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Prospects for improved seasonal Arctic sea ice predictions from multivariate data assimilation

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A B S T R A C T

Predicting the summer Arctic sea ice conditions a few months in advance has become a challenging priority. Seasonal prediction is partly an initial condition problem; therefore, a good knowledge of the initial sea ice state is necessary to hopefully produce reliable forecasts. Most of the intrinsic memory of sea ice lies in its thickness, but consistent and homogeneous observational networks of sea ice thickness are still limited in space and time. To overcome this problem, we constrain the ocean–sea ice model NEMO-LIM3 with gridded sea ice concentration retrievals from satellite observations using the ensemble Kalman filter. No sea ice thickness products are assimilated. However, thanks to the multivariate formalism of the data assimilation method used, sea ice thickness is globally updated in a consistent way whenever observations of concentration are available. We compare in this paper the skill of 27 pairs of initialized and uninitialized seasonal Arctic sea ice hindcasts spanning 1983–2009, driven by the same atmospheric forcing as to isolate the pure role of initial conditions on the prediction skill. The results exhibit the interest of multivariate sea ice initialization for the seasonal predictions of the September ice concentration and are particularly encouraging for hindcasts in the 2000s. In line with previous studies showing the interest of data assimilation for sea ice thickness reconstruction, our results thus show that sea ice data assimilation is also a promising tool for short-term prediction, and that current seasonal sea ice forecast systems could gain predictive skill from a more 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, including heuristic statements, public surveys, statistical inference from empirical relationships and dynamical forecasting. The Sea Ice Outlook initiative (http://www.arcus.org/search/seaiceoutlook) provides a good overview of the status of current efforts. However, as outlined by Stroeve et al. (2014), the skill of the predictions is generally low when the observed sea ice cover departs significantly from the trend line, meaning that more research is needed before reliable forecasts can be issued on an operational basis. Predictions obtained from ocean–sea ice models (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), deserve 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, at least, rely on realistic initial conditions. Specifically, a significant part of the predictability of summer Arctic sea ice is associated to its initial 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).

Several studies have made use of sea ice thickness products to directly constrain sea ice models (Mathiot et al., 2012; Lindsay et al., 2012; Lisæter et al., 2007). Most of the products (see for example the compilation listed by Lindsay, 2013) suffer from

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undersampling in space and/or time, allowing only for corrections of sea ice thickness in the vicinity of the measurements, and only when these measurements are conducted. Because of their wide coverage, satellite-based retrievals of sea ice thickness bear probably the greatest promise for initializing the sea ice cover in large-scale models. However, satellites monitor sea ice freeboard or draft, rather than thickness directly. To retrieve sea ice thickness, the thickness of snow on sea ice and values for snow and ice densities must be known; they are often taken climatological or constant (Kwok et al., 2008; Laxon et al., 2013). Although very valuable, satellite products for ice thickness are therefore still subject to substantial uncertainties and biases (Zygmuntowska et al., 2014; Schweiger et al., 2011).

Alternatively, sea ice concentration products can also be used to constrain sea ice models. Passive microwave measurements of sea ice concentration made by satellites are not free of errors (Eastwood et al., 2011), but benefit from a much better spatial and temporal coverage than observations of sea ice thickness. In this work, we propose to indirectly initialize sea ice thickness by the assimilation of sea ice concentration, using the ensemble Kalman filter (EnKF) in the global ocean–sea ice model NEMO-LIM3. 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, following this so-called "multivariate" scheme, sea ice thickness can be updated continuously all over the Arctic basin, an achievement that would not have been possible based on thickness data only given the substantial inhomogeneities. The interest of such a multivariate approach for sea ice thickness has already been demonstrated for both Arctic and Antarctic sea ice (Lisæter et al., 2003; Mathiot et al., 2012; Massonnet et al., 2013). Continuing the work initiated by these studies, the present paper provides further perspectives for this data assimilation method in the particular case of seasonal prediction.

The ocean–sea ice model and the data assimilation method are presented in Section 2. We explain why the EnKF is an appropriate methodology when one or several variables are difficult to observe directly, or suffer from undersampling. We extract, from the data assimilation run, a set of 27 March initial states between 1983 and 2009, that are used as initial conditions for 27 seasonal Arctic sea ice prediction experiments, or simply "hindcasts". It is worth noting that we run these hindcasts with assimilation turned off, but under prescribed atmosphere, as we wish to test the pure sensitivity of sea ice to its initial conditions. We assess the skill of these initialized seasonal hindcasts against the skill of uninitialized seasonal hindcasts in Section 3. The initialized simulations are found to be more skillful than uninitialized ones for the months of August and September, with clearer improvements over 2000–2009 than 1983–1999. We discuss these results in light of differences in the sea ice and ocean initial states in Section 4, with a focus on the year 2007 – the minimum sea ice extent of the time series. We close with a conclusion in Section 5.

2. Data and methods

2.1. General model configuration

NEMO-LIM3 is a 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 ($\sim 2^\circ$ resolution), with mesh refinement around the equator and at the poles. The sea ice model LIM3 explicitly resolves the sub-grid scale sea ice thickness distribution using five ice categories with lower bounds equal to 0, 0.63, 1.33, 2.25 and 3.84 m, respectively. 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 (Large and Yeager, 2004) complete the forcing. We follow the formulation described in Goosse, 1997 to compute the atmosphere–sea ice and atmosphere–ocean turbulent and radiative fluxes. River runoff rates are taken from the climatological dataset of Baumgartner and Reichel, 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 data assimilation method that can be implemented to constrain geophysical systems (Evensen, 2003). We redirect the reader to Mathiot et al. (2012) and Massonnet et al. (2013) for a general description about how the EnKF is implemented in our ocean–sea ice model, but we repeat hereunder the two main characteristics of this filter.

The first key characteristic of the filter is to approximate the forecast 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, each with a perturbed version of the atmospheric forcing (Mathiot et al., 2012) as to generate ensemble spread. The second key characteristic of the EnKF lies in its multivariate formalism: any single element of the ocean–sea ice vector is updated, with a proportionality factor that is changing with time and space, this factor being precisely prescribed in the forecast error covariance matrix.

The update of the whole state vector is a non-trivial problem when data assimilation is applied to ocean–sea ice models (Lisæter et al., 2003). As an example, we display in Fig. 1 the correlations between NEMO-LIM3 sea ice concentration and mean grid cell thickness, obtained from an ensemble of 25 members each subject to a perturbation in the atmospheric forcing. In winter (left panel), the relationship is positive in the marginal ice zone. This is about where the 0 °C isotherm lies in the atmospheric forcing; members that undergo cold conditions in the marginal zones will then grow more ice, resulting in an increase in both concentration and thickness. In late summer however (right panel of the figure), the correlations may become negative. When new and thin ice forms alongside thick and multi-year ice during freeze-up, the average thickness will be lower if the thin ice is more extensive (Lisæter et al., 2003). The total ice concentration may also decrease and the total thickness increase in the presence of ridging, a process that is simulated in our model. In any case, the correlations reported in Fig. 1 point towards the fact that the relationships between ice concentration and thickness are complex since the sign of the relationship depends on space and time.

In this study, no sea ice thickness data are assimilated. We assimilate only satellite-retrieved observations of sea ice concentration from the Ocean and Sea Ice Satellite Application Facility (Eastwood et al., 2011). These reprocessed products include space- and time-varying estimates of uncertainties, which are required in the EnKF scheme. The products were interpolated on the ORCA2 grid, between January 1979 and October 2009 (they will become operational on a real-time basis soon). 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