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4   **Medium-range predictability of early summer sea ice thickness distribution in**

5   **the East Siberian Sea based on the TOPAZ4 ice-ocean data assimilation system**

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16

Abstract

17

18   Accelerated retreat of Arctic Ocean summertime sea ice has focused attention on the potential use

19   of the Northern Sea Route (NSR), for which sea ice thickness (SIT) information is crucial for safe

20   maritime navigation. This study evaluated the medium-range (lead time below 10 days) forecast

21   skill of SIT distribution in the East Siberian Sea (ESS) in early summer (June–July) based on the

22   TOPAZ4 ice ocean data assimilation system. Comparison of the operational model SIT data to

23   reliable SIT estimates (hindcast, satellite, and in situ data) showed that the TOPAZ4 reanalysis

24   reproduces qualitatively the tongue-like distribution of SIT in ESS in early summer and the

25   seasonal variations. Pattern correlation analysis of the SIT forecast data over 3 years (2014–2016)

26   reveals that the early summer SIT distribution is skillfully predicted for a lead time of up to 3 days,

27   but that the prediction skill drops abruptly after the 4th day, which is related to dynamical process

28   controlled by synoptic-scale atmospheric fluctuations. For longer lead times (>4 days), the

29   thermodynamic melting process takes over, which makes most of the remaining prediction skill. In

30   July 2014, during which an ice-blocking incident occurred, relatively thick SIT (~150 cm) was

31   simulated over the ESS, which is consistent with the reduction of vessel speed. These results

32   suggest that TOPAZ4 sea ice information has a great potential for practical applications in

33   summertime maritime navigation via the NSR.

34

1 Introduction

During recent decades, sea ice cover in the Northern Hemisphere has shown remarkable reduction and the largest rates of decrease of 100,000 km^2 $decade^{-1}$ has been observed in the western Arctic Ocean in summer [Cavalieri and Parkinson, 2008]. Sea ice retreat influences the light conditions for phytoplankton photosynthesis activity [Wassmann, 2011], and the resultant meltwater influences the marine environment via ocean acidification [Yamamoto-Kawai et al., 2011]. In winter, shrinkage of the sea ice area in marginal seas, such as the Barents Sea changes the surface boundary conditions of the atmosphere, influences planetary waves, and causes blocking events that are one of the possible causes of the recent severe winters in mid-latitude regions [Honda et al., 2009; Inoue et al., 2012; Mori et al., 2014; Overland et al., 2015; Petoukhov and Semenov, 2010; Screen, 2017].

In contrast to these climatic consequences and problems for the marine ecosystem caused by the reduction in sea ice, the retreat of Arctic sea ice has new opportunities for commercial maritime navigation. It has been reported that exploitation of shipping routes in the Arctic Ocean, i.e., the Northern Sea Route (NSR), could reduce the navigational distance between Europe and Asia by about 40% in comparison with routes via the Suez Canal [Schøyen and Bråthen, 2011]. Melia et al. [2016] discussed the possibility of a viable trans-Arctic shipping route in the 21st century, based on the Coupled Model Intercomparison Project Phase 5 (CMIP5) global climate model simulation. Currently, the summertime use of the NSR by commercial vessels such as cargo ships and tankers has increased [Eguíluz et al., 2016]. Therefore, obtaining precise information on sea ice condition and evaluating the forecast skill of operational sea ice models have become urgent issues.

Many previous studies have examined the predictability of summertime sea ice change in the Arctic Ocean in terms of its coverage [Wang et al., 2013] and motion [Schweiger and Zhang, 2015]. Kimura et al. [2013] reported a good correlation of the spatial distribution of summertime sea ice concentration (SIC) with winter ice divergence/convergence. Their study indicated that sea ice

60 thickness (SIT) or sea ice volume before the melt season is a source of predictability for

61 summertime SIC. Recently, their study was supported by hindcast experiments undertaken using a

62 climate model, in which the SIC in the East Siberian Sea (ESS) was shown to have significant

63 seasonal prediction skill [Bushuk et al., 2017]. The significant impacts of SIT condition on the

64 seasonal prediction of SIC in the Arctic Ocean have been highlighted by many studies [Lindsay et

65 al., 2008; Holland et al., 2011; Blanchard-Wrigglesworth and Bitz, 2014; Collow et al., 2015; Melia

66 et al., 2015; Chen et al. 2017; Melia et al. 2017]. Thus, the persistence of SIT or sea ice volume is

67 one of the key factors determining the skill of seasonal predictions of summertime sea ice area.

68   Earlier studies have focused primarily on the seasonal to interannual predictability of SIC or

69 sea ice area in the Arctic Ocean; thus, subseasonal variation in SIT and its predictability have not

70 been examined fully for near-term route planning. Although the summertime sea ice extent has

71 rapidly decreased on interannual timescale, substantial sea ice area still remains in critical stretches

72 of the NSR such as the ESS in early summer (June−July). Since precise information regarding SIT

73 and its near-future condition is crucial for icebreaker operations [Tan et al., 2013; Pastusiak, 2016],

74 it is important to clarify the medium-range (3 to 10 days lead time) predictability of summertime

75 SIT in the Arctic Ocean.

76   Synoptic-scale fluctuations of cyclone and anticyclone is greater over the Arctic Ocean and

77 Eurasia in summer than in winter [Serreze and Barry, 1988; Serreze and Barrett, 2008]. In recent

78 years, there is a risk that an Arctic cyclone becomes extremely developed and covered the entire

79 Pacific sector [Simmonds and Rudeva, 2012; Yamagami et al. 2017]. Because the ESS corresponds

80 to the route of Arctic cyclones generated over the Eurasian Continent [Orsolini and Sorteberg,

81 2009], it is expected that synoptic-scale atmospheric fluctuations would influence substantially the

82 spatial distribution of SIT and ice motion in the ESS. Ono et al. [2016] highlighted the importance

83 of atmospheric prediction skill on medium-range forecasts of sea ice distribution in the ESS based

84 on a case of an extreme cyclone that occurred on 6 August 2012. On the other hand, earlier studies

85 pointed out that the sea ice melting process is important for the long-term prediction of summertime

86 sea ice extent [e.g., Bushuk et al., 2017]. But the relative importance of dynamical and

87 thermodynamic processes on the medium-range forecast skill of summertime sea ice properties has

88 not yet been well understood.

89   Since 2010, ice−ocean forecasts and a 20-years reanalysis are available for the Arctic Ocean,

90 based on the TOPAZ ocean data assimilation system (Towards an Operational Prediction system for

91 the North Atlantic European coastal Zones) in its 4th version [Sakov et al., 2012]. The Norwegian

92 Meteorological Institute provides 10-day forecast products in daily mean fields, forced at the

93 surface by the European Centre for Medium-Range Weather Forecasts (ECMWF) operational

94 atmospheric forecasts, updated daily and distributed by the Copernicus Marine Environment

95 Monitoring Services (http://marine.copernicus.eu). The reliability of the corresponding TOPAZ4

96 reanalysis data has been evaluated previously through comparison with in situ and satellite SIT data

97 [Xie et al. 2017]. They showed the SIT in the TOPAZ4 reanalysis data are comparable to observed

98 values over the Beaufort Gyre and central Arctic Ocean, although the SIT overall shows a negative

99 bias of several dozen centimeters throughout a year. Thus, it is expected that the SIT data in the

100 TOPAZ reanalysis data should also be reliable in the ESS even in the melting season, and the

101 forecast SIT data should show skillful prediction skill on medium-range time scale.

102   In this study, we examined the predictability of the early summer SIT distribution in the ESS

103 on the medium-range timescale and discussed its underlying physical mechanisms, based on the

104 TOPAZ4 forecast dataset and trivial dynamical and thermodynamical models. Section 2 describes

105 the data and methods. Section 3 evaluates the reliability of the SIT data in the TOPAZ4 reanalysis

106 data through comparison with all available in situ and satellite observations, as well as operational

107 model analyses, with particular emphasis on the ESS. In section 4, we examine the predictability of

108 the SIT distribution in the ESS based on TOPAZ4 forecast data. Section 5 examines the relationship

109 between sea ice conditions and vessel speed during an ice-blocking event that occurred in July 2014.

110   A discussion and the derived conclusions are presented in section 6.

111

112   **2 Data and Methods**

113   This study used daily mean sea ice data derived from the TOPAZ4 Arctic sea ice forecast

114   system dataset, in which the SSM/I SIC data, hydrographic temperature and salinity data,

115   along-track sea level anomaly, and satellite estimates of ice drift and sea surface temperature were

116   assimilated, but sea ice thickness was not yet assimilated in this version of the reanalysis [Simonsen

117   et al. 2017]. The TOPAZ4 system was designed as a regional ice–ocean coupled system forced with

118   atmospheric flux data. The ocean model of TOPAZ4 is based on version 2.2 of HYCOM, which

119   uses isopycnical vertical coordinates in the ocean interior and z level coordinates in the near-surface

120   layer. The sea ice model uses an elastic–viscous–plastic rheology [Hunke and Dukowicz, 1997].

121   The thermodynamic processes are based on a three-layer thermodynamic model with one snow and

122   2 ice layers [Semtner, 1976] with a modification for subgrid-scale ice thickness heterogeneities

123   [Fichefet and Morales Maqueda, 1997]. The model domain covers the Arctic Ocean and the North

124   Atlantic, and the lateral boundaries are relaxed to monthly mean climatological data. The spatial

125   resolution is 12–16 km with 28 hybrid layers, which constitutes eddy-permitting resolution in low-

126   and mid-latitude regions but not in the Arctic Ocean. In this system, in situ hydrographic

127   observations are assimilated together with satellite observations of the ocean such as sea surface

128   temperature and sea level anomaly. Since this system assimilates the SIC and sea ice velocity (but

129   the latter only in cold season), one should expect adequate simulation of SIT through the ridging

130   process [Stark et al. 2008]. It has been reported that the SIT of the TOPAZ4 reanalysis data has

131   substantial negative bias from 2001 to 2010 due to excessive snowfall, which has been modified

132   after 2011 [Xie et al., 2017]. Therefore, this study used SIT data from 1 January 2011 to 31

133   December 2014.

134   The data assimilation method of TOPAZ4 is a deterministic version of the ensemble Kalman

135 filter (EnKF) [Sakov and Oke, 2008] with an ensemble of 100 dynamical members. Since EnKFs

136 have time-dependent state error covariances, this method is suitable for data assimilation of

137 anisotropic variables in areas close to the sea ice edge [Lisæter et al. 2003, Sakov et al. 2012]. The

138 TOPAZ4 reanalysis data were produced with the 6-hourly forcing from the ERA Interim reanalysis

139 [Dee et al., 2011]. The surface turbulent heat flux and momentum flux were both calculated using

140 bulk formula parameterizations [Kara et al., 2000; Large and Pond, 1981]; thus, instead of the

141 ERA-Interim fluxes themselves. The forecast and reanalysis systems have almost the same settings

142 and their results are similar during their overlap period (not shown).

143   To evaluate the prediction skill of the TOPAZ4 forecast system, we used daily mean sea ice

144 forecast data during 3 recent years from 2014 to 2016 [Simonsen et al. 2017]. A probabilistic

145 10-member ensemble forecast was performed with the ECMWF medium-range (up to 10 days)

146 atmospheric forecast data updated daily, out of which only the ensemble average is used. To

147 produce 10 ensemble members in the TOPAZ4 forecast system, the ECMWF global atmospheric

148 forecast data as well as several parameters of sea ice model are perturbed by adding stochastic

149 forcing term [Evensen, 2003]. In this study, we excluded the forecast data in July 2014, because of

150 a real-time forecast production incident (the forecast were in free-running mode then) [H. Engedahl,

151 personal communication]. Since the forecast data were only provided weekly before 2016, the total

152 of 150 cases was assembled during the study period. The skill core was quantified using pattern

153 correlation coefficients (PCCs), which are used widely in deterministic forecast verification

154 [Barnett and Schlesinger, 1987]:

155
$$PCC = \frac{\sum_{ij=1}^{N}\left(f_{ij}-\overline{f}_{ij}\right)\left(a_{ij}-\overline{a}_{ij}\right)}{\sqrt{\sum_{ij=1}^{N}\left(f_{ij}-\overline{f}_{ij}\right)^{2}}\sqrt{\sum_{ij=1}^{N}\left(a_{ij}-\overline{a}_{ij}\right)^{2}}} \qquad (1)$$

156 where f_{ij} and a_{ij} are forecast and analysis sea ice variables, respectively. The overbar denotes the

157 average values over the analyzed area (see Fig. 1a); thus the PCC reflects the correlation of

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158 observed and signal anomalies relative to their respective spatial means.

159   To evaluate the reliability of the SIT values in the TOPAZ4 reanalysis data in early summer,

160 we mainly used the Pan-Arctic Ice Ocean Modeling and Assimilation System (PIOMAS) outputs,

161 which are derived from the coupled ice–ocean modeling and assimilation system based on the

162 Parallel Ocean Program POP and the Thickness and Enthalpy Distribution (TED) sea ice model,

163 forced with NCEP-NCAR reanalysis data [Zhang et al., 2003]. In this dataset, SIC and sea surface

164 temperature are assimilated by adoptive nudging, and many studies [Schweiger et al., 2011; Lindsay

165 and Zhang, 2006; Stroeve et al., 2014] have compared PIOMAS output with observed SIT data and

166 found it the most reliable estimate of observed SIT in the Arctic Ocean [Laxon et al., 2013; Wang et

167 al. 2016].

168   As an alternative SIT data to evaluate the SIT distribution in the ESS, we used the merged

169 product of CryoSat-2 (CS2) and the Soil Moisture and Ocean Salinity (SMOS) SIT products

170 (hereafter, CS2SMOS) from 2011 to 2014 [Ricker et al. 2017], which were provided by the online

171 sea-ice data platform "meereisportal.de" (For details, acknowledgement) [Grosfeld et al. 2016].

172 These data are interpolated to 25-km resolution based on optimal interpolation and they are

173 available from October to April. In general, CS2 data have large uncertainty in the estimation of

174 SIT of <1 m, while the SMOS relative uncertainties are lowest for very thin ice. Thus, the merged

175 product is − to date − considered the best estimate of the satellite-based SIT distribution in and

176 around the ESS, although it was reported that there is potential negative bias in mixed first-year and

177 multiyear ice regions such as the Beaufort Sea [Ricker et al. 2017].

178   For the melting season (May–July), there is no reliable estimate of SIT distribution in the ESS,

179 we therefore used only in situ SIT data of autonomous ice mass balance (IMB) buoys obtained near

180 the ESS [Perovich et al., 2013]. During 2011 to 2014, total 4 buoys are available in a whole year

181 including the melting season (the period in each buoy is listed in Table 1). To compare the

182 two-dimensional SIT data with IMB buoy data, we re-gridded the gridded SIT data along the IMB

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183 buoy trajectories. This comparison method is almost identical to that adopted by Sato and Inoue

184 [2017] who compared IMB buoy data with SIT data of the NCEP-CFSR reanalysis. Before

185 comparing the gridded SIT data with IMB buoy data in each grid point, we reconstructed these SIT

186 data on a 0.25° latitude–longitude grid by applying bilinear interpolation. The temporal and

187 horizontal resolutions of the observed and simulated SIT data are summarized in Table 1.

188   To examine the source of medium-range predictability in SIT distribution, we also used

189 ECMWF atmospheric forecast data on a 1.25° latitude–longitude grid from 2013 to 2016, derived

190 from the THORPEX Interactive Grand Global Ensemble through its data portal

191 (http://tigge.ecmwf.int). This dataset is very similar to the atmospheric forecast data used in the

192 TOPAZ4 operational forecast system [Simonsen et al. 2017]. For the examination of atmospheric

193 forecast skill, we used 51 ensemble daily means of zonal and meridional wind speed at 10-m height

194 on the same days as the TOPAZ4 forecast data at lead times of 0–10 day.

195   To evaluate the influence of sea ice condition on vessel speed in the ESS including the Laptev

196 and Kara Seas, we used the vessel speed data derived from Automatic Identification System (AIS)

197 from two tankers during their passage through the ESS on 4–26 July 2014, which were provided by

198 Shipfinder (http://jp.shipfinder.com/). The temporal resolution is about 2 to 3 hours, depending on

199 the timing and relative location of the satellite track and the ground-based receiver station of AIS

200 signal. Their ice classes correspond to IA Super in the Finnish–Swedish Ice Class Rules, and these

201 vessels are capable of navigating sea ice regions in which SIT is up to 50–90 cm. Both tankers were

202 likely to be hindered considerably by ice conditions, even under escort by Russian nuclear-powered

203 ice-breakers; thus, these AIS data are considered suitable for a case study of the influence of SIT on

204 icebreaker speed.

205

206 **3 Comparisons between TOPAZ4 and other available SIT data**

207   Figure 1a shows the spatial distribution of PIOMAS SIT in July in the Arctic marginal seas of

208 the Laptev Sea, ESS, and Chukchi Sea. The PIOMAS shows the tongue-like distribution of SIT,

209 characterized by relatively thick ice (>1.0 m) extending from the North Pole to the ESS. Since in

210 this region, sea ice motion tends to be converging during winter [Kimura et al. 2013], the sea ice is

211 likely to increase the thickness by ridging and rafting and thus remains until the next early summer.

212 These features are qualitatively simulated in the TOPAZ4 reanalysis data (Fig. 1b). The PCC of the

213 climatological SIT between TOPAZ4 and PIOMAS in the Arctic marginal seas (70°−80°N,

214 120°E−160°W, shown in Fig. 1a) is larger than 0.9 from March to July. The PCCs of the

215 climatological SIT between TOPAZ4 and CS2SMOS from March to April are 0.86 and 0.82, which

216 are comparable to those of PIOMAS (Table 2).

217   From the difference map of the climatological SIT between TOPAZ4 reanalysis data and

218 PIOMAS output, the TOPAZ4 SIT is thicker near the coast with ~50 cm (Fig. 1c), although the SIT

219 in the offshore region is underestimated. These positive and negative biases compensate each other

220 and thus the mean bias of the TOPAZ4 SIT is 21 cm in July, which is smaller than in winter (Table

221 3). The seasonal reduction of the SIT bias in TOPAZ4 is also found in the comparison between the

222 TOPAZ4 and CS2SMOS (Table 3). In fact, a similar positive bias emerges in comparison with the

223 climatological SIT in CS2SMOS in April (Fig. 2). It should be noted that a larger positive bias in

224 TOPAZ4 is located solely in the region of the Beaufort Gyre, with about 50 cm excess thickness

225 (Fig. 1c and 2c). Since in this region, both SIT data sets show some negative bias relative to the

226 independent SIT estimates derived from U.S. submarine data [Schweiger et al. 2011] and airbone

227 electromagnetic induction (EM) thickness measurements [Ricker et al. 2017], this positive bias may

228 be partly related to the underestimation of PIOMAS and CS2SMOS SITs, themselves.

229   Figure 3 shows the time series of daily mean SIT derived from PIOMAS and TOPAZ4

230 reanalysis and 7-days mean SIT derived from CS2SMOS, averaged over the ESS (70°−80° N,

231 150°−180° E, shown in Fig. 1a). The TOPAZ4 SIT data are reasonably similar to the seasonal cycle

232 of PIOMAS and CS2SMOS data with maxima in April–May and minima in October–November. In

233 particular, the TOPAZ4 SIT is within the standard deviation of PIOMAS SIT anomaly in each grid

234 relative to the area-averaged value in early summer (June-July). The monthly mean biases of

235 TOPAZ4 SIT data relative to PIOMAS in June and July are smaller than those in March to May

236 (Table 3). It should be noted that the TOPAZ4 SIT data in 2011 are strongly underestimated in early

237 summer. This might be related to the persistence of the negative bias until 2010 [Xie et al., 2017].

238   In the freezing season, the TOPAZ4 SIT in the ESS tends to be thinner than the PIOMAS SIT,

239 and seems comparable to the CS2SMOS SIT. The monthly mean bias of TOPAZ4 SIT relative to

240 CS2SMOS SIT is -23 cm and 1 cm in March and April, respectively (Table 3). On the other hand,

241 we should pay attention to the possibility that the CS2SMOS SIT may be underestimated in this

242 region, because the CS2SMOS highly depends on the reliability of merging two SIT data, which are

243 CryoSat-2 and SMOS SIT products [Ricker et al. 2017]. To check the possibility that the CS2SMOS

244 SIT has a negative bias in this area, we briefly examined the ice type data which were used for the

245 determination of merged SIT products. In the period from 2011 to 2013, the uncertainty of

246 CS2SMOS SIT is out of range for that of PIOMAS, but the CS2SMOS SIT is comparable to that for

247 PIOMAS in 2014 when the sea ice is classified as multi-year ice (Fig. 3). This result implies that the

248 CS2SMOS SIT is underestimated in the ESS due to the large fraction of SMOS SIT products even

249 in the sea ice thicker than 1 m.

250   Finally, we compared the SIT data in TOPAZ4 with the in-situ observations available in and

251 around the ESS. Although the location of these buoy data are not fully delimited in the ESS focused

252 in this study the ESS on which we focused in this study, these data seem to be appropriate for our

253 purpose, because the range of the climatological SIT in these region is similar to that in the ESS

254 (Fig. 1a). The direct comparison between the TOPAZ4 and IMB shows that the mean bias and root

255 mean square error of TOPAZ4 is 8.3 cm and 30 cm, respectively (Fig. 4). In particular, the TOPAZ4

256 SIT data shows a good correspondence with IMB buoy data in 2014, which is near the ESS in July

257 (Fig. 1a and Table 1). These results support the reliability of TOPAZ4 SIT data in the ESS in early

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258   summer. Thus, at least the overall spatial distribution of SIT in the ESS is qualitatively simulated in

259   the TOPAZ4 and the inherent negative bias is suppressed in early summer, which is partly related to

260   the compensation by the positive bias near the shelf region of the ESS.

261

262   **4. Medium-range forecast skill of SIT distribution in the ESS**

263   In this section, we evaluate the prediction skill of SIT based on the PCCs between the analysis

264   and predicted data in the ESS. However, before this evaluation, we examine the mean fields and the

265   variability of the SIT and SIC distributions in early summer. Figure 5a presents the spatial

266   distribution of the climatological SIT and SIC in July, which shows that relatively thick sea ice (~1

267   m) covers 50%−70% of the ESS. Along the zone of the sea ice edge, the temporal standard

268   deviation of the daily mean SIT anomaly is relatively large with the maximum value of 0.6 m in the

269   coastal region (Fig. 5b) and the area-averaged value is maximum in July−August (Fig. 5c). Since

270   the SIT reduction rate in the ESS is strongest in these months (Fig. 5c) and the storm activity is

271   prevalent for periods of several days [Orsolini and Sorteberg, 2009], it is likely that dynamical and

272   thermodynamically-induced SIT variations are large. Note that the RMS of the SIC anomaly

273   averaged over the ESS also shows a similar seasonal cycle (not shown). Thus, it is meaningful to

274   examine the medium-range predictability of early summer SIT distribution in the ESS.

275   Figure 6a shows the seasonal dependency of PCC between the predicted and analyzed SIT at

276   lead times of 0−9 days. We found that the overall prediction skill is relatively low in warm season

277   (June-September) with a larger spread compared with the cold season (October−May). This result is

278   roughly consistent with the larger variance of the SIT anomaly in the warm season in the ESS (Fig.

279   5c). A large portion of the prediction skill at the lead times of 0−3 days can be explained by the

280   persistency effect based on the initial SIT (Fig. 6b). The contribution of the operational model on

281   the forecast skill is less than 5% at shorter timescale (<3 days) (Fig. 6c), but the contribution of the

282   operational model gradually increases at longer lead times except in May and October. In July, the

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283 contribution of the operational model on the prediction skill reaches ~15% at 7 day lead time. These

284 results indicate that the operational model substantially improves the medium-range prediction skill

285 of the SIT distribution in summer.

286   Figure 7a shows the PCC of SIT distribution averaged in early summer (June−July). The SIT

287 distribution is predicted skillfully for a lead time of up to 3 days (Fig. 7a); however, the prediction

288 skill decreases abruptly at a lead time of 4 days, in which the standard deviation is also relatively

289 large. Such an abrupt reduction of the prediction skill and the enhanced standard deviation are also

290 found in May and September, although the absolute values of the reduction rates are smaller than in

291 July. Since the influence of sea ice melt is small in these months (Fig. 5c), the abrupt reduction of

292 early summer SIT prediction skill might be attributable to dynamical advection of sea ice.

293   To examine the influence of dynamical processes on the prediction skill of early summer SIT

294 distribution, we consider the prediction skill of sea ice velocities and surface wind velocities. The

295 prediction skill of sea ice velocity stays on a high level (>0.8) with small spread for a lead time of

296 up to 3 days, but decreases down to 0.6−0.7 for a lead time of 4 days (Fig. 7b). The early summer

297 prediction skill of surface wind speed also shows the same abrupt decrease at a lead time of 4 days,

298 and the rate of decrease of prediction skill is larger in meridional direction (Fig. 7c). Since the SIT

299 distribution has a tongue-like distribution (Fig. 5a), it is suggested that the meridional component of

300 SIT advection is sensitive to the sea ice transport in ice-edges, which influences the SIT distribution

301 in the ESS. These results confirm that the prediction skills of the sea ice velocities are strongly

302 related to those of surface wind speeds in the ESS.

303   Figure 8 shows the temporal evolutions of SIT and ice velocity for analysis and a forecast

304 bulletin starting from 2nd July 2015, which is a typical case of the abrupt decrease in the prediction

305 skill of SIT as well as sea ice velocities for a lead time of 4 days (Fig. 8; lower panel). For lead

306 times of +0 (2 July) to +2 days (4 July), the spatial distributions of SIT and ice velocity are

307 predicted skillfully with only small differences between them (Fig. 8; right panels). At a lead time

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308　of +4 days (6 July), the analyzed sea ice velocity is directed northwestward in the ESS, which is

309　related to the cyclonic circulation over the Novosibirsk Islands; however, the predicted sea ice

310　velocity is directed southwestward. At a lead time of +6 days, the predicted and analyzed sea ice

311　velocities are largely unrelated. The resultant onshore anomaly of sea ice velocity leads to positive

312　and negative anomalies in SIT in the coastal and offshore regions, respectively. We also examined

313　the time evolutions of the surface wind velocities in the atmospheric forecast data, and found them

314　very similar to the sea ice velocity fields (not shown). These results indicate that the abrupt

315　reduction of the prediction skill of early summer SIT in the ESS is related to a deficiency in the

316　prediction of Arctic cyclone formation.

317　　　Further, we examine diagnostically the ice drift speed and direction based on a classical

318　free-drift theory [Leppäranta, 2005], using the sea ice speed of TOPAZ4 reanalysis data and ERA

319　interim atmospheric wind data in July 2011– 2014. The general solution of sea ice speed (u) can be

320　described as complex numbers:

321
$$u = \alpha e^{-i\theta} U_a + U_{wg} \tag{2}$$

322　where U_a, and U_{wg} are the wind speed and geostrophic water velocities, respectively. The terms α

323　and θ are the wind factor and the deviation angle of ice motion from the surface wind, respectively,

324　where a positive angle is in counterclockwise direction. If we neglect the geostrophic water velocity

325　U_{wg}, the wind factor and deviation angle can be obtained in the following form:

326
$$\alpha^4 + 2\sin\theta_w RNa\alpha^3 + R^2 Na^2 \alpha^2 - Na^4 = 0, \tag{3}$$

327
$$\theta = \arctan\left(\tan\theta_w + \frac{RNa}{\alpha\cos\theta_w}\right) - \theta_a, \tag{4}$$

328　where θ_w and θ_a are the boundary layer turning angles of water and air, respectively. The turning

329　angle θ is the angle between the vectors of the ice–water stress and the sea ice motion, which is a

330　consequence of the viscous effect within the ocean boundary layer. The Nansen number Na is

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331   defined by $\sqrt{\rho_a C_a / \rho_w C_w}$, where ρ_a and ρ_w represent the density of air and water, respectively, and

332   C_a and C_w are air and water drag coefficients, respectively. The Rossby number R is defined by

333    $\left(\rho h_{ice} f\right)/\left(\rho_w C_w N a |U_a|\right)$, where ρ is the ice density, f is the Coriolis parameter, and $|U_a|$ is the speed

334   of the surface wind. To calculate the wind factor α and the deviation angle θ under a given surface

335   wind speed, we used constant parameters of $C_a = 1.2 \times 10^{-3}$, $C_w = 5 \times 10^{-3}$, $\rho_a = 1.3$ kg m^{-3}, $\rho_w =$

336   1026 kg m^{-3}, $\rho = 910$ kg m^{-3}, $f = 1.3 \times 10^{-4}$ s^{-1}, and $\theta_w = 20°$, which are values typical of the Arctic

337   Ocean [McPhee, 2012]. The value of α was calculated numerically from a 4th-order polynomial (Eq.

338   (3)).

339   On a first order approximation, the daily mean sea ice speed is linearly proportional to the

340   surface wind speed (10-m height) averaged over a part of the ESS (Fig. 9a). The correlation

341   between them is 0.96, which is significant at the 99% confidence level, based on the Monte Carlo

342   simulation [Kaplan and Glass, 1995]. The regression coefficient of ice speed onto the 10-m wind

343   speed is 0.022, which is consistent with the well-known 2% relationship between the speed of ice

344   and the surface wind speed [Thorndike and Colony, 1982]. The number of the TOPAZ4 ice speed

345   data within ±20% of the theoretical value is 79 days, which accounts for 63% of the total analyzed

346   period. Note that the observed regression coefficient is somewhat larger than the theoretical value

347   (0.018) averaged over the range of surface wind speed of 2–10 m s^{-1} calculated from Eq. (2). Since

348   the classical free drift theory [Leppäranta, 2005] neglects both the Ekman layer velocity and the

349   ocean geostrophic velocity, the absence of an ice-ocean boundary layer is likely to underestimate

350   the wind-induced ice velocity [Park and Stewart, 2016]. The deviation angle of sea ice motion in

351   TOPAZ4 is estimated as 20°–40° under a wind condition >5 m s^{-1}, but it gradually increases to

352   40°–70° under weaker wind conditions of <5 m s^{-1} (Fig. 9b). The decrease of the deviation angle as

353   the surface wind strengthens is also consistent with earlier studies [Thorndike and Colony, 1982].

354   These observed deviation angles are comparable with their theoretical values calculated using Eq.

15

355 (4). The finding that the estimated values of the wind factor and the deviation angle are

356 approximately within the range of typical surface wind parameters (i.e., 2% for the wind factor and

357 30° for the deviation angle) in the Arctic Ocean confirms that sea ice velocity in the ESS is

358 controlled predominantly by wind stress drag: thus, the influence of ocean currents is not essential.

359   It is interesting that the prediction skill of SIT in early summer remains ~0.9 for the PCC core

360 at the lead times longer than 4 days (Fig. 7a), despite the poorer prediction skill of sea ice velocity

361 (Fig. 7b). This suggests that the SIT prediction skill after a lead time of 4 days is not strongly

362 attributed to the dynamical process but rather the thermodynamic process (i.e., the melting process

363 of sea ice). To evaluate the effect of sea ice melting on SIT prediction skill, we roughly estimated

364 the thermodynamic SIT change based on a simple sea ice melting model, as follows:

365
$$h^p\left(t\right) = h^a\left(t_0\right) + \Delta t \times d\overline{h}\,/\,dt \tag{5}$$

366 where h^p is the predicted thermodynamic SIT change, h^a is the initial condition, which is

367 derived from the analysis SIT, and $d\overline{h}\,/\,dt$ is the rate of reduction of SIT due to sea ice melting. It

368 is known that the summertime surface heat flux in the Pacific sector of the Arctic Ocean is

369 dominated by the shortwave radiation flux [Perovich et al. 2007; Steele et al. 2008]. Recently, the

370 seasonal evolution of sea ice retreat in early summer has been found to be explained well by a

371 simplified ice–ocean coupled model, in which shortwave radiation is assumed constant [Kashiwase

372 et al. 2017]. Therefore, as the melting rate of the SIT in each year, we used the reduction rate of SIT

373 calculated from the climatological analysis SIT data during 2013–2016, which is likely to reflect the

374 typical thermodynamic melting rate in recent years and the SIT change due to transient sea ice

375 advection seems to be negligible. Here, we also evaluate the prediction skill of the persistency in the

376 initial SIT in the ESS (first term of the RHS in Eq. (5)).

377   Figure 10 shows the prediction skills of early summer SIT distribution in the ESS based on the

378 simple sea ice melting and persistency models. The prediction skill of the simple melting model,

379   which is lower than the full physics model, is very similar to that of the persistency model up to 3

380   days. However, the prediction skill of the simple melting model is comparable with that of the full

381   physics model after a lead time of 4 days, which is higher than that of persistency. Figure 11 shows

382   the temporal evolutions of SIT difference between the forecast and analysis data in each prediction

383   model in the period 2–9 July 2015. From the lower panel of Fig. 11, we found that the prediction

384   skill of the full physics model is higher than the simple melting and persistency models for lead

385   times of 0–5 days, but comparable with the prediction skill of the simple melting model at longer

386   lead times (> 6 days). In the SIT difference map of the full-physics model minus the operational

387   analysis, a positive anomaly (i.e., overestimation of SIT), is evident along the sea ice edge at a lead

388   time of 4 days, and then gradually increases until a lead time of 8 days. For the case of the simple

389   melting model, a similar positive anomaly emerges at a lead time of 4 days, but the positive

390   anomaly appears stationary along the coastal region, compared to the full physics model. The

391   persistency model overestimates SIT over the entire region during the prediction. These results

392   support the idea that the melting process is important in the prediction of early summer SIT over

393   longer timescales.

394

395   **5. Case study of ice-blocked incident in the ESS in July 2014**

396   In the perspective of operational application of the TOPAZ4 sea ice data to the maritime

397   navigation of the NSR, we briefly examine the relationship between the sea ice conditions and AIS

398   vessel speed data for the case of an ice-blocking incident involving two vessels, based on the

399   TOPAZ4 reanalysis data. Figure 12 shows the vessel tracks during July 4–30 2014, when the two

400   vessels became blocked in the ESS for about one week. During this period, SIT in excess of 100 cm

401   is found in the ESS with the maximum thickness of 150 cm. A joint statistical analysis of the daily

402   mean SIT in the TOPAZ4 reanalysis and the vessel speed along the route indicates that vessel speed

403   is significantly anticorrelated with SIT (-0.56) during the entire passage (Fig. 13a), significant at

404   the 99 % confidence level based on a Monte Carlo technique [Kaplan and Glass, 1995]. We also

405   examined the corresponding SIC data in TOPAZ4 reanalysis data, but the correlation between the

406   vessel speed and SIC is -0.41 (Fig. 13b), which is insignificant at 99% confidence level. The scatter

407   plots for SIC indicates that the SIC value is partly insensitive to the vessel speed higher than 5 knot.

408   Thus, these results suggest that the vessel speed was influenced by sea ice stress due to SIT and

409   indirectly supports the reliability of the daily mean SIT of the TOPAZ4 reanalysis data in the ESS

410   in early summer.

411

412   **6. Summary and discussion**

413   In this study, the medium-range forecast skill of early summer SIT distribution in the ESS was

414   evaluated using the TOPAZ4 data assimilation system. Comparisons between the operational model,

415   observed, and TOPAZ4 reanalysis SIT data showed that the TOPAZ4 reanalysis qualitatively

416   reproduces the tongue-like distribution of SIT in the ESS in early summer, and its seasonal variation

417   (maximum in April–May and minimum in October–November) including the rates of advance and

418   melting of sea ice in the ESS). Although in this region, the inherent negative bias of SIT in TOPAZ4

419   is relatively large in March to May, the bias is reduced in early summer (June-July) within ~±20 cm

420   due to the excess of SIT along the coastal region in the ESS. The TOPAZ4 SIT data also shows a

421   good correspondence with IMB buoy data in and around the ESS with the mean bias of ~9 cm and

422   the root mean square error of ~30 cm. Thus, the TOPAZ4 SIT data could be considered reliable

423   estimates for the ESS even in the absence of satellite observations in summer.

424   For the positive bias of the SIT in TOPAZ4 along the coastal region of the ESS, there is a

425   possibility that the SIT estimates (PIOMAS and CS2SMOS) used for the comparison are

426   themselves underestimated. Schweiger et al. [2011] pointed out that the SIT of PIOMAS is

427   underestimated by -17cm in the basin area of the Arctic Ocean including the Beaufort Sea where the

428   heavy deformed sea ice formation occurs. Also, it was reported that the CS2SMOS SIT data tend to

429 underestimate SIT in regions where multi-year ice and first-year ice are formed, due to the relative

430 accuracy of CryoSat-2 and SMOS and the merging algorithm [Ricker et al. 2017]. Since in the ESS,

431 sea ice motion is strongly converging during winter [Kimura et al. 2013], there is a possibility that

432 the sea ice in the ESS is also heavily deformed to form sea ice thicker than 1 m along the coastal

433 region. In fact, our analysis based on the AIS data suggests that SIT in excess of 100 cm is found

434 near the coast of the ESS. Thus, for a precise evaluation of the SIT distribution in the ESS, the

435 further improvement of ice-type as well as denser in-situ SIT measurements are needed.

436   The prediction skill of the SIT distribution in the TOPAZ4 forecast system was examined in

437 the ESS using a pattern correlation analysis. Although the prediction skill was relatively lower in

438 early summer (June–July) with a large spread, the SIT distribution was predicted skillfully for a

439 lead time of up to 3 days, and the prediction skill drops abruptly after the 4th day. A similar change

440 in prediction skill was also found for sea ice velocity and surface wind speed over the ESS.

441 Diagnostic analysis of the sea ice velocity variability revealed that the early summer ice speed and

442 direction over the EES could be explained well by the free-drift mechanism with a wind factor of

443 2.2 % and a deviation angle of 30°–50°. Their results suggested that the large reduction of

444 prediction skill could be attributed to the process of dynamical advection of sea ice; thus, the

445 prediction of early summer SIT distribution will depend on precise prediction of the surface wind.

446 Our comprehensive analysis supports an earlier study that suggested the dynamical processes have

447 an essential role in the prediction skill of sea ice distribution on short timescales [Ono et al., 2016].

448   The time evolution of SIT and the related ice velocity relates the large difference between the

449 forecast and analysis data at a lead time of 4 days to the low forecast skills for an Arctic cyclone

450 event. Jung and Matsueda [2017] highlighted that large-scale atmospheric fluctuations in the Arctic

451 region in winter are predicted skillfully for lead times of up to 5 days in the operational forecast

452 system, which is very similar to the prediction skill in mid-latitude regions. However, Yamagami et

453 al. [2018] reported that the skillful prediction of Arctic cyclones generated in summer is limited to 4

454 days, which is shorter than the case for the mid-latitudes [Froude, 2010]. As this area is located near

455 the transit zone of summertime storm tracks generated over Eurasia [Serreze and Barry, 1988], the

456 predictability of Arctic cyclones could be an important factor in the determination of the lead time

457 of surface wind speed and thus, of the SIT distribution in the ESS. The low prediction skill of the

458 meridional wind and ice speed suggested that the meridional component of sea ice advection

459 contributes substantially to the SIT distribution in the ESS. Since it was reported that additional

460 radiosonde observations over the Arctic Ocean have considerable impact on the prediction skill in

461 synoptic-scale fluctuations [Inoue et al., 2015; Yamazaki et al., 2015], additional radiosonde

462 observations acquired over the Arctic Ocean could lead to further extension of the lead time for

463 medium-range forecast skill of SIT distribution.

464   Based on sensitivity experiments using a simple melting and a persistency model, it was found

465 that the longer timescale prediction of SIT in early summer could be attributed to the

466 thermodynamic melting process. As the shortwave radiation flux is maximum in early summer

467 (June–July), the change of SIT due to the advection in relation to synoptic-scale atmospheric

468 fluctuations is likely to be smaller than the thermodynamic SIT reduction along the sea ice edge.

469 Although the recognition of the importance of the thermodynamic melting process on sea ice

470 prediction on seasonal timescales has been pointed out by earlier studies [Kimura et al. 2013;

471 Bushuk et al. 2017; Kashiwase et al. 2017], our study clarified that the influence has a substantial

472 role on the medium-range forecast of early summer SIT distribution. Thus, the influence of sea ice

473 advection on early summer sea ice prediction is limited to a lead time of 4–5 days, but is dominated

474 by the thermodynamic melting process in later stage of the lead times. In other words, the SIT

475 prediction skill in early summer is not necessarily worse at the longer timescale. It is noteworthy

476 that the dynamical process is not unimportant for the long-term prediction in the SIT distribution in

477 early summer, because the skillful prediction skill at a lead time of 3 days is important as the initial

478 conditions for the melting process dominated for a lead time longer than 4 days. Thus, it is

20

479 concluded that the atmospheric prediction skill for a lead time of up to 3 days contributes to the

480 short and medium-range prediction skill of the SIT distribution in early summer.

481   In view of the operational application of the TOPAZ4 sea ice data to the navigation in NSR,

482 this study found that during an ice-blocking event that affected two tankers in the ESS in July 2014,

483 significant SIT (~150 cm) was simulated over the ESS by TOPAZ4. Given that the SIT is found to

484 be underestimated by 20 cm in TOPAZ4, the true SIT is expected to be above 150 cm. Statistical

485 analysis suggested that vessel speed was significantly anticorrelated with the daily mean SIT

486 variations (−0.56) rather than the SIC (−0.41). This result demonstrated the reliability of the early

487 summer SIT distribution in the TOPAZ4 reanalysis data and its high potential for operational use in

488 support of maritime navigation of the NSR. However, this result was only based on a case study of

489 two ships in July 2014. To clarify the determinant factor on vessel speed, comprehensive statistical

490 analysis will be needed based on the speed data of different types of vessel.

491   Future projections for storm track activity (intensity and number) under the scenario of Arctic

492 climate change have been addressed by several researchers. For example, based on control

493 experiments using climate models, Bengtsson et al. [2006] found that summertime storm activity is

494 expected to increase. Orsolini and Sorteberg [2009] found that the number of storms, particularly

495 along the Eurasian Arctic coast, could increase in the future, because of the local enhancement of

496 the meridional temperature gradient between the Arctic Ocean and the warmed Eurasian continent.

497 Nishii et al. [2015] supported that their findings based on analyses using the CMIP3 and CMIP5

498 global climate model simulations, although they highlighted that the CMIP projections had

499 considerable uncertainty. Thus, further investigations of the formation and the development

500 mechanisms of summertime Arctic cyclones are needed for the improvement of the prediction skill

501 of atmospheric wind conditions, which are responsible for the forecast skill of early summer sea ice

502 distribution over 4 days.

503

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690   distribution model in generalized curvilinear coordinates. Mon. Wea. Rev. 131, 681–697.

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692 **Table 1.** List of observed and simulated sea ice thickness datasets

Data sources		Period	Spatial resolution	Time step
TOPAZ4	Reanalysis	2011–2014	12.5 km	Daily
	Forecast	2013–2016	12.5 km	Daily
CS2SMOS		2011–2014 (October to April)	~25 km	7 days
IMB	2011K	1 September 2011 to 14 May 2012	Point-wise	Hourly
	2012I	14 August 2012 to 21 December 2012		
	2012J	25 August 2012 to 3 August 2013		
	2014B	26 March to 29 July 2014		
PIOMAS		2011–2014	~0.8°	Daily

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694 **Table 2.** Pattern correlations of monthly mean climatologies of SIT in TOPAZ4 with those in
695 PIOMAS and CS2SMOS over the Arctic marginal seas (Laptev, East Siberian, and Chukchi Seas)

Month	Mar.	Apr.	May	Jun.	Jul.
PIOMAS	0.92	0.93	0.93	0.92	0.92
CS2SMOS	0.86	0.82	–	–	–

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697 **Table 3.** Monthly mean biases of TOPAZ4 SIT in the ESS relative to the CS2SMOS and PIOMAS
698 SIT data

SIT bias (cm)	Mar.	Apr.	May	Jun.	Jul.
CS2SMOS	−23	<1	-	-	-
PIOMAS	-65	-63	-56	-23	21

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Figure captions

Figure 1. Spatial distribution of climatological monthly mean of SIT (cm) in July during 2011–2014: (a) PIOMAS, (b) TOPAZ4 reanalysis, and (c) their difference (cm). The boundaries of the ESS and Arctic marginal seas are indicated in panel a by thick and thin lines, respectively. In panel a, the trajectories of IMB buoys for 2011K, 2012I, 2012J, and 2014B (see Table 1 for the details of each buoy data) are shown by black, red, blue and green dots, respectively.

Figure 2. Spatial distribution of climatological monthly mean of SIT (cm) in April during 2011–2014: (top) CS2SMOS, (middle) TOPAZ4 reanalysis, and (bottom) their difference (cm).

Figure 3. Time series of daily mean SIT (cm) averaged over the ESS (rectangular region denoted by black line in Fig. 1 (a)) derived from CS2SMOS (black), TOPAZ4 reanalysis (red), and PIOMAS (blue) from January 2011 to August 2014. For CS2SMOS data, 7 day mean values are shown. The standard deviations of area-averaged data are shown by vertical lines, respectively. The ice types (2: first-year ice, 3: multi-year ice) used for the choice of satellite SIT retrievals in CS2SMOS are shown by green bar. The scale for the ice type is located on the right vertical axis.

Figure 4. The comparisons of the daily mean SITs derived from IMB buoy data with the corresponding SIT in TOPAZ4 reanalysis data from 2011 to 2014 in and around the ESS. The SIT data are re-sampled per 7 days. The regression lines onto IMB buoy data and the reference unit line are shown by solid and dashed lines, respectively.

Figure 5. Spatial distribution of (a) monthly mean (colors) climatological SIT (m) in the TOPAZ4 reanalysis and (b) the RMS variability of daily mean SIT (colors) in July during 2011–2014. The monthly mean of climatological SIC (white contours) in July is indicated in panel (a). The rectangular region enclosing the ESS (70°–80°N, 150°–180°E) is shown in panel (b). (c) Time series of monthly mean SIT (grey shade) and RMS of TOPAZ4 reanalysis (black line) averaged over the ESS. The scale of the RMS is indicated on the right axis.

Figure 6. The prediction skill (PCC) of SIT forecast in the ESS (70°–80°N, 150°–180°E) in each

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725   month obtained from (a) operational forecast model and (b) persistency of the initial value,

726   averaged from 2014–2016. The standard deviations of the PCCs are shown with white contours. In

727   panel c, the fraction of variance explained by operational forecast relative to the persistency (%) is

728   shown by contour (the region where the fraction is larger than 10% is shaded).

729   **Figure 7.** PCCs between forecast and analysis (a) SIT, (b) zonal and meridional ice speed, and (c)

730   zonal and meridional surface wind speed from operational TOPAZ4 data in early summer

731   (June–July) averaged on 2014–2016. Error bar indicates the standard deviation of the PCCs.

732   **Figure 8.** Temporal evolution of SIT (cm; colors) and ice velocity (m s^{-1}; vectors) distribution for

733   (left) analysis, (center) forecast, and (right) the difference between forecast and analysis at

734   increasing lead times from +0 day to +6 days initialized on 2nd July 2015. The corresponding PCCs

735   for the SIT (black), zonal (red) and meridional ice speeds (blue) in the ESS (right-lower panel of the

736   time evolution) are shown in the lower panel. The scale for the PCCs of the zonal and meridional

737   ice speeds is indicated on the right axis.

738   **Figure 9.** (a) Relationship between 10m wind speed (m s^{-1}) in the ERA Interim reanalysis data and

739   sea ice speed (m s^{-1}) in the TOPAZ4 reanalysis averaged over a part of the ESS (72°–76° N,

740   150°–170° E) during 1–31 July 2011–2014. Broken and solid lines indicate the regression line of

741   ice speed on 10m wind speed ($y = 0.0224x - 0.0112$) and the theoretical ice speed estimated based

742   on classical free-drift theory, respectively. (b) Angle (degrees) of sea ice velocity relative to surface

743   wind vectors averaged over the ESS. Positive values indicate sea ice drift is to the right of the wind

744   direction. Solid curve indicates the wind–ice velocity angle estimated based on classical free-drift

745   theory.

746   **Figure 10.** The PCCs between forecast and analysis SIT from the full physics model (black),

747   persistency (red), and a simple melting model (blue) in early summer (June–July) averaged from

748   2014–2016. Error bar indicates the standard deviation of the PCCs.
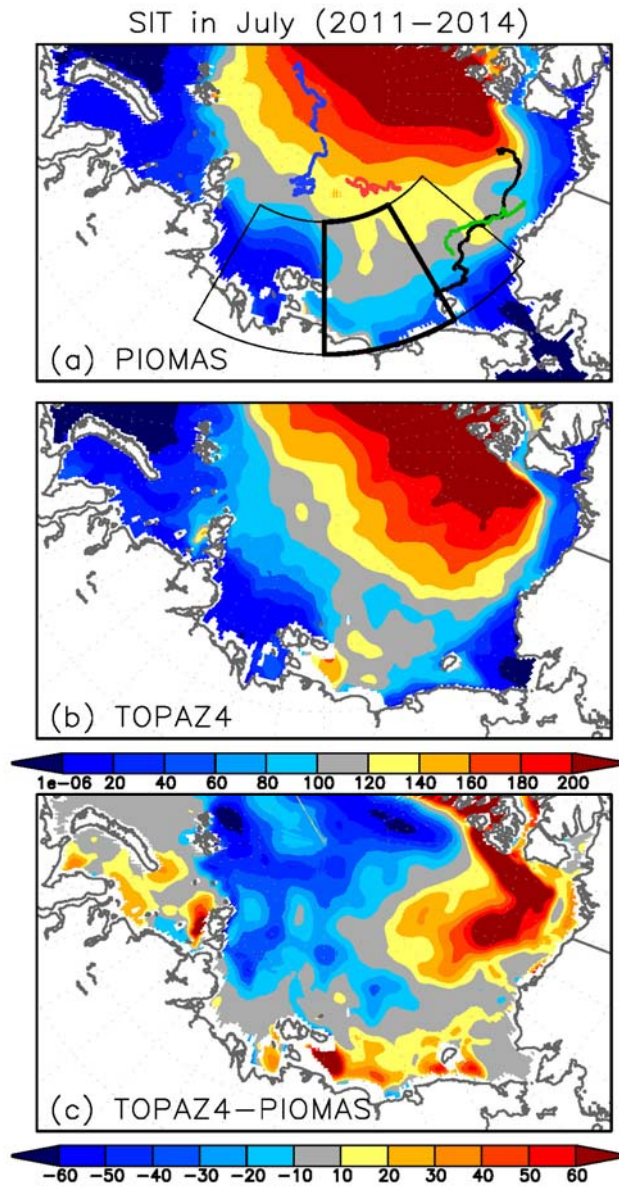
749   **Figure 11.** Temporal evolution of SIT differences (cm; colors) between the forecast and analysis

750 data at lead times increasing from +2 to +8 days, initialized on 2nd July 2015. In each panel, the sea

751 ice edge of the analysis, defined by 30% SIC, is shown. Corresponding PCCs for the full physics

752 model (black), a simple melting model (red) and persistency (blue) in the ESS (right-lower panel of

753 the time evolution) are shown in the lower panel.

754 **Figure 12.** Trajectory of the two tankers over the ESS based on AIS data. The routes cross the ESS

755 from the Laptev Sea on 4 July 2014 to the port of Yamal on 31 July 2014, via the port of Pevek on

756 20 July 2014. The forward route is highlighted by green circles. The SIT (cm; colors) and SIC (%;

757 contours) averaged over the period of the forward route are shown**.**

758 **Figure 13.** Scatter plots of hourly vessel speeds (knots) and (a) daily mean SIT (cm) and (b) SIC

759 (%) in TOPAZ4 reanalysis from 4–30 July 2014. In each panel, the regression line of vessel speed

760 onto each variable is shown by broken line.

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SIT in July (2011–2014)

(a) PIOMAS

(b) TOPAZ4

1e-06 20 40 60 80 100 120 140 160 180 200

(c) TOPAZ4−PIOMAS

−60 −50 −40 −30 −20 −10 10 20 30 40 50 60

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Figure 1. Spatial distribution of climatological monthly mean of SIT (cm) in July during 2011–
2014: (a) PIOMAS, (b) TOPAZ4 reanalysis, and (c) their difference (cm). The boundaries of the
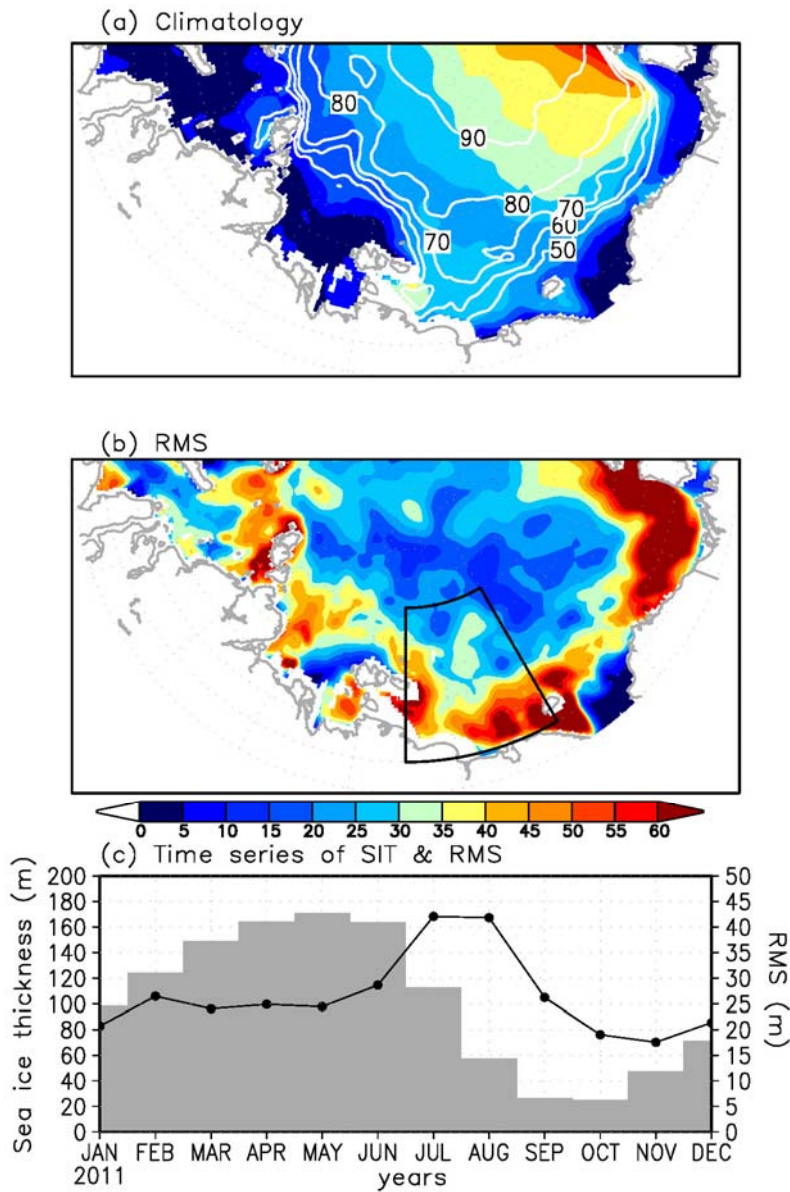ESS and Arctic marginal seas are indicated in panel a by thick and thin lines, respectively. In panel
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SIT in April (2011−2014)

(a) CS2SMOS

(b) TOPAZ4

1e−06 20 40 60 80 100 120 140 160 180 200

(c) TOPAZ4−CS2SMOS

−60 −50 −40 −30 −20 −10 10 20 30 40 50 60

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Figure 2. Spatial distribution of climatological monthly mean of SIT (cm) in April during 2011–

2014: (top) CS2SMOS, (middle) TOPAZ4 reanalysis, and (bottom) their difference (cm).

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Figure 3. Time series of daily mean SIT (cm) averaged over the ESS (rectangular region denoted

by black line in Fig. 1 (a)) derived from CS2SMOS (black), TOPAZ4 reanalysis (red), and

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Monthly means of PC in HI (ESS) from 2014 to 2016

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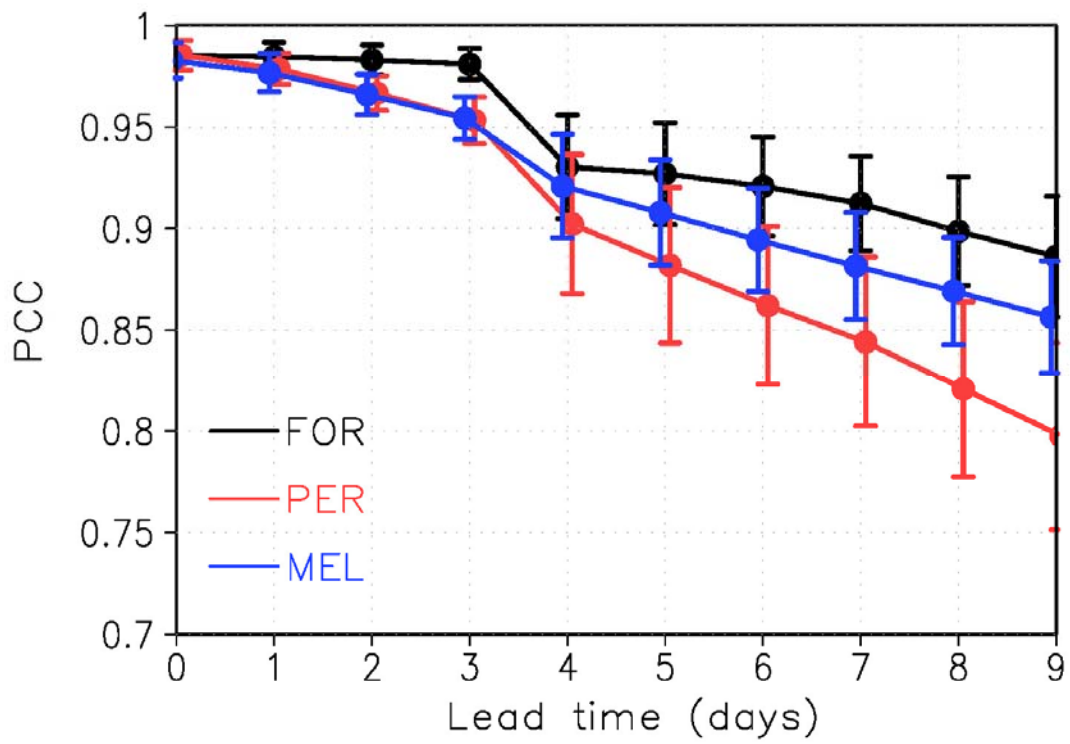
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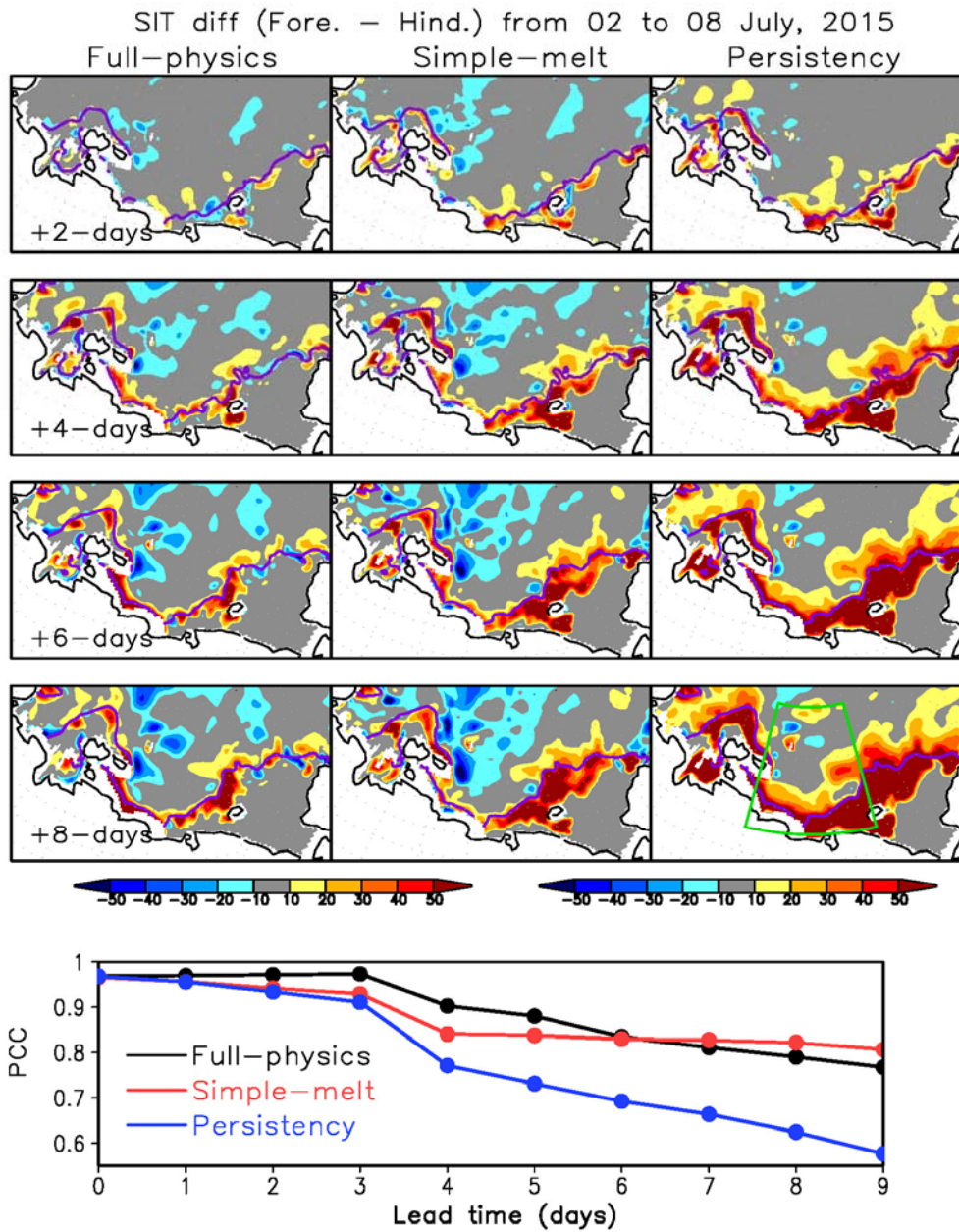
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Figure 10. The PCCs between forecast and analysis SIT from the full physics model (black),

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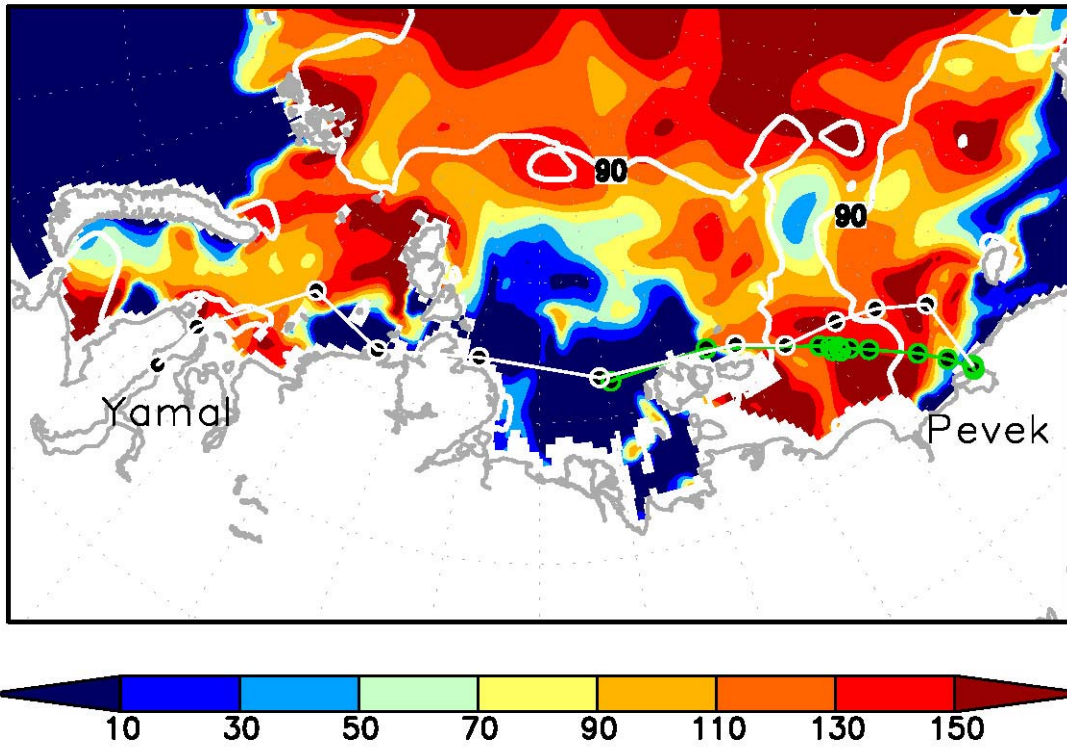2014–2016. Error bar indicates the standard deviation of the PCCs.

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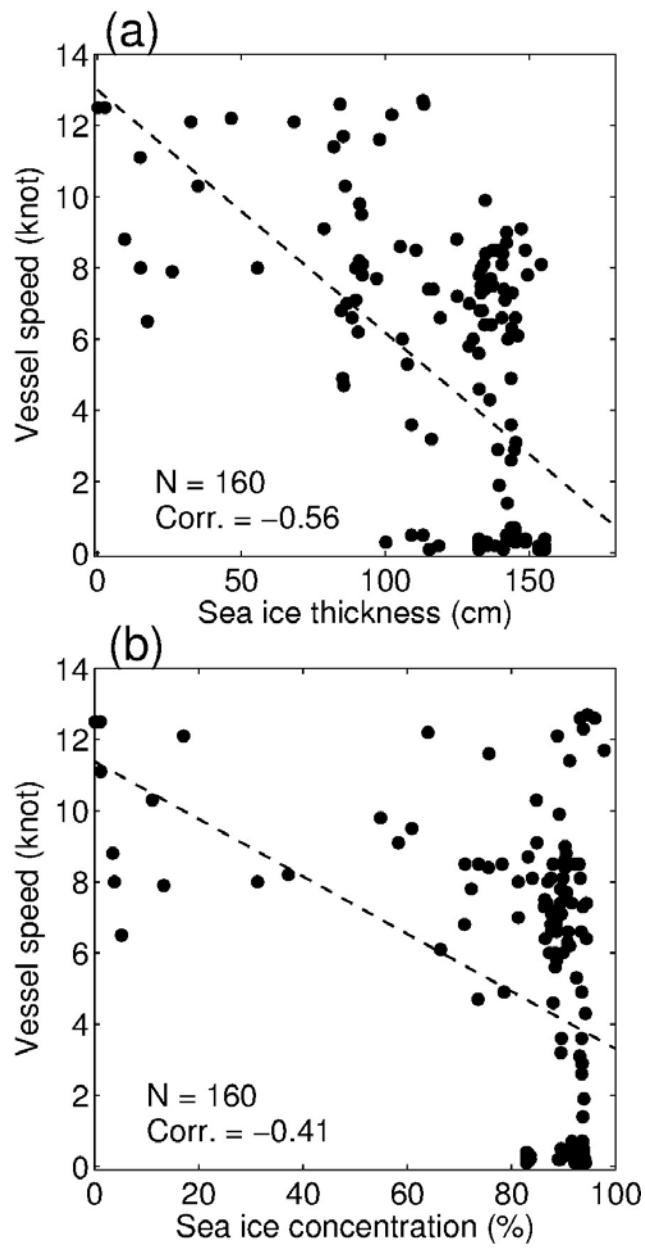
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