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Sea ice prediction using the ECMWF coupled forecast system

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The presence of sea ice can have a range of impacts on the atmosphere and ocean. It interacts with the surface fluxes through its albedo as well as acting as a barrier to the exchange of heat and momentum between the atmosphere and ocean. It also impacts the freshwater exchange, through salinity changes when it melts and freezes.

As well as predicting the sea ice itself, sea ice also has a role as a potential source of predictability for the atmosphere. Sea ice is therefore, becoming an increasingly important component of the Earth system to capture in global forecast systems. Increases in computing power are allowing us to run ocean-atmosphere coupled forecast models from the medium to extended range. ECMWF is currently developing a fully coupled atmosphere-wave-ocean-sea-ice model (Janssen et al. 2013) for forecasts from the medium to extended range. In this study, we present results for initial tests of the model on the long forecast range. We focus on predicting the Arctic summer sea ice conditions which may be the most beneficial for society and where there is the greatest year to year variability. Initial results show some skill at monthly lead times; comparable with results from other centers. The results also hint at large systematic errors that can limit the forecast skill.

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1. Introduction:

In the past, the importance of the prediction of the extent and thickness of sea ice has been considered for activities where it has direct impact, such as shipping and fisheries and on climatic timescales where it influences the Earth's albedo and hence the radiation balance. As weather forecasting systems become increasingly complex, observational and modelling evidence has shown that sea ice may also play a role in providing predictability to medium and extended range weather forecasts (e.g. Balmaseda et al. 2010). A necessary first step for the potential predictability in these forecasting systems to be realised is that they can model the observed sea ice evolution and then in turn, capture the processes that provide predictability to the forecast parameters of interest.

Sea ice predictability has been assessed in different model and observational frameworks (e.g. Tietsche et al. 2013, Blanchard-Wrigglesworth et al. 2011, Koenigk and Mikolajewicz, 2009) and it was found that sea ice is predictable out to interannual lead times. Blanchard-Wrigglesworth et al. (2011) showed that the predictability varies seasonally and that sea ice area may be predictable for several months with increased predictability in the early autumn. As well as persistence providing predictability to the sea ice, the study also found a re-emergence mechanism in the observations due to the persistence sea surface temperature (SST) anomalies, which form in the melt season and are still present when ice is growing. The models also show summer to summer memory due the persistence of thickness anomalies. Chevallier, & Salas-Mélia, (2012) have shown with their model that the thicker ice provides memory in the system; it is therefore important to initialise the model with a good estimate of the ice thickness.

Current forecast systems at ECMWF persist the sea ice concentration field for the first 15 days of the forecast and then relax the sea ice towards a recent (5 year) climatology (monthly forecast system) or use the observed evolution of one of the previous 5 years (seasonal forecast system). These methods are unable to capture the rapid changes in sea ice that occur during the melt and freeze up seasons as well as missing the important feedbacks that occur between the ice and the atmosphere and ocean, which can lead to large interannual variability in sea ice concentration and thickness.

Here we present results using a dynamic-thermodynamic sea ice model (LIM2, Fichefet et al., 1997) in the ECMWF seasonal forecast system, to test its ability to predict September sea ice area. Current sea ice analysis products that are used to initialise forecast models only provide information about sea ice concentration. We assess the impact of different techniques for initialising the sea ice state in terms of concentration and thickness for seasonal forecasts. We then go on to use the "best" initial conditions to predict the September Arctic sea ice extent at varying lead times from 2-8 months over the period from 1990-2012. Our results show that forecasts from very different initial conditions show an underestimation of the negative anomalies; suggesting that these errors are dominated by model deficiencies.

2. Initialisation of Sea Ice:

We need to initialise the sea ice model in terms of concentration and thickness. Current sea ice analysis products that are used to initialise forecast models only provide information about sea ice concentration, sea ice thickness measurements are not operationally available in real time and methods to use this type of data in forecast systems still need to be developed. As the thickness has been shown in previous studies to provide a large part of the predictability of the sea ice cover, it is crucial to generate initial thickness conditions that are close to observations. We therefore use a combination of data we do have available to generate initial conditions for the sea ice and ocean in the model. We force the ocean ice model with atmospheric forcing (wind stress, temperature, humidity etc.) from ERA-Interim (Dee et al., 2011). There is no SST data assimilation. We use a nonlinear nudging scheme as described in detail in Tang et al., (2013).

3. Ensemble Predictions of September Area:

Predictions (hindcasts) are made of September sea ice area, starting with initial conditions for 1st February, May and August; for the hindcast period 1985-2012. The ocean and sea ice state are taken from nonlinear ice nudging run. The atmospheric state is taken from ERA-Interim. To take into account the uncertainty in the initial conditions we create an ensemble of forecasts. Each ensemble member has a perturbed atmospheric and oceanic initial conditions. We do not make any attempt at this stage to perturb the sea ice initial conditions. We create 30 perturbed initial conditions and run a control integration where no perturbations are made to the analysis. Results are therefore presented from a 31 member ensemble. These hindcasts do not assimilate any ocean data, it is likely that we would improve the hindcasts further if this information were also included. The forecasts are started at different lead times, February, May and August to assess the predictable limit of September sea ice cover in our forecast system.

Figure 1 shows the ensemble mean prediction of sea ice area anomaly relative to the period 1985-1999. This period was chosen as the reference as it is before the downward trend in September sea ice started. We show the observed ice area anomaly and that predicted for the lead times of 2, 5 and 8 months. **Table 1** presents the anomaly correlation between the observed sea ice area anomaly and that of the ensemble mean of the three different hindcast sets. At all three lead times, the model is able to capture the downward trend of the sea ice extent anomaly. As expected the interannual variability is generally well captured in the August hindcasts and to a lesser extent with the May starts. We remove the linear trend from the hindcasts to determine the skill in predicting the interannual variability without the trend. The results in **Table 1** show that the main skill comes from capturing the trend. Hindcasts initialised in February and May do not melt enough ice in the summer season. The results shown in **Figure 1** also highlight that the ensemble mean is unable to capture the very low ice events. To consider this further we show the spread of each ensemble for the May start dates in **Figure 2**. The observations are marked by triangles and each ensemble member by a plus (+) symbol. We see that for many years the observations lie within the spread of the ensemble, except in the cases of high ice loss.

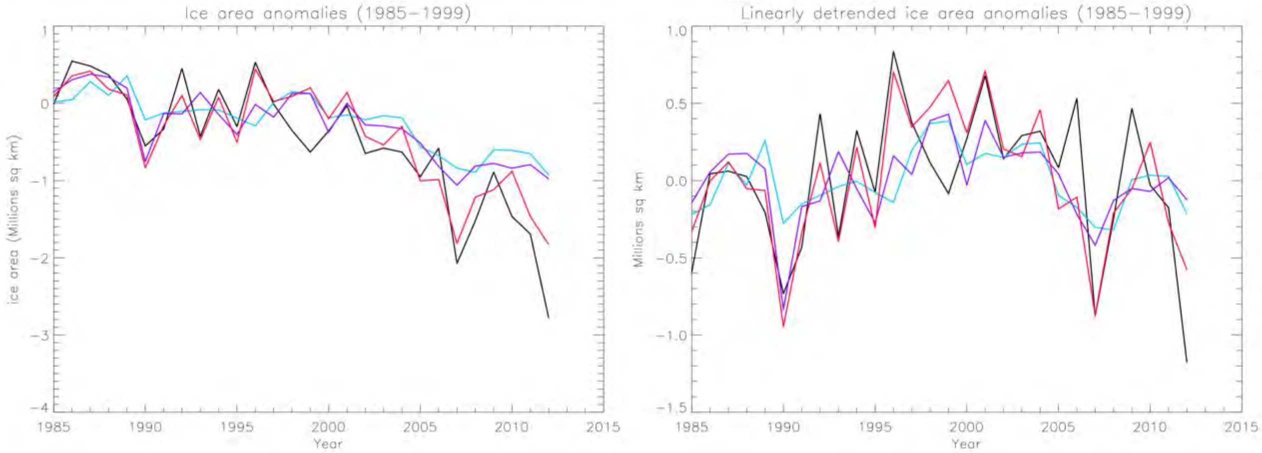

Figure 1: September Ice Area anomalies (relative to the 1985-1999 mean) for NCEP analysis (black), and ensemble mean hindcasts initialised in February (blue), May (purple) and August (red).

Table1: Skill of hindcasts (as measured by the anomaly correlation of the time series) in predicting September sea ice area starting in February, May and August.

Hindcast start month	*Anomaly correlation*	*Anomaly correlation (detrended)*
February	0.81	0.42
May	0.82	0.49
August	0.92	0.80

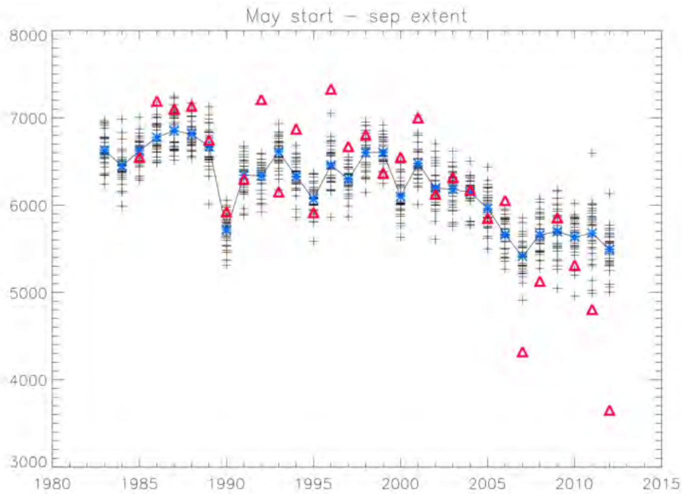

Figure 2: September ice cover for the May hindcasts for individual ensemble members shown with black plus (+) symbol, observed September ice cover (red triangles) and the ensemble mean (blue stars).

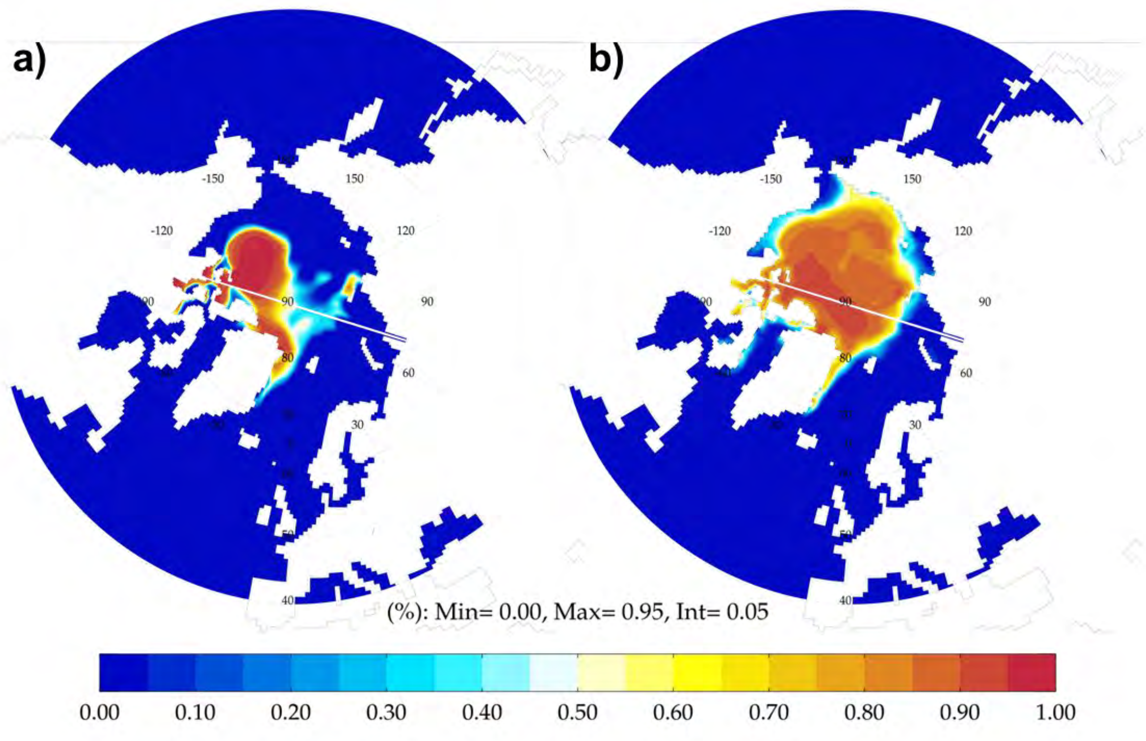

Figure 3: 2007 September Sea ice concentration for (a) ocean-ice model forced with atmospheric fluxes and predicted using May initial conditions (b).

To investigate what may be limiting the predictability experiments we considered the sea ice cover for 2007. We compare to the ice cover that was produced when the ocean–ice model is forced with observed fluxes it produces a low ice extent (**Figure 3a**), this is similar to observations (compare with the ERA-Interim sea ice in **Figure 4a**). This suggests that coupled model errors dominate the prediction at a 5 month lead time as shown by comparing the ensemble mean hindcast produced by from the May initialisation. We compared the hindcast using May initial conditions when the sea ice thickness is initialised close to observations and those when the thickness is too large and find that the September results are very similar; any predictability in the initial conditions is lost due to model's inability to capture the melt season well.

One potential source of error introduced in the coupled model is the albedo. In the coupled model the surface radiation balance uses the sea ice albedo from the sea ice model. As there is no parameterization of melt ponds in LIM2 the ice albedo tends to be too high (0.65 compared to observed values 0.55) which will lead to less melting. We carried out an experiment where we provided the radiation scheme with observed climatology of sea ice albedo. In the ensemble mean sea ice volume was reduced by 25%, which is largely due to concentration changes, but the area covered was only reduced by 15% and the extent was only reduced by about 5%.

Another source of error is the large scale atmospheric circulation, which although may not be predictable at long lead times may contribute to the ice cover errors and may provide an upper bound to the sea ice predictability. The large scale atmospheric circulation of the summer of

2007 had an anomalous dipole pattern, with a low pressure on the eastern side of the pole and high pressure to the western side, which led to a circulation that advected ice out of the Arctic basin through the Fram Strait. The hindcast ensemble mean circulation by contrast looked much closer to climatology with the high pressure located over the Beaufort Sea and the low pressure was centred over Siberia. We performed relaxation experiments whereby the atmosphere of the coupled model is relaxed towards the ERA-Interim analysis. We carried out these experiments with single ensemble members. **Figure 4** shows the monthly mean sea ice cover for August 2007, we chose to show this monthly mean as it is a pure “melt” month rather than September, which also includes refreezing. We see a reduction in the sea ice cover in the Beaufort Sea and central Arctic Basin due to increased advection from the Beaufort Gyre region of the Arctic towards the Fram Strait. When experiments were combined with the using the climatological albedo we saw a greater reduction in ice concentration, but still did not perfectly capture the dramatic ice loss of 2007. This suggests that other processes may be still be missing from our coupled system.

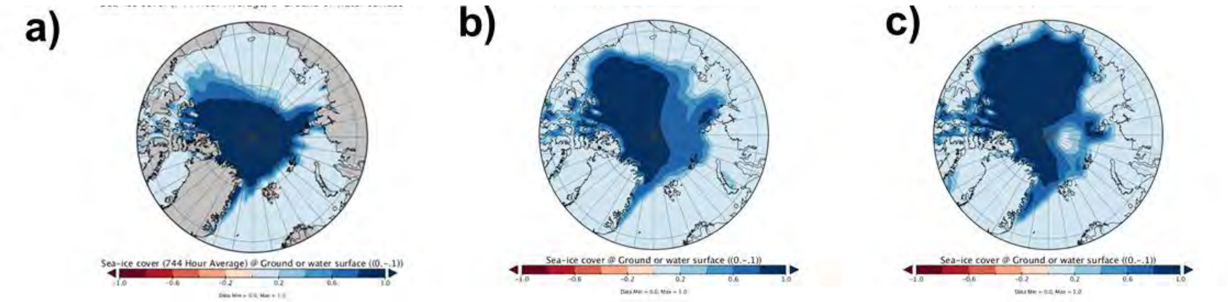

Figure 4: August 2007 sea ice cover for (a) ERA-Interim, (b) the relaxed atmosphere experiment, (c) standard coupled model.

4. Conclusions and future work:

In the current coupled system a large proportion of the skill in predicting September sea ice area is due to capturing the trend. When we consider the detrended data we only show skill at a 1-2 month lead time, at longer lead times the anomaly correlation is below 0.5. The large scale losses of summer Arctic sea ice in 2007 and 2012 are not correctly reproduced in the coupled model. Initial investigations suggest that errors in ice albedo and the large scale circulation may be the main cause, but do not fully explain the model errors that are seen, suggesting that we are still missing physical processes or feedback mechanisms within our coupled system.
Use of a more complex sea ice model within our coupled system may improve predictions of the summer ice cover. A multi-category ice scheme may improve the modelling the loss of the thinner ice and a melt pond scheme would better capture the feedback of increased temperatures and albedo over the summer period.

Coupled processes such as wave-ice interaction may become more important for thin summer ice conditions and are currently not captured in our system, this is the focus of future development work.

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