has been used to assess the

![Fig. 1. Topography and observations coverage in the Red Sea. (a) Important sites mentioned in the text are indicated. (b) Time evolution of temperature (blue) and salinity (green) data profiles coverage is shown. (c),(d) Various observations coverage in August 2001 and January 2016, respectively.](image)
advective pathways of the Red Sea Outflow Water (RSOW) and its connection to the adjacent Indian Ocean (Menezes 2021), despite the poorly resolved flow exchange at the BAM. Global model outputs were also analyzed to assess ongoing and future climate variations in the RS (Shaltout 2019; Agulles et al. 2021).

Many studies stressed the need for developing dedicated reanalyses to better describe the local features of the regional ocean basins (Edwards et al. 2015; Francis et al. 2020; De Souza et al. 2021), while others demonstrated the positive impact of model resolution (Kirtman et al. 2012), atmospheric forcing (Dinniman et al. 2015; Lewis et al. 2019), enhanced observations networks (Balmaseda et al. 2007; Oke et al. 2015; Fujii et al. 2015; Sanikommu et al. 2017), and advanced assimilation techniques (Weaver et al. 2003; Vialard et al. 2003; Storto et al. 2020) in various basins, including the Red Sea (Sanikommu et al. 2020; Krokos et al. 2021). Several efforts were directed toward generating high-resolution regional reanalyses for various coastal and marginal seas (e.g., Han et al. 2011; Seo et al. 2015; Nishikawa et al. 2021; Escudier et al. 2021), but very few intercompared the regional and global reanalyses (Uotila et al. 2019; Amaya et al. 2023).

Here we present the first effort to develop a high-resolution ensemble reanalysis for a full basin, the Red Sea, using a state-of-the-ensemble Kalman filter–based data assimilation system. We further stress and demonstrate for the community at large the importance of investing the required efforts and resources to generate such regional ocean reanalyses, through both qualitative and quantitative assessments. The generated Red Sea Reanalysis was extensively analyzed and evaluated against widely used global ocean reanalyses. We showcase the value of this regional reanalysis at capturing the important features across the range of time scales, such as the basin’s mesoscale eddies, seasonal overturning circulation, interannual variabilities, and long-term trends, when all global ocean reanalyses failed in one way or another to produce these crucial features of the Red Sea general circulation. The Red Sea Reanalysis was further successfully validated against independent observations that were intentionally not assimilated for comparisons with the global reanalyses. Hereafter, the second section describes the Red Sea Reanalysis and its underlying assimilation system. The third section details the datasets and evaluation methods. The fourth section presents quantitative and qualitative analyses of the Red Sea and global reanalyses and their representation of the RS climatology, variability, and trends. A general discussion concludes this study in the fifth section.

The RSRA

We developed and implemented a hybrid ensemble data assimilation system (Sanikommu et al. 2020; Toye et al. 2020) to generate the RS regional reanalysis (RSRA). The system uses a 4-km-resolution Massachusetts Institute of Technology Ocean General Circulation Model (MITgcm; Marshall et al. 1997) to estimate flow-dependent background ensembles, and an ensemble adjustment Kalman filter (EAKF) of the Data Assimilation Research Testbed (DART) to assimilate the observations (Anderson et al. 2000; Hoteit et al. 2013). The MITgcm domain covers the entire RS basin (Fig. 1), including the Gulfs of Suez, Aqaba, and a part of the Gulf of Aden where an open boundary connects it to the Arabian Sea (Zhan et al. 2020; Krokos et al. 2021, 2022). It is forced here with in-house 3-hourly 5 km atmospheric forcing fields (surface radiation, freshwater, and momentum fluxes) generated specifically for the Red Sea region using an assimilative Weather Research and Forecasting (WRF) Model (refer to appendix A). The open boundary conditions (OBCs) for temperature, salinity, and horizontal velocity are prescribed daily from the GLORYS global ocean reanalysis (Lellouche et al. 2013, 2021). The hybrid system is implemented with 50 flow-dependent and 250 static seasonal ensembles, accounting for uncertainties in the ocean initial conditions and atmospheric fields (Sanikommu et al. 2020). The flow-dependent members in the hybrid ensemble are
updated with the data and model dynamics at every assimilation cycle and the static members are preselected for each month from a long-term historical (here, 20 years) model run. The reader is referred to Toye et al. (2020) for a detailed description of the hybrid ensemble assimilation system. As outlined in Table 1, the system assimilates four types of observations: satellite level-4 sea surface temperature (SST), satellite along-track level-2 altimeter sea level anomalies (SLA), and in situ temperature ($T$) and salinity ($S$) profiles, every 3 days. The observational errors are assumed uncorrelated. Constant observational error variance of $(4 \text{ cm})^2$ is used for SLA (Sanikommu et al. 2020; Toye et al. 2020). The rest of the assimilated variables (SST, $T$, and $S$ profiles) are assimilated using flow dependent observational errors that vary in both space and time as described in appendix B. Satellite-derived SST and SLA observations provide a more uniform spatial and temporal coverage over the Red Sea basin (Figs. 1b–d). The $T$ and $S$ data profiles are generally sparse, with less than 50 $T$ profiles and 20 $S$ profiles per month most of the time (Fig. 1b). Observational campaigns in the northern RS in August 2001 provided about 1,600 $T$ profiles. Combined profiling of $T$ and $S$ is rare until 2015, but the situation remarkably improved between 2015 and 2019.

RSRA is generated for the period 2000–19 using the configuration of HYBDexp of Toye et al. (2020), except for four main changes: 1) a high-resolution atmospheric forcing generated by overlaying the uncertainties of the coarser-resolution atmospheric ensemble of European Centre for Medium-Range Weather Forecasts (ECMWF), 2) incorporation of flow-dependent representational errors for SST, and temperature ($T$) and salinity ($S$) profile observations (Sanikommu et al. 2019), and 3) assimilation of high-resolution SST observations. The details of the changes are outlined in the online supplemental material (https://doi.org/10.1175/BAMS-D-21-0287.2).

**Datasets**

**Global ocean reanalyses.** Daily averaged fields from three widely used global ocean reanalyses were analyzed for intercomparison with RSRA: 1) 25-km-resolution Ocean Reanalysis System 5 (ORAS5; Zuo et al. 2019) of ECMWF, 2) 8-km-resolution GLORYS (Lellouche et al. 2021) developed within the framework of Copernicus Marine Environment Monitoring Service (CMEMS), Mercator Ocean, and 3) 8-km-resolution Navy Coupled Ocean Data Assimilation (NCODA) system from the HYCOM consortium (Cummings and Smedstad 2013). ORAS5 and GLORYS are available over the entire study period (2000–19), whereas NCODA

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**Table 1. Summary of RSRA and global reanalyses configurations. A list of the abbreviations and expansions of the acronyms can be found in appendix D.**

<table>
<thead>
<tr>
<th></th>
<th>RSRA</th>
<th>ORAS5</th>
<th>GLORYS</th>
<th>NCODA</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model</strong></td>
<td>4 km MITgcm</td>
<td>25 km NEMO</td>
<td>8 km NEMO</td>
<td>8 km HYCOM</td>
</tr>
<tr>
<td><strong>Atmospheric forcing</strong></td>
<td>50-member WRF 5 km</td>
<td>75 km ERA-Interim</td>
<td>75 km ERA-Interim + 40 km ERA5</td>
<td>50 km NOGAPS</td>
</tr>
<tr>
<td><strong>Assimilation scheme</strong></td>
<td>Hybrid-EAKF</td>
<td>3D-VAR + FGAT + IAU</td>
<td>SEEK + FGAT + IAU + 3D-VAR</td>
<td>3D-VAR</td>
</tr>
<tr>
<td><strong>SST</strong></td>
<td>25 km Reynolds + 5 km OSTIA</td>
<td>100 km HadISST2 + 5 km OSTIA</td>
<td>25 km Reynolds</td>
<td>Empirical SSTs from satellite level-2 radiances + in situ from all available sources; data thinning imposed using Rossby radius of deformation (100–60 km between 10° and 30°N)</td>
</tr>
<tr>
<td><strong>SSH</strong></td>
<td>Level-2 altimeter SLA + model MSSH</td>
<td>Level-2 altimeter SLA + model MSSH</td>
<td>Level-2 altimeter SLA + hybrid MDT</td>
<td>Synthetic profiles derived from level-2 altimeter SSH</td>
</tr>
<tr>
<td><strong>T&amp;S</strong></td>
<td>EN4</td>
<td>EN4</td>
<td>CORAV4.1</td>
<td>USGODAE datasets; synthetic salinity when no T&amp;S pair</td>
</tr>
<tr>
<td><strong>Assimilation cycle</strong></td>
<td>3 days</td>
<td>5 days</td>
<td>7 days</td>
<td>Daily</td>
</tr>
</tbody>
</table>
is only available between 2000 and 2015. The selected reanalyses represent a diverse range of the available global ocean reanalyses in terms of model’s configurations, assimilation frameworks, treatment of observations, etc., as outlined in Table 1.

**Validation datasets.** Three independent in situ observational datasets that have not been assimilated in any of the examined reanalyses are used for assessing the $T$ and $S$ fields. The first two datasets we collected by survey cruises that were jointly conducted by Woods Hole Oceanographic Institute (WHOI) and King Abdullah University of Science and Technology (KAUST) (Bower and Farrar 2015). The first cruise covered the period of March–May 2010 and collected 111 $T$ and $S$ profiles in the northeastern half of the RS. The second cruise covered the period of September–October 2011 and collected 262 $T$ and $S$ profiles from the central and northeastern half of the RS. The third in situ dataset was collected by a glider operated by KAUST in the northern RS (27°–27.5°N, 34.9°–35.6°E) between October 2015 and May 2016, which provided 1,170 $T$ and $S$ profiles (Asfahani et al. 2020).

Another independent dataset is available from the multimission satellite-based 25-km-resolution weekly level-4 optimally interpolated sea surface salinity (SSS) product (hereafter OISSS) provided by CMEMS (Droghei et al. 2018). OISSS exhibited about 0.37 psu root-mean-square difference (RMSD) with the above-mentioned in situ (10 m) salinity observations.

Along-track altimeter level-2 sea surface height (SSH) data, with suggested $\sim$4 cm accuracy, are also used to examine the temporal evaluation of the reanalyses SSH fields together with altimeter merged daily averaged 25-km-resolution level-4 SSH from CMEMS (Mertz et al. 2017). All the SSH datasets, including observations and reanalyses, were adjusted to the long-term-mean RS MITgcm SSH (MSSH) as explained in Sanikommu et al. (2019). The reanalyses SST were compared against the observations-based 25-km-resolution Reynolds (Reynolds et al. 2007) and 5-km-resolution Operational Sea Surface Temperature and Sea Ice Analysis (OSTIA) SST products (Stark et al. 2007; Donlon et al. 2012) before and after April 2006, respectively. OSTIA SST exhibited about 0.38°C RMSD when compared to the above-mentioned in situ surface (10 m) temperature observations.

**RSRA versus global reanalyses**

**Quantitative assessment.** Table 2 presents various statistical skills of SST and SSS as resulting from the different reanalyses against all available independent in situ observations at 10 m. In general, all the reanalysis products compare well for SST, although global reanalyses exhibit slightly elevated errors compared to RSRA. The reanalyses skills differ significantly for SSS. GLORYS and ORAS5 are strongly biased, while NCODA and RSRA perform better than even the satellite products. We further compared the climatological seasonal cycles of SSS, SST, and SSH of the reanalysis products and the satellite-based products. The global

<table>
<thead>
<tr>
<th>Sea surface temperature (°C)</th>
<th>In situ</th>
<th>Satellite</th>
<th>RSRA</th>
<th>ORAS5</th>
<th>GLORYS</th>
<th>NCODA</th>
</tr>
</thead>
<tbody>
<tr>
<td>STD</td>
<td>2.74</td>
<td>2.81</td>
<td>2.76</td>
<td>2.75</td>
<td>2.69</td>
<td>2.28</td>
</tr>
<tr>
<td>Bias</td>
<td>−0.02</td>
<td>−0.05</td>
<td>−0.25</td>
<td>−0.06</td>
<td>−0.27</td>
<td></td>
</tr>
<tr>
<td>RMSD</td>
<td>0.38</td>
<td>0.39</td>
<td>0.41</td>
<td>0.40</td>
<td>0.44</td>
<td></td>
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</table>

<table>
<thead>
<tr>
<th>Sea surface salinity (psu)</th>
<th>In situ</th>
<th>Satellite</th>
<th>RSRA</th>
<th>ORAS5</th>
<th>GLORYS</th>
<th>NCODA</th>
</tr>
</thead>
<tbody>
<tr>
<td>STD</td>
<td>0.50</td>
<td>0.41</td>
<td>0.44</td>
<td>0.28</td>
<td>0.71</td>
<td>0.45</td>
</tr>
<tr>
<td>Bias</td>
<td>−0.17</td>
<td>0.03</td>
<td>−1.68</td>
<td>−0.44</td>
<td>−0.04</td>
<td></td>
</tr>
<tr>
<td>RMSD</td>
<td>0.37</td>
<td>0.30</td>
<td>1.71</td>
<td>0.57</td>
<td>0.25</td>
<td></td>
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</tbody>
</table>
Reanalyses show nonnegligible biases both at annual and seasonal time scales (Figs. 2a–c), unlike the regional RSRA which shows negligible biases. For instance, when compared to satellite products, GLORYS and ORAS5 underestimate the annual-mean SSS by 1.3–1.5 psu, with relatively larger biases in summer. NCODA overestimates the annual-mean SSS by ~0.7 psu, with larger biases in winter.

We further examined the spatiotemporal changes in RMSDs of the reanalysis products against the different satellite observations (Figs. 3 and 4). The RMSDs exhibit marked variations in both time and space, with RSRA producing the least variations in RMSD. The seasonality in the SSS RMSDs mostly reflect seasonal biases. There is seasonality in the SST and SSH RMSDs as well, peaking in summer and winter months, respectively. The large discrepancies in the volume transports at the BAM Strait (discussed in the “Water exchange with the Indian Ocean and seasonal overturning circulation” section) explains the SSS errors, whereas the SSH errors are more related to the unbalanced transport rates (refer to the “Water exchange with the Indian Ocean and seasonal overturning circulation” section). The large SST RMSDs during summer is due to the challenges of representing the spatiotemporal gradients in the northern parts of the Gulf of Aden by the global ocean models, which are associated with seasonal wind-induced coastal upwelling (Johns et al. 1999; Aiki et al. 2006; Al Saafani 2008; Gittings et al. 2017). In general, assimilating high-resolution SST data helps to constrain the models better, as can be seen from the improved performances (of above 30%) of ORAS5/RSRA from 2006 onward, after switching from assimilating the coarse 100 km HadISST2/25 km Reynolds data to the higher-resolution 5 km OSTIA on March 2006. In contrast, GLORYS always assimilated the coarse Reynolds SST data. Although NCODA directly assimilates along-track level-2 SSTs, the spatial distances between two consecutive observations (100–60 km between 10° and 30°N) are cut down significantly by a data thinning approach, which may explain its larger RMSDs.

To assess the reanalyses in the subsurface, we present in Fig. 5 the depth-wise RMSDs of (Fig. 5a) temperature and (Fig. 5b) salinity against the independent in situ observations. All four reanalyses exhibit larger temperature RMSDs in the thermocline layer (50 m depth) because of the sharp gradients, as expected, especially GLORYS and NCODA (>1°C). The temperature RMSDs of the global reanalyses are larger than those of RSRA practically at all depths, reaching 0.6°C in the thermocline and 0.1°C in the deep layers. Although NCODA achieves the lowest RSMDs in salinity, overall, RSRA follows closely with RMSDs lower than 0.2 psu and within the prescribed observational errors.

Figure 6 plots the latitude–depth differences of the subsurface temperature and salinity between the reanalyses and in situ CTD observations collected during the WHOI/KAUST summer cruise conducted during 15 September–8 October 2011. RSRA is significantly

Fig. 2. Monthly climatology of domain-averaged (a) SSS (psu), (b) SST (°C), and (c) SSH (cm) from level-4 gridded products (OISSS for SSS, OSTIA for SST, and CMEMS-L4 for SSH; black), RSRA (red), ORAS5 (blue), GLORYS (magenta), and NCODA (green). The monthly climatologies are based on the period 2001–19 and for the whole Red Sea basin.
closer to the observations. NCODA shows spurious saline waters in the southern RS, while GLORYS and ORAS5 suggest spurious fresh and cold waters. The differences with the observations are particularly large for ORAS5.

**Dynamics and general circulation.**

**Mesoscale variability.** We first compare the variability of the surface currents and SSH as resulting from the four reanalyses (refer to supplementary Movies 1 and 2). The currents in the eddy-permitting ORAS5 are generally sluggish and the mesoscale eddies are barely identified, whereas the currents in the eddy-resolving reanalyses GLORYS, NCODA, and RSRA are brisk and the circulation is dominated by energetic mesoscale eddies (Sofianos and Johns 2007; Zhan et al. 2014, 2016). The currents are generally dominated by geostrophy and RSRA is clearly the closest to the satellite observations.

Figure 7a displays the eddy kinetic energy (EKE) in the RS basin from the different reanalyses and satellite observations. Since no observations of surface currents are available in the RS, the EKE was computed using geostrophic velocities (refer to appendix C for the formulas).
The identification of eddies was based on Okubo–Weiss (Okubo 1970; Weiss 1991) formula following Chang and Oey (2014) (refer to appendix C for Okubo–Weiss formulas). The satellite-based estimates of EKE exhibit significant variability with biannual peaks, one in winter and another in summer corroborating the findings from the earliest studies (Zhan et al. 2018). The winter peak mainly corresponds to the cyclonic eddies in the north, while the peak in summer corresponds to the dipole eddy system in the central RS (refer to next paragraphs). The biannual peaks are weak in NCODA and ORAS5, which only reproduce the prominent summer peak with a phase delay of 1 month. In addition, the EKE is significantly overestimated (underestimated) in NCODA (ORAS5), whereas RSRA and GLORYS compare well with the satellite observations.

Figures 7b–k compare SSH snapshots from the four reanalyses and satellite-based level-4 product on 16 August 2011 in the central RS (CRS; Figs. 7b–f) and on 6 November 2011 in the
The corresponding satellite altimeter level-2 along-track fields are overlaid on the spatial maps. The CRS hosts a dipole of opposite polarity around the Tokar Gap latitude of 19°N, and an anticyclonic eddy (ACE) centered around 21°N above the dipole (hereafter NACE). The dipole, composed of a cyclonic eddy (CE) north of 19°N and ACE south of 19°N (hereafter SACE) manifests the ocean response to strong cross-basin Tokar wind jet occurring every summer (Zhai and Bower 2013; Zhan et al. 2018). The NACE is a semipermanent summer feature, and its generation was tied to the along-axis winds and topographic variations (e.g., Quadfasel and Baudner 1993; Sofianos and Johns 2007). All the reanalyses reproduce the SACE, but show noticeable differences in the size and intensity of the NACE/CE. These two eddies are not captured by ORAS5 while their strength is largely underestimated/overestimated in NCODA. GLORYS simulates the NACE well, but largely underestimates the features of the CE. In comparison, RSRA captures the size and intensity of the dipole remarkably well, albeit to a slightly underestimated NACE.

Figure 7g displays an anomalous wintertime CE in the NRS (Papadopoulos et al. 2015). Merged altimeter data indicate two CEs in the NRS on 6 November 2011—an intensified and large CE in the far north (CE-1) and another smaller and weaker CE in the southern edge of the NRS (CE-2). The global reanalyses reproduce CE-1 even though ORAS5 and GLORYS significantly underestimates its intensity. CE-2 is not captured by ORAS5 and GLORYS. NCODA captures both CE-1 and CE-2, but with marked differences in terms of size and location. CE-1 in NCODA is smaller and squeezed. In contrast, the intensity and size of these eddies are well captured by RSRA, which seems to capture CE-2 even better than the level-4 observational product.

**Water exchange with the Indian Ocean and seasonal overturning circulation.** The RS exchanges water with the Indian Ocean through the BAM. The BAM mean depth of 180 m and length of 35 km are major limiting factors for coarse-resolution models to properly resolve the water exchanges across this narrow strait (e.g., Johns and Sofianos 2012;
Yao et al. 2014a,b). The in situ observations of volume transports across the BAM Strait were available only between June 1996 and November 1997 (Murray and Johns 1997). Inferences about the volume transports at the strait were mainly based on the high-resolution model outputs validated against these 1.5-yr observations. These studies suggest that the water transport through the BAM reverses seasonally from a two-layer pattern in winter to a three-layer in summer (Murray and Johns 1997; Yao et al. 2014a,b). The two-layer transport in winter consists of the inflow of the relatively fresher Gulf of Aden Surface Water (GASW) and the deep highly saline RSOW. The three-layer exchange in summer is characterized by an outflow of warm and saline water at the surface from the RS (RSSW), an inflow of cool and fresh Gulf of Aden Intermediate Water (GAIW), and a weak deep outflow (RSOW) near the bottom. The water exchange through the BAM is a critical feature of the RS circulation as it characterizes the overturning circulation inside the basin (Yao et al. 2014a,b; Sofianos and Johns 2015). The GASW feeds the upper part of the RS overturning cell and gradually becomes saltier and cooler before sinking in the north, ultimately returning southward as the RS Intermediate Water (RSIW) and RSOW at the intermediate and deep layers, respectively (Yao et al. 2014b). During summer, the upper part of the overturning cell is sustained by the inflow of GAIW in the subsurface layers,
which can be tracked as a distinct water mass up to 24°N (Yao et al. 2014a). The examined reanalyses are analyzed here in terms of their ability to describe the water transport through the BAM, and at reproducing the general features of the overturning circulation inside the basin, represented by the integrated volume transport across the basin.

Figure 8 compares the climatological volume transport through the BAM from the four reanalyses. The transport is computed separately for each of the water masses, namely, the surface water mass (SURW comprising both RSSW and GASW), GAIW, and RSOW, as the depth integration of the vertical profiles of meridional velocity. The profiles correspond to the exchanges over a section near 13°N, and the layer interfaces are defined as the zero crossing depths of the vertical transport profiles. The monthly transport climatology of the

Fig. 7. Relative skills of the reanalysis products at representing the mesoscale eddies. (a) Time series of eddy kinetic energy (EKE; m² s⁻²) in the Red Sea as estimated from the geostrophic currents computed using daily averaged SSH from CMEMS-L4 (black), RSRA (red), ORAS5 (blue), GLORYS (magenta), and NCODA (green). The EKE time series uses 90-day smoothing to better visualize the differences among the reanalyses. (b),(g) The spatial maps of daily averaged SSH (in cm) corresponding to (b) 16 Aug and (g) 6 Nov 2011 from merged altimeter CMEMS-L4. Similar plots are shown for (c),(h) RSRA, (d),(i) ORAS5, (e),(j) GLORYS, and (f),(k) NCODA. Along-track SSH observations of the corresponding day are also overlaid on each map.
RS water masses presented in Figs. 8a–c shows that all reanalyses capture the wintertime two-layer structure and generally agree in the magnitude of the simulated transports. They, however, exhibit significant differences in the simulation of transport rates during the summer three-layer exchange pattern.

Considerable differences appear also in the magnitudes of the simulated water mass transports. The peak volume transport of GASW and RSOW based on observations and models during February, representative of the winter two-layer exchange, was estimated between 0.4 and 0.6 Sv (1 Sv ≡ 10^6 m³ s⁻¹) (Sofianos and Johns 2015; Xie et al. 2019). RSRA provides the best estimates, predicting transports within the observed range. In comparison, ORAS5 peak volume transport of GASW (positive values in Fig. 8a) is more than double the observed. GLORYS also overestimates the peak volume transport of RSOW by at least 0.4 Sv, while NCODA underestimates both GASW and RSOW by about 0.2 Sv. The transport rates are unbalanced in all the global reanalyses, reaching up to 0.3 Sv in ORAS5, and 0.1 Sv each in NCODA and GLORYS. These are the results of dynamical inconsistencies related to the nature of their sequential assimilation schemes, and the large forecasting errors of their coarse models (Hoteit et al. 2018; Moore et al. 2019; Storto et al. 2019). Despite being also generated by a sequential ensemble data assimilation scheme, RSRA transports through the BAM are nearly balanced, as have been already shown in Sanikommu et al. (2019). The used high-resolution MITgcm tuned for the Red Sea efficiently assimilated the incorporated data using a hybrid ensemble, providing much improved forecasts that reduced the size of the assimilation update, the main contributor to the dynamical unbalance.

The discrepancies in the transport of water masses through the BAM during winter are also manifested in the basin overturning circulation. Figure 9 displays the latitude–depth distribution of the along-basin streamfunction from all reanalyses for February (left panel) and August (right panel), representative of the winter and summer conditions, respectively. Although the spatial extent of the SURW propagation is almost similar in all products during winter, its vertical extent varies significantly, with those of ORAS5 and NCODA being deeper and shallower, respectively. Differences among the reanalyses are also pronounced for the northward extent of the subsurface return flow, which is representative of the formation site of RSOW (Figs. 9a–d). The return flow at intermediate depths, characterizing the RSOW water mass transport, initiates at around 24°N and about 150 m depth in GLORYS, while it is found deeper (220 m) and extends further north (25°N) in ORAS5 and RSRA, in line with previous studies (Yao et al. 2014b; Sofianos and Johns 2015). In contrast, the RSOW in NCODA during winter is initiated at deeper layers (beyond 250 m) at 20°N.

Discrepancies in the volume transport through the BAM and the seasonal overturning circulation between the reanalyses become even more pronounced during summer. RSOW flows at its minimum rate between 0.05 and 0.1 Sv, while both GAIW and RSSW flow at their

**Fig. 8.** Volume transport through the BAM for (a) SURW, (b) GAIW, and (c) RSOW. The volume transports are estimated from the monthly climatologies of RSRA (red), ORAS5 (blue), GLORYS (magenta), and NCODA (green), over the period 2000–15. Units of volume transport are in Sv (10^6 m³ s⁻¹).
peak rates of 0.2–0.3 Sv in August (Sofianos and Johns 2015; Xie et al. 2019). After its intrusion, the GAIW flows at around 50 m depth and reaches up to 24°N (Yao et al. 2014a). All global reanalyses fail to properly reproduce the three-layer transport during summer. ORAS5 markedly overestimates the outflowing RSSW (negative values in Fig. 8a) and the inflowing GAIW by 3 times the observed rates. It further misses the RSOW deep outflow. As a result, thicker layers of RSSW are simulated flowing southward, initiating approximately at 24°N, while the intrusion of GAIW reaches the deeper layers between 80 and 120 m, and its extent is limited to 18°N (Fig. 9f). NCODA suggests the largest transport underestimations for all the three water masses. Moreover, its intruding GAIW partially upwells at 15°N, inhibiting the southward propagation of the RSSW at around 16°N, which weakens its southward flow. GLORYS is able to capture the three-layer transport pattern and the GAIW northward propagation, reaching up to 23°N, which is close to its reported meridional extent (Yao et al. 2014a). However, it overestimates the transport rates for both GAIW and RSOW by at least 50%. In contrast, RSRA captures well the three-layer summer transport but its RSSW is transported through a relatively thinner layer and is slightly weaker.

The climatological biases in the water exchanges through the BAM can cause important deficiencies in the simulation of the salinity field inside the RS. For instance, the absence of GAIW in NCODA manifested as a significant positive salinity bias in the southern RS, whereas the overestimation of the GASW and GAIW led to spurious fresh waters in GLORYS and ORAS5 (Fig. 6). The coarse resolution of ORAS5, which cannot accommodate the
two northern gulfs contributing to the renewal of the RS deep and intermediate layers (Papadopoulos et al. 2015; Yao and Hoteit 2018), has further negatively affected the quality of its salinity field.

**Interannual Variability and Trends.** Global ocean reanalyses do not generally well capture the interannual variability and trends of regional basins (Lee et al. 2009; Balmaseda et al. 2015; Storto et al. 2019). Here, we examine the linear trends (Table 3) and the interannual variability (Table 4) of detrended monthly anomalies (with respect to monthly climatology) for SSS, SST, and SSH averaged over the RS basin (Fig. 10). The reanalyses show considerable discrepancies in terms of identifying anomalous years, especially for SSS and SST, particularly GLORYS. For instance, GLORYS identifies the winter of 2001/02 and year 2019 as the years of high and lowest saline waters, respectively. In contrast, the other reanalyses, including RSRA, identify them as normal years. Unlike GLORYS, these three reanalyses do not further suggest significant SSS variability at interannual scales, in line with OISSS.

All four reanalyses suggest significant interannual SST variability (Fig. 10b), with marked differences. GLORYS misinterprets the 2007/08 winter and 2015 summer seasons as anomalously cold. It further overestimates the SST interannual variability by 20% (Table 4). RSRA and ORAS5 show good agreement with the satellite-based SST at representing both the interannual variability and the anomalous years.

Comparing the sea level anomalies (Fig. 10c), RSRA is clearly the closest to the satellite-based product. The anomalously low sea levels during 2000/01, which were linked to incessant La Niña conditions during the period 1998–2001 (Abdulla and Al-Subhi 2021), are misrepresented in NCODA and ORAS5. Despite this, the interannual variability of SSH is overall reasonably well described by all four reanalyses.

In terms of long-term changes, the RS was suggested to experience significant increasing trends in recent decades in SST (Krokos et al. 2019; Chaidez et al. 2017) and sea level (Abdulla and Al-Subhi 2021). The long-term trends in SST during the satellite era were reported to be a combined effect of global warming and a positive phase of natural SST oscillations (Krokos et al. 2019). Similarly, global warming and remote forces contributed to

<table>
<thead>
<tr>
<th>Satellite</th>
<th>RSRA</th>
<th>ORAS5</th>
<th>GLORYS</th>
<th>NCODA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sea surface temperature (°C decade⁻¹)</td>
<td>0.13</td>
<td>0.13</td>
<td>0.09</td>
<td>0.45</td>
</tr>
<tr>
<td>2007–19</td>
<td>0.09</td>
<td>0.45</td>
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<td>0.14</td>
<td>0.21</td>
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<tr>
<td>Sea surface height (mm year⁻¹)</td>
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<td>5.9</td>
<td>4.6</td>
<td>3.8</td>
</tr>
<tr>
<td>2000–19</td>
<td>6.2</td>
<td>6.1</td>
<td>4.0</td>
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<tr>
<td>2000–15</td>
<td>6.2</td>
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**Table 4.** Interannual variability of SSS (psu), SST (°C), and SSH (m) from interpolated level-4 and reanalysis products. The interannual variability is represented by the standard deviation of the detrended monthly anomalies averaged over the RS basin. The analyzed time series span the period 2000–19 for all the datasets except for NCODA, which is only available between 2000 and 2015.
the sea level rise in the RS during the satellite era (Abdulla and Al-Subhi 2021). Post-2000, the sea level in the RS has risen at a faster rate, recovering from the La Niña–induced dip in sea level between 1998 and 2001. Table 3 outlines the linear trends in SST and SSH, between 2007–19 and 2000–19, respectively. The satellite-based SST and SSH products indicate positive trends of magnitude 0.13°C decade\(^{-1}\) and 6 mm yr\(^{-1}\), respectively, in line with those reported post-2000 by Abdulla and Al-Subhi (2021). The reanalyses also show increasing trends in SST and SSH, but exhibit significant differences in terms of the rising rate. ORAS5 underestimates SST and SSH trends by 30% and 23%, respectively. GLORYS overestimates the SST trend by 250% and underestimates that of SSH by 35%. NCODA underestimates the sea level rise by 70% and reports a 2.5 times higher rate of SST trend (trends until 2015 are considered here). RSRA trend rates are clearly markedly closer to the satellite-based estimates.

Fig. 10. Time series of (a) SSS, (b) SST, and (c) SSH detrended monthly anomalies averaged over the entire RS for the interpolated observational products (black), RSRA (red), ORAS5 (blue), GLORYS (magenta), and NCODA (green). The observational products for SSS, SST, and SSH are OISSS, OSTIA, and CMEMS-L4, respectively. The monthly anomalies are computed by removing the corresponding monthly mean from the monthly climatology over the period 2000–19. For OSTIA and NCODA, the monthly climatologies are computed based on 2007–19 and 2000–15, respectively. The monthly anomalies were detrended.
Discussion

Global ocean reanalyses are not expected to well describe the local features of regional ocean basins as they are configured at coarse resolutions and tuned for the global circulations. Yet these are widely used to study and describe regional oceans and coastal areas, emphasizing the need for generating dedicated regional reanalyses. A 20-yr (2000–19) high-resolution regional reanalysis was generated for the RS (RSRA) using an ensemble data assimilation system built on a 4 km regional configuration of the MITgcm and DART. RSRA was evaluated and compared against three widely used global ocean reanalyses across a range of spatio-temporal scales.

The mesoscale features in the Red Sea, dominated by eddies, are as expected best represented by RSRA. These cannot be well reproduced by the coarse-resolution global models. Comparisons against available in situ and satellite observations suggest that RSRA agrees best with the observations practically for all ocean variables, while its surface salinity is even found closer to the in situ measurements than the satellite product. RSRA further well captures the marked seasonal reversal of the water exchange with the Indian Ocean (from two layers in winter to three layers in summer) and the associated overturning cells inside the RS basin. None of the global reanalyses were able to properly reproduce this important seasonal feature, especially the summer three-layer shift, critical for the functioning of the Red Sea and its ecosystem (e.g., Raitos et al. 2011; Dreano et al. 2016). The interannual variability and trends are also reproduced remarkably well by RSRA, while the global reanalyses show marked discrepancies with the observations, misguiding the identification of some anomalous years.

The improved description of the Red Sea general circulation that results from RSRA is significant and will translate into more robust datasets for various scientific and societal applications. For instance, improved representation of the upper ocean temperatures would provide better assessments of the evolution and trends of marine heat waves. Similarly, better representation of the mesoscale circulation would lead to improved predictions of oil spill trajectories, which are of great concern for the protection of the unique Red Sea coral reef system (Vankayalapati et al. 2022). Likewise, the lower skill of the global reanalysis products in simulating the exchanges through the straits, especially the transport biases through the BAM, would significantly affect the assessment of their effects on the physical–biological functioning of the Red Sea, such as the role of the nutrient rich water entering the basin from the Gulf of Aden, and importantly its fate (Churchill et al. 2014; Dreano et al. 2016). In particular, the overestimation of RSOW volume transports through the BAM in GLORYS may call for a careful examination of the conclusions on the advective pathways and transit times of RSOW into the Arabian Sea (Menezes 2021). The list goes on. Developing global reanalyses at high resolutions may not be sufficient to cater to such important needs, and specifically tuned regional models and assimilation schemes are required instead. The higher quality of RSRA can be primarily attributed to its regionally tuned model, higher-resolution grid, its high-resolution driving ensemble atmospheric forcing, and a better description of the errors and their multivariate correlations by the assimilation scheme achieved through flow-dependent ensembles accounting for uncertainties in the model input fields.

Although the Red Sea hosts some unique features in the global ocean, it is also similar to other regional/marginal seas in terms of geographical, dynamical, and computational aspects. For instance, semienclosed seas and gulfs such as the Mediterranean Sea, the Arabian Gulf, and the Gulf of Mexico are connected to the global ocean through narrow straits, which cannot be well represented with coarse-resolution grids. Moreover, the importance of accurately resolving the mesoscale circulation evidenced in this study is of general importance, as mesoscale eddies are also prominent features in the Mediterranean Sea, the Bay of Bengal, the Arabian Gulf, the South China Sea, the Gulf of Mexico, etc. (Wang et al. 2003; Kämpf and...
Sadrinasab 2006; Chelton et al. 2011; Mkhinini et al. 2014; Rudnick et al. 2015; Dandapat and Chakraborty 2016). Hence, the results of this study are also viable for other regional seas. This is the first work to implement an ensemble Kalman filter assimilating observations using flow-dependent background error statistics to generate a high-resolution regional reanalysis. Generating high-resolution regional reanalysis for such seas would be a major step toward better understanding the circulation in these basins and managing their resources.

The better description of the history of the RS by RSRA will allow better studying the basin’s physical and biological processes, and can also be used to support various governmental and industrial applications and developments. The quality of RSRA and its flow-dependent ensembles will further provide the basis for future studies and extensions focusing for instance on quantifying the uncertainty of its fields, and producing probabilistic maps for different forward and backward transport applications (El Mohtar et al. 2018; Hammoud et al. 2021).

We will work in the future on enhancing RSRA for better description of the RS features. This includes increasing the horizontal and vertical resolutions and incorporating tides in the background model, which should improve the representation of the submesoscales and the mixed layer variations, especially near the coasts. Increasing the ensemble size will be possible in the near future and is expected to further improve the background uncertainties and therefore the ocean state estimates. A better representation of the uncertainties of the atmosphere, currently imposed as those of ECMWF, through dynamical downscaling should also better describe the ocean beneath. Incorporating other sources of uncertainties, as, for instance, in the model bathymetry, ocean boundary conditions, and various parameterization schemes, is also a direction for future improvements.

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Data availability statement. Data analyzed in this study were openly available at locations cited in the reference section, except for the regional Red Sea Reanalysis (RSRA). The RSRA data used for the present study are freely available at https://doi.org/10.6084/m9.figshare.23597115.

Appendix A: Atmospheric forcing
High-resolution atmospheric forcing is critical for driving eddy-resolving ocean models, particularly for basins surrounded by complex topography (e.g., Myksvoll et al. 2012; Huot et al. 2021), dominated by mesoscale eddies (e.g., Schaeffer et al. 2011), or subject to coastal upwelling (Albert et al. 2010), such as the Red Sea.

A 5-km-resolution atmospheric reanalysis was generated for 40 years (1980–2019) for the Arabian Peninsula (AP), comprising the Red Sea (RS), by dynamically downscaling the European Centre for Medium-Range Weather Forecast (ECMWF) global reanalysis, and assimilating various satellite (Quick Scatterometer, Windsat, Advanced Scatterometer, and geostationary satellites), and in situ (synoptic stations, METAR, ship, rawinsonde, and pilot balloon) observations into a Weather Research and Forecast (WRF) Model (Viswanadhapalli et al. 2017; Hoteit et al. 2021). The AP reanalysis was extensively validated and used to study the regional meteorological and ocean conditions (e.g., Langodan et al. 2017a,b; Ellis et al. 2019; Dasari et al. 2019, 2020, 2021; Viswanadhapalli et al. 2020), and to force regional ocean models (e.g., Langodan et al. 2014, 2016a,b, 2017b; Zhan et al. 2019, 2022; Krokos et al. 2022). Simulations of the RS general circulation were indeed performed using the MITgcm (Marshall et al. 1997) forced by the AP reanalysis and ECMWF. The analysis of the outputs
of these runs (not shown here) suggests that the simulations driven by the high-resolution regional reanalysis better reproduce the main features of the RS general circulation than those driven by ECMWF atmospheric fields, particularly the water exchange with through the BAM and the representation of the mesoscale eddy variability.

To account for uncertainties in the atmospheric forcing we forced the flow-dependent ensemble of the hybrid Red Sea data assimilation system with an ensemble of atmospheric fields. A 6-hourly, 50-member, 50-km-resolution ensemble of atmospheric fields are available from ECMWF archives (Bougeault et al. 2010; Buizza 2014; Swinbank et al. 2016). This ensemble was interpolated to 3-hourly resolution. We then generated a 3-hourly, 5-km-resolution, 50-member atmospheric ensemble of surface fluxes for the Red Sea by adding the interpolated ECMWF ensemble anomalies (without the ensemble mean) to the high-resolution AP reanalysis, and used them to force the flow-dependent ensemble to generate RSRA.

Appendix B: Flow-dependent observational errors

We implemented flow-dependent observational error variances for all assimilated data except for sea level anomaly (SLA), which used a static and spatially uniform error variance of (4 cm)². This value was selected after trial and error experiments using different values of SLA error variance (Sanikommu et al. 2020).

Sea surface temperature. We assimilated two level-4 SST products. The first product up to March 2006 is the 25-km-resolution Reynolds SST (Reynolds et al. 2007), provided by the National Oceanic and Atmospheric Administration (NOAA) by blending Advanced Very High Resolution Radiometer (AVHRR) infrared satellite and in situ SST observations. The second, available from April 2006, is the high-resolution daily averaged level-4 Operational Sea Surface Temperature and Sea Ice Analysis (OSTIA; Stark et al. 2007; Donlon et al. 2012), prepared by the Met Office (https://podaac.jpl.nasa.gov). OSTIA is generated on a 0.054° (~5 km) grid by combining SST data from various satellites and in situ observations. Both products were generated using an optimal interpolation method to blend the observations. They further provide information about the estimates of the interpolation errors of their level-4 fields.

The assimilation of SST accounts for the various sources of observational errors, including instrument, interpolation, and representational errors (RE). Flow-dependent REs are estimated from the OSTIA data following the method of Sanikommu et al. (2019). REs were deemed not necessary for Reynolds SST, as its 25 km resolution is already close to the resolving scales of the 4 km Red Sea model (Oke and Sakov 2008; Sanikommu et al. 2019). This resulted in larger observational error ranges for OSTIA (0.6°–2°C)² in comparison to those of Reynolds (0.6°–1.1°C)².

Temperature and salinity profiles. The flow-dependent REs for temperature and salinity are estimated at every observation location (x) and analysis time (t) using the following expression, as suggested by Behringer et al. (1998):

\[
SF = \left| \frac{dT(x,t)}{dz} - \frac{dT(x,t)}{dz_{\text{min}}} \right| \times \frac{dT(x,t)}{dz_{\text{max}}},
\]

where SF is scaling factor, \( dT(x,t)/dz \) is the smoothened (in the vertical direction) tracer gradient of the concurrent observed tracer profile, and \( dT(x,t)/dz_{\text{min}} \) and \( dT(x,t)/dz_{\text{max}} \) are...
respectively the minimum and maximum vertical gradients in the observed tracer gradient profile. Following Behringer et al. (1998), the RE so estimated is added to a uniform standard error (SE) to obtain the total observational error for the corresponding tracer profile. Here, the SE encompasses instrumentation error and sets a lower limit for the total observational error. In the above expression, the term within the open brackets varies between 0 and 1; thus, the larger the vertical gradient, the closer the term to unity. The factors SF and SE enforce observational errors between SE and (SE + SF).

We tuned the constants SE and SF such that the temperature error variances vary between \((0.3^\circ C)^2\) at the surface, and reach up to \((0.7^\circ C)^2\) in the thermocline layers and \((0.1^\circ C)^2\) below 500 m. Similarly, the salinity error variances vary between \((0.05 \text{ psu})^2\) and \((0.4 \text{ psu})^2\) with lower values at depth and larger values at the halocline layers. In comparison to the static temperature and salinity errors implemented in Toye et al. (2020), the flow-dependent errors implemented here have led to marked improvements in the Red Sea state estimates, particularly for the subsurface temperature and salinity (results not shown), in agreement with the results of Sanikommu et al. (2019).

**Appendix C: Computation of eddy kinetic energy**

In the present study, we analyzed eddy kinetic energy using zonal \((u)\) and meridional \((v)\) components of geostrophic currents. We compute the EKE by first identifying eddies using Okubo–Weiss parameter (Okubo 1970; Weiss 1991), which is defined as

\[
\omega = \frac{\partial v}{\partial x} - \frac{\partial u}{\partial y} = S_n + S_s - \omega^2,
\]

where \(S_n = \frac{\partial u}{\partial x} - \frac{\partial v}{\partial y}\) and \(S_s = \frac{\partial v}{\partial x} + \frac{\partial u}{\partial y}\) are the normal and shear components of strain. \(\omega = \frac{\partial v}{\partial x} - \frac{\partial u}{\partial y}\) is the relative vorticity. The formula computes the relative dominance of strain and vorticity. Eddies are connected regions of vorticity, in which vorticity is the leading component than the two strain terms.

We define eddy as a region where the values of \(W\) is smaller than a threshold \(W_0\). Following Chang and Oey (2014), we chose \(W_0 = -0.2 \sigma_\omega\) and \(\sigma_\omega\) is the spatial standard deviation of \(W\).

We then compute kinetic energy of the above identified eddy regions using the formulas

\[
\text{EKE} = \frac{1}{M} \sum_{i=1}^{M} \int \{[(0.5(u_i^2 + v_i^2))] / A_i\} \, dx \, dy \quad \text{in m}^2 \text{s}^{-2}
\]

where \(A\) is the area of an eddy, and \(M\) is the index of identified eddies in the Red Sea.

**Appendix D: Abbreviations**

- **NEMO** Nucleus for European Modelling of the Ocean
- **SEEK** Singular evolutive extended Kalman filter
- **FGAT** First guess at appropriate time
- **IAU** Incremental analysis update
- **NOGAPS** Navy Operational Global Atmospheric Prediction System
- **EN4** The name EN4 refers to version 4 of the quality controlled temperature and salinity profiles collected under ENACT/ENSEMBLES projects; Enhanced ocean data Assimilation and Climate Prediction (ENACT) and ENSEMBLES are European commission programs
- **CORAV4.1** Coriolis Ocean Datasets for Reanalysis, version 4.1
- **USGODAE** U.S. Global Ocean Data Assimilation Experiment
- **MDT** Mean dynamic topography