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## New SMOS Sea Surface Salinity with reduced systematic errors and improved variability

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### Abstract :

Salinity observing satellites have the potential to monitor river fresh-water plumes mesoscale spatio-temporal variations better than any other observing system. In the case of the Soil Moisture and Ocean Salinity (SMOS) satellite mission, this capacity was hampered due to the contamination of SMOS data processing by strong land-sea emissivity contrasts. Kolodziejczyk et al. (2016) (hereafter K2016) developed a methodology to mitigate SMOS systematic errors in the vicinity of continents, that greatly improved the quality of the SMOS Sea Surface Salinity (SSS). Here, we find that SSS variability, however, often remained underestimated, such as near major river mouths. We revise the K2016 methodology with: a) a less stringent filtering of measurements in regions with high SSS natural variability (inferred from SMOS measurements) and b) a correction for seasonally-varying latitudinal systematic errors. With this new mitigation, SMOS SSS becomes more consistent with the independent SMAP SSS close to land, for instance capturing consistent spatio-temporal variations of low salinity waters in the Bay of Bengal and Gulf of Mexico. The standard deviation of the differences between SMOS and SMAP weekly SSS is <0.3 pss in most of the open ocean. The standard deviation of the differences between 18-day SMOS SSS and 100-km averaged ship SSS is 0.20 pss (0.24 pss before correction) in the open ocean. Even if this standard deviation of the differences increases closer to land, the larger SSS variability yields a more favorable signal-to-noise ratio, with  $r^2$  between SMOS and SMAP SSS larger than 0.8. The correction also reduces systematic biases associated with man-made Radio Frequency Interferences (RFI), although SMOS SSS remains more impacted by RFI than SMAP SSS. This newly-processed dataset will allow the analysis of SSS variability over a larger than 8 years period in regions previously heavily influenced by land-sea contamination, such as the Bay of Bengal or the Gulf of Mexico.

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### Highlights

► Improved SMOS salinity systematic error correction from Kolodziejczyk et al. (2016) ► Refined variability of sea surface salinity near e.g. major river mouths ► Consistent mesoscale patterns observed by SMOS and SMAP satellite missions

**Keywords** : SMOS, Sea Surface Salinity, SMAP

## 44 1. Introduction

45 With 8 years and counting, the Soil Moisture and Ocean Salinity (SMOS) European mission  
46 (Kerr et al., 2010; Font et al., 2010) provides the longest record for Sea Surface Salinity  
47 (SSS<sup>a</sup>) monitored from space over the global ocean (2010-present). The pioneered SMOS  
48 (2010-) and Aquarius (2011-2015) (Lagerloef, 2008) satellite missions have demonstrated the  
49 capability of L-band radiometry for monitoring SSS from space (e.g. Reul et al., 2014a;  
50 Lagerloef, 2012).

51 Salinity is a key ocean variable that plays a fundamental role in the density-driven global  
52 ocean circulation, the water cycle, and climate (Siedler et al., 2001). Salinity controls the  
53 density of sea water, together with temperature. At the ocean surface, in cold waters ( $T = 2$   
54  $^{\circ}\text{C}$ ), a SSS change of  $\sim 0.1 \text{ pss}^{\text{b}}$  is equivalent, in terms of density, to a sea surface temperature  
55 (SST) change of  $1^{\circ}\text{C}$ . SSS variations therefore greatly constrain the global thermohaline  
56 circulation as salinity drives the high latitude convective overturning. In warmer regions  
57 ( $T=28^{\circ}\text{C}$ ), a  $0.44 \text{ pss}$  change is equivalent to a  $1^{\circ}\text{C}$  change in terms of density. Salinity  
58 stratification within a near isothermal layer (known as the barrier layer, e.g. Lukas and  
59 Lindstrom, 1991) can furthermore inhibit the vertical mixing of heat and momentum, and  
60 play a role in major phenomena such as the El Niño Southern Oscillation (e.g. Vialard and  
61 Delecluse, 1998), the southwest monsoon rain distribution (e.g. Shenoi et al. 2002) or the  
62 oceanic productivity (e.g. Picaut et al. 2001). Finally, SSS is considered as a passive tracer of

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<sup>a</sup> SSS will hereafter refer to the salinity measured between 1 cm -as monitored by satellite measurements- and at a few meters depth -as monitored by most *in situ* measurements.

<sup>b</sup> pss is used here as an equivalent to gram of salt per kilogram of standard sea water, see UNESCO (1985) for more details

63 the hydrological cycle, recording for instance its intensification in response to anthropogenic  
64 climate change (e.g. Durack et al. 2012). For all these reasons, SSS has been designated as an  
65 ECV (Essential Climate Variable) by the Global Climate Observing System (GCOS).

66 SMOS data has enabled the study of salinity changes associated with two El Niño events  
67 (Hasson et al. submitted) and a La Niña event (Hasson et al. 2014), climate variability in the  
68 equatorial Indian Ocean (Durand et al. 2013), decadal salinity changes in the subtropical  
69 Pacific Ocean (Hasson et al. 2013) or North Atlantic Ocean (Grotsky et al. 2017). The spatial  
70 resolution and spatio-temporal coverage of the SMOS mission (50 km resolution; global  
71 coverage every 3 to 5 days) also allow the unprecedented detection of SSS mesoscale features  
72 associated with the transport across frontal regions (e.g. Reul et al., 2014b; Kolodziejczyk et  
73 al., 2015), very hardly accessible from Aquarius measurement (100-150 km resolution; global  
74 coverage every 8 days).

75 SMOS demonstrated performance in monitoring open-ocean salinity variations has been  
76 impressive so far. SMOS results have, however, been disappointing close to land, for instance  
77 in the Bay of Bengal, where Aquarius and more recently the Soil Moisture Active Passive  
78 (SMAP; 2015-) mission perform better (Akhil et al. 2016 and Fournier et al. 2017).

79 SMOS is an Earth Explorer mission. It carries an L-band Microwave Interferometric  
80 Radiometer with Aperture Synthesis (MIRAS), which is the first interferometer and the first  
81 L-band radiometer observing Earth from space. L-band (1.4 GHz) is a passive protected  
82 frequency band but many SMOS measurements are corrupted by unexpected man-made  
83 Radio Frequency Interferences (RFI) (Oliva et al., 2012). SMOS SSS is also affected by the  
84 presence of nearby landmasses up to several hundreds of kilometers into the ocean, likely an  
85 effect of imperfect synthetic aperture image reconstruction in the present SMOS data

86 processing (more on limitations in the present SMOS image reconstruction is presented in  
87 Anterrieu et al., 2015).

88 Other two satellite missions measuring SSS from space, Aquarius (Lagerloef et al., 2008)  
89 (2011-2015) and SMAP (Piepmeier et al., 2017) (2015-present), are equipped with classical  
90 L-band radiometers. Hence, they are expected to suffer less land-sea contamination than  
91 SMOS. Aquarius and SMAP were launched subsequently to SMOS and have benefited from  
92 a better RFI-protected onboard processing.

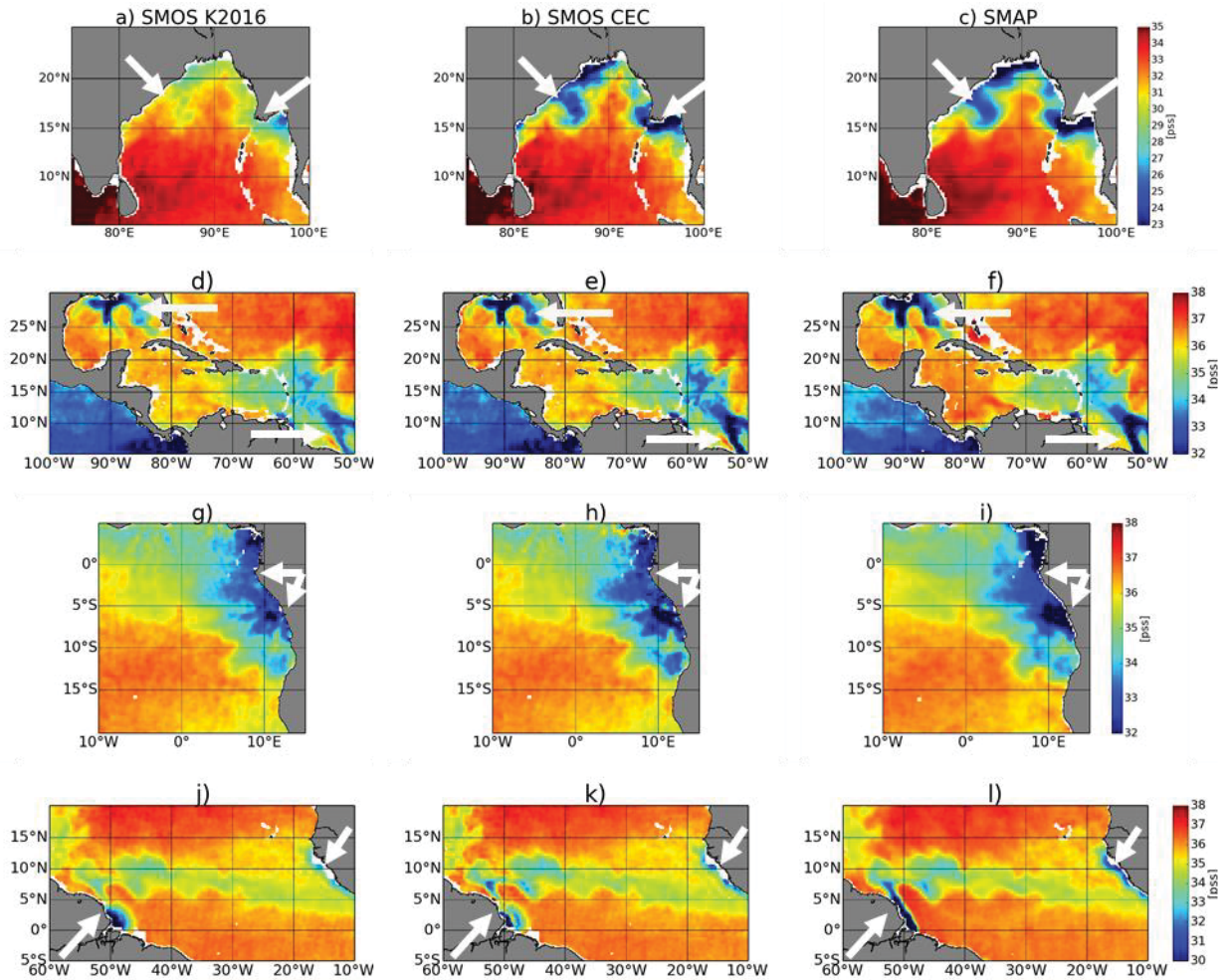
93 The unique length of SMOS record and its high spatio-temporal resolution (comparable to the  
94 more recent SMAP mission) are strong motivations for improving its processing in order to  
95 mitigate RFI and land-sea contaminations on the retrieved SSS. The validation of satellite  
96 SSS using *in situ* SSS measurements is, however, very challenging in coastal areas where  
97 contaminations are strong, *in situ* data are very sparse and variability is high, such as in river  
98 plumes (Delcroix et al. 2005; Boutin et al. 2016). Hence, in addition to using *in situ* SSS, we  
99 take advantage of SMAP SSS to assess corrections to the SMOS SSS.

100 Kolodziejczyk et al. (2016) (K2016 hereafter) have developed a Bayesian methodology to  
101 mitigate SSS systematic errors due to land-sea contamination. The method is described in  
102 detail in Section 3.3 of the present paper. It brings a clear improvement in most areas, with a  
103 32% decrease of the RMSD globally with respect to ship measurements. Some examples  
104 below, however, indicate much lower SSS values in SMAP than in K2016 SMOS retrievals,  
105 in particular near river mouths. In the Bay of Bengal, for instance, fresh water originating  
106 from the Ganges-Brahmaputra (GB) is transported southward by the East India Coastal  
107 Current (EICC) after the monsoon, forming a ~200 km fresh water tongue along the Indian  
108 coast, up to 10 pss fresher than in the central Bay of Bengal (Chaitanya et al. 2014). Fournier

109 et al. (2017) demonstrated the SMAP capacity to monitor the modulation of this freshwater  
110 tongue extent by climate variability and mesoscale eddies stirring the freshwater plume away  
111 from the coast. This peculiar pattern is more than 3 pss fresher in SMAP SSS than SMOS  
112 K2016 SSS (Figure 1 a and c). Fournier et al. (2016) similarly used SMAP data to study an  
113 unusual freshening associated with anomalous advection of the Mississippi River plume in  
114 the Gulf of Mexico. While this freshening is also detected by SMOS K2016 (Figure 1 d), it is  
115 saltier than in SMAP SSS (Figure 1 f). Such overestimation of K2016 SSS by SMAP relative  
116 to SMOS in the low salinity regime also occurs in the eastern tropical Atlantic (Figure 1 g, i,  
117 Congo and Niger river mouths, Reul et al. 2014a) and western tropical Atlantic (Amazon and  
118 Orinoco, Figure 1 j, l). SMOS K2016 default in retrieving the freshest SSS of the major river  
119 plumes illustrates the need of an improved processing in variable, low-salinity regions near  
120 land.

121 The purpose of this paper is to present a revised version of the K2016 methodology. The  
122 main changes aim at taking the SSS natural variability into consideration in the land-sea  
123 contamination correction and at adding a correction for the seasonally-varying latitudinal  
124 biases.

125 Ancillary datasets are detailed in section II. An overview of the SMOS SSS retrieval, of the  
126 K2016 SMOS processing and a description of the revised methodology are given in section  
127 III. Comparisons with ancillary data sets are presented in section IV and V. They are  
128 summarized and discussed in section VI.



129

130 Figure 1: Satellite SSS: SMOS SSS corrected according to (a, d, g, j) K2016 methodology, (b, e, h, k)  
 131 the method described in this paper (CEC); (c, f, i, l) SMAP SSS. 4 case study areas : (a, b, c) : Bay of  
 132 Bengal - August 21<sup>st</sup> 2015; (d, e, f) : Gulf of Mexico – August 18<sup>th</sup> 2015 ; (g, h, i) : Eastern Tropical  
 133 Atlantic Freshwater Pools – April 14<sup>th</sup> 2016; (j, k, l) : Amazon plume – October 21<sup>st</sup> 2015. SMOS and  
 134 SMAP SSS is averaged over a SMOS repetitive orbit sub-cycle (18 days) and two SMAP repetitive  
 135 orbit cycles (16 days) respectively. Striking fresh SSS features in better agreement with SMOS (new  
 136 version) and SMAP are indicated with white arrows.

137

## 138 2. Data

139 Three types of ancillary data are used in this study. The *In situ* Analysis System (ISAS) SSS  
 140 is used both to set the long term mean reference of our correction and to qualitatively indicate  
 141 the most trustable SMOS SSS data in our correction process as described in Section 3. It is

142 also used to check the SMOS SSS variability. SMAP and ship SSS are used for independent  
143 assessment.

## 144 **2.1 *In Situ* Analyzed SSS**

145 Monthly gridded fields of salinity derived from *in situ* measurements are obtained from the  
146 ISAS (*In situ* Analysis System) v6 algorithm, an optimal interpolation (Bretherton, 1976) tool  
147 developed for the synthesis of the Argo global dataset (Gaillard et al., 2016). We use the  
148 fields reconstructed at 5 m depth on a half degree horizontal grid. The ISAS Near Real Time  
149 (NRT) products are available since 2010. In addition, over the 2002-2012 period, ISAS13  
150 (Gaillard, 2015) fields have been produced after a refined quality check of the Argo profiles.  
151 Data are preprocessed for ISAS13 using a climatological test and followed by a visual control  
152 of suspicious profiles. The interpolation is based on delayed mode Argo floats, TAO-  
153 TRITON-PIRATA-RAMA moorings and MEMO (Marine Mammals) data.  
154 The ISAS-NRT fields (2010-present) are used by the correction method whereas ISAS13 (till  
155 2012) and ISAS-NRT (from 2013 to 2016) fields are used for the assessment presented  
156 Section 4.

## 157 **2.2 SMAP SSS**

158 The SMAP mission (Piepmeier et al. 2017) provides L-band radiometric observations since  
159 April 2015. While its main objective is the observation of soil moisture, the observed  
160 brightness temperatures (Tb) are also used to retrieve SSS (Fore et al. 2016a). SMAP SSS  
161 characteristics are quite close to those of SMOS in terms of spatio-temporal coverage and  
162 spatial resolution (~50 km). In approximately 3 days, SMAP achieves global coverage and it  
163 has an exact orbit repeat cycle of 8 days. The SMAP L-band microwave radiometer,  
164 however, uses a conical scanning antenna instead of a synthetic aperture imaging antenna. As



165 stated in the introduction, a particular attention was put on filtering the RFI (Mohammed et  
166 al. 2016) and their impact is expected to be limited compared to SMOS. SMAP also suffers  
167 from land-sea contamination but, given that SMAP carries a real aperture antenna, the  
168 contamination is not expected to be as spatially variable as with SMOS. We use level 3  
169 SMAP SSS produced at the Jet Propulsion Laboratory using the Combined Active Passive  
170 (CAP version 3) algorithm (Fore et al. 2016b). A complete description of the CAP v3  
171 algorithm can be found in Fore et al. (2016a), but a brief description follows. The CAP  
172 algorithm is only applied to passive measurement as the radar failed a few months after  
173 launch. It includes specific Tb corrections for land and galactic noise contaminations, and a  
174 global Tb bias adjustment (latitude and time-dependent). After correction, the rms difference  
175 of SMAP retrieved SSS with respect to Hycom SSS in the vicinity to land is less than 1.5pss.  
176 Level 2 SSS is retrieved from SMAP Tb measurements using a constrained objective  
177 function minimization. Data are mapped on a  $0.25^\circ$  grid using a Gaussian weighting with a  
178 search radius of approximately 45 km and a half-power radius of 30 km. They are  
179 aggregated in level 3 maps produced daily with an 8-day running-average time window.  
180 CAPv3 SMAP SSS agrees well with in situ SSS. Tang et al. 2017 found a rms difference of  
181 0.26 pss between weekly SMAP SSS and buoy SSS. They also show that SMAP and SMOS  
182 SSS depict salinity fluctuations very close to in situ SSS.

### 183 **2.3 Ship SSS**

184 Salinity data provided by thermosalinographs (TSG) installed on voluntary merchant ships  
185 are used as ground truth. A full description of the data can be found in Alory et al. (2015).  
186 They provide SSS estimates with an  $\sim 2.5$  km resolution along the ship track and are  
187 independent from the ISAS analyses. Samples are taken at a few meters depth. Noise on  
188 individual ship SSS is estimated to be on the order of 0.08 pss (Alory et al. 2015). In the

189 presence of strong vertical stratification, TSG and satellite SSS are expected to differ as the  
190 L-band radiometer skin depth is about 1 cm (Boutin et al. 2016). This may occur under heavy  
191 rain conditions or in river plumes. Because of their singular spatio-temporal resolution, ship  
192 measurements, however, provide invaluable information on the spatial variability of SSS  
193 unresolved by Argo.

### 194 **3. SMOS data and processing methodology**

195 The SMOS mission (Kerr et al., 2010) provides SSS measurements from space since January  
196 2010. The SMOS satellite is on a sun-synchronous circular orbit with a local equator-crossing  
197 time at 6 AM on the ascending node and with a repeat sub-cycle of 18 days. It carries a 2-D  
198 interferometric radiometer, the MIRAS instrument. This groundbreaking technology was  
199 chosen as it involves much lighter antennas than real aperture antennas, and while getting  
200 ground spatial resolution on the order of 50 km at L-band frequency requires a huge antenna.  
201 The synthetic aperture antenna approach involves the reconstruction of an image using spatial  
202 Fourier components as derived from the correlations between numerous antenna elements (69  
203 in case of SMOS). The SMOS bi-dimensional multi-angular images of  $T_b$  are reconstructed  
204 with a spatial resolution in the field of view ranging between about 35 km and 100 km (50  
205 km on average). In this paper, we use the SSS retrieved within the center part of the field of  
206 view that extends at +/-400 km away from the center of the satellite swath. Global ocean  
207 coverage is then achieved after about 5 days. Individual  $T_b$ s are very noisy (1.6-3.2 K) and  
208 lead to a typical noise on SSS of the order of 0.6 pss in tropical and subtropical regions on  
209 pixel-wise SSS retrievals (Hernandez et al., 2015; Supply et al., 2017). However, owing to  
210 the very good spatio-temporal coverage of SMOS, averaging SMOS SSS over typically one  
211 month and  $100 \times 100 \text{ km}^2$  results in an accuracy close to 0.2 pss in the open ocean, after  
212 removing a climatological mean of SMOS systematic errors (Boutin et al., 2016).

213 In the following, before describing the new SSS correction methodology developed in the  
 214 present paper, we recall in section 3.1, the principle of the along track (level 2, L2) SMOS  
 215 SSS retrieval from Tb measurements, and, in section 3.2, the basis for the K2016 correction  
 216 method applied to L2 SSS.

### 217 **3.1 SMOS SSS level 2 retrieval**

218 The SMOS L2 SSS is retrieved from Level 1 (L1) Tb through a maximum-likelihood  
 219 Bayesian approach in which Tb measured in the antenna reference frame,  $Tb^{meas}$ , are  
 220 compared with Tb simulated using a forward radiative transfer model,  $Tb^{mod}$  (see a general  
 221 description of the retrieval algorithm in Zine et al. (2008)). The retrieved parameters,  $P_i$ , and  
 222 their associated theoretical error, are estimated through the minimization of the  $\chi^2$  cost  
 223 function:

$$224 \chi^2 = \sum_{n=1}^N \frac{[Tb_n^{meas} - Tb_n^{mod}(\theta_n, P_i \dots)]^2}{\sigma_{Tbn}^2} + \sum_{n=1}^M \frac{[P_i - P_{i0}]^2}{\sigma_{P_{i0}}^2}, \quad (1)$$

225 where  $N$  is the number of measurements available for retrievals in vertical and horizontal  
 226 polarizations at different incidence angles  $\theta_n$ .  $N$  is typically 120 to 240 within +/-400 km  
 227 from the center of the track.  $\sigma_{An}$  is taken equal to the SMOS brightness temperature noise  
 228 (between 1.6 and 3.2K depending on the location within the field of view) plus a small term  
 229 that takes into account an error originating from the radiative transfer model error (see Zine et  
 230 al. 2008 for more details).  $M$  is the number of physical parameters,  $P_i$  (SSS, wind, sea surface  
 231 temperature and ionospheric total electronic content) that are adjusted by the retrieval;  $P_{i0}$  and  
 232  $\sigma_{P_{i0}}$  are a priori values for  $P_i$  and their associated errors respectively.

233 In the present study, we use SSS produced at the Data Production Center (CPDC) of the  
 234 Centre Aval de Traitement des Données SMOS (CATDS) in its RE05 version (Vergely and

235 Boutin, 2017). Daily SSS fields are provided on a 25-km resolution EASE 2 (Equal-Area  
236 Scalable Earth 2) grid (Brodzik et al. 2012) for ascending and descending orbits separately  
237 (CATDS, 2017a). L1 Tbs, radiative transfer models (roughness model 1) and retrieval  
238 scheme used in CATDS CPDC RE05 are identical to the ones used in the European Space  
239 Agency level 2 ocean salinity processor version 622 (ESA L2OS v622) (see a description in  
240 SMOS-Ocean Expert Support Laboratories (2014)). The main difference between the  
241 CATDS RE05 and the ESA v622 processing involves the Tb outlier filtering. No Tb outlier  
242 filtering is applied when retrieving SSS with ESA L2 OS V622. The absence of Tb outlier  
243 filtering enables an easier detection of RFI-polluted SSS through a larger  $\chi^2$  value (equation  
244 1). This, however, removes pixels that are systematically contaminated by the presence of  
245 nearby land, which could be mitigated by our correction. K2016 correction method was  
246 indeed developed using ESA v5 processing in which an outlier filtering of  $Tb^{meas}$  was  
247 performed and it was able to mitigate part of the RFI biases. In the CATDS RE05  
248 processing, a  $3 \sigma_{Tbn}$  filtering is applied to  $(Tb^{meas}-Tb^{mod})$  before performing the SSS retrieval.  
249 Some tests (not shown) performed on SSS retrieved from filtered and from non-filtered Tb  
250 datasets confirm that the correction presented in this paper is more efficient when used in  
251 conjunction with a Tb filtering.

252

### 253 **3.2 K2016 land-sea contamination correction**

254 In this section, we briefly review the K2016 methodology. The K2016 correction aims at  
255 mitigating systematic errors constant with time and was shown to efficiently correct land-sea  
256 contamination in many regions. Given the 18-day sub-cycle of SMOS, a given location over  
257 the ocean is observed with the same SMOS measurement geometry every ~18 days; within

258 18 days, it is sampled by several SMOS SSS measurements which are located at various  
 259 locations across the swath,  $x_{\text{swath}}$ . The K2016 methodology considers that the long term  
 260 (2010-2014) SSS variability observed by SMOS has to be rather similar whatever  $x_{\text{swath}}$  and  
 261 the orbit orientation  $x_{\text{orb}}$ . Relative biases,  $b_{\text{land}}$ , with respect to a reference SSS,  $\text{SSS}_{\text{ref}}$ , are  
 262 derived from SMOS SSS through a least square minimization approach, and through a series  
 263 of iterations that will be described below. A consistent set of SMOS SSS,  $\text{SSS}_{\text{K2016}}$ , is  
 264 obtained as:

$$265 \text{SSS}_{\text{K2016}}(t, \phi, \lambda, x_{\text{swath}}, x_{\text{orb}}) = \text{SSS}_{\text{ref}}(t, \phi, \lambda) - b_{\text{land}}(\phi, \lambda, x_{\text{swath}}, x_{\text{orb}}) \quad (2)$$

266 where  $t$  is the time of the measurement,  $\phi$ , and,  $\lambda$ , are respectively the latitude and the  
 267 longitude of the considered location over the ocean.  $x_{\text{swath}}$  is sampled within 25 km wide bins.

268  $b_{\text{land}}$  and  $\text{SSS}_{\text{ref}}$  are derived as follows. Defining  $p = (\text{SSS}_{\text{ref}}, b_{\text{land}})^T$ ,  $p_0$  the *a priori* values of  $p$ ,  
 269  $y_0$  the SMOS SSS, the estimated values of  $p$ ,  $p_{\text{est}}$ , are derived as:

$$270 p_{\text{est}} = p_0 + C_p \cdot G^T \cdot (G \cdot C_p \cdot G^T + R)^{-1} \cdot [y_0 - f(p_0)] \quad (3)$$

271 where  $G$  is the matrix of derivatives of observations with respect to the parameters (also  
 272 called observational operator),  $R$  is the covariance matrix for the observation error,  $C_p$  is the  
 273 covariance matrix for the *a priori* error on the parameters  $p$ .  $C_p$  is parametrized as a function  
 274 of an acceptable standard deviation of SSS,  $\sigma_{\text{SSSref}}$ , over a correlation timescale  $\tau$ .

275 The minimization is repeated four times, twice with  $\tau=16$  days (corresponding to a 18-day  
 276 Gaussian smoothing window), then twice with  $\tau=8$  days (corresponding to a 9-day Gaussian  
 277 smoothing window). At each iteration, a new set of *a priori* values for  $p$  and for  $\sigma_{\text{SSSref}}$  are  
 278 computed. During the first iteration, the *a priori* values of  $\text{SSS}_{\text{ref}}$ ,  $\text{SSS}_{\text{ref}0}$ , are taken as the  
 279 median of SMOS SSS at the center of its swath over the 2010-2014 period, the *a priori* value

280 of  $b_{\text{land}}$  is equal to 0,  $\sigma_{\text{SSSref}}$  is taken equal to 0.3 pss, and the observation errors are taken  
 281 equal to the theoretical error associated with the L2 SMOS SSS retrieval,  $E_{\text{SSS\_L2}}$ .  $\text{SSS}_{\text{ref1}}$  and  
 282  $b_{\text{land1}}$  are computed from the  $p$  and  $\sigma_{\text{SSSref}}$  solutions of the first iteration. During the second  
 283 iteration, SSS outliers, linked primarily to RFI contamination, are detected using a 3-sigma  
 284 outlier detection: if the difference between the L2 SMOS SSS and  $(\text{SSS}_{\text{ref1}} - b_{\text{land1}})$  is larger  
 285 than 3 times  $E_{\text{SSS\_L2}}$ , the error on the measurement indicated in the matrix  $R$  is artificially  
 286 increased.  $\text{SSS}_{\text{ref2}}$  and  $b_{\text{land2}}$ , estimated at the end of step 2, are used to produce the 18 day  
 287  $\text{SSS}_{\text{K2016}}$  fields. The third and fourth iterations aims at optimizing  $\text{SSS}_{\text{ref}}$  and  $b_{\text{land}}$  at 9 day  
 288 resolution. During the third iteration,  $\text{SSS}_{\text{ref2}}$  and  $b_{\text{land2}}$  are taken as *a priori* parameters,  $\tau$  is  
 289 reduced to 8 days and  $\sigma_{\text{SSSref}}$  is increased to 0.5 pss resulting in  $\text{SSS}_{\text{ref3}}$  and  $b_{\text{land3}}$ . The fourth  
 290 step leading to  $\text{SSS}_{\text{ref4}}$  and  $b_{\text{land4}}$  is similar to the second one using the same *a priori* values as  
 291 in step 3. At the end, an additional term is added to the estimated bias, to ensure that the 4-  
 292 year (2010-2014) median average of  $\text{SSS}_{\text{K2016}}$  equals the 4-year median average of ISAS SSS  
 293 for each latitude and longitude:

$$294 \quad b_{\text{land}}(\phi, \lambda, x_{\text{swath}}, x_{\text{orb}}) = b_{\text{landx}}(\phi, \lambda, x_{\text{swath}}, x_{\text{orb}}) - (\text{med}(\text{SSS}_{\text{ref}}(t, \phi, \lambda)) - \text{med}(\text{SSS}_{\text{ISAS}}(t, \phi, \lambda))) \quad (4)$$

295 with  $b_{\text{landx}}$  equals to  $b_{\text{land2}}$  in the case of 18-day corrected field estimates, or to  $b_{\text{land4}}$  in the  
 296 case of 9-day corrected fields. Note that the last term of Equation (4) is the only external  
 297 information used in the entire correction process and does not modify the temporal variability  
 298 of the observed fields.

299 The K2016 methodology was developed based on SMOS SSS processed with ESA L2OS  
 300 version 550. In order to provide consistent comparison of the K2016 corrected SSS  
 301 ( $\text{SSS}_{\text{K2016}}$ ) and the newly corrected dataset presented in this paper ( $\text{SSS}_{\text{J2018}}$ ),  $\text{SSS}_{\text{K2016}}$  was re-  
 302 computed using the L2 SMOS SSS version used for  $\text{SSS}_{\text{J2018}}$  i.e. CATDS RE05.

### 303 3.3 New correction

304 In the present paper, we add a correction for seasonally-varying latitudinal biases,  $b_{lat}$ , and we  
305 update the land-sea contamination correction,  $b_{land}$ , with respect to K2016.  $b_{lat}$  and  $b_{land}$  are  
306 assumed to be additive, so that the corrected SSS,  $SSS_{J2018}$ , is expressed as:

$$307 \text{SSS}_{J2018}(t, \phi, \lambda, x_{swath}, x_{orb}) = \text{SSS}_{ref}(t, \phi, \lambda) - b_{land}(\phi, \lambda, x_{swath}, x_{orb}) - b_{lat}(\phi, x_{swath}, x_{orb}, m) \quad (5)$$

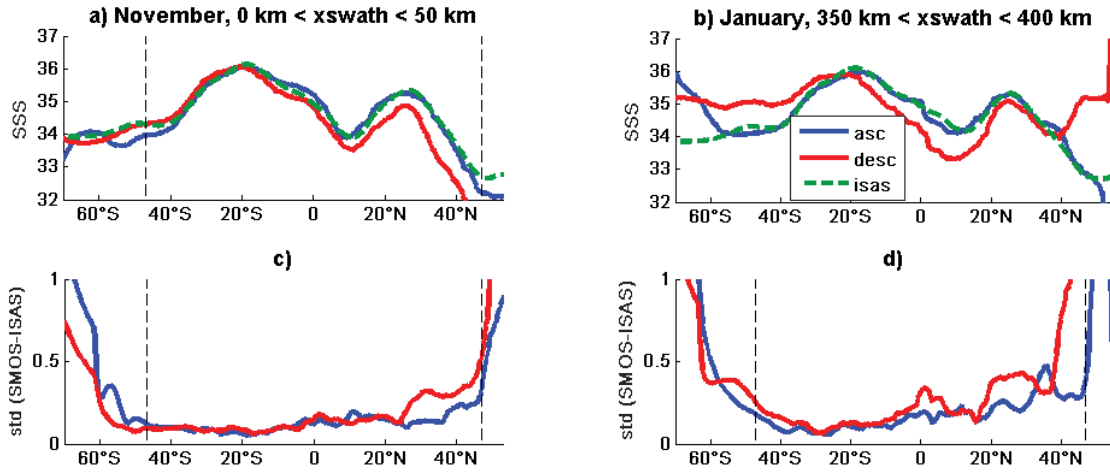
308 where  $m$  is the month of the SMOS pass. In a last step, similar to K2016 (equation 4), the 7-  
309 year (2010-2016) median average of the corrected SSS is adjusted, for each latitude and  
310 longitude, to the 7-year median average of ISAS SSS. The latter is the only quantitative  
311 information external to SMOS data used in the correction process and does not modify the  
312 temporal variability to the observed fields.

#### 313 3.3.1 Observed seasonally-varying latitudinal biases

314 Further than 1000 km from the coastline, land-sea contamination is not detectable but  
315 seasonally-varying latitudinal biases are observed. They mostly depend on  $x_{swath}$ ,  $x_{orb}$ , and the  
316 month of the year. The two examples on Figure 2 illustrate the behavior for two extreme  
317 cases. In November (Figure 2 a-c), in the center of the swath, SMOS SSS latitudinal  
318 variations are very close to ISAS SSS latitudinal variations on ascending orbits but not on  
319 descending orbits. In January (Figure 2 b-d), descending orbits at the edge of the swath  
320 display strong biases with respect to ISAS while ascending orbits do not. The systematic  
321 errors are quite stable from year to year, as indicated by the standard deviation of the 2011 to  
322 2016 monthly latitudinal SMOS minus ISAS SSS difference (Figure 2c and d). It is not true  
323 at high latitudes where, in most cases, both the mean and standard deviation of the  
324 differences are high. This is likely associated with an effect of ice contamination. Systematic  
325 errors observed over other ocean basins are similar (see Appendix A1). These systematic

326 errors could originate from imperfect estimates of the sun or galactic noise contributions (Yin  
 327 et al. 2013).

328



329 Figure 2 : Two examples of 2011-2016 latitudinal profiles of mean SSS (a; b) and of the standard  
 330 deviation of the 2011-2016 monthly differences between SMOS SSS and ISAS SSS (c; d). The  
 331 latitudinal means and standard deviations are computed over the Pacific Ocean further than 1200 km  
 332 from any coast: green: ISAS, blue: SMOS ascending orbits; red: SMOS descending orbits; a;c)  
 333 November; middle of the swath (0-50 km from the center of the swath); b; d) January; edge of the  
 334 swath (350-400 km from the center of the swath). Dashed vertical lines indicate 47°N and 47°S.

335

### 336 3.3.2 Correction for seasonally-varying latitudinal biases

337  $b_{lat}$  is determined separately for ascending and descending orbits, on a monthly basis, and is  
 338 assumed to be independent of the longitude and of the year. We neglect interannual variations  
 339 that could result from variation in sun activity, as they appear to be an order of magnitude  
 340 smaller than the seasonal biases (see section 3.3.1). The correction is estimated from Pacific  
 341 Ocean orbits further than 1200 km from continental coasts, in order to avoid land-sea  
 342 contamination ( $b_{land}$  in Eqn 4 vanishes in this case) and because the northern latitudes in the  
 343 Pacific Ocean are less affected by RFI than in the Atlantic Ocean. For  $x_{swath}$  locations and  
 344 seasons not very affected by RFI at high latitudes, we checked that biases are similar in the



345 Pacific and Atlantic Ocean (see Appendix A1). For each  $x_{\text{swath}}$  and  $x_{\text{orb}}$ , twelve sets of  
346 monthly latitudinal corrections are estimated by comparing SMOS SSS on contaminated and  
347 non-contaminated  $x_{\text{swath}}$  intervals. The first step is to choose a set of non-contaminated  $x_{\text{swath}}$   
348 for each month and for each  $x_{\text{orb}}$  that is used as reference in our correction methodology. The  
349 non-contaminated  $x_{\text{swath}}$  locations are identified from comparisons between 6-year averaged  
350 (2011-2016) monthly latitudinal SSS profile at  $0.25^\circ$  resolution derived for each SMOS  $x_{\text{swath}}$   
351 location and from ISAS as described in Appendix A1. The 2010 year is not considered for the  
352 correction estimate as the calibration of the MIRAS instrument was not very stable during the  
353 SMOS commissioning period (January to June 2010). The latitudinal profiles of the unbiased  
354 SMOS SSS at reference  $x_{\text{swath}}$  locations determined for a given month, are averaged together  
355 to provide a reference SSS latitudinal profile. The latitudinal correction is then estimated as  
356 the median difference, per  $5^\circ$  latitude, over the EASE2 grid latitudinal sampling, between the  
357 latitudinal profiles of the SMOS SSS at contaminated  $x_{\text{swath}}$  and the reference SSS latitudinal  
358 profile. The SMOS SSS latitudinal profiles differ from the ones based on ISAS SSS at high  
359 latitudes (Figure 2). This difference may be explained by remaining RFI contamination in the  
360 northern latitudes but also by sea-ice contamination extending equatorward to about 1000 km  
361 from the ice edge. On ascending and on most descending latitudinal profiles, large  
362 differences between SMOS and ISAS SSS are indeed found poleward of  $47^\circ\text{N}$  (see two  
363 examples on Figure 2). Some degradation also occurs between  $40^\circ$  and  $47^\circ\text{N}$  (see a worse  
364 case on Figure 2d). It concerns only a few  $x_{\text{swath}}$  and months on descending orbits and is  
365 therefore rather limited. In the Southern Ocean, in Spring and Summer (Figure 2a-b), large  
366 differences only appear way south of  $47^\circ\text{S}$ . However, in Winter, especially in the Atlantic  
367 Ocean where the ice edge can be as north as  $55^\circ\text{S}$ , large differences can reach  $47^\circ\text{S}$ . As a

368 compromise, in the following, the correction is applied only to latitudes within 47°S-47°N  
369 and results will be limited to this latitudinal range.

### 370 *3.3.3 Updated land-sea contamination correction*

371 Before estimating the land-sea contamination correction, we apply seasonally-varying  
372 latitudinal corrections determined as described in the previous section. Actually, an imperfect  
373 correction of sun and galactic noise effects is expected to generate systematic seasonal biases  
374 whatever the distance to the coast.

375 With respect to K2016, we make the following changes:

- 376 • In K2016, the covariance matrix of observation error,  $R$ , was filled with  
377  $E_{SSS\_L2}$  times the Identity matrix. With this approach, the observation errors  
378 depend only on the Jacobian of the modelled Tbs with respect to the retrieved  
379 parameters, on the a priori error on SMOS Tbs (equal to the SMOS  
380 radiometric noise) and on the a priori errors on auxiliary parameters. It does  
381 not take into account the actual differences between SMOS observed and  
382 modelled Tbs. In most cases, this difference is very close to the radiometric  
383 noise (e.g. Yin et al. 2012) and the associated  $\chi$  (equation 1) normalized by the  
384 root mean square of  $N$ ,  $\chi_N$ , is close to 1. However, in case of polluted areas  
385 (e.g. RFI),  $\chi_N$  becomes larger than 1. In the updated method, the errors  
386 specified in  $R$  are set to  $(E_{SSS\_L2} \cdot \chi_N)$  in order to take observed mismatches  
387 between SMOS measured and modelled Tbs into account. In case  $\chi_N$  is greater  
388 than 3, the particular SMOS SSS retrieval is not used in the correction  
389 estimate.

- 390
- In K2016,  $\sigma_{SSS_{ref}}$  was a fixed value (0.3 pss for  $\tau=16$  days; 0.5 pss for  $\tau=8$  days).  $\sigma_{SSS_{ref}}$  now uses an estimate of the SSS natural variability standard deviation,  $\sigma_{SSS_{nat}}$ , as derived from SMOS measurements themselves. We derive  $\sigma_{SSS_{nat}}$  using a two-step iterative procedure, in which we first compute debiased SSS using  $\sigma_{SSS_{ref}}=0.3$  pss for each grid point over the whole period as before, then we recompute debiased SSS using  $\sigma_{SSS_{ref}}$  equal to the standard deviation of the debiased SSS from step 1.  $\sigma_{SSS_{nat}}$  is taken as the standard deviation of the debiased SSS obtained in step 2. In the open ocean  $\sigma_{SSS_{nat}}$  is very close to the value we used in the previous version (0.3 pss) (Figure 3 a), but it is much larger in regions characterized by large inputs of freshwater, such as river plumes (e.g. Amazon plume, Bay of Bengal, Gulf of Mexico), rainy areas (e.g. Intertropical Convergence Zone, eastern and western tropical Pacific fresh pools) and areas characterized by numerous mesoscale features (e.g. Gulf Stream, south east of the Arabian Sea). With this variable  $\sigma_{SSS_{ref}}$  we allow  $SSS_{ref}$  to vary more temporally in high variability regions through equation (3).
- The biases are derived from 7 years (2010-2016) of SMOS data instead of 4 years in K2016.
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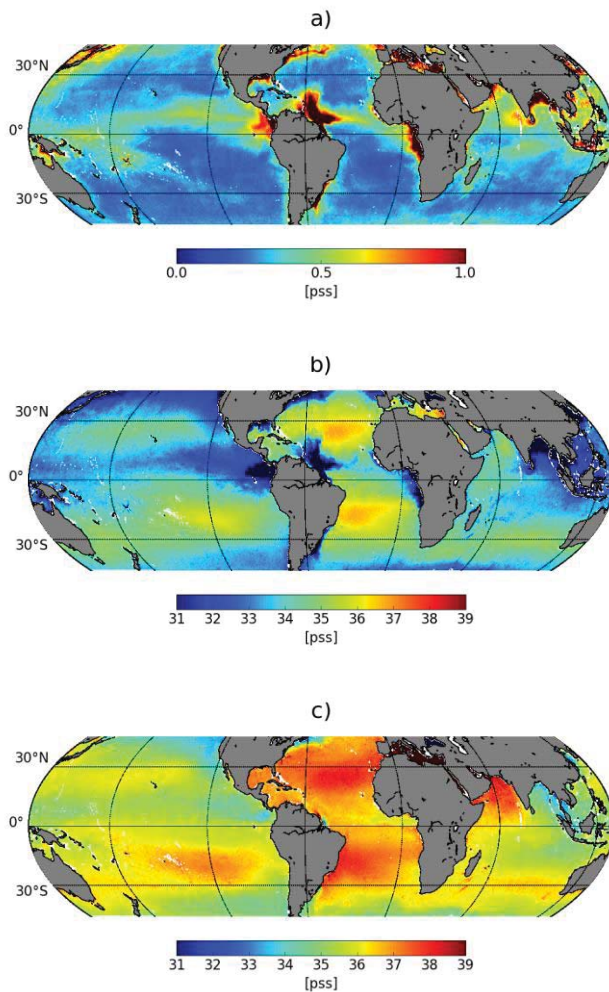
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413 Figure 3 : a) SSS variability ( $\sigma_{SSS_{nat}}$ ) derived from 7 years of SMOS filtered and corrected SSS (after  
 414 debiasing and filtering): large values are observed in river plumes and in rainy areas (ITCZ, SPCZ. b)  
 415 Minimum and c) maximum of the SSS as derived from 18-day CEC LOCEAN that are used in the  
 416 mapping of debiased near-real time products (see section 3.4).

417

### 418 3.4 Mapping methods

419 All SMOS level 3 maps shown in this paper include only SSS retrieved under moderate wind  
 420 speed ( $3-12 \text{ m s}^{-1}$ ) and within  $\pm 400 \text{ km}$  from the center of the swath.

421 The non-bias corrected SMOS SSS is taken from the CATDS CPDC RE05 default  
 422 processing. Daily SMOS SSS retrieved over ascending and descending orbits are combined  
 423 to produce level 3 fields (L3P) (CATDS, 2017b). L3P fields over a  $25 \times 25 \text{ km}^2$  EASE 2 grid

424 are obtained from SMOS SSS weighted by  $E_{SSSL2}$  and averaged within monthly and ~ 10  
425 days  $25 \times 25$  km<sup>2</sup> bins. Measurements are filtered based on SSS retrieval quality flags and  
426 avoiding regions suffering from major contaminations on Tb (e.g. galactic noise). A full  
427 description of the procedure is available in Vergely and Boutin (2017).

428 Two sets of level 3 bias-corrected SMOS SSS fields are considered in this paper. The same  
429 biases are applied (equation 5) but the filtering and mapping methods are different, partly due  
430 to operational constraints in CATDS CPDC processing. One set, named L3Q, is processed in  
431 near real time by the CATDS CPDC operational chain using a mapping procedure similar to  
432 the one applied to L3P products. The other set, named CEC, is processed in delayed time by  
433 the LOCEAN expertise center (CEC) of CATDS with a filtering and mapping procedure  
434 similar to K2016. Hence, in the result section, changes brought by our new correction with  
435 respect to non-corrected SSS will be evaluated by studying L3P and L3Q fields. Changes  
436 with respect to K2016 methodology will be evaluated by studying K2016 and CEC fields.  
437 The main characteristics of the L3P, K2016, CEC and L3Q processing are summarized in  
438 Table 1.

Table 1: Summary of the main characteristics of the CATDS products and methods

	Original K2016	L3P	K2016 in this paper	CEC	L3Q
<i>References</i>					
CATDS Name	CEC LOCEAN debias_v0	CPDC L3P	-	CEC LOCEAN debias_v2	CPDC L3Q
Dataset reference	-	CATDS, 2017b	-	Boutin et al. 2017	CATDS, 2017c
<i>Input data processing</i>					
Level 1 data	ESA v5	ESA v6	ESA v6	ESA v6	ESA v6
Level 2 data	ESA v550	CATDS RE05 L2P	CATDS RE05 L2P	CATDS RE05 L2P	CATDS RE05 L2P
Tb outlier sorting	Yes	Yes	Yes	Yes	Yes
<i>Correction Methodology</i>					
Land-sea contamination correction	Yes	No	Yes	Yes	Yes
Latitudinal bias correction	No	No	No	Yes	Yes
Reference period	2010-2014	-	2010-2014	2010-2016	2010-2016
$\sigma_{SS_{ref0}}$ (18-day)	0.3 pss	-	0.3 pss	$\sigma_{SS_{Shat}}$	$\sigma_{SS_{Shat}}$
Errors in R matrix	$E_{SS_{L2}}$	-	$E_{SS_{L2}}$	$E_{SS_{L2}} \cdot \chi_N$	$E_{SS_{L2}} \cdot \chi_N$
<i>L3 fields</i>					
Gridding method	Smoothing over R=50 km	Bin average (25 km grid)	Median nearest neighbors (25 km grid)	Median nearest neighbors (25 km grid)	Bin average (25 km grid)
Filtering	$SS_{ref} \pm 3 \cdot E_{SS_{L2}}$	L2 flags	$SS_{ref} \pm 3 \cdot E_{SS_{L2}}$	$SS_{ref} \pm 3 \cdot E_{SS_{L2}} \cdot \chi_N$	$SS_{ref} \pm 3 \cdot E_{SS_{L2}} \cdot \chi_N$ & $SS_{min} - 2 \cdot (E_{SS_{L2}} \cdot \chi_N)$

\*NB : The K2016 processing shown in the present paper has been recomputed from CATDS RE05 processing and using the same filtering as in

CEC product

442 We now describe in detail the mapping and filtering procedures for generating L3P and CEC  
443 fields:

- 444 • At the CATDS CEC LOCEAN, SSS gridded fields at 25x25 km<sup>2</sup> resolution,  
445 named CEC SSS in the rest of the paper, are built from the combination of  
446 debiased SSS which have been filtered from outliers in the course of the biases  
447 estimates (see description of steps 2 and 4 in K2016 methodology (section  
448 3.2)). Debiased SSS are temporally averaged using a convolution with a  
449 Gaussian kernel with a full width of either 9 or 18 days at half maximum. In  
450 addition, a median filtering over nearest neighbors is applied to reduce  
451 remaining noise. CEC fields are built every 4 days over the 2010-2016 period  
452 (Boutin et al. 2017). From the 18-day CEC SSS fields over the 2010-2016  
453 period, a minimum (SSSmin) and maximum (SSSmax) SSS is estimated at  
454 each grid point (Figure 3b and c) and is used to filter the operational CATDS  
455 CPDC products (see below).
- 456 • The CATDS CPDC operational chain provides near-real time data, at the  
457 expense of a less-refined data filtering. Biases are estimated as described  
458 previously and are applied (equation 4) to daily L3P SSS. For each orbit  
459 orientation, we define upper and lower acceptable bounds for daily SSS, based  
460 on acceptable absolute values and on SSS natural variability. The upper bound  
461 is the minimum value between 40 pss and  $SSS_{max} + 2 \cdot (E_{SSS\_L2} \cdot \chi_N)$ ; the lower  
462 bound is the maximum value between 5 pss and  $SSS_{min} - 2 \cdot (E_{SSS\_L2} \cdot \chi_N)$ . SSS  
463 with  $(E_{SSS\_L2} \cdot \chi_N)$  larger than 3 pss are filtered out. Level 3 SSS fields, named  
464 L3Q in the rest of the paper, are then obtained using a simple average of the  
465 SSS weighted by  $(E_{SSS\_L2} \cdot \chi_N)$  over one month or ~ 10-day. A full description

466 of the procedure is available in Vergely and Boutin (2017). Corrected fields  
467 are produced in near-real time at various spatial resolution (CATDS, 2017c).  
468 In this paper we use the 25 km resolution products.

#### 469 **4. Comparison to ISAS**

470 Before assessing the new CEC and L3Q SSS fields with products which are not used in the  
471 correction method, we compare the corrected and non-corrected SMOS SSS fields with ISAS  
472 SSS fields. The comparison is restricted to L3P and L3Q SMOS SSS fields because these two  
473 fields are mapped using the same methodology.

474 Even if ISAS SSS is used as a guide to choose the reference  $x_{\text{swath}}$  in the latitudinal  
475 correction, we recall that the only quantitative ISAS information entering our method is the  
476 7-year median average of the ISAS SSS fields. The amplitude of temporal variability is  
477 independent of ISAS SSS variability. It is thus informative to compare the SSS temporal  
478 variability detected by SMOS and ISAS.

479 By construction, the 7-year mean SMOS minus ISAS SSS difference is expected to be small.  
480 It is nevertheless non-zero everywhere as we apply a more stringent filtering in the course of  
481 the correction estimate than in the L3Q bin average computation. At less than 800 km from  
482 coasts, the mean difference between SMOS SSS and ISAS SSS is reduced from -0.5 pss to -  
483 0.07 pss (Table 2). The remaining -0.07 pss difference is likely due to the lack of *in situ*  
484 measurement in very fresh areas in the vicinity of land (less than 2000m depth) and to non-  
485 Gaussian short-scale SSS variability smoothed out by ISAS objective mapping. In addition,  
486 SMOS samples the very near surface measurement ( $\sim 1\text{cm}$ ) while most *in situ* measurements  
487 used in ISAS analysis are performed close to 5m depth (Boutin et al. 2016). The standard



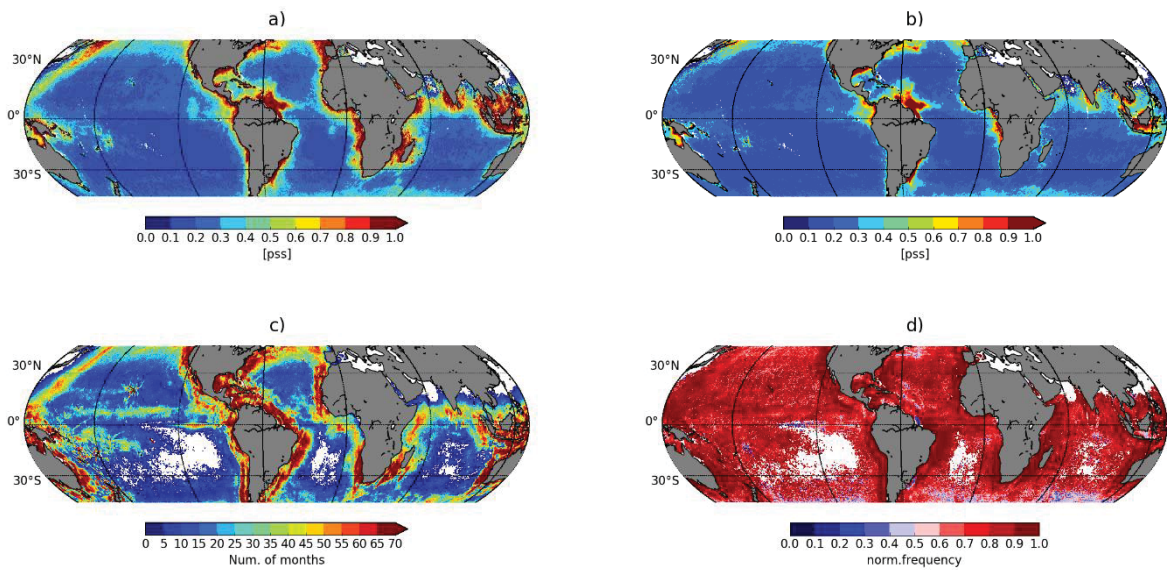
488 deviation of the differences (Figure 4 a & b) is much reduced in the vicinity of continents,  
 489 except in river plumes areas but there, it could be an effect of ISAS smoothing.

490 Table 2: Statistics of monthly SMOS SSS (only pixels with more than 8 SMOS SSS retrievals in  
 491 ascending and descending orbits are considered) minus ISAS SSS ; 2010-2016

	Number of pixels	Mean bias (SMOS – ISAS)	std(SMOS-ISAS)
45°S-45°N distance to coast <800 km			
SMOS without correction (L3P)	1542456	-0.53	0.63
SMOS with correction (L3Q)	1917346	-0.07	0.49
45°S-45°N distance to coast >800 km			
SMOS without correction (L3P)	5316809	-0.10	0.26
SMOS with correction (L3Q)	5429659	-0.02	0.20

492

493 In order to more precisely quantify the improvements between the L3Q and L3P SMOS SSS,  
 494 we detect the number of months, N, between July 2010 and December 2016, for which the  
 495 absolute value of the difference between the L3Q and the L3P SSS is larger than a threshold,  
 496 T equal to 0.2 pss (Figure 4).



497 Figure 4 : Monthly SMOS SSS compared to monthly ISAS SSS from July 2010 to December 2016.  
498 Standard deviation of the differences for a) L3P SMOS SSS; b) L3Q SMOS SSS. c) Number of  
499 months with differences between L3P and L3Q SMOS SSS greater than 0.2 pss. d) Frequency with  
500 which corrections identified on Figure c) correspond to decreased bias with respect to ISAS (i.e. L3Q  
501 SMOS SSS closer to ISAS SSS than L3P SMOS SSS): red color means that the correction improves  
502 most of the time; blue color means that the correction degrades most of the time. Blank colors in  
503 figures c) and d) mean no change above the 0.2 pss threshold or no data in the L3P version (the  
504 comparison is done only for valid L3P SSS).

505

506 As expected, the number of months affected by the correction in a given pixel is higher in the  
507 vicinity of continents. In a next step we evaluate how frequently the changes correspond to  
508 improvements. For these months significantly affected by the correction, we thus compute the  
509 number of months with L3Q SSS closer to SSS<sub>isas</sub> than to L3P SSS. In most areas, the  
510 correction brings monthly SMOS SSS closer to monthly ISAS SSS in 60% to 100% of the  
511 cases (Figure 4d). This is not true in the Gulf Stream region close to 40°N, probably because  
512 ISAS is not able to reproduce SSS mesoscale variability recorded by SMOS (Reul et al.  
513 2014b), nor close to 10°S in the western Pacific Ocean and in the middle Indian Ocean, two  
514 regions strongly affected by RFI. It is nevertheless remarkable that other regions affected by  
515 RFI such as the north-western Pacific Ocean are improved most of the time, suggesting that  
516 the RFI disturbances there are sufficiently stable in time to be partly mitigated by our  
517 correction.

## 518 **5. Assessment of the corrected fields**

### 519 **5.1 Comparison to SMAP SSS**

520 SMAP CAP SSS has a similar spatial resolution as SMOS CEC SSS, SMAP passes are at  
521 6AM and 6PM local time like SMOS, so that the spatio-temporal sampling of SMOS and  
522 SMAP are really comparable. SMAP SSS are much better filtered from RFI, hence providing  
523 an unprecedented monitoring of main river plumes in the vicinity of continents. On the other

524 hand, SMAP Tb calibration is more challenging than for AQUARIUS (Fore et al. 2016a), so  
525 that the absolute value of SMAP SSS may remain imprecise to about 0.2 pss in low to mid-  
526 latitudes of the open ocean, but biases up to 0.45 pss, which origin remains unclear, have also  
527 been reported during certain periods in the Bay of Bengal (Tang et al. 2017, their Figures 5  
528 and 12 respectively). It is out of the scope of this paper to study SMAP CAP SSS biases. We  
529 focus the investigation on the SSS variability measured by both sensors.

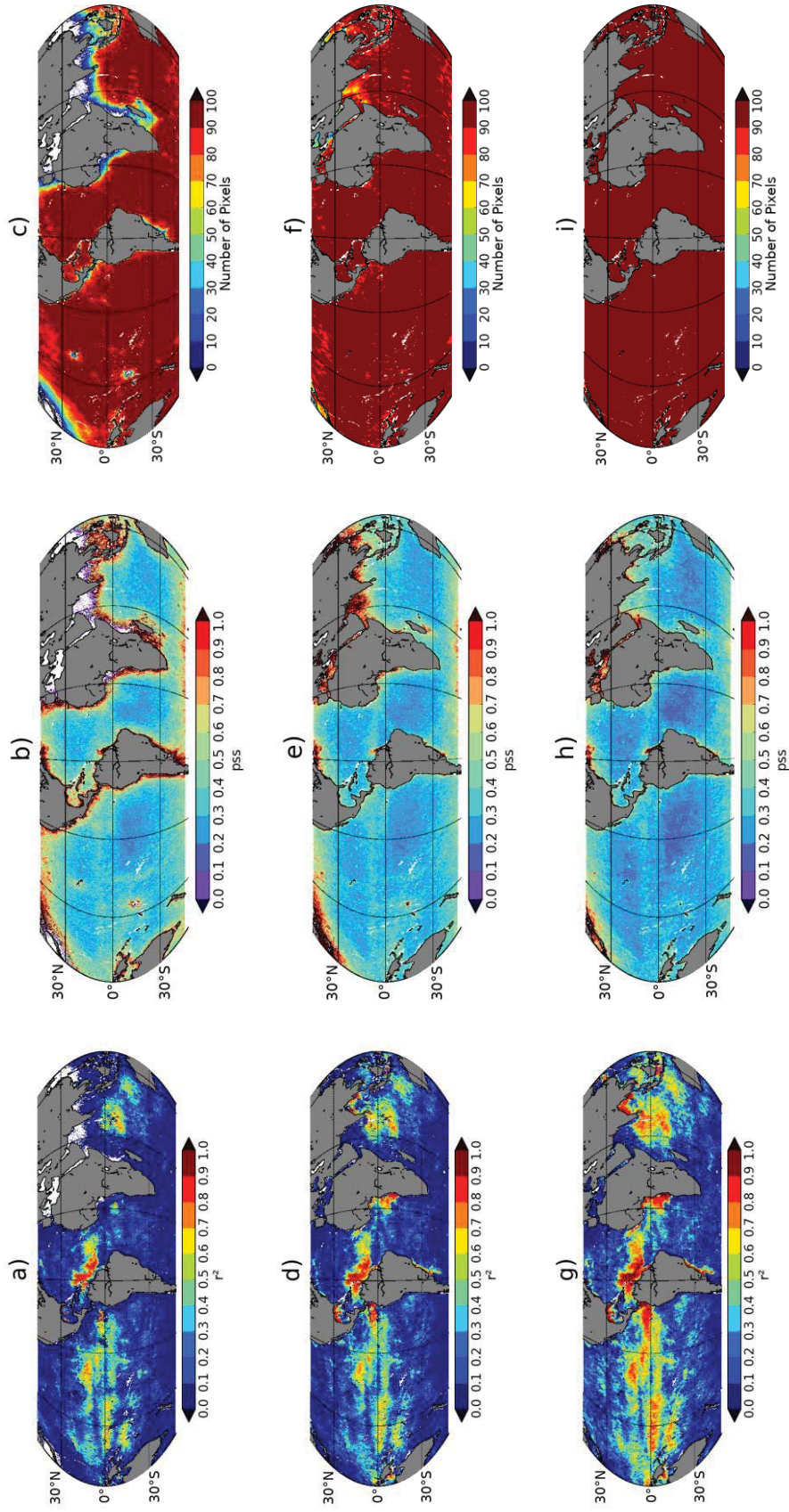
530 The various SMOS SSS fields are compared with SMAP SSS fields over the period between  
531 April 2015 and December 2016. Two ranges of temporal resolutions are considered, one  
532 close to one week, another one close to 18 days. The choices of the average durations are  
533 guided by the satellite repetitive orbit cycle and sub-cycle in order to get, for each instrument,  
534 the most even spatial coverage. In the following, for simplicity, 10-day L3P, L3Q and 9-day  
535 CEC SMOS SSS fields compared with 8-day SMAP SSS fields are referred to as ‘weekly’  
536 comparisons. Comparisons between 18-day SMOS SSS fields from K2016 and CEC  
537 processing with 16-day SMAP SSS are referred to as ‘bi-weekly’ comparisons. We always  
538 compare fields centered on the same time (at  $\pm 12$  hours), in order to minimize the effect of  
539 the different durations.

540 At global scale and ‘weekly’ resolution (Figure 5), standard deviations of the SMOS minus  
541 SMAP SSS differences are reduced in the vicinity of large continents and of RFI sources (e.g.  
542 Fiji island, Hawaiï island, south of Madagascar) from more than 0.6 pss before correction  
543 (L3P, Figure 5 b) to less than 0.4 pss after correction (L3Q, Figure 5 e; CEC, Figure 5 h)  
544 becoming comparable to open ocean values. In addition, the number of valid pixels is  
545 increased, especially in the vicinity of large continents (Figure 5 c, f and i). The improvement  
546 is better with CEC fields than with L3Q fields due to the improved filtering. The square of  
547 the Pearson correlation coefficient,  $r^2$ , is as good or better when considering L3Q instead of

548 L3P SSS (Figure 5 d and a).  $r^2$  indicates the proportion of variance contained in SMAP SSS  
549 that is explained by SMOS SSS. Hence, if the natural SSS variability is low relatively to the  
550 satellite SSS noise,  $r^2$  is expected to remain small whereas if the natural variability is large  
551 compared to the satellite SSS noise,  $r^2$  is expected to increase. This is what is observed.  $r^2$  is  
552 in particular increased from less than 0.5 to above 0.5 in the north of the Gulf of Mexico, in  
553 the Gulf of Guinea, in the Bay of Bengal (no valid measurements exist there in the L3P  
554 processing) and to the north of the Amazon plume. The improvement is even larger when  
555 considering CEC SSS (Figure 5 i) instead of L3Q SSS due to the different filtering and  
556 mapping procedures: then,  $r^2$  in the above-identified regions becomes higher than 0.8. These  
557 large values of  $r^2$  correspond to regions of large natural SSS variability, much larger than the  
558 SSS noise, as will be shown below. On the other hand, in most regions of the open ocean  
559 where SSS variability is on the same order or smaller than SSS noise,  $r^2$  remains small. If  
560 instead of considering all the available SMOS SSS pixels (Figure 5), the comparison is made  
561 using only SSS pixels available in every SSS products (Appendix A2), the standard  
562 deviations of the differences are comparable or slightly lower in regions polluted by RFI but  
563 this is at the expense of many measurements which contain meaningful variability as  
564 indicated by high  $r^2$  on Figure 5.

565 Figure 5 indicates a clear improvement of L3Q and CEC fields with respect to L3P fields. In  
566 comparison with K2016 (not shown), standard deviations of the SMOS CEC 18-day SSS  
567 minus SMAP SSS differences are very similar (within +/-0.05 pss) in major parts of the  
568 ocean, but in the regions identified above where  $r^2$  became larger than 0.8, they are locally  
569 improved by more than 0.5 pss; these regions are further studied below. We observe some  
570 degradation (standard deviations of the SMOS minus SMAP SSS differences increase by up  
571 to 0.3 pss) in some regions (the Mediterranean Sea, the Arabian Sea, the north-western part of

572 the Pacific Ocean) strongly affected by RFI and for which L3P fields do not provide valid  
573 measurements. In these regions, however,  $r^2$  obtained with both CEC and K2016 versions  
574 remain less than 0.2.



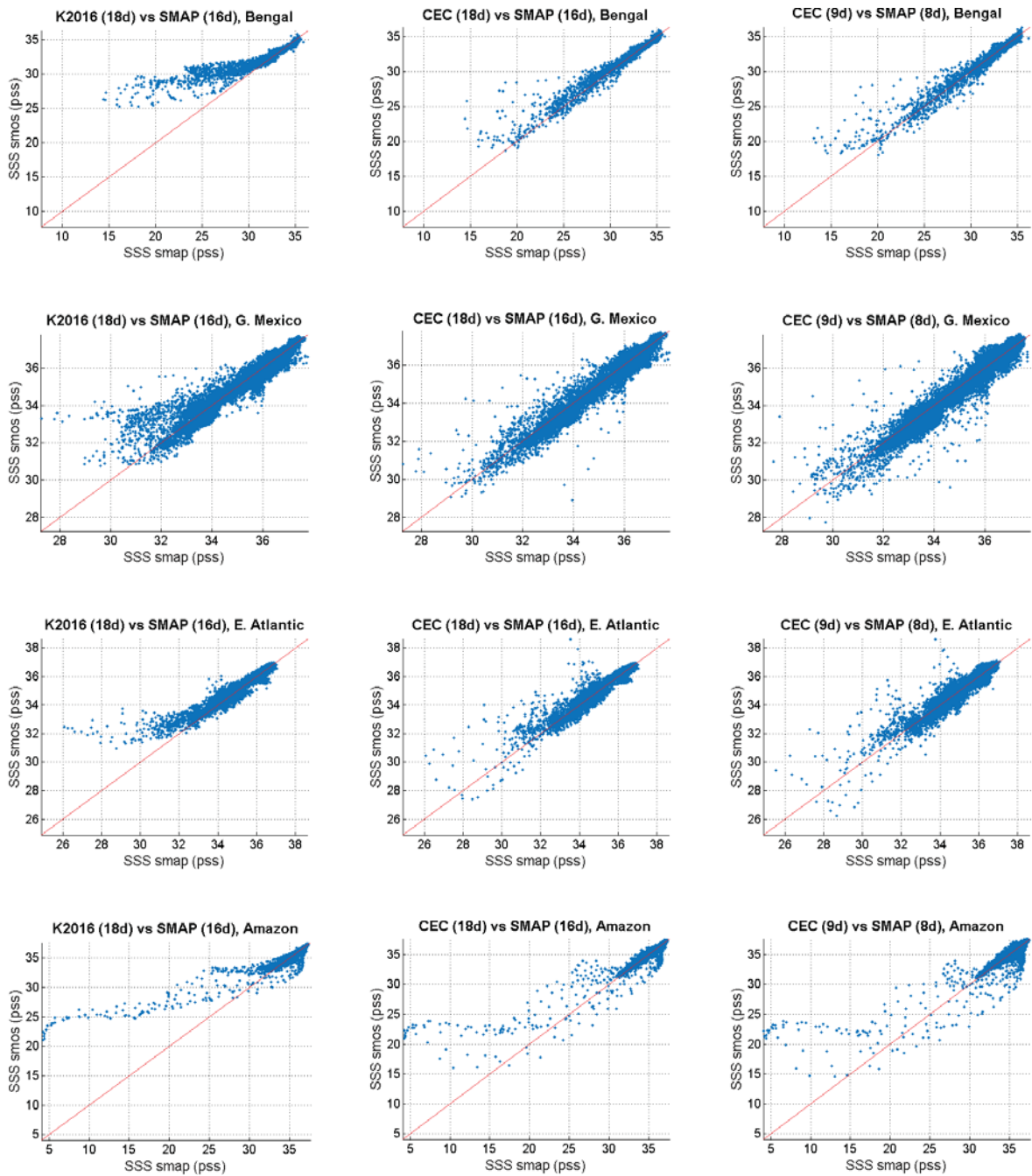
575 Figure 5: Comparison of SMOS and SMAP 'weekly' SSS: (a, d, g)  $r^2$ , (b, e, h) standard deviation of the differences, (c, f, i) number of pixels used in the  
 576 comparisons. (a, b, c) 10-day L3P SMOS SSS, (d, e, f) 10-day L3Q SMOS SSS, (g, h, i) 9-day CEC SMOS SSS. Same indicators but when considering only  
 577 the pixels available in the four products are presented in Appendix A2.

578 We now detail more quantitatively the comparisons between SMAP and SMOS K2016 / CEC  
579 SSS in four regions with very variable salinities (Bay of Bengal; Gulf of Mexico; Eastern  
580 Tropical Atlantic Freshwater Pools; Amazon plume), identified on Figure 5 as having a high  
581  $r^2$  after correction and already presented in the introduction. Contamination by RFI is very  
582 strong in the Bay of Bengal and in the Eastern Tropical Atlantic Freshwater Pools (see very  
583 small number of valid L3P measurements (Figure 5c)) and moderate in the two other regions.  
584 The coast geometry is very different in these 4 regions: the Bay of Bengal and Gulf of  
585 Mexico are semi-enclosed ocean areas so that land-sea contamination of an ocean pixel is  
586 expected to come from more than  $290^\circ$  of different directions, while the other two regions are  
587 surrounded in more than  $180^\circ$  around the points by the ocean.

588 As shown on the maps of Figure 1 and on the corresponding scatter plots (Figure 6, two left  
589 columns), the new SMOS CEC SSS captures fresh SSS patterns much closer to the ones in  
590 SMAP SSS and remains close to SMAP SSS in other SSS ranges. For instance, in the Bay of  
591 Bengal (Figure 1 a-c), the comma-shaped fresh SSS around  $85^\circ\text{E}$  and  $17^\circ\text{N}$  corresponds to  
592 fresh water originating from the Ganges-Brahmaputra trapped in an eddy (Fournier et al.  
593 2017) and the one near  $15^\circ\text{N}$ ,  $95^\circ\text{E}$ , to the Irrawady discharge. In the Gulf of Mexico (Figure  
594 1 d-f), the horseshoe-shaped fresh SSS coming from Texas flooding and transported by ocean  
595 currents (Fournier et al. 2016) is better captured, as well as the Eastern Tropical Atlantic  
596 Freshwater Pools (Figure 1 g-i) and the Amazon and Orinoco plumes (Figure 1 j-l). The  
597 statistics of the SMOS SSS minus SMAP SSS differences are reported in Table 3. The  
598 median of the differences between SMOS and SMAP SSS and  $\text{std}(\text{SMOS}-\text{SMAP})$  are  
599 decreased in all regions. The L1 norm estimator  $\text{std1}$  (equal to  $\text{median}(\text{abs}(x-\text{median}$   
600  $(x)))/0.67$ , and that is less affected by the outliers than  $\text{std}$ ), and  $r^2$  are clearly improved in the  
601 Bay of Bengal; the improvement is less in other regions because of the larger proportion of

602 higher SSS values, and less stringent noise filtering at moderate SSS. For SSS less than 25psa  
603 in the Amazon plume and in the Bay of Bengal, SMOS SSS remains in some cases higher  
604 than SMAP SSS.

605





606 Figure 6 : Scatter plots of SMOS corrected fields versus SMAP SSS on the 4 regions and fresh events  
 607 periods illustrated on Figure 1: first line: Bay of Bengal; 2<sup>nd</sup> line: Gulf of Mexico; 3rd line : Eastern  
 608 Tropical Atlantic Freshwater Pools; 4th line : Amazon plume. First column: SMOS K2016 SSS;  
 609 second column: SMOS 18-day CEC SSS; last column: SMOS 9-day CEC SSS.

610 Table 3: Statistics of (SMOS SSS – SMAP SSS) corresponding to scatter plots of Figure 6

K2016 (18d) – SMAP (16d)				CEC (18d) - SMAP (16d)				CEC (9d) - SMAP (8d)			
median	std	std1	r <sup>2</sup>	median	std	std1	r <sup>2</sup>	median	std	std1	r <sup>2</sup>
<i>Bay of Bengal</i>											
0.10	2.00	0.56	0.85	0.02	0.77	0.38	0.95	-0.03	0.81	0.41	0.95
<i>Gulf of Mexico</i>											
-0.02	0.50	0.29	0.90	-0.06	0.39	0.30	0.94	-0.06	0.45	0.37	0.93
<i>Eastern Tropical Atlantic Freshwater Pools</i>											
0.04	0.42	0.23	0.92	0.01	0.39	0.23	0.91	0.05	0.44	0.29	0.90
<i>Amazon Plume</i>											
-0.14	1.00	0.20	0.83	-0.13	0.82	0.20	0.85	-0.11	0.87	0.25	0.80

611

612 The time series of the indicators reported in Table 3 are plotted for each case study region on  
 613 Figure 7 to Figure 10. ‘Bi-weekly’ indicators confirm that during periods with large SSS  
 614 variability detected by SMAP (black line on top right figures) and low SSS (black line on top  
 615 left figures), r<sup>2</sup> (bottom left figures) and std(SMOS-SMAP) (bottom right figures) are  
 616 systematically improved for CEC with respect to K2016: r<sup>2</sup> becomes larger than 0.9 except in  
 617 the Amazon plume (~0.8). This is not systematically the case during periods with low SSS  
 618 variability and salty SSS when sometimes K2016 performs slightly better in term of r<sup>2</sup> and  
 619 std(SMOS-SMAP): this is likely because our method neglects seasonal variation of  $\sigma_{SSS_{nat}}$ .  
 620 Nevertheless, the worse r<sup>2</sup> obtained with CEC SSS relative to K2016 SSS correspond in  
 621 reality to weak degradations of the corrected SSS, given the noise in both SMOS and SMAP  
 622 SSS and the low SSS variability; on the contrary, the improved r<sup>2</sup> correspond to very  
 623 significant improvements in the detection of fresh SSS in highly variable regions.

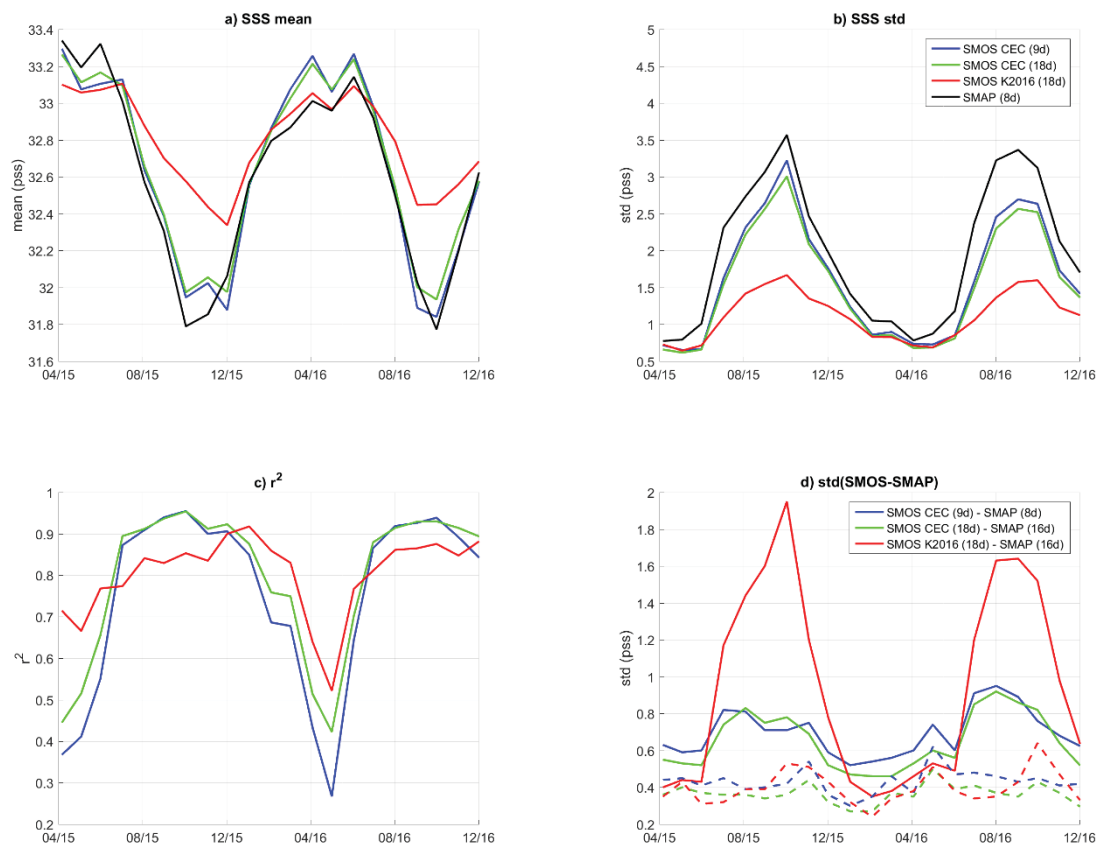
624 std1 (dashed lines on bottom right figures) is on the order of 0.3 pss, which is consistent with  
625 a noise on each ‘bi-weekly’ satellite SSS product on the order of 0.2 pss. Tang et al. 2017  
626 found a standard deviation of 0.17 pss between monthly SMAP and moorings SSS over the  
627 open ocean, a value comparable to the one we find with monthly-100 km SMOS-ship  
628 comparisons that will be described in section 5.2.

629 The standard deviations of the SSS (SSS std (top right figures)) obtained with CEC products  
630 are much closer to the SSS std of the ‘weekly’ SMAP products than the ones obtained with  
631 the ‘bi-weekly’ K2016 products during highly variable periods; during periods with low  
632 variability all SSS std are very close to each other. Nevertheless, except in the Gulf of  
633 Mexico, SSS std are slightly larger for SMAP SSS than for CEC SSS. This possibly indicates  
634 that our method still underestimates SSS natural variability in some cases. This may also be  
635 due to the adjustment to the 7-year median of ISAS SSS: for instance, the fresh water along  
636 the Brazil coast at 50°W-5°N is observed as a continuous tongue in the SMAP SSS map  
637 (Figure 1l), and as a discontinuous one in the SMOS SSS maps (Figure 1j - 1k) which is due  
638 to a discontinuity in the 7-year median of ISAS SSS (not shown). Further validation with  
639 external ground truth of SMOS and SMAP SSS would be necessary to confirm the origin of  
640 this discrepancy.

641 It is also instructive to consider the statistics obtained with ‘weekly’ products (Figure 6, right  
642 column and Figure 7 to Figure 10, blue lines) as SSS during periods with large freshwater  
643 discharges can be very variable at short time scales. In most cases,  $r^2$  and std(SMOS-SMAP)  
644 obtained with ‘weekly’ products are slightly worse than the ones obtained with ‘bi-weekly’  
645 products, because the noise is higher in the ‘weekly’ products but it nevertheless remains  
646 small relative to the natural variability. It is only in Fall, in the Bay of Bengal, when the SSS  
647 std is larger than 2.5 pss, that the  $r^2$  and std(SMOS-SMAP) with the ‘weekly’ CEC product

648 are comparable to the  $r^2$  and  $\text{std}(\text{SMOS-SMAP})$  with ‘bi-weekly’ CEC product, the noise  
 649 becoming negligible relative to the SSS natural variability. Hence, in very variable regions,  
 650 the ‘weekly’ CEC maps could improve the monitoring of fresh spatial structures varying  
 651 within 18 days.

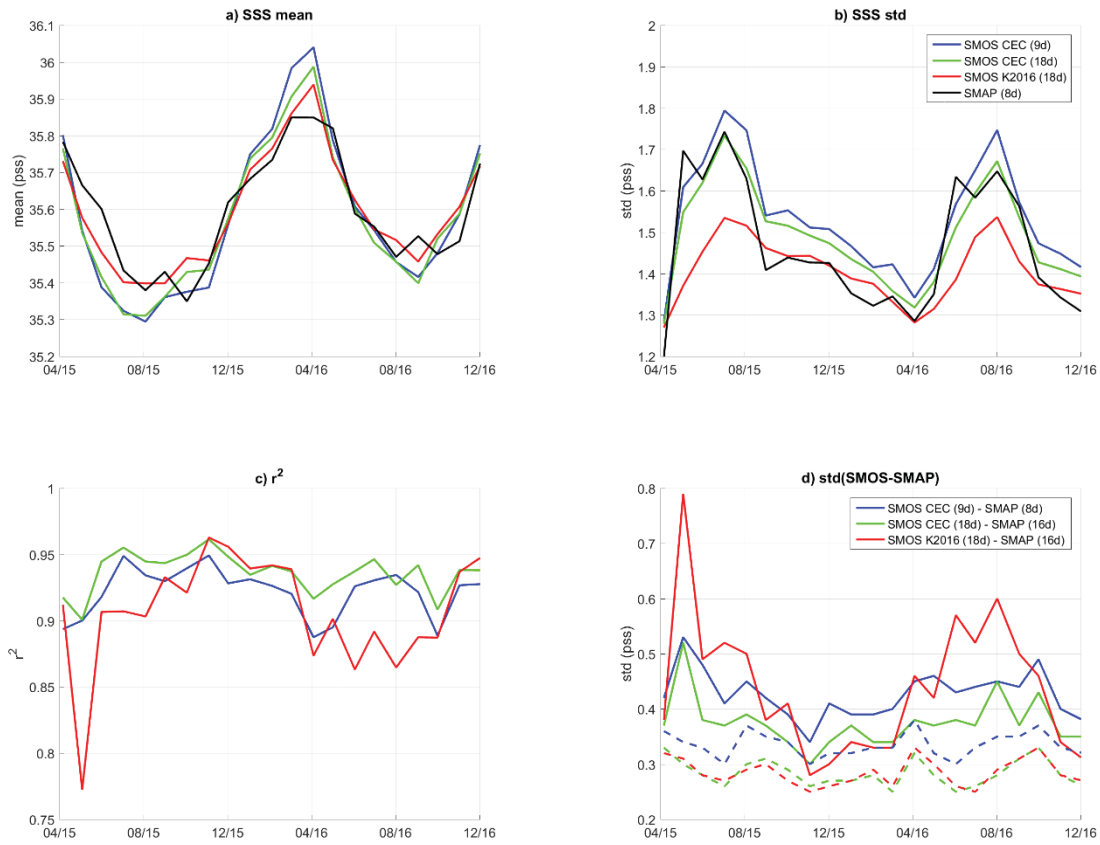
652



653 Figure 7: Time series of statistical parameters computed over the Bay of Bengal case study area, April  
 654 2015 to December 2016: a) mean SSS; b) SSS standard deviation; c) square of the Pearson correlation  
 655 coefficient ( $r^2$ ) between SMOS and SMAP SSS; d) Standard deviation of the SMOS minus SMAP  
 656 SSS differences (plain line) using L1 norm (dotted line). ‘Weekly’ SMOS CEC(blue), ‘bi-weekly’  
 657 SMOS CEC (green), ‘bi-weekly’ SMOS K2016 (red), ‘weekly’ SMAP (black).

658

659

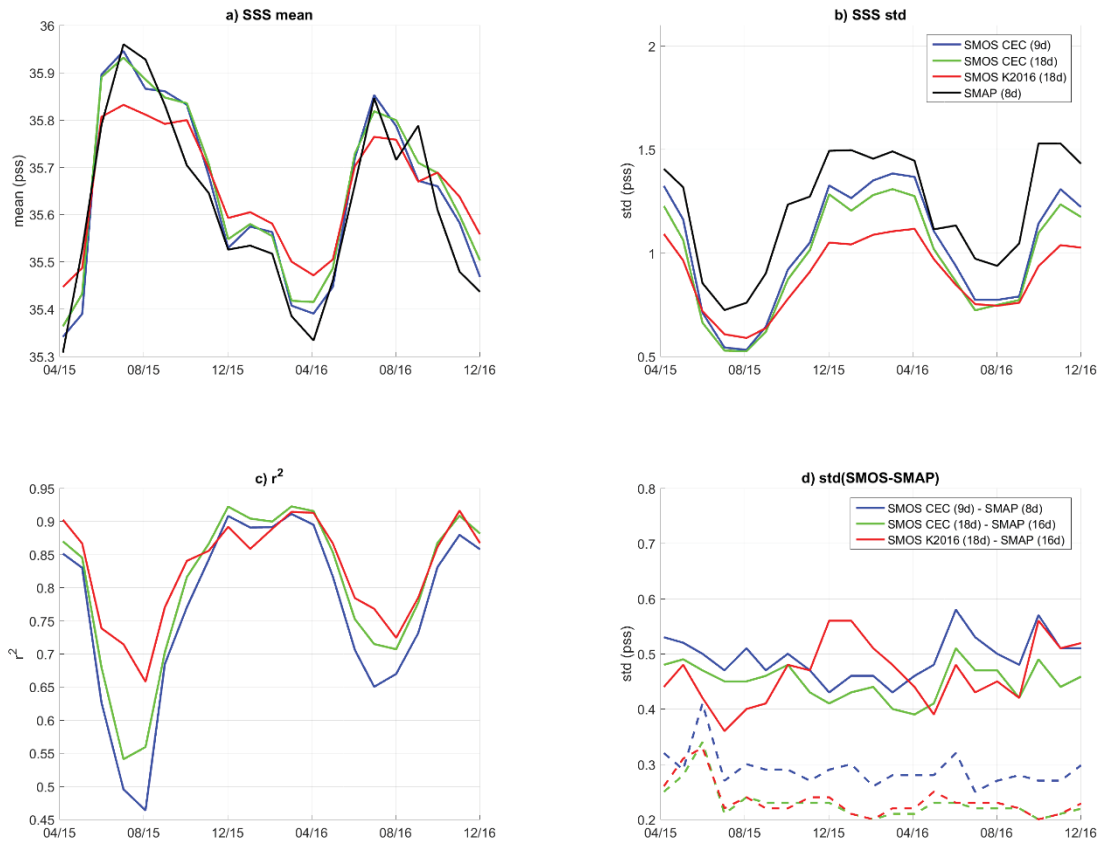


660

661 Figure 8: Time series of statistical parameters computed over the Gulf of Mexico case study area,  
 662 April 2015 to December 2016: a) mean SSS; b) SSS standard deviation; c) square of the Pearson  
 663 correlation coefficient ( $r^2$ ) between SMOS and SMAP SSS; d) Standard deviation of the SMOS minus  
 664 SMAP SSS differences (plain line) using L1 norm (dotted line). ‘Weekly’ SMOS CEC(blue), ‘bi-  
 665 weekly’ SMOS CEC (green), ‘bi-weekly’ SMOS K2016 (red), ‘weekly’ SMAP (black).

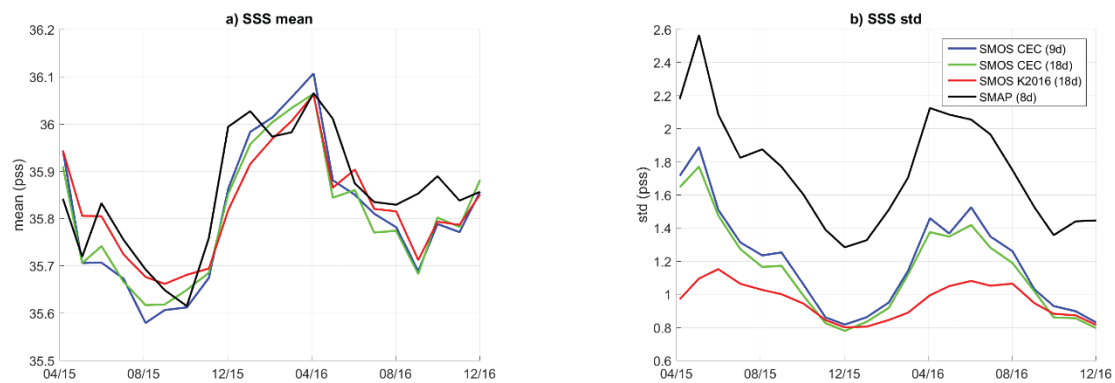
666

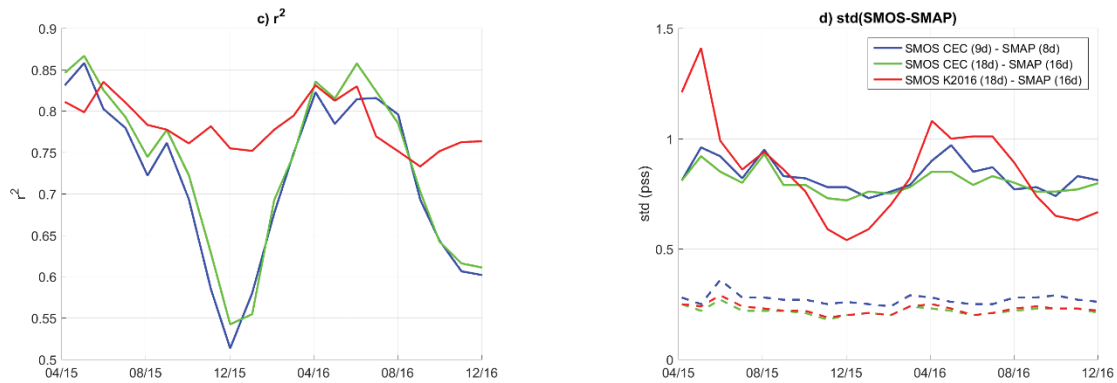
667



668 Figure 9: Time series of statistical parameters computed over the Eastern Tropical Atlantic Freshwater  
 669 Pools case study area, April 2015 to December 2016: a) mean SSS; b) SSS standard deviation; c)  
 670 square of the Pearson correlation coefficient ( $r^2$ ) between SMOS and SMAP SSS; d) Standard  
 671 deviation of the SMOS minus SMAP SSS differences (plain line) using L1 norm (dotted line).  
 672 ‘Weekly’ SMOS CEC(blue), ‘bi-weekly’ SMOS CEC (green), ‘bi-weekly’ SMOS K2016 (red),  
 673 ‘weekly’ SMAP (black).

674





675 Figure 10: Time series of statistical parameters over the Amazon plume case study area, April 2015 to  
 676 December 2016: a) mean SSS; b) SSS standard deviation; c) square of the Pearson correlation  
 677 coefficient ( $r^2$ ) between SMOS and SMAP SSS; d) Standard deviation of the SMOS minus SMAP  
 678 SSS differences (plain line) using L1 norm (dotted line). ‘Weekly’ SMOS CEC(blue), ‘bi-weekly’  
 679 SMOS CEC (green), ‘bi-weekly’ SMOS K2016 (red), ‘weekly’ SMAP (black).

680

## 681 5.2 Comparison to ship SSS

682 Merchant ship transects are used to get ground-truth measurements at various distances from  
 683 the coast. With respect to SMAP SSS, ship SSS is less uncertain but its spatio-temporal  
 684 sampling and resolution is very different from SMOS SSS.

685 In a first step, we consider the scales of SSS variability captured by the various SMOS SSS  
 686 versions and by the ship SSS far from coast. We focus on the subtropical region ( $50^{\circ}\text{W}$ -  
 687  $20^{\circ}\text{W}$ ;  $15^{\circ}\text{N}$ - $40^{\circ}\text{N}$ ) of the north Atlantic in 2013. This region is chosen because it is very  
 688 well covered by regular ship tracks spaced by approximately one month, it is strongly  
 689 impacted by the seasonally-varying latitudinal biases, it is characterized by mesoscale  
 690 variability that is not resolved by the ISAS analysis (Kolodziejczyk et al. 2015; Sommer et al.  
 691 2015), and it is not used for choosing the reference dwell lines of the seasonal latitudinal  
 692 correction. We analyze below the density spectra (Figure 11, top) and the squared coherence  
 693 (Figure 11, bottom) of ISAS, of 10-day L3P and L3Q, of 18-day CEC with ship SSS. Our  
 694 analysis focuses on wavelengths between 1400 km and 150 km, in order to minimize the

695 influence of the limited length of the selected ship tracks (about 2800 km) and of scales  
696 resolved by SMOS (50 km). We recall here that coherence quantifies the correlation between  
697 two quantities for a given wavenumber band. While at 1400 km wavelength ISAS and ship  
698 SSS are very coherent, due to the subsampling of Argo measurements (1 profile per 10 days  
699 per  $3^\circ \times 3^\circ$ ) and to the horizontal scales of the optimal interpolation ( $\sim 300$  km), the ISAS  
700 spectrum (Figure 11, top, green line) dramatically drops as well as its squared coherence  
701 (Figure 11, bottom) for shorter wavelengths.

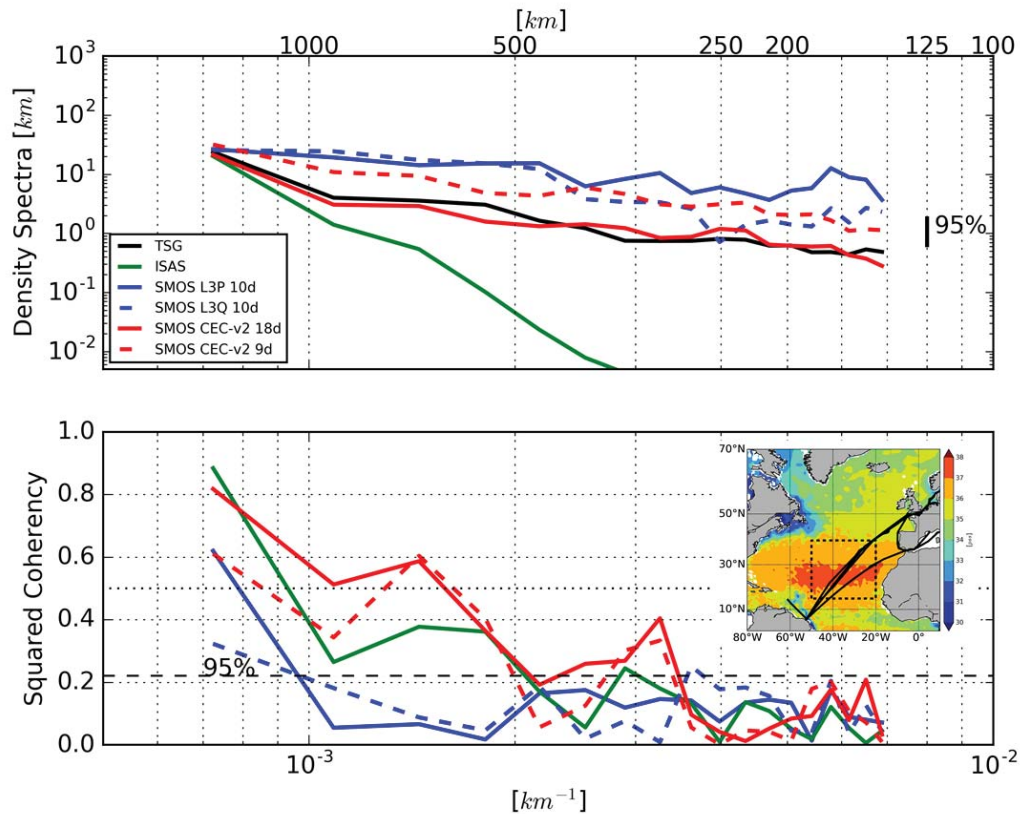
702 Whatever the wavelength, the density spectra (Figure 11 top) of the 18-day CEC SSS is  
703 closer to the one of the ship SSS than the 10-day L3P and L3Q. The density spectrum of the  
704 9-day CEC SSS is very similar to the one of the 10-day L3Q for spatial wavelengths between  
705 150 and 330 km. For longer wavelengths, the density spectrum of 9-day CEC SSS is  
706 intermediate between the 18-day CEC and the 10-day L3Q, indicating that at large scale,  
707 where the temporal variability between 9 days and 18 days is expected to be small, the  
708 different filtering and gaussian mapping applied to CEC products is more effective at  
709 reducing the SMOS SSS noise than the min/max filtering and bin average mapping applied to  
710 L3Q products. Up to 150 km, the density spectra of the 18-day CEC and ship SSS are in  
711 remarkable agreement. This is in fact quite surprising because the MIRAS and TSG  
712 instrumental noises are not expected to lead to the same SSS errors and because the temporal  
713 sampling of SMOS (about 8 passes over 18 days) and of ship ( $\sim$ one transect per month) are  
714 very different. Given the expected noise in level 2 SMOS retrieved SSS (0.6 pss), the median  
715 filtering over nearest neighbor pixels at 25 km distance in the SMOS CEC product, and the  
716 SMOS temporal sampling, the noise on the 18-day CEC SSS is expected to be on the order of  
717 0.15 pss. Noise on individual ship SSS is estimated to be less, on the order of 0.08 pss (Alory  
718 et al. 2015) but the temporal sampling is worse. Hence, the similarity in the two density

719 spectra suggests that the SSS error due to instrumental noise that is larger in SMOS than in  
720 ship SSS, is compensated, over 18 days, by the better temporal sampling in SMOS than in the  
721 ship data.

722 The squared coherence (Figure 11 bottom) of the 18-day CEC SSS is almost at the same level  
723 (above 0.7) as the squared coherence of ISAS SSS at a 1400 km wavelength, and is always at  
724 a higher and significant level for wavelengths up to 300 km. The 18-day CEC squared  
725 coherence decreases with decreasing spatial wavelengths. This can be due to instrumental  
726 noise, to the different temporal sampling of SMOS and ship and to spatially moving  
727 structures within 18 days. The 18-day CEC squared coherence becomes not significant at  
728 95% for wavelengths smaller than 300 km. Considering that at least 3 samples are necessary  
729 to resolve a 300 km wavelength signal, this result indicates that 18-day CEC and ship SSS  
730 capture similar scales of variability up to about 100 km. This is rather consistent with the  
731 spatial integration of SMOS measurement (50 km) in addition to the median filtering over  
732 nearest neighbor pixels at 25 km applied on CEC products.

733 The level of coherence is much less both with the 10-day L3P and L3Q products, due to a  
734 lower signal to noise ratio.





735

736 Figure 11 : Top: Density spectra; Bottom: Coherence between ship SSS and SMOS or ISAS SSS. The  
 737 spatial frequency (1/wavelength (km)) is indicated below the bottom plot, whereas the corresponding  
 738 wavelengths (km) are indicated above the top plot. Vertical dashed lines correspond to spatial  
 739 frequencies regularly spaced in logarithmic coordinates. Northern subtropical Atlantic (see box on the  
 740 color map) in 2013. Ship SSS measured on regular merchant ships transects (14 regular transects in  
 741 2013) (black), ISAS SSS (green), 10-day SMOS L3P (blue line), 10-day SMOS L3Q (dashed blue  
 742 line), 18-day SMOS CEC (red line), 9-day SMOS CEC (red dashed line).

743

744 We will now investigate global statistics for the difference between SMOS and ship SSS.

745 Consistent with the weak coherence observed between the ship SSS and the 10-day L3P and

746 L3Q SSS, 9-day CEC and 10-day L3P or L3Q are of worse quality than the 18-day CEC and

747 monthly L3P and L3Q fields. Hence, in the following comparisons, we only consider

748 monthly L3P, L3Q and 18-day CEC fields. Ships provide within a few hours numerous

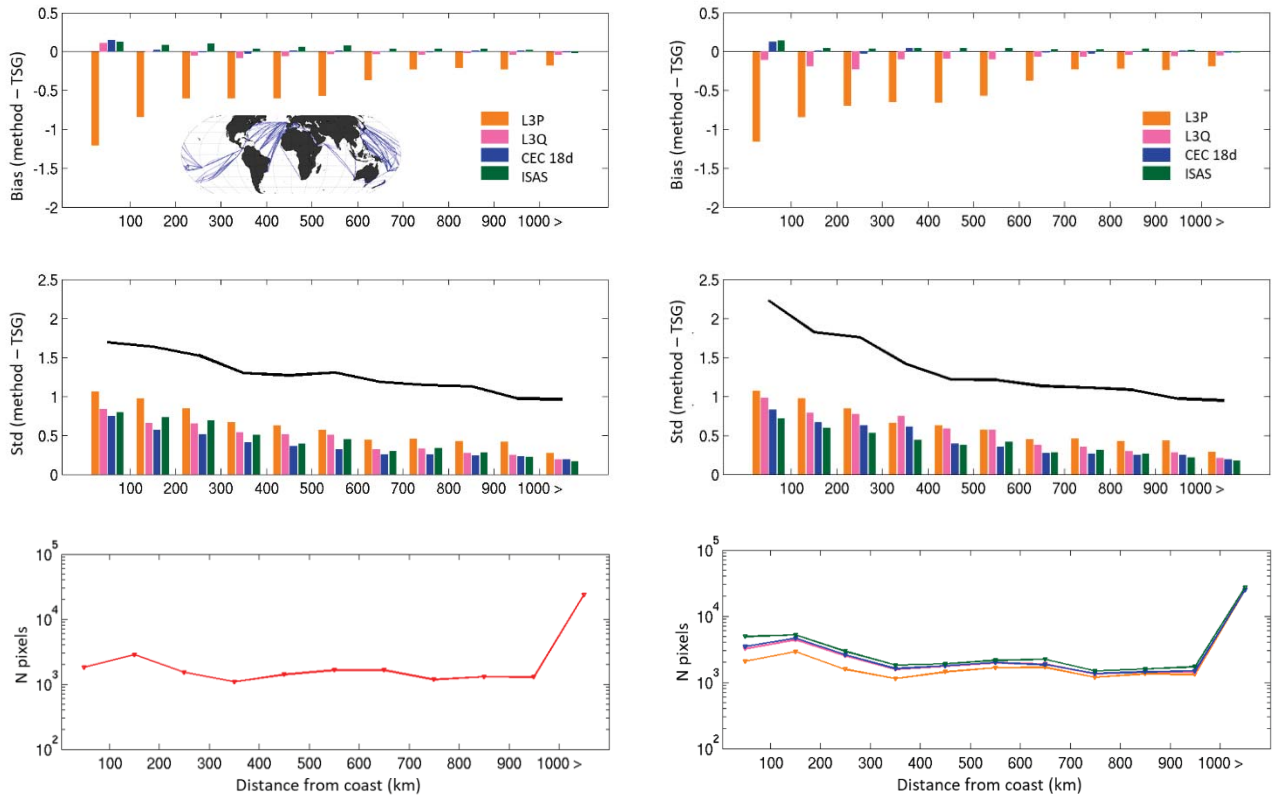
749 measurements within a satellite pixel. In the following, the SSS variability sampled by each

750 ship and by SMOS is smoothed over +/-50 km. This smoothing cannot be identical for the

751 two platforms because of their different spatio-temporal sampling. SMOS observes a surface  
752 (two dimensions) whereas ship measurements are taken along a route (one dimension).  
753 However, this method is expected to reduce the misfit between in situ and SMOS  
754 observations coming from the spatial subsampling of SSS variability within a satellite pixel  
755 by point measurements (Boutin et al. 2016). Mean differences and standard deviation of the  
756 differences between SMOS SSS and ship SSS, named Std(SMOS-Ship) in the following, are  
757 shown in Figure 12, as a function of the distance from the coast. Two sets of comparisons are  
758 presented, involving either only SMOS pixels common to L3P fields (i.e. the ones the less  
759 affected by RFI pollution) (Figure 12, left) or all valid pixels for each product (Figure 12,  
760 right). The number of valid pixels is increased by nearly a factor 2 when approaching the  
761 coast with L3Q and CEC fields with respect to L3P fields (Figure 12, bottom right). The  
762 mean differences (Figure 12, top) obtained with monthly L3P are less than -0.5 pss up to 600  
763 km from the coast. The mean differences with CEC fields are systematically less than 0.05  
764 pss (in absolute value), further than 100 km from the coast, a very clear improvement with  
765 respect to L3P. Similar improvement is observed with monthly L3Q when considering only  
766 pixels common to L3P (Figure 12, left); the mean differences are, however, slightly more  
767 negative when considering all valid pixels, indicating that the filtering is more efficient at  
768 removing SSS outliers in CEC than in L3Q processing. At less than 100 km from the coast,  
769 the mean difference with CEC product reaches 0.15 pss, a value close to the mean difference  
770 between ISAS and ship SSS, consistent with local overestimate of the long term SSS mean by  
771 ISAS, as suggested by SMOS and SMAP SSS comparisons in the Amazon plume along the  
772 coast (Figure 1 and section 5.1). However, the scatter plot (not shown) between CEC and ship  
773 SSS in the region of the Amazon plume is very scattered at low SSS and it was not possible  
774 to identify a systematic bias.

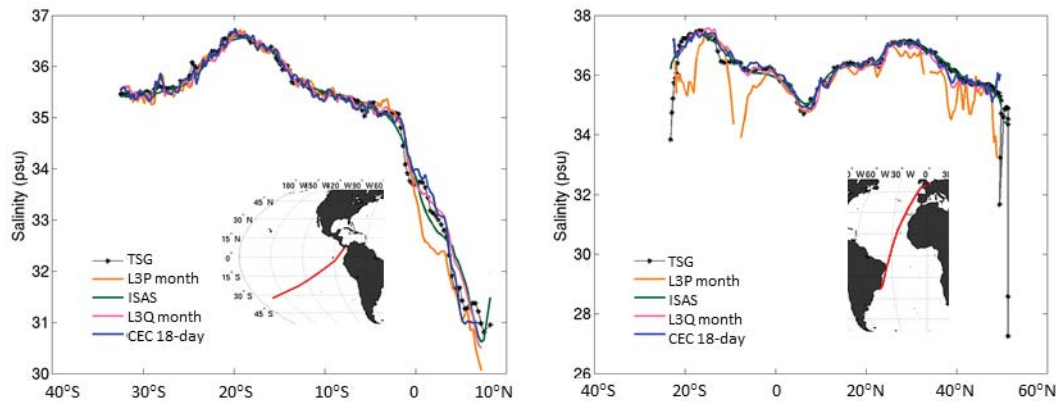
775 Std(SMOS-Ship) is clearly improved whatever the distance to the coast. Further than 1000  
776 km from the coast, it is equal to 0.20 pss with CEC, 0.21 pss with L3Q while it is 0.24 pss  
777 with L3P. It increases when approaching the coast: in the 100-200 km class and when  
778 considering all valid pixels, it equals to 0.64 pss with CEC, 0.69 pss with L3Q, 0.78 pss with  
779 L3P. When approaching the coast, the ship SSS variability is increased too (black lines on  
780 Figure 12, middle right) and it is likely that part of the Std(SMOS-Ship) induced by the  
781 different temporal sampling of SMOS and ships increases when approaching the coast.  
782 Consequently, while Std(SMOS-Ship) is increased by a factor 3 between 100-200 km and  
783 further than 1000 km from the coast, the signal to noise ratio is increased by only a factor 1.5  
784 between these two classes. Similarly, Std(SMOS-Ship) and ship SSS std are lower when  
785 considering only L3P pixels than when considering all valid pixels, so that the signal to noise  
786 ratio in both cases remains similar. When considering all valid pixels (Figure 12, middle  
787 right), the std difference obtained with ISAS remains slightly less than the ones obtained with  
788 CEC and L3Q SSS in all the classes considered except for the range from 500 to 900 km  
789 (Figure 12, middle right). On the contrary, when considering only pixels common to L3P,  
790 (Figure 12, middle left), CEC SSS better captures SSS variability than ISAS in all the classes  
791 up to 900 km from a coast. Two typical ship comparisons illustrate these features. On Figure  
792 13 (left), a transect in the South Pacific is quite well sampled by L3P, except between the  
793 equator and 4°N where the L3Q and CEC SSS is closer to ship SSS. ISAS SSS appears to be  
794 smoother than SMOS SSS, as expected from the optimal interpolation. On Figure 13 (right) a  
795 ship transect crosses the North Atlantic Ocean in September 2013, a period of moderate RFI.  
796 The L3P SSS is very discontinuous due to RFI disturbances in the north and to land-sea  
797 contamination south of the equator. The L3Q and CEC SSS are more numerous and closer to

798 ship SSS than L3P SSS, even though the L3Q SSS appears to be more affected by RFI than  
 799 the 18-day CEC SSS north of 40°N.



800 Figure 12 : Statistics of ship comparisons (May 2010-August 2016) binned as a function of the  
 801 distance from the nearest coast: top) mean difference; middle) standard deviation of the differences;  
 802 the black line indicates the standard deviation of ship SSS in each class; bottom) number of pixels  
 803 used in the comparisons. Left: considering only the SMOS pixels common to all versions; right:  
 804 considering all pixels available in each version. Ship and SMOS SSS are integrated over 100 km.  
 805 Orange: monthly SMOS L3P ; pink : monthly SMOS L3Q; light blue : 18-day SMOS CEC; green :  
 806 ISAS.

807



808

809 Figure 13 : Examples of comparisons between ship SSS (black stars line) and SMOS SSS: orange:  
 810 non corrected (L3P), purple: monthly L3Q corrected, light blue :18-day CEC corrected; green : ISAS.  
 811 Left) from 2014-08-21 to 2014-09-03, Matisse ship. Right) from 2013-08-21 to 2013-09-03, Santa  
 812 Cruz ship. All SSS products have been smoothed over +/-50 km.

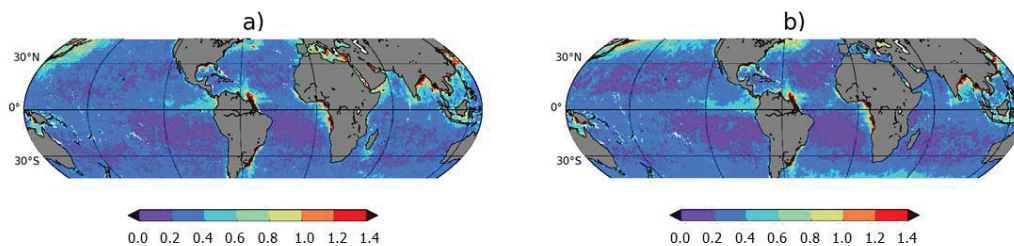
813

## 814 6. Discussion and Perspectives

815 Retrieving accurate SSS from SMOS measurements in the vicinity of continents is very  
 816 challenging. The land-sea brightness temperature contrasts induce a contamination of the  
 817 retrieved SSS signal, up to about 1000 km from the coast. This contamination is very variable  
 818 across the SMOS swath. The origin of this pollution is very complex. It is likely related to an  
 819 imprecise characterization of the 69 individual antenna patterns constituting the SMOS  
 820 synthetic antenna, preventing a reliable theoretical modelling of the correction in the current  
 821 SMOS image reconstruction process. The land-sea contamination has thus to be mitigated  
 822 empirically. When doing so, the main difficulty is to distinguish the SMOS signal resulting  
 823 from natural SSS variability from ones contaminated by RFI, whose sources are often located  
 824 near coasts. To make matters worse, the typical RFI signature yields low SSS, and the largest  
 825 SSS natural variability often occurs in low SSS regions, e.g. from river plumes or high rain  
 826 regime. The K2016 methodology developed for correcting SSS affected by land-sea  
 827 contamination was very efficient in many areas, but not in those characterized by strong

828 natural variability, as it implicitly assumed that natural SSS variability was negligible relative  
829 to SMOS SSS noise. The revised correction methodology presented in this paper includes  
830 information on the amplitude of natural SSS variability inferred from SMOS measurements.  
831 We further add a seasonally- and latitudinally-dependent bias correction.

832 The SMOS corrected SSS is much more consistent to the independent SMAP SSS than  
833 K2016, both in terms of SSS patterns and amplitude (Table 3). The SMOS SSS is, however,  
834 slightly noisier than SMAP: in the open ocean (Pacific ITCZ region), Supply et al. 2017  
835 found an error of 0.6 pss on L2 SMOS SSS and of 0.5 pss on L2 SMAP SSS. This difference  
836 is explained by the radiometric accuracy of the respective instruments and by the SMAP  
837 flight hardware that allows efficient detection and filtering of most RFI (Mohammed et al.  
838 2016) unlike SMOS. Nevertheless, both satellite missions record very similar SSS variability  
839 at weekly time scale that is not resolved by mapped Argo data (Figure 14). On average over  
840 47°N-47°S, the standard deviation of the difference between SMOS CEC and ISAS SSS  
841 (Figure 14a) is 0.33 pss while the standard deviation of the difference between SMAP and  
842 ISAS SSS (Figure 14b) is 0.31 pss. The geographical distribution of this variability is very  
843 consistent with the small-scale variability of SSS observed by ship measurements (see Figure  
844 6 of Boutin et al. 2016) with minima in the subtropics and maxima in coastal areas, in the  
845 vicinity of river plumes or in regions characterized by strong mesoscale fronts, such as the  
846 Gulf Stream.



847

848 Figure 14 : Standard deviation of ‘weekly’ satellite SSS minus ISAS SSS between 47°N and 47°S,  
849 over the year 2016. a) SMOS CEC, b) SMAP CAP.

850

851 The only quantitative external information entered in the correction algorithm is the 7-year  
852 median of ISAS SSS that fixes the absolute calibration of the SMOS SSS in each pixel but  
853 does not influence its variability. In seasonally-varying latitudinal biases correction, ISAS  
854 SSS serves only in a qualitative way for choosing the SMOS cross-swath locations used as  
855 reference. The implemented correction removes most of the systematic errors and brings  
856 clear improvement when compared with *in situ* ground truths measurement or with SMAP  
857 SSS. Nevertheless, some refinements could still be envisioned. The absolute calibration based  
858 on ISAS median SSS leads to some inaccuracies in very near coastal pixels. This issue could  
859 probably be improved in the future by analyzing to what extent the absolute calibration is  
860 sensitive to the time period under consideration for computing the median and by merging  
861 information coming from ISAS SSS with other SSS fields. A further step could be taken by  
862 merging SMOS and SMAP information in order to build a level 4 product taking advantage  
863 of synoptic spatio-temporal coverage of satellite data for monitoring SSS variability and  
864 using *in situ* SSS for the absolute calibration of SSS fields. Future studies should also pay  
865 more attention to the bias seasonal and interannual variability as a function of sun activity  
866 and of land Tb variability which have been neglected in our study.

867 Our method corrects SMOS SSS retrieved with a Bayesian approach at level 2, as described  
868 in Zine et al. 2008 and as implemented in ESA and CATDS operational processors. Such a  
869 retrieval method takes advantage of the expected consistency between the various Tbs  
870 measured at various incidence angles at a given distance across the swath and takes the  
871 radiometric accuracy of each Tb into account. The land-sea contamination is expected to add  
872 variability and biases on the SMOS Tbs at a given distance across the swath, so that the

873 quality of the Bayesian retrieval is downgraded. In order to cope with this caveat, a  
874 systematic correction at Tb level has been implemented in ESA L2 OS processor v662,  
875 before the retrieval of SSS. The biases in the vicinity of land and the standard deviation of the  
876 difference with respect to ISAS are much reduced (Spurgeon and SMOS-Ocean Expert  
877 Support Laboratories, 2017), but flagged SSS (poor quality retrieval) remain in many coastal  
878 areas. Thus, the accuracy of the retrieved SSS is in general not as good as the one obtained  
879 with our correction at the SSS level (Level-3). The better performance of our methodology is  
880 likely due to the fact that we account for SSS variability. Given all the non-SSS geophysical  
881 effects affecting Tbs (roughness effect, galactic noise etc...), it is very difficult to account for  
882 SSS variability when dealing with Tbs measured at different angles within the field of view.  
883 Nevertheless, future work should explore a two-step correction, first performed at Tb level to  
884 improve the Bayesian L2 retrieval and second performed at SSS level.

885 An alternative debiasing method from a non-Bayesian approach has also been proposed by  
886 Olmedo et al (2017). Contrary to our approach, Olmedo et al. (2017) retrieve SSS from single  
887 angular Tb measurements, they filter SSS outliers using statistical indicators of the 3-year  
888 SSS histogram per incidence angle classes. They adjust the absolute value of SMOS SSS by  
889 adding the World Ocean Atlas climatology. An analysis (not shown) of the 9-day De-biased  
890 non-Bayesian SMOS SSS fields available from the Barcelona Expertise Center which have  
891 been obtained with an objective analysis in the regions and periods shown in Figure 1  
892 indicates that the striking fresh features are captured at a similar level as what was obtained  
893 with K2016 methodology, consistent with the fact that the statistical indicators used to filter  
894 outliers do not depend on the SSS natural variability.

895 While SMAP SSS is expected to be much less affected by RFI, some disturbances remain in  
896 some regions (Mohammed et al. 2016) and the calibration of SMAP data is also challenging



897 (Fore et al. 2016b, Meissner and Wentz, 2016). Hence, when dealing with a local scientific  
898 study, dedicated comparisons with *in situ* ground truth are highly recommended in order to  
899 precisely estimate the validity of satellite SSS in a given region and period with respect to the  
900 natural variability that is considered. This should be facilitated in the future with the  
901 development of the SMOS Pilot Mission Exploitation Platform (PI-MEP).

902 The CATDS/CPDC L3Q SSS is currently limited to 47°S-47°N as we could not define  
903 unbiased SMOS reference dwell lines poleward of this latitude. This is likely because of  
904 imperfect correction for surface roughness and ice contamination which can extend up to  
905 1000 km from the ice edge and which is much more difficult to mitigate than land-sea  
906 contamination as the ice edge is moving. Future studies should focus at correcting the ice  
907 contamination and improving roughness correction. In addition, in regions contaminated with  
908 highly variable RFI over the 7-year period, such as the northernmost parts of the Atlantic and  
909 Pacific Oceans, the land-sea contamination correction becomes very tricky. In our study, RFI  
910 affected Tbs are filtered out using a three-sigma filtering applied on SMOS Tbs before  
911 retrieving SSS and using a Chi filtering applied on L2 SSS. Future studies should look at  
912 improving this filtering.

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920 SMAP CAP SSS is produced at Jet Propulsion Laboratory. It is available on [ftp://podaac-](ftp://podaac-ftp.jpl.nasa.gov/allData/smap/)  
921 [ftp.jpl.nasa.gov/allData/smap/](ftp://podaac-ftp.jpl.nasa.gov/allData/smap/). ISAS 13 analysis fields are made freely available by  
922 Laboratoire d'Océanographie Physique et Spatiale (LOPS) ([http://www.umn-lops.fr/SNO-](http://www.umn-lops.fr/SNO-Argo/Products/ISAS-T-S-fields)  
923 [Argo/Products/ISAS-T-S-fields](http://www.umn-lops.fr/SNO-Argo/Products/ISAS-T-S-fields)). Near real time ISAS analysis are produced by the Coriolis  
924 data center and are freely available via CMEMS web site CMEMS-Copernicus Services:  
925 <http://marine.copernicus.eu/>. SSS data derived from thermosalinograph instruments installed  
926 onboard voluntary observing ships were collected, validated, archived, and made freely  
927 available by the French Sea Surface Salinity Observation Service ([http://www.legos.obs-](http://www.legos.obs-mip.fr/observations/sss/)  
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## 931 REFERENCES

- 932 Akhil, V. P., M. Lengaigne, F. Durand, J. Vialard, A. V. S. Chaitanya, M. G. Keerthi, V. V.  
933 Gopalakrishna, J. Boutin, and C. de Boyer Montégut (2016), Assessment of seasonal and  
934 year-to-year surface salinity signals retrieved from SMOS and Aquarius missions in the Bay  
935 of Bengal, *International Journal of Remote Sensing*, 37(5), 1089-1114,  
936 doi:10.1080/01431161.2016.1145362.
- 937 Alory G., T. Delcroix, P. Téchiné, D. Diverrès, D. Varillon, S. Cravatte, Y. Gouriou, J.  
938 Grelet, S. Jacquin, E. Kestenare, C. Maes, R. Morrow, J. Perrier, G. Reverdin, and F.  
939 Roubaud (2015), The French contribution to the Voluntary Observing Ships network of Sea  
940 Surface Salinity. *Deep Sea Res.*, 105, 1-18, doi:10.1016/j.DSR.2015.08.005.
- 941 E. Anterrieu, M. Suess, F. Cabot, P. Spurgeon and A. Khazâal (2015), An Additive Mask  
942 Correction Approach for Reducing the Systematic Floor Error in Imaging Radiometry by  
943 Aperture Synthesis," in *IEEE Geoscience and Remote Sensing Letters*, vol. 12, no. 7, pp.  
944 1441-1445, doi: 10.1109/LGRS.2015.2406912.
- 945 Arias, M. and SMOS-Ocean Expert Support Laboratories, 2016, L2OS v622 Reprocessing  
946 Report, SO-RP-ARG-GS-0100 Issue:2, 29 February 2016, available on  
947 [https://smos.argans.co.uk/docs/technotes/SO-RP-ARG-GS-](https://smos.argans.co.uk/docs/technotes/SO-RP-ARG-GS-0100_L2OS_Reprocessing_Report_v2.0_160229.pdf)  
948 [0100\\_L2OS\\_Reprocessing\\_Report\\_v2.0\\_160229.pdf](https://smos.argans.co.uk/docs/technotes/SO-RP-ARG-GS-0100_L2OS_Reprocessing_Report_v2.0_160229.pdf).
- 949 Boutin J., Vergely J.L., Marchand S. (2017). SMOS SSS L3 debias v2 maps generated by  
950 CATDS CEC LOCEAN. <http://doi.org/10.17882/52804>.

951 Bretherton, F.P., R.E. Davis and C.B. Fandry (1976) Technique for Objective Analysis and  
952 Design of Oceanographic Experiments Applied to Mode-73. *Deep-Sea Research*. 23:559-582.

953 Brodzik, M. J., B. Billingsley, T. Haran, B. Raup, M. H. Savoie (2012) EASE-Grid 2.0:  
954 Incremental but Significant Improvements for Earth-Gridded Data Sets. *ISPRS International*  
955 *Journal of Geo-Information*, 1(1):32-45, doi:10.3390/ijgi1010032.

956 CATDS (2017a). CATDS-PDC L3OS 2P - Daily valid ocean salinity values product from  
957 SMOS satellite. CATDS (CNES, IFREMER, LOCEAN). [http://doi.org/10.12770/77edd308-](http://doi.org/10.12770/77edd308-4296-4774-b6f3-5b38301cee18)  
958 [4296-4774-b6f3-5b38301cee18](http://doi.org/10.12770/77edd308-4296-4774-b6f3-5b38301cee18).

959 CATDS (2017b). CATDS-PDC L3OS 3P mixed - Average 10 days & monthly salinity field  
960 product from SMOS satellite (mixed orbits). CATDS (CNES, IFREMER, LOCEAN).  
961 <http://doi.org/10.12770/75ccd428-74b5-45db-879e-37ab98fa28a1>

962 CATDS (2017c). CATDS-PDC L3OS 3Q mixed - Debiased average 10 days & monthly  
963 salinity field product from SMOS satellite (mixed orbits). CATDS (CNES, IFREMER,  
964 LOCEAN, ACRI). <http://doi.org/10.12770/0f02fc28-cb86-4c44-89f3-ee7df6177e7b>

965 Chaitanya, A.V.S., M. Lengaigne, J. Vialard, V.V. Gopalakrishna, F. Durand, Ch.  
966 Krantikumar, V. Suneel, F. Papa and M. Ravichandran (2014), Fishermen-operated salinity  
967 measurements reveal a “river in the sea” flowing along the east coast of India, *Bull. Am. Met.*  
968 *Soc.*, 95, 1897-1908.

969 Delcroix, T., M. McPhaden, A. Dessier, and Y. Gouriou (2005), Time and space scales for  
970 sea surface salinity in the tropical oceans. *Deep Sea. Res.*, 52/5, 787-813,  
971 doi:10.1016/j.dsr.2004.11.012.

972 Durack, P. J., Wijffels, S. E., and Matear, R. J. (2012), Ocean salinities reveal strong global  
973 water cycle intensification during 1950 to 2000. *Science*, 336(6080), 455-458.

974 Font, J., A. Camps, A. Borges, M. Martin-Neira, J. Boutin, N. Reul, Y. H. Kerr, A. Hahne,  
975 and S. Mecklenburg (2010), SMOS: The Challenging Sea Surface Salinity Measurement  
976 From Space, *Proceedings of the IEEE*, 98(5), 649-665.

977 Fore, A. G., S. H. Yueh, W. Tang, B. W. Stiles, and A. K. Hayashi (2016a), Combined  
978 active/passive retrievals of ocean vector wind and sea surface salinity with SMAP. *IEEE*  
979 *Trans. Geosci. Remote Sens.*, 54(12):7396-7404, December 2016.

980 Fore, A., S. Yueh, W. Tang, and A. Hayashi, (2016b), SMAP Salinity and Wind Speed Data  
981 User's Guide Version 3.0, JPL, 30 December 2016.

982 Fournier, S., J. T. Reager, T. Lee, J. Vazquez-Cuervo, C. H. David, and M. M. Gierach  
983 (2016), SMAP observes flooding from land to sea: The Texas event of 2015, *Geophys. Res.*  
984 *Lett.*, 43, 10,338–10,346, doi:10.1002/2016GL070821.

985 Fournier, S., Vialard, J., Lengaigne, M., Lee, T., Gierach, M. M., & Chaitanya, A. V. S.  
986 (2017), Modulation of the Ganges-Brahmaputra river plume by the Indian Ocean dipole and  
987 eddies inferred from satellite observations. *Journal of Geophysical Research: Oceans*, 122,  
988 9591–9604. <https://doi.org/10.1002/2017JC013333>.

989 Gaillard F. (2015), ISAS-13 temperature and salinity gridded fields. SEANOE.  
990 <http://doi.org/10.17882/45945>.

- 991 Gaillard, F., T. Reynaud, V. Thierry, N. Kolodziejczyk and K. von Schuckmann (2016), *In*  
992 *situ*-Based Reanalysis of the Global Ocean Temperature and Salinity with ISAS: Variability  
993 of the Heat Content and Steric Height, *J. Clim.*, 29, 1305-1323, doi:10.1175/JCLI-D-15-  
994 0028.1.
- 995 Grodsky, S. A., N. Reul, B. Chapron, J. A. Carton, and F. O. Bryan (2017), Interannual  
996 surface salinity on Northwest Atlantic shelf, *J. Geophys. Res. Oceans*, 122, 3638–3659,  
997 doi:10.1002/2016JC012580.
- 998 Hasson, A., T. Delcroix, J. Boutin, R. Dussin, and J. Ballabrera-Poy (2014), Analyzing the  
999 2010–2011 La Niña signature in the tropical Pacific sea surface salinity using *in situ* data,  
1000 SMOS observations, and a numerical simulation, *Journal of Geophysical Research: Oceans*,  
1001 119(6), 3855-3867, doi:10.1002/2013JC009388.
- 1002 Hasson, A., M. Puy, J. Boutin, E. Guilyardi (2018), Northward Propagation across the  
1003 Tropical North Pacific Ocean Revealed by Surface Salinity: How El Nino Anomalies Reach  
1004 Hawaii?, *Journal of Geophys. Res.*, *in revision*.
- 1005 Hernandez, O., Boutin, J., Kolodziejczyk, N., Reverdin, G., Martin, N., Gaillard, F., Reul, N.,  
1006 & Vergely, J.L. (2014). SMOS salinity in the subtropical North Atlantic salinity maximum: 1.  
1007 Comparison with Aquarius and *in situ* salinity. *Journal of Geophysical Research: Oceans*,  
1008 119, 8878-8896.
- 1009 Kerr, Y. H., et al. (2010), The SMOS Mission: New Tool for Monitoring Key Elements of the  
1010 Global Water Cycle, *Proceedings of the IEEE*, 98(5), 666-687.
- 1011 Kolodziejczyk, N., O. Hernandez, J. Boutin, and G. Reverdin (2015a), SMOS salinity in the  
1012 subtropical North Atlantic salinity maximum: 2. Two-dimensional horizontal thermohaline  
1013 variability, *J. Geophys. Res. Oceans*, 120, 972–987, doi:10.1002/2014JC010103.
- 1014 Kolodziejczyk, N., G. Reverdin, J. Boutin, and O. Hernandez (2015b), Observation of the  
1015 surface horizontal thermohaline variability at mesoscale to submesoscale in the north-eastern  
1016 subtropical Atlantic Ocean, *Journal of Geophysical Research: Oceans*, 120(4), 2588-2600,  
1017 doi:10.1002/2014JC010455.
- 1018 Kolodziejczyk, N., J. Boutin, J.L. Vergely, S. Marchand, N. Martin, and G. Reverdin (2016).  
1019 Mitigation of systematic errors in SMOS sea surface salinity. *Remote Sensing of*  
1020 *Environment*, 180, 164-177.
- 1021 Lagerloef, G., et al. (2008), The Aquarius/SAC-D mission: Designed to meet the salinity  
1022 remote sensing challenge *Oceanography*, 21(1), 68–81.
- 1023 Lagerloef, G. (2012), Satellite mission monitors ocean surface salinity, *Eos Transactions of*  
1024 *the AGU*, 93(25), 233-234.
- 1025 Meissner, T. and F. J. Wentz (2016), Remote Sensing Systems SMAP Ocean Surface  
1026 Salinities [Level 2C, Level 3 Running 8-day, Level 3 Monthly], Version 2.0 validated  
1027 release. Remote Sensing Systems, Santa Rosa, CA, USA. Available online at  
1028 [www.remss.com/missions/smap](http://www.remss.com/missions/smap), doi: 10.5067/SMP20-3SPCS.
- 1029 Mohammed, P. N. , M. Aksoy J. R. Piepmeier J. T. Johnson A. Bringer (2016), SMAP L-  
1030 band microwave radiometer: RFI mitigation prelaunch analysis and first year on-orbit  
1031 observations, *IEEE Trans. Geosci. Remote Sens.*, vol. 54 no. 10 pp. 6035-6047.

- 1032 Oliva, R., Daganzo-Eusebio, E., Kerr, Y., Mecklenburg, S., Nieto, S., Richaume, P., Gruhier,  
1033 C. (2012), SMOS Radio frequency interference scenario: status and actions taken to improve  
1034 the RFI environment in the 1400–1427-MHz passive band. *IEEE Trans. Geosci. Remote*  
1035 *Sens.* 50 (5), 1427–1440.
- 1036 Olmedo, E., Martínez, J., Turiel, A., Ballabrera-Poy, J., & Portabella, M. (2017), Debiased  
1037 non-Bayesian retrieval: A novel approach to SMOS Sea Surface Salinity. *Remote Sensing of*  
1038 *Environment*, 193, 103-126.
- 1039 Picaut, J., M. Ioualalen, T. Delcroix, F. Masia, R. Murtugudde, and J. Vialard (2001), The  
1040 oceanic zone of convergence on the eastern edge of the Pacific warm pool: A synthesis of  
1041 results and implications for ENSO and biogeochemical phenomena, *J. Geophys. Res.*, 106,  
1042 2363–2386.
- 1043 Piepmeier J. R. *et al.*, (2017), SMAP L-Band Microwave Radiometer: Instrument Design and  
1044 First Year on Orbit," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 55, no.  
1045 4, pp. 1954-1966, doi: 10.1109/TGRS.2016.2631978.
- 1046 Reul N., and Coauthors (2014a), Sea Surface Salinity Observations from Space with the  
1047 SMOS Satellite: A New Means to Monitor the Marine Branch of the Water Cycle. *Surveys In*  
1048 *Geophysics*, 35(3), 681-722.
- 1049 Reul, N., B. Chapron, T. Lee, C. Donlon, J. Boutin, and G. Alory (2014b), Sea surface  
1050 salinity structure of the meandering Gulf Stream revealed by SMOS sensor, *Geophysical*  
1051 *Research Letters*, 41(9), 3141-3148, doi:10.1002/2014gl059215.
- 1052 Shenoi, S. S. C., D. Shankar (2002), Differences in heat budgets of the near-surface Arabian  
1053 Sea and Bay of Bengal: Implications for the summer monsoon, *J. Geophys. Res.*, 107(C6),  
1054 doi:10.1029/2000JC000679,.
- 1055 SMOS-Ocean Expert Support Laboratories (2014), SMOS L2 OS Algorithm Theoretical  
1056 Baseline Document, SO-TN-ARG-GS-0007, available on  
1057 [https://smos.argans.co.uk/docs/deliverables/delivered/ATBD/SO-TN-ARG-GS-0007\\_L2OS-](https://smos.argans.co.uk/docs/deliverables/delivered/ATBD/SO-TN-ARG-GS-0007_L2OS-ATBD_v3.11_140905.pdf)  
1058 [ATBD\\_v3.11\\_140905.pdf](https://smos.argans.co.uk/docs/deliverables/delivered/ATBD/SO-TN-ARG-GS-0007_L2OS-ATBD_v3.11_140905.pdf).
- 1059 Sommer, A., Reverdin, G., Kolodziejczyk, N., and Boutin, J. (2015), Sea Surface Salinity and  
1060 Temperature Budgets in the North Atlantic Subtropical Gyre during SPURS Experiment:  
1061 August 2012-August 2013. *Frontiers in Marine Science*, 2, 107.
- 1062 Spurgeon and SMOS-Ocean Expert Support Laboratories (2017), L2OS v662 Reprocessing  
1063 Report, SO-RP-ARG-GS-0109, available on  
1064 [https://earth.esa.int/documents/10174/477987/SMOS-Level-2-Ocean-Salinity-v662-](https://earth.esa.int/documents/10174/477987/SMOS-Level-2-Ocean-Salinity-v662-Reprocessing-Report/3587ea20-45d1-49a5-a6ca-084d1bf988b6?version=1.4)  
1065 [Reprocessing-Report/3587ea20-45d1-49a5-a6ca-084d1bf988b6?version=1.4](https://earth.esa.int/documents/10174/477987/SMOS-Level-2-Ocean-Salinity-v662-Reprocessing-Report/3587ea20-45d1-49a5-a6ca-084d1bf988b6?version=1.4).
- 1066 Supply, A., J. Boutin, J.-L. Vergely, N. Martin, A. Hasson, G. Reverdin, C. Mallet, N. Viltard  
1067 (2017), Precipitation Estimates from SMOS Sea Surface Salinity, *QJRMS*,  
1068 doi:10.1002/qj.3110.

- 1069 Tang, W., A. Fore, S. Yueh, T. Lee, A. Hayashi, A. Sanchez-Franks, B. King, D.  
 1070 Baranowski, and J. Martinez (2017), Validating SMAP SSS with in-situ measurements.  
 1071 Remote Sensing Environ.. <https://doi.org/10.1016/j.rse.2017.08.021>.
- 1072 Vergely and Boutin (2017), SMOS OS level 3: the Algorithm Theoretical Basis Document  
 1073 (v300), 05/05/2017, available on  
 1074 [http://www.catds.fr/content/download/78841/1005020/file/ATBD\\_L3OS\\_v3.0.pdf?version=3](http://www.catds.fr/content/download/78841/1005020/file/ATBD_L3OS_v3.0.pdf?version=3)  
 1075 .
- 1076 Vialard, J. and P. Delecluse (1998), An OGCM Study for the TOGA Decade. Part I : Role of  
 1077 Salinity in the Physics of the Western Pacific Fresh Pool. Journal of Physical Oceanography,  
 1078 28, 1071 - 1088.
- 1079 Yin, X., Boutin, J., & Spurgeon, P. (2012). First assessment of SMOS data over open ocean:  
 1080 Part I; Pacific Ocean. IEEE Transactions on Geoscience and Remote Sensing, 50(5), 1648–  
 1081 1661.
- 1082 Yin, X., J. Boutin, P. Spurgeon, Biases Between Measured and Simulated SMOS Brightness  
 1083 Temperatures Over Ocean: Influence of Sun (2013), IEEE Journal of Selected Topics in  
 1084 Applied Earth Observations and Remote Sensing, doi: 10.1109/JSTARS.2013.2252602.
- 1085 Zine, S., J. Boutin, J. Font, N. Reul, P. Waldteufel, C. Gabarró, J. Tenerelli, F. Petitcolin, J.  
 1086 L. Vergely, M. Talone, and S. Delwart (2008), Overview of the SMOS sea surface salinity  
 1087 prototype processor, *IEEE T. Geosci. Remote Sensing*, 46, 621-645.

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1089 **List of Figure Captions:**

1090 Figure 1 : Satellite SSS: SMOS SSS corrected according to (a, d, g, j) K2016 methodology, (b, e, h, k)  
 1091 the method described in this paper (CEC); (c, f, i, l) SMAP SSS. 4 case study areas : (a, b, c) : Bay of  
 1092 Bengal - August 21<sup>st</sup> 2015; (d, e, f) : Gulf of Mexico – August 18<sup>th</sup> 2015 ; (g, h, i) : Eastern Tropical  
 1093 Atlantic Freshwater Pools – April 14<sup>th</sup> 2016; (j, k, l) : Amazon plume – October 21<sup>st</sup> 2015. SMOS and  
 1094 SMAP SSS are averaged over respectively a SMOS repetitive orbit sub-cycle (18 days) and two  
 1095 SMAP repetitive orbit cycles (16 days). Striking fresh SSS features in better agreement with SMOS  
 1096 (new version) and SMAP are indicated with black arrows.

1097 Figure 2: Two examples of 2011-2016 latitudinal profiles of mean SSS (a; b) and of the  
 1098 standard deviation of the 2011-2016 monthly differences between SMOS SSS and ISAS SSS  
 1099 (c; d). The latitudinal means and standard deviations are computed over the Pacific Ocean

1100 further than 1200 km from any coast: green: ISAS, blue: SMOS ascending orbits; red: SMOS  
1101 descending orbits; a;c) November; middle of the swath (0-50 km from the center of the  
1102 swath); b; d) January; edge of the swath (350-400 km from the center of the swath). Dashed  
1103 vertical lines indicate 47°N and 47°S.

1104 Figure 3: a) SSS variability ( $\sigma_{SSSnat}$ ) derived from 7 years of SMOS filtered and corrected  
1105 SSS (after debiasing and filtering): large values are observed in river plumes and in rainy  
1106 areas (ITCZ, SPCZ. b) Minimum and c) maximum of the SSS as derived from 18-day CEC  
1107 LOCEAN that are used in the mapping of debiased near-real time products (see section 3.4).

1108 Figure 4: Monthly SMOS SSS compared to monthly ISAS SSS from July 2010 to December 2016.  
1109 Standard deviation of the differences for a) L3P SMOS SSS; b) L3Q SMOS SSS. c) Number of  
1110 months with differences between L3P and L3Q SMOS SSS greater than 0.2pss. d) Frequency with  
1111 which corrections identified on Figure c) correspond to decreased bias with respect to ISAS (i.e. L3Q  
1112 SMOS SSS closer to ISAS SSS than L3P SMOS SSS): red color means that the correction improves  
1113 most of the time; blue color means that the correction degrades most of the time. Blank colors in  
1114 figures c) and d) mean no change above the 0.2 pss threshold or no data in the L3P version (the  
1115 comparison is done only for valid L3P SSS).

1116 Figure 5: Comparison of SMOS and SMAP ‘weekly’ SSS: (a, d, g)  $r^2$ , (b, e, h) standard  
1117 deviation of the differences, (c, f, i) number of pixels used in the comparisons. (a, b, c) 10-  
1118 day L3P SMOS SSS, (d, e, f) 10-day L3Q SMOS SSS, (g, h, i) 9-day CEC SMOS SSS.  
1119 Same indicators but when considering only the pixels available in the four products are  
1120 presented in Appendix A2.

1121 Figure 6: Scatter plots of SMOS corrected fields versus SMAP SSS on the 4 regions and  
1122 fresh events periods illustrated on Figure 1: first line: Bay of Bengal; 2<sup>nd</sup> line: Gulf of  
1123 Mexico; 3rd line : Eastern Tropical Atlantic Freshwater Pools; 4th line : Amazon plume. First

1124 column: SMOS K2016 SSS; second column: SMOS 18-day CEC SSS; last column: SMOS 9-  
1125 day CEC SSS.

1126 Figure 7: Time series of statistical parameters computed over the Bay of Bengal case study  
1127 area, April 2015 to December 2016: a) mean SSS; b) SSS standard deviation; c) square of the  
1128 Pearson correlation coefficient ( $r^2$ ) between SMOS and SMAP SSS; d) Standard deviation of  
1129 the SMOS minus SMAP SSS differences (plain line) using L1 norm (dotted line). ‘Weekly’  
1130 SMOS CEC(blue), ‘bi-weekly’ SMOS CEC (green), ‘bi-weekly’ SMOS K2016 (red),  
1131 ‘weekly’ SMAP (black).

1132 Figure 8: Time series of statistical parameters computed over the Gulf of Mexico case study area,  
1133 April 2015 to December 2016: a) mean SSS; b) SSS standard deviation; c) square of the Pearson  
1134 correlation coefficient ( $r^2$ ) between SMOS and SMAP SSS; d) Standard deviation of the SMOS  
1135 minus SMAP SSS differences (plain line) using L1 norm (dotted line). ‘Weekly’ SMOS CEC(blue),  
1136 ‘bi-weekly’ SMOS CEC (green), ‘bi-weekly’ SMOS K2016 (red), ‘weekly’ SMAP (black).

1137 Figure 9: Time series of statistical parameters computed over the Eastern Tropical Atlantic Freshwater  
1138 Pools case study area, April 2015 to December 2016: a) mean SSS; b) SSS standard deviation; c)  
1139 square of the Pearson correlation coefficient ( $r^2$ ) between SMOS and SMAP SSS; d) Standard  
1140 deviation of the SMOS minus SMAP SSS differences (plain line) using L1 norm (dotted line).  
1141 ‘Weekly’ SMOS CEC(blue), ‘bi-weekly’ SMOS CEC (green), ‘bi-weekly’ SMOS K2016 (red),  
1142 ‘weekly’ SMAP (black).

1143 Figure 10: Time series of statistical parameters over the Amazon plume case study area, April 2015 to  
1144 December 2016: a) mean SSS; b) SSS standard deviation; c) square of the Pearson correlation  
1145 coefficient ( $r^2$ ) between SMOS and SMAP SSS; d) Standard deviation of the SMOS minus SMAP  
1146 SSS differences (plain line) using L1 norm (dotted line). ‘Weekly’ SMOS CEC(blue), ‘bi-weekly’  
1147 SMOS CEC (green), ‘bi-weekly’ SMOS K2016 (red), ‘weekly’ SMAP (black).



1148 Figure 11: Top: Density spectra; Bottom: Coherence between ship SSS and SMOS or ISAS SSS. The  
1149 spatial frequency (1/wavelength (km)) is indicated below the bottom plot, whereas the corresponding  
1150 wavelengths (km) are indicated above the top plot. Vertical dashed lines correspond to spatial  
1151 frequencies regularly spaced in logarithmic coordinates. Northern subtropical Atlantic (see box on the  
1152 color map) in 2013. Ship SSS measured on regular merchant ships transects (14 regular transects in  
1153 2013) (black), ISAS SSS (green), 10-day SMOS L3P (blue line), 10-day SMOS L3Q (dashed blue  
1154 line), 18-day SMOS CEC (red line), 9-day SMOS CEC (red dashed line).

1155 Figure 12: Statistics of ship comparisons (May 2010-August 2016) binned as a function of  
1156 the distance from the nearest coast: top) mean difference; middle) standard deviation of the  
1157 differences; the black line indicates the standard deviation of ship SSS in each class; bottom)  
1158 number of pixels used in the comparisons. Left: considering only the SMOS pixels common  
1159 to all versions; right: considering all pixels available in each version. Ship and SMOS SSS  
1160 are integrated over 100 km. Orange: monthly SMOS L3P ; pink : monthly SMOS L3Q; light  
1161 blue : 18-day SMOS CEC; green : ISAS.

1162 Figure 13: Examples of comparisons between ship SSS (black stars line) and SMOS SSS: orange: non  
1163 corrected (L3P), purple: monthly L3Q corrected, light blue :18-day CEC corrected; green : ISAS.  
1164 Left) from 2014-08-21 to 2014-09-03, Matisse ship. Right) from 2013-08-21 to 2013-09-03, Santa  
1165 Cruz ship. All SSS products have been smoothed over +/-50 km.

1166 Figure 14: Standard deviation of 'weekly' satellite SSS minus ISAS SSS between 47°N and  
1167 47°S, over the year 2016. a) SMOS CEC, b) SMAP CAP.

1168 Figure 15: SSS latitudinal profiles in December 2011(top left), 2012 (top right), 2013 (bottom  
1169 left), 2014 (bottom right) in the Atlantic Ocean (1200 km from continents)- SMOS ascending  
1170 orbits (blue), descending orbits (red), ISAS(green).

1171 Figure 16: SSS latitudinal profiles in December 2011(top left), 2012 (top right), 2013 (bottom  
1172 left), 2014 (bottom right) in the Pacific Ocean (1200 km from continents)- SMOS ascending  
1173 orbits (blue), descending orbits (red), ISAS(green).

1174 Figure 17: Median of SMOS minus ISAS SSS absolute differences as a function of dwell line  
1175 location and year, for the month of January (left), May (middle) and September (right), for  
1176 ascending (top) and descending (bottom) orbits. The black lines indicate the range of selected  
1177  $x_{swath}$ .

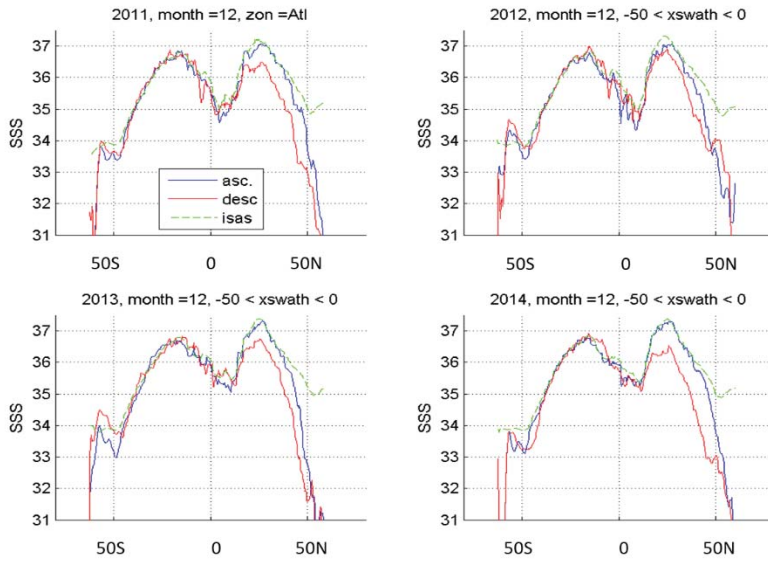
1178 Figure 18: ‘Weekly’ comparison of SMOS and SMAP SSS: (a, c, e) square of the Pearson  
1179 correlation coefficient ( $r^2$ ), (b, d, f) standard deviation of the difference. (a, b) L3P SMOS  
1180 SSS, (c, d) L3Q SMOS SSS, (e, f) CEC SMOS SSS. Only pixels common to the four  
1181 products are considered in the comparisons.

1182

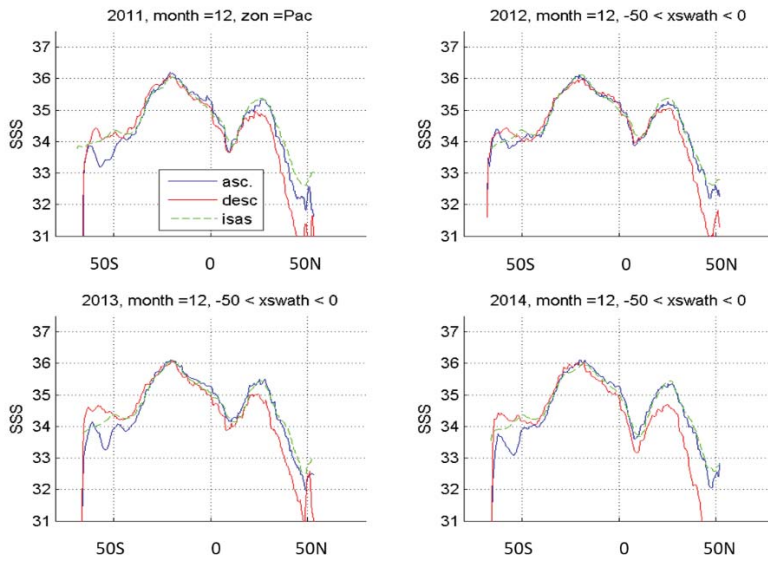
1183

1184 **Appendix A1: Selection of the region and of the reference  $x_{swath}$  to be used for**  
1185 **the seasonal latitudinal correction:**

1186 Given the high RFI contamination in the northern latitudes of the Atlantic Ocean and given  
1187 the relatively small area further than 1000 km from the continents in the Atlantic Ocean, we  
1188 choose to estimate the seasonally-varying latitudinal biases from Pacific Ocean orbits only.  
1189 Nevertheless, before doing this choice, we checked, on  $x_{swath}$  and periods not very affected by  
1190 RFI at high latitudes, that biases are similar in the Pacific and Atlantic Ocean. We observe  
1191 that the differences between ocean basins are on the same order of magnitude as the  
1192 interannual variability of the biases as illustrated with a few examples on Figure 15 and on  
1193 Figure 16.



1195  
 1196 Figure 15: SSS latitudinal profiles in December 2011(top left), 2012 (top right), 2013 (bottom left), 2014  
 1197 (bottom right) in the Atlantic Ocean (1200 km from continents)- SMOS ascending orbits (blue), descending  
 1198 orbits (red), ISAS(green).

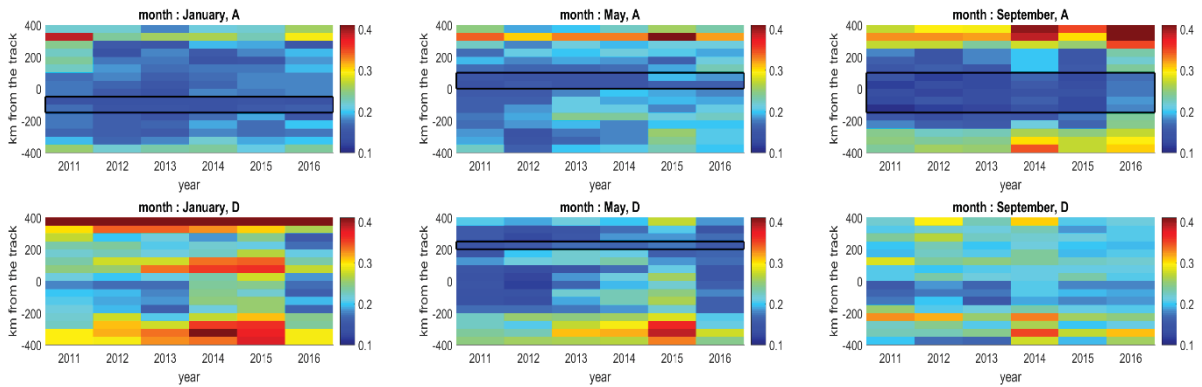


1199  
 1200 Figure 16: SSS latitudinal profiles in December 2011(top left), 2012 (top right), 2013 (bottom left), 2014  
 1201 (bottom right) in the Pacific Ocean (1200 km from continents)- SMOS ascending orbits (blue), descending  
 1202 orbits (red), ISAS(green).

1203

1204 Over the 2011-2016 period, for each  $x_{swath}$ , each month and each  $x_{orb}$ , reference  $x_{swath}$  are  
 1205 chosen as the ones having relatively weak and stable (from one year to another) SMOS minus  
 1206 ISAS SSS differences (DIFF) over the 45°S-45°N latitudinal range. We did not define a

1207 quantitative criterion for this selection because the patterns of DIFF strongly vary from one  
 1208 month to another, from ascending to descending orbits and as a function of latitude (not  
 1209 shown). During most months, reference  $x_{\text{swath}}$  are located on ascending orbits only. We  
 1210 illustrate the location of the reference  $x_{\text{swath}}$  with respect to the median of SMOS minus ISAS  
 1211 SSS absolute differences for the months of January, May and September (Figure 17). The  
 1212 locations of all the selected reference  $x_{\text{swath}}$  are reported in Table 4.



1213 Figure 17: Median of SMOS minus ISAS SSS absolute differences as a function of dwell line location  
 1214 and year, for the month of January (left), May (middle) and September (right), for ascending (top) and  
 1215 descending (bottom) orbits. The black lines indicate the range of selected  $x_{\text{swath}}$ .

1216

1217 Table 4: Reference  $x_{\text{swath}}$  locations

	Ascending orbits	Descending orbits
January	[-150 -50] km	-
February	[-250 -100] km	-
March	[-250 -100] km	-
April	[0 100] km	[150 200] km
May	[0 100] km	[200 250] km
June	[50 100] km	[50 100] km

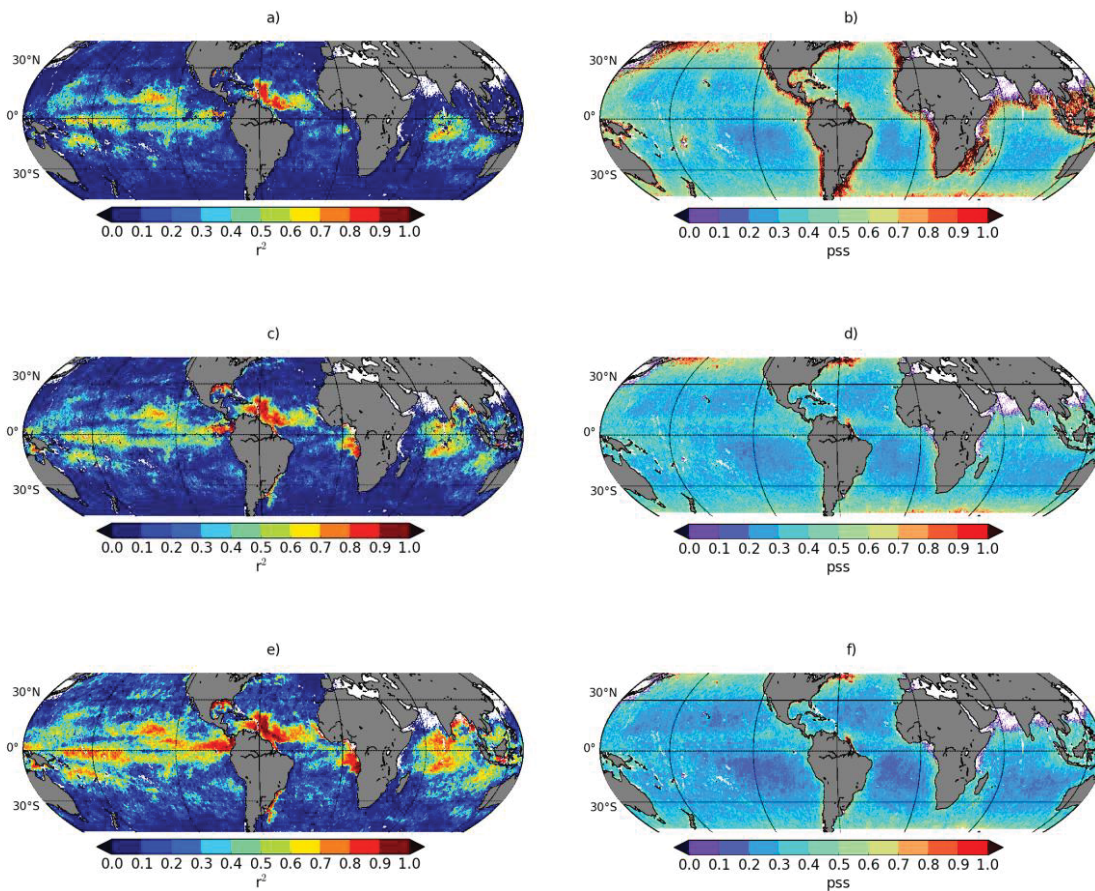
July	[-150 50] km	[50 100] km
August	[-250 250] km	[-50 100] km
September	[-150 100] km	-
October	[-50 100] km	-
November	[-250 -100] km	-
December	[-100 -50] km	-

1218

1219

1220 **Appendix A2: SMOS-SMAP SSS comparison considering only pixels common**

1221 **to all SSS fields:**



1222 Figure 18: ‘Weekly’ comparison of SMOS and SMAP SSS: (a, c, e) square of the Pearson  
1223 correlation coefficient ( $r^2$ ), (b, d, f) standard deviation of the difference. (a, b) L3P SMOS  
1224 SSS, (c, d) L3Q SMOS SSS, (e, f) CEC SMOS SSS. Only pixels common to the four  
1225 products are considered in the comparisons.