Assimilation of sea surface salinities from SMOS in an Arctic coupled ocean and sea ice reanalysis

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Abstract

1 In the Arctic, the Sea Surface Salinity (SSS) plays a key role in processes related to

2 water mixing and sea ice. However, the lack of salinity observations causes large

3 uncertainties in Arctic Ocean forecasts and reanalysis. Recently the Soil Moisture and Ocean

4 Salinity (SMOS) satellite mission was used by the Barcelona Expert Centre to develop an

5 Arctic SSS product. In this study, we evaluate the impact of assimilating this data in a

6 coupled ocean-ice data assimilation system. Using the Deterministic Ensemble Kalman filter

7 from July to December 2016, two assimilation runs respectively assimilated two successive

8 versions of the SMOS SSS product, on top of a pre-existing reanalysis run. The runs were

9 validated against independent in-situ salinity profiles in the Arctic. The results show that the

10 biases and the Root Mean Squared Differences (RMSD) of SSS are reduced by 10% to 50%

11 depending on the area, and highlight the importance of assimilating satellite salinity

12 data. The time series of Freshwater Content (FWC) further shows that its seasonal cycle can

13 be adjusted by assimilation of the SSS products, which is encouraging to assimilate SSS in a

14 long-time reanalysis to better reproduce the Arctic water cycle.

16 **Keywords**: Arctic Ocean; Sea Surface Salinity; FWC; SMOS;

1. Introduction

The Arctic Ocean is undergoing a dramatic warming, resulting in the loss of sea ice documented by previous studies (e.g., Johannessen et al., 1999; Stroeve and Notz, 2018). Sea ice melt contributes freshwater to the Arctic Ocean, together with precipitation and river flux, and has far-reaching effects on the Arctic Ocean environment (Carmack et al., 2016). The Arctic observing system, compared to other oceans, lacks the capability to provide a complete picture of ocean salinity, particularly because of obstruction by sea ice. A complete reconstruction of Arctic environmental variables thus requires a data assimilative numerical model capable of propagating information below sea ice during the winter as practiced by ocean operational forecast systems (such as Dombrowsky, 2009; Fujii et al., 2019). As with other ocean data assimilation (DA) applications, Arctic reanalysis products of ocean and sea ice play an important role in understanding climate change and its mechanisms. In recent years, many studies (e.g., Storto et al., 2019; Uotila et al., 2019) evaluated the quality of the Arctic reanalysis products and recommended experiments to maximize the usefulness of new observations, as done by Kaminski et al. (2015) and Xie et al. (2018). However, there are no impact studies of salinity observations in the Arctic to our knowledge.

Ocean salinity has been used to study the water cycle for the last 20 years (e.g., Curry et al., 2003; Boyer et al., 2005; Yu, 2011; Yu et al., 2017). A recent review paper showed a stabilization of the Freshwater Content (FWC) in the Arctic Basin, although observations indicate that the Beaufort Gyre keeps getting fresher (Solomon et al., 2021). Salinity variations have far-reaching implications for ocean mixing, water mass formation, and ocean general circulation, but suffer from large uncertainties in the Arctic, mainly due to sparse observations and the lack of a steady-state reference time period (e.g., Stroh et al., 2015; Xie et al., 2019). Measuring Sea Surface Salinity (SSS) from passive microwave remote sensing is a comparatively new but promising way to reduce the uncertainty in salinity. Launched in November 2009, the Microwave Imaging Radiometer using Aperture Synthesis (MIRAS) instrument of the European Space Agency's (ESA) Soil Moisture and Ocean Salinity (SMOS) mission measures the brightness temperatures (T_B) of the sea surface at different frequency bins. The passive 2-D interferometric radiometer on the satellite operating in L-band (1.4 GHz) is sensitive to water salinity and sufficiently free from electromagnetic interference (e.g., Font et al., 2010; Kerr et al., 2010). Since May 2010, SMOS operationally provides SSS records over the global ocean (Mecklenburg et al., 2012). During the last 12 years, large improvements have been introduced in the SMOS data processing chain, increasing the accuracy and coverage of the salinity data up to levels that were unthinkable at the beginning of the mission (Martin-Neira et al. 2016, Olmedo et al., 2018; Reul et al., 2020; Boutin et al., 2022).

53   Furthermore, the assimilation of satellite-derived SSS products using an ensemble DA

54   method has been found to significantly improve the surface and subsurface salinity fields in

55   the tropics (Lu et al. 2016). The advantages of assimilating three SSS products from SMOS,

56   Aquarius (ref., Lee et al, 2012), and the Soil Moisture Active Passive Mission (SMAP; e.g.,

57   Tang et al., 2017) into a global ocean forecast system using a 3D-Var DA method have also

58   been demonstrated by Martin et al (2019). Their results show the benefits of assimilating

59   both the SMOS and SMAP datasets in the intertropical convergence zone in the tropical

60   Pacific. However, very few studies have investigated the impact of assimilating SSS products

61   in the Arctic or high latitudes. Since the beginning, the SSS retrieval from SMOS in cold

62   regions has been very challenging for three main reasons: i) the lower sensitivity of T_B to

63   salinity in cold waters leads to larger errors (Yueh et al., 2001; e.g, the sensitivity drops from

64   0.5 to 0.3 K PSU^{-1} when sea surface temperature decreases from 15 to 5°C); ii) land-sea

65   and ice-sea contaminations resulting from abrupt changes of T_B values across these two

66   interfaces, combined with the large ground footprint of SMOS; iii) the requirement of a well-

67   observed steady-state period for the removal of biases. Addressing these challenges in the

68   SMOS salinity retrieval approach, Olmedo et al. (2017) introduced a non-Bayesian retrieval

69   method to de-bias the Level 1 baseline (L1B) salinity against the reference SSS from Argo

70   data (Argo, 2022). Level 1 data from the satellite is available within 24 hours, but the

71   additional processing steps require high-quality auxiliary data so Level 3 and 4 SSS are only

72   provided in delayed mode. Starting with the ESA L1B (v620) product from SMOS, the

73   Barcelona Expert Centre (BEC) released Version 2.0 of the Arctic gridded SSS product (25

74   km resolution; Olmedo et al., 2018). Xie et al. (2019) evaluated the V2.0 SSS product and

75   another gridded Arctic SMOS SSS product developed by LOCEAN (Boutin et al., 2018)

76   during the years 2011-2013. These two SSS observation sets, together with an Arctic

77   reanalysis (Xie et al., 2017) and one objective analysis product (Greiner et al. (2021)

78   describe an updated version of this product), were validated against in-situ observations and

79   compared with two climatology datasets: the World Ocean Atlas of 2013 (WOA2013, Zweng

80   et al., 2013) and the Polar science center Hydrographic Climatology (PHC 3.0, Steele et al.,

81   2001). They found considerable discrepancies among the different gridded SSS products,

82   especially in the freshest seawater (<24 psu). The intercomparison of these Arctic SSS

83   products shows room for improvement of the SMOS-based SSS in the Arctic.

84   Recently, under the framework of the ESA project Arctic+Salinity (AO/1-9158/18/I-BG), and

85   further development of the non-Bayesian scheme (Olmedo et al., 2017), the effective

86   resolution of SSS data was enhanced both in space and time (Martínez et al., 2022). The

87   new version of the SSS product (V3.1) has the capability to monitor mesoscale structures

88   and river discharges (e.g., Martínez et al., 2022). This new product provides daily maps

89   (Level 4) of 9-day averages in the Arctic on a regular 25 km grid and covers a longer time

90   period 2011-2019, and are released through the BEC portal (http://bec.icm.csic.es/ and also

91   at DOI: 10.20350/digitalCSIC/12620; last accessed May 2022). The major differences in the

92   estimation of the two SSS products (V2.0 and V3.1) are detailed in the Algorithm Theoretical

93   Baseline Document (ATBD) of the Arctic+Salinity project (Martínez et al., 2020). Figure 1

94   shows that in comparison to V2.0, V3.1 provides wider coverage in the marginal seas around

95   the Arctic and is also fresher as indicated by the 26 psu isoline.

96   The two successive versions of the BEC SMOS SSS products are assimilated into the

97   TOPAZ Arctic reanalysis system (detailed in Section 2) during the summer of 2016. These

98   two assimilation runs are compared to the Arctic reanalysis without assimilation of satellite

99   SSS data which is identical to the product ARCTIC_REANALYSIS_PHYS_002_003 in the

100 Copernicus Marine Services. The model validation against independent observations

101 presents the differences stemming from these two SSS products, although they are from the

102 same initial data source (SMOS). Their impact on the assimilation in the Arctic coupled ice-

103 ocean model shows large differences, thereby motivating further efforts to improve SSS

104 retrievals in the cold Arctic.

105 The paper is organized as follows: Section 2 briefly describes the coupled ocean and sea ice

106 data assimilation system and the assimilation experiments; Section 3 describes the in-situ

107 observations and the validation metrics; results presented in Section 4 include the validation

108 using independent SSS observations, separated into different ocean basins. Section 4 also

109 examines the impact of SSS assimilation on the weekly increments of other related variables

110 near the surface, and explores the integrated effect on the freshwater simulated by the

111 model. In Section 5, the findings of this study and future perspectives are summarized.

112

113 **2. Assimilation system and experimental design**

114 *2.1 The Arctic ocean and sea-ice coupled data assimilation system*

115 TOPAZ is a coupled ocean and sea ice data assimilation system, built using the

116 Deterministic Ensemble Kalman Filter (DEnKF; Sakov et al., 2012) to simultaneously

117 assimilate multiple types of observations for the ocean and sea ice (Xie et al., 2017). The

118 ocean model in this system uses version 2.2 of the Hybrid Coordinate Ocean Model

119 (HYCOM; Chassignet et al., 2003) with a low-distortion square grid at a horizontal resolution

120 of 12-16 km. The river discharge input is climatological, using the ERA-Interim (Dee et al.,

121 2011) runoffs channeled in a simple hydrological model, which tends to underestimate the

122 amplitude of the seasonal cycle and thus produces a saline bias at the surface (Xie et al.

123 2019). The coupled sea ice model uses a single-category thermodynamic model (Drange

124 and Simonsen, 1996) and dynamics by the modified elastic-viscous-plastic rheology

125 (Bouillon et al., 2013) from an early version of the CICE model (Lisæter et al. 2003). The

126 model covers the Arctic Ocean and the whole north Atlantic Ocean (shown in Fig. 1 in Xie et

127 al., 2017). A seasonal inflow of Pacific Water is imposed across the Bering Strait, based on

128 observed transports (Woodgate et al., 2012). At all lateral boundaries, the temperature and

129 salinity stratifications are relaxed to a climatology combining version 2.0 of WOA2013 and

130 version 3.0 of PHC with a 20-grid cells buffer zone. To avoid a potential model drift, the

131 surface salinity is relaxed to the combined climatology as mentioned above, with a 30-day

132 timescale, but the relaxation is suppressed wherever the difference from climatology exceeds

133 0.5 psu to avoid the artificial formation of bulk surface freshwater layers.

134   For simplification, the two steps of the assimilation system can be translated by the

135 following concept expressions (update and model propagation):

136
$$\mathbf{X}_a = \mathbf{X}_f + \mathbf{K}(\mathbf{y} - H\mathbf{X}_f) \tag{1}$$

137
$$\mathbf{X}_f = M(\mathbf{X}_a) \tag{2}$$

138   Where the matrix $\mathbf{X}$ represents the model state with all 3-D and 2-D variables needed by

139 the model forward integration, represented by the operator M. The subscripts 'a' and 'f'

140 respectively indicate the analyzed model state obtained through optimization after DA and

141 the model forecast. The vector $\mathbf{y}$ is composed of the quality-checked observations during the

142 weekly cycle, and the observation operator H gives the model equivalent of the observations.

143 The innovation term (in parentheses in Eq.1) represents the differences between the model

144 and the various observations in the observation space.

145   For the ensemble data assimilation method, the matrix $\mathbf{X}$ includes the dynamical members

146 of the model states as different columns and further evolutes according to Eqs. 1 and 2 as

147 described in the DEnKF. The TOPAZ model runs an ensemble of 100 members. The $\mathbf{K}$

148 matrix (Kalman gain) is calculated using the ensemble covariance matrix. Like other square

149 root versions of the Ensemble Kalman Filter, the DEnKF splits Eq. 1 into two steps: the $\mathbf{K}$

150 calculation is applied to the ensemble mean, and the anomalies are updated to match a

151 target analysis covariance (more details in Sakov et al., 2012). Using a 7-day assimilation

152 cycle, we use the DEnKF to assimilate different types of ocean and ice observations,

153 including along-track sea level anomaly (SLA), sea surface temperature (SST), in-situ

154 profiles of temperature and salinity, sea ice concentrations (SIC) and sea ice drift products all

155 sourced from the Copernicus Marine Environment Monitoring Services (CMEMS;

156 https://marine.copernicus.eu). The same TOPAZ system provides a 10-day forecast of ocean

157 physics and biogeochemistry in the Arctic (Bertino et al., 2021) every day via the CMEMS

158 portal.

159

2.2 Assimilation experiments and the observation error estimate for SSS

To evaluate the impact of the assimilation of two versions of the SSS products on TOPAZ model runs, a control assimilation experiment (Exp0) and two parallel assimilation experiments (ExpV2, ExpV3) for a 6-month time period (July to December 2016) were performed. Exp0 assimilates all available ocean and sea ice data, except the satellite SSS products. On the other hand, ExpV2 and ExpV3 additionally assimilate the BEC SSS products V2.0 and V3.1, respectively. Details of the three assimilation runs are listed in Table 1.

Observation error is a key parameter in any DA system: too small values lead to overfitting, while too large values make the assimilation inefficient. The salinity errors from passive microwave instruments were previously estimated by Vinogradova et al. (2014): the zonal average of standard errors north of 60°N was estimated at 0.6 psu. In a recent study, Xie et al. (2019) evaluated the SMOS-based SSS products using in-situ observations and revealed strong regional dependence for the V2.0 product errors: smaller than 0.4 psu in the Northern Atlantic but increasing dramatically to 1 psu in the Nordic seas and over 2 psu in the central Arctic. Undoubtedly, the salinity observation errors from passive microwave instruments are higher in high latitudes than elsewhere. Furthermore, in the Beaufort Sea (as Fig. 12a in Xie et al., 2019), the error of the SSS V2.0 product and the Arctic reanalysis product from TOPAZ (same as Exp0 used in this study) both show an inverse relationship between SSS values and SSS errors. Hence, we use an empirical error function for ExpV2 and ExpV3 adjusted to the discrepancies as shown in Eq. 3, following Xie et al. (2019):

$$E_{SSS} = max\left\{E_{int}, \left[0.6 + \frac{6}{1+exp\left(\frac{SSS-16}{5}\right)}\right]^2\right\} \tag{3}$$

Where E_{int} is the instrumental error variance estimated by the data provider, that part is absent from the V2.0 product. Eq. 3 yields more conservative error estimates than the providers, which also prevents the discontinuities caused by strong assimilation updates (as an example noticed by Balibrea-Iniesta et al., 2018). The settings for all other observation types are identical to those applied in Xie et al. (2017). By construction, the observation errors are always larger for the V3.1 than the V2.0 product, but in fresh waters they are identical. This implies that the assimilation may pull the analysis closer to the V2.0 than the V3.1 product in the more saline waters, but they are otherwise treated on equal footing, ignoring the a priori expectation that the most recent product should be more reliable.

3. In-situ SSS observations for validation

193   All in-situ salinity profiles were collected from various repositories and cruises (as shown in

194   Fig. 2). Salinity measurements were extracted near the surface over the Arctic domain during

195   the experimental time period. The sanity check procedures include: i) location check to

196   remove SSS observations in the model land mask; ii) omit the invalid profiles if the top depth

197   is deeper than 8 m; iii) remove redundant observations. Since the model does not reproduce

198   local gradients of the vertical salinity profiles shown in Supply et al. (2020), all the salinity

199   profiles are averaged over the upper 8 meters below the surface. This also avoids the loss of

200   the profiles that do not reach the surface.

201   ● *Data from the Beaufort Gyre Experiment Project (BGEP)*

202   The BGEP has maintained an observing system in the Canadian Basin since 2003 and

203   provides in-situ observations over the Beaufort Gyre every summer. Although the BGEP has

204   maintained three bottom-tethered moorings since 2003, the shallowest depth of the

205   measured profiles for temperature and salinity is below 50 m. Hence, in this study, we only

206   use the Conductivity Temperature Depth (CTD) dataset from the cruise in 2016

207   (https://www2.whoi.edu/site/beaufortgyre/data/ctd-and-geochemistry/, last access: 14th

208   February 2022). SSS observations from these CTD profiles in the time period from 13th Sep

209   to 10th Oct 2016 are represented by the red triangles in Fig. 2.

210   ● *Data from Oceans Melting Greenland (OMG)*

211   The project Oceans Melting Greenland was funded by NASA to understand the role of the

212   ocean in melting Greenland's glaciers. Over a five-year campaign, this project collected

213   temperature and salinity profiles by Airborne eXpendable Conductivity Temperature Depth

214   (AXCTD) launched from an aircraft (*e.g.*, Fenty, et al, 2016). The deployed probe can sink to

215   a depth of 1000 meters, connected with a float by a wire. The measured temperature and

216   conductivity are then sent back to the aircraft. These salinity profiles collected during the first

217   OMG campaign in 2016 are downloaded from

218   https://podaac.jpl.nasa.gov/dataset/OMG_L2_AXCTD/ (last access: 10th February 2022). The

219   SSS from OMG distributed around Greenland, from 13th Sep to 10th Oct 2016 are shown as

220   the inverted blue triangles in Fig. 2.

221   ● *Data from the International Council for the Exploration of the Sea (ICES)*

222   Salinity profiles were also obtained from the ICES portal (https://www.ices.dk). Shown as

223   blue squares in Fig. 2, the locations of the profiles during the last 6 months of 2016 are

224   dense in the Nordic Seas and restricted to north of 58°N for this study. Valid salinity profiles

225   from ICES (last access: 9th February 2022) are obtained from 6th July to 23rd Nov in 2016.

226   ● *Data from other cruises at the Arctic Data Center (ADC)*

227 Surface salinity observations from scientific cruises are obtained from the Arctic Data

228 Center portal (https://arcticdata.io/catalog/data; last access: 17th Feb 2022). During the

229 model experiment, the first relevant cruise in ADC was SKQ201612S which was operated by

230 University of Alaska Fairbanks with the RV Sikuliaq. This cruise collected data from Nome,

231 Alaska on 3rd September, to the northeast Chukchi Sea, and then back to Nome at the end of

232 September 2016. The temperature and salinity profiles were collected by a Sea-Bird 911

233 CTD instrument package. All measurements at each station were done both down- and up-

234 cast ways. To produce water column profiles at each station, the down-cast data were

235 binned at 1 m intervals (Goñi et al.,2021). Besides the CTD profiles of SKQ201612S, more

236 seawater samples were collected via the surface underway system on the RV Sikuliaq.

237 Through a sea chest below the waterline (e.g., 4-8 m), the uncontaminated seawater was

238 pumped into the ship and the corresponding filtration system supplies samples every 3 hours

239 to the sensors (More details in Goñi et al., 2019). These SSS observations were obtained on

240 the 9th-27th of September, indicated as blue crosses in Fig. 2.

241 Moreover, SSS measurements were also collected from the Seabird CTD on board Sir

242 Wilfrid Laurier (SWL), but only in July 2016. This cruise is part of the annual monitoring from

243 the Canadian Coast Guard Service (Cooper et al., 2019). The SSS observations are

244 obtained near the Bering Strait close to the Pacific boundary of our model.

245 After filtering the diurnal signals by daily averages in observed surface salinity, all valid SSS

246 measurements from the above data sources are compared with the daily average SSS of the

247 three assimilation experiments listed in Table 1. The model data has been collocated with

248 the observations for validation. To estimate the forecast differences to observations, we use

249 the standard statistical moments:

250 $$Bias = \sum_{i=1}^{N} \sum_{1}^{O_i}(H\overline{\mathbf{X}}_i - \mathbf{y}_i) \ / \sum_{i=1}^{N} O_i \qquad (4),$$

251 $$MSD = \sqrt{\sum_{i=1}^{N} \sum_{1}^{O_i}(H\overline{\mathbf{X}}_i - \mathbf{y}_i)^2 / \sum_{i=1}^{N} O_i} \qquad (5),$$

252 Where i is the ith day, O_i represents the number of observations on this day, and N

253 represents the total number of days depending on the source of observations. Then $\overline{\mathbf{X}}_i$

254 represents the model daily average of the ensemble mean at the observation time. H is an

255 operator to extract the SSS simulation from the model at the observed location. The model

256 performance can then be quantitatively compared between the three assimilation runs.

257 In addition, we further introduce a two-sample Student's t-test to evaluate the significance of

258 the change of SSS bias in ExpV2/ExpV3 with respect to Exp0. Compared to in-situ

259 observations, the SSS misfits in Exp0 are the error array $\mathbf{e}_1$. The corresponding error array

260   from ExpV2 or ExpV3 is called $\mathbf{e_2}$. Thus, considering the null hypothesis H0: $\mathbf{\bar{e}_1}$ and $\mathbf{\bar{e}_2}$ are

261   the means of indiscernible random draws, the t-value can be calculated as follows:

262
$$t = \frac{|\mathbf{\bar{e}_2} - \mathbf{\bar{e}_1}|}{\sqrt{s_1^2/(n_1 - 1) + s_2^2/(n_2 - 1)}}$$

263   Where $s_1(s_2)$ is the standard deviation in the $\mathbf{e_1}(\mathbf{e_2})$, and n_1 (n_2) is the number of observations.

264   For every t-value, the p-value from the above equation is the probability that random errors

265   would prove H0 wrong. Low p-values (<0.05) indicate that the change of bias due to

266   assimilation is significant.

267

268   **4.   Results**

269   *4.1 Diagnosing using assimilation statistics*

270   The SSS innovations in the two assimilation runs of ExpV2 and ExpV3 are compared in Fig.

271   3, together with the number of assimilated SSS observations and the ensemble spread

272   calculated by the ensemble standard deviation. The total number of observations is at its

273   maximum in September when the sea ice cover is minimal. Since both versions of the SSS

274   product share the same time frequency (9-day average) and gridded format, the number of

275   assimilated observations in the two runs reached a maximum in the middle of September

276   (gray lines in Fig. 3). But the maximal number of SSS in ExpV3 shows higher than in ExpV2.

277   For ExpV2, the Root Mean Square (RMS) of the SSS innovation varies between 0.4 and 1.2

278   psu, but the mean of SSS innovation, calculated as the observation minus the model

279   simulation (cf. the bracket in Eq.1), shows a saline bias of 0.4 psu, highest in September.

280   However, in ExpV3 the salinity bias quickly disappears after a few data assimilation cycles.

281   The RMS of the SSS innovation is larger in ExpV3 between 0.6 and 1.6 psu, which can partly

282   be explained by the higher effective resolution of the V3.1 product and the double penalty

283   effect. In ExpV3, the RMS of the SSS innovation (the red line) jumps down after the first SSS

284   assimilation step. The RMS of SSS innovations and the observation errors both decrease

285   from summer to winter, following a seasonal cycle as the areas of fresher water get gradually

286   ice-covered. The domain-averaged observation errors are only slightly larger in ExpV3 than

287   in ExpV2, as explained above, and the RMS of SSS innovations becomes lower than the

288   observation errors near the end of the run, which indicates that the observation errors for the

289   V2.0 SSS have been overestimated.

290   In the top panels of Fig. 4, the SSS maps are shown for the control run (Exp0) in August and

291   September 2016, respectively. For Exp0 in August, low salinity waters are found in the

292   Beaufort Sea near the Mackenzie River and along the East Siberian coast. In September, the

293   fresher waters, below 30 psu, bridge the two areas in Exp0 probably due to sea ice melt,

294   although the lowest salinity near the Siberian coast remains unchanged from August to
295   September (as indicated by the 28 psu isoline). Compared with the SSS observations from
296   SMOS (Fig. 1), these two low-salinity waters are clearly underestimated in Exp0. Meanwhile,
297   the relatively saline 32 psu isoline crosses both the Eurasian basin and the Baffin Bay. In the
298   Laptev Sea, due to the significant effects of river runoff and ice melt, the salinity shows a
299   strong gradient from the southeast to the northern part. During winter, the salinity increases
300   to 34 psu, and decreases in summer near to 30 psu (Janout et al., 2017). In the northwest
301   Laptev Sea, the saline tongue of 32 psu extends eastward to the Taymyr Peninsula (TP).
302   North of the TP, the Kara Sea freshwater meets with the Atlantic Water pathways from the
303   Fram Strait and Barents Sea (shown in Figure 1 of Janout et al., 2017). Close to the TP, the
304   observations at the mooring profiles in Janout et al. (2017) show much fresher surface
305   salinity (29 psu) than the subsurface salinity (32 psu) in summer. Compared to the SMOS
306   SSS maps (shown in Fig. 1), only the V3.1 product shows the 32 psu isolines around the TP.
307   Another difference between the two SMOS products arises in the Chukchi Sea where the
308   V3.1 product is more saline than both the V2.0 product and SSS in Exp0.
309   The middle and bottom panels of Fig. 4 show the SSS differences in August and
310   September 2016 between the SSS assimilation runs and the control run. Figure 4c and 4d
311   both show a freshening of the coastal areas in the Kara Sea, Laptev Sea, and East Siberian
312   Sea, but in ExpV3 the freshening is stronger and wider (Fig. 4e and 4f). In the Beaufort Sea,
313   ExpV2 mainly brings a local freshening near the mouth of the Mackenzie River in August,
314   which then spreads out along the coast in September. The freshening in the BS brought by
315   ExpV3 affects a broader area, even including the Canadian Archipelago. ExpV3 also
316   freshens the SSS on both sides of Greenland Island. From August onwards, the SSS in
317   ExpV3 freshens by over 1 psu along the whole east Greenland coast, which clearly does not
318   happen in ExpV2. In fact, the 32 psu isoline in ExpV3 (not shown) extends hundreds of
319   kilometers further to the South East Greenland coast in comparison to Exp0 and ExpV2. The
320   rest of the Greenland coast is also fresher by 0.5 psu in ExpV3 during both months. This is a
321   sign of a consistent change in the V3.1 product.
322   Even though most of the SSS assimilation leads to a freshening of the surface, a few
323   locations show higher salinity than Exp0, these are different from ExpV2 to ExpV3. For
324   example, the saline increment near the Bering Strait is larger in ExpV3 in excess of 1 psu,
325   consistently with the difference between the two remote sensing products (Fig. 1).
326   Other increases in SSS concern small areas near estuaries and are more common in ExpV3.
327   The increase to the west of the Yamal Peninsula can be explained by a model setup bias in
328   the location of the Ob river but compensated by the SSS assimilation. In the above

329 comparisons of SSS maps, the central Arctic is not discussed, since the region is covered by
330 sea ice and the effect of assimilation is indirect.
331
332   *4.2 Comparison with independent in-situ observations*
333 Quality-checked in-situ observations in the Central Arctic are very unevenly distributed. After
334 pooling all platforms together, we further investigate the SSS misfits in six subregions of the
335 Arctic (Fig. 2 and Table 2). This section will present statistics of differences to independent
336 in-situ observations, separately considering marginal seas.
337
338 *Beaufort Sea (BS):* Figure 5 shows the scatterplots of SSS in the three runs against in-situ
339 observations from BGEP, OMG, and ICES. In the Beaufort Sea (top panel in Fig. 5), the
340 observed SSS varies in a range of 26-29 psu. The range of SSS in Exp0 is much smaller,
341 between 29-31 psu with a saline bias of 2.6 psu and an RMSD of 2.7 psu, but otherwise, it
342 shows a reasonably linear relationship (r=0.59). The SSS bias in Exp0 has the same value
343 as in Xie et al. (2019), although estimated using the BGEP observations in a different time
344 period (2011-2013). The range of SSS in ExpV2 is slightly improved to 28-30.5 psu. Further,
345 the bias is reduced by 0.5 psu, corresponding to bias and RMSD reductions of respectively
346 13.5% and 10.5% with respect to Exp0. In ExpV3, the SSS range is much closer, between
347 26.5 and 30.5 psu, and the resulting bias and RMSD reductions of SSS are respectively
348 26.3% and 17.3% with respect to Exp0. Both the bias reduction in ExpV2 and ExpV3 relative
349 to Exp0 pass the significance test ($\alpha = 0.05$) through Student's t-test. Furthermore,
350 compared to all in-situ SSS in BS (top panels in Fig. 7), the SSS misfits in ExpV3 show a
351 stronger reduction by 26.0% for bias and 20.6% for RMSD. ExpV2 reduces these errors by
352 half as much (13.5% for bias and 11.5% for RMSD). These results clearly indicate that the
353 new version of the SSS is more beneficial for data assimilation in the Beaufort Sea.
354
355 *Chukchi Sea (CS)*: Fig. 6 shows the SSS deviations as a function of time during the SKQ
356 cruise route. Figure 6a shows the surface levels from CTDs. The saline bias (2.8 psu) is
357 more pronounced than in the Beaufort Sea, which we attribute to the proximity to the model
358 boundary in the Bering Strait, relaxed to climatological values, where the interannual
359 variability of Pacific water is not included. After assimilating SSS products, a reduction of the
360 bias is observed during September, by 15.5% in ExpV2 and up to 22.2% in ExpV3. The
361 comparison to underway surface water samples (Fig. 6b) also shows an error reduction of
362 around 15%, though fewer differences between ExpV2 and ExpV3.
363 Considering other cruise data in the CS (Fig. 7; bottom panels), the SSS in Exp0 shows
364 almost uniform values with a saline bias of about 2.3 psu and an RMSD of 2.6 psu. A recent

365   observational study by Goñi et al. (2021) shows that the surface salinity of the CS during late

366   summer varies between 28-30 psu during the time period 2016-2017. The range of SSS

367   observations considered here is slightly broader (27-32 psu). The assimilation of SSS

368   products reduces the misfits (bias and RMSD). As in the BS, the SSS in ExpV3 has more

369   significant reductions in bias (17.7%) and RMSD (16.4%). After assimilation, the deviations

370   are in the same range as found in the BS. All the bias reductions in ExpV2 and ExpV3 are

371   significant compared to Exp0 through the t-test ($\alpha = 0.05$).

372

373   *Greenland Sea (GS)*: Most SSS observations around Greenland are from the OMG

374   programme, shown as the blue downward triangles in Fig. 2. Considering first all SSS

375   observations from OMG, the SSS misfits in the three runs (shown in the middle panels of Fig.

376   5) show smaller bias and RMSD than in the BS and the CS. However, the SSS in ExpV3 still

377   brings significant error reductions with a reduction of 32.6%/9.4% of the bias and RMSD

378   compared to Exp0. Notably, the SSS misfits in ExpV2 are almost identical to Exp0, which

379   indicates that the V2.0 SSS product was not informative there.

380   We now separate the evaluation in the East and West of Greenland covering the GS and

381   Baffin Bay (BB) areas as shown in Fig. 2 (also listed in Table 2). The top panel of Fig. 8

382   shows that all SSS observations available in the GS vary between 27 and 35 psu. This large

383   range includes fresh coastal waters, Arctic water, and Atlantic Water. The three assimilation

384   runs show different saline biases, especially for salinities lower than 30 psu. While in

385   observations the minimum salinity is below 28 psu, it only reaches 30 psu in ExpV3, and 31

386   psu in both Exp0 and ExpV2. As a result, the bias reduction in ExpV3 is over 50% and the

387   RMSD decreased by about 10.5% in the GS. ExpV2 is disappointingly similar to Exp0. This

388   is also the case in BB (shown in Fig. 8 bottom row), where differences between ExpV2 and

389   Exp0 are less than 0.02 psu. In contrast, ExpV3 reduces the SSS bias but does not

390   significantly reduce the RMSD in the BB. One possible explanation is the double-penalty

391   effect because the V3.1 product has a higher effective resolution than V2.0. This can be

392   seen in Fig. 8 as the ExpV3 values are more scattered.

393   Finally, we examine the SSS deviations in the Barents Sea and the Norwegian Sea. The

394   SSS bias and RMSD are the lowest in ExpV3 in Table 2, even though the reductions are not

395   as significant as in the area of fresher surface waters. Compared to the ICES observations

396   distributed in the North Atlantic and the Nordic Seas (blue squares in Fig. 2), the scatterplots

397   of Exp0 and ExpV2 are nearly identical (see the bottom panels in Fig. 5). The minimum

398   salinity in these two runs is 32 psu. The SSS bias and RMSD in both runs are also similar

399   (differences less than 0.01 psu). In contrast, lower salinity values are found in ExpV3, below

400   32 psu, although the saline bias remains around 0.5 psu on average. Notably, the SSS in

401   ExpV3 shows that data assimilation can reduce the bias by 15% compared to Exp0, but the

402   RMSD only reduced about 0.03 psu, also possibly due to the double penalty effect. This also

403   suggests that the improvements near the coast will be the next challenge for future versions

404   of the SSS product.

405

406   *4.3 Impact analysis of SSS assimilation*

407   The above section has demonstrated that the assimilation of remote sensing SSS generally

408   improves the match to independent in-situ measurements, although the improvements are

409   location-dependent. Since large areas are void of in-situ measurements, the increment for

410   other surface variables will also be interpreted for understanding the impacts incurred. The

411   increments are the differences between the analysis and the forecast. The calculation of

412   them is the result of the innovations of all assimilated observations multiplied by the Kalman

413   gain, as computed in Eq. (1). Since the DEnKF update is multivariate, we present the impact

414   of the assimilation on other model variables closely related to the SSS: SST and SIC. Since

415   the only difference in the setting between the three runs is the assimilation of SSS, we can

416   attribute the differences to the impact of SSS observations. In theory, if both the model and

417   observations were unbiased, the increments of other assimilated variables should generally

418   decrease because of the presence of a new SSS term in the denominator of the Kalman

419   Gain(The ensemble covariance matrices contain off-diagonal blocks of correlation between

420   SSS and dynamically related variables and so the assimilated observations usually compete

421   with each other). However, the SSS biases originating either from the model or observations

422   also affect the other model variables and increase the innovations on the following

423   assimilation step and thus the consecutive increments. Hypothetically, wherever the forecast

424   errors are caused by SSS errors, the increments of other variables should diminish. Figure 9

425   compares the time-averaged increments of SIC and seawater temperature in the top 3-m

426   layer (considered as SST here) in the three runs. The sign of the increments remains overall

427   the same across the three experiments, both for SST and SIC. The SST increments in the

428   three runs are negative in the open ocean and positive near the ice edge, as shown in the

429   right column of Fig. 9.

430   The SST increments in Exp0 and in ExpV2 are nearly identical, but in ExpV3 there are few

431   areas such as in the Kara Sea and in the Laptev Sea where the SST increments have been

432   suppressed. These are locations where the SSS and SST are positively correlated, so the

433   updated SSS by assimilation is also helpful in reducing the water temperature misfits near

434   the surface. The changes in SST are however small with respect to the large SSS

435   differences in Figure 4. In Exp0, the SIC increments are small (<5%) inside the ice pack. The

436   satellite SIC observations are assimilated every week and help to correctly position the ice

437   edge (Sakov et al., 2012). The increments exceed 5% along the ice edge, as can be seen in

438   the northern Barents Sea.

439   The assimilation of the V2.0 SSS product also shows minimal differences from Exp0 partly

440   because of the conservative sea ice mask in the V2.0 SMOS SSS. The SIC increments are

441   opposite to those of SST, showing that the assimilation warms the surface water where ice is

442   removed, which is consistent with Lisæter et al. (2003). Only minor differences between

443   ExpV2 and ExpV0 are visible along all areas swept by the ice edge during the 6-month

444   experiment, for example in the Kara Sea. In contrast, the assimilation of the V3.1 SSS

445   product shows larger changes in SIC increments than in ExpV2 with a broader area of

446   negative increments (removed ice) in the northern Barents Sea. This is not visibly related to

447   the SST increments but to the freshening caused by the assimilation of V3.1 SSS as SSS

448   and SIC are positively correlated in the northern Barents Sea, as shown by Fig. 2 in Sakov et

449   al. (2012). The increased SIC increments may be an indication that the SSS freshening could

450   be excessive.

451   Since the whole water column is updated by assimilation, the freshwater content is also

452   modified by the assimilation of SSS. There are however complex relationships between SSS

453   and FWC as shown by Fournier et al. (2020). The changes in FWC in the Arctic are

454   calculated as in Eq. (6) derived from Proshutinsky et al. (2009), although this method was

455   initially intended for the Beaufort Sea. Applying the same formula for interpolation of in-situ

456   observations, Proshutinsky et al. (2020) estimated the time-averaged summer freshwater

457   content in the Beaufort Gyre region in two time periods (1950-1980 and 2013-2018). In the

458   latter period, they located the FWC centre in the Beaufort Sea around (150°W, 75°N) and

459   drew the 20-m isoline over more than 5 degrees of latitude and nearly 30 degrees of

460   longitude on average. When compared to the earlier reference period, the FWC in the

461   Beaufort Sea has increased and its centre has shifted westward.

462   Following Proshutinsky et al. (2009), the model FWC in the Arctic is estimated as:

463    $$FWC = \int_{z_0}^{z_{ref}}(1 - \frac{S_{(z)}}{S_{ref}})dz \qquad (6)$$

464   Where the reference salinity value S_{ref} is taken at 34.8 psu, z_{ref} is the depth of the reference

465   salinity or the sea bed, and $S(z)$ is the salinity profile. Figure 10 shows the FWC on two

466   representative days, September 20th and October 20th, 2016. In Exp0, the reanalysis

467   reproduces the typical FWC distribution in the Arctic with a maximum in the Beaufort Sea.

468   The 20 m isolines in Fig. 10a and 10d show an increase in spatial coverage during October,

469   consistent with Rosenblum et al. (2021), but the 20 m isoline is not extending as far as 170°E

470   compared to Proshutinsky et al. (2020). After the assimilation of SSS products (either V2.0 or

471   V3.1), the amplitude and the spatial distribution of the FWC maximum increase slightly in the

472   Beaufort Sea (see Fig. 10b and 10c). A much larger increase of FWC appears on the East

473   Siberian shelf and in the coastal areas of the Laptev Sea and eastern Kara Sea, although to

474   a different extent in ExpV2 and in ExpV3. In the eastern Kara Sea, the FWC increases over a

475   wider area in ExpV2 than in ExpV3. To the west of the Yamal Peninsula, ExpV3 shows a

476   negative anomaly related to an incorrect location of the model river runoff, corrected in later

477   versions of the model. The SSS assimilation is able to correct the related fresh bias. In the

478   central Arctic, although the assimilated SSS measurements are masked by the sea ice

479   cover, the FWC differences north of 84°N are more pronounced in October than in

480   September, which indicates the advection of SSS increments by the Transpolar Drift Stream

481   (Rigor et al., 2002; Balibrea-Iniesta et al., 2018). These results suggest that the SSS

482   assimilation of both versions of SMOS satellite-based acts compensates for the insufficient

483   river summer runoff, redistributes the freshwater in the Arctic, and adjusts the freshwater

484   budget. However, because of the limited in-situ data, the above assessment remains

485   preliminary.

486   Further, we compare the daily time series of Arctic-averaged FWC from the three runs to the

487   north of 70°N (Fig. 11). The FWC increases in October-November to reach its maximum, and

488   gradually decreases thereafter. The impact of the week-long data assimilation cycles is

489   visible as instantaneous jumps on the three curves of the time series, but the assimilation of

490   SSS does not cause unrealistic imbalances. The FWC increases substantially due to SSS

491   assimilation, by about 25 cm. Notably, the assimilation of version 3.1 SSS causes a faster

492   increase during the first two months. Due to the absence of ground truth data in 2016, the

493   above comparison is not fully verified, but the timing of the peak is in better agreement with

494   the seasonal freshwater storage presented by the Ice-Tethered Profiler (ITP) data in Fig. 4a

495   of Rosenblum et al. (2021). In addition, we also notice that the amplitude of the seasonal

496   FWC seems too small in all experiments in Fig. 11, which can be related to insufficient thick

497   ice in TOPAZ (Uotila et al., 2019). More concrete evidence about the changed FWC will be

498   provided when the longer assimilation of the satellite-based SSS product is finished in the

499   near future.

500

501   **5.   Summary and discussions.**

502   The gridded SSS products from the SMOS satellite undoubtedly provide a way to constrain

503   errors in salinity, especially for an ocean reanalysis system. The present study is the first

504   observing system simulation experiment for the assimilation of SMOS SSS in the Arctic. In

505   this study, based on the TOPAZ reanalysis system, we compared a reanalysis assimilating

506 conventional observations with two new reanalysis runs which additionally assimilated two
507 versions of the SMOS SSS products from BEC.
508 After comparison with independent SSS observations from CTD and surface water samples
509 along cruise tracks, near-surface salinity errors have been significantly reduced compared to
510 the control experiment (Exp0). In the Beaufort Sea, the SSS bias and RMSD in ExpV3 are
511 reduced respectively by 26.0% and 20.6%. In ExpV2, the RMSD reduction is smaller (by
512 11.5%). In the Chukchi Sea, the reduction in SSS misfits in ExpV3 (bias:17.7%; RMSD:
513 16.4%) is also larger than in ExpV2 (bias: 15.5%; RMSD: 13.7%). Around Greenland, the
514 difference between the two products is even more pronounced, with a significant reduction in
515 the SSS bias (32.6%) and RMSD (9.4%) in ExpV3, while there is no notable improvement in
516 ExpV2. The difference is larger in the East Greenland Sea. The direct assimilation of SSS
517 from SMOS is more efficient at constraining the near-surface salinity than the multivariate
518 impact of other observations. This finding is also consistent with other SSS assimilation
519 experiments in the tropics (Chakraborty et al., 2015; Tranchant et al., 2019). Conversely,
520 when considering the multivariate impact of SSS on SIC (in Fig. 9) we find that the
521 assimilation of the V2 product does not affect the assimilation of sea ice concentrations while
522 the V3.1 product causes an increase in the negative increments, which could be an
523 indication of excessive freshening along the Siberian coast. In contrast, the increments of
524 SST in the open ocean are smaller in ExpV3, indicating a synergy effect of SST and SSS.
525 Overall, our data assimilation system did not detect obvious inconsistencies between the
526 SMOS SSS product and other assimilated observations.
527
528 Furthermore, this study shows error reductions of SSS when assimilating the V3.1 product
529 from SMOS even outside of the central Arctic in the Nordic Seas and along the Norwegian
530 coast. Moreover, our analysis shows how the spatial distribution of Arctic FWC changes as a
531 result of assimilating the two SMOS products. The time series of averaged FWC north of
532 70°N shows that the FWC in the whole central Arctic can be increased by about 25 cm using
533 DA. Our experiments show that the Arctic FWC can be redistributed horizontally after
534 assimilation, but the latter effect requires a longer assimilation run to be evaluated.
535 As a summary of the quantitative SSS comparisons (Table 2), the overall score of each
536 assimilation setup for each subregion can be defined by its ability to reduce the SSS bias
537 and RMSD by more than 9% relative to Exp0 (Fig. 2). The threshold value of 9% is not fully
538 arbitrary, referring to the reduction of SSS RMSD in GS, where the bias reduction is
539 significant (through the t-test). If both bias and RMSD meet this objective, we give a score of
540 1, but of 2 if only one of them is met. If neither of them exceeds 9%, the score is set to 3.
541 Thus outside of the central Arctic, the v2.0 SSS product loses its impact on the TOPAZ

542 system, but the V3.1 SSS brings significant impacts across the Arctic and further out, and

543 clearly benefits from its refined effective resolution (Martínez et al., 2022). Since there was

544 little evidence of a double-penalty effect in the validation RMSD apart from Baffin Bay, we

545 consider that the assimilation of the higher-resolution signals was efficient. However, the

546 assimilation did not improve the SSS significantly in the Barents Sea or other areas where

547 SSS gradients are weak. These may require higher accuracy to distinguish the Atlantic

548 waters from other water masses of salinity only slightly below 35 psu. To further improve the

549 SSS product, a combination with the Aquarius sensor using the same L-band frequency

550 (e.g., Lee et al, 2012), and SMAP (e.g., Tang et al., 2017; Reul et al., 2020) is desirable.

551

552 **Data availability.** All the in-situ observations for validation in this study are open access as

553 indicated in Sect. 3. The model results from Exp0 are the released TOPAZ reanalysis, which

554 is freely available from CMEMS (http://marine.copernicus.eu) or

555 https://doi.org/10.11582/2022.00043. The other assimilation experiments can be provided

556 freely upon personal communication.

557

558 **Author contributions**. JX initiated the design and carried out the assimilation

559 experiments. LB and RR contributed to the result interpretation. JM provided the SSS data.

560 CG and RC contributed to the uncertainty of the satellite data. All the authors contributed to

561 editing and correcting this paper.

562

563 **Competing interests.** The authors declare that they have no conflict of interest.

564

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577

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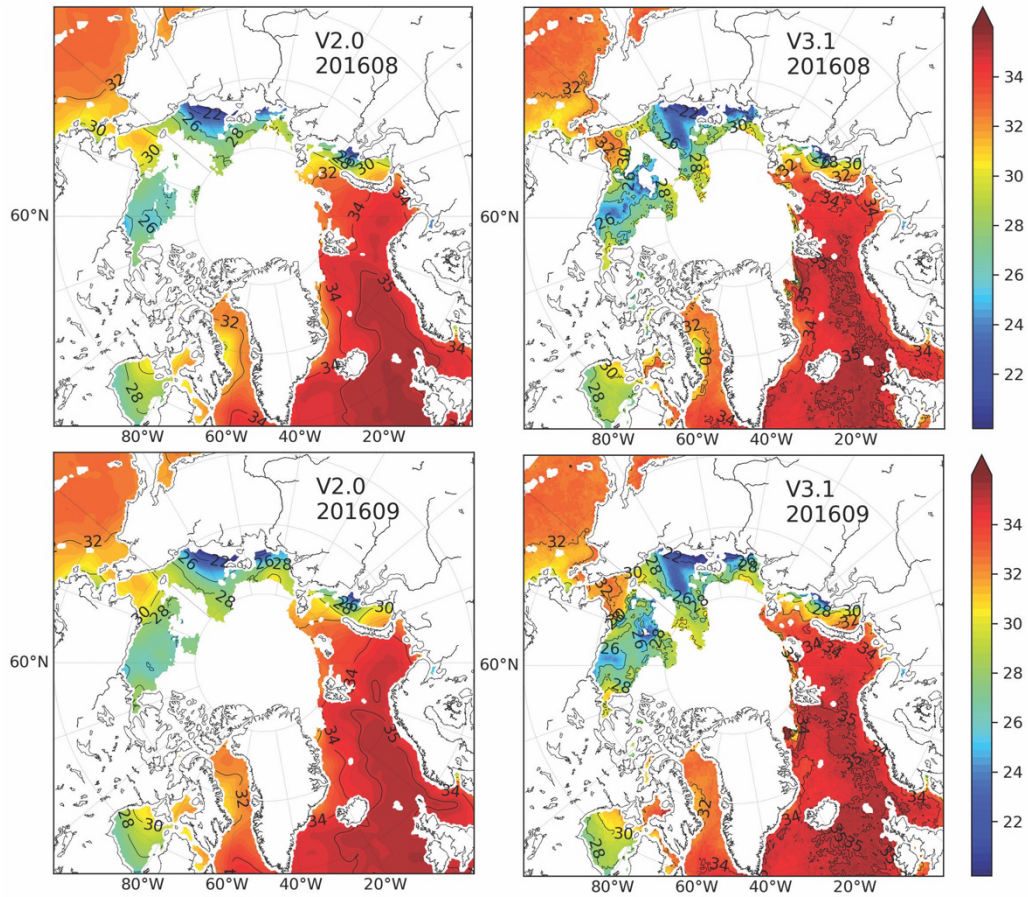
792

Table 1. Settings of the three assimilation runs in 2016 with and without SSS.

	Assimilated obs.	Initial model states	End date of assimilation	SSS Observation Errors
Exp0	SST, SLA, T/S profile, SIC, SIT, and SID	6th July	28th Dec.	N/A
ExpV2	SSS V2.0 + obs. used in Exp0	6th July	28th Dec.	Eq. 3
ExpV3	SSS V3.1 + obs. used in Exp0	6th July	28th Dec.	Eq. 3

Table 2. Evaluation of SSS misfits (unit: psu) in the three assimilation runs according to the 6 areas indicated by the blue dashed lines in Fig. 2. The numbers in bold indicate the smallest misfit with a reduction of at least 9% relative to Exp0. The overall score depends on whether the bias and RMSD are reduced by at least 9%. If both criteria are met, the score equals 1, it is 2 if only one of them is met, and 3 otherwise. The star subscript means the bias changes passed the significance test using Student's t-test ($\alpha = 0.05$).

Areas in Fig. 2	Number of obs.	Bias (psu)			RMSD (psu)			Overall score	
		Exp0	ExpV2	ExpV3	Exp0	ExpV2	ExpV3	ExpV2	ExpV3
BS	98	2.81	2.43	***2.08***	2.87	2.54	***2.28***	1*	1*
CS	137	2.32	1.96	***1.91***	2.62	2.26	***2.19***	1*	1*
BSS	189	1.35	1.34	1.30	2.50	2.49	2.47	3	3
NS	669	0.43	0.44	***0.37***	1.19	1.19	1.16	3	2
GS	254	0.50	0.51	***0.24***	1.43	1.43	***1.28***	3	1*
BB	89	0.35	0.37	***0.12***	1.22	1.20	1.22	3	2

813 **Fig. 1** Monthly SSS of Aug (top line) and Sep (bottom line) in 2016 from SMOS

814 products of BEC V2.0 (left) and V3.1 (right). Note: the solid isolines of SSS are 22,

815 26, 28, 30, 32, 34, and 35 psu.

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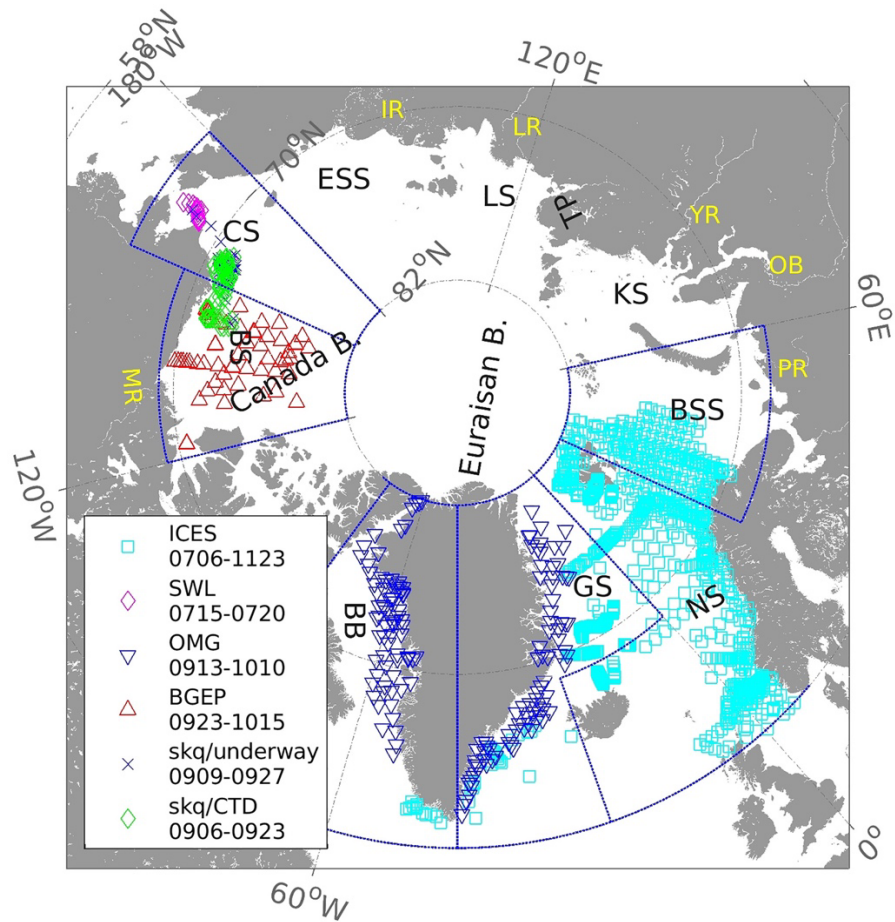
818   **Fig**. 2 Locations of the observed SSS from in-situ profiles and surface samples by

819   cruises from July to December 2016. The marks note 6 observation sources, see the

820   details in Section 2.3. The marginal seas delineated are the Beaufort Sea (BS),

821   Chukchi Sea (CS), East Siberian Sea (ESS), Laptev Sea (LS), Kara Sea (KS), Barents

822   Sea (BSS), Greenland Sea (GS), Norwegian Sea (NS), and Baffin Bay (BB). The main

823   rivers around the Arctic region are the Mackenzie River (MR), Pechora (PR), the Ob

824   (OB), Yenisey River (YR), Lena River (LR), and Indigirka River (IR). TP indicates the

825   Taymyr Peninsula.

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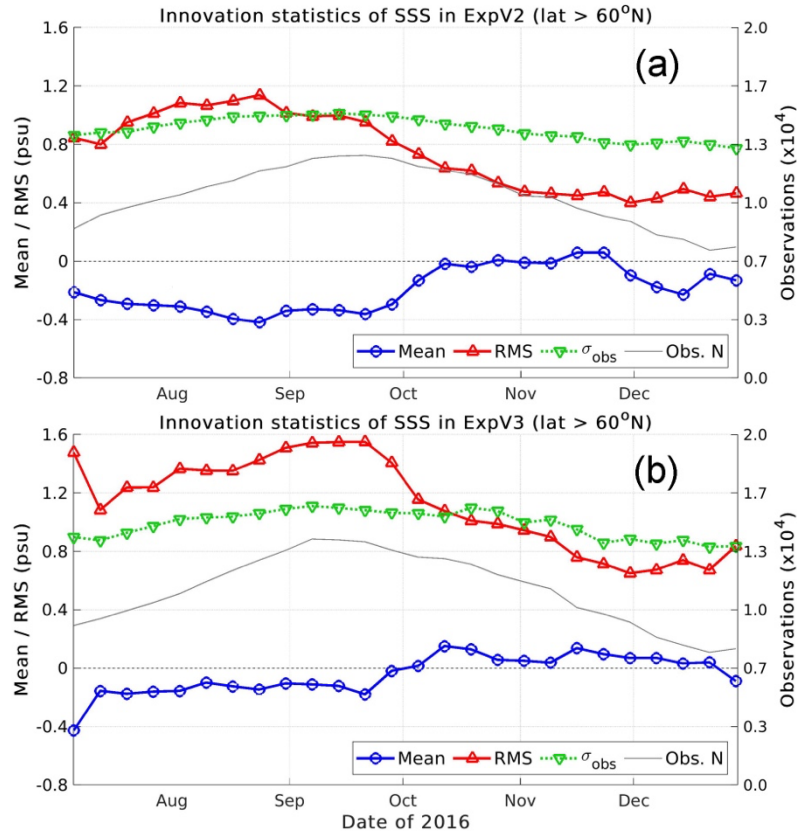
827 **Fig.** 3 Innovation statistics of SSS in the Arctic (>60ºN) from ExpV2 (a) and ExpV3

828 (b). The line with red triangles is the root mean squared innovation, and the blue

829 dotted line shows the mean of innovations north of 60°N. The gray line represents

830 the number of observations assimilated, and the green line with inverted triangles is

831 the observation error standard deviation in the two runs.

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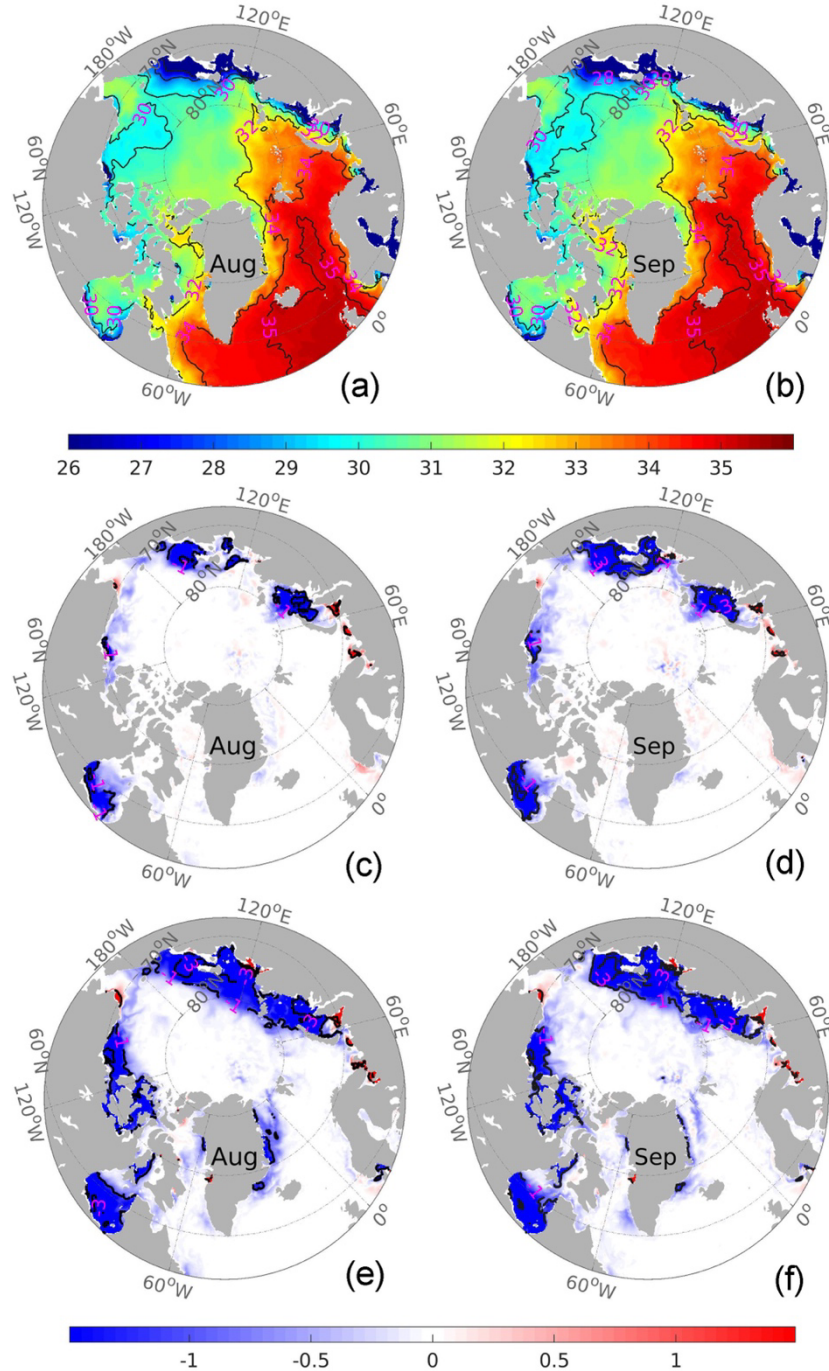
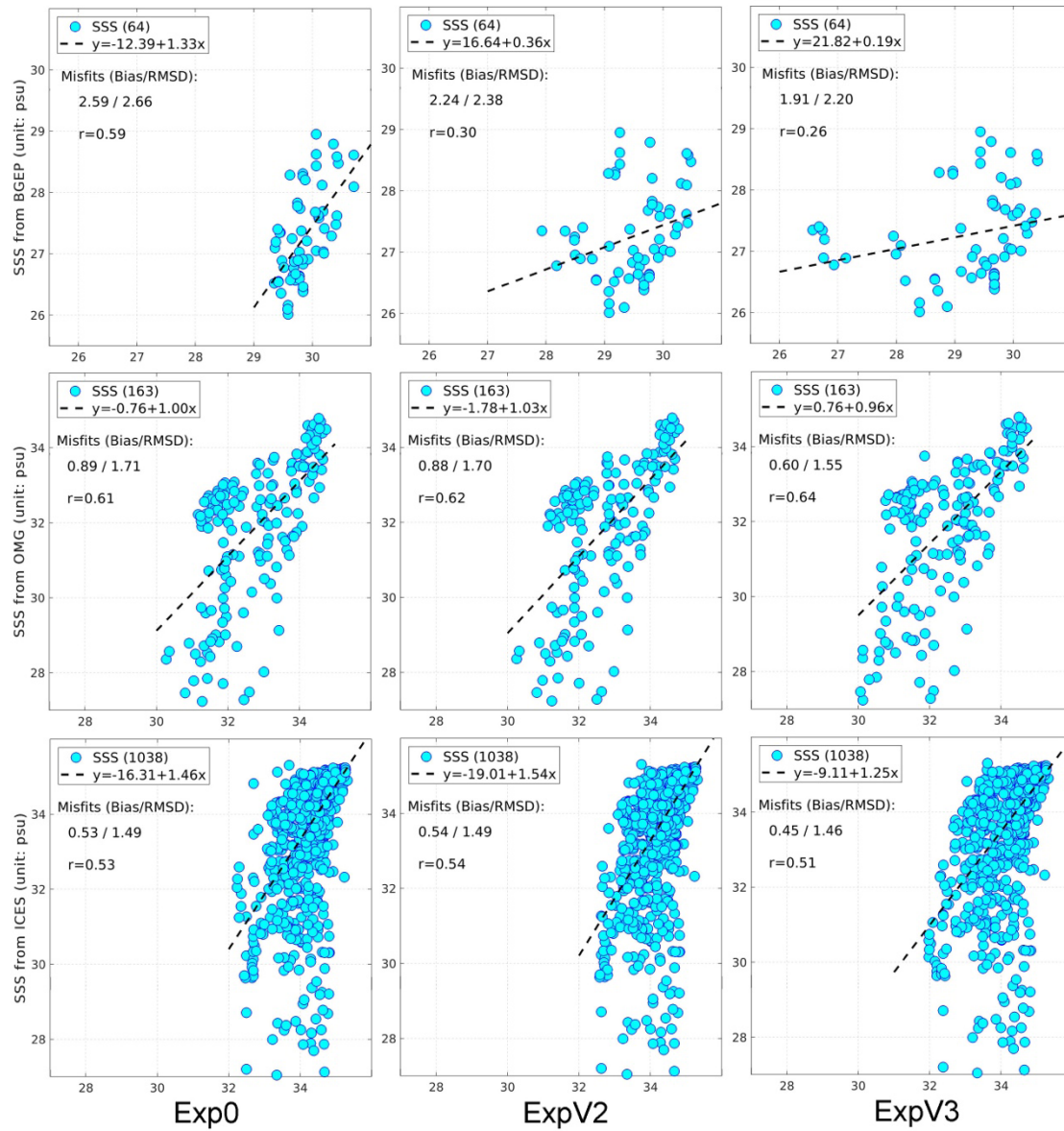


Fig. 4 **Top**: Monthly simulated SSS (unit: psu) from Exp0 in August (left column) and September 2016 (right column). The black isolines indicate the 26, 28, 30, 32, 34, and 35 psu, respectively. **Middle and bottom**: monthly SSS differences in ExpV2 (middle line) and ExpV3 (bottom line) with respect to Exp0. The black lines are -3, -1, 1, and 3 psu.

839   **Fig**. 5 Scatterplots of SSS in the TOPAZ assimilation runs against in-situ profiles

840   (Top: from BGEP in the Beaufort Sea; Middle: from OMG in both Greenland Seas;

841   Bottom: from ICES in the Nordic Seas as indicated in Fig.1 and descriptions in 2.1).

842   The statistics of SSS misfits are indicated in each panel with the bias and the RMSD,

843   respectively, the number of observations is given between parentheses. The dark

844   dashed line represents the linear regression, and r is the linear correlation coefficient.

845   All the correlation coefficients are over the 95% significance test (α=0.05).

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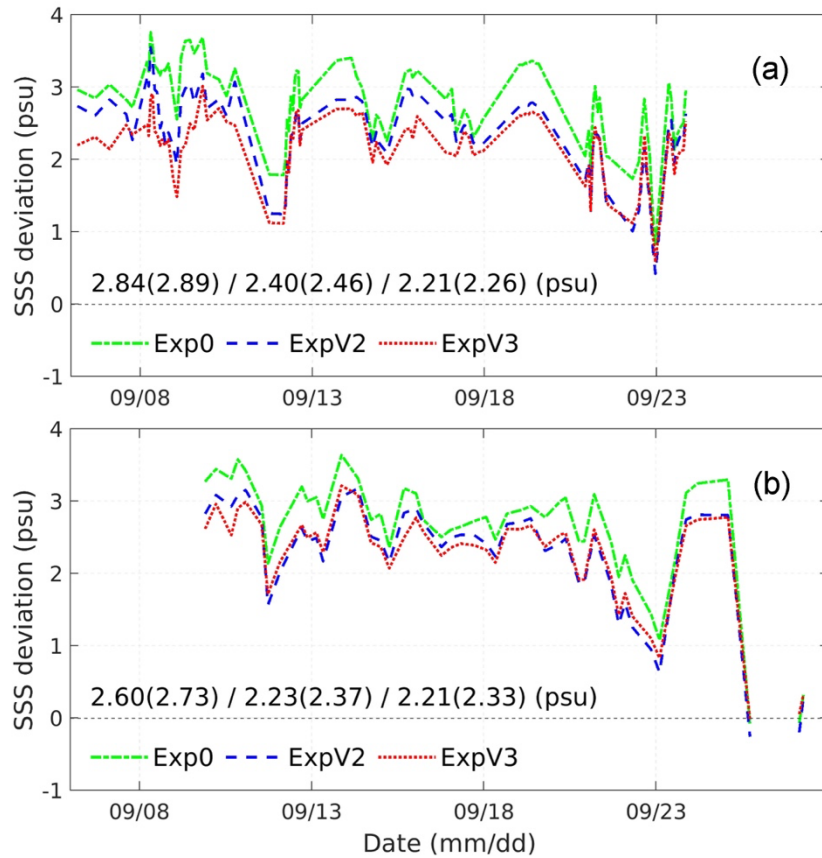
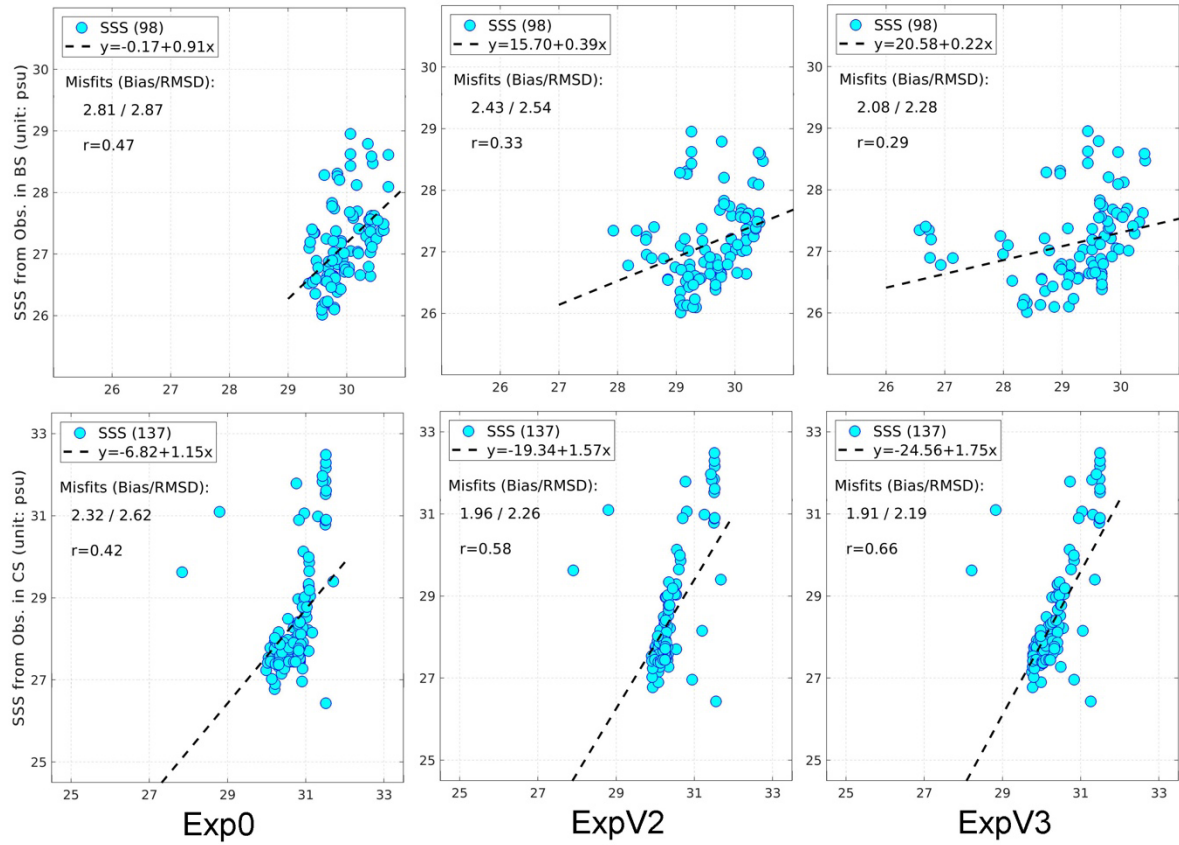

847 **Fig**. 6 Model-minus-observations SSS differences in the three assimilation runs

848 against the SSS recorded in the Beaufort Sea and the Chukchi Sea along the SKQ

849 cruise in 2016: a) from CTD profiles; b) from surface water samples underway in the

850 same cruise. The biases are indicated in the same order and the corresponding

851 RMSD are between parentheses.

852

853 **Fig**. 7 Scatterplots of SSS (unit: psu) in the three assimilation runs Exp0, ExpV2, and

854 ExpV3 against the CTD observations collected by different cruises in 2016. **Top**:

855 Beaufort Sea; **Bottom**: Chukchi Sea as shown in Fig.1. All the correlation coefficients

856 are over the 95% significance test (α=0.01).

857

858 **Fig**. 8 Scatterplots of SSS (unit: psu) in the three assimilation runs Exp0, ExpV2, and

859 ExpV3 against CTD observations from OMG and ICES in 2016. **Upper**: East

860 Greenland Sea; **Bottom**: Baffin Bay as shown in Fig.1. The statistics of SSS misfits

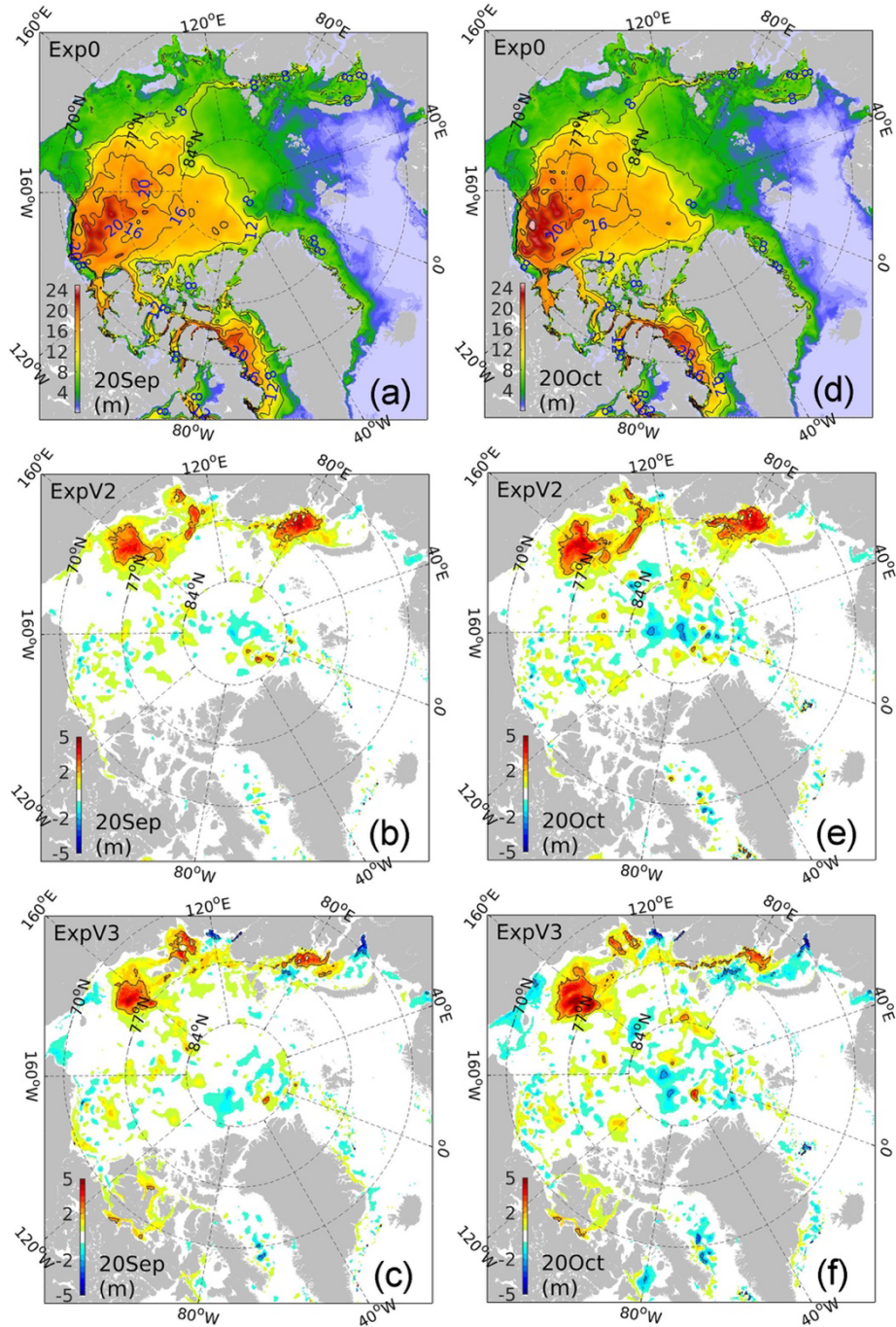
861 are indicated in each panel with the bias and the RMSD respectively, and the number

862 of observations is given between parentheses. The dark dashed line represents the

863 linear regression, and r is the linear correlation coefficient. All the correlation

864 coefficients are over the 95% significance test (α=0.01).

865

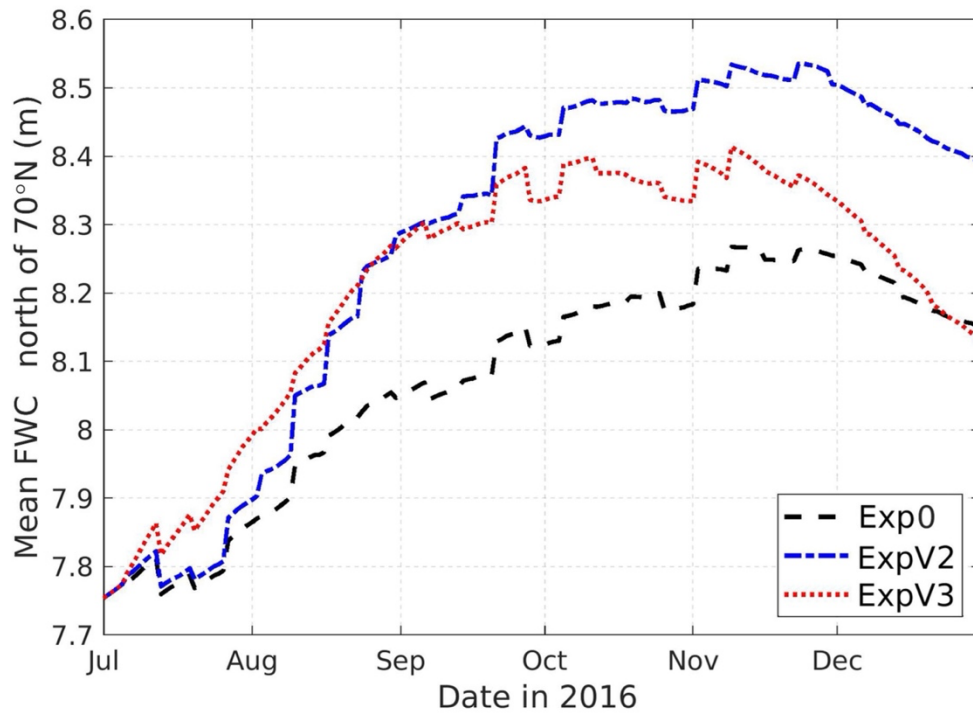
Fig 9. Averaged increments for the 6-months period (Top: in Exp0; Middle: in ExpV2; Bottom: in ExpV3). The figure shows the European Arctic for clarity. Left column: sea ice concentration (unit: %) with isolines of ± 5%. Right column: SST with isolines of ± 0.1°C.

871 **Fig. 10 Top**: Freshwater contents (unit: m) on 20th September and 20th October 2016

872 in the Arctic Ocean from the three assimilation runs: Exp0. The interval of isolines is

873 4 meters. **Middle and bottom**: the FWC differences in ExpV2 (middle line) and

874 ExpV3 (bottom line) concerning that in Exp0. The black lines indicate -2 m and 2 m

875 differences.

876

877   **Fig** 11. Arctic-wide averaged freshwater content (unit: m) in the central Arctic (>70°N)

878   from July to December 2016 for Exp0 (dark dashed), ExpV2 (blue dashed), and ExpV3

879   (red dotted).