1   **Assessment of Arctic and Antarctic Sea Ice Predictability in CMIP5 Decadal Hindcasts**

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3   Chao-Yuan Yang[1], Jiping Liu[1], Yongyun Hu[2], Radley M. Horton[3], Liqi Chen[4], Xiao Cheng[5]

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5   [1]Department of Atmospheric and Environmental Sciences, University at Albany, State University

6   of New York, Albany, NY, USA

7   [2]Department of Atmospheric and Oceanic Sciences, School of Physics, Peking University,

8   Beijing, China

9   [3]Columbia University Center for Climate Systems Research and NASA Goddard Institute for

10   Space Studies, New York, NY, USA

11   [4]Key Laboratory of Global Change and Marine-Atmospheric Chemistry, Third Institute of

12   Oceanography, SOA, Xiamen, China

13   [5]College of Global Change and Earth System Science, Beijing Normal University, Beijing, China

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18   Corresponding author:

19   Chao-Yuan Yang

20   Department of Atmospheric and Environmental Sciences

21   University at Albany, State University of New York

22   Albany, NY, 12222 USA

23   Email: cyang4@albany.edu

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24   **Abstract**

25   This paper examines the ability of coupled global climate models to predict decadal

26   variability of Arctic and Antarctic sea ice. We analyze decadal hindcasts/predictions of 11

27   CMIP5 models. Decadal hindcasts exhibit a large multi-model spread in the simulated sea ice

28   extent, with some models deviating significantly from the observations. For the models having

29   large biases and using full-field initialization, the predicted sea ice extent quickly drifts away

30   from the initial constraint, deteriorating the decadal predictive skill. The anomaly correlation

31   analysis between the decadal hindcast and observed sea ice suggests that in the Arctic, for most

32   models, the areas showing significant predictive skill become broader associated with increasing

33   lead times. This area expansion is largely because nearly all the models are capable of predicting

34   the observed decreasing Arctic sea ice cover. Sea ice extent in the north Pacific has better

35   predictive skill than that in the north Atlantic (particularly at a lead-time of 3-7 years), but there

36   is a re-emerging predictive skill in the north Atlantic at a lead-time of 6-8 years. In contrast to

37   the Arctic, Antarctic sea ice decadal hindcasts do not show broad predictive skill at any time

38   scales, and there is no obvious improvement linking the areal extent of significant predictive skill

39   to lead-time increase. This might be because nearly all the models predict a retreating Antarctic

40   sea ice cover, opposite to the observations. For the Arctic, the predictive skill of the MMEE

41   outperforms most models and the persistence prediction at longer time scales, which is not the

42   case for the Antarctic.

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1. Introduction

Decadal climate prediction is a new and rapidly evolving research area driven by societal demand for climate information to inform climate adaptation strategies (e.g., Meehl et al., 2009, 2013; Vera et al., 2010). As a boundary between the ocean and atmosphere, sea ice plays an important role in the climate system and acts as an important indicator of climate change through dynamic and thermodynamic processes and various feedbacks (i.e., albedo, insulation and buoyancy). Thus, sea ice simulation and prediction is one of the most challenging and important issues in decadal climate prediction, i.e., Meehl et al. (2009) emphasized the importance of sea ice treatment in climate models as large uncertainties remain for decadal climate prediction.

In the past few decades, Arctic sea ice has been declining (e.g., Serreze et al., 2007; Arctic Report Card, 2015). Trends in Arctic sea ice extent are negative for all months (e.g., Comiso, 2008, 2012; Cavalieri and Parkinson, 2012) largely due to thinning and loss of the perennial sea ice cover (Kwok et al., 2009), but are largest at the end of the summer melt season. September Arctic sea ice extent has declined by 0.87×10^6 km^2 for the period 1979-2014, with a pronounced decreasing trend of sea ice concentrations in the arc extending from the Beaufort Sea to the Barents Sea (> 95% significance, Fig. 1a). The possibility of an ice-free Arctic in the coming decades (Stroeve et al., 2007, 2012; Boé et al., 2009; Wang and Overland, 2009, 2012; Zhang, 2010; Massonnet et al., 2012; Liu et al., 2013) would have profound impacts on Arctic maritime activities (e.g., opening of shorter shipping routes) and ecosystems (e.g., changing solar radiation in the upper ocean and influencing primary productivity), and extreme weather and climate in mid- and high-latitudes (e.g., Liu et al., 2012; Francis and Vavrus, 2012; Smith and Stephenson, 2013; WWRP/PPP, 2013; Stroeve et al., 2014).

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66   By contrast, Antarctic sea ice has been expanding (e.g., Liu et al., 2004; Turner et al., 2009;

67   Comiso et al., 2011; Parkinson and Cavalieri, 2012). Trends in Antarctic sea ice extent are

68   positive for all months. Unlike the almost uniform Arctic sea ice decreases, the trends in

69   Antarctic sea ice concentrations show strong regional variations, although the NASA's Ice,

70   Cloud, and land Elevation Satellite showed that Antarctic sea ice thickness has a small negative

71   trend during 2003-2008 (Kurtz and Markus, 2012). September Antarctic sea ice extent has

72   increased by 0.24×10^6 km^2 per decade during 1979-2014, with a pronounced positive trend of

73   sea ice concentrations in the Ross Sea partially offset by a negative trend in the Bellingshausen

74   and Weddell Seas (Fig. 1b). The limited understanding of some of the mechanisms responsible

75   for the observed decrease (increase) in Arctic (Antarctic) sea ice makes sea ice prediction

76   challenging (e.g., Kattsov et al., 2010; Richter-Menge et al., 2012; Bindoff et al., 2013; Goosse

77   et al., 2015).

78   Most sea ice predictability studies have focused on the Arctic and the

79   seasonal-to-interannual time scale. An outlook of September Arctic sea ice extent has been

80   solicited from research community since 2008. Stroeve et al. (2014) showed that the median July

81   (the same was true for June and August) prediction value for September sea ice cover was off by

82   a large margin in 2009, 2012 (record low), and 2013. Koenigk and Mikolajewicz (2009)

83   suggested sea ice cover has low predictability in the central Arctic but some predictability at sea

84   ice edge zones in the MPI ECHAM5-OM climate model. Holland et al. (2011) showed potential

85   predictability of sea ice cover with a few months lead-time in the NCAR Community Climate

86   System Model version 3 (CCSM3). They also suggested that the persistence of sea ice thickness

87   anomalies is much higher than that of sea ice extent anomalies, which might point to a pathway

88   towards greater predictability as models improve their simulation of sea ice thickness.

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89   Predictability of sea ice cover with e-folding time scales of 2-5 months has been identified in

90   several climate models (Day et al., 2014a). A few modeling studies also showed continuous

91   predictability of sea ice cover for 1-2 years, and intermittent predictability for 2-4 years

92   (Blanchard-Wrigglesworth et al., 2011b; Day et al., 2015; Tietsche et al., 2013, 2014; Guemas et

93   al., 2014). In contrast to the Arctic, there are limited efforts on examining predictability of

94   Antarctic sea ice. Using the NCAR CCSM3 model, Holland et al. (2013) showed initial-value

95   predictability of sea ice for a few months in the edge around Antarctica.

96   To date, relatively little attention has been paid to assessing prediction skill of sea ice at

97   decadal timescales for the Arctic and Antarctic in current-day climate models. Decadal sea ice

98   prediction entails a combination of initial value and climate forcing issues. At decadal timescales,

99   internal climate variability affects sea ice (i.e., some aspects of climate internal variability may

100   be predictable, Collins and Allen, 2002; Smith et al., 2007; Keenlyside et al., 2008; Meehl et al.,

101   2009; Pohlmann et al., 2009; Mochizuki et al., 2012), as does prescribed external scenarios (e.g.,

102   greenhouse gases and other radiatively important agents). Blanchard-Wriggleworth et al. (2011b)

103   suggested that predictability of Arctic sea ice beyond 3 years is largely influenced by climate

104   forcing rather than initial values. The growing dominance of climate forcings is likely to

105   introduce some potential predictability since it accounts for increasingly large portions of sea ice

106   change from present conditions (e.g., National Research Council, 2012). Guemas et al. (2014)

107   also underlined that predicting future change of Arctic sea ice on decadal timescales is

108   challenging due to initialization problems (i.e., the initial shocks due to sparse observations,

109   limitations of reanalysis data, and ensemble generation methods).

110   The recent Coupled Model Intercomparison Project Phase 5 (CMIP5) has implemented an

111   experiment to simulate and predict decadal climate variability (Meehl et al., 2009; Taylor et al.,

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112   2012) in support of the Intergovernmental Panel in Climate Change Fifth Assessment Report.

113   The validation of decadal hindcasts is an important step for improving decadal predictions, since

114   it can elucidate issues in initialization methods and model responses to natural variability and

115   climate forcings. In this study, we examine the capability of CMIP5 decadal hindcasts to

116   simulate the mean and decadal variability of Arctic and Antarctic sea ice extent.

117   **2. Models and data**

118   Eleven CMIP5 models are used to evaluate the decadal hindcast/prediction of sea ice in both

119   the Arctic and Antarctic. These eleven models provide a set of 10-year long hindcast simulations,

120   which was initialized every five-years from 1981 to 2006. The purpose of initialization is to start

121   coupled global climate models close to the most realistic possible sea ice state. In general, the

122   initialization for the CMIP5 decadal hindcast/prediction can be divided into two approaches, full

123   initialization and anomaly initialization. For the full initialization approach, the initial model

124   state is replaced by the best available estimate of the observed sea ice state (i.e., satellite

125   observation and ocean analysis). This efficiently reduces the initial error due to the systematic

126   bias in the presence of model deficiencies. However, as the model is integrated for the decadal

127   hindcast/prediction, the simulation tends to drift away from the best-estimated sea ice state no

128   matter how small the initial error is. The anomaly initialization approach partly addresses this

129   problem by assimilating observed sea ice anomalies on the modeled sea ice state with focus on

130   predicting future sea ice anomalies.

131   Table 1 provides a summary of the initialization approaches and data source of the initial sea

132   ice state for each individual model. More detailed information about the set-up of the decadal

133   experiment can be found in Meehl et al. (2009) and Taylor et al. (2012). For each individual

134   model, all ensemble members of the 10-year long hindcast/prediction that are archived at

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135   http://cmip-pcmdi.llnl.gov/cmip5/data_portal.html are used (see Table 1 for more information).

136   Each ensemble member was generated by slightly different initial conditions. Here we focus on

137   September Arctic (seasonal minimum) and Antarctic (seasonal maximum) sea ice. The reasons

138   that we focus on September Antarctic sea ice, rather than the month of seasonal minimum like

139   the Arctic are 1) sea ice in the Antarctic largely melts away (confined to the coastal Antarctica)

140   during the seasonal minimum (i.e. February or March), and 2) September sea ice extent has a

141   significant increasing trend.

142   Satellite-derived sea ice extent and concentration in the Arctic and Antarctic are used to

143   evaluate the CMIP5 decadal hindcast. They are obtained from the National Snow and Ice Data

144   Center, which are derived from the Nimbus-7 Scanning Mutichannel Microwave Radiometer

145   (SSMR), and DMSP Special Sensor Microwave/Imager (SSM/I), and Special Sensor Microwave

146   Imager and Sounder (SSMIS) sensors (Comiso 2000; Fetterer et al., 2002, 2010). Because the

147   observation and models have different horizontal resolution (see details in Table 1), before

148   performing the assessment we interpolate all the data (satellite observation and model

149   simulations) to horizontal resolution of 1 degree. The multi-model ensemble mean (MMEE) is

150   calculated based on the equally weighted average of 69 total ensemble members (Table 1).

151   **3. Prediction skill of CMIP5 decadal hindcasts**

152   **3.1 Arctic sea ice**

153   We evaluate the model simulation and prediction skill by comparing sea ice extent between

154   each individual model and satellite observations. Figure 2 shows the time series of September

155   Arctic sea ice extent from the simulation of the 10-year hindcast for each model and observation

156   from 1981 to 2015. It is immediately apparent that the models exhibit very different magnitudes

157   of September sea ice extent. CanCM4, CFSv2, GEOS-5 and GFDL-CM2.1 simulate a smaller

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158   ice extent compared to the observation during the entire period; CFSv2 has the least sea ice cover

159   of any of the models. By contrast, BCC-CSM1.1, CCSM4, FGOALS-g2 and MIROC5 simulate

160   a larger ice extent. The simulated ice extent of HadCM3, IPSL-CM5A-LR and MPI-ESM-MR

161   are comparable to the observations, but they cannot reproduce the anomalously low sea ice cover

162   since 2007 (i.e., record lows in 2007 and 2012). We note that the models that are initialized with

163   values close to various estimates of sea ice state (direct and indirect full-field initialization, see

164   Table 1), drift towards their modeled sea ice state within a few year integrations, particularly

165   BCC-CSM1.1, CanCM4, CCSM4, CFSv2 and FGOALS-g2. Hence improved initializations do

166   not necessarily mitigate drift, although they significantly reduce the model bias at the initial step.

167   By contrast, the models that are initialized with various estimates of sea ice anomaly (direct and

168   indirect anomaly initialization) tend to have smaller drift problems during the integration.

169   To quantify the skill of each individual model and MMEE in predicting the evolution of sea

170   ice, we calculate the anomaly correlation coefficient (ACC) between the predicted and observed

171   September sea ice concentration anomaly in each grid box as follows.

$$ACC = \frac{\sum_{i=1}^{n}[P(i,t) - \overline{P}(t)] \cdot [O(i,t) - \overline{O}(t)]}{\sqrt{\sum_{i=1}^{n}[P(i,t) - \overline{P}(t)]^2 \cdot \sum_{i=1}^{n}[O(i,t) - \overline{O}(t)]^2}}$$

172   where P is the predicted sea ice concentration and $\overline{P}(t)$ is calculated as $\overline{P}(t) = \sum_{i=1}^{n} P(i,t)$; O is

173   the observed sea ice concentration and $\overline{O}(t)$ is calculated as $\overline{O}(t) = \sum_{i=1}^{n} O(i,t)$. i is the start

174   year and t is the lead year. Here the ACCs of the ensemble mean of each individual model and

175   MMEE for lead-times of 1, 3-5 and 6-8 years are discussed. For example, for the lead-time of

176   3-5 years, the data for the 1981 initialization is the average value of 1983-1985, the data for the

177   1986 initialization is the average value of 1988-1990, and so on. This means the adjacent data

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178   points in the time-series have a time interval of 5-years, and this time-series is compared to the

179   average of the same three years in the observations.

180   For the lead-time of 1-year, for some models only scattered predictive skill (> 95%

181   significance) in forecasting September sea ice concentration anomalies are found, generally in

182   the arc around the periphery of the Arctic Basin extending from north of Alaska to northeast of

183   Siberia (top panel of Fig. 3). The MMEE shows small clustered areas of significant ACCs

184   between the Beaufort and eastern Siberian Seas, whereas areas near the central Arctic Ocean has

185   the least predictive skill (negative ACCs, Fig. 3l in the top panel). In general, the areas of

186   significant ACCs in CCSM4, MIROC5 and MPI-ESM-MR are similar to that of the MMEE.

187   For the lead-time of 3-5 years, the areas of significant predictive skill become broader for

188   the majority of the models compared to those of 1-year, covering large parts of the northern

189   Beaufort, Chukchi, eastern Siberian and Laptev Seas (bottom panel of Fig. 3). The exceptions are

190   CFSv2 and GEOS-5. CFSv2 has too little sea ice cover in the Arctic Ocean due to the

191   aforementioned drift problem. The ACCs of GEOS-5 for the lead-time of 3-5 year are even

192   smaller than those of 1-year for the area of ACCs exceeding the 95% confidence level. The

193   MMEE shows large clustered areas of significant ACCs in the arc around the Arctic Basin

194   extending from north of Alaska to north of Siberia (Fig. 3l in the bottom panel). Again, the

195   central Arctic Ocean towards the Canadian Archipelago and northern Greenland Sea shows the

196   least predictive skill.

197   The results for the lead-time of 6-8 years are broadly similar to those of the lead-time of 3-5

198   years, although the areas of significant predictive skill are relatively broader for the majority of

199   the models (not shown). The MMEE also shows enlarged areas of significant ACCs relative to

200 those of 3-5 year, i.e., along the eastern coast of the Greenland (not shown). Overall, the MMEE

201 has better prediction skill relative to individual models for all lead times, although the MMEE

202 does not universally outperform every single constituent models.

203 Figure 4 shows the predicted trend (slope of a linear regression) as a function of lead times

204 after applying a 3-year average to filter out high frequency variability. For each individual model,

205 the trend is calculated based on its ensemble mean (see No. of ensemble members in Table 1).

206 All the models reproduce the observed negative trend, except that BCC-CSM1.1 has positive

207 trend at the lead-time of 1-3 and 2-4 years. However, the simulated negative trends show very

208 different magnitude, ranging from about -0.2 to -0.9×10^6 km^2 per decade. Compared to the

209 observation, there is a systematic underestimation of the decreasing trend throughout the

210 integration period for all decadal hindcasts. This is particularly true for the lead-time of 6-8 and

211 7-9 years (i.e., about -0.6×10^6 km^2 per decade for the MMEE vs. -1.2×10^6 km^2 per decade for the

212 observation), because those longer lead times are weighted towards inclusion of more recent

213 years in the observations with accelerated decline of Arctic sea ice.

214 To figure out to what extent the identified areas with significant ACCs at different lead times

215 are caused by the decadal decreasing trend, we remove the linear trend in the predicted and

216 observed sea ice concentration in each grid box. As shown in Fig. 5, after the trend is removed,

217 the areas with significant ACCs become much smaller relative to those of Fig. 3, especially for

218 the lead-time of 3-5 and 6-8 years. This suggests that high predictability found in Fig. 3 at longer

219 time scales is largely due to the decreasing Arctic sea ice in recent decades. Thus the relatively

220 long prediction skill over the areas of the northern Beaufort, Chukchi, eastern Siberian and

221 Laptev Seas is influenced by long-term sea ice reduction.

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222   To further examine the prediction skill of Arctic sea ice variability in the context of regional

223   climate variability, we generate three sea ice extent indices: 1) the entire Arctic, 2) the north

224   Pacific, and 3) the north Atlantic. Sea ice variability in the north Pacific and north Atlantic is

225   modulated by different dominant decadal oscillations. Previous studies suggested that sea ice in

226   the Bering and Beaufort Seas is correlated with the Pacific Decadal Oscillation (PDO), which

227   has undergone a transition from a dominantly positive phase to a more negative phase in recent

228   decades (Lindsay and Zhang 2005; Zhang et al., 2010; Wendler et al., 2014). Sea ice in the north

229   Atlantic, particularly the ice export through Fram Strait and import from the Barents Sea, is

230   significantly affected by the phases of the North Atlantic Oscillation (e.g., Kwok, 2000; Rigor

231   and Wallace, 2004). Enfield et al. (2001) linked North Atlantic sea ice variability to the Atlantic

232   Multidecadal Oscillation (AMO) using the time frequency analysis of historical and paleo

233   records. Day et al. (2012) suggested that up to 30% of the north Atlantic sea ice decline during

234   1979-2010 might be attributed to the natural cycle of the AMO by analyzing five CMIP3 models.

235   Here we define the north Pacific sea ice index as the total September sea ice extent in the

236   Chukchi, East Siberian, and Laptev Seas (120°E-150°W and 62.5°N-80°N). The north Atlantic

237   sea ice index is defined as the total September sea ice extent in the Greenland, Norwegian, and

238   Barents Seas (40°W-80°E and 60°N-84°N, see boxes in Fig. 1). A 3-year average is also applied

239   to these indices.

240   The predictive skill for these indices is also measured by the anomaly correlation coefficient

241   between the model hindcast and observation. Figure 6 shows the ACC as a function of lead times

242   for the ensemble mean of each individual model and MMEE. To provide additional perspective

243   on the relative skill of the decadal experiments, the anomaly correlation coefficient of the

244   persistence prediction is also shown. Persistence prediction is the simplest way to produce a

245   forecast, which assumes sea ice state at the time of the forecast will not change. The horizontal

246   lines in Fig. 6 represent different confidence level. For the entire Arctic (Fig. 6a), the anomaly

247   correlation coefficient of most models exhibits certain predictive skill (> 95% significance),

248   except BCC-CSM1.1 for the lead-time of 1-3 and 2-4 years. Four models (CCSM4, FGOALS-g2,

249   GFDL-CM2.1 and MIROC5) show comparable or better predictive skill relative to the

250   persistence prediction for all the analyzed lead-times. The MMEE has more skillful results than

251   most of the individual model predictions during the entire period. The north Pacific sea ice index

252   has lower prediction skill and larger inter-model spread compared to those of the entire Arctic

253   index (Fig. 6c). In the north Pacific, only two models (GFDL-CM2.1 and MIROC5) show

254   comparable skill to the persistence prediction for the lead-time of 1-3 and 2-4 years. After 3-5

255   years, six models (CanCM4, CCSM4, FGOALS-g2, GFDL-CM2.1, MIROC5 and

256   MPI-ESM-MR) have better skill than the persistence prediction, which is also the case for the

257   MMEE. In general, the predictive skill of the north Atlantic sea ice index is poor compared to

258   both the entire Arctic and north Pacific indices, particularly for the lead-time from 3-5 to 5-7

259   years (insignificant ACCs). However, we note that in the north Atlantic sector all the models

260   show better predictive skill than the persistence prediction for the first three lead-times.

261   Additionally, all the models, except CanCM4, appear to have a re-emerging predictive skill for

262   the north Atlantic sea ice after 6-8 years (Fig. 6e). Overall, the MMEE has more skillful results

263   than that of the persistence prediction.

264   After removing the linear trend (Fig. 6b, d, f), the predictive skill of the above indices

265   decreases dramatically with very large inter-model spread. The MMEE only shows more skillful

266   results than the persistence prediction between 3-5 and 5-7 years for the north Pacific index.

267   **3.2 Antarctic sea ice**

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268   Here we apply the same analysis in section 3.1 for Antarctic sea ice. Figure 7 shows time

269   series of September sea ice extent from the 10-year hindcast for each individual model and the

270   observations during 1981-2015. FGOALS-g2, GEOS-5, and MIROC5 produce significantly less

271   sea ice compared to the observation for the entire period with GEOS-5 having the smallest sea

272   ice extent of all the models. BCC-CSM1.1, CanCM4, and HadCM3 produce more sea ice

273   relative to the observations. The sea ice extent simulated by CCSM4, CFSv2, GFDL-CM2.1,

274   IPSL-CM5A-LR and MPI-ESM-MR is comparable to the observations, but they cannot

275   reproduce the gradual increase of Antarctic sea ice in recent years (e.g., Comiso et al., 2011). As

276   in the Arctic, the models that use direct and indirect full-field initialization tend to drift towards

277   their modeled sea ice state within a few years of initialization.

278   Figure 8 shows the anomaly correlation coefficient of each individual model and MMEE for

279   the lead-time of 1 and 3-5 years. For the 1-year lead-time, small scattered areas with predictive

280   skill greater than 95% confidence level in the Southern Ocean are found in most models. The

281   location of these scattered areas differs by model, although the MMEE shows small clustered

282   areas of significant ACCs in the central Weddell Sea (top panel of Fig. 8l). There is no

283   improvement for the predictive skill for most models and the MMEE as the lead-time increases

284   to 3-5 years (bottom panel of Fig. 8) and 6-8 years (not shown). Overall, the predictive skill of

285   the MMEE does not outperform most models for all the lead-times.

286   The observed and predicted trends for different lead times are shown in Fig. 9. The observed

287   trends are positive for all the lead-times, and increase to ~0.35×10^6 km^2 per decade as recent

288   years are considered. By contrast, most models show negative trends, i.e., BCC-CSM1.1 has

289   negative trends ranging from -0.6×10^6 km^2 to -1×10^6 km^2 per decade. CCSM4 and FGOALS-g2

290   have increasing trends before 3-5 year and 5-7 year leads, respectively, but decreasing trends

291   thereafter. CFSv2 shows increasing trends after 2-4 year leads. However, these three

292   positive-trending models cannot simulate the magnitude of observed positive trends.

293   Again, we remove linear trends in both the model hindcast and observation, and then

294   calculate the ACC. After the linear trend is removed, the areas having significant predictive skill

295   become broader for the majority of the models compared to those of the raw data (Fig. 10 vs. Fig.

296   8), particularly for the lead-time of 3-5 and 6-8 years. Moreover, most models and the MMEE

297   have good predictive skill in the Ross Sea. As indicated by the MMEE, much of Antarctica's

298   coast has poor predictive skill (negative ACCs, Fig. 8l).

299   Here we generate three regional sea ice extent indices: 1) the entire Antarctic, 2) the

300   central-eastern south Pacific and 3) the south Atlantic. We define the central-eastern south

301   Pacific index as the total September sea ice extent in the eastern Ross, Bellingshausen and

302   Amundsen Seas (165°W-75°W and 50°S-80°S) and the south Atlantic index as the total

303   September sea ice extent in the Weddell Sea (60°W-0° and 50°S-75°S, see boxes in Fig. 1).

304   Figure 11 shows the anomaly correlation coefficient as a function of lead times for the

305   ensemble mean of each individual model, the MMEE and the persistence prediction. For the

306   entire Antarctic, none of models can predict the observed sea ice variability (i.e., their

307   simulations are negatively correlated with the observations), except for CCSM4 and

308   GFDL-CM2.1, which show significant prediction skill (> 95% significance) at the lead-time of

309   1-3 years (Fig. 11a). Moreover, the persistence prediction is superior to the prediction of each

310   individual model and the MMEE. For the central-eastern south Pacific index, almost all the

311   models show poor predictive skill for almost all the lead-times, although CFSv2, GFLD-CM2.1

312   and HadCM3 exhibit significant skill at 1-3, 2-4 and 4-6 years, respectively. Unlike the entire

313   Antarctic, the MMEE of the central-eastern south Pacific shows better skill than that of the

314   persistence prediction, although neither is statistically significant (Fig. 11c). For the south

315   Atlantic index (Fig. 11e), almost all the models also do not have predictive skill (the ACCs are

316   not statistically significant), although CCSM4 has significant skill at the lead-time of 5-7 years.

317   However, the MMEE shows surprisingly significant skill, much better than the persistence

318   prediction, at 6-8 years (> 95% significance).

319   After removing linear trends in Fig. 11a, c, e, we note that there is no obvious improvement

320   in predictive skill for the entire Antarctic and the central-eastern south Pacific indice, but the

321   inter-model spread is increased (Fig. 11b, d). It is also noted that for the south Atlantic index, the

322   MMEE shows significant skill after 4-6 years (Fig. 11f).

323   **4. Discussion and conclusion**

324   This assessment provides a snapshot of the interannual to decadal predictability of sea ice in

325   the Arctic and Antarctic for the current-day coupled global climate models as part of the CMIP5

326   decadal prediction experiment.

327   Our evaluation shows that for many models, there are substantial discrepancies between the

328   decadal hindcast and observed September sea ice extent. For instance, in the Arctic, as

329   mentioned previously, CFSv2 dramatically underestimates September sea ice cover, leading to

330   pronounced drift in the first three years of the decadal hindcast. In contrast, CFSv2 simulates a

331   larger March sea ice extent ($2\text{-}3\times10^6$ km^2 more than the observation, not shown). Hence there is

332   an excessive melt of sea ice through the melting season which is due to not only the

333   underestimate of observed September sea ice cover, but also the overestimate of observed March

334   sea ice cover (March minus September). Such large errors have the potential to propagate

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335 through other components of the climate system. This excessive melt greatly increases

336 freshwater in the Arctic Ocean and export of fresh water through Fram Strait into the northern

337 Atlantic. Following Koenigk et al. (2007), we calculate the freshwater export through Fram strait

338 using the following formula:

$$Q = \int_{z=B}^{T} \int_{x=x0}^{x1} u \left(\frac{S_{ref} - S}{S_{ref}} \right) dx dz$$

339 where B is the bottom of the ocean layer (here B = 100m), T is ocean surface; x0 and x1 are end

340 points of the selected cross-section (here the cross-section is along 74°N and between 30°W and

341 10°E); S, Sref are salinity and reference salinity (Sref = 34.8 psu). As shown in Fig. 12, there is a

342 pronounced increase of the freshwater export through Fram Strait into the northern Atlantic

343 during the first 4 years of integration, although the amount of the freshwater export decreases

344 gradually after that. Such freshwater propagation into the North Atlantic results in a weakening

345 of deep water formation in the Greenland Sea. Also shown in Fig. 12, the volume transport of the

346 Atlantic Meridional Overturning Circulation (AMOC) at 40°N in CFSv2 (which is too weak at

347 the beginning of the integration) decreases substantially during the decadal hindcast (4Sv after

348 10-year integration), which is a factor of 3-4 smaller than the observation (18.7Sv in

349 Cunningham et al., 2007; 17.2Sv in Smeed et al., 2014; McCarthy et al., 2015). Thus incorrect

350 prediction of sea ice in the Arctic could influence the AMOC prediction, which is a key source of

351 decadal predictability for European climate (Jackon et al., 2015), and has global impacts at

352 longer timescales.

353   It is well-known that brine rejection during sea ice growth strongly influences the formation

354 of the Antarctic Bottom Water (AASW). In the Antarctic, as mentioned previously, GEOS-5

355 simulates much less September sea ice extent, a factor of about 6 less than the observation,

356 which is also the case for March sea ice extent (not shown). The underestimation of sea ice

357 coverage might result in insufficient brine rejection through the freeze-up period in the GEOS-5.

358 This insufficient brine rejection is due to not only the underestimate of observed September sea

359 ice cover alone, but also the underestimate of observed March sea ice cover. Export of AABW

360 constitutes a key component of the meridional overturning circulation in the Southern Ocean

361 (Lumpkin and Speer 2007). The systematic underestimation of sea ice coverage results in a

362 weaker Deacon Cell in the Southern Ocean (~4Sv, Fig. 13) compared to the estimate of 20Sv

363 from Döös et al. (2007). Therefore, models that have large biases in simulating sea ice extent

364 (e.g., CFSv2 for the Arctic, GEOS-5 for the Antarctic) result in degraded predictive skill in sea

365 ice as well as other variables.

366 By performing the anomaly correlation analysis, we found that in the Arctic most models

367 only show small clustered areas with significant predictive skill at the lead-time of 1-year. As the

368 lead-time increases, for most models, the areas with significant predictive skill expand, covering

369 much of the northern Beaufort, Chukchi, eastern Siberian, and Laptev Seas. Such expansion is

370 largely due to the fact that almost all the models can predict observed negative trends of Arctic

371 sea ice, although the magnitude of the trend simulated by most models is still smaller than

372 observed. After the linear trend is removed, the areas with significant predictive skill at longer

373 time scales shrink greatly.

374 The analysis of regional indices suggests that sea ice in the Atlantic side has lower

375 predictability than that of the Pacific side. This is perhaps counterintuitive, since the AMO is

376 well predicted compared to the PDO (Kim et al., 2012). We do note that, for the Atlantic side of

377 the Arctic, most models show re-emerging predictive skill at the lead-time of 6-8 years. This

378 might be associated with the existence of interior AMOC pathways. A stronger (weaker) AMOC

379   results in warming (cooling) in the subpolar gyre after several years, contributing to enhanced

380   decadal predictability of sea ice in the north Atlantic sector (e.g., Mahajan et al. 2011; Zhang and

381   Zhang, 2015). In contrast to our results focusing on September sea ice, some idealized modeling

382   studies (Koenigk and Mikolakewicz 2009; Koenigk et al., 2012), which assess predictive skills

383   relative to their model climate, suggested annual and decadal mean sea ice concentration has

384   higher potential predictability for the Atlantic side than that of the Pacific side. Germe et al.

385   (2014) showed that the potential predictability of the winter Arctic sea ice extent comes mainly

386   from the Atlantic sector, while the Pacific sector seems unpredictable beyond the first year.

387   Further research is needed to explore the differences across model configurations.

388   By contrast, Antarctic sea ice does not show promising predictive skills at longer time scales.

389   Unlike in the Arctic counterpart, there is no obvious change in the areas showing significant

390   predictive skill as the lead-time increases. This might be because most models cannot predict

391   observed increasing Antarctic sea ice in recent decades. Instead almost all decadal hindcasts

392   predict a decrease of Antarctic sea ice, which is also true for the simulation in recent decades and

393   in response to forced simulations that include increased greenhouse gases in the atmosphere (e.g.,

394   Liu and Curry, 2010; Turner et al., 2013; Shu et al., 2015). Further investigating a range of other

395   variables such as simulated sea ice thickness, sea ice velocity, near surface wind, and ocean

396   stratification will help elucidate the reasons why the trends in these models are different from

397   observations. However, after the trend is removed, most models suggest that large parts of the

398   eastern south Pacific do have some predictive skill. Previous studies (e.g., Liu et al., 2002) have

399   showed that the intensification of the Hadley Circulation in the eastern equatorial Pacific during

400   El Nino leads to an equatorward shift of the storm track in the eastern south Pacific. This leads to

401   the changes of the regional Ferrel Circulation in the eastern Pacific, which cause an anomalous

402 poleward mean meridional heat flux into the sea ice zone in the eastern south Pacific and limits

403 sea ice growth there. Thus, relatively good sea ice predictability in the eastern south Pacific

404 might be related to the ENSO teleconnection. Holland and Raphael (2006) further showed that a

405 number of climate models have the ability in simulating the observed ENSO teleconnection in

406 sea ice in the eastern south Pacific and Atlantic. The analysis of regional indices suggests that the

407 MMEE has skillful results in the south Atlantic beyond 4-6 years, whether or not the trend is

408 removed.

409 An issue in this assessment is the relatively small sample size because of the limited number

410 of start years of the decadal prediction experiment. To promote both the science and practice of

411 decadal prediction, the CMIP phase 6 recommends ensembles of 10-year hindcast/prediction for

412 all years from 1960 to the end of the CMIP6 period (10 members recommended), which will be

413 helpful to obtain better statistics. As demonstrated in this study and previous studies, large biases

414 in models strongly influence sea ice prediction at decadal time scales. Thus continued efforts are

415 needed to identify, understand and reduce model errors, i.e., Kharin et al. (2012) demonstrated a

416 technique to correct non-linear drifts in decadal hindcasts. Some multi-model studies put efforts

417 on this issue for some climate variables (e.g., Bellucci et al., 2014; Doblas-Reyes et al., 2013;

418 Goddard et al., 2012).

419 Recent studies suggested that different initialization approaches and the density of

420 observations used in the initialization significantly affect the predictability of sea ice. Zunz et al.

421 (2015) tested three initialization approaches and found that the spread of ensembles at decadal

422 time scales can be reduced when more complicated data assimilation procedures and denser

423 observations are used to initialize the hindcasts. To date, only limited models have implemented

424 initialization of sea ice concentration (see Table 1 for details). Moreover, to better predict sea ice,

425   the accurate sea ice initialization requires not only sea ice concentration, but also variables (i.e.

426   sea ice thickness) influence surface energy fluxes and, thereby, ocean-atmosphere interaction. At

427   seasonal timescales, the initialization of sea ice thickness has been shown to be crucial for

428   summer prediction (e.g., Day et al. 2014b). Some studies (e.g., Blanchard-Wrigglesworth et al.

429   2011a; Koenigk and Mikolajewicz, 2009) suggested that the persistence of sea ice thickness

430   anomalies is much higher than that of sea ice concentration anomalies. Higher predictability of

431   Arctic sea ice thickness (volume) with respect to that of Arctic sea ice cover has been found at

432   longer time scales (e.g., Guemas et al., 2014). However, sea ice thickness has not yet been

433   initialized in CMIP5 models because of sparse observations. In this assessment, based on Table 1,

434   11 CMIP5 models can be separated into two groups: direct and indirect sea ice initialization. The

435   direct initialization includes CanCM4, CFSv2 and GEOS-5. Other models are indirect

436   initialization. Based on this division, we cannot conclude that the models initialized directly has

437   better performance on predictive skills compared to those initialized indirectly. CanCM4 has

438   broader area with significant predictive skill at longer lead-times (Figure 3). Its predictive skill is

439   better than some models (e.g., BCC-CSM1.1, HadCM3, IPSL-CM5A-LR), comparable with

440   CCSM4 and GFDL-CM2.1, but worse than MIROC5 and MMEE. On the other hand, CFSv2 has

441   strong model drift so that the predicted sea ice is substantially less than the observations.

442   GEOS-5 has nearly no skill on predicting observed sea ice variability. From this comparison, it is

443   not clear whether direct sea ice initialization is better than indirect sea ice initialization. Other

444   processes important for simulating sea ice evolution include the ocean below sea ice (i.e.,

445   temperature and salinity), which, due to its long persistence time, provides constraints on

446   predictions of sea ice at longer time scales. Thus, efforts should be devoted to further

447   development of initialization of the Arctic Ocean and Southern Ocean, which requires sufficient

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448   observations and improved assimilation methods.

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676   **Figure Captions:**

677   Figure 1. Linear trends of September sea ice concentration for (a) Arctic and (b) Antarctic during

678   the period of 1979-2014. The meshed areas denote the trends above 95% confidence level. Boxes

679   indicate the areas used to generate the regional sea ice indices.

680   Figure 2. Time series of September Arctic sea ice extent (seasonal minimum) from the

681   simulations of the 10-year hindcast for each ensemble member of each individual model (thin

682   gray line), the ensemble mean of each individual model (thick red line) and satellite observation

683   (black line) from 1981 to 2015.

684   Figure 3. Anomaly correlation coefficients between the simulated and observed Arctic

685   September sea ice concentration anomalies for the lead-time of 1-year (top panel) and 3-5 years

686   (bottom panel). The correlation coefficient 0.61, 0.73 and 0.88 represents 90%, 95% and 99%

687   confidence levels, respectively.

688   Figure 4. The predicted trends (slope of a linear regression) of September Arctic sea ice extent

689   anomalies as a function of the lead-time after applying a 3-year average.

690   Figure 5 same as Figure 3, but for detrended September sea ice concentration anomalies.

691   Figure 6. Anomaly correlation coefficients between the simulated and observed Arctic

692   September sea ice extent anomalies for the three regional indices (the entire Arctic, Pacific and

693   Atlantic) as a function of the lead-time. The top and bottom panels are the original and detrended

694   time series, respectively. The horizontal dashed and solid lines represent 90%, 95% and 99%

695   confidence levels, respectively. The thick gray line is the persistence prediction.

696   Figure 7. Time series of September Antarctic sea ice extent (seasonal minimum) from the

697   simulations of the 10-year hindcast for each ensemble member of each individual model (thin

698   gray line), the ensemble mean of each individual model (thick red line) and satellite observation

699   (black line) from 1981 to 2015.

700   Figure 8. Anomaly correlation coefficients between the simulated and observed Antarctic

701   September sea ice concentration anomalies for the lead-time of 1-year (top panel) and 3-5 years

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703   confidence levels, respectively.

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706   Figure 10. same as Figure 8, but for detrended September sea ice concentration anomalies.

707   Figure 11. Anomaly correlation coefficients between the simulated and observed Antarctic

708   September sea ice extent anomalies for the three regional indices (the entire Antarctic, eastern

709   Pacific and Atlantic) as a function of the lead-time. The top and bottom panels are the original

710   and detrended time series, respectively. The horizontal dashed and solid lines represent 90%, 95%

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712   Figure 12. (a) Freshwater export through Fram Strait (the cross-section along 74°N and between

713   30°W and 10°E), (b) Atlantic Ocean meridional overturning streamfunction in September

714   averaged for all decadal hindcasts from 1981 to 2015 for the CFSv2 (upper panel) and (c) time

715   series of stream function averaged over 40-55N, 500-1500m as indicated by the black in upper

716   panel (lower panel). The thin gray line represents each ensemble member and the thick black line

717   represents the ensemble mean.

718   Figure 13. Atlantic Ocean meridional overturning streamfunction in September averaged for all

719   decadal hindcasts from 1981-2015 for GEOS-5 (upper panel) and time series of stream function

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721   thin gray line represents each ensemble member and the thick black line represents the ensemble

722   mean.

723

724 Table 1 Summary of initialization methods and data sources used for the CIMP5 decadal
725 hindcast/prediction

Model	Resolution (sea ice model)	Ensemble members	Sea ice assimilation method and data source
BCC-CM1.1	1 lon x 1-1/3 lat	4	None, but the initial sea ice indirectly influenced by nudging T to SODA ocean reanalysis
CanCM4	~2.8 lon x 2.8 lat	10	Full-field using SIC from HadISST1.1 and SIT from model-based climatology (Merryfield et al., 2013)
CCSM4	0.9 lon x 1.25 lat	10	Full-field using bias-corrected CORE2-forced ocean hindcast
CFSv2	0.5 lon x 0.5 lat	4	Full-field using NCEP climate forecast system reanalysis
FGOALS-g2	1 lon x 1 lat	3	None, but the initial sea ice indirectly influenced by nudging T and S to an ocean reanalysis
GEOS-5	1 lon x 1 lat	3	Full-field using GEOS-iODAS
GFDL-CM2.1	~1 lon x 0.75 lat	10	None, but the initial sea ice indirectly influenced by atmospheric and ocean data (Msadek et al. 2014)
HadCM3	1.25 lon x 1.25 lat	10	Anomaly-field using Met Office Hadley Centre sea ice data (HadISST)
IPSL-CM5A-LR	~2 lon x 2 lat	6	None, but the initial sea ice indirectly influenced by the assimilation of T and S anomalies from observations
MIROC5	1 lon x 1 lat	6	None, but the initial sea ice is indirectly influenced by the assimilation of T and S from an objective analysis of Ishii and Kimoto (2009)
MPI-ESM-MR	~0.4 lon x 0.4 lat	3	None, but the initial sea ice indirectly influenced by the assimilation of T and S anomalies from a forced ocean run using NCEP reanalysis (Müller et al., 2012)

726 SIC: sea ice concentration; SIT: sea ice thickness, T: ocean temperature, S: salinity

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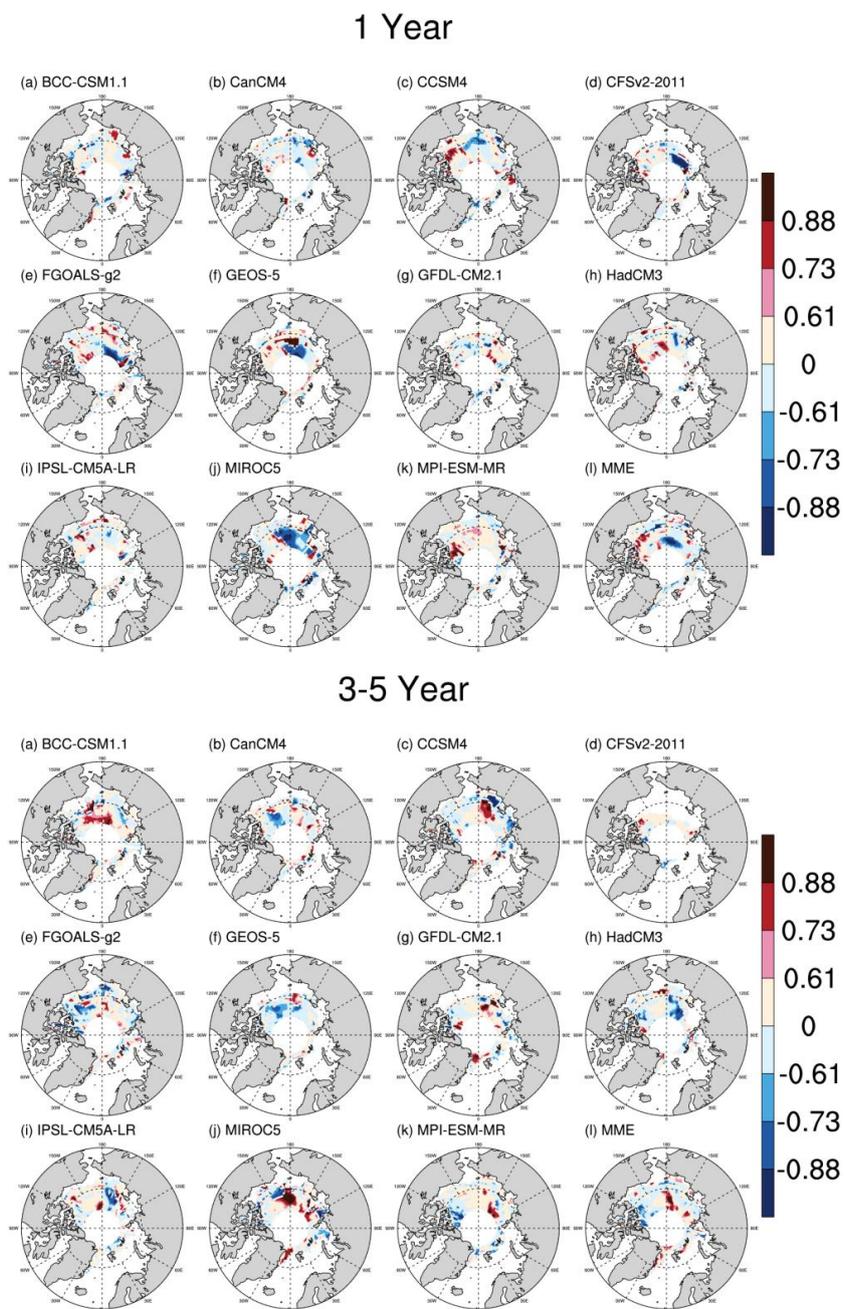
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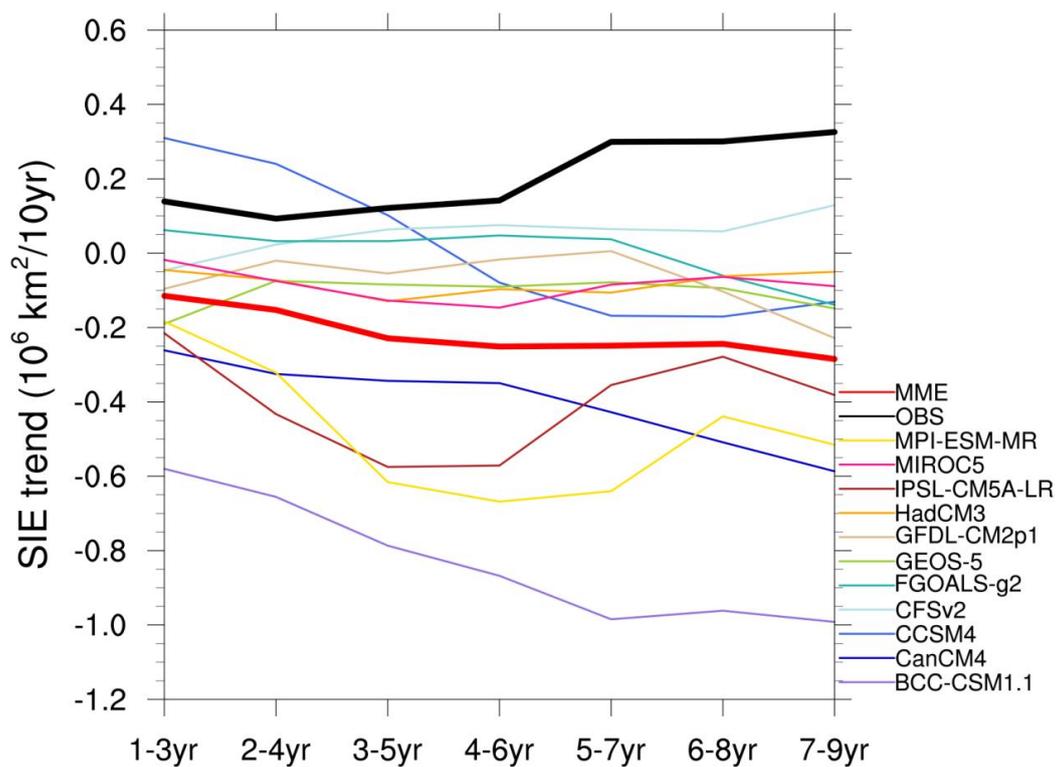
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