Towards seasonal Arctic shipping route predictions

Melia, N., Haines, K. ORCID: https://orcid.org/0000-0003-2768-2374, Hawkins, E. ORCID: https://orcid.org/0000-0001-9477-3677 and Day, J. J. (2017) Towards seasonal Arctic shipping route predictions. Environmental Research Letters, 12 (8). ISSN 1748-9326 doi: https://doi.org/10.1088/1748-9326/aa7a60 Available at https://centaur.reading.ac.uk/71728/

It is advisable to refer to the publisher’s version if you intend to cite from the work. See Guidance on citing.
Published version at: https://doi.org/10.1088/1748-9326/aa7a60
To link to this article DOI: http://dx.doi.org/10.1088/1748-9326/aa7a60

Publisher: Institute of Physics

Publisher statement: Open Access

All outputs in CentAUR are protected by Intellectual Property Rights law, including copyright law. Copyright and IPR is retained by the creators or other copyright holders. Terms and conditions for use of this material are defined in the End User Agreement.

www.reading.ac.uk/centaur

CentAUR
Central Archive at the University of Reading
Towards seasonal Arctic shipping route predictions

This content has been downloaded from IOPscience. Please scroll down to see the full text.
2017 Environ. Res. Lett. 12 084005
(http://iopscience.iop.org/1748-9326/12/8/084005)
View the table of contents for this issue, or go to the journal homepage for more

Download details:

IP Address: 134.225.109.120
This content was downloaded on 14/08/2017 at 10:17

Please note that terms and conditions apply.

You may also be interested in:

Improved sub-seasonal meteorological forecast skill using weighted multi-model ensemble simulations
Niko Wanders and Eric F Wood

Skilful seasonal predictions of Baltic Sea ice cover
Alexey Yu Karpechko, K Andrew Peterson, Adam A Scaife et al.

Skillful seasonal predictions of winter precipitation over southern China
Bo Lu, Adam A Scaife, Nick Dunstone et al.

Predicting uncertainty in forecasts of weather and climate
T N Palmer

What is the current state of scientific knowledge with regard to seasonal and decadal forecasting?
Doug M Smith, Adam A Scaife and Ben P Kirtman

Singular vectors, predictability and ensemble forecasting for weather and climate
T N Palmer and Laure Zanna

Reliability of African climate prediction and attribution across timescales
Fraser C Lott, Margaret Gordon, Richard J Graham et al.

Demonstration of successful malaria forecasts for Botswana using an operational seasonal climate model
Dave A MacLeod, Anne Jones, Francesca Di Giuseppe et al.

Transit navigation through Northern Sea Route from satellite data and CMIP5 simulations
Vyacheslav C Khon, Igor I Mokhov and Vladimir A Semenov
Towards seasonal Arctic shipping route predictions

N Melia1,2,3, K Haines1, E Hawkins2 and J J Day2

1 National Centre for Earth Observation, Department of Meteorology, University of Reading, Reading, United Kingdom
2 NCAS-Climate, Department of Meteorology, University of Reading, Reading, United Kingdom
3 Author to whom any correspondence should be addressed. E-mail: nathanael.melia@reading.ac.uk

Keywords: seasonal forecasts, climate prediction, Arctic shipping, Arctic sea-ice, climate change impacts

Abstract

The continuing decline in Arctic sea-ice will likely lead to increased human activity and opportunities for shipping in the region, suggesting that seasonal predictions of route openings will become ever more important. Here we present results from a set of 'perfect model' experiments to assess the predictability characteristics of the opening of Arctic sea routes. We find skilful predictions of the upcoming summer shipping season can be made from as early as January, although typically forecasts show lower skill before a May 'predictability barrier'. We demonstrate that in forecasts started from January, predictions of route opening date are twice as uncertain as predicting the closing date and that the Arctic shipping season is becoming longer due to climate change, with later closing dates mostly responsible. We find that predictive skill is state dependent with predictions for high or low ice years exhibiting greater skill than medium ice years. Forecasting the fastest open water route through the Arctic is accurate to within 200 km when predicted from July, a six-fold increase in accuracy compared to forecasts initialised from the previous November, which are typically no better than climatology. Finally we find that initialisation of accurate summer sea-ice thickness information is crucial to obtain skilful forecasts, further motivating investment into sea-ice thickness observations, climate models, and assimilation systems.

1. Introduction

Satellite observations have revealed that Arctic sea-ice is in a state of rapid decline and global climate models unanimously project this decline to continue through the 21st century (Stroeve and Notz 2015). This decline has led to an increase in transit shipping through the Arctic Ocean (Melia 2016, Eguíluz et al 2016), with Arctic routes projected to open more frequently, for longer, (Smith and Stephenson 2013, Stephenson et al 2013) and become faster to traverse (Melia et al 2016). However models also indicate, as shown in IPCC AR5 (e.g. Collins et al (2013) figure 12.31), that considerable inter-annual variability in Arctic sea-ice, and therefore in Arctic sea route accessibility will remain throughout the century, even in summer, and that trans-Arctic routes will continue to close during the winter months. This suggests a growth in demand for seasonal forecasts of Arctic sea-ice as humans come into greater contact with an increasingly variable and mobile Arctic Ocean (Eicken 2013, Meier et al 2014, Stewart et al 2007). This need has motivated the development of initialised operational seasonal sea-ice prediction systems (e.g. Chevallier et al (2013), Sigmond et al (2013), Wang et al (2013), Peterson et al (2014), and the SEARCH Sea Ice Outlook, (Hamilton and Stroeve 2016)), and is a motivating factor behind the Year of Polar Prediction (YOPP) from mid-2017 to mid-2019 (Jung et al 2016).

To assess whether there is potential for skilful seasonal predictions of Arctic sea route openings we make use of the Arctic Predictability and Prediction on Seasonal-to-Interannual TimEscales (APPOSITE) dataset (Tietsche et al 2014, Day et al 2016) which follows an idealised 'perfect model' approach whereby initial-value ensemble-predictions are verified against the model itself rather than observations, inspired by earlier predictability studies by Griffies and Bryan (1997) and Collins et al (2006). Perfect model experiments do not suffer from model error because
the model is used to predict itself. Another key aspect of this experiment is the perfect knowledge of the initial state variables, which allows the importance of memory for individual variables to be quantified (Dunstone et al. 2011). Previous such studies focusing on Arctic sea-ice find an initialisation month dependence for predictability (Day et al. 2014b) and large forecast errors of sea-ice thickness (SIT) around the coasts (Tietsche et al. 2014, Goessling et al. 2016, Blanchard-Wrigglesworth et al. 2016) which may be especially relevant for predicting Arctic sea routes. Analysis of regional skill of Arctic sea-ice forecasts shows that Russia’s Northern Sea Route (NSR) and the Kara and Barents Sea are most predictable (Krikken et al. 2016).

For destination shipping in the Arctic, such as the resupply of fuel to Arctic communities before and after the winter freeze season (Brooks and Frost 2012), predicting the opening and closing of the season is also of vital importance; this was illustrated by a notable December 2016–January 2017 voyage along the NSR, when on the return leg a flotilla suddenly became stuck in thick sea-ice (The Siberian Times 2017).

The models and experiments used in this study are described in section 2. The effect of a changing climate on the predictability of season length is examined in section 3. Section 4 uses seasonal predictions calibrated with observations to examine the effect of forecast lead time on the paths predicted for the fastest open routes. This lead time dependence is further developed in section 5. Finally section 6 examines the impact of not initialising SIT information (mimicking a lack of SIT observations) to forecast skill. Section 7 is a summary and discussion.

2. Climate models used and experimental design

Three separate climate models are used to examine aspects of the seasonal predictability of opening Arctic sea routes (table 1, figure 1), based on the available APPOSITE model simulations (Day et al. 2016).

2.1. Climate models used

The CanCM4 model is used by the operational Canadian Sea Ice Prediction System (CanSIPS) (Sigmond et al. 2013, Merryfield et al. 2013). It is the only model used here which has both been run with estimated historical forcings, and has perfect model predictability experiments with ensemble start dates every year from 1979–2010. A warmer climate has been linked to increased variability of the Arctic summer sea-ice extent (Goosse et al. 2009); the CanCM4 transient climate simulations (section 3) provide an opportunity to directly assess changes to seasonal predictability between the earlier and later years (DeSole et al. 2014, Ehsan et al. 2013).

The Max Plank Institute’s Earth System Model (MPI-ESM-LR) (Notz et al. 2013, Jungclaus et al. 2013)
has a relatively realistic representation of present day Arctic sea-ice compared to many of the Coupled Model Intercomparison Project (CMIP) 3 and CMIP5 climate models (Stroeve et al 2014). We utilise a present-day control simulation of MPI-ESM-LR, and the simulations are further enhanced by applying a mean and variance bias correction (MAVRIC) based on a sea-ice thickness reanalysis, as detailed in Melia et al (2015). Krikken et al (2016) find that calibration techniques such as these reduce forecast errors and improve skill for operational systems. The resulting realistic ice distributions mean that this model can be used to test how predictions of the fastest open water routes through the Arctic vary with lead time.

The HadGEM1.2 model (Johns et al 2006, Shaffrey et al 2009) has the widest selection of winter, spring and summer initialisation dates and can therefore be used to examine the effect of lead time. We use these simulations to examine the effect of initialising SST information (Day et al 2014a). The model is similar to HadGEM1, the CMIP3 version of the UK Hadley Centre climate model, described in Johns et al (2006) and McLaren et al (2006). The mean sea-ice extent and volume in HadGEM1.2 is biased high compared to observations during the satellite era, however multimodel predictability studies indicate that the ice extent and volume predictability is fairly typical of other models (Tietsche et al 2014).

2.2. Truth simulations and ensemble initialisation

To diagnose the predictability of sea route openings in MPI-ESM-LR and HadGEM1.2 a suite of ensemble predictions were utilised. ‘Truth’ simulations were defined from a number of well-spaced start dates throughout the length of the control simulation (all with ‘present-day’ radiative forcings defined in table 1). In order to sample different sea-ice conditions, start dates were chosen to sample a range of high, medium, and low summer sea-ice extent and volume states, see Tietsche et al (2014). For each of these years a multi-member ensemble is initialised from several different months prior to the sea-ice minimum. Initial conditions for the ensemble generation are taken from the control simulation at each date, along with a spatially varying Gaussian white noise perturbation to the sea surface temperatures (with a standard deviation, \(\sigma < 10^{-4}\) K) for each ensemble member (Day et al 2016). The difference in the evolution of each ensemble member is solely determined by the chaotic nature of the simulated climate system. With CanCM4, experiments were initialised from a transient simulation with historical radiative forcings (see section 3 for more details).

2.3. Sea routes

Typically Arctic predictability experiments attempt to predict metrics such as sea-ice extent and volume. However, for shipping routes, ice presence and thickness along specific routes through the Arctic Ocean are of primary importance. In most of the analyses (sections 3, 5, and 6) we define a set of six fixed routes for both the NSR off Russia’s northern coast and for the North West Passages (NWP) through the Canadian Archipelago (see Melia et al (2016) and supplementary information) and examine whether any of them are navigable in the simulations. To examine the effect of forecast lead time on route selection (section 4) an explicit ‘fastest-route algorithm’ from Melia et al (2016) is used. Two vessel classes are considered. Standard open water (OW) vessels which can navigate through 0.15 m thick sea-ice (sections 3 and 4), and Polar Class 6 (PC6) vessels which can navigate through 1.2 m thick sea-ice (sections 5 and 6) (Transport Canada 1998). Route navigability is binary (i.e. a route is either open or closed), so different vessel classes will give quantitatively different values, however the qualitative predictability characteristics and trends investigated are robust.

3. Season length and predictability in a transient climate

In CanCM4 the historical simulation uses all forcings (greenhouse gases, aerosols, volcanic eruptions etc.) and ‘perfect’ predictions are initialised from January of each year from 1979–2010, with ten ensemble members. Here we focus on the predictability of OW conditions for the NSR passages. CanCM4 has a low mean sea-ice bias, and therefore NSR openness is more analogous to mid-21st century high-emission conditions, based on the bias corrected GCM simulations in Melia et al (2015).

The initialised simulations illustrated in figure 2 show a 54% lengthening of the shipping season from 104 to 160 d over the 32 years, on average resulting from earlier openings and later closing dates increasing the season length by 1.7 d per year. The later closing of the season accounts for 60% of this trend and the earlier opening accounts for 40%. The ensemble forecast range in season length is from 0 d to 180 d, with a mean length of 130 d, and a standard deviation of 38 d, showing that interannual variability is far larger than the forced signal. It is precisely because of this high inter-annual variance that there is such a pressing need for dynamic Arctic seasonal predictions.

The high variance in open season length exhibited in figure 2, suggests that predictability from January is low. For all years at least one January ensemble member predicts an ice-free NSR as early as June; however, in five of the years some members show an entirely closed NSR for OW vessels. The ensemble standard deviation for predicting the opening dates is 26 d, double the 13 d for predicting the closing date.

4 The southernmost NSR versions pass through the Sannikov and Dmitry Laptev Straits which have shallow bathymetry (drafts of 13 and 6.7 m) which limits their use for larger ships (Buixadé Farré et al 2014).
This is due to the larger variability in climatological SIT for all simulations along the NSR for opening dates compared to closing dates (see supplementary information available at stacks.iop.org/ERL/12/084005/mmedia). These findings are supported by Sigmond et al. (2016) by using sea-ice concentration data to attribute the low skill of sea-ice retreat forecasts (opening dates) to the variable persistence of initial sea-ice anomalies, whereas the sea-ice advance forecasts (closing dates) benefit from the more predictable in ocean temperature variability, which is the dominant mechanism in determining the sea-ice growth season. However it is clear that while the longer term changes to the season length, driven by external forcings, are predictable, predicting the NSR opening date for any particular year, at least from January, is more challenging.

4. Present day predictability and route selection

The MPI-ESM-LR simulations with the MAVRIC sea-ice calibration allow for a 'close to real world' assessment of forecast optimum routes from different lead times using 12 years of ensemble predictions. As the predictions have a binary outcome (open/closed route) we define a 'skilful forecast' here as exhibiting a Brier Skill Score (BSS) of greater than zero (Wilks 1995, Hamill and Juras 2006). The BSS compares the ensemble probability forecast with the climatological probability. A score of one is returned if all ensemble members perfectly match the 'truth', zero indicates that the forecast performs equivalent to the climatology, scores less than zero indicate a performance worse than climatology, or a 'forecast bust'. The BSS is a hard test to score as skilful as a lot of emphasis is placed on correct timings, and a negative BSS can often hide useful information within the forecast ensembles (Mason 2004); for example a predictions that forecasts a short season length (a few weeks), but misplaces the timing of the season could be ascribed a negative BSS. The timeseries panels of figure 3 show the probability (fraction of ensemble members) that routes are open to OW vessels on the NSR. By eye, it is clear that the blue (July) probabilities are generally much closer to the grey shading ('truth') than the pink (November) probabilities. The July initialised forecasts show greater than climatological skill in 10 out of 12 years, twice as many as forecasts from the previous November (which have equivalent to climatological skill).

The forecast skill is state dependent. For high ice years where the deterministic control simulation or 'truth' is entirely closed (years: 2104, 2185, 2223, 2263 and 2273) the July forecasts show high levels of skill with an average BSS of 0.89, while the November forecasts exhibit positive skill in only three of these years. For median ice conditions (years: 2114, 2142, 2168 and 2285) route opening skill is the most difficult to predict, showing no average skill from either July (BSS = −0.01) or November forecasts. In particular, year 2285 forecasts are a 'bust', highlighting the
potential for unpredictable weather to reduce forecast skill. For low ice years showing extended open conditions (years: 2200, 2228, 2237), the July forecasts have an average BSS = 0.75 while the November forecasts show no skill.

In addition to the binary open/closed metric we also examine the effect of decreasing forecast lead time on the path of the optimum (fastest) predicted route, following the method developed in Melia et al (2016). We select the mid-season date of September 15th to characterise the season peak for the most open years (2200, 2228, and 2237); where all ensemble members from the July forecasts are open, while half the forecasts from November are closed. We define the ‘forecast route deviation’ as the mean spatial distance of the forecast routes from the true optimal September 15th route. For routes starting from European ports the forecast route deviation initialised from November is on average 1098 km based on utilising both the NWP and the NSR (using only ensemble members that are open), while the July forecasts all remain confined to the NSR and show a far tighter spatial grouping, with route deviations of only 195 km, a six-fold improvement over November forecasts. For routes starting from North American ports, via the NWP, variations arise from whether the shorter ‘northern NWP’ via the M’Clure strait is open or if the longer and less ice prone ‘southern NWP’ is required. The NWP route opening is more sensitive as ice present at a few key grid cells in the Canadian Archipelago can completely shut the route forcing a re-routing via the NSR. The open NWP routes from the November forecasts show a deviation of 686 km; by July this error has reduced to 253 km, approximately a three-fold improvement.

The MPI-ESM-LR simulations show significant improvement in forecast skill for route openness and route accuracy when predictions are made from July compared to the previous November. At eight months apart however initial sea-ice states are very different and it is desirable to test predictions from intermediate lead times. These are examined in the following section with HadGEM1.2, where ensembles are available from January, May and July initialisation dates.
5. Predictability lead time barriers

Fundamental time limits to predictive skill are expected in the climate system due to the non-linear chaotic nature of the governing physics (Lorenz 1963). For example, Collins et al (2002) find a spring predictability barrier for perfect model predictions of El Niño, which is also seen in real-world predictions. Experiments by Day et al (2014b) also find Arctic sea-ice area and volume predictions initialised on or before May 1st often show little skill, and are not statistically different from predictions made from as early as January and which are only marginally better than climatology. Route openings need not follow the same pattern as these pan-Arctic results so we use these same simulations to examine the lead time skill dependence of predicting the opening of the NSR. HadGEM1.2 has a high SIT climatological bias (figure 1) and the NSR never becomes ice-free, so we examine the prospects for Polar Class 6 (PC6) vessels, which can break through up to 1.2 m of ice, instead of OW vessels, on the NSR.

Figure 4 shows that predictions made from July are on average better than from either May or January initialisations. The bottom right image in figure 4 collects the BSS statistics for each year and finds a median BSS for January = 0.44, May = 0.31 and July = 0.71. The BSS from May are no better than from January, despite the lower lead time, supporting the presence of a predictability barrier around May, before which skillful forecasts are problematic.

However, as in the MPI-ESM-LR predictions in section 4, we find that skill is state dependent, and this dependency extends to the predictability barrier as well. In figure 4 high ice conditions resulting in closed routes (years: 2180, 2230, 2292 and 2330) are more predictable, with July BSS > 0.95 and predictability as far in advance as January with mean BSS > 0.6, indicating that no strong predictability barrier is present. Caution is still required, evident for example in the forecast bust of May 2230 (BSS —0.6). Low ice conditions resulting in largely open routes in figure 4 (years: 2202, 2267 and 2359) show more strongly increasing predictability with decreasing forecast lead time. Year 2202 shows a dramatic improvement from the July predictions compared to May and January, which do no better than climatology. However for years 2267 and 2359 the May and January predictions still have some skill, which further improves by July. Medium or marginal ice conditions with short open route periods (years: 2164, 2304 and 2345) actually have decreased skill with shorter lead times because the predictions struggle to capture the timing of the short open route windows. At shorter lead times the forecasts do capture more of these short route openings but still miss the timing, thus the season average difference between the forecast and the truth becomes greater and is penalised by the strict BSS.

6. Initialising sea-ice thickness

Previous studies have shown that sea-ice thickness initialisation is an important requirement for predictions of summer sea-ice extent (Guemas et al 2016, Collow et al 2015, Day et al 2014a); however, observations of SIT during the melt season are more challenging than for sea-ice concentration and hence their assimilation into seasonal forecast systems is problematic. In this section we investigate their importance for shipping route forecasts by examining
the effect of resetting SIT initial conditions to climatological values in forecast simulations, following (Day et al. 2014a).

We use the same HadGEM1.2 years studied in section 5 with only the January and July ensemble start dates, and compare two parallel sets of simulations which are initialised with (i) true SIT (as above) and (ii) climatological SIT initial conditions, leaving the concentrations practically unchanged (further details are given in Day et al. (2014a)). The ‘SIT-initialised’ simulations are hereafter referred to as SITINIT, and the climatological (SITCLIM) experiment is analogous to having no SIT observations in an operational prediction system; similar to the current operational forecast situation in summer where sea-ice concentration is known, but SIT is not. The Climate Forecast System Reanalysis (CFSR) handles this by relaxing the model SIT field to that of the Pan-Arctic Ice Ocean Modelling and Assimilation System (PIOMAS) (Collow et al. 2015).

The median BSS (figure 5, bottom right panel) are, for January initialisations SITCLIM = 0.18, SITINIT = 0.44, and July initialisations, SITCLIM = −0.45, SITINIT = 0.71. The addition of the initialised SIT information for the January predictions leads to an increase of the BSS compared to using climatological SIT data. It follows that some of the skill available in January is attributed to SIT initialisation and the remainder from other sources e.g. ocean heat content (Guemas et al. 2016).

For the July initialisations the effect of removing the SIT information is larger than in the January initialisations, with the median July BSS becoming worse than both the January initialisations and climatology. Low ice conditions resulting in open routes (figure 5, years: 2202, 2267, and 2359) generally show similar SITCLIM predictions to SITINIT; medium or marginal ice conditions resulting in short windows of open routes (figure 5, years: 2164, 2304 and 2345) also show similar behaviour. However, high ice conditions resulting in closed routes (figure 5, years: 2180, 2230, 2292 and 2330) for July SITCLIM are forecast ‘busts’ with a mean BSS of −1.47 compared to July SITINIT BSS of 0.98. The source of the July busts is the relatively short time for SITCLIM conditions to recover to SITINIT conditions, compounded by the dominance of positive feedbacks on sea-ice evolution in the melt season helping to maintain or grow the SITCLIM anomalies (see supplementary information).

The January SITCLIM simulations exhibit better BSS than the July SITCLIM simulations. This is partly due to the larger SITCLIM anomaly recovery time from January than from July. Additionally, during the freeze season, negative feedbacks dominate the sea-ice evolution, largely due to an ice growth-thickness relationship (thin ice grows faster than thick ice e.g. Bitz and Roe (2004) and Tietsche et al. (2011)), which acts to reduce the SITCLIM perturbation to the SITINIT conditions (see supplementary information), a phenomenon not present following the July initialisations.

7. Discussion

We have examined the predictability of Arctic sea route accessibility in a range of idealised ‘perfect model’ simulations using several different climate models, taking advantage of the available ensemble runs.
The analysis of seasonal sea-ice predictions in a transient climate using estimated historical forcings in the CanCM4 model (figure 2) shows the shipping season extending, with later closing dates contributing most to this extension, but still with substantial variability from year-to-year. Predictions for the opening date of shipping routes in any given year are less accurate than predicting the closing dates due to greater climatological variability in the melt season (see supplementary information).

Forecasting from July in the MPI-ESM-LR model (figure 3), the ice conditions in mid-September are well enough predicted for the optimum route to be identified with a position error of only 195 km, a six-fold improvement over forecasts from the previous November which show equivalent skill to climatology. This is accurate enough to be able to predict which straits on the NSR or NWP are most likely to be available for routing. This has important logistical planning implications as many of these channels have draft restrictions, and foreknowledge may help inform on vessel size limits and whether ice-breaker escort will be required. Since applications for sailing the NSR are needed several weeks to months in advance this July information, available at least two months ahead of likely crossing, is potentially operationally useful (Arctic Logistics Information Office 2016).

Regulations for the NSR, such as vessel class restrictions, are adapted according to heavy, medium, or light ice years. We find that predictive skill is fundamentally correlated with these operational conditions which could enhance guidance for the upcoming season. High ice years, leading to completely closed routes, possess the most predictability, and can generally be skilfully identified as far in advance as January. Skilful forecasts are also possible for low ice years, resulting in open route forecasts also as far in advance as January, although these predictions typically exhibit less skill than in high ice years. However, predictions for median ice years with marginal accessibility show little to no skill in identifying the timing of the short accessibility periods, even when forecasts are initialised from July conditions; however, alternative skill metrics may be able to reveal useful information, about the season length for example, within these forecasts (Mason 2004). With respect to operational shipping considerations, the state dependent predictability configuration is valuable since higher confidence can be ascribed early on to pivotal ‘go/no-go’ decisions, but lower confidence will be apparent with a split ensemble when conditions are likely to be marginal and caution would likely be applied regardless. However, there are still likely to be forecast ‘busts’ in some years due to unpredictable weather conditions.

The HadGEM1.2 model suggests that May sometimes presents a predictability threshold, after which predictive skill increases; although skilful forecasts are possible before May, particularly for high ice conditions (figure 4). Generally we find that there is no forecast improvement in the four months from January to May, with forecast skill then rapidly increasing from May 1st to July 1st. Simulations with HadGEM1.2 that replace initial sea-ice thickness (SIT) with climatological values (Day et al 2014a) provide insight into the performance limitations for sea route predictions due to the lack of summer SIT observations, which up to now have not been available beyond May (Tilling et al 2016), which coincides with this crucial time for seasonal sea-ice forecasts. Seasonal route predictions with initialised SIT information in this period show that skilful predictions of sea route openings are possible for approximately 70% of years (figure 5), but positive feedbacks present during the melt season, combined with only climatological SIT information, dramatically reduce forecast skill, showing the high sensitivity to the SIT information used to initialise summer sea-ice forecasts. During this melt period sea-ice mobility increases and hence the role of the atmosphere becomes more important. Experiments that assimilate additional radiosonde data into a forecasting system, by Inoue et al (2015) using the Earth Simulator (Ohfuchi et al 2004), and Ono et al (2016) using a mesoscale eddy-resolving ice-ocean coupled model (that explicitly treats ice floe collisions in marginal ice zones) (De Silva et al 2015), drastically improve sea-ice forecasts for the NSR region.

All these results are based upon perfect model simulations and as such illustrate the potential predictability available within operational systems (Hawkins et al 2015, Serreze and Stroeve 2015, Shi et al 2015, Eade et al 2014). Future work into seasonal Arctic shipping forecasts should focus on analysis of operational prediction hindcast products, such as the CanSIPS (Sigmond et al 2013) and the UK Met Office’s GloSea5 system (MacLachlan et al 2015), as these will provide a direct measure of operational predictability.

Our findings indicate that seasonal predictions for Arctic sea routes are potentially possible. Acquiring this foresight will be of vital importance to increasing Arctic operations, considering that operating in the hostile polar environment requires months of preplanning. Although operational seasonal predictions for the Arctic region are still an emerging field of climate science, results presented here quantify their potential, reinforcing the call for continued investment into improving models and further developing Arctic observation networks so that the potential seasonal forecast skill demonstrated here can be realised.

Acknowledgments

We thank the anonymous reviewers and the editor for their guidance. N Melia, E Hawkins, and J Day are supported by the APPOSITE project (grant NE/I029447/1), funded by the UK Natural Environment
Research Council (NERC) as part of the Arctic Research Programme. N Melia is also supported by the ERGODICS project (grant NE/J005894/1), funded by NERC, as part of the Next Generation Weather and Climate Prediction Programme. E Hawkins is also funded by a NERC Fellowship and the National Centre for Atmospheric Science. J Day is also funded by an AXA Fellowship. K Haines is partly funded by the National Centre for Earth Observation. The authors declare no competing financial interests. The data used are listed in Table 1 of this paper and techniques developed in Melia et al. (2015, 2016). We acknowledge the World Climate Research Programme’s Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modelling groups for producing and making available their model output. For CMIP the US Department of Energy’s Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals.

ORCID

N Melia @ https://orcid.org/0000-0003-1138-7776

References

Arctic Logistics Information Office 2016 Northern sea route information office legislation (Center for High North Logistics) (www.arctic-log.info/en_legislation)

Bitz C M and Roe G H 2004 A mechanism for the high rate of sea-ice thinning in the Arctic Ocean J. Clim. 17 3623–32

Blanchard-Wrigglesworth E et al 2016 Multi-model seasonal forecast of Arctic sea-ice: forecast uncertainty at pan-Arctic and regional scales Clim. Dyn. accepted (https://doi.org/10.1007/s00382-016-3588-9)

Brooks M R and Frost J D 2012 Providing freight services to remote Arctic communities: are there lessons for practitioners from services to Greenland and Canada’s northeast? Res. Trans. Bus. Manage. 4 69–78

Buixadé Farré A et al 2014 Commercial Arctic shipping through the Northeast Passage: routes, resources, governance, technology, and infrastructure Polar Geogr. 37 298–324

Chevallier M, Salas y Melía D, Voldoire A, Déqué M and Garric G 2013 Seasonal forecasts of the Pan-Arctic sea-ice extent using a GCM-based seasonal prediction system J. Clim. 26 6092–104

Collins M et al 2006 Interannual to decadal climate predictability in the north atlantic: a multimodel-ensemble study J. Clim. 19 1195–203

Collins M, Frame D, Sinha B and Wilson C 2002 How far ahead could we predict El Niño? Geophys. Res. Lett. 29 130–1–4

Collins M et al 2013 Climate change 2013: the physical science basis Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change T F Stocker et al (Cambridge: Cambridge University Press) pp 1029–136

Collow T W, Wang W, Kumar A and Zhang J 2013 Improving Arctic sea-ice prediction using PIOMAS initial sea-ice thickness in a coupled ocean–atmosphere model Mon. Weather Rev. 141 4618–30

Day J J, Hawkins E and Tietzche S 2014a Will Arctic sea-ice thickness initialization improve seasonal forecast skill? Geophys. Res. Lett. 41 7566–75

Day J J, Hawkins E and Tietzche S 2015 Dataset: Collection of Multi-model Data from the Arctic Predictability and Prediction on Seasonal-to-Interannual Time-scales (APPOSITE) Project (NCAS British Atmospheric Data Centre)

Day J J et al 2016 The Arctic predictability and prediction on seasonal-to-interannual timescales (APPOSITE) data set version 1 Geosci. Model Dev. 9 2255–70

Day J J, Tietzche S and Hawkins E 2014b Pan-Arctic and regional sea-ice predictability: initialization month dependence J. Clim. 27 4371–90

De Silva I W A, Yamaguchi H and Ono J 2015 Ice–ocean coupled computations for sea-ice prediction to support ice navigation in Arctic sea routes Polar Res. 34 23008

DeSole T, Yan X, Dirmeyer P A, Fennessy M and Althouser E 2014 Changes in seasonal predictability due to global warming J. Clim. 27 300–11

Dunstone N J, Smith D M and Eade R 2011 Multi-year predictability of the tropical Atlantic atmosphere driven by the high latitude North Atlantic Ocean Geophys. Res. Lett. 38 L14701

Eade R, Smith D, Scaife A, Wallace E, Dunstone N, Hermanson L and Robinson N 2014 Do seasonal-to-decadal climate predictions underestimate the predictability of the real world? Geophys. Res. Lett. 41 5620–8

Eguituz V M, Fernández-Gracia J, Irigasen X and Duarte C M 2016 A quantitative assessment of Arctic shipping in 2010–2014 Sci. Rep. 6 30682

Ehsan M A, Kang I-S, Almazroui M, Abid M A and Kucharski F 2013 A quantitative assessment of changes in seasonal potential predictability for the twentieth century Clim. Dyn. 41 2697–709

Eicken H 2013 Ocean science: Arctic sea-ice needs better forecasts Nature 497 431–3

Goessling H F, Tietzche S, Day J J, Hawkins E and Jung T 2016 Predictability of the Arctic sea-ice edge Geophys. Res. Lett. 43 1642–50

Goosse H, Arzel O, Bitz C M, deMontety A and Vancoppenolle M 2009 Increased variability of the Arctic summer ice extent in a warmer climate Geophys. Res. Lett. 36 L23702

Griffies S M and Bryan K 1997 Predictability of North Atlantic multidecadal climate variability Science 275 181–4

Guemas V, Chevallier M, Déqué M, Bellprat O and Doblas-Reyes F 2016 Impact of sea-ice initialization on sea-ice and atmosphere prediction skill on seasonal timescales Geophys. Res. Lett. 43 3889–96

Hamill T M and Juras J 2006 Measuring forecast skill; is it real skill or is it the varying climatology? Q. J. R. Meteorol. Soc. 132 2905–23

Hamilton L C and Stroeve J 2016 400 Predictions: the SEARCH sea ice outlook 2008–2015 Polar Geogr. 39 274–87

Hawkins E, Tietzche S, Day J J, Melia N, Haines K and Keeley S 2015 Aspects of designing and evaluating seasonal-to-interannual Arctic sea-ice prediction systems Q. J. R. Meteorol. Soc. 142 672–83

Inoue J, Yamazaki A, Ono J, Dethloff K, Maturilli M, Neuber R, Jungclaus J H, Fischer N, Haak H, Lohmann K, Matei Matei D, Nikolajewicz U, Notz D and von Storch J S 2013 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 Sys. 5 422–46

Kirkken F, Schmets M, Vlot W, Guesnas V and Hazeleger W 2016 Skill improvement of dynamical seasonal Arctic sea-ice forecasts Geophys. Res. Lett. 43 5124–32


Shaffrey L C et al 2015 Arctic sea-ice trends, variability and implications for seasonal ice forecasting Phil. Trans. R. Soc. A 373 20140159
Shaffrey L C et al 2009 UK HiGEM: the new UK high-resolution global environment model—model description and basic evaluation J. Clim. 22 1861–96
Shi W, Schaller N, MacLeod D, Palmer T N and Weisheimer A 2015 Impact of hindcast length on estimates of seasonal climate predictability Geophys. Res. Lett. 42 1534–9
Sigmond M, Fyle J C, Flato G M, Kharin V V and Merryfield W J 2013 Seasonal forecast skill of Arctic sea-ice area in a dynamical forecast system Geophys. Res. Lett. 40 529–34
Sigmond M, Reader M C, Flato G M, Merryfield W J and Tivy A 2016 Skillful seasonal forecasts of Arctic sea-ice retreat and advance dates in a dynamical forecast system Geophys. Res. Lett. 43 12457–65
Smith L C and Stephenson S R 2013 New Trans-Arctic shipping routes navigable by midcentury Proc. Natl Acad. Sci. USA 110 E1193–E5
Stephenson S R, Smith L C, Brigham L W and Agnew J A 2013 Projected 21st-century changes to Arctic marine access Clim. Change 118 885–99
Stewart E J, Howell S E L, Draper D, Yackel J and Tivy A 2007 Sea-ice in Canada’s Arctic: implications for cruise tourism Arctic 60 370–80
Stroeve J, Barrett A, Serreze M and Schweiger A 2014 Using records from submarine, aircraft and satellite to evaluate climate model simulations of Arctic sea-ice thickness Cryosphere 8 1839–45
Stroeve J and Notz D 2015 Insights on past and future sea-ice evolution from combining observations and models Glob. Planet. Change 135 119–32
The Siberian Times 2017 Icebreakers make historic Arctic voyage, then get stuck in frozen sea on return journey (17 January 2017)
Tietse S, Day J I, Guemas V, Hurlin W J, Keeley S P E, Matei D, Msadek R, Collins M and Hawkins E 2014 Seasonal to interannual Arctic sea-ice predictability in current global climate models Geophys. Res. Lett. 41 1035–43
Tietse S, Notz D, Jungclaus J H and Marotzke J 2011 Recovery mechanisms of Arctic summer sea-ice Geophys. Res. Lett. 38 L02707
Tilling R L, Ridout A and Shepherd A 2016 Near-real-time Arctic sea-ice thickness and volume from CryoSat-2 Cryosphere 10 2003–12
Transport Canada 1998 Arctic Ice Regime Shipping System (AIRSS) Standards Transport Publication 12259 E
Wang W, Chen M and Kumar A 2013 Seasonal prediction of Arctic sea-ice extent from a coupled dynamical forecast system Mon. Weather Rev. 141 1375–94
Wilks D S 1995 Statistical Methods in the Atmospheric Sciences vol 59 (Cambridge, MA: Academic)
Zhang I and Rothrock D 2003 Modeling global sea-ice with a thickness and enthalpy distribution model in generalized curvilinear coordinates Mon. Weather Rev. 131 845–61