**Geoscientific Model Development**

Open Access

Discussions

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

J. J. Day[1], S. Tietsche[2], M. Collins[3], H. F. Goessling[4], V. Guemas[5,6], A. Guillory[7], W. J. Hurlin[8], M. Ishii[9], S. P. E. Keeley[2], D. Matei[10], R. Msadek[6], M. Sigmond[11], H. Tatebe[12], and E. Hawkins[1]

[1]NCAS-Climate, Department of Meteorology, University of Reading, Reading, UK
[2]European Centre for Medium-Range Weather Forecasts, Reading, UK
[3]College of Engineering, Mathematics and Physical Sciences, University of Exeter, Exeter, UK
[4]Alfred Wegener Institute, Helmholtz Centre for Polar and Marine Research, Bremerhaven, Germany
[5]Institut Català de Ciències del Clima, Barcelona, Spain
[6]CNRM/GAME, Toulouse, France
[7]British Atmospheric Data Centre, Rutherford Appleton Laboratory, Chilton, UK
[8]Geophysical Fluid Dynamics Laboratory, Princeton, NJ, USA
[9]Meteorological Research Institute, Tsukuba, Japan
[10]Max Planck Institute for Meteorology, Hamburg, Germany

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

GMDD

8, 8809–8833, 2015

APPOSITE

J. J. Day et al.

Title Page

Abstract | Introduction

Conclusions | References

Tables | Figures

◄ | ►

◄ | ►

Back | Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

[11]Canadian Centre for Climate Modelling and Analysis, Environment Canada, Victoria, Canada
[12]Japan Agency for Marine-Earth Science and Technology, Yokohama, Japan

Correspondence to: J. J. Day (j.j.day@reading.ac.uk)

Title Page

Abstract | Introduction

Conclusions | References

Tables | Figures

◄ | ►

◄ | ►

Back | Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

## 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

Unprecedneted climate change in the Arctic has opened up oportunities for buniness 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 apreciation 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).

**APPOSITE**

J. J. Day et al.

◄ | ►

◄ | ►

Back | Close

Full Screen / Esc

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). Appart 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
5  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
10  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

15  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
20  between 8 and 16 members was generated, dependingon 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
25  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.

Back | Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

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 it's lowest extent, and human activity in the 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 pre-dictability 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
5  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:

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

10  where $\langle \cdot \rangle_i$ denotes the expectation value, to be calculated by summing over the speci-fied 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 be-tween two independent realisations. Significance of this is calculated using an $f$ test, following Collins (2002).
15      The second metric is the anomaly correlation coefficient (ACC). This is defined as:

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

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
20  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 interanual 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).

Back    Close

Full Screen / Esc

# 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
5  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).
10   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
15  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, mpiesm, …), `variable` is the CMOR name for a given climate variable
20  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 en-
25  semble member number for ensemble predictions (e.g. 2005Jul3); or simply contains "1" for a control run.

For example,

**GMDD**

8, 8809–8833, 2015

**APPOSITE**

J. J. Day et al.

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

```
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 en-
semble member of an ensemble started on the 1 July 2005.

## References

Blanchard-Wrigglesworth, E., Armour, K. C., Bitz, C. M., and DeWeaver, E.: Persistence and Inherent Predictability of Arctic Sea Ice in a GCM Ensemble and Observations, J. Climate, 24, 231–250, doi:10.1175/2010JCLI3775.1, 2011a. 8816

Blanchard-Wrigglesworth, E., Bitz, C., and Holland, M.: Influence of initial conditions and climate forcing on predicting Arctic sea ice, Geophys. Res. Lett, 38, L18503, doi:10.1029/2011GL048807, 2011b. 8812, 8813

Chevallier, M., Salas y Mélia, D., Voldoire, A., Déqué, M., and Garric, G.: Seasonal Forecasts of the Pan-Arctic Sea Ice Extent Using a GCM-Based Seasonal Prediction System, J. Climate, 26, 6092–6104, doi:10.1175/JCLI-D-12-00612.1, 2013. 8811

Collins, M.: Climate predictability on interannual to decadal time scales: the initial value problem, Clim. Dynam., 19, 671–692, doi:10.1007/s00382-002-0254-8, 2002. 8812, 8817

Collins, M., Frame, D., Sinha, B., and Wilson, C.: How far ahead could we predict El Niño?, Geophys. Res. Lett., 29, 130-1–130-4, doi:10.1029/2001GL013919, 2002. 8812, 8819

Collins, M., Botzet, M., Carril, A. F., Drange, H., Jouzeau, A., Latif, M., Masina, S., Otteraa, O. H., Pohlmann, H., Sorteberg, A., Sutton, R., and Terray, L.: Interannual to decadal climate predictability in the North Atlantic: a multimodel-ensemble study, J. Climate, 19, 1195–1203, 2006. 8813

Conkright, M. E., Locarnini, R. A., Garcia, H. E., O'Brien, T. D., Boyer, T. P., Stephens, C., and Antonov, J. I.: World Ocean Atlas 2001: Objective analyses, data statistics, and figures:

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

Day, J. J., Hawkins, E., and Tietsche, S.: Will Arctic sea ice thickness initialization improve seasonal forecast skill?, Geophys. Res. Lett., 41, 7566–7575, doi:10.1002/2014GL061694, 2014a. 8812

Day, J. J., Tietsche, S., and Hawkins, E.: Pan-Arctic and Regional Sea Ice Predictability: Initialization Month Dependence, J. Climate, 27, 4371–4390, doi:10.1175/JCLI-D-13-00614.1, 2014b. 8816

Day, J., Hawkins, E., and Tietsche, S.: Collection of Multi-model Data from the Arctic Predictability and Prediction On Seasonal-to-Interannual Time-scales (APPOSITE) Project, NCAS British Atmospheric Data Centre, doi:10.5285/45814db8-56cd-44f2-b3a4-92e41eaaff3f, 2015. 8813, 8819

DelSole, T., Yan, X., Dirmeyer, P. A., Fennessy, M., and Altshuler, E.: Changes in seasonal predictability due to global warming, J. Climate, 27, 300–311, 2014. 8814

Donner, L. J., Wyman, B. L., Hemler, R. S., Horowitz, L. W., Ming, Y., Zhao, M., Golaz, J.-C., Ginoux, P., Lin, S.-J., Schwarzkopf, M. D., Austin, J., Alaka, G., Cooke, W. F., Delworth, T. L., Freidenreich, S. M., Gordon, C. T., Griffies, S. M., Held, I. M., Hurlin, W. J., Klein, S. A., Knutson, T. R., Langenhorst, A. R., Lee, H.-C., Lin, Y., Magi, B. I., Malyshev, S. L., Milly, P. C. D., Naik, V., Nath, M. J., Pincus, R., Ploshay, J. J., Ramaswamy, V., Seman, C. J., Shevliakova, E., Sirutis, J. J., Stern, W. F., Stouffer, R. J., Wilson, R. J., Winton, M., Wittenberg, A. T., and Zeng, F.: The Dynamical Core, Physical Parameterizations, and Basic Simulation Characteristics of the Atmospheric Component AM3 of the GFDL Global Coupled Model CM3, J. Climate, 24, 3484–3519, doi:10.1175/2011JCLI3955.1, 2011. 8827

Eade, R., Smith, D., Scaife, A., Wallace, E., Dunstone, N., Hermanson, L., and Robinson, N.: Do seasonal to decadal climate predictions underestimate the predictability of the real world?, Geophys. Res. Lett., 41, 5620–5628, doi:10.1002/2014GL061146, 2014. 8812

Eicken, H.: Ocean science: Arctic sea ice needs better forecasts, Nature, 497, 431–433, doi:10.1038/497431a, 2013. 8811

Emmerson, C. and Lahn, G.: Arctic Opening: Opportunity and Risk in the High North, Tech. rep., Lloyds, Chattham House, 2012. 8811

Title Page

Abstract | Introduction

Conclusions | References

Tables | Figures

|◄ | ►|

◄ | ►

Back | Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

Germe, A., Chevallier, M., Salas y Mélia, D., Sanchez-Gomez, E., and Cassou, C.: Interannual predictability of Arctic sea ice in a global climate model: regional contrasts and temporal evolution, Clim. Dynam., 43, 2519–2538, doi:10.1007/s00382-014-2071-2, 2014. 8818

Goosse, H., Arzel, O., Bitz, C. M., de Montety, A., and Vancoppenolle, M.: Increased variability of the Arctic summer ice extent in a warmer climate, Geophys. Res. Lett., 36, L23702, doi:10.1029/2009GL040546, 2009. 8815

Griffies, S. and Bryan, K.: A predictability study of simulated North Atlantic multidecadal variability, Clim. Dynam., 13, 459–487, 1997a. 8812

Griffies, S. M. and Bryan, K.: Predictability of North Atlantic Multidecadal Climate Variability, Science, 275, 181–184, doi:10.1126/science.275.5297.181, 1997b. 8812

Griffies, S. M., Winton, M., Donner, L. J., Horowitz, L. W., Downes, S. M., Farneti, R., Gnanadesikan, A., Hurlin, W. J., Lee, H.-C., Liang, Z., Palter, J. B., Samuels, B. L., Wittenberg, A. T., Wyman, B. L., Yin, J., and Zadeh, N.: The GFDL CM3 Coupled Climate Model: Characteristics of the Ocean and Sea Ice Simulations, J. Climate, 24, 3520–3544, doi:10.1175/2011JCLI3964.1, 2011. 8827

Guemas, V., Blanchard-Wrigglesworth, E., Chevallier, M., Day, J. J., Déqué, M., Doblas-Reyes, F. J., Fučkar, N. S., Germe, A., Hawkins, E., Keeley, S., Koenigk, T., Salas y Mélia, D., and Tietsche, S.: A review on Arctic sea-ice predictability and prediction on seasonal to decadal time-scales: Arctic Sea-Ice Predictability and Prediction, Q. J. Roy. Meteorol. Soc., in press, doi:10.1002/qj.2401, 2014. 8812, 8813

Hawkins, E., Tietsche, S., Day, J. J., Melia, N., Haines, K., and Keeley, S.: Aspects of designing and evaluating seasonal-to-interannual Arctic sea-ice prediction systems, Q. J. Roy. Meteorol. Soc., in press, doi:10.1002/qj.2643, 2015. 8812, 8818

Hazeleger, W., Wang, X., Severijns, C., Ştefănescu, S., Bintanja, R., Sterl, A., Wyser, K., Semmler, T., Yang, S., v. d. Hurk, B., v. Noije, T., v. d. Linden, E., and v. d. Wiel, K.: EC-Earth V2.2: description and validation of a new seamless earth system prediction model, Clim. Dynam., 39, 2611–2629, doi:10.1007/s00382-011-1228-5, 2012. 8827

Holland, M. M., Bitz, C. M., Tremblay, B., and Bailey, D. A.: The role of natural versus forced change in future rapid summer Arctic ice loss, in: Arctic sea ice decline: observations, projections, mechanisms, and implications, edited by: DeWeaver, E., Bitz, C., and Tremblay, B., vol. 180 of Geophys. Monogr. Ser., AGU, Washington, 2008. 8815

Title Page

Abstract | Introduction

Conclusions | References

Tables | Figures

◄ | ►

◄ | ►

Back | Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

Holland, M. M., Bailey, D. A., and Vavrus, S.: Inherent sea ice predictability in the rapidly changing Arctic environment of the Community Climate System Model, version 3, Clim. Dynam., 36, 1239–1253, 2010. 8812, 8813, 8814

Holland, M. M., Blanchard-Wrigglesworth, E., Kay, J., and Vavrus, S.: Initial-value predictability of Antarctic sea ice in the Community Climate System Model 3, Geophys. Res. Lett., 40, 1–4, doi:10.1002/grl.50410, 2013. 8819

Jin, E. K., Kinter, J. L., Wang, B., Park, C.-K., Kang, I.-S., Kirtman, B. P., Kug, J.-S., Kumar, A., Luo, J.-J., Schemm, J., Shukla, J., and Yamagata, T.: Current status of ENSO prediction skill in coupled ocean–atmosphere models, Clim. Dynam., 31, 647–664, doi:10.1007/s00382-008-0397-3, 2008. 8812

Johns, T. C., Durman, C. F., Banks, H. T., Roberts, M. J., McLaren, A. J., Ridley, J. K., Senior, C. A., Williams, K. D., Jones, A., Rickard, G. J., Cusack, S., Ingram, W. J., Crucifix, M., Sexton, D. M. H., Joshi, M. M., Dong, B.-W., Spencer, H., Hill, R. S. R., Gregory, J. M., Keen, A. B., Pardaens, A. K., Lowe, J. A., Bodas-Salcedo, A., Stark, S., and Searl, Y.: The new Hadley Centre climate model (HadGEM1): Evaluation of coupled simulations, J. Climate, 19, 1327–1353, 2006. 8827

Jung, T., Kasper, M. A., Semmler, T., and Serrar, S.: Arctic influence on subseasonal midlatitude prediction, Geophys. Res. Lett., 41, doi:10.1002/2014GL059961, 2014. 8811

Jungclaus, J. H., Fischer, N., Haak, H., Lohmann, K., Marotzke, J., Matei, D., Mikolajewicz, U., Notz, D., and von Storch, J. S.: Characteristics of the ocean simulations in the Max Planck Institute Ocean Model (MPIOM) the ocean component of the MPI-Earth system model, J. Adv. Model. Earth Syst., 5, 422–446, doi:10.1002/jame.20023, 2013. 8827

Koenigk, T. and Mikolajewicz, U.: Seasonal to interannual climate predictability in mid and high northern latitudes in a global coupled model, Clim. Dynam., 32, 783–798, doi:10.1007/s00382-008-0419-1, 2009. 8813

Massonnet, F., Fichefet, T., and Goosse, H.: Prospects for improved seasonal Arctic sea ice predictions from multivariate data assimilation, Ocean Model., 88, 16–25, doi:10.1016/j.ocemod.2014.12.013, 2015. 8812

Merryfield, W. J., Lee, W.-S., Boer, G. J., Kharin, V. V., Scinocca, J. F., Flato, G. M., Ajayamohan, R. S., Fyfe, J. C., Tang, Y., and Polavarapu, S.: The Canadian Seasonal to Interannual Prediction System. Part I: Models and Initialization, Mon. Weather Rev., 141, 2910–2945, doi:10.1175/MWR-D-12-00216.1, 2013. 8827

Title Page

Abstract | Introduction

Conclusions | References

Tables | Figures

|◄ | ►|

◄ | ►

Back | Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

Msadek, R., Vecchi, G. A., Winton, M., and Gudgel, R. G.: Importance of initial conditions in seasonal predictions of Arctic sea ice extent, Geophys. Res. Lett., 41, doi:10.1002/2014GL060799, 2014. 8812

Notz, D., Haumann, F. A., Haak, H., Jungclaus, J. H., and Marotzke, J.: Arctic sea-ice evolution as modeled by Max Planck Institute for Meteorology's Earth system model, J. Adv. Model. Earth Syst., 5, 173–194, doi:10.1002/jame.20016, 2013. 8827

Peterson, K. A., Arribas, A., Hewitt, H. T., Keen, A. B., Lea, D. J., and McLaren, A. J.: Assessing the forecast skill of Arctic sea ice extent in the GloSea4 seasonal prediction system, Clim. Dynam., doi:10.1007/s00382-014-2190-9, 2014. 8811

Pohlmann, H., Botzet, M., Latif, M., Roesch, A., Wild, M., and Tschuck, P.: Estimating the decadal predictability of a coupled AOGCM, J. Climate, 17, 4463–4472, 2004. 8812

Rayner, N. A., Parker, D. E., Horton, E. B., Folland, C. K., Alexander, L. V., Rowell, D. P., Kent, E. C., and Kaplan, A.: Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century, J. Geophys. Res., 108, 4407, doi:10.1029/2002JD002670, 2003. 8830

Schröder, D., Feltham, D. L., Flocco, D., and Tsamados, M.: September Arctic sea-ice minimum predicted by spring melt-pond fraction, Nature Clim. Change, 4, 353–357, doi:10.1038/nclimate2203, 2014. 8812

Schweiger, A., Lindsay, R., Zhang, J., Steele, M., Stern, H., and Kwok, R.: Uncertainty in modeled Arctic sea ice volume, J. Geophys. Res., 116, C00D06, doi:10.1029/2011JC007084, 2011. 8831

Shaffrey, L. C., Stevens, I., Norton, W. A., Roberts, M. J., Vidale, P. L., Harle, J. D., Jrrar, A., Stevens, D. P., Woodage, M. J., Demory, M. E., Donners, J., Clark, D. B., Clayton, A., Cole, J. W., Wilson, S. S., Connolley, W. M., Davies, T. M., Iwi, A. M., Johns, T. C., King, J. C., New, A. L., Slingo, J. M., Slingo, A., Steenman-Clark, L., and Martin, G. M.: U.K. HiGEM: The New U.K. High-Resolution Global Environment Model–Model Description and Basic Evaluation, J. Climate, 22, 1861–1896, doi:10.1175/2008JCLI2508.1, 2009. 8827

Shi, W., Schaller, N., MacLeod, D., Palmer, T. N., and Weisheimer, A.: Impact of hindcast length on estimates of seasonal climate predictability, Geophys. Res. Lett., 42, 1554–1559, doi:10.1002/2014GL062829, 2015. 8812

Sidorenko, D., Rackow, T., Jung, T., Semmler, T., Barbi, D., Danilov, S., Dethloff, K., Dorn, W., Fieg, K., Goessling, H. F., Handorf, D., Harig, S., Hiller, W., Juricke, S., Losch, M., Schröter, J., Sein, D. V., and Wang, Q.: Towards multi-resolution global climate modeling with

ECHAM6–FESOM. Part I: model formulation and mean climate, Clim. Dynam., 44, 757–780, doi:10.1007/s00382-014-2290-6, 2014. 8827

Sigmond, M., Fyfe, J. C., Flato, G. M., Kharin, V. V., and Merryfield, W. J.: Seasonal forecast skill of Arctic sea ice area in a dynamical forecast system, Geophys. Res. Lett., 40, 529–534, doi:10.1002/grl.50129, 2013. 8811, 8816, 8827

Smith, D. M., Cusack, S., Colman, A. W., Folland, C. K., Harris, G. R., and Murphy, J. M.: Improved Surface Temperature Prediction for the Coming Decade from a Global Climate Model, Science, 317, 796–799, doi:10.1126/science.1139540, 2007. 8812

Stephenson, S. R., Smith, L. C., Brigham, L. W., and Agnew, J. A.: Projected 21st-century changes to Arctic marine access, Clim. Change, 118, 885–899, doi:10.1007/s10584-012-0685-0, 2013. 8811

Tietsche, S., Notz, D., Jungclaus, J. H., and Marotzke, J.: Predictability of large interannual Arctic sea-ice anomalies, Clim. Dynam., 41, 2511–2526, doi:10.1007/s00382-013-1698-8, 2013. 8813

Tietsche, S., Day, J. J., Guemas, V., Hurlin, W. J., E. Keeley, S. P., Matei, D., Msadek, R., Collins, M., and Hawkins, E.: Seasonal to interannual Arctic sea ice predictability in current global climate models, Geophys. Res. Lett., 41, 1035–1043, doi:10.1002/2013GL058755, 2014. 8813, 8816, 8819, 8833

Wang, W., Chen, M., and Kumar, A.: Seasonal Prediction of Arctic Sea Ice Extent from a Coupled Dynamical Forecast System, Mon. Weather Rev., 141, 1375–1394, doi:10.1175/MWR-D-12-00057.1, 2013. 8811

Watanabe, M., Suzuki, T., O'ishi, R., Komuro, Y., Watanabe, S., Emori, S., Takemura, T., Chikira, M., Ogura, T., Sekiguchi, M., Takata, K., Yamazaki, D., Yokohata, T., Nozawa, T., Hasumi, H., Tatebe, H., and Kimoto, M.: Improved Climate Simulation by MIROC5: Mean States, Variability, and Climate Sensitivity, J. Climate, 23, 6312–6335, doi:10.1175/2010JCLI3679.1, 2010. 8827

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

| Model | CTRL length | Forcing year | Start dates | Start months | Ensemble size | References |
|---|---|---|---|---|---|---|
| HadGEM1.2 | 249 | 1990 | 10 | Jan, May, Jul | 16 | Johns et al. (2006) Shaffrey et al. (2009) |
| MPI-ESM | 200 | 2005 | 12 (Jul), 16 (Nov) | Jul, Nov | 9 (Jul), 16 (Nov) | Notz et al. (2013) Jungclaus et al. (2013) |
| GFDL-CM3 | 200 | 1990 | 8 | Jan, Jul | 16 | Donner et al. (2011) Griffies et al. (2011) |
| EC-Earth2.2 | 200 | 2005 | 9 | Jul | 8 | Hazeleger et al. (2012) |
| MIROC5.2 | 100 | 2000 | 8 | Jan, Jul | 8 | updated from Watanabe et al. (2010) |
| E6F | 200 | 1990 | 18 | Jan, Jul | 9 | Sidorenko et al. (2014) |
| CanCM4 | 45 | transient (1970–2014) | 32 | Jan, Jul, | 10 | Sigmond et al. (2013) Merryfield et al. (2013) |
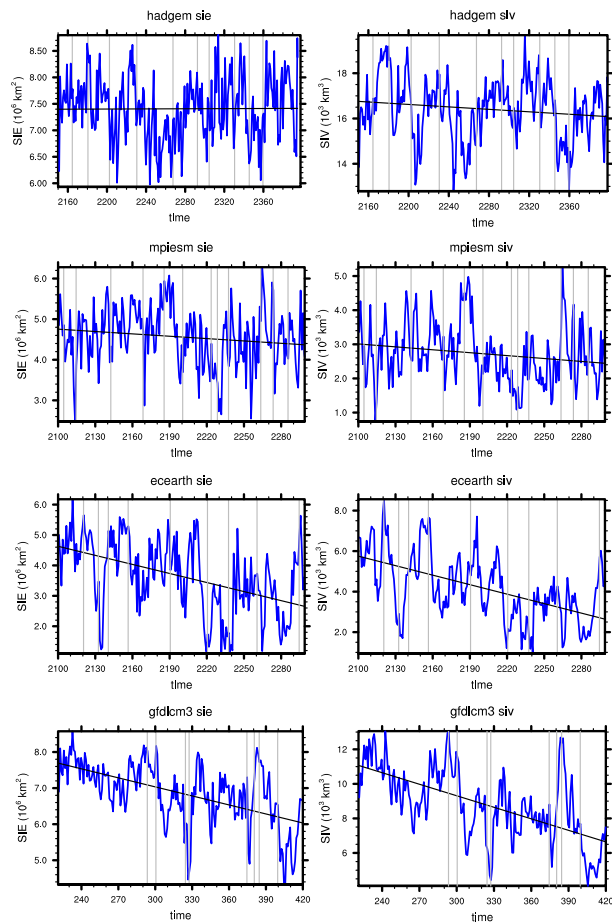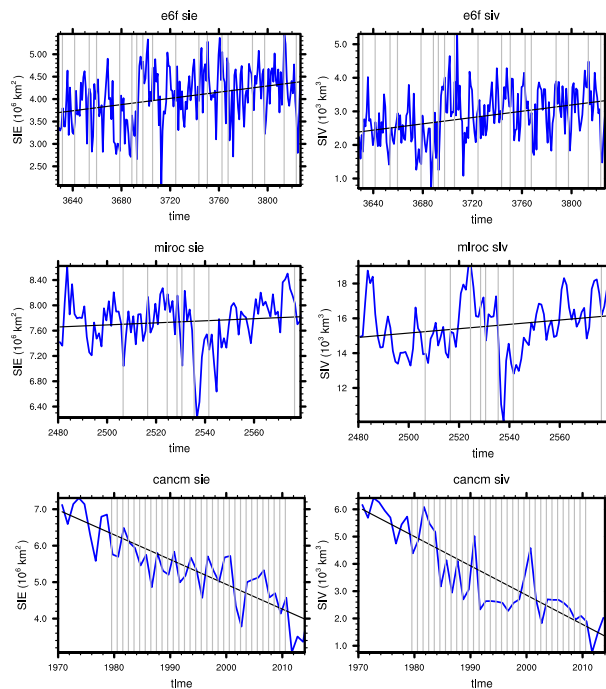
Figure 1.

**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.

Title Page

Abstract | Introduction

Conclusions | References

Tables | Figures

|◄ | ►|

◄ | ►

Back | Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion
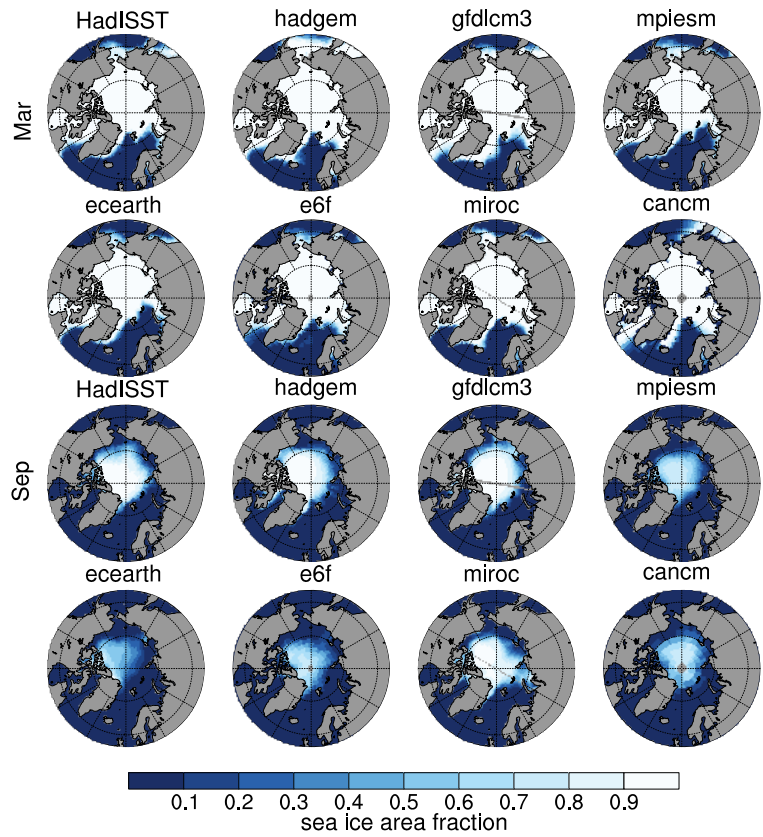
**Figure 2.** Average sea-ice concentration in present-day model control simulations and from HadISST (1983–2012) (Rayner et al., 2003).
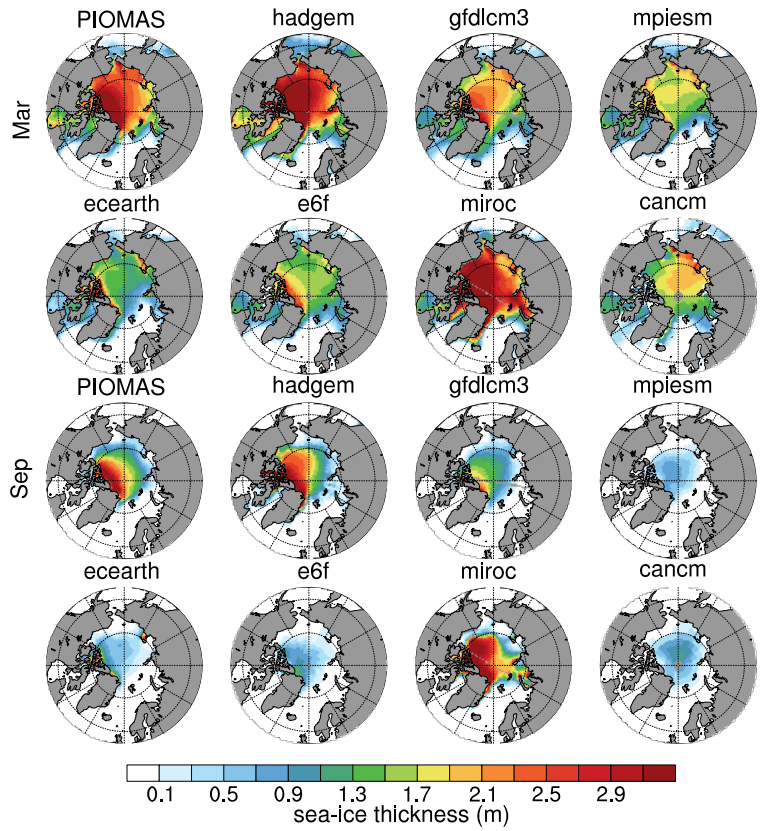
**Figure 3.** Average sea-ice thickness in present-day model control simulations and from PI-OMAS (1983–2012) (Schweiger et al., 2011).

Title Page

Abstract | Introduction

Conclusions | References

Tables | Figures

|◄ | ►|

◄ | ►

Back | Close
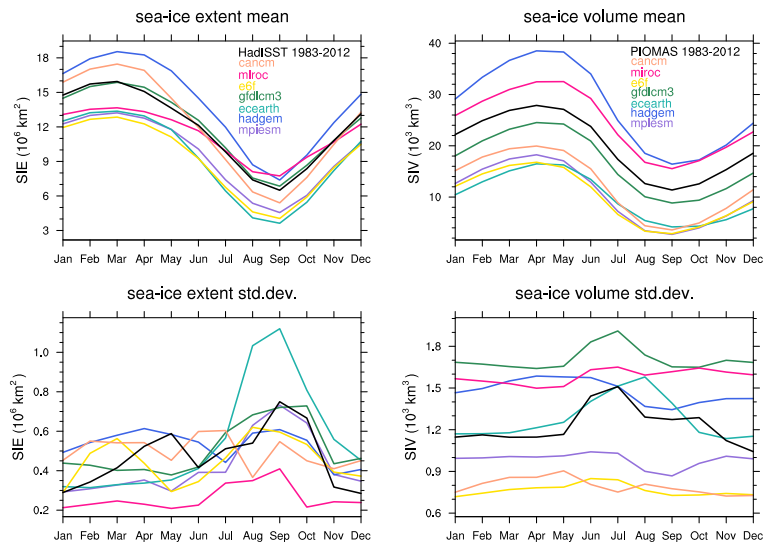
Full Screen / Esc

Printer-friendly Version

Interactive Discussion

**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.

Full Screen / Esc

Printer-friendly Version

Interactive Discussion
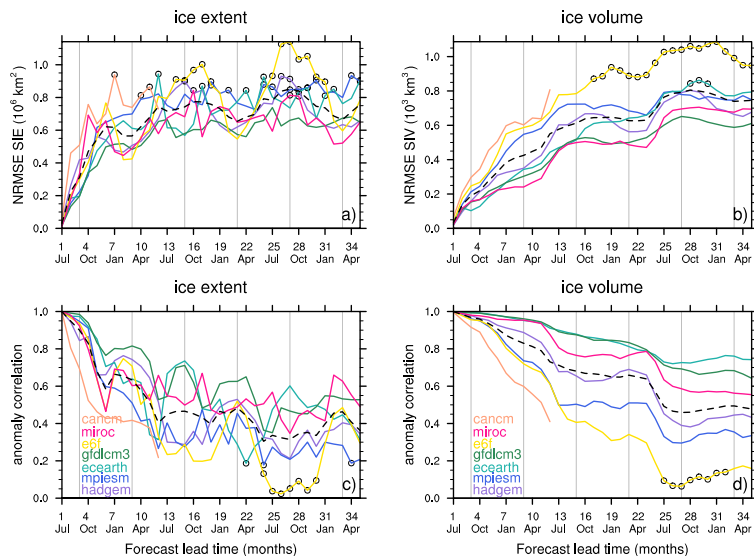
**Figure 5. (a)** and **(b)** Lead-time dependence of SIE NRMSE and SIV NRMSE for all models. **(c)** and **(d)** Lead-time dependence of SIE ACC and SIV ACC for all models. September and March are marked by thin gray vertical lines. Dashed lines represent the averages across models. Circles indicate where metrics do not indicate significant predictability (at 95 %). Updated from Tietsche et al. (2014).