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Towards seasonal Arctic shipping route predictions

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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

Table 1. Details of the simulations.

Model[a]	Control years	Forcing as year	Start dates	Initialisation months	Ensemble size	Arctic Ocean resolution
CanCM4	32	1979–2010	32	January	10	≈14 km
MPI-ESM-LR	200	2005	12	November, July	9	≈12 km
HadGEM1.2	249	1990	10	January, May, July	16	≈12 km

[a]The APPOSITE model dataset is described by Day *et al* (2016) and is available at Day *et al* (2015).
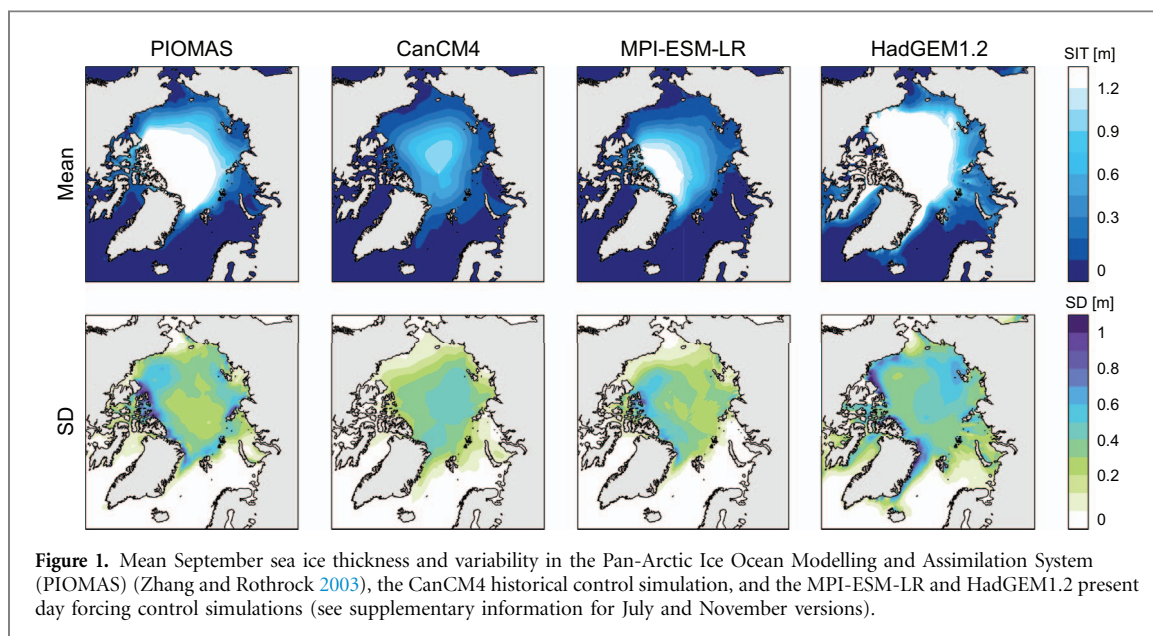

Figure 1. Mean September sea ice thickness and variability in the Pan-Arctic Ice Ocean Modelling and Assimilation System (PIOMAS) (Zhang and Rothrock 2003), the CanCM4 historical control simulation, and the MPI-ESM-LR and HadGEM1.2 present day forcing control simulations (see supplementary information for July and November versions).

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 (DelSole *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 SIT 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 multi-model 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[4]. 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.
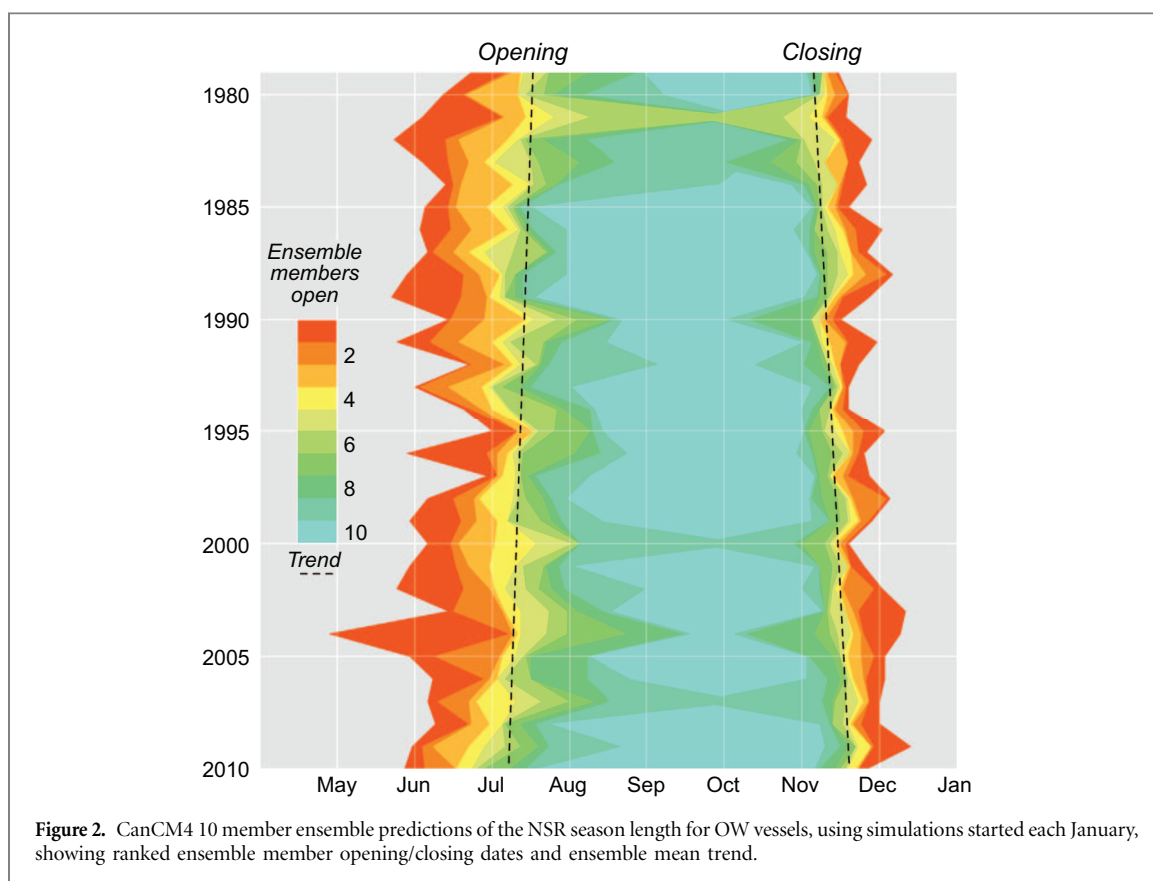
3. Season length and predictability in a transient climate

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.

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[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).

Figure 2. CanCM4 10 member ensemble predictions of the NSR season length for OW vessels, using simulations started each January, showing ranked ensemble member opening/closing dates and ensemble mean trend.
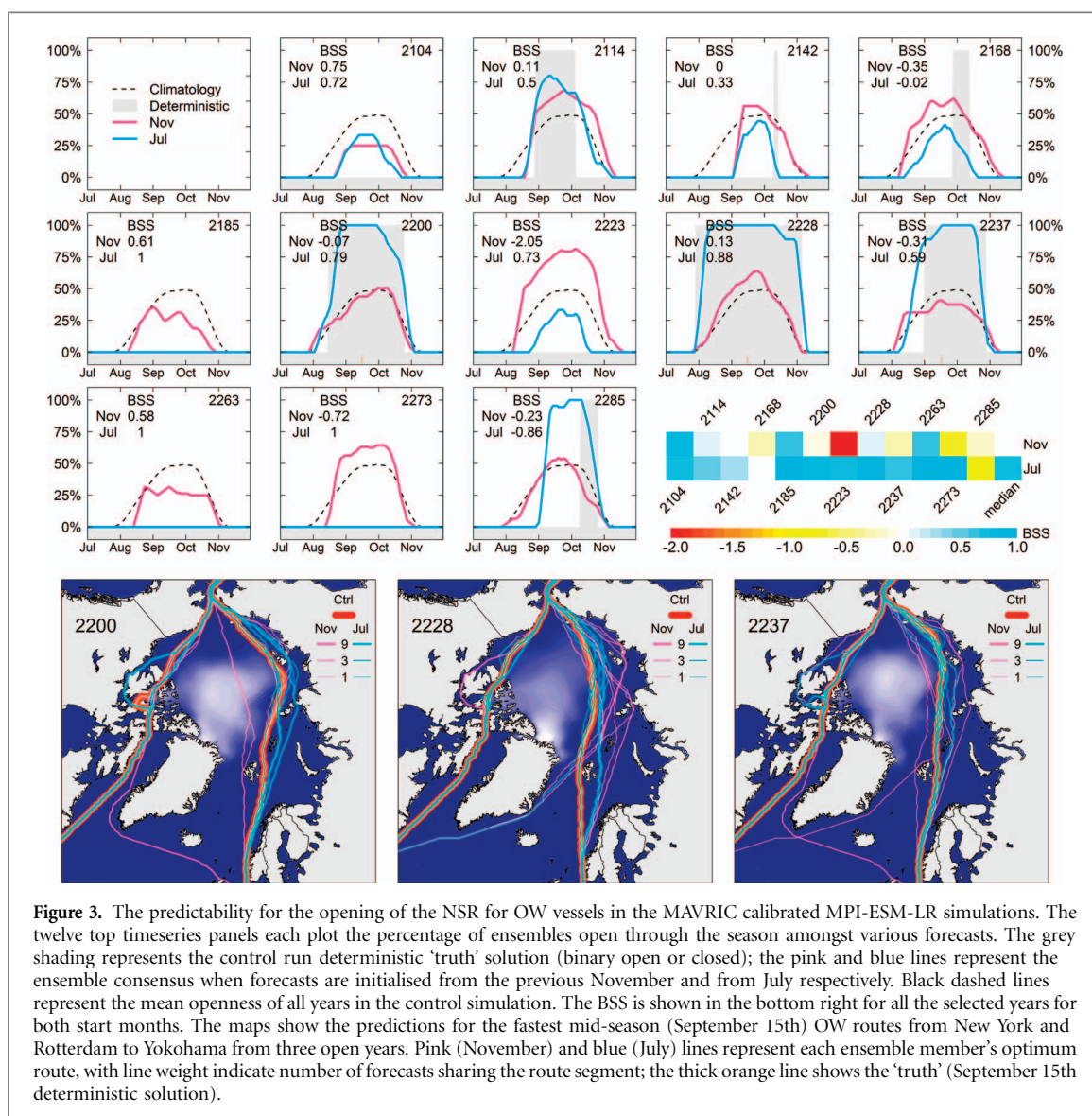
This is due to the larger variability in climatological SIT for all simulations along the NSR for opening dates compared to closing dates (see supplementary information available at stacks.iop.org/ERL/12/084005/mmedia). These findings are supported by Sigmond *et al* (2016) by using sea-ice concentration 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

Figure 3. The predictability for the opening of the NSR for OW vessels in the MAVRIC calibrated MPI-ESM-LR simulations. The twelve top timeseries panels each plot the percentage of ensembles open through the season amongst various forecasts. The grey shading represents the control run deterministic 'truth' solution (binary open or closed); the pink and blue lines represent the ensemble consensus when forecasts are initialised from the previous November and from July respectively. Black dashed lines represent the mean openness of all years in the control simulation. The BSS is shown in the bottom right for all the selected years for both start months. The maps show the predictions for the fastest mid-season (September 15th) OW routes from New York and Rotterdam to Yokohama from three open years. Pink (November) and blue (July) lines represent each ensemble member's optimum route, with line weight indicate number of forecasts sharing the route segment; the thick orange line shows the 'truth' (September 15th deterministic solution).

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.
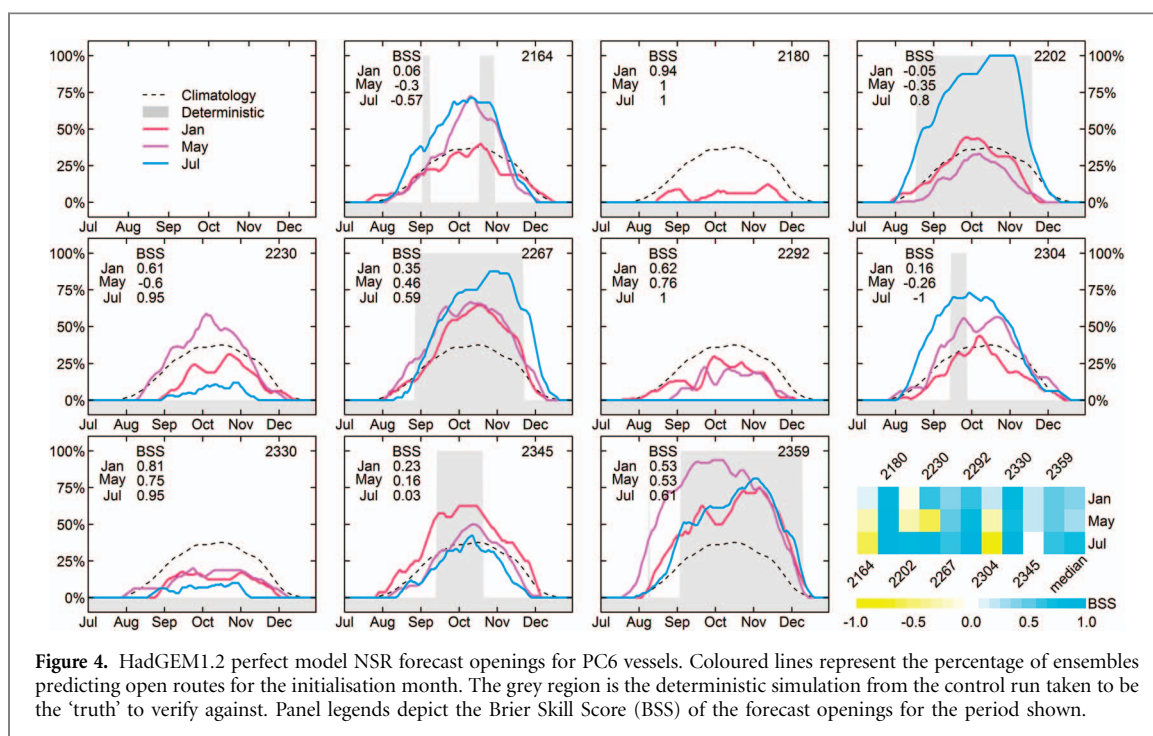
Figure 4. HadGEM1.2 perfect model NSR forecast openings for PC6 vessels. Coloured lines represent the percentage of ensembles predicting open routes for the initialisation month. The grey region is the deterministic simulation from the control run taken to be the 'truth' to verify against. Panel legends depict the Brier Skill Score (BSS) of the forecast openings for the period shown.

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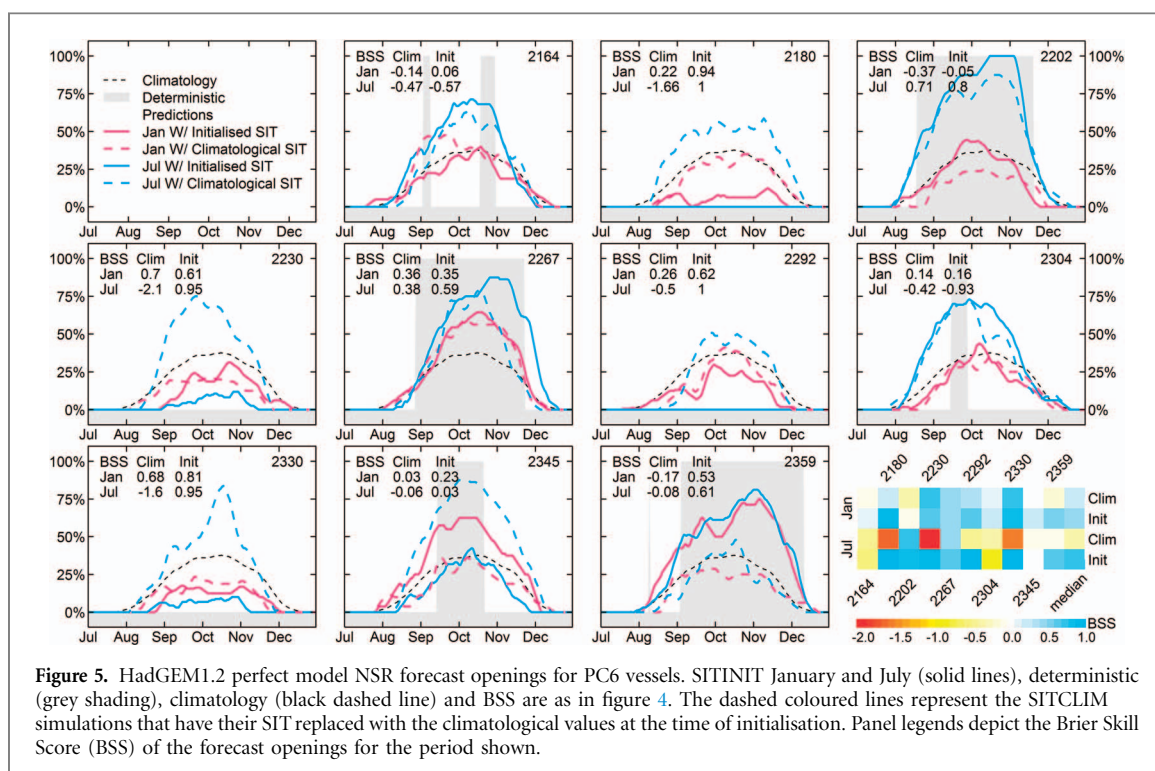
Figure 4 shows that predictions made from July are on average better than from either May or January initialisations. The bottom right image in figure 4 collects the BSS statistics for each year and finds a median BSS for January = 0.44, May = 0.31 and July = 0.71. The BSS from May are no better than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

Figure 5. HadGEM1.2 perfect model NSR forecast openings for PC6 vessels. SITINIT January and July (solid lines), deterministic (grey shading), climatology (black dashed line) and BSS are as in figure 4. The dashed coloured lines represent the SITCLIM simulations that have their SIT replaced with the climatological values at the time of initialisation. Panel legends depict the Brier Skill Score (BSS) of the forecast openings for the period shown.

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

(table 1). 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 pre-planning. 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.

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