The Arctic Predictability and Prediction on Seasonal-to-Interannual TimEscales (APPOSITE) data set

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Abstract

Recent decades have seen significant developments in seasonal-to-interannual timescale climate prediction capabilities. However, until recently the potential of such systems to predict Arctic climate had not been assessed. This paper describes a multi-model predictability experiment which was run as part of the Arctic Predictability and Prediction On Seasonal to Inter-annual Timescales (APPOSITE) project. The main goal of APPOSITE was to quantify the timescales on which Arctic climate is predictable. In order to achieve this, a coordinated set of idealised initial-value predictability experiments, with seven general circulation models, was conducted. This was the first model intercomparison project designed to quantify the predictability of Arctic climate on seasonal to inter-annual timescales. Here we present a description of the archived data set (which is available at the British Atmospheric Data Centre) and an update of the project’s results. Although designed to address Arctic predictability, this data set could also be used to assess the predictability of other regions and modes of climate variability on these timescales, such as the El Niño Southern Oscillation.

1 Introduction

Unprecedented climate change in the Arctic has opened up opportunities for business in diverse sectors such as fossil fuel and mineral extraction, shipping and tourism but put pressure on local communities, who are dependent on the ice for their livelihoods (Emmerson and Lahn, 2012; Stephenson et al., 2013). The need for these stakeholder groups to avoid hazardous sea ice and weather conditions has increased demand for Arctic sea ice forecasts at seasonal-to-interannual time scales (Eicken, 2013). These local interests and a growing appreciation of the importance of the Arctic in mid-latitude weather phenomena (Jung et al., 2014) have motivated the development of seasonal sea ice prediction systems (e.g. Sigmond et al., 2013; Chevallier et al., 2013; Wang et al., 2013; Peterson et al., 2014) which are initialised from observations.
It has previously been shown that these sea ice prediction systems are significantly skillful at predicting summer sea ice cover, but diagnosing the source of forecast errors is problematic (Guemas et al., 2014). Forecast errors may be due to both inadequate representation of important physical processes in the model (e.g. melt ponds, Schröder et al., 2014) or inadequate knowledge of initial-state vector variables, such as sea ice thickness (Day et al., 2014a; Msadek et al., 2014; Massonnet et al., 2015), which is not currently used to initialise operational forecasts. Sea ice predictability is also inherently limited due to chaotic atmospheric variability (Blanchard-Wrigglesworth et al., 2011b; Holland et al., 2010). If the skill of a given forecast system is already close to this fundamental limit it will not be possible to further increase the leadtime at which the forecast is skillful.

To determine if there is the potential to improve the operational prediction systems, we consider a more idealized situation. The “perfect-model” approach to estimating predictability involves producing initial-value ensemble-predictions with a General Circulation Model (GCM), which are verified against the model itself rather than against observations of the real world (following Griffies and Bryan, 1997b). It is therefore not hampered by changes to the observational network over time or changes in predictability due to secular climate change, which hampers this kind of analysis in the real world. It therefore provides an upper bound for the predictive skill obtainable in a world governed by the same physical equations as the model (Hawkins et al., 2015), though may not necessarily be an upper bound for the limit of predictability in the real world (Eade et al., 2014; Shi et al., 2015).

The perfect model approach has previously been used to quantify and understand predictability of coupled modes of climate variability, such as the Atlantic Meridional-Overturning Circulation (AMOC) (e.g. Griffies and Bryan, 1997a; Collins, 2002; Pohlmann et al., 2004) and the El Niño Southern Oscillation (ENSO) (Collins et al., 2002), leading to the development of operational seasonal-to-decadal prediction systems based on atmosphere-ocean climate models (e.g. Smith et al., 2007; Jin et al., 2008).
Using this approach Collins et al. (2006) demonstrated that the timescale on which the AMOC is predictable varies from model to model. These inter-model differences in predictability arise because different GCMs have different representations of the underlying physical equations and parameters. It is therefore likely that there will be inter-model differences in predictability for other climate variables, so in order to assess uncertainty in model based estimates of the limit of predictability it is important to conduct such analyses in multiple GCMs. The APPOSITE model intercomparison was designed to diagnose the limit of initial-value predictability of Arctic sea ice in multiple GCMs. Previous studies had estimated this limit in individual climate models, but with different experiment design. All these experiments demonstrated initial-value predictability on seasonal-to-interannual timescales but with significant differences in the details (Blanchard-Wrigglesworth et al., 2011b; Holland et al., 2010; Koenigk and Mikolajewicz, 2009; Tietsche et al., 2013; Guemas et al., 2014). However, because the experimental protocol was inconsistent between the studies, it was not clear whether differences in predictability were inherent in the models themselves or due to differences in the experimental set-up. For the APPOSITE ensemble a consistent protocol was followed so that differences in predictability were only the result of differences in the models themselves. The first results of this project were presented in Tietsche et al. (2014).

Here we present a detailed description of the APPOSITE experiment archived at the British Atmospheric Data Centre (BADC) (Day et al., 2015) and an update on the results of Tietsche et al. (2014), including more models than available at the time of publication. The paper is outlined as follows: Sect. 2 describes the experiment in detail as well as the mean state of the models used, Sect. 3 includes an update of the results of Tietsche et al. (2014) followed by the conclusions in Sect. 4. Additional details of the data set, archived at the BADC, are included as Appendix A.
2 Description of the simulations

Seven different coupled climate models performed simulations for APPOSITE (see Table 1). Six of these models followed the same experimental protocol, which is described in Sect. 2.1 and 2.2. One model, CanCM4, followed a slightly different protocol which is described in Sect. 2.3.

2.1 Control simulations

Predictability of the climate system changes with mean climate (DelSole et al., 2014; Holland et al., 2010) complicating the assessment of predictability in a transient climate. The experimental protocol therefore asked for both control simulations and ensemble predictions to be conducted in GCMs with forcing fixed at present-day values.

Since the perfect-model approach uses initial conditions generated by the model itself, present-day control simulations with each model were run under fixed present-day radiative forcings. For practical reasons the year that the forcings correspond to differ, but by no more than a decade or two (see Table 1). Apart from MPI-ESM, which was initialised from year 2005 of the CMIP5 historical simulation, all other models were initialised in a static state from present day ocean temperature and salinity profiles (e.g. Conkright et al., 2002). After a spin-up period of about 100 years, each model is integrated for at least 100 more years to fully sample the model’s mean state, the remaining climate drift, and the models internal variability. It is worth noting that some of these simulations have significant drifts in the mean sea ice climatology (see Figs. 1 and 2).

All of the models are full atmosphere-ocean-seaice GCMs and each has a fully prognostic sea ice component. These account for changes in sea ice due to both thermodynamic and advective processes that result from stress internal to the sea ice as well as through interaction with the atmosphere and ocean. Like all components of the GCMs, the sea ice models have both structural and conceptual differences. The most significant of which are their treatment of sea ice dynamics, like the local ice thickness
distribution, vertical heat flux through the ice, and heat exchange at the ice-ocean interface. Except for HadGEM1.2, E6F and MIROC5.2 the versions of the models used were those submitted to the Coupled Model Intercomparison Project Phase 5 (CMIP5). These models have been well tested and evaluated against observations and their strengths and weaknesses are well-documented (see references in Table 1). However, in order to understand differences in sea ice predictability, we focus on differences in their sea ice mean state and variability.

The sea ice mean state and variability in the control runs differ considerably from model-to-model and to the observations (see Figs. 2, 3 and 4). Before calculating the standard deviation, shown in Fig. 4, a linear trend was removed from sea ice extent and volume timeseries for each model. Interannual variability of summer sea ice extent appears to be negatively correlated to its mean, in line with previous studies (Goosse et al., 2009; Holland et al., 2008). This does not appear to be the case for winter.

2.2 Ensemble predictions

To diagnose the inherent predictability in each of these models, we performed a suite of ensemble predictions. The number of start dates selected from the control run differs from model to model and ranges between 8 and 18. These were chosen to sample a range of high, low and medium sea ice states, while keeping start dates well spaced in time to consider them independent (see Fig. 1). For each start date an ensemble of between 8 and 16 members was generated, depending on the model. The initial conditions were taken from the control run and each member differs only by a perturbation to the sea surface temperature field. This perturbation takes the form of randomly-generated spatially-uncorrelated Gaussian noise, with a standard deviation of $10^{-4}$ K. Such a perturbation is so small that it is equivalent to assuming perfect knowledge of the initial conditions. For a given start date, differences in the evolution of each ensemble member are solely determined by the chaotic nature of the simulated climate system. Each ensemble was run for 3 years, with the exception of MIROC5.2, which was run for 3.5 years.
A minimum contribution for models to be included in the APPOSITE experiment was to submit a control run and predictability experiments started on the 1st July, which allows an assessment of seasonal predictions of the late-summer sea ice conditions, when the sea ice is at its lowest extent, and human activity in the Arctic Ocean is largest. Although we restrict our analysis to the simulations started in July, some groups have also submitted simulations started in January, May and November (see Table 1 for details). Note that operational predictions are more commonly started in May. We decided to start our simulations later due to the presence of an early summer, predictability barrier, which might lead to a sharply decreased skill in predicting the late-summer minimum (Blanchard-Wrigglesworth et al., 2011a; Day et al., 2014b).

2.3 CanCM4 transient experiments

The set of simulations with the CanCM4 model use a different protocol, in order to facilitate direct comparison of these simulations with the CanSIPS operational seasonal prediction system, which uses the same climate model (Sigmond et al., 2013). The CanCM4 simulations were different in two key respects. Firstly, they were run under a transient climate, with observed historical forcing agents prescribed. Secondly, initial-value ensembles were generated every year and only run for 1 year. In all other regards, such as the method of ensemble generation, these simulations are the same as the other APPOSITE perfect model simulations.

3 Perfect model intercomparison

An intermodel comparison of Arctic sea ice predictability, using four climate models, was published in Tietsche et al. (2014). Here we present an update of this study, including the MIROC5.2, E6F and CanCM4 climate models.
3.1 Metrics

Two predictability metrics, as defined by Collins (2002), were used to quantify predictability in this study. These make use of the fact that in a perfect model study, such as this, any ensemble member may be chosen as “the truth” or “the forecast”. Therefore it is possible to increase the effective sample size by taking each member as “the truth” in turn, and comparing it with every other member as “the forecast”. The Normalised Root Mean Squared Error (NRMSE) compares forecast RMSE to the climatological variability:

\[
\text{NRMSE} = \frac{\sqrt{\langle (x_{kj} - x_{ij})^2 \rangle_{i,j,k\neq i}}}{\sqrt{2\sigma^2}}
\] (1)

where \(\langle \cdot \rangle_i\) denotes the expectation value, to be calculated by summing over the specified index with appropriate normalization, \(x_{ij}(t)\) is the sea ice extent at lead time \(t\) for the \(i\)th member of the \(j\)th ensemble. The denominator is the climatological RMSE between two independent realisations. Significance of this is calculated using an \(f\) test, following Collins (2002).

The second metric is the anomaly correlation coefficient (ACC). This is defined as:

\[
\text{ACC} = \frac{\langle (x_{ij} - \mu_j)(x_{kj} - \mu_j) \rangle_{i,j,k\neq j}}{\langle (x_{ij} - \mu_j)^2 \rangle_{i,j}}
\] (2)

where \(\mu_j\) is the climatological mean at the time of the \(j\)th ensemble prediction.

At some lead-time, both of these metrics become insignificantly different from their asymptotic limit (0 for ACC and 1 for NRMSE), and the lead-time at which this happens can be used to define the limit of predictability. However, it appears that the NRMSE metric is more conservative than the ACC metric and becomes insignificant at an earlier lead time (see Fig. 5). Thus using both metrics gives some spread in the estimate of the time when the limit of predictability is actually reached.
3.2 Fixed forcing experiments

Although sea ice extent predictability decreases rapidly during the first year, with the exception of EC-Earth, all models (and both metrics) show significant levels of predictability for the first year. After the first year of simulation, two of the models, MIROC5.2 and GFDL-CM3, show significant levels of predictability at all later lead times. At the other end of the predictability spectrum, E6F is only intermittently predictable after the first year. Predictability in E6F (and to a lesser extent HadGEM1.2) has a strong seasonal cycle with months surrounding the winter extent maximum significantly predictable until the end of the simulation and no significant summer predictability after the first year.

Sea ice volume is much more predictable than sea ice extent in all models. Apart from E6F all models exhibit significant predictability in all 3 years of the simulations. In a prognostic predictability analysis with decadal simulations, Germe et al. (2014) similarly found that winter sea ice extent was predictable out to seven years in their model, compared to three years in summer and found that volume was predictable out to nine years ahead.

3.3 CanCM4 transient experiments

Both the NRMSE and ACC metrics indicate lower levels of predictability in CanCM4 for sea ice extent and sea ice volume. It is possible that the CanCM4 model actually has inherently lower levels of initial-value predictability than the other models. However, there are reasons to expect that both metrics will be more conservative using the transient protocol.

In the case of NRMSE, detrending a short timeseries reduces the climatological variance since without multiple ensemble members to estimate the forced trend, some internal variability is removed in attempting to remove the forced trend (see Hawkins et al., 2015).

In the case of ACC, the reference climate (which is a linear fit to the control run) is a much closer fit in the case of the short CanCM4 transient control run than it is for the
long fixed forcing control runs, which have large decadal anomalies. This will reduce the correlation and is analogous to the way that the ACC between two timeseries is reduced by removing the trend from both.

4 Conclusions

We have presented the protocol for the APPOSITE Arctic sea ice predictability multi-model intercomparison. The mean state and variability of Arctic sea ice cover in the models was compared to observed estimates and the limit of initial-value Arctic sea ice extent and volume predictability was estimated from each of the models, updating the results of Tietsche et al. (2014).

The results of this analysis can be summarised:

– The winter sea ice extent is predictable at interannual timescales (or possibly longer timescales) in all models.

– There is significant intermodel spread in the timescale at which summer sea ice extent is predictable, with some models not showing any interannual or longer timescale predictability, and others showing significant predictability throughout all months of the 3 year simulations.

– Sea ice volume is much more predictable than sea ice extent.

The data used in this study are archived at the BADC (Day et al., 2015). As well as enabling the results of the APPOSITE project to be reproduced, this will also allow these predictability experiments to be further utilised to improve understanding of predictability of other variables, such as Antarctic sea ice cover (e.g. Holland et al., 2013) or even ENSO (e.g. Collins et al., 2002).
Appendix A: Database description

APPOSITE requested a specific set of variables from participants focused on sea ice analysis, but many other variables have been archived besides. The file and directory naming convention, followed by the archived data set, is very similar to that followed by CMIP5 (http://cmip-pcmdi.llnl.gov/cmip5/output_req.html).

APPOSITE required participants to prepare their data files so that they meet the following constraints.

- Data files are in netCDF file format and ideally conform to the climate and forecast (CF) metadata convention (outlined on the website http://cf-pcmdi.llnl.gov). In instances where it was not possible to produce fully CF compliant netCDF files, participants were required to follow the CMOR variable naming convention.

- There must be only one output variable per file.

- The file names have to follow the file naming convention outlined below.

Each variable is contained in a single directory of a directory tree with the following structure:

```
<model>/<runtype>/<submodel&frequency>/<variable>
```

Where runtype is “ctrl” or “pred” for the control run or ensemble predictions respectively, model is the name of the climate model (e.g. hadgem1_2, mpiems, ...), variable is the CMOR name for a given climate variable and submodel&frequency indicates the model sub-component and frequency (e.g. Amon, Aday, Omon and Oday).

Files are named using the following convention:

```
<variable>_<submode& frequency>_<model>_<runtype>_<run>_<time>.nc
```

Where run is a concatenated string including the start year, prediction start month and ensemble member number for ensemble predictions (e.g. 2005Jul3); or simply contains “1” for a control run.

For example,
tas_Amon_hadgem1_2_ctrl_r1_200501-200512.nc for control runs, or
tas_Amon_hadgem1_2_pred_2005Jul3_200507-200806.nc for the 3rd ensemble member of an ensemble started on the 1 July 2005.

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References


CD-ROM documentation, US Department of Commerce, National Oceanic and Atmospheric Administration, National Oceanographic Data Center, Ocean Climate Laboratory, NODC Internal Report 17, Silver Spring MD, 17 p., 2002. 8814


Table 1. Details of simulations submitted to the APPOSITE database.

<table>
<thead>
<tr>
<th>Model</th>
<th>CTRL length</th>
<th>Forcing year</th>
<th>Start dates</th>
<th>Start months</th>
<th>Ensemble size</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>HadGEM1.2</td>
<td>249</td>
<td>1990</td>
<td>10</td>
<td>Jan, May, Jul</td>
<td>16</td>
<td>Johns et al. (2006) Shaffrey et al. (2009)</td>
</tr>
<tr>
<td>GFDL-CM3</td>
<td>200</td>
<td>1990</td>
<td>8</td>
<td>Jan, Jul</td>
<td>16</td>
<td>Donner et al. (2011) Griffies et al. (2011)</td>
</tr>
<tr>
<td>EC-Earth2.2</td>
<td>200</td>
<td>2005</td>
<td>9</td>
<td>Jul</td>
<td>8</td>
<td>Hazeleger et al. (2012)</td>
</tr>
<tr>
<td>MIROC5.2</td>
<td>100</td>
<td>2000</td>
<td>8</td>
<td>Jan, Jul</td>
<td>8</td>
<td>updated from Watanabe et al. (2010)</td>
</tr>
<tr>
<td>E6F</td>
<td>200</td>
<td>1990</td>
<td>18</td>
<td>Jan, Jul</td>
<td>9</td>
<td>Sidorenko et al. (2014)</td>
</tr>
</tbody>
</table>
Figure 1.
Figure 1. Timeseries of monthly mean September sea ice extent (sie, left column) and sea ice volume (siv, right column) in each model’s control simulation (blue) with the line of best fit to data (black). Vertical grey lines indicate start years used to initialise simulations.
Figure 2. Average sea-ice concentration in present-day model control simulations and from HadISST (1983–2012) (Rayner et al., 2003).
Figure 3. Average sea-ice thickness in present-day model control simulations and from PIOMAS (1983–2012) (Schweiger et al., 2011).
Figure 4. Seasonal cycle of monthly mean sea-ice extent (a), volume (b) and standard deviation of sea ice extent (c) and volume (d) in present-day model control simulations. The HadISST observations of sea ice extent and PIOMAS reconstruction of ice volume are included as a reference.
Figure 5. (a) and (b) Lead-time dependence of SIE NRMSE and SIV NRMSE for all models. (c) and (d) Lead-time dependence of SIE ACC and SIV ACC for all models. September and March are marked by thin gray vertical lines. Dashed lines represent the averages across models. Circles indicate where metrics do not indicate significant predictability (at 95%). Updated from Tietsche et al. (2014).