Prospects for better seasonal Arctic sea ice predictions from multivariate initialization

F. Massonnet, H. Goosse, T. Fichefet

Predicting the summer Arctic sea ice conditions a few months in advance has become a challenging priority. A good knowledge of the initial sea ice state is necessary to hopefully produce skillful forecasts. However, most of the intrinsic memory of sea ice lies in its thickness distribution and observational networks of sea ice thickness are often more limited in space and time than the ones for ice concentration. To overcome this problem, we constrain the ocean–sea ice model NEMO-LIM3 forced by atmospheric reanalyses, with real observations of sea ice concentration using the ensemble Kalman filter. Because of the multivariate nature of this filter, sea ice thickness is globally updated in a consistent way whenever observations of ice concentration are available. We report in this paper the skill of 27 retrospective seasonal Arctic sea ice forecasts (1983-2009) initialized in March, with NEMO-LIM3 forced by atmospheric reanalyses. The results clearly exhibit the added value of multivariate sea initialization for seasonal prediction of the September ice concentration, in particular during the last decade. This suggests that current seasonal sea ice forecast systems could gain predictive skill from a realistic sea ice initialization.

1. Introduction

Seasonal predictions of the summer Arctic sea ice cover are regarded by many as a valuable source of information for economic, strategic or societal reasons [AMAP, 2011]. There exists several approaches to make such predictions, each with different levels of confidence. The Sea Ice Outlook initiative (http://www.arcus.org/search/seaiceoutlook) provides a good overview of the nature of current efforts. These include public surveys, heuristic statements, statistical inference from empirical relationships and dynamical forecasting. Predictions obtained from ocean–sea ice model forecasts [Zhang et al., 2008; Lindsay et al., 2012], or from fully-coupled general circulation models (GCMs) [Wang et al., 2012; Chevallier et al., 2013; Sigmond et al., 2013], are of particular interest. Indeed, in the rapidly changing Arctic environment, past statistical relationships may not hold [Holland and Stroeve, 2011] so that empirically-based predictions may be of limited use for the coming years or decades.

Because of the time scales involved, seasonal Arctic sea ice prediction with climate models requires a good knowledge of both initial and boundary conditions. As an example, Kauker et al. [2009] estimated that the September 2007 sea ice area anomaly was in part (66%) determined by past ocean and sea ice conditions in June, the rest of the anomaly being attributed to the integrated effects of atmospheric conditions between June and September. Consequently, a dynamical forecast system that seeks to predict summer Arctic sea ice conditions should rely on realistic initial conditions.

Specifically, a significant part of the predictability of summer Arctic sea ice is known to reside in its thickness [Holland and Stroeve, 2011; Chevallier and Salas-Mélia, 2012; Wang et al., 2012]. The probability that a parcel of ice melts at the end of summer is indeed closely related to its thickness in winter [Maslanik et al., 2007; Goosse et al., 2009]. Unfortunately, observations of sea ice thickness suffer from severe undersampling. Direct assimilation of the few available sea ice thickness measurements is possible [Mathiot et al., 2012; Lindsay et al., 2012] but this only allows for a sea ice thickness update in the vicinity of the measurements.

In this work, we take a sideways approach and indirectly initialize the sea ice thickness distribution. We assimilate observations of global sea ice concentration every 5 days between 1979 and 2009 into the ocean–sea ice model NEMO-LIM3 with the ensemble Kalman filter (EnKF). Contrary to simple nudging, this filter updates all ocean and sea ice variables as long as they are related to the assimilated variable —here, sea ice concentration. Thus, sea ice thickness is updated continuously in all seasons and all over the Arctic basin, from 1979 to 2009. The positive impact of such a multivariate approach for sea ice thickness has already been demonstrated for both Arctic and Antarctic sea ice [Mathiot et al., 2012; Massonnet et al., 2013]. The present paper contains additional evidence that the EnKF is a suitable method for estimating the full sea ice state.

The ocean–sea ice model and data assimilation method are presented in Section 2. We then extract, from the data assimilation run, a set of 27 winter initial states that are used as initial conditions for seasonal Arctic sea ice hindcast experiments. We run these seasonal hindcasts under prescribed atmosphere, as we wish to test the pure sensitivity of sea ice to its initial conditions. We assess the skill from these seasonal prediction runs compared to the control, uninitialized run in Section 3 and discuss the benefits of initialization in in Section 4. We close with a conclusion in Section 5.

2. Data and methods

2.1. General model configuration

NEMO-LIM3 is a state-of-the-art global ocean–sea ice model, consisting of the ocean model OPA9 [Madec, 2008] coupled to the Louvain-la-Neuve sea ice model, version 3 [LIM3, Vancoppenolle et al., 2009]. OPA9 is a finite difference, hydrostatic, primitive equation oceanic GCM designed for climate studies. OPA9 runs on the ORCA2 grid (≈2° resolution), with mesh refinement around the equator and at the poles. The sea ice model solves the subgrid-scale sea ice thickness distribution with 5 ice categories. The interested reader is redirected to Madec [2008].
and Vancoppenolle et al. [2009] for a detailed description of the ocean and sea ice models.

The ocean–sea ice model is driven by atmospheric reanalyses and climatologies. The 2-m surface air temperatures and 10-m winds from the NCEP/NCAR reanalysis project [Kalnay et al., 1996] force the model on a daily basis and vary from year to year. Monthly climatologies of relative humidity [Trenberth et al., 1989], total cloudiness [Berliand and Strokina, 1980] and precipitation [Xie and Arkin, 1997] complete the forcing. We follow the formulation described in Gosse [1997] to compute the atmospheric–sea ice and atmosphere–ocean turbulent and radiative heat fluxes. River runoff rates are taken from the climatological dataset of Baumgartner and Reichen [1976] combined with a mean seasonal cycle derived from the Global Runoff Data Centre data [GRDC, 2000].

2.2. Sea ice data assimilation

The ensemble Kalman filter (EnKF) is a widely-used data assimilation method well validated for geophysical systems [Evensen, 2003]. The first key idea of the filter is to approximate the true model error covariance matrix using a finite number of model forecasts, instead of explicitly forwarding this matrix in time. In our case, we let 25 members evolve in time with a perturbed version of the atmospheric forcing [Mathiot et al., 2012] as to generate ensemble spread. When observations are available, each of the model forecasts is corrected proportionally to its misfit to observations. The second key idea of the EnKF lies in its multivariate formulation allowing the model error covariance matrix to be defined in time and space, this constant being precisely prescribed in the model error covariance matrix. We redirect the interested reader to Mathiot et al. [2012] and Massonnet et al. [2013] for a more general description of the setup.

We assimilate observations of sea ice concentration from the Ocean and Sea Ice Satellite Application Facility [Eastwood et al., 2011] between January 1979 and October 2009 (the products will become operational on a real-time basis soon). To our knowledge, this is the only product that provides space- and time-varying estimates of ice concentration uncertainties, which are required in the EnKF scheme. The ocean–sea ice state is updated every 5 days. In order to prevent ensemble collapse, we perform a localized analysis [Sakov and Bertino, 2010], with a localization radius of 800 km.

2.3. Setup

We decided to exclude the years 1979-1982 from the analysis (1) to let NEMO-LIM3 adjust to the constraints imposed by the EnKF and (2) because of a known warm bias in the NCEP/NCAR reanalysis in the early 1980s in the Beaufort and Laptev Seas (B. Tartunvillé, unpublished manuscript). We have therefore 27 years (1983-2009) for which we can test our seasonal sea ice prediction system. For each of them, we ran a 2-year simulation initialized the 25th of February of the year (aka “March initialization”), with initial conditions taken from the data assimilation run described in the previous section. This collection of initialized seasonal hindcasts is referred to as “initialized” runs in the remainder of the text. In parallel, we conducted the 27 equivalent simulations without initialization, i.e. with initial conditions taken from a control simulation where no data assimilation is applied (similar to the reference simulation extensively described in Vancoppenolle et al. [2009]). This collection of uninitialized seasonal experiments is hereafter referred to as “control” runs.

We remind the reader that both control and initialized ocean–sea ice simulations are, at all times, driven by atmospheric reanalyses and climatologies. We deliberately designed this setup to test, under identical and controlled atmospheric conditions, the sensitivity of September sea ice prediction skill to initial winter conditions.

Our primary metric for evaluation of seasonal hindcasts is the Root Mean Squared Error (RMSE) of sea ice concentration $a$, at time $t$:

$$\text{RMSE}(t) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} w_i (a(t)_{i}^{\text{OBS}} - a(t)_{i}^{\text{MOD}})^2}$$

where $i = 1, \ldots, N$ are the grid point index, and the $w_i$'s are the weights ensuring consistent ponderation by the grid cell area. The RMSE is by definition positive, and will increase wherever the modeled and observed sea ice concentrations differ from each other. The RMSE as a metric is insightful because it does not allow model errors to compensate spatially, as is the case if sea ice area or extent are used [Notz, 2013].

3. Results

We show in Fig. 1 the evolution of the average RMSE in sea ice concentration through the first 24 months after initialization in March. At the time of initialization (March), the initialized simulation is by definition subject to a lower error than the control simulation. The skill is then rapidly lost within 3 months, but appears again higher (lower error) in August and September. The skill of the initialized simulation then returns to the control skill, but some differences are visible even 18 months after initialization in September of the next year: in 73% of the cases the skill of the initialized run is higher 18 months after the initialization.

In Fig. 2, we plot for each year the model error in September obtained from the control and initialized runs. It ap-

![Figure 1](image-url)
pears again clearly that the skill of September sea ice concentration is higher when the sea ice cover is initialized in March. The departure from the control run is particularly marked for the last decade, with the RMSE dropping from 15% to 10% in 2005 and from 17% to 13% in 2007, for example. We will discuss this feature in the next section.

For the sake of completeness, we also present in Fig. 3 the interannual evolution of September Arctic sea ice extent as forecast by the control and initialized runs. Sea ice extent is calculated as the sum of grid cell areas where ice concentration is larger than 15%. Therefore, it does not allow to measure whether or not the simulated ice cover has correct spatial patterns. In fact, minor changes are noticed between the control and initialized runs: for example, the detrended correlation of September sea ice extent with the observations is 0.83 in the control run, and 0.89 in the initialized run. It is also interesting to note that the extent in September 2007 is the same in observations and in the two simulations, but that a pointwise comparison does indicate a difference between those two simulations (Fig. 2). We discuss in more details the simulation of the 2007 Arctic sea ice minimum in the next section.

4. Discussion

The evolution of model error in the few months after initialization (Fig. 1) highlights that sea ice initialization is beneficial immediately after the initialization time, but also in summer. In other words, the information from surface conditions is rapidly forgotten but re-emerges at the end of the melt season. Bearing in mind that our simulations do not include an interactive atmospheric model but are rather conducted under prescribed atmospheric conditions, we suggest the following explanation to interpret Fig. 1:

- In winter, sea ice concentrations are nearly identical in both simulations because they approach 100% wherever the prescribed 2-m air temperatures are below the seawater freezing point.
- In spring, surface air temperatures start to rise above the sea ice melting point. Sea ice concentration decreases first in the the marginal zones, where ice is thin. The small differences in sea ice thickness provided by the EnKF in the marginal ice zone may delay/advance the timing of ice retreat by a few days, but not significantly to have clear impacts on the RMSE in spring (Fig. 1).
- In summer, the whole Arctic basin is experiencing positive surface air temperatures. In an earlier study using NEMO-LIM3, Goosse et al. [2009] related the probability that an ice parcel melts in late summer to its average thickness. Below 1.24 m (above 2.33m), they found this probability to be lower than 10 % (larger than 90%) based on a 1979-2006 simulation. We suggest that the updates in sea ice thickness provided by the EnKF can shift local ice thickness in either the thin (< 1.24m) or thick (> 2.33m) categories, thereby changing the fate of sea ice concentration in late summer.
- In fall, similarly to winter conditions, sea ice concentration rapidly grows to 100% wherever the surface air temperatures are below the seawater freezing point, regardless of the local sea ice thickness.

As reported in Fig. 2, the skill of September sea ice concentration in the initialized runs departs from the skill of the control runs from the late 1990s onwards. We suspect, following the arguments of Goosse et al. [2009], that this is intimately related to the fact that the probability for an ice parcel to melt in summer decreases nonlinearly with the average sea ice thickness. In a regime of thick (> 2.33m) ice, this probability is very low, and the updates from the assimilation do not alter significantly this probability as the ice thickness remains anyway above this limit. This is what happens up to the mid-1990s. In a regime of intermediate thickness (less than 2.33 m but larger than 1.24 m), the probability to melt decreases sharply, so that the updates from the assimilation have clear impact on the presence of ice or not at the end of the melt season (from the mid 1990s to 2009).

Ultimately, as sea ice might become very thin (< 1.24 m) in a near future, we expect again that the impact of assimilation will be small because the ice will have anyway a very high probability to melt away in September: the Arctic will be at this stage in a regime of seasonal ice.

To illustrate the role played by the winter sea ice thickness distribution on the September sea ice concentration, we pick the emblematic year of 2007. We choose this year because it is the time of the absolute minimum in sea ice extent over our period (1983-2009), but also because the distribution of observed ice concentration in September 2007 was somewhat peculiar (Fig. 4), with a long “tongue” of ice extending...
from Greenland to Siberia. The control run, while simulating a correct sea ice extent (Fig. 2), overestimates sea ice concentration in the Beaufort Sea and the Baffin Bay, and underestimates it between the North Pole and the Laptev Sea (Fig. 4b). With the same sea ice extent, the initialized run shows in addition a more realistic ice distribution (Fig. 4d). The ultimate cause for the difference between the two simulations must lie in the sea ice initial conditions, since the model in both seasonal hindcasts was forced with the same atmospheric data. Indeed, the corresponding maps of winter sea ice thickness (Fig. 4a and c) reveal substantial differences. It is for example straightforward to note that ice is thicker in the initialized run at the location of the “tongue” six months later, and is logically able to survive during these six months.

Our setup is far from being perfect and complete. By running the ocean–sea ice simulations with prescribed atmospheric fields, some important atmosphere–sea ice feedbacks are not taken into account. However, this setup has the advantage to isolate the specific role of sea ice initial conditions on the September prediction under fully controlled atmospheric conditions. Additional initialization of the ocean surface/3D temperatures/salinities would probably lead to an increase of the forecast skill in winter. Actually, we ran the 27 seasonal predictions with sea ice initialization in September, but did not notice any improvement in skill for March next year (not shown here). This was to be expected, because previous studies have shown that the area and volume of sea ice in September are poor predictors for subsequent March sea ice area [Blanchard-Wiggins et al., 2011; Chevalier and Salas-Mélia, 2012]. In winter, the position of the marginal ice zone is rather controlled by ocean heat flux convergence [Bitz et al., 2005] or by atmospheric heat flow. In the same line, we did not find re-emergence of skill in the Southern Ocean sea ice (not shown here) as identified in Fig. 1 for the Arctic in winter. With proper ocean initialization, we could expect such skill [Holland et al., 2013].

5. Conclusion

In the next decades, summer Arctic sea ice extent is expected to continue on its decline [Stroeve et al., 2012; Massonnet et al., 2012; Wang and Overland, 2012]. Under reduced ice conditions, the use of historical predictor-predictand relationships, traditionally invoked for seasonal sea ice prediction [e.g., Tivy et al., 2007] may be of limited use [Holland and Stroeve, 2011]. Resorting to fully-coupled models is an appealing solution, provided that (1) these include the essential atmosphere-sea ice and ocean-sea ice feedbacks [Wang et al., 2012], and (2) they are initialized properly.

In this work we have run retrospective ocean–sea ice simulations with prescribed atmospheric forcing but with different sea ice initial conditions, which has permitted to isolate the added value of sea ice initialization for summer Arctic sea ice prediction. Our results have two implications. (1) A realistic initialization of the sea ice cover can be carried out by simple assimilation of sea ice concentration, provided that the assimilation is conducted in a consistent multivariate framework. Initializing sea ice concentration only [as in, e.g., Sigmond et al., 2013] may be insufficient to sustain and transport memory from winter to summer [Tietsche et al., 2012]. (2) For identical atmospheric conditions, predictions starting from initialized states provide more realistic sea ice areal distributions in summer, with notable improvements in the past decade.

There are many sources of uncertainty that will hamper the realization of skillful seasonal Arctic sea ice predictions in the next years. Our results show at least that a consistent initialization of the winter sea ice conditions is necessary to provide realistic distributions of subsequent summer sea ice cover.

Acknowledgments. François Massonnet is a F.R.S.-FNRS Research Fellow. Hugues Goosse is a F.R.S.-FNRS Senior Research Associate. This work was partly funded by the European Commissions 7th Framework Programme, under Grant Agreement number 226520, COMBINE project (Comprehensive Modelling of the Earth System for Better Climate Prediction and Projection). It was also partly supported by the Belgian Science Federal Policy Office (BELSPO).

References

AMAP. Snow, water, ice and permafrost in the arctic (swipa): Climate change and the cryosphere. Technical report, Arctic Monitoring and Assessment Programme (AMAP), Gausadalen 21, N-0549 Oslo, Norway (www.amap.no), 2011.


March 2007 sea ice thickness

CONTROL

INITIALIZED

September 2007 sea ice concentration

OBS

Figure 4. (Left) Sea ice thickness distribution in March 2007 from the control run (top) and the initialized run (bottom). (Right) Sea ice concentration distribution in September for the corresponding simulations. The pink line denotes the 15% ice edge contour from observations [Comiso and Nishio, 2008].


