



HAL
open science

Bay of Bengal Sea surface salinity variability using a decade of improved SMOS re-processing

Valiya Parambil Akhil, Jérôme Vialard, Matthieu Lengaigne, Madhavan Girijakumari Keerthi, Jacqueline Boutin, Jean-Luc Vergely, Fabrice Papa

► **To cite this version:**

Valiya Parambil Akhil, Jérôme Vialard, Matthieu Lengaigne, Madhavan Girijakumari Keerthi, Jacqueline Boutin, et al.. Bay of Bengal Sea surface salinity variability using a decade of improved SMOS re-processing. *Remote Sensing of Environment*, 2020, 248, pp.111964. 10.1016/j.rse.2020.111964 . hal-03017400

HAL Id: hal-03017400

<https://hal.science/hal-03017400>

Submitted on 21 Nov 2020

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Highlights

- The new debiased CATDS SMOS SSS product resolves major issues in the Bay of Bengal
- New SMOS has a comparable quality with SMAP and Aquarius, but over a full decade
- Confirms the post-monsoon southward transport of low saline water by the EICC
- Confirms that this transport is interannually modulated by the Indian Ocean Dipole

1

2

Bay of Bengal Sea Surface Salinity variability using a decade of

3

improved SMOS re-processing

4

5

6

V.P. Akhil¹, J. Vialard², M. Lengaigne^{2, 3}, M. G. Keerthi², J. Boutin², J.L. Vergely⁴,

7

and F. Papa⁵

8

9

10

¹ CSIR-NIO, Goa-India

11

² LOCEAN-IPSL/Sorbonne Universités, CNRS/ IRD/ MNHN, Paris-France

12

³ Indo-French Cell for Water Sciences, IISc/NIO/IITM/IRD Joint International Laboratory, India

13

⁴ ACRI-st, Guyancourt, France

14

⁵ LEGOS, IRD/CNES/CNRS/UPS, Toulouse-France

15

16

Submitted to *Remote Sensing of Environment*

17

18

19

Corresponding author: V.P. Akhil (Email: akhil@nio.org)

20

21 **Abstract**

22 Monsoon rain and rivers bring a large freshwater input to the Northern Bay of Bengal
23 (BoB), yielding low Sea Surface Salinity (SSS) after the monsoon. The resulting sharp
24 upper-ocean salinity stratification is thought to influence tropical cyclones intensity and
25 biological productivity by inhibiting vertical mixing. Despite recent progresses, the
26 density of *in situ* data is far from sufficient to monitor the BoB SSS variability, even at
27 the seasonal timescale. The advent of satellite remotely-sensed SSS (SMOS, Aquarius,
28 SMAP) offers a unique opportunity to provide synoptic maps of the BoB SSS every ~8
29 days. Previous SMOS SSS retrievals did not perform well in the BoB. Here, we show
30 that improved systematic error corrections and quality control procedures yield a much
31 better performance of the new “debiased v4” CATDS level-3 SSS from SMOS (~0.8
32 correlation, 0.04 bias and 0.64 root-mean-square difference to more than 28000
33 collocated *in situ* data points over 2010-2019). The SMOS product now performs
34 equivalently to Aquarius, and is slightly inferior to SMAP over the BoB. In particular,
35 SMAP and SMOS are able to capture salinity variations close to the east coast of India
36 ($r > 0.8$ within 75-150 km of the coast). They thus capture the seasonal freshening there,
37 associated with equatorward advection of the Northern BoB low-salinity water by the
38 East Indian Coastal Current (EICC) after the summer monsoon. The 10-year long SMOS
39 record further allows to describe the BoB interannual SSS variability, which is strongest
40 in boreal fall in relation with the Indian Ocean Dipole (IOD). Positive IOD events
41 induce a weakening of the southward export of freshwater by the EICC, and hence
42 negative SSS anomalies in the Northern BoB and positive ones along the East Indian
43 coast. This confirms results from earlier studies based on modelling, sparse *in situ* data,
44 or shorter satellite records, but this time from a 10-year long SSS record. Overall, our
45 study indicates that the new SMOS retrieval can be confidently used to monitor the BoB

46 SSS and to study its mechanisms. We end by a brief description of the BoB SSS
47 anomalies associated with the extreme 2019 IOD event and highlight the very good
48 performance over the BoB of a new multi-satellite product developed by the European
49 Space Agency merging SMOS, Aquarius and SMAP data.

50 **Highlights**

- 51 • The new debiased CATDS SMOS SSS product resolves major issues in the Bay of
52 Bengal
- 53 • New SMOS has a comparable quality with SMAP and Aquarius, but over a full
54 decade
- 55 • Confirms the post-monsoon southward transport of low saline water by the EICC
- 56 • Confirms that this transport is interannually modulated by the Indian Ocean Dipole

57

58 **Keywords:** Bay of Bengal, Sea Surface Salinity, SMOS, SMAP, AQUARIUS, East
59 Indian Coastal Current, Indian Ocean Dipole

60

61 **1. Introduction**

62 The Bay of Bengal (hereafter, BoB) is one of the rainiest areas of the Asian
63 summer monsoon region. As a result, this relatively small basin receives large
64 freshwater inputs during and shortly after the summer monsoon, dominantly as rain in
65 the northeastern basin, but also from two large rivers: the Ganga-Brahmaputra in the
66 north and the Irrawaddy in the northeast (e.g. Akhil et al., 2014; Chaitanya et al., 2014;
67 Papa et al., 2010; see Figure 1 for the location of these rivers). This basin is hence
68 characterized by low surface salinity during and after the summer monsoon (e.g. Rao
69 and Sivakumar, 2003), leading to a sharp upper-ocean salinity stratification (e.g. Shetye,
70 1993; Thadathil et al., 2016).

71 The stabilizing effect of this near-surface freshening is thought to have important
72 climatic consequences by inhibiting vertical mixing. The haline stratification indeed
73 reduces the vertical mixing of heat during and after the summer monsoon (e.g. de Boyer
74 Montegut et al., 2007; Thadathil et al., 2016; Shenoi et al., 2002; Krishnamohan et al.,
75 2018), although the overall influence on climatological sea surface temperature (and
76 thus rainfall) may be weak due to compensating processes (Krishnamohan et al., 2018).
77 The salinity stratification also inhibits vertical mixing below tropical cyclones (e.g.
78 Neetu et al., 2012; Sengupta et al., 2008), thereby reducing the air-sea coupling negative
79 feedback, and strengthening post-monsoon cyclones (Neetu et al., 2019). It is also
80 believed to inhibit vertical mixing of nutrients and to reduce marine biological
81 productivity in the BoB (Prasanna Kumar et al., 2002). For all those reasons, it is
82 important to monitor Sea Surface Salinity (hereafter, SSS) variations in this basin.

83 The strong seasonality of the freshwater forcing yields strong SSS seasonal
84 variations in the BoB. The northeastern BoB indeed experiences an intense freshening

85 right after the monsoon, attributable to the freshwater forcing from rivers and rain (e.g.
86 Rao and Sivakumar, 2003; Akhil et al., 2014). This fresh pool expands southward in the
87 following months as a narrow fresh tongue in a ~100km wide strip along the East Indian
88 coast, a feature nicknamed “river in the sea” by Chaitanya et al. (2014). This river in the
89 sea results from the southward export of the northeastern BoB freshening by the East
90 Indian Coastal Current (hereafter, EICC), a narrow western boundary current that flows
91 southward in boreal fall, before vertical mixing restores higher salinities during winter
92 (Chaitanya et al., 2014; Akhil et al., 2014). The Indian Ocean Dipole (hereafter, IOD;
93 Saji et al., 1999), an Indian Ocean interannual climate mode, modulates the “river in the
94 sea” southward expansion, through its remote impact on the EICC (Akhil et al., 2016a;
95 Fournier et al., 2017; Sherin et al., 2018). At smaller scales, oceanic eddies also induce
96 meandering of the salinity front, exporting freshwater offshore (Benshila et al., 2014;
97 Hareesh Kumar et al., 2013; Sengupta et al., 2016; Fournier et al., 2017).

98 The sparse *in situ* SSS data has for long prevented a detailed description of
99 basin-scale BoB SSS variability, especially at the relatively fine spatial scales associated
100 with the “river in the sea”. Salinity climatologies built from historical *in situ* data
101 compilation (e.g. Chatterjee et al., 2012; Antonov et al., 2010) provided a rough
102 description of the BoB SSS seasonal cycle, but their limited data coverage resulted in an
103 excessive smoothing of the SSS structure and particularly of coastally confined river in
104 the sea (Chaitanya et al., 2014). While punctual near-shore cruises provided snapshots of
105 this coastal freshening (Shetye et al., 1996) as well as its meandering induced by eddies
106 (Hareesh Kumar et al., 2013), *in situ* observations are still not dense enough to allow a
107 systematic and detailed description of the BoB SSS spatio-temporal variability despite
108 recent improvements due to the Argo program. As an illustration, Figure 1a,b shows that
109 available *in situ* observations are not able to capture the basin-scale seasonal mean SSS

110 pattern associated with the 2015 positive IOD and the 2016 negative IOD, with a dearth
111 of *in situ* data near the coastline where SSS signals are the strongest. The surface salinity
112 measurements from recent satellite missions may help to improve this description but
113 satellite monitoring of BoB SSS is complex, because of strong “Radio-Frequency
114 Interferences” (RFI) in Asia (Oliva et al., 2016), and pollution of the signal over sea by
115 nearby land signals (Anterrieu et al., 2015).

116 Three recent spaceborne missions may help improving the BoB SSS description.
117 Measurements from the Soil Moisture and Ocean Salinity (SMOS) mission of the
118 European Space Agency (ESA) launched in 2009 have a mean resolution close to 50km,
119 theoretically sufficient to monitor small-scale structures such as the narrow “river in the
120 sea”. But unfortunately, because of the complex antennas geometry, the land
121 contamination and radio frequency interference (RFI) extends up to ~1000km away
122 from coast (Reul et al., 2013, Oliva et al 2016). The large antenna lobes make the land
123 contamination very dependent on the orientation of the satellite track relative to the coast
124 (Boutin et al., 2018). Until recently, this resulted in virtually useless SSS retrievals in the
125 BoB (Boutin et al., 2013; Subrahmanyam et al., 2013; Akhil et al., 2016b). The land
126 contamination mitigation is conceptually simpler for the two other spaceborne missions
127 of the National Aeronautics and Space Administration (NASA), namely the
128 Aquarius/Sac-D mission launched in 2011 and the Soil Moisture Active Passive (SMAP)
129 mission launched in 2015 (Meissner et al., 2018; Fore et al., 2017). Given the resolution
130 of its main antenna lobes, Aquarius however only provides SSS measurements at an
131 effective resolution of ~150km, which can only resolve the BoB large-scale SSS patterns
132 but not the “river in the sea” (Akhil et al., 2016b). In addition, the Aquarius mission
133 ended in 2015 due to an unrecoverable hardware failure. In contrast, SMAP provides
134 SSS retrieval at a spatial resolution similar to that of SMOS, and suffers from lighter

135 land contamination issues compared to SMOS (Reul et al., 2013). As a result, SMAP
136 provides unprecedented views of small-scale BoB SSS features, including the influence
137 of mesoscale eddies and of the IOD on the river in the sea (Fournier et al., 2017). As
138 already demonstrated in Fournier et al. (2017), Figure 1c,d indeed illustrates that the
139 river in the sea extends ~800 km further south in fall 2016 (negative IOD) than in fall
140 2015 (positive IOD), hence providing the first observational confirmations of previous
141 modelling results (Akhil et al., 2016a).

142 Monitoring the full spectrum of SSS variations in the BoB however requires
143 longer time series than those currently provided by SMAP. A recent reprocessing of
144 SMOS data with an improved correction of systematic errors and refined quality control
145 procedures (Boutin et al., 2018) demonstrated that SMOS data could provide a data
146 quality close to that of SMAP. This recent dataset may allow monitoring the BoB spatio-
147 temporal SSS variations over a longer period (~10 years) than SMAP (~5 years). In the
148 current paper, we analyse an updated version of this dataset to investigate whether the
149 most recent SMOS reprocessing can provide accurate SSS retrievals in BoB, especially
150 near the coast. SSS patterns derived from this new product in fall 2015 and 2016 are
151 indeed very similar to those depicted by SMAP (Figure 1e-f), suggesting that it may be
152 useful to complement SMAP data before 2015. Section 2 describes our methodology and
153 datasets. Section 3 assesses how the Boutin et al. (2018) reprocessing improves the
154 SMOS SSS retrieval in the BoB, based on a comparison to available *in situ* observations,
155 to previous SMOS retrieval and to Aquarius and SMAP retrievals. Section 4 takes
156 advantage of the 10-year long (2010 to 2019) SMOS record to describe BoB SSS
157 seasonal cycle and interannual variability. Section 5 provides a summary and discussion.
158 We also briefly discuss the very promising performance over the BoB of a new merged
159 SMOS-Aquarius-SMAP data product developed by the European Space Agency (ESA).

160

161 **2. Dataset and methods**

162 **2.1. SSS datasets**

163 We analyse SSS datasets derived from different satellites (SMOS, Aquarius and
164 SMAP). The SMOS-old and Aquarius datasets are described in more details in Akhil et
165 al. (2016b), and the SMAP dataset in Fournier et al. (2017). Their most salient
166 characteristics are summarized below.

167 The SMAP platform was launched on 31 January 2015 and began operating from
168 April 2015. We use the version-4.3 SMAP SSS, gridded Level-3 dataset, distributed by
169 the “Jet Propulsion Laboratory (JPL)”, at 8-days temporal and 0.25° spatial resolution.
170 This product is available from the 6th April 2015 to near real time (Yueh et al., 2013,
171 2014) and is analysed up to 30th December 2019 in the present paper. For Aquarius
172 (Lagerloef et al., 2008), we analyse the Version-5, Level 3 gridded, SSS dataset,
173 released by the NASA “Physical Oceanography Distributed Active Archive Center
174 (PODAAC)”, which provides 7 day running-means at 1° resolution, between August
175 2011 and June 2015. The approximate effective resolution is $\sim 60\text{km}$ for SMAP and
176 150km for Aquarius. A description of the products version, data repository, temporal
177 and spatial resolution and analysed period is provided in Table 1.

178 As mentioned in the introduction, we also analyse two versions of the SMOS
179 data. The first one (“SMOS-old” in the following) is the dataset described in Akhil et al.
180 (2016b); i.e. the version-2, Level-3 gridded SMOS SSS research product, produced by
181 the “CATDS/Ifremer”, at a horizontal resolution of 0.25° for 10-day running means. The
182 second dataset (“SMOS-new” in the following) is the Level-3 gridded SMOS SSS

183 ‘debiased’ version-4 (Boutin et al., 2018) generated by the “LOCEAN/ACRI-ST
184 Expertise Center”, with resolution of 0.25° for 9-day running means, from January 2010
185 to September 2019. The effective resolution of these two datasets is approximately
186 70km. SMOS-old SSS were de-biased using a crude method which did not take the
187 geometry of the coast into account and excluded pixels that were too far away from the
188 *in situ* climatology in 5°x5° pixels. SMOS-new uses an improved systematic error
189 correction near land, and a less rigorous quality control of the radiometric measurements
190 in regions where the SSS variability is large, as in Boutin et al. (2018). One of the main
191 changes between the ‘debiased’ version-4 we use here and ‘debiased’ version-2 in
192 Boutin et al. (2018) is an improved adjustment of the absolute SSS close to coast, by
193 adjusting the upper quantile of the SMOS SSS to the ISAS *in situ* climatology (Gaillard
194 et al., 2016) instead of the median (equation 4 of Boutin et al., 2018). This significantly
195 improves the comparison of SMOS ‘debiased’ v4 to SMAP SSS, relative to the
196 ‘debiased’ v2 (not shown).

197

198 **2.2. *In situ* salinity data**

199 The *in situ* dataset used to quantitatively validate these satellite products gathers
200 all the BoB SSS measurements in the “World Ocean Database” (hereafter WOD; Boyer
201 et al., 2018; Garcia et al., 2018) over the 2010 to 2019 period. The main contributors to
202 this dataset are Argo profilers (“Array for Real-Time Geostrophic Oceanography”,
203 Roemmich et al., 2009). This dataset also includes XCTD (“eXpendable Conductivity-
204 Temperature-Depth”) profiles, moored buoys data, ocean drifters and glider data. As
205 WOD gathers different data sources, the depth at which these measurements are
206 retrieved varies from 1 to 5m. As discussed in Chaitanya et al. (2015) and Akhil et al.

207 (2016b), the error arising from these diverse sampling depths is negligible relative to
208 horizontal SSS variations within retrieved data grid cells in this region. This dataset
209 includes more than 28000 valid measurements but its coverage is rather heterogeneous
210 as indicated in Figure 2a, with a dense sampling in the central BoB but sparse data close
211 to the coasts and in the Andaman Sea. These *in situ* data are binned into a $1^\circ \times 1^\circ$
212 monthly gridded dataset by taking the median of individual measurements in every bin.
213 A similar gridding is performed for the various satellite datasets. We further define four
214 BoB sub-regions that are outlined on Figure 2b. The NBoB (“Northern BoB”, 86°E to
215 94°E and 16°N to 23°N) exhibits the largest SSS variations. The WBoB (“western
216 BoB”, 80°E to 84°E and 6°N to 16°N) encompasses the “river in the sea” during fall.
217 The ANDA (“Andaman Sea”, 94°E to 99°E and 6°N to 18°N) also host a prominent
218 variability. The CBoB (“Central BoB”, 84°E to 94°E and 6°N to 16°N) is the region of
219 weakest variability.

220 We also use the 15°N and 90°E RAMA (“Research Moored Array for African-
221 Asian-Australian Monsoon Analysis and Prediction”; McPhaden et al., 2009) mooring
222 salinity data at 5m-depth to validate the satellite at this location. The mooring does not
223 provide 5m data after May 2018, so the validation of the satellite with RAMA is
224 restricted to the January 2010 to May 2018 period. The newly updated climatology -
225 WOA18 (Zweng et al., 2018) with $0.25^\circ \times 0.25^\circ$ degree horizontal resolution is also used
226 for qualitatively validating the satellite data salinity seasonal cycle in Figure 8.

227 **2.3. Ancillary datasets**

228 For Sea Level Anomalies (SLA), we use AVISO dataset
229 (“www.aviso.oceanobs.com/fr/accueil/index.html”; Ducet et al., 2000), which merges
230 data from different altimeters. The BoB surface circulation is obtained from the GEKCO

231 (“Geostrophic and Ekman Current Observatory”; Sudre et al., 2013) surface current
232 available from October 1992 to present. This product includes both surface geostrophic
233 currents derived from altimetry and the Ekman flow derived from scatterometer winds.
234 We use satellite-derived monthly estimates of Ganges-Brahmaputra river discharge at
235 the river mouths (Papa et al., 2010), estimated from the joint use of *in situ* level-
236 discharge rating curves and altimetry-derived water level at the river mouth (Papa et al.,
237 2012). This dataset is unfortunately available up to 2016 only.

238 In the following section, we will define several climate modes indices. Those
239 indices are traditionally defined from Sea Surface Temperature (SST), for which we use
240 NOAA OI-SST v2 data
241 (<https://www.esrl.noaa.gov/psd/data/gridded/data.noaa.oisst.v2.highres.html>). But we
242 will see that a SST-based index maybe not the best choice for the Indian Ocean Dipole
243 (IOD), and will propose alternatives, in particular based on Outgoing Longwave
244 Radiation (OLR, a proxy of deep atmospheric convection) or Wind Stress (the force
245 exerted by wind per unit ocean surface). Wind stresses up to August 2019 are calculated
246 from the ERA-Interim daily winds by using the bulk formula $\tau = \rho C_D U^* |U|$, where ρ
247 the density of the air, C_D the drag coefficient (here assumed to be 1.2×10^{-3}), and U the
248 wind vector at 10-m height. We use the National Oceanic and Atmospheric
249 Administration interpolated OLR data
250 (https://www.esrl.noaa.gov/psd/data/gridded/data.interp_OLR.html).

251 **2.4. Climate indices**

252 We will relate interannual SSS variations in the BoB to well-known modes of
253 climate variability. The Indian Ocean Dipole (Saji et al., 1999) peaks in boreal fall
254 (typically September-November). In its positive phase, the IOD is characterized by cold

255 SST anomaly along the coast of Java and Sumatra and warm SST anomaly over the
256 western Indian Ocean (Fig. 3b). Because of this SST anomaly pattern, a classical index
257 proposed to characterize the IOD is the Dipole Mode Index (hereafter DMI; Saji et al.,
258 1999), defined as the September-November (SON) average difference between SST
259 anomalies in the western (50° to 70° E and 10° N to 10° S) and eastern (90° to 110° E and
260 10° S to 0°) equatorial Indian Ocean.

261 It has been argued before that the DMI not only tracks dynamical perturbations
262 associated with the IOD, but also more high frequency SST anomalies driven by
263 synoptic atmospheric variability (e.g. Dommenges and Jansen, 2009), and that some
264 other indices may be more accurate to represent the ocean-atmosphere coupling that
265 characterizes the IOD (e.g. Shaaban and Roundy, 2017). Positive IOD events are for
266 instance also characterized by reduced atmospheric convection in the eastern Indian
267 Ocean, as evidenced by the positive OLR anomalies in this region (Fig. 3b). It has hence
268 been suggested that an OLR based index could better distinguish IOD events than the
269 classical SST-based DMI index (Shaaban and Roundy, 2017). We have thus defined an
270 OLR-based Dipole Index (hereafter, ODI) inspired from that of Shaaban and Roundy
271 (2017), but simply defined as average SON OLR interannual anomalies in the western
272 (50° to 70° E and 10° N to 10° S) equatorial Indian Ocean minus those in the eastern (90°
273 to 110° E and 10° S to 0°) equatorial Indian Ocean. Those are the same boxes as those
274 used for the DMI, and their choice is justified by the statistically significant OLR signals
275 there (Fig. 3b).

276 Positive phase of IOD are also associated with easterly wind stress anomalies
277 over the eastern Equatorial Indian Ocean (Fig. 3a). We have thus defined a Wind stress-
278 based Dipole Index (WDI) as the average SON zonal wind stress anomaly over the

279 eastern equatorial Indian Ocean (EEIO, 5°N-5°S; 75°E-100°E). Those wind stress
280 anomalies induce a clear basin-scale Sea Level Anomalies (SLA) response (e.g. Webster
281 et al. 1999; Suresh et al. 2018), with downwelling (i.e. positive SLA) along the south
282 central Indian Ocean (Fig. 3a) in boreal fall (Webster et al. 1999; Keerthi et al., 2013)
283 and upwelling (i.e. negative SLA) along the Java Sumatra coast. We hence also defined a
284 SLA-based Dipole Index (SDI) as the average SON SLA in the south central Indian
285 Ocean SCIO, 5°S-15°S; 65°E-90°E) minus that near the Java/Sumatra coast (JSC; 0°-
286 10°S; 95°E-105°E).

287 The time evolution of the four IOD indices (the classical DMI and our SDI,
288 WDI, and ODI indices) over the 1993-2018 period is displayed on Figure 3c. While all
289 these indices share a lot in common, the DMI index departs from all the other indices in
290 both 2017 and 2018, two years within our 2010-2018 study period. Statistics in Table 2
291 indicate that the DMI is the least consistent with the other indices (Table 2), with
292 correlations ranging from 0.83 with the ODI to 0.89 with the SDI. In contrast, the SDI is
293 strongly correlated with the WDI (correlation 0.97) a to a slightly lesser extend with the
294 ODI. I.e. the IOD ocean-atmosphere signals seem to be better characterized by its SLA,
295 OLR (atmospheric convection) and wind stress signals than by the DMI. This is not only
296 true over the entire 1993-2018 period, but even more over our 2010-2018 study period
297 (number in brackets in Table 2). In the text, we will thus use the SDI to characterize the
298 IOD, and find that SSS interannual anomalies are more correlated with the SDI than
299 with the DMI. We will not mention correlations with the ODI and WDI for the sake of
300 brevity, but these two last indices also yield higher correlations with the IOD signals that
301 we will discuss. In short, the SDI, ODI or WDI are better indices of the IOD than the
302 DMI.

303 Finally, we will also use the Nino3.4 index, which corresponds to SSTA
304 averaged over central equatorial Pacific (170°W-120°W; 5°N-5°S) from November to
305 January, to characterize the El Niño Southern Oscillation (ENSO) phase. The IOD is
306 indeed often phase-locked with ENSO (e.g. Annamalai et al. 2003), and it is sometimes
307 delicate to distinguish a signal caused by one or the other (e.g. Currie et al. 2013;
308 Keerthi et al. 2013).

309

310 **3. Validation**

311 In this section, we evaluate SMOS-new SSS dataset in terms of spatial coverage
312 and agreement with *in situ* observations. We first illustrate the much better performance
313 of SMOS-new against SMOS-old dataset (section 3.1), and then focus on SMOS-new
314 and compare its performance to that of the Aquarius and SMAP datasets (section 3.2).

315 **3.1. SMOS-new vs. SMOS-old**

316 Figure 2 displays the percentage of 1° x 1° monthly values that can be retrieved
317 from *in situ*, SMOS-old, SMOS-new, Aquarius and SMAP data. As discussed in Akhil
318 et al. (2016b), many pixels of the SMOS-old product are flagged as bad values (Fig. 2c),
319 in particular over the northern BoB. As a result, SMOS-old only achieves a nearly
320 complete coverage south of 15°N, with a northward decrease of the data coverage down
321 to < 10% close to the Ganges-Brahmaputra estuary. In contrast, the SMOS-new product
322 achieves a complete coverage over the entire domain (Fig. 2d). This coverage is far
323 better than the one achieved from *in situ* data (Fig. 2b,d). *In situ* data typically achieves a
324 ~20% coverage in central BoB, but does neither sample coastal regions nor the
325 Andaman Sea. SMOS-new has thus a superior coverage to SMOS-old and very superior
326 coverage to *in situ* data.

327 Figure 4 compares SMOS-new and SMOS-old observations against *in situ* data.
328 The statistics for this comparison are provided for the entire datasets, but also between
329 brackets for common data between SMOS-old, SMOS-new and *in situ* data, to allow a
330 fair comparison. Both sets of statistics in fact indicate a clear improvement of SMOS-
331 new relatively to SMOS-old, with an increase in correlation (~ 0.8 vs. 0.6) as well as a
332 reduction of the bias (~ 0.1 vs. -0.14) and root mean square difference (rmsd; ~ 0.6 vs.
333 0.95). This clear improvement remains valid when comparing both datasets separately
334 for the four regions displayed in Figure 2b (not shown). As shown in Figure 4, this
335 improvement is partly due to the tendency of SMOS-old to overestimate low SSS (in the
336 25-32 pss range) and to underestimate high SSS (above 34 pss), which largely
337 disappears in SMOS-new.

338 This broad analysis demonstrates the clear improvement of SMOS-new relative
339 to SMOS-old and we will focus in the following on a more thorough evaluation of
340 SMOS-new, in comparison with SMAP and Aquarius.

341 **3.2. SMOS-new vs. Aquarius and SMAP**

342 Figures 2d,e,f allow comparing the spatial coverage of SMOS-new, Aquarius and
343 SMAP. The three products achieve a full coverage in most of the BoB, and only differ
344 through their spatial resolution and coverage close to coasts. SMAP intermittently
345 provides a couple of additional values close to coasts relative to SMOS-new. Both
346 products are clearly superior to Aquarius in terms of data coverage, due to the lower
347 resolution of Aquarius and some missing values in grid-points in the vicinity of coasts.

348 Figure 5 further provides statistics for comparisons between satellite products
349 and co-located *in situ* data over their common periods (August 2011 to June 2015 for
350 SMOS-New vs. Aquarius on Figure 5a; April 2015 to October 2019 for SMOS-new vs.

351 SMAP on Figure 5b), *i.e.* these statistics are strictly comparable as they compare the
352 satellites to identical common *in situ* samples. SMOS-new and Aquarius have an almost
353 identical performance ($r \sim 0.8$, $rmsd \sim 0.65$ and $bias \sim 0.15$). One may however argue
354 that this is not a fair comparison, since SMOS SSS has a higher spatial resolution (0.25°
355 for the new SMOS product) than Aquarius (1°). We have hence re-gridded SMOS to the
356 Aquarius 1° grid through spatial averaging. The resulting 1° SMOS-new has an almost
357 identical fit to observations compared to SMOS-new on its native grid. This is a bit
358 surprising, because there are a lot of fine-scale ($< 1^\circ$) salinity structures in the BoB (e.g.
359 Wijesekera et al., 2016), and one would thus expect finer-resolution product to capture
360 them better, and yield less representativity errors. The almost equivalent performance of
361 SMOS-new product at these two resolutions could either arise from the fact that the
362 SMOS-new product effective resolution is about 70km in the BoB, or that SMOS has
363 grid-point, unphysical noise, and whatever is gained in term of representativity is lost
364 due to this noise. SMAP behaves slightly better than SMOS-new in the BoB (Fig. 5b),
365 with slightly higher correlation (0.85 vs. 0.81) and lower rmsd (0.59 vs. 0.65). It does,
366 however, have a slightly larger bias (0.08 vs. 0.11).

367 Figure 5 evaluated the three remotely sensed SSS over the entire BoB. This
368 validation has also been performed separately for the NBoB, WBoB, CBoB and ANDA
369 regions (not shown), resulting in a similar conclusion: statistics of comparison with *in*
370 *situ* SSS are generally equivalent with Aquarius and SMOS-new, and slightly better with
371 SMAP than both products. Aquarius however performs slightly better than SMOS-new
372 in the central BoB but this is compensated by a better SMOS-new performance in the
373 Northern BoB and Andaman regions. Figure 6 provides an alternative regional
374 validation of the SMOS-new dataset, by plotting box-averaged time series of *in situ* and
375 SMOS-new SSS, both for co-located data at *in situ* points (continuous lines) and for the

376 box-average SMOS-new data (dashed line), for the NBoB, WBoB, CBoB and ANDA
377 regions. Figure 6 first clearly demonstrates that the *in situ* data sampling is clearly not
378 sufficient for estimating the box-averaged SSS (compare the red dashed and continuous
379 lines), especially in the NBoB and ANDA boxes. This figure also indicates an
380 outstanding phase agreement between SMOS-new and *in situ* collocated data, with
381 correlations exceeding 0.8 in all boxes other than CBoB. The correlation is weakest for
382 the CBoB region (0.75), where the SSS variability is the weakest, hence yielding an
383 unfavourable signal to noise ratio.

384 Since the central BoB seems to be a region where SMOS-new performs slightly
385 worse than elsewhere in the BoB (Fig. 6), we provide a comparison of SMOS-new,
386 SMAP and Aquarius with monthly-averaged salinity at 5 m depth from the 15°N and
387 90°E RAMA mooring in Figure 7. This comparison confirms that SMOS-new has a
388 degraded performance relative to SMAP and Aquarius in the central BoB, with lower
389 correlations and higher rmsd to *in situ* data (both over the entire period or when
390 compared based on the same observational sample). Despite this degraded performance
391 compared to other products, SMOS-new still captures SSS variability in the central BoB
392 relatively well, with a 0.79 correlation and 0.40 pss rmsd over the entire period (January
393 2010- May 2018). Even if SMOS-new performs less accurately in the central BoB, it is
394 still perfectly capable of detecting interannual anomalies such as the ~2 pss freshening
395 events in 2012, 2013, 2014 and 2017 (Fig. 7).

396 Another traditionally difficult region for satellite products to accurately retrieve
397 SSS is the coastal region of WBoB, due to more prevalent RFI (Oliva et al., 2016) and
398 contamination by signals from land (land brightness temperatures being typically about
399 twice larger as those over the sea). This is particularly unfortunate along the East Indian

400 coast, where the “river in the sea” is associated with strong seasonal and interannual SSS
401 signals (Chaitanya et al., 2014; Akhil et al., 2014; Akhil et al., 2016a). In order to infer
402 whether satellite data can be trusted in this region, Figure 8 provides the correlation
403 between the three satellite products and co-located data points and the standard deviation
404 of their difference (STDD), as a function of the distance to the east coast of India (within
405 10°N-20.5°N, 78°E-90°E). In all products, the correlation drops close to the coast. This
406 drop only occurs very close to the coast in SMAP (from $r \sim 0.9$ at 100km to 0.85 at
407 50km), which is a clearly superior product along the east coast of India. The decrease at
408 the coast is however weaker for SMOS-new (from $r \sim 0.8$ at 200km to $r \sim 0.75$ at 50km off
409 the coast) than for Aquarius ($r \sim 0.83$ at 350km to $r \sim 0.65$ at 150km). Comparing the
410 amplitude of the unbiased error (estimated as the standard deviation of the difference
411 between the product and *in situ* data) with the amplitude of SSS variations for each
412 product (estimated from the product and *in situ* data standard deviation) further allows
413 evaluating if the accuracy of the measurements is smaller than the signal, *i.e.* if the
414 signal to noise ratio is favourable. This is not so much the case for Aquarius, for which
415 the STDD is $\sim 80\%$ of the amplitude of the variability at 150 km away from the coast.
416 SMOS-new and SMAP both allow to retrieve data closer to the coast, and to clearly
417 monitor the increase in variability due to the “river in the sea” in the last 200 km from
418 the coast. While the STDD increases close to the coast in both products, this typical
419 error remains smaller than the signal to be measured, with a signal twice larger than the
420 noise for SMAP. This result thus indicates that SMOS-new and SMAP are both able to
421 capture the coastal SSS variations associated with the “river in the sea”, with a better
422 performance for SMAP. However, Figure 8a-c also indicates that the typical error
423 becomes closer to the STD away from the coast (at 500km), illustrating that the lower
424 SMOS-new performance in the central BoB (Fig. 6c) is indeed partly due to weaker

425 signal-to-noise ratio there, as suggested above.

426 **4. Bay of Bengal SSS variability from a decade of SMOS data**

427 In the previous section, we have established the capability of SMOS-new, SMAP
428 and Aquarius datasets to map large-scale variability of SSS in the BoB, including the
429 regions close to the East Indian coast for SMOS and SMAP. In this section, we will
430 describe the ability of these datasets to describe the BoB SSS seasonal cycle and
431 interannual variability. We will then take advantage of the 10 years of SMOS data to
432 describe BoB seasonal cycle. As SMOS-new record only extends up to September 2019
433 and the dominant modes of interannual variability peaks during and after September, the
434 analysis of interannual SSS variability is restricted to 9 years (January 2010 to
435 December 2018). We will however describe the SSS variability associated with an
436 unusually strong IOD event in 2019 using August-December 2019 SMAP data (and
437 show that it is consistent with SMOS-new data over August and September 2019).

438 **4.1. Seasonal cycle**

439 Figure 9 displays seasonal SSS maps constructed from the WOA18, SMOS-new,
440 SMAP and Aquarius products, over the full period over which each product is available.
441 While the SMAP (4-5 years) and Aquarius (3-4 years) records are too short to provide a
442 precise estimate of the seasonal cycle, we underline that we only intend a qualitative
443 comparison of the three satellites seasonal cycle with that from WOA18 (we already
444 performed a quantitative comparison to *in situ* data in section 3). The newly available 25
445 km-resolution WOA18 has finer structures than previous versions, which were
446 excessively smooth (Akhil *et al.* 2014). It captures meridional SSS variations, with
447 lowest SSS in the Northern BoB in SON (i.e. after the large rainfall and river runoff
448 peak towards the end of the Southwest monsoon, e.g. Chaitanya *et al.*, 2014). WOA18

449 also captures better fine-scale features such as the sharp SSS gradients at the river
450 mouths and the post-monsoon “river in the sea” along the Western BoB, although this
451 freshwater tongue hugging the East Indian coast is discontinuous in this dataset (Fig.
452 9c). The three satellite datasets reveal a similar seasonal salinity pattern, with low
453 salinity (below 30 pss) close to the Ganges-Brahmaputra and Irrawaddy river mouths
454 from June to February, but SMOS and Aquarius fail to capture the SSS signature of
455 those two rivers during the dry season (MAM). The “river in the sea”, associated with
456 equatorward advection of the low salinity water in the Northern BoB by the southward
457 post-monsoon EICC (Akhil et al., 2014; Chaitanya et al., 2014) is clearest in SMOS-new
458 (Fig. 10a) and SMAP during boreal fall, where its freshening signature can be tracked as
459 far south as the east coast of Sri Lanka. In contrast, Aquarius and WOA18 display a less
460 coastally-trapped and more discontinuous freshening along the East Indian coast that
461 does not reach the Sri Lankan east coast. Overall, SMOS-new and SMAP thus tend to
462 display finer-scale structures than the other datasets.

463 Figure 10b further displays a SSS (contours) and along-shore currents (colors,
464 with blue/negative indicating southward currents) latitude-time section, averaged within
465 200 km of the East Indian coast (red box in Fig. 10a). This Figure is comparable to
466 Figure 6 in Akhil et al. (2014) modelling study or Figure 8 of Chaitanya et al. (2014)
467 observational study and displays very similar features. The Northern BoB starts
468 freshening in June onward during the monsoon onset, reaches its lowest climatological
469 SSS in September, and goes back to pre-monsoon values by January-February. The
470 southward expansion of this low salinity water along the East Indian coast coincides
471 with the development of the southward EICC in October, while the return to pre-
472 monsoon values starts occurring before the EICC turns northward (Fig. 10b), as pointed
473 out by Akhil et al. (2014) and Chaitanya et al. (2014). Through a detailed upper ocean

474 salinity budget, these last studies demonstrated that advection is the main cause for the
475 “river in the sea” southward expansion, while vertical mixing strongly contributes to
476 restoring the coastal SSS to pre-monsoon values. The 10-year long SMOS-new dataset
477 yields salinity variations that are consistent with those conclusions.

478 **4.2. Interannual variability**

479 The insufficient *in situ* data coverage (Fig. 2a,b) only allows a rough description
480 of the observed BoB SSS interannual variations. Based on gridded *in situ* data products,
481 Pant et al. (2015) and Chaitanya et al. (2015) both reported strong interannual SSS
482 variations in the western BoB. The observational study of Pant et al. (2015) and the
483 modelling results of Akhil et al. (2016a) indicate that the IOD plays a prominent role in
484 driving interannual SSS variability in boreal fall, in the northern and western BoB. Both
485 studies indicate that the IOD remotely drives current anomalies through the coastal
486 Kelvin waves propagation, which modulates the EICC intensity. The remote control of
487 the IOD on the EICC is confirmed by the observational & modelling study of Sherin et
488 al. (2018), which however does not discuss the resulting SSS anomalies. Here, we take
489 advantage of the 9 year-long SMOS-new dataset to investigate if satellite SSS data
490 yields a consistent description to that in those studies.

491 Figure 11 confirms that largest year-to-year SSS variations in the northern and
492 western BoB occur during September-November in the SMOS-new data, in agreement
493 with Akhil et al. (2016a) modelling study. We have hence performed an “Empirical
494 Orthogonal Function” (hereafter, EOF) analysis on the September to November (SON)
495 average SSS anomalies (Fig. 12). We focus on the first EOF as it represents 43.2% of
496 the total SSS anomalies variance, compared to less than 20% for higher modes. It is
497 associated with opposite polarity SSS anomalies in the northern and western BoB (Fig.

498 12b). Its principal component (PC1) has a 0.65 to 0.84 correlation with the four different
499 IOD indices described in the method section (significantly different from zero above the
500 95% confidence level when considering each year as an independent sample). The
501 correlation with ENSO is much weaker ($r=0.07$), and not statistically significant. This
502 confirms that the leading mode of SSS anomalies in the BoB is strongly related to the
503 IOD variability, with positive IOD events generally leading to negative SSS anomalies
504 in the northern BoB and positive SSS anomalies along the west coast of BoB, in
505 agreement with Akhil et al. (2016a) modelling study and Pant et al. (2015) *in situ* data
506 analysis. The correlation with PC1 is largest when considering the SDI (SLA-based IOD
507 index, $r\sim 0.84$). This indicates a tight relation between the BoB SSS interannual
508 anomalies and the SLA (and hence circulation) anomalies associated with the IOD,
509 consistently with the results of Pant et al. (2015) and Akhil et al. (2016a). Because of
510 this tight link, and because the DMI erroneously points to IOD events to 2017 and 2018
511 (Fig. 3c), we will hereafter mostly use the SDI as our best indicator of the IOD
512 circulation anomalies.

513 Red arrows on Figure 12b display the GEKCO surface current anomalies
514 obtained through a linear regression on PC1 time series. They indicate northward current
515 anomalies along the East Indian coast, i.e. EICC weakening. The associated SLA signal
516 (Fig. 12c) confirms that the EICC weakens during positive IOD events, in association
517 with upwelling coastal Kelvin waves emanating from the equatorial region, as suggested
518 by previous studies (Aparna et al., 2012, Akhil et al., 2016a, Suresh et al. 2018; Sherin et
519 al., 2018). The EICC normally exports Northern BoB fresh water southward along the
520 East Indian coast (Fig. 10a). Positive IODs weaken the EICC, hence resulting in a
521 weaker southward fresh water export along the East Indian coast, qualitatively consistent
522 with the typical negative anomalies in the northern BoB and positive anomalies in the

523 western BoB (Fig. 12b). This is qualitatively consistent with the role of advection.

524 Figures 13 and 14 further allow detailing the year-to-year SSS variations along
525 the East Indian coast over the 2010-2018 period and their main drivers. Figure 13 shows
526 the SDI, and the SSS and along-shore currents latitude-time section along the Indian
527 coast (red box in Fig. 10a). This period encompasses two positive IOD years (2011 and
528 2015) and two negative IOD years (2010, 2016; Fig. 13a). The EOF analysis in Figure
529 12ab and the case study of Fournier et al. (2017) indicate that the “river in the sea” tends
530 to be less (more) developed during positive (negative) IOD years. This is confirmed by
531 Figure 13bc: no clear “river in the sea” and positive SSS anomalies along the East Indian
532 coast are depicted in 2011 and 2015, while a clearer “river in the sea” and negative SSS
533 anomalies are seen in 2010 and 2016. The 2016 negative SSS anomalies are weak,
534 however, and there are other years (such as 2013) that can also yield negative SSS
535 anomalies along the East Indian coast. This indicates that the IOD is not the sole
536 controller of year-to-year SSS variations along the East Indian coast, and we will come
537 back to this point in the discussion.

538 Let us now examine the year-to-year variations of SSS in the two regions with
539 the strongest SSS variability (East Indian coast and northern BoB) in more details.
540 Figure 14 displays time series of Northern BoB Ganges-Brahmaputra runoff anomalies,
541 SSS anomalies in the northern and western BoB as well as along-shore current
542 anomalies along the East Indian coast over the 2010-2018 period. The dashed line shows
543 the part of the interannual anomalies that are attributable to the IOD (obtained as the part
544 that is linearly related to the IOD, through regression on the SDI). In general, the
545 interannual variability of the northern BoB freshwater fluxes is quite independent from
546 that of the IOD over the period we consider ($r \sim -0.4$ between Ganges-Brahmaputra runoff

547 and SDI). There is, however, a stronger control of the Northern ($r \sim -0.7$) and
548 southwestern BoB SSS ($r \sim 0.8$) and along-shore current ($r \sim 0.7$) anomalies by the IOD, as
549 discussed earlier.

550 For instance, the northern BoB exhibits the strongest anomalous saltening in
551 2010 and 2016 (plain lines in Fig. 14b) in agreement with typical negative IOD years
552 (compare the dashed and plain lines for these two years in Fig. 14b). The northern BoB
553 freshens during the 2011 and 2015 positive IOD years, but more than would normally be
554 expected in 2011. The anomalous saltening along the East Indian coast is strongest in
555 2011 and 2015, consistent with a positive IOD those two years (Fig. 14d). The
556 anomalous freshening along the East Indian coast is however weaker than expected in
557 2016 (e.g. weaker than in 2012, a neutral IOD year). This underlines again that, with
558 only 40% of the variance explained at the basin scale, the IOD is not the sole
559 phenomenon that controls the interannual SSS variability in the BoB. Snapshots of the
560 SSS (not shown) for instance suggest that a mesoscale eddy resulted in exporting a lot of
561 freshwater from the “river in the sea” to the basin interior in 2016, hence diverting the
562 fresh water from its along-shore southward path, and resulting in the relatively weak
563 SSS anomalies for a negative IOD year in 2016.

564 Finally, some years with no IOD event can be associated with non-negligible
565 SSS anomalies in the BoB. Let us focus on year 2012, which exhibits a positive but
566 modest IOD index value. This year is associated with anomalously fresh SSS anomalies
567 in the northern BoB, larger than what expected from the IOD index value that year (Fig.
568 14a). This behaviour may be attributable to anomalously strong Ganges-Brahmaputra
569 runoff in 2012 (Fig. 14a,b). This is coherent with Akhil et al. (2016a) modelling results
570 that indicate that the second EOF of BoB SSS variability during boreal fall is associated

571 with northern BoB SSS variations in response with the Ganges-Brahmaputra interannual
572 anomalies. We will discuss this further in section 5.2. A strong anomalous freshening in
573 the northern BoB is also observed in 2017, a year with a very weak IOD index value.
574 The unavailability of Ganges-Brahmaputra runoffs data after 2016 however prevents
575 assessing the role of freshwater forcing on this anomalous event.

576 **4.3. The 2019 positive IOD**

577 The availability of SMOS data until September 2019 and of SMAP data up to
578 present gives us the opportunity to describe the anomalous SSS pattern in the BoB
579 related to the extreme positive IOD event in fall 2019 (Doi et al., 2020). We used the
580 common SMOS and SMAP period to compute interannual anomalies, and the common
581 August and September 2019 months indeed confirm that SMOS and SMAP are quite
582 consistent over these two months. We will thus focus on SMAP to describe SSS
583 anomalies associated with the strong 2019 IOD.

584 The circulation and SSS anomalies in October-November 2019 are qualitatively
585 consistent with those deduced from the Figure 12 EOF analysis, with a weaker than
586 usual EICC associated with salty anomalies along the southern portion of coast of India,
587 and fresh anomalies in the Northern BoB. The salty anomaly along the entire coast of
588 India, associated with an unusually weak EICC had actually already started in August
589 and September, when the fresh anomaly was more confined to the vicinity of the
590 Ganges-Brahmaputra river mouth. While those anomalies are roughly consistent with
591 those of the EOF analysis, they are very large, possibly due to the very large IOD
592 amplitude in 2019 (Doi et al., 2020). There is also a very strong modulation of the
593 salinity field by mesoscale activity, as noted previously by Fournier et al. (2017).
594 Finally, the case of 2019 suggests that the EOF analysis pattern develops in two stages,

595 first with positive SSS anomalies along the coast of India, and then with negative
596 anomalies in the Northern BoB. The exact timing of this development and strong
597 modulation by the mesoscale field suggest that more years will be needed in order to
598 obtain a robust estimate of the dominant pattern of IOD-induced SSS variability in the
599 BoB from remotely sensed data. This is further discussed in section 5.

600

601 **5. Summary and Discussion**

602 **5.1. Summary**

603 Past studies have underlined that the BoB SSS distribution can influence the
604 intensity of tropical cyclones and the marine productivity by acting as a barrier to the
605 upward mixing of colder water and nutrients into the surface mixed layer (Prasanna
606 Kumar et al., 2002; Neetu et al., 2019). This is a strong motivation for a reliable
607 monitoring of the year-to-year SSS variations in the BoB. In this paper, we show that
608 currently available *in situ* data are not sufficiently dense to allow a proper mapping of
609 the fine SSS structure in the BoB, even at seasonal timescale. In contrast, the SMOS,
610 Aquarius, and SMAP satellite missions can provide synoptic maps of the basin SSS
611 every ~8 days with a resolution of ~50-100 km. The first attempts to estimate BoB SSS
612 from SMOS were unsuccessful (Boutin et al., 2013; Subrahmanyam et al., 2013; Akhil
613 et al., 2016b), because of a suboptimal processing of systematic errors and too stringent
614 quality control in that dataset. The new processing of Boutin et al. (2018) introduces an
615 improved systematic-error correction and better accounts for the amplitude of the SSS
616 signal during the quality control. Over the BoB, this results in a 100% spatial coverage
617 for $\frac{1}{4}^\circ$ SSS maps every 4 days over the 2010-2019 period that capture the basin-scale
618 SSS variability well (0.81 correlation, 0.10 bias and 0.65 rms-difference relative to more

619 than 26000 collocated 1-4 m depth *in situ* data over the basin). Comparison with SMAP
620 and Aquarius data further indicate that the new SMOS processing has a similar
621 performance to Aquarius (but better spatial resolution) and slightly inferior performance
622 to SMAP over the BoB. The new SMOS processing has a degraded performance in the
623 central BoB but still compares well with RAMA mooring data at 15°N-90°E (0.79
624 correlation, 0.00 bias and 0.37 rms-difference). Despite errors that increase toward the
625 coast of India, SMOS and SMAP still retain a favourable signal-to-noise ratio, and high
626 correlations with available *in situ* observation datas close to the coast ($r \sim 0.74$ for SMOS
627 and 0.83 for SMAP 75 km away from the coast).

628 The advantage of the SMOS new processing relative to SMAP and Aquarius is
629 the length of its record (~ 10 years), that allows examining the BoB SSS seasonal cycle
630 and interannual variability and to compare it with previous studies, based on either
631 modelling or sparse *in situ* data. The new SMOS processing confirms that the largest
632 seasonal signals are related to a northern BoB freshening during and shortly after the
633 southwest monsoon, and its southward expansion along the west coast of India in fall,
634 due to advection by the EICC. The strongest interannual variability occurs during
635 September-November, in association with the IOD. Remote forcing associated with the
636 IOD modulates the EICC intensity through coastal Kelvin waves radiating from the
637 equatorial strip to the western BoB. The EICC is anomalously weak during positive IOD
638 events, resulting in less southward freshwater export, and hence negative SSS anomalies
639 to the north of the BoB and positive SSS anomalies along the East Indian coast.
640 Opposite anomalies occur during negative IOD events. These anomalies are however
641 modulated by other processes than the IOD. For instance, Ganges-Brahmaputra River
642 discharge variations seem to also contribute to northern BoB SSS anomalies during
643 some years. Similarly, eddies induce strong offshore transport, and thus modulate SSS

644 along the East Indian coast.

645 **5.2. Discussion**

646 Let us first compare the results of the present study with previous analyses.
647 Previous studies of the BoB SSS either relied on modelling or on sparse *in situ* data that
648 do not resolve the strong salinity gradients. First, the present study confirms large SSS
649 seasonal signals in the northern BoB during and after the monsoon (e.g. Akhil et al.,
650 2014; Rao and Sivakumar, 2003). Most importantly, it confirms that a fresh salinity
651 tongue associated with steep salinity gradients develop along the East Indian coast after
652 the summer monsoon, in agreement with sparse observations from cruises (e.g. Shetye et
653 al., 1993; Hareesh Kumar et al., 2013), modelling results (Jensen, 2001; Akhil et al.,
654 2014), observations collected directly at the coast (Chaitanya et al., 2014) and a case
655 study using SMAP data (Fournier et al., 2017). It also confirms that the IOD is the
656 dominant contributor to BoB SSS interannual variability, as suggested from *in situ*
657 observations (Pant et al., 2015), modelling (Akhil et al., 2016a) or a case study with
658 SMAP data (Fournier et al., 2017). Our results also show a clear link between those SSS
659 anomalies and the EICC modulation in response to the IOD remote influence through
660 coastal Kelvin wave circumnavigating the BoB, confirming the modelling results of
661 Akhil et al. (2016a).

662 But our results also illustrate that, with 43% of explained variance, the IOD is
663 not the only phenomenon to control the boreal fall BoB SSS anomalies. Akhil et al.
664 (2016a) modelling study found a second EOF mode (16% of the total variance)
665 associated with local SSS anomalies in the northern BoB in response to Ganges-
666 Brahmaputra River discharge variations. While those discharge variations seem to
667 qualitatively match some of the deviations from the expected IOD signals over the

668 period we consider (Fig. 14), the higher order EOFs of the SMOS data or a regression to
669 Ganges Brahmaputra runoff data do not reveal any consistent signal with those
670 discussed by Akhil et al. (2016a). We suspect that this is because the SMOS satellite
671 record is still too short to extract the weaker-amplitude variability (relative to the IOD
672 signal) associated with the Ganges-Brahmaputra river discharge variations. We also find
673 possible influences of mesoscale eddies in modulating the SSS interannual signals along
674 the East Indian coast, consistent with Fournier et al. (2017). Finally, wind intensity may
675 also partly control SSS variations through their impact on vertical mixing, which has
676 been shown to have a prominent vertical mixing processes in eroding the upper-ocean
677 salinity stratification in the BoB (Akhil et al., 2014, 2016a).

678 We have attempted a budget approach to estimate the processes that explain the
679 seasonal and interannual variability of SSS more quantitatively. We were however not
680 able to close the budget, and we suspect that this is associated with the large
681 uncertainties on the mixed layer depth estimate, that translate into large uncertainties on
682 the estimation of the effect of rain and runoff freshwater fluxes. We hence think that an
683 approach combining modelling and a validation by *in situ* observations would currently
684 be the best approach to explain the mechanisms of SSS variability. The good agreement
685 between the SMOS SSS seasonal cycle and that described by Akhil et al. (2014) and
686 with the IOD-induced SSS signals in Akhil et al. (2016a) hence suggest that advection is
687 the main process that induces the seasonal southward expansion of the Northern BoB
688 freshwater along the East Indian coast and its interannual modulation. The existence of a
689 second mode of interannual variability of the northern BoB, in relation with Ganges-
690 Brahmaputra runoff variations in Akhil et al. (2016a) modeling study yet has to be
691 confirmed from direct observations. Future research, relying on the synergy between
692 satellite and *in situ* observations along with modeling will be essential in order to tackle

693 and answer those scientific questions.

694 A first step in that direction is the recent release of a merged dataset, that
695 combines the SMOS, Aquarius and SMAP satellite retrievals into a single SSS dataset,
696 as part of the Climate Change Initiative (CCI) of the European Space Agency (ESA). A
697 description of this dataset and its data are both available from <http://cci.esa.int/salinity> for
698 details. The CCI SSS dataset has the advantage of providing calibrated global SSS fields
699 over a long 9-year period (2010-2018), as SMOS, but also to further reduce SSS errors
700 by also using the Aquarius and SMAP data. Figure 16 provides a first evaluation of the
701 quality of this product for the BoB, by comparing its fit to co-located *in situ* data over
702 the SMOS-new, Aquarius and SMAP data periods. Note that, as for Figure 5, only
703 common data samples to each pair of datasets are used to compute the statistics in each
704 panel of Figure 16. This analysis demonstrates that the CCI-SSS product performs better
705 than any of the single-satellite datasets over their common period. This is also the case
706 when this analysis is performed for the BoB subregions on Figure 2b (not shown). This
707 analysis indicates that CCI-SSS product is likely to be the best alternative to describe
708 and understand the BoB SSS variability in future studies. As this dataset becomes
709 longer, it will allow an increasingly accurate description of the BoB SSS interannual
710 variability.

711

712

713

714

715

716 **Acknowledgments.** The authors thank CNES (“Centre National d’Etudes Spatiales”) for
717 the funding support to this Research (project “TOSCA SMOS-Ocean”). The authors
718 thank Stéphane Marchand for his help in handling SMOS data. We also thank IRD
719 (“Institut de Recherche pour le Développement”) for the financial support to the
720 collaboration on Indian Ocean research with the CSIR-NIO (“CSIR- National Institute
721 of Oceanography, India”). AVP thank the Director of CSIR-NIO for his encouragement.
722 ML and FP are grateful to “Indo-French Cell for Water Sciences”. Keerthi MG is
723 supported through a postdoctoral fellowship from CNES. This is NIO contribution
724 number xxxx.

725

726 **References**

- 727 Akhil, V.P., Durand, F., Lengaigne, M., Vialard, J., Keerthi, M.G., Gopalakrishna, V.V.,
728 Deltel, C., Papa, F. and de Boyer Montégut, C., 2014. A modeling study of the
729 processes of surface salinity seasonal cycle in the Bay of Bengal. *Journal of*
730 *Geophysical Research: Oceans*, 119(6), pp.3926-3947.
- 731 Akhil, V.P., Lengaigne, M., Vialard, J., Durand, F., Keerthi, M.G., Chaitanya, A.V.S.,
732 Papa, F., Gopalakrishna, V.V. and de Boyer Montégut, C., 2016a. A modeling
733 study of processes controlling the Bay of Bengal sea surface salinity interannual
734 variability. *Journal of Geophysical Research: Oceans*, 121(12), pp.8471-8495.
- 735 Akhil, V.P., Lengaigne, M., Durand, F., Vialard, J., Chaitanya, A.V.S., Keerthi, M.G.,
736 Gopalakrishna, V.V., Boutin, J. and de Boyer Montégut, C., 2016b. Assessment of
737 seasonal and year-to-year surface salinity signals retrieved from SMOS and
738 Aquarius missions in the Bay of Bengal. *International Journal of Remote Sensing*,
739 37(5), pp.1089-1114.
- 740 Annamalai, H., Murtugudde, R., Potemra, J., Xie, S. P., Liu, P., & Wang, B. (2003).
741 Coupled dynamics over the Indian Ocean: Spring initiation of the zonal mode.
742 *Deep Sea Research Part II: Topical Studies in Oceanography*, 50(12-13), 2305-
743 2330.
- 744 Anterrieu, E., Suess, M., Cabot, F., Spurgeon, P., and Khazâal, A., 2015. An Additive
745 Mask Correction Approach for Reducing the Systematic Floor Error in Imaging
746 Radiometry by Aperture Synthesis. *IEEE Geoscience and Remote Sensing Letters*,
747 vol. 12, no. 7, pp. 944 1441-1445, doi: 10.1109/LGRS.2015.2406912.
- 748 Antonov, J.I., Seidov, D., Boyer, T. P., Locarnini, R. A., Mishonov, A. V., Garcia, H. E.,
749 Baranova, O. K., Zweng, M. M. and Johnson, D. R., 2010. *World Ocean Atlas*
750 2009, Volume 2: Salinity, edited by S. Levitus, 184 pp., U.S. Govt. Print. Off.,
751 Washington, D.C. Aquarius User Guide, Document # JPL D-70012, National
752 Aeronautics and Space Administration, Physical Oceanography Distributed Active
753 Archive Center (PO.DAAC), Jet Propulsion Laboratory, 41 pp., 2011.
- 754 Aparna, S.G., McCreary, J.P., Shankar, D. and Vinayachandran, P.N., 2012. Signatures

755 of Indian Ocean Dipole and El Niño–Southern Oscillation events in sea level
756 variations in the Bay of Bengal. *Journal of Geophysical Research: Oceans*,
757 117(C10).

758 Benschila, R., Durand, F., Masson, S., Bourdallé-Badie, R., de Boyer Montégut, C., Papa,
759 F. and Madec, G., 2014. The upper Bay of Bengal salinity structure in a high-
760 resolution model. *Ocean Modelling*, 74, 36-52.

761 Boutin, J., Martin, N., Reverdin, G., Yin, X. and Gaillard, F., 2013. Sea surface
762 freshening inferred from SMOS and ARGO salinity: impact of rain. *Ocean*
763 *Science*, 9(1), 183–192

764 Boutin, J., Vergely, J.-L. and Khvorostyanov, D., 2018. SMOS SSS L3 maps generated
765 by CATDS CEC LOCEAN. debias V3.0. SEANOE.
766 <http://doi.org/10.17882/52804#57467>

767 Boyer, T.P., Baranova, O.K., Coleman, C., Garcia, H.E., Grodsky, A., Locarnini, R.A.,
768 Mishonov, A.V., Paver, C.R., Reagan, J.R., Seidov, D., Smolyar, I.V., Weathers,
769 K.W. and Zweng, M.M., 2018. World Ocean Database 2018. A. V. Mishonov,
770 Technical Editor, NOAA Atlas NESDIS 87.

771 Chaitanya, A.V.S., Lengaigne, M., Vialard, J., Gopalakrishna, V.V., Durand, F.,
772 Kranthikumar, C., Amritash, S., Suneel, V., Papa, F. and Ravichandran, M., 2014.
773 Salinity measurements collected by fishermen reveal a “river in the sea” flowing
774 along the eastern coast of India. *Bulletin of the American Meteorological Society*,
775 95(12), pp.1897-1908.

776 Chaitanya, A.V.S., Durand, F., Mathew, S., Gopalakrishna, V.V., Papa, F., Lengaigne,
777 M., Vialard, J., Kranthikumar, C. and Venkatesan, R., 2015. Observed year-to-
778 year sea surface salinity variability in the Bay of Bengal during the 2009–2014
779 period. *Ocean Dynamics*, 65(2), pp.173-186.

780 Chatterjee, A., Shankar, D., Shenoi, S.S.C., Reddy, G.V., Michael, G.S., Ravichandran,
781 M., Gopalakrishna, V.V., Rao, E.R., Bhaskar, T.U. and Sanjeevan, V.N., 2012. A
782 new atlas of temperature and salinity for the North Indian Ocean. *Journal of Earth*
783 *System Science*, 121(3), pp.559-593.

784 Currie, J.C., M. Lengaigne, J. Vialard, D.M. Kaplan, O. Aumont, S.W.A. Naqvi and O.
785 Maury, 2013: Indian Ocean Dipole and El Niño/Southern Oscillation impacts on
786 regional chlorophyll anomalies in the Indian Ocean, *Biogeosciences*, 10, 6677-
787 6698.

788 de Boyer Montégut, C., Mignot, J., Lazar, A. and Cravatte, S., 2007. Control of salinity
789 on the mixed layer depth in the world ocean: 1. General description. *Journal of*
790 *Geophysical Research: Oceans*, 112(C6).

791 Doi, T., Behera, S. K., & Yamagata, T., 2020. Predictability of the super IOD event in
792 2019 and its link with El Niño Modoki. *Geophysical Research Letters*, doi :
793 10.1029/2019GL086713.

794 Dommenget, D., & Jansen, M. (2009). Predictions of Indian Ocean SST indices with a
795 simple statistical model: A null hypothesis. *Journal of climate*, 22(18), 4930-4938.

796 Ducet, N., Le Traon, P. Y. and Reverdin, G., 2000. Global high-resolution mapping of
797 ocean circulation from TOPEX/POSEIDON and ERS-1 and -2, *J. Geophys. Res.:*
798 *Oceans*, 105(C8), 19,477–19,498.

799 Durand, F., Shankar, D., Birol, F. and Shenoi, S.S.C., 2009. Spatiotemporal structure of
800 the East India Coastal Current from satellite altimetry. *Journal of Geophysical*
801 *Research: Oceans*, 114(C2).

802 Fore A., Yueh, S., Tang, W. and Hayashi, A., 2017. SMAP Salinity and Wind Speed
803 Data User's Guide Version 4.0, Jet Propulsion Laboratory California Institute of
804 Technology.

805 Fournier, S., Vialard, J., Lengaigne, M., Lee, T., Gierach, M.M. and Chaitanya, A.V.S.,
806 2017. Modulation of the Ganges- Brahmaputra River plume by the Indian Ocean
807 dipole and eddies inferred from satellite observations. *Journal of Geophysical*
808 *Research: Oceans*, 122(12), pp.9591-9604.

809 Garcia, H. E., Boyer, T. P., Locarnini, R. A., Baranova, O. K. and Zweng, M. M., 2018.
810 World Ocean Database 2018: User's Manual (prerelease). A.V. Mishonov,
811 Technical Ed., NOAA, Silver Spring, MD (Available at
812 https://www.NCEI.noaa.gov/OC5/WOD/pr_wod.html).

813 Gaillard, F., Reynaud, T., Thierry, V., Kolodziejczyk, N. and von Schuckmann, K.,
814 2016. In situ-based reanalysis of the global ocean temperature and salinity with
815 ISAS: Variability of the heat content and steric height. *Journal of Climate*, 29(4),
816 pp.1305-1323.

817 Hareesh Kumar, P.V., Mathew, B., Kumar, M.R.R., Rao, A.R., Jagadeesh, P.S.V.,
818 Radhakrishnan, K.G. and Shyni, T.N., 2013. ‘Thermohaline front’ off the east coast
819 of India and its generating mechanism. *Ocean Dynamics*, 63(11-12), pp.1175-
820 1180.

821 Keerthi, M. G., M. Lengaigne, J. Vialard, C. de Boyer Montégut and P.M.
822 Muraleedharan, 2013: Interannual variability of the Tropical Indian Ocean mixed
823 layer depth, *Clim. Dyn.*, 40, 743-759.

824 Krishnamohan, K.S., Vialard, J., Lengaigne, M., Masson, S., Samson, G., Pous, S.,
825 Neetu, S., Durand, F., Shenoi, S.S.C., Madec, G., Is there an effect of Bay of
826 Bengal salinity on the northern Indian Ocean climatological rainfall?, *Deep-Sea*
827 *Research Part II* (2019), doi: [https:// doi.org/10.1016/j.dsr2.2019.04.003](https://doi.org/10.1016/j.dsr2.2019.04.003)

828 Lagerloef, G., Colomb, F.R., Le Vine, D., Wentz, F., Yueh, S., Ruf, C., Lilly, J., Gunn,
829 J., Chao, Y.I., DECHARON, A. and Feldman, G., 2008. The Aquarius/SAC-D
830 mission: Designed to meet the salinity remote-sensing challenge. *Oceanography*,
831 21(1), pp.68-81.

832 McPhaden, M.J., Meyers, G., Ando, K., Masumoto, Y., Murty, V.S.N., Ravichandran,
833 M., Syamsudin, F., Vialard, J., Yu, L. and Yu, W., 2009. RAMA: the research
834 moored array for African–Asian–Australian monsoon analysis and prediction.
835 *Bulletin of the American Meteorological Society*, 90(4), pp.459-480.

836 Meissner, T., Wentz, F. and Le Vine, D., 2018. The salinity retrieval algorithms for the
837 NASA Aquarius version 5 and SMAP version 3 releases. *Remote Sensing*, 10(7),
838 p.1121.

839 Neetu, S., Lengaigne, M., Vincent, E.M., Vialard, J., Madec, G., Samson, G., Ramesh
840 Kumar, M.R. and Durand, F., 2012. Influence of upper- ocean stratification on
841 tropical cyclone- induced surface cooling in the Bay of Bengal. *Journal of*

842 Geophysical Research: Oceans, 117(C12).

843 Neetu, S., Lengaigne, M., Vialard, J., Samson, G., Masson, S., Krishnamohan, K.S. and
844 Suresh, I., 2019. Premonsoon/Postmonsoon Bay of Bengal Tropical Cyclones
845 Intensity: Role of Air- Sea Coupling and Large- Scale Background State.
846 Geophysical Research Letters, 46(4), pp.2149-2157.

847 Oliva, R., Daganzo, E., Richaume, P., Kerr, Y., Cabot, F., Soldo, Y., Anterrieu, E., Reul,
848 N., Gutierrez, A., Barbosa, J. and Lopes, G., 2016. Status of Radio Frequency
849 Interference (RFI) in the 1400–1427 MHz passive band based on six years of
850 SMOS mission. Remote sensing of environment, 180, pp.64-75.

851 Pant, V., Girishkumar, M.S., Udaya Bhaskar, T.V.S., Ravichandran, M., Papa, F. and
852 Thangaprakash, V.P., 2015. Observed interannual variability of near- surface
853 salinity in the Bay of Bengal. Journal of Geophysical Research: Oceans, 120(5),
854 pp.3315-3329.

855 Papa, F., Bala, S.K., Pandey, R.K., Durand, F., Gopalakrishna, V.V., Rahman, A. and
856 Rossow, W.B., 2012. Ganga- Brahmaputra river discharge from Jason- 2 radar
857 altimetry: An update to the long- term satellite- derived estimates of continental
858 freshwater forcing flux into the Bay of Bengal. Journal of Geophysical Research:
859 Oceans, 117(C11).

860 Papa, F., Durand, F., Rossow, W.B., Rahman, A. and Bala, S.K., 2010. Satellite
861 altimeter- derived monthly discharge of the Ganga- Brahmaputra River and its
862 seasonal to interannual variations from 1993 to 2008. Journal of Geophysical
863 Research: Oceans, 115(C12).

864 Prasanna Kumar, S., Muraleedharan, P.M., Prasad, T.G., Gauns, M., Ramaiah, N., De
865 Souza, S.N., Sardesai, S. and Madhupratap, M., 2002. Why is the Bay of Bengal
866 less productive during summer monsoon compared to the Arabian Sea?.
867 Geophysical Research Letters, 29(24), pp.88-1.

868 Rao, R.R. and Sivakumar, R., 2003. Seasonal variability of sea surface salinity and salt
869 budget of the mixed layer of the north Indian Ocean. Journal of Geophysical
870 Research: Oceans, 108(C1), pp.9-1.

- 871 Reul, N., Fournier, S., Boutin, J., Hernandez, O., Maes, C., Chapron, B., Alory, G.,
872 Quilfen, Y., Tenerelli, J., Morisset, S. and Kerr, Y., 2014. Sea surface salinity
873 observations from space with the SMOS satellite: A new means to monitor the
874 marine branch of the water cycle. *Surveys in Geophysics*, 35(3), pp.681-722.
- 875 Roemmich, D., Johnson, G. C., Riser, S., Davis, R., Gilson, J., Owens, W. B., Garzoli,
876 S. L., Schmid, C. and Ignaszewski, M., 2009. The Argo Program: Observing the
877 global ocean with profiling floats. *Oceanography*, 22(2), 34–43.
- 878 Saji, N.H., Goswami, B.N., Vinayachandran, P.N. and Yamagata, T., 1999. A dipole
879 mode in the tropical Indian Ocean. *Nature*, 401(6751), p.360.
- 880 Sengupta, D., Goddalahundi, B.R. and Anitha, D.S., 2008. Cyclone- induced mixing
881 does not cool SST in the post- monsoon north Bay of Bengal. *Atmospheric
882 Science Letters*, 9(1), pp.1-6.
- 883 Sengupta, D., Bharath Raj, G.N., Ravichandran, M., Sree Lekha, J. and Papa, F., 2016.
884 Near- surface salinity and stratification in the north Bay of Bengal from moored
885 observations. *Geophysical Research Letters*, 43(9), pp.4448-4456.
- 886 Shaaban, A. A., & Roundy, P. E. (2017). OLR perspective on the Indian Ocean Dipole
887 with application to East African precipitation. *Quarterly Journal of the Royal
888 Meteorological Society*, 143(705), 1828-1843.
- 889 Shenoi, S.S.C., Shankar, D. and Shetye, S.R., 2002. Differences in heat budgets of the
890 near- surface Arabian Sea and Bay of Bengal: Implications for the summer
891 monsoon. *Journal of Geophysical Research: Oceans*, 107(C6), pp.5-1.
- 892 Sherin, V.R., Durand, F., Gopalkrishna, V.V., Anuvinda, S., Chaitanya, A.V.S.,
893 Bourdallé-Badie, R., and Papa, F., 2018. Signature of Indian Ocean Dipole on the
894 western boundary current of the Bay of Bengal. *Deep Sea Research Part I:
895 Oceanographic Research Papers*, 136, 91-106.
- 896 Shetye, S.R., 1993. The movement and implications of the Ganges—Bramhaputra runoff
897 on entering the. *Current Science*, 64(1), 32–38.
- 898 Shetye, S. R., Gouveia, A. D., Shankar, D., Michael, G. S. and Nampoothiri, G., 1996.

899 Hydrography and circulation of the western Bay of Bengal during the Northeast
900 Monsoon, *Journal of Geophysical Research*, 101, 14,011 – 14,025.

901 Sudre, J., Maes, C. and Garçon, V., 2013. On the global estimates of geostrophic and
902 Ekman surface currents. *Limnology and Oceanography: Fluids and Environments*,
903 3(1), pp.1-20.

904 Subrahmanyam, B., Grunseich, G. and Nyadjro, E.S., 2012. Preliminary SMOS salinity
905 measurements and validation in the Indian Ocean. *IEEE Transactions on*
906 *Geoscience and Remote Sensing*, 51(1), pp.19-27.

907 Suresh, I., Vialard, J., Lengaigne, M., Izumo, T., Parvathi, V. and Muraleedharan, P.M.,
908 2018. Sea level interannual variability along the west coast of India. *Geophysical*
909 *Research Letters*, 45(22), pp.12-440.

910 Thadathil, P., Suresh, I., Gautham, S., Prasanna Kumar, S., Lengaigne, M., Rao, R.R.,
911 Neetu, S. and Hegde, A., 2016. Surface layer temperature inversion in the Bay of
912 Bengal: Main characteristics and related mechanisms. *Journal of Geophysical*
913 *Research: Oceans*, 121(8), pp.5682-5696.

914 Webster, P. J., Moore, A. M. , Loschnigg, J. P. and Leben, R. R., 1999. Coupled
915 ocean- atmosphere dynamics in the Indian Ocean during 1997–98, *Nature*, 401,
916 356–360, doi:10.1038/43848.

917 Wijesekera, H.W., Shroyer, E., Tandon, A., Ravichandran, M., Sengupta, D., Jinadasa,
918 S.U.P., Fernando, H.J., Agrawal, N., Arulananthan, K., Bhat, G.S. and
919 Baumgartner, M., 2016. ASIRI: An ocean–atmosphere initiative for Bay of
920 Bengal. *Bulletin of the American Meteorological Society*, 97(10), pp.1859-1884.

921 Yueh, S.H., Tang, W., Fore, A.G., Neumann, G., Hayashi, A., Freedman, A., Chaubell,
922 J. and Lagerloef, G.S., 2013. L-band passive and active microwave geophysical
923 model functions of ocean surface winds and applications to Aquarius retrieval.
924 *IEEE Transactions on Geoscience and Remote Sensing*, 51(9), pp.4619-4632.

925 Yueh, S., Tang, W., Fore, A., Hayashi, A., Song, Y.T. and Lagerloef, G., 2014. Aquarius
926 geophysical model function and combined active passive algorithm for ocean
927 surface salinity and wind retrieval. *Journal of Geophysical Research: Oceans*,

928 119(8), pp.5360-5379.

929 Zweng, M. M, Reagan, J. R., Seidov, D., Boyer, T. P., Locarnini, R. A., Garcia, H. E.,
930 Mishonov, A. V., Baranova, O. K., Paver, C. R., Weathers, K. W., Smolyar, I.
931 (2018): World Ocean Atlas 2018, Volume 2: Salinity. NOAA Atlas NESDIS (Vol.
932 82). <https://www.nodc.noaa.gov/OC5/woa18/pubwoa18.html>

Name in this paper	Obtained from	Product version	Temporal resolution	Spatial grid resolution	Analyzed period
SMOS-old	https://www.catds.fr/Products/Available-products-from-CEC-OS/CEC-Ifremer-Dataset-V02	“SSS_SMOS_L3_CATDS_CECOS_V02”	10day running mean maps every 10 days	0.25°X0.25°	May 2010 to June 2017
SMOS-new	https://www.catds.fr/Products/Available-products-from-CEC-OS/CEC-Locean-L3-Debiased-v4	“L3_DEBIAS_LOCEAN_v4”	9day running mean maps every 4 days	0.25°X0.25°	January 2010 to September 2019
Aquarius	https://podaac.jpl.nasa.gov/dataset/AQUARIUS_L3_SSS_CAP_7DAY_V5	“L3m_7D_SCI_V5.0”	7day running mean maps every 7days	1°X1°	August 2011 to June 2015
SMAP	https://podaac.jpl.nasa.gov/dataset/SMAP_JPL_L3_SSS_CAP_8DAY-RUNNINGMEAN_V43	“L3V4.3_SSS_8DAYS_R13080”	8day running mean maps every day	0.25°X0.25°	April 2015 to December 2019

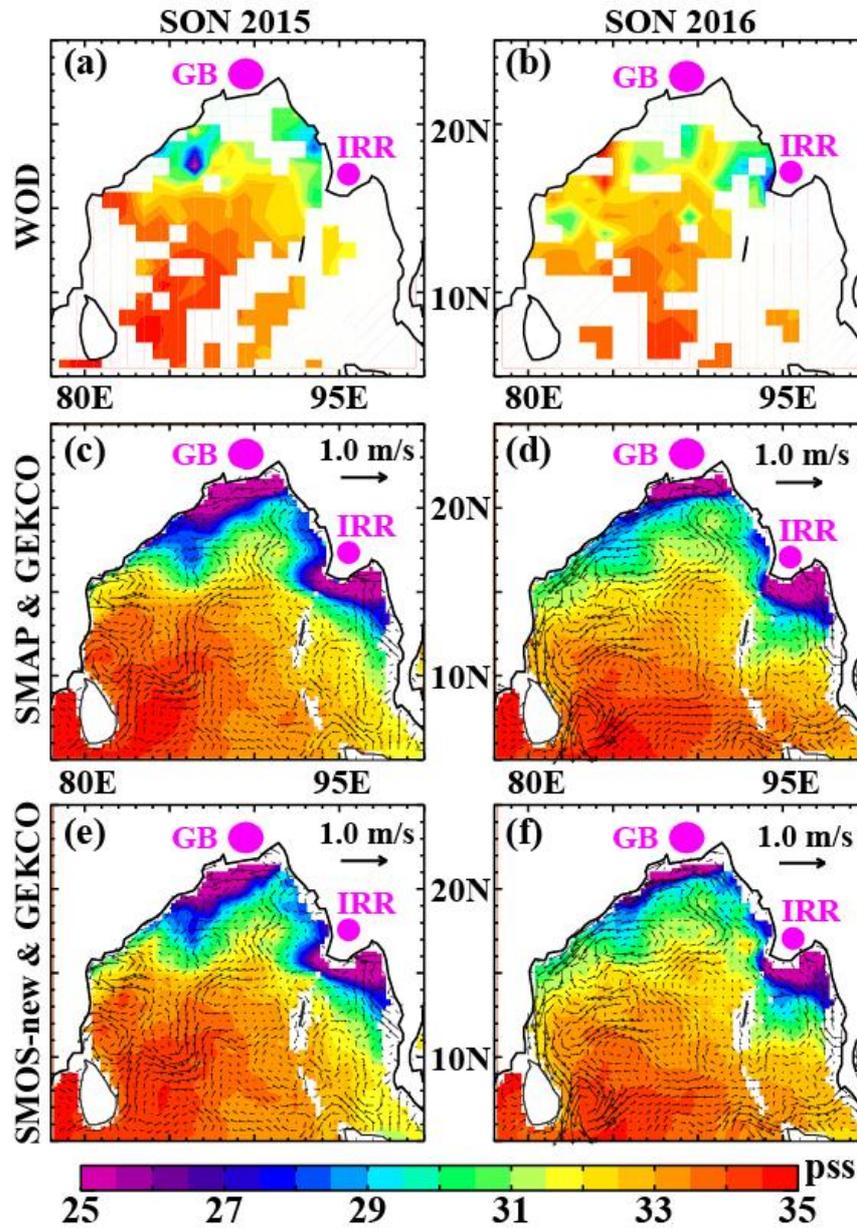
934 **Table 1.** Sea Surface Salinity products used in the current study. More details on the
935 differences between the two SMOS datasets used in this study can be found on the
936 CATDS (Centre Aval de Traitement des Données SMOS) website at
937 “https://www.catds.fr/content/download/68781/file/OS_L3_products_Differences_and_ProsCons.pdf”.

939

Correlation	DMI	SDI	ODI	WDI
DMI	1 (1)	0.89 (0.86)	0.83 (0.74)	0.88 (0.78)
SDI	0.89 (0.86)	1 (1)	0.91 (0.92)	0.97 (0.96)

940 **Table 2.** Correlation between the four IOD indices used in this study over the 1993-2018
941 period, with values over the 2010-2018 study period within brackets The DMI index is
942 the SSTA-based index introduced by Saji et al. (1999). ODI (Outgoing longwave
943 radiation-based dipole index) is the alternative index proposed by Shaaban and Roundy
944 (2017). We also propose two indices that focus on the oceanic dynamical response based
945 on sea level anomalies (SDI for Sea level Dipole Index) and zonal wind stress anomalies
946 (WDI for Wind stress Dipole Index). The definition of these four IOD indices is detailed
947 in Figure 3 and in the method section. The correlations provided in this table are all
948 significantly different from zero above the 99% confidence level, considering each year
949 as an independent sample.

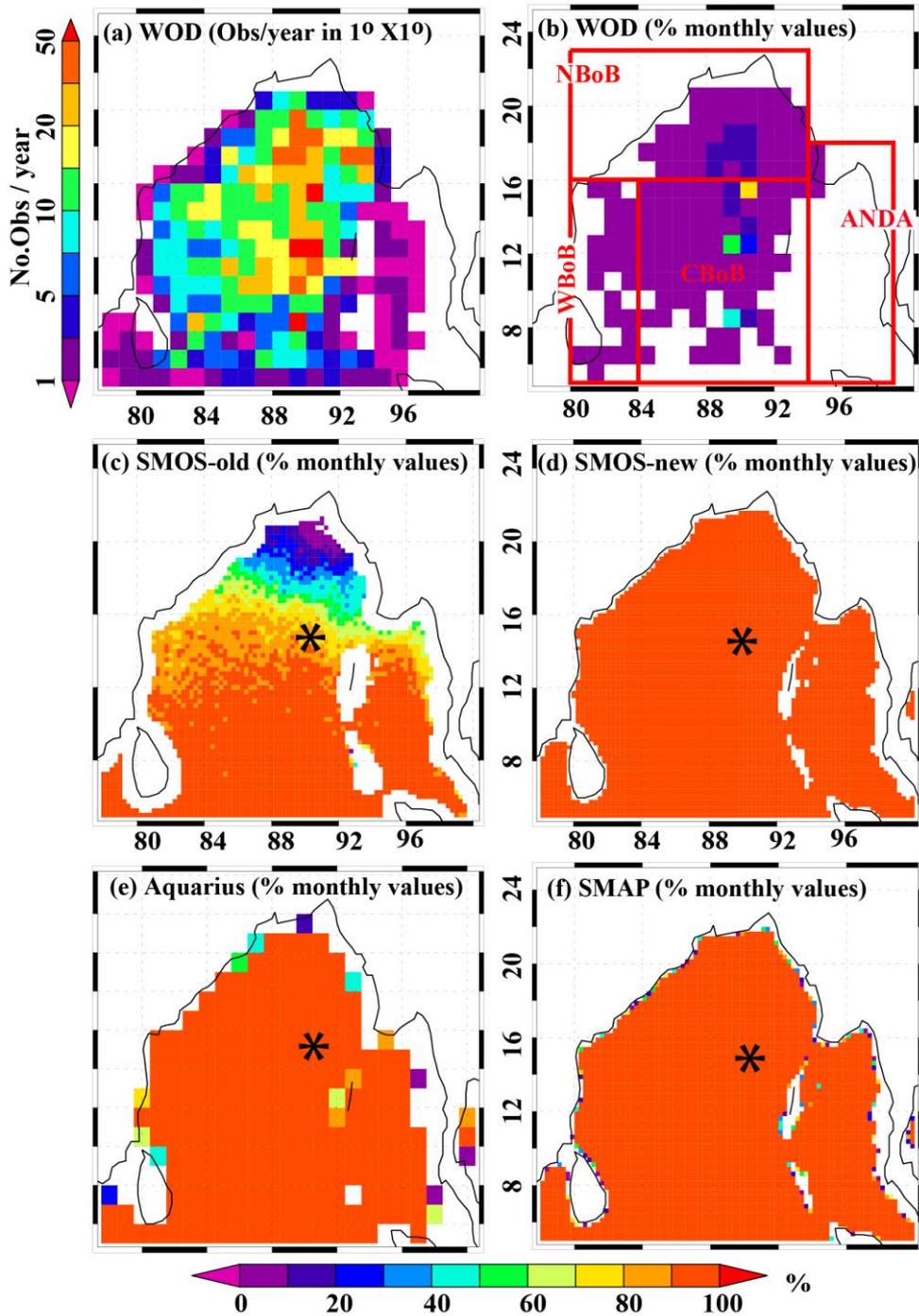
950



951

952 **Figure 1.** September to November (SON) average map of (a, b) World Ocean Data
 953 (WOD) sea surface salinity (SSS), (c, d) SMAP SSS (color) and GEKCO currents
 954 (vector), (e, f) SMOS-new SSS (color) and GEKCO currents (vector) for (1st column)
 955 2015 and (2nd column) 2016. The location of the Ganges-Brahmaputra (GB) and
 956 Irrawaddy (IRR) estuaries, the two main river systems in to the Bay of Bengal (BoB),
 957 are marked on the panels.

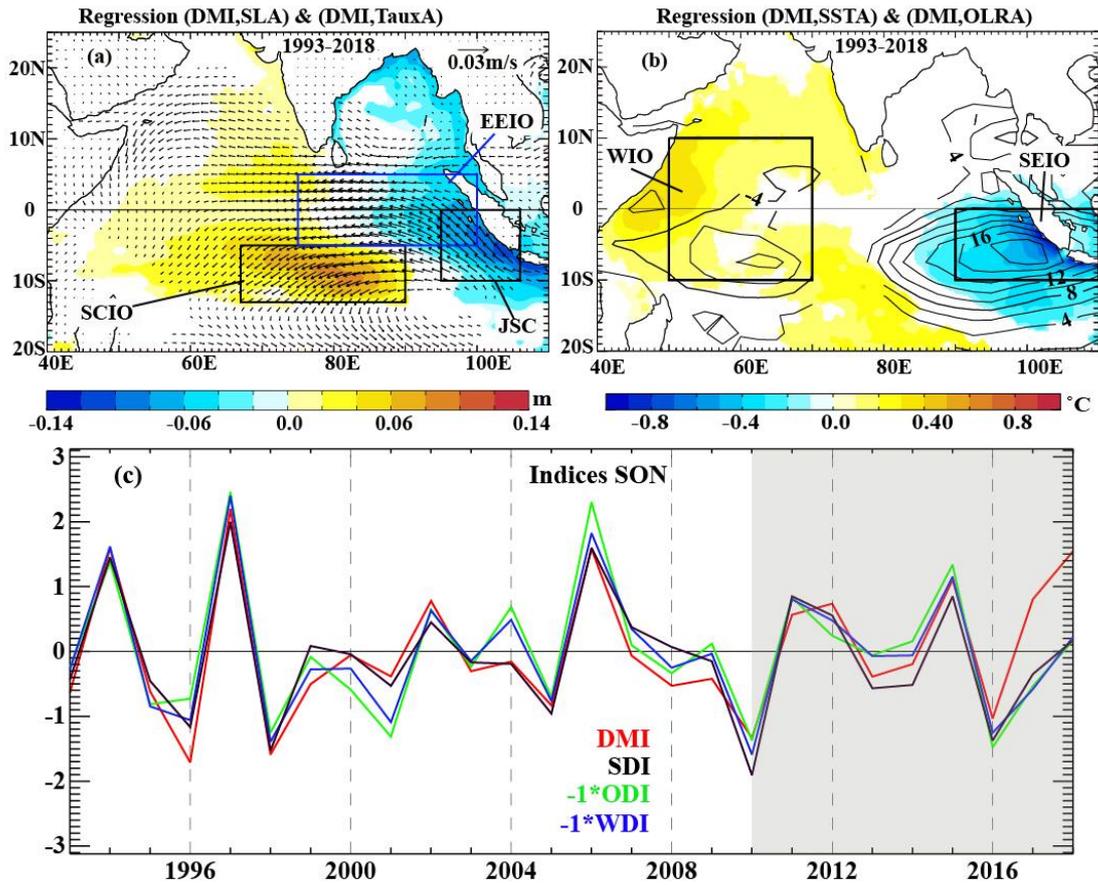
958



959

960 **Figure 2.** (a) Total number of WOD *in situ* observations, per year and per $1^\circ \times 1^\circ$ boxes
 961 above 5m depth. (b - f) Percent of months with SSS data from (b) WOD (only $1^\circ \times 1^\circ$
 962 pixels having more than 5 data per month are considered as valid SSS data), (c) SMOS-
 963 old, (d) SMOS-new, (e) Aquarius and (f) SMAP. See **Table 1** for the time period
 964 covered by each dataset. The star indicates the $[15^\circ\text{N}, 90^\circ\text{E}]$ RAMA mooring location.

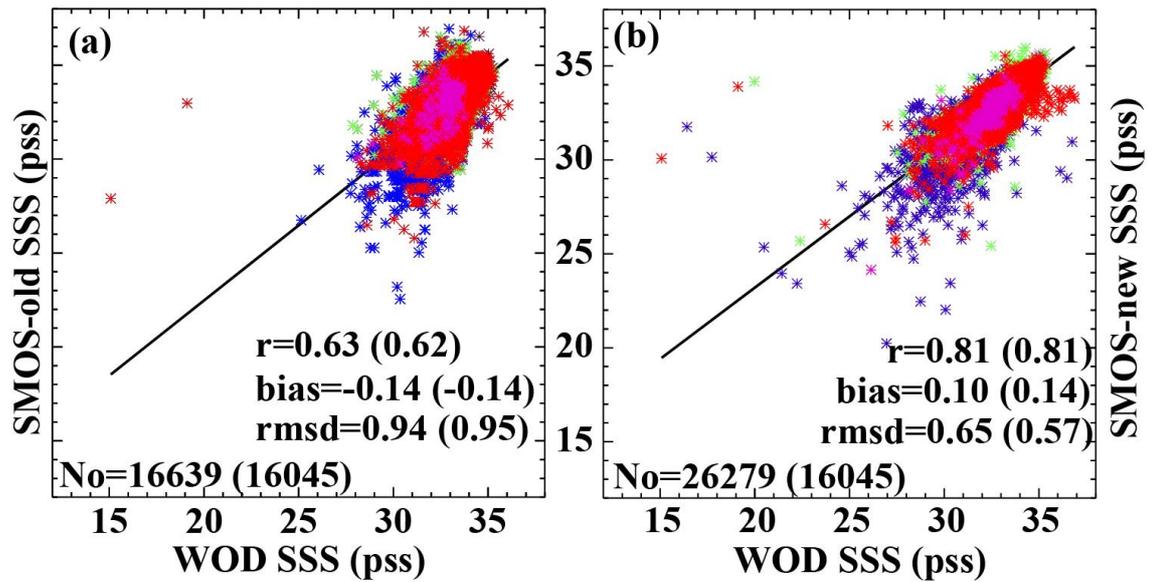
965



966

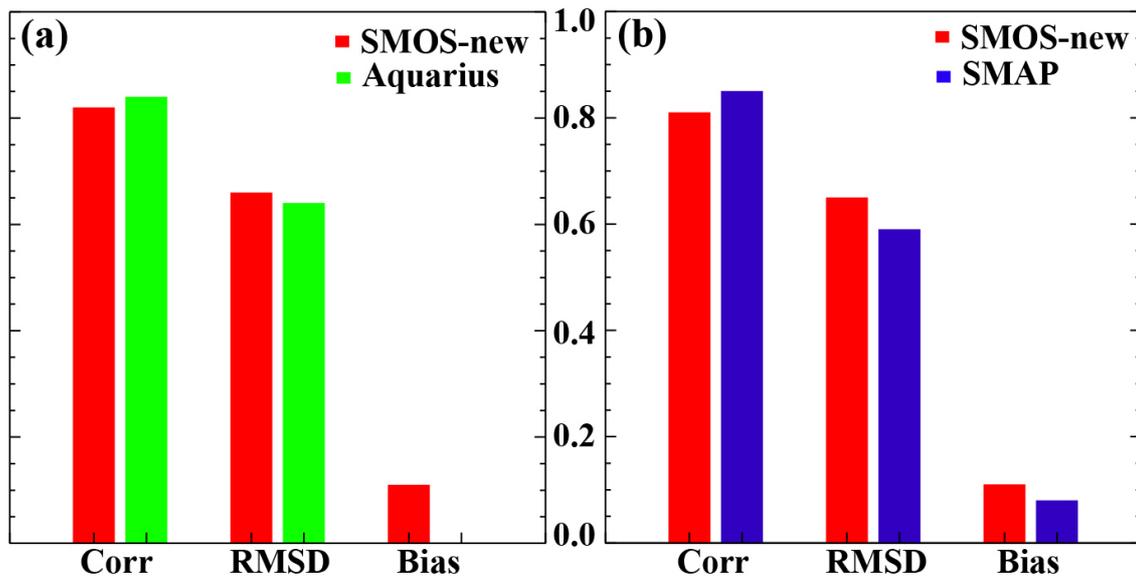
967

968 **Figure 3.** Regression of interannual anomalies of (a) wind stress (vectors) and sea level
 969 (colors) and (b) SST (colors) and Outgoing Longwave Radiation (OLR, W.m⁻²,
 970 contours) onto the DMI in September-October-November (SON) over the 1993-2018
 971 period. Values are masked only when they are not significantly different from zero at the
 972 90% confidence level. (c) Time series of the four IOD indices used in this study over
 973 1993-2018 period. The sea level dipole index (SDI) is computed as the SLA difference
 974 between the south central Indian Ocean and Java/Sumatra Coast (see black frames on
 975 panel a denoted respectively SCIO and JSC). The wind stress dipole index (WDI) is
 976 taken as the zonal wind stress averaged over the eastern equatorial Indian Ocean (see
 977 blue box denoted EEIO on panel a). The OLR-based index (ODI) is computed as the
 978 difference of OLR anomalies between the western Indian Ocean and the southeastern
 979 Indian Ocean (see black frames on panel b denoted respectively WIO and SEIO, those
 980 are the same boxes as those used to define the DMI by Saji et al. 1999). Correlations
 981 between these different indices are provided on Table 2. The shading on panel (c)
 982 highlights the 2010-2018 period, for which the interannual variability of Sea Surface
 983 Salinity is analyzed in the current paper.



984
 985
 986
 987
 988
 989
 990
 991

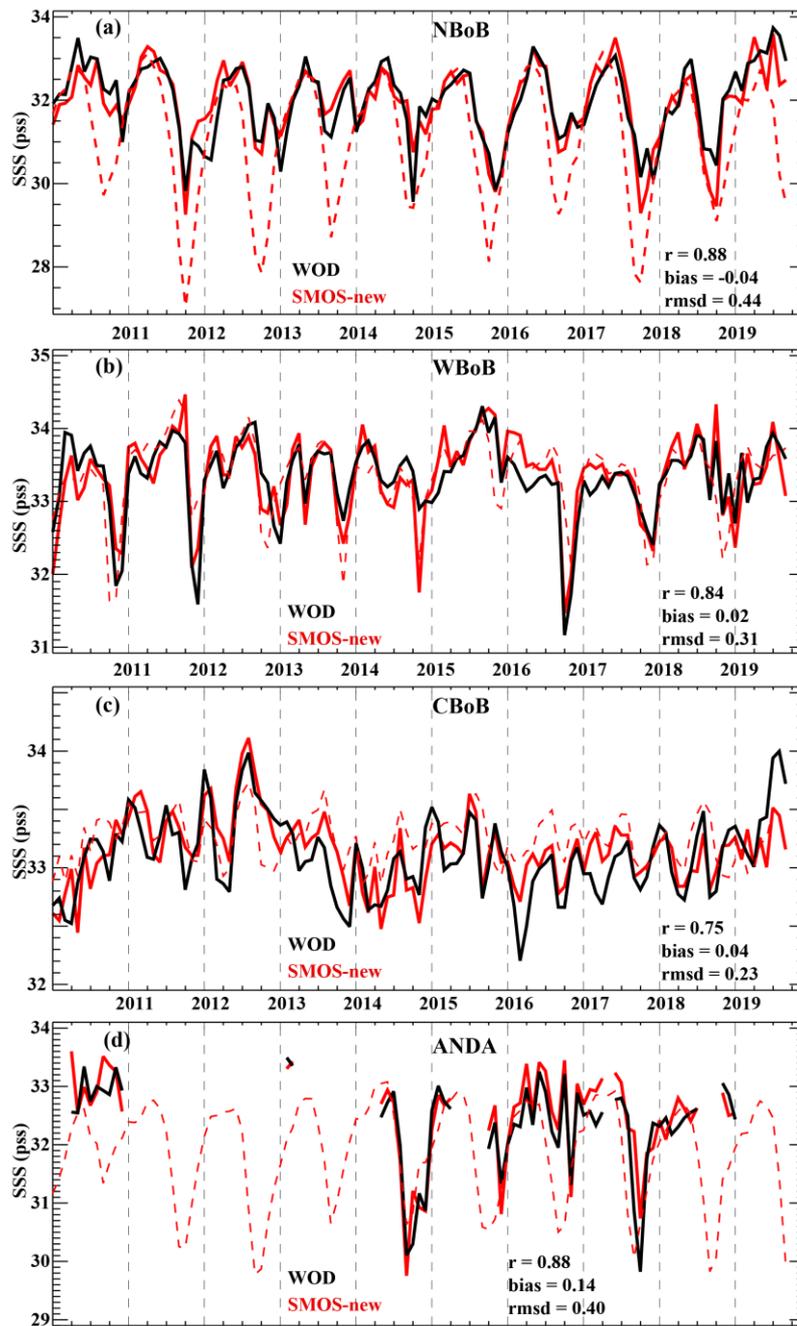
Figure 4. Scatterplot of co-located WOD Bay of Bengal (BoB) SSS against (a) SMOS-old (2010-2017) and (b) SMOS-new (2010 to 2019). The correlation (r), bias, and root-mean-square difference (rmsd) to the WOD data are indicated on each panel (the number in brackets provide those statistics for the common period to WOD, SMOS-old and SMOS-new).



993

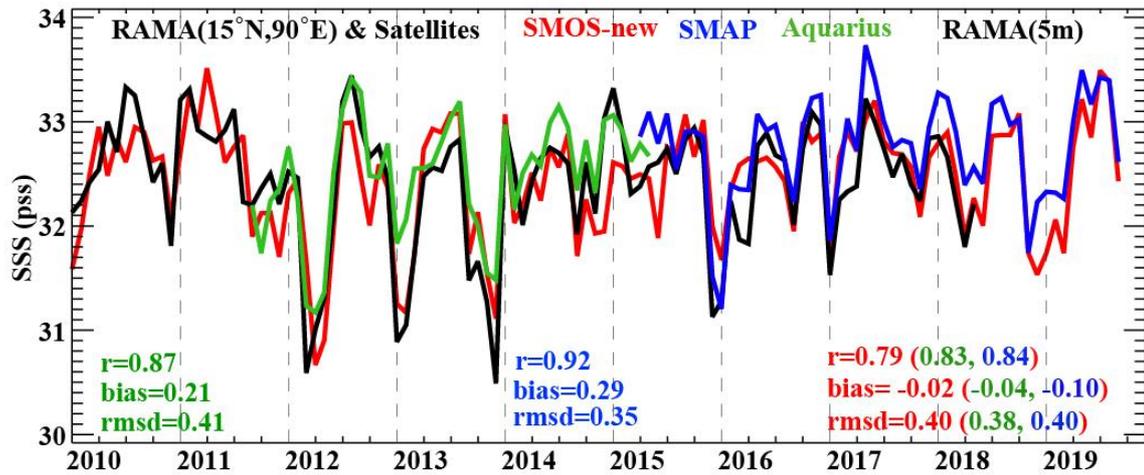
994 **Figure 5.** (a) Bar diagrams of statistics of comparisons between co-located SMOS-new
 995 and Aquarius with *in situ* data over their common period (August 2011 to June 2015)
 996 and over the entire BoB. (b) Same as (a) but for SMOS-new & SMAP (April 2015 to
 997 October 2019). The statistics on this figure are strictly comparable, since both satellite
 998 datasets on each panel are compared to their common co-located *in situ* data sample. The
 999 Y-axis scale in the middle is common to both panels. The correlation has no unit, and
 1000 the RMSD and bias are in °C.

1001



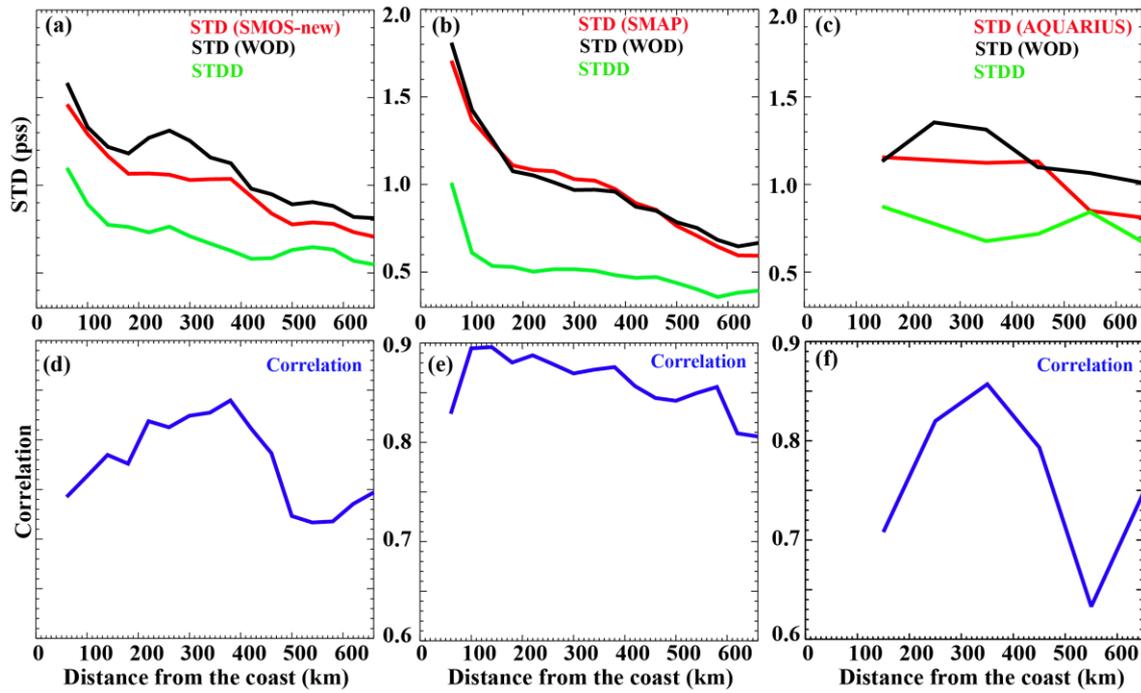
1002

1003 **Figure 6.** Timeseries of averaged co-located SMOS-new (red continuous line) and
 1004 WOD SSS (black continuous line) within the (a) NBoB, (b) WBoB, (c) CBoB and (d)
 1005 ANDA regions (see figure 2 for their definitions). The corresponding statistics are
 1006 indicated on each panel (these statistics differ from the ones in Figure 7, because these
 1007 are based on box-averaged quantities, not on individual co-located measurements). The
 1008 red dashed curve shows the box averaged SMOS-new data in each region (different from
 1009 the red full curve because it accounts for values everywhere in the box, not just for co-
 1010 located values with *in situ* data).



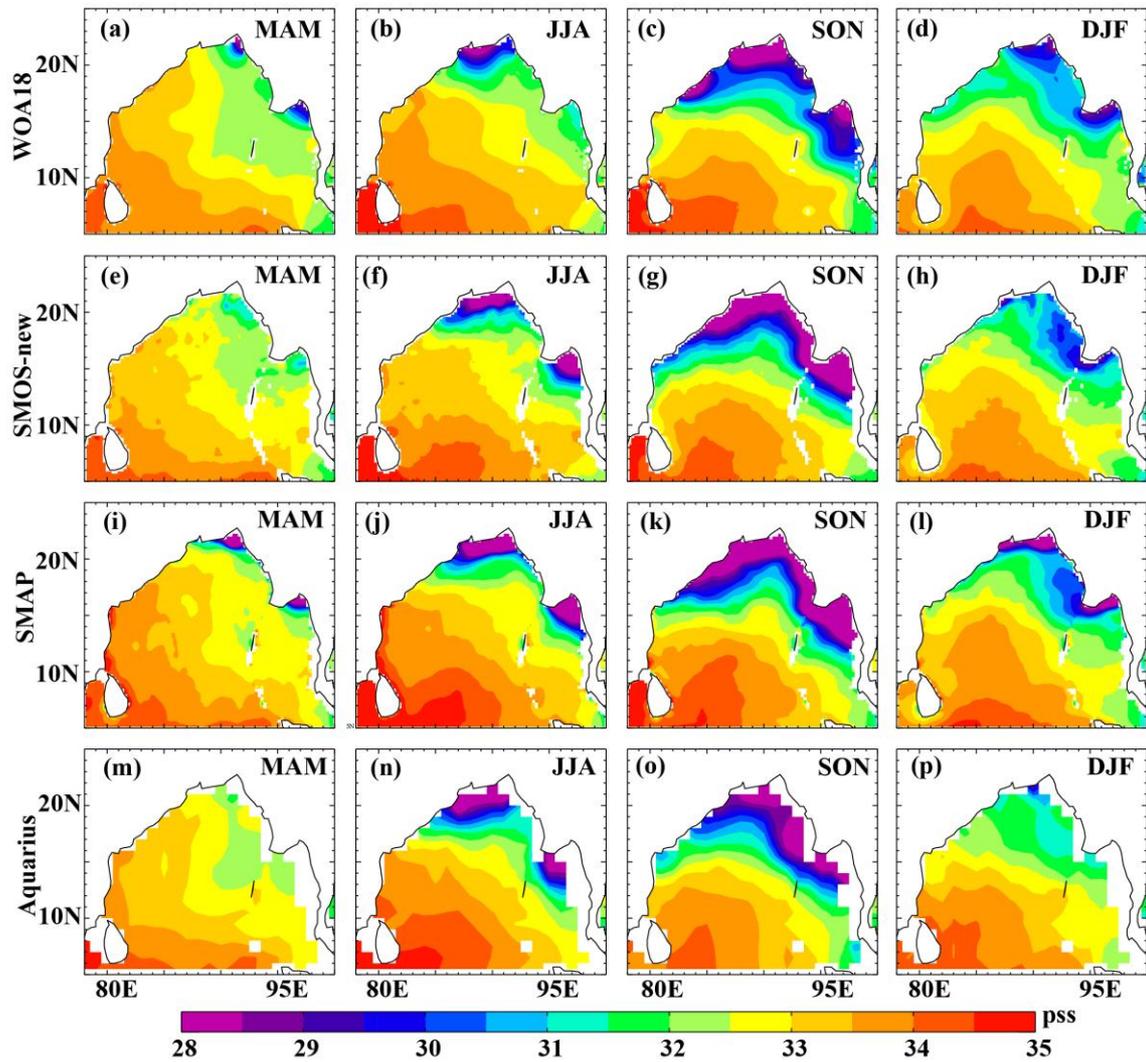
1011
 1012
 1013
 1014
 1015
 1016
 1017
 1018
 1019

Figure 7. Time series of the salinity at 5m depth from the 15°N-90°E RAMA mooring (black) and co-located SMOS-new (red), Aquarius (green) and SMAP (blue) satellite data. The correlation (r), bias and root-mean-square difference (rmsd) of each dataset to RAMA are given in red for SMOS-new, green for Aquarius and blue for SMAP. The number in brackets give the SMOS-new statistics for the period common to Aquarius (in green) and SMAP (in blue).

1021
1022

1023 **Figure 8.** (a) Standard deviation (STD, $^{\circ}\text{C}$) of co-located SMOS-new SSS (red) and
 1024 WOD SSS (black), and standard deviation of their difference (STDD, $^{\circ}\text{C}$, green) as a
 1025 function of distance to the coast (40-km wide bins) from east coast of India 10°N - 20.5°N
 1026 and 78°E - 90°E . (d) Correlation coefficient between SMOS-new SSS (blue) and co-
 1027 located WOD SSS as a function of distance to the coast (40-km wide bins) from east
 1028 coast of India 10°N - 20.5°N and 78°E - 90°E . (b, e) Same as a, d but for SMAP. (c, f)
 1029 Same as a, d but for Aquarius (but using 100-km wide bins).

1030

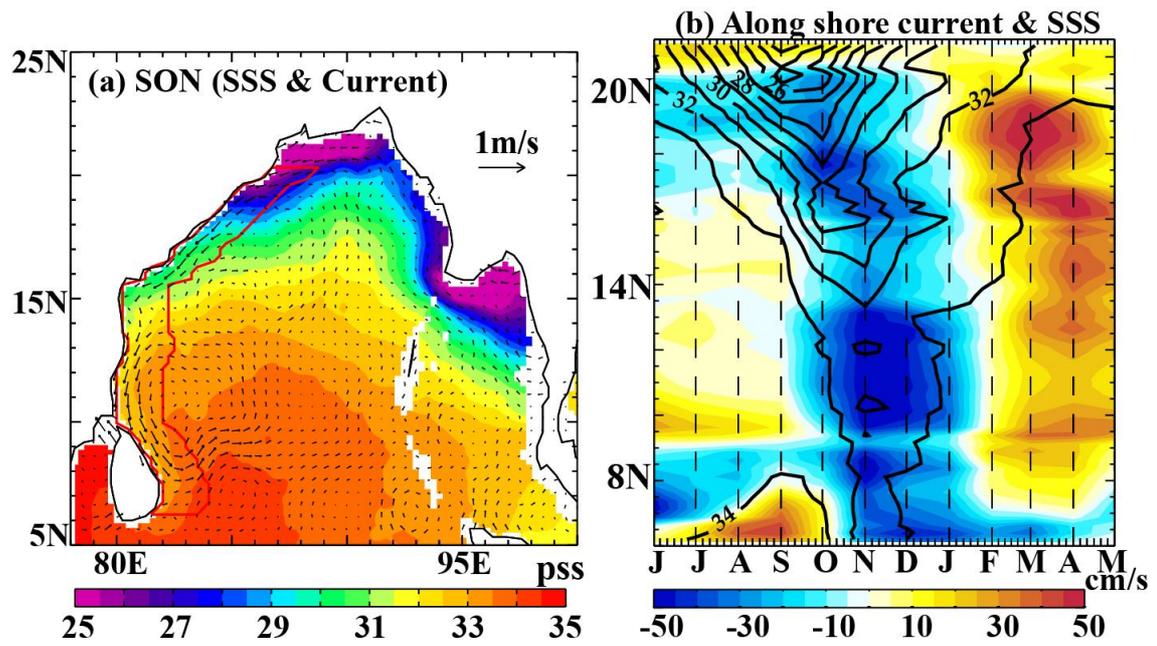


1031

1032

1033 **Figure 9.** Seasonal climatology of SSS in the BoB from (a-d) WOA18, (e-h) SMOS-
 1034 new (January 2010-September 2019), (i-l) SMAP (April 2015-December 2019) and (m-
 1035 p) Aquarius (August 2011-June2015).

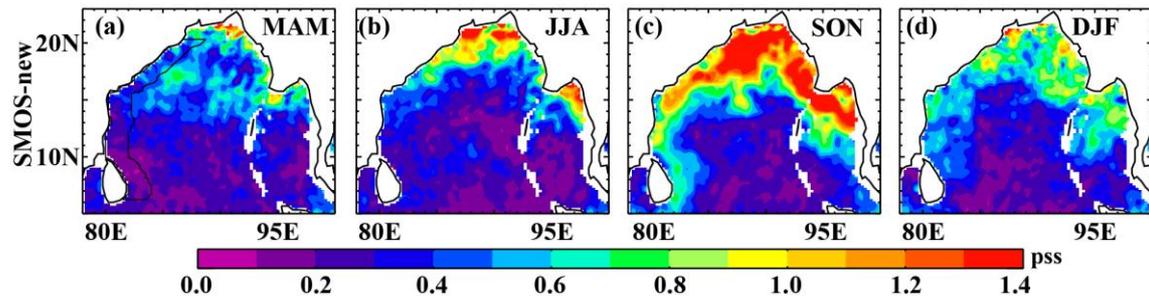
1036



1037

1038 **Figure 10.** (a) Climatological SON SMOS-new SSS (color) and SON GEKCO surface
 1039 current (vectors). The red frame on panel (a) indicates the region used for the latitude-
 1040 time section on panel (b). (b) Latitude-time section of the SMOS-new SSS (contours,
 1041 pss) and GEKCO along-shore current (color, negative values indicate southward current)
 1042 seasonal cycle in the coastal box defined in (a).

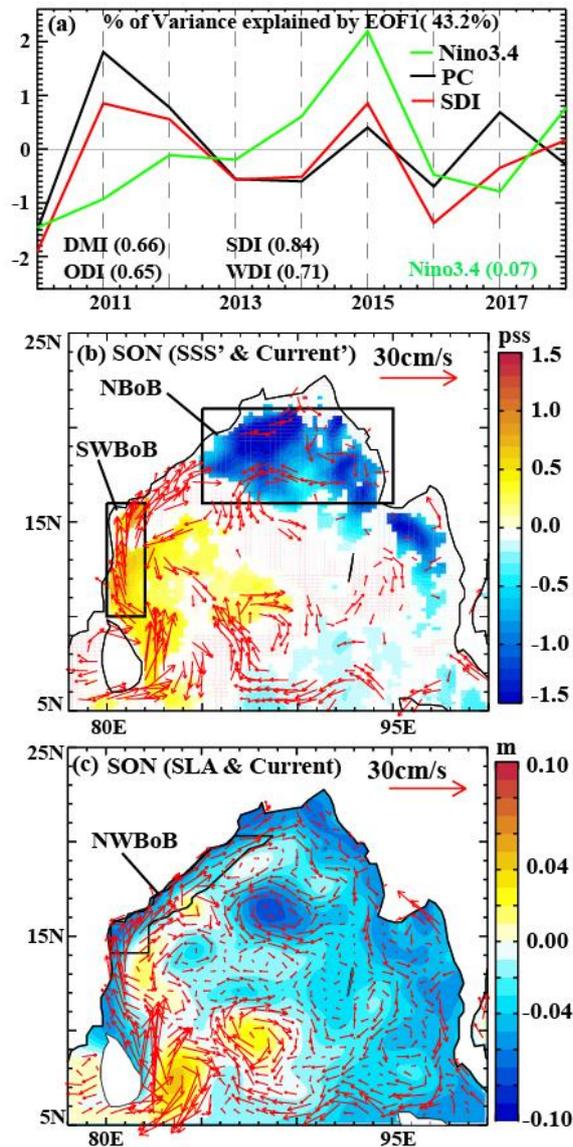
1043



1044

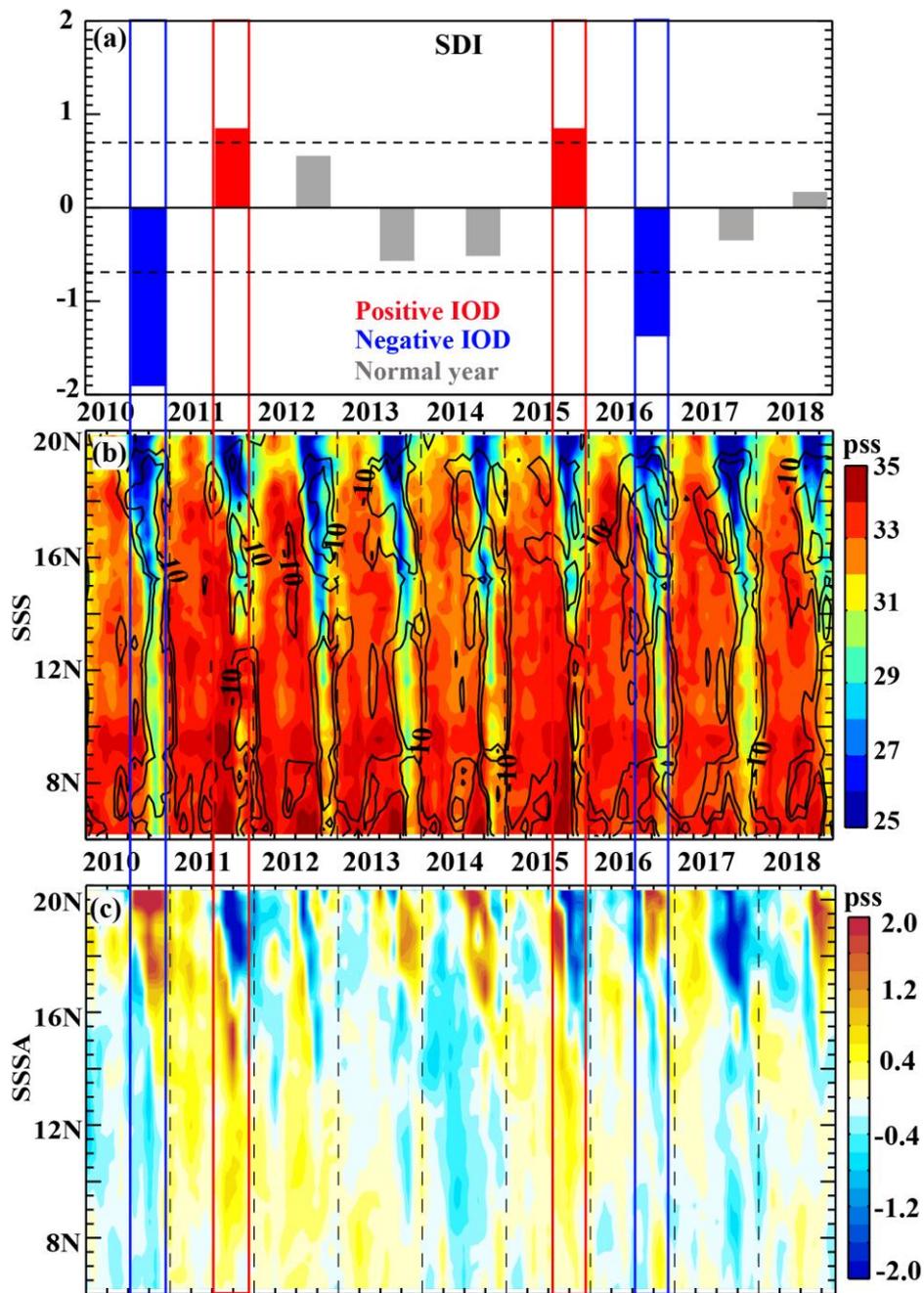
1045 **Figure 11.** Standard deviation of SMOS-new (January 2010-September 2019) SSS
 1046 interannual anomalies for (a) MAM, (b) JJA, (c) SON and (d) DJF. The black frame on
 1047 panel (a) indicates the box that is used for the latitude-time section in Figure 12.

1048



1049

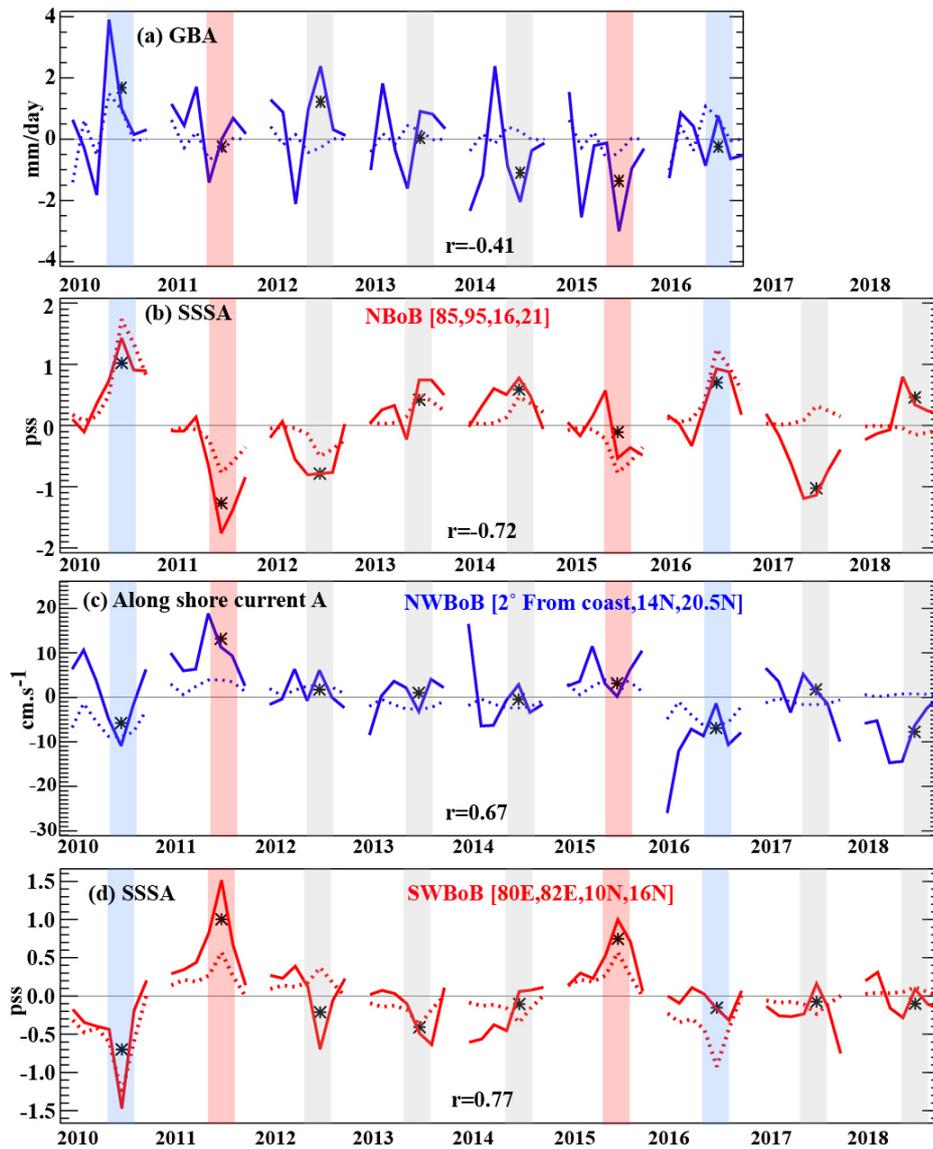
1050 **Figure 12.** (a) Time series of the normalized principal component (PC1) of the first
 1051 mode from an empirical orthogonal function (EOF) analysis of SON SMOS-new SSS
 1052 interannual anomalies (black), normalized SON SLA-based Dipole Mode Index (SDI,
 1053 red, see figure 3 and method section for definition) and ENSO index (Niño34, green)
 1054 over the 2010-2018 period. The correlation of PC1 with the four different IOD indices
 1055 and Niño3.4 index defined in the method section are indicated at the bottom of the panel.
 1056 (b) Regression of SON SMOS-new SSS interannual anomalies (SSS', color) and
 1057 GEKCO surface current interannual anomalies (Current', vectors) to PC1 over the 2010-
 1058 2018 period. Signals that are not significantly different from zero at the 90% confidence
 1059 level are masked. (c) Regression of SON AVISO SLA (shading), GEKCO surface
 1060 current interannual anomalies (vectors) to SON SDI over the 2010-2018 period. The
 1061 frames on panels (b) and (c) are used in Figure 14.



1062

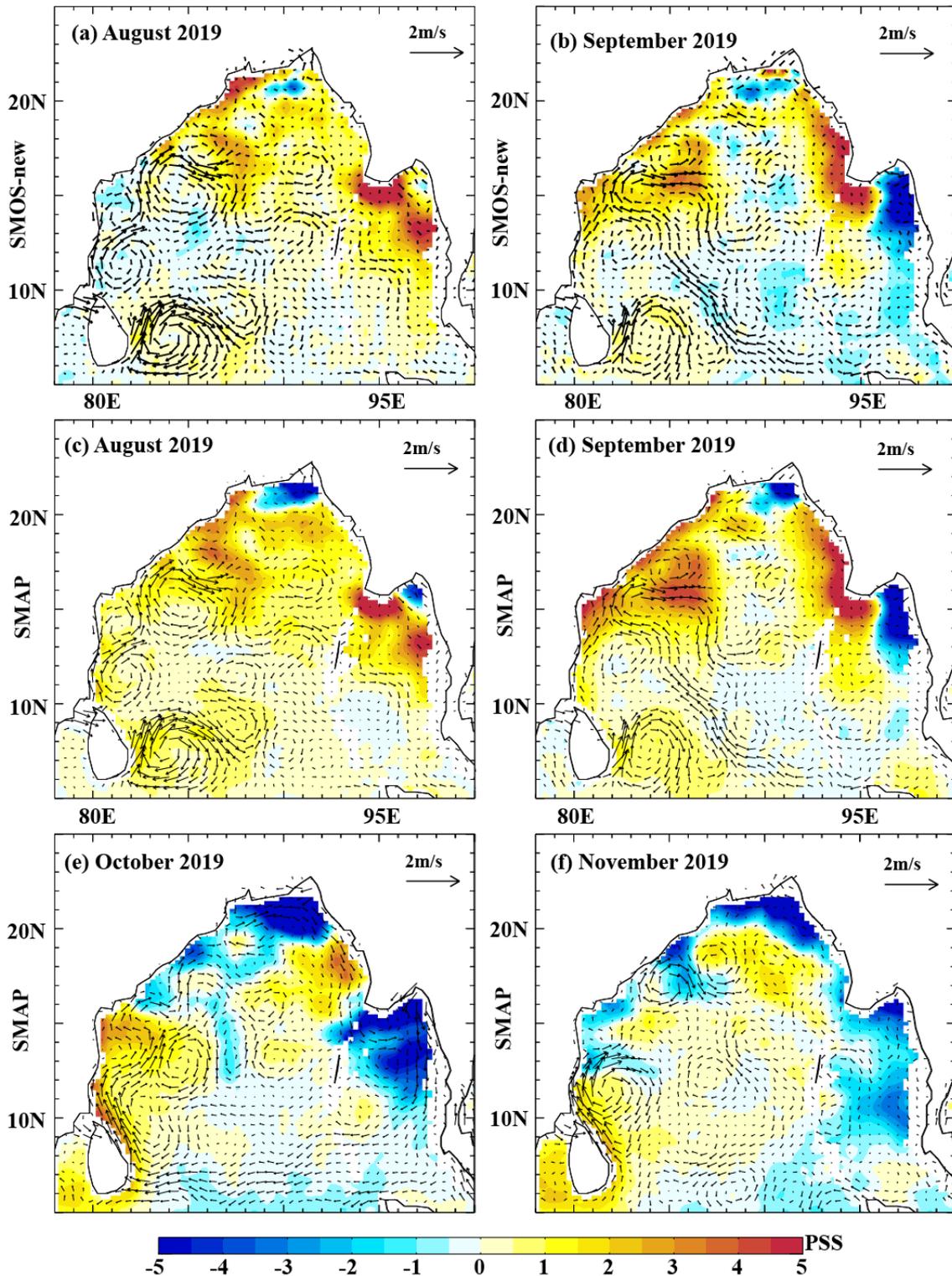
1063 **Figure 13.** (a) Bar diagram of average SON SLA-based dipole index (SDI) from 2010 to
 1064 2018. Latitude time section along the East Indian coast (boxes on Figure 10a and 11a) of
 1065 monthly (b) SMOS-new SSS (colors, pss) and GEKCO along-shore current (Contour,
 1066 cm/s; only southward currents are plotted as continuous contours every 0.1 m.s^{-1}), (c)
 1067 SMOS-new SSS interannual anomalies (colors, pss). The blue (red) frames delineate the
 1068 September-November period of the two negative (positive) IOD years in 2010 and 2016
 1069 (2011 and 2015).

1070



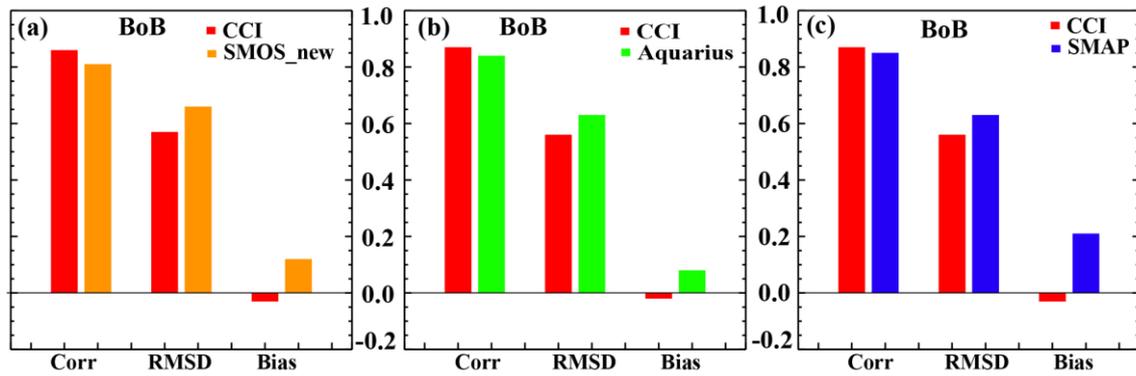
1071

1072 **Figure 14:** Time series of June to December for (a) Ganges-Brahmaputra River
 1073 discharge anomaly (GBA, Blue; converted in $\text{mm}\cdot\text{day}^{-1}$ in NBoB oceanic area depicted
 1074 on Figure 2b), (b) SSS anomaly in NBoB (red), (c) along-shore current anomaly (blue)
 1075 in northwestern BoB (NWBoB, i.e. 2° from the coast along the east Indian coast; 14°N -
 1076 20.5°N ; see frame on Figure 12c), (d) SSS anomaly (red) in southwestern BoB
 1077 (SWBoB; 80°E - 82°E - 10°N - 16°N ; see frame on Figure 12b). Dotted lines correspond to
 1078 “typical” IOD signals, obtained by regressing interannual anomalies on the normalized
 1079 SDI). Bars indicate the SON period (red for positive IOD years, blue for negative years
 1080 and grey for normal years, derived from the SDI). Stars represent the mean SON values.
 1081 The correlation (r) between the SON SDI and SON interannual anomalies of each
 1082 variable is given on each panel.



1083

1084 **Figure 15:** (a-b) August and September 2019 SMOS-new SSS anomalies (color)
 1085 overlaid with GEKCO current anomaly (vector). (c-f) August to November 2019 SMAP
 1086 SSS anomalies (color) overlaid with GEKCO current anomaly (vector). For this plot, the
 1087 climatology is computed using the common June 2015 to May 2019 SMOS-new and
 1088 SMAP period.



1089

1090 **Figure 16:** Bar diagrams of comparisons between satellite products and co-located *in*
 1091 *situ* SSS data over the entire BoB. The merged CCI-SSS product (2010 to October 2018)
 1092 is compared with (a) SMOS-new, (b) Aquarius and (c) SMAP over their common
 1093 periods. The statistics on this figure are strictly comparable, since both satellite datasets
 1094 on each panel are compared to the same common *in situ* data sample.