Multi-week Prediction Skill Assessment of Arctic Sea Ice Variability in the CFSv2
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1. Introduction
Recently, National Oceanic and Atmospheric Administration has initiated activities to improve skill of forecasts in weeks 3-4 time-range to extend weather forecast capability beyond the conventional range of 10-15 days. While Arctic sea ice forecast at seasonal time scales has received considerable attention (Bushuk et al. 2017), very limited work has been done on shorter time scales. In this study, a fully coupled atmosphere-ocean model is used to evaluate forecast skill of weekly mean sea ice from week 1 to week 6 for Arctic regions using the NCEP’s Climate Forecast System version 2 (CFSv2). This is the first effort to diagnose and assess multi-week Arctic sea ice prediction skill from a coupled atmosphere-ocean model.

2. The forecast model, data and processing method
The retrospective forecast data analyzed in this study is from the fully coupled CFSv2 model (Saha et al., 2014). Raw forecast data include output from four 45-day forecast runs from 0000, 0600, 1200, 1800 UTC each day. This study focuses on the analysis of weekly-mean anomalies from CFSv2 for 0-week to 5-week lead. For each forecast starting day, the following steps are taken to produce weekly average of ensemble mean forecast: (1) forecast runs from latest three days were used to form a lagged ensemble of 12 runs; (2) daily average of 12-run ensemble mean is computed for 42 target days; (3) non-overlapping 7-day weekly average is calculated from daily ensemble mean for 0-week lead (day 1 to day 7 average) to 5-week lead (day 36-day 42 average). The forecast data of ensemble-mean weekly average is then rearranged according to lead time and target (or verification) week.

For the assessment of the CFSv2 performance, the sea ice concentration (SIC) data from National Snow and Ice Data Center (NSIDC) (Cavalieri et al., 1996; Fetterer et al., 2002) during 2000–2015 is used. To facilitate the calculation, and for a consistent comparison, the corresponding observational data are re-arranged following the CFSv2 forecast structure to form the weekly average of SIC for each target verification week starting from each calendar day between 2000–2015 both for NASA Team and NASA Bootstrap algorithms.

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The average of SIC using NASA Team and NASA Bootstrap algorithms is then calculated and used for verification.

For both forecast and observation, a 16-year (2000–2015) average of 7-day mean SIC is calculated for each starting date from Jan 1st to Dec 31st (d=1–365); for forecast, calculation is done for each lead time (L0-L5). The climatology for each starting date (d) is defined as the 31-day (d-15 to d+15) running mean of the resulting 16-year average and is denoted as $F_c (d, L)$ for the forecast and $O_c (d)$ for the observation.

Three types of anomalies are calculated: total anomaly, interannual anomaly, and submonthly anomaly. The total anomaly is calculated as the deviation of total weekly-mean values of SIC from the climatology. The interannual anomaly is defined as the monthly mean of the total anomaly. The submonthly anomaly is the deviation of the total anomaly from the interannual anomaly. The interannual anomaly is further divided into two components, the trend interannual anomaly and detrended interannual anomaly.

### 3. Results

Figure 1 shows the spatial pattern of total weekly anomaly variance of NSIDC Arctic SIC anomaly for 4 target months (March, June, September and December) during 2000–2015. Large variance is generally located near the sea ice edge indicated by the 15% SIC black contours. The Arctic SIC shows relatively high variability in different Arctic regions during different months: Bering Sea and Sea of Okhotsk during March; Chukchi, Kara and Barents Seas during June, Beaufort, East Siberian and Laptev seas during September; Barents Sea during December.

For a quantitative comparison, Table 1 lists the contributions of different components, including the trend interannual, detrended interannual, and submonthly variability, to the observed total SIC variance averaged over Arctic regions (50°N-90°N) for 4 target months (March, June, September and December). As shown in Table 1, the Arctic SIC shows the largest (smallest) variability in September (December). The total SIC variability is dominated by detrended interannual variability, which accounts for more than 60% of the total variance. The contribution of submonthly

<table>
<thead>
<tr>
<th>NSIDC SIC variance ($\times 10^3$)</th>
<th>Mar</th>
<th>Jun</th>
<th>Sep</th>
<th>Dec</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>9.024</td>
<td>13.788</td>
<td>23.686</td>
<td>8.859</td>
</tr>
<tr>
<td>Trend (13.6%)</td>
<td>1.226</td>
<td>1.447</td>
<td>4.567</td>
<td>0.827</td>
</tr>
<tr>
<td>Interannual (64.1%)</td>
<td>5.788</td>
<td>9.506</td>
<td>16.156</td>
<td>5.428</td>
</tr>
<tr>
<td>Intraseasonal (22.3%)</td>
<td>2.011</td>
<td>2.835</td>
<td>2.963</td>
<td>2.604</td>
</tr>
</tbody>
</table>

Fig. 2 Anomaly Correlation Coefficient (ACC) between CFSv2 forecast and observations for total SIC anomalies at L3 for 4 target months of (a) March, (b) June, (c) September and (d) December.
anomalies accounts for about 20% of the total variance in March/June, 12.5% in September and 29.4% in December. Submonthly variance is 2-3 times as strong as the trend variance for March, June and December except for September in which submonthly variance is weaker than the trend variance.

Multi-week sea ice prediction skill for pan Arctic as well as individual Arctic regions is analyzed. CFSv2 captures general features of the Arctic sea ice variability, with the largest bias in marginal ice zone region.

Figure 2 shows the spatial Anomaly Correlation Coefficient (ACC) of total and interannual SIC anomalies between CFSv2 week-4 forecast and observations. The CFSv2 shows good skill at L3. The Arctic Ocean shows the highest prediction skill during September, particularly in the regions of Chukchi Sea, Beaufort Sea and East Siberian Sea where the ACC is above 0.6. The results demonstrate the multi-week prediction skill is dominated by the prediction of interannual variability although predictions of both interannual and submonthly anomalies contribute to the prediction skill.

The utility of a forecast greatly depends on the geographic characteristics of the forecast skill. Regional SIC forecast skill is especially important to the stakeholders. The ACC decreases with lead time and is region and season dependent. The ACC is relatively high for Kara and Barents Sea for all seasons. During March, the ACC is higher in Bering Sea, Sea of Okhotsk/Japan and Gulf of St. Lawrence. During June, the ACC is higher in Greenland Sea and Hudson Bay. During September, the ACC is higher in Greenland Sea, Arctic Ocean and Canadian Archipelago. During December, higher prediction skill is found in Bering Sea, Hudson Bay and Sea of Okhotsk/Japan.

Spatial and seasonal variations of the forecast ACC (anomaly correlation coefficient) skill show that the sea ice at a specific location is most predictable when this location is near the marginal zone having large sea ice variance (Figs. 1 and 2). This means that for each location there exist months for which the prediction skill is higher than the adjacent months. The skill in the month of maximum ACC (MMA) represents the best performance of the forecast system. Distribution of the maximum ACC skill among the months of melt season (April to September) at L3 is plotted in Fig. 3a with corresponding month when the maximum ACC skill is realized is shown in Fig. 3b with values 4-9 for April-September. Overall, the maximum ACC during the melt season progressively moves from south to north (Fig. 3b) with the mean sea ice concentration in the MMA increasing with latitude (Fig. 3c). The spatial distribution of maximum ACC shows a relationship with the distribution of the variance (Fig. 3d), that is, areas of larger variance corresponds to larger values of ACC. Taking 0.5 as a useful level of ACC for skillful prediction, predictability of weekly mean sea ice concentration near marginal zones is about 5-6 weeks. Prediction skill for Northern Hemisphere sea ice extent (SIE) is above 0.6 for the entire 6 target weeks and is strongly affected by interannual variability.

**Fig. 3** Statistics for melt season (April to September) for 3-week lead time (L3). (a) Maximum monthly mean anomaly correlation coefficient (ACC) from April to September, (b) Month of maximum monthly mean ACC (MMA), (c) NSIDC SIC mean for MMA, and (d) NSIDC SIC variance for MMA.
4. Summary and discussion

This study examines Arctic sea ice weekly-mean variability and multi-week prediction skill in the CFSv2. While many studies on seasonal sea ice predictions have been published, this study appears to be the first effort to analyze sea ice prediction skill at multi-week lead time using a dynamical forecast system. The assessment in this study is based on the output from the operational NCEP CFSv2, whose configuration is not optimal and the seasonal sea ice prediction can be improved with an improved initial sea ice thickness (Collow et al., 2015). In addition, while we have analyzed the contributions of sea ice variations and their prediction from trend interannual, detrended interannual, and submonthly variabilities, it will be useful to determine how these variations are contained in the initial conditions and how the memory of the components (e.g., sea ice, ocean, and atmosphere) of the forecast system affect the subsequent sea ice evolution. Understanding the impact of the initialization of each component will also provide guidance as to where the critical effort in improving the initialization of the forecast system should be made.

References


Fetterer F., K. Knowles, W. Meier, and M. Savoie, 2002: Sea Ice Index. National Snow and Ice Data Center: Boulder, CO.