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Advanced Prediction in Polar regions and beyond: Modelling, observing system design and LInkages associated with a Changing Arctic climaTE

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Interim evaluation of initialization experiments investigating the impact of novel observations in the coupled atmosphere–land–ocean–sea ice system

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EXECUTIVE SUMMARY

Initial-value information is a key source of polar predictability at sub-seasonal to seasonal time scales. However, how to constrain numerical models with actual observations at initial prediction time is a technical and scientific challenge. The observational network is sparse and not all physically relevant variables for initialization are well monitored. In addition, numerical models used in predictions have their own biases, which introduces numerical instabilities and shocks after initialization. One objective of APPLICATE WP4 is to deliver recommendations for optimal initialization strategies of weather and climate models. In this "interim" deliverable, progress is presented on the initialization of novel products and on the use of novel assimilation techniques. It is found that sea ice initialization can benefit the skill in the North Atlantic Oscillation (NAO) prediction, but that sea ice has to be initialized in a consistent way with the ocean underneath to avoid initial shocks. In retrospective seasonal prediction experiments, initialization of sea ice thickness gives promising results for forecasting the summer sea ice edge position, a diagnostic of interest for a wide range of stakeholders. Finally, a new scheme has been developed for assimilation of continental snow in a multi-layer model, opening prospects for enhanced land-surface-induced predictability at sub-seasonal time scales. The work summarized in this deliverable is still ongoing, will be continued until the end of the project, and will result in further recommendations for optimal initialization techniques to be applied in WP5.

1. INTRODUCTION

Background and objectives

One key objective of APPLICATE is to deliver enhanced environmental predictions in polar regions and beyond, at time scales ranging from a few weeks to a few seasons. At these time scales, knowledge from initial conditions is critical to provide forecasts with added value over trivial forecasts such as climatology or simple persistence. However, the sparseness and incompleteness of the observational record is a severe limitation in our ability to equip numerical weather and climate prediction systems with consistent three-dimensional information for all the relevant variables that are thought to provide skill. Likewise, possible inconsistencies between the prescribed initial state and the numerical models' preferred state can lead to spurious shocks, instabilities and long-term drift that can degrade predictive skill. What observations to use and how to assimilate them in weather and climate prediction systems is therefore an important question, tackled exhaustively in APPLICATE WP4, with the goal to (1) providing recommendations for the future of observing systems and (2) providing recommendations for the optimal way to initialize predictive models.

The first task of WP4 (Task 4.1) aimed at establishing the added value of observations in current analyses and reanalyses of the atmosphere, ocean and sea ice. The value of these observations was underlined in the case of atmospheric analyses and forecasts, but it was also found that current reanalyses struggle in transferring information from "observables" (those variables that are directly assimilated) to "non-observables" (those variables that are not assimilated yet are relevant for providing predictive skill). A summary of these findings is available in Deliverable 4.1 submitted together with the current one.

The second task of WP4 (Task 4.2) aims at establishing how the current observing network could be enhanced to produce a better estimation of the state of the Arctic at initialization time and to improve forecast skill in the Arctic and beyond. This is first done by conducting selected data-denial experiments, that is, forecast experiments in which the initial observational network coverage is deliberately degraded. This is also done by asking the question of optimal sampling: given a set of stations, what is the optimal strategy to best estimate the system's state? That work is currently under way and will result in a document to be delivered at the end of the project (Deliverable 4.2).

Task 4.3 is a natural extension of Task 4.1 and 4.2. This "frontier" task proposes to use novel data sets and novel initialization approaches to advance our predictive capacity well beyond current levels. Final recommendations on the optimal approach (which data set(s) to use, how to assimilate them in model) will be delivered at the end of the project (Deliverable 4.3, month 48). The present interim deliverable is therefore a preliminary view on what has been achieved so far based on work that is still ongoing.

2. METHODOLOGY

Three prediction systems are considered in this report. The European Centre for Medium-range Weather Forecasts (ECMWF) system is first used to test the assimilation of data in, and initialization of, a new multi-layer continental snow model (Sec. 2.1). The EC-Earth coupled climate model is then used to test the initialization of sea ice concentration (Sec. 2.2). Finally, the Met Office's GloSea coupled prediction system is used to test the assimilation of sea ice thickness (Sec. 2.3). The overall details of each prediction and initialization system are first presented, and results are given in the next section (Sec. 3).

2.1 ECMWF system: Strategy for snow assimilation in a multi-layer scheme

The ECMWF Integrated Forecastying System (IFS) is used for analysis and medium-range weather forecasts. In Task 4.3.3, the assimilation of snow information is tested in a new multi-layer snow scheme. The multi-layer snow model in development for the ECMWF IFS (as part of WP2) has up to five layers in the vertical (thus labelled ML5) for describing the snowpack thermodynamics and hydrological processes. This finer vertical discretization enables representing different timescales in the snow-atmosphere interactions, going from the diurnal cycle to fast synoptic transitions and up to seasonal and interannual variability.

The ECMWF snow data assimilation makes use of in-situ snow-depth (SYNOP) and satellite snow cover (IMS) observations to mitigate snow accumulation errors developed by the coupled forecast model that can result from erroneous meteorological forcing or misrepresented snow processes. These snow observations (snow depth and snow cover) characterize only the bulk state of the snowpack, thereby not providing direct information for each of the multi-layer snow fields. While more elaborate snow data assimilation schemes (e.g. Kalman filters or Variational methods) could propagate the information in each of the layer, currently the Optimum Interpolation (OI) snow analysis works exclusively on a single-layer snow.

To take full advantage of the ML5 multi-layer scheme consistent snow initial conditions for each of the multi-layer snow fields must be generated to avoid spin-up and drifts issues in coupled forecasts. An initialization procedure called “warm-start” is generally needed for new parameterizations with an increased number of prognostic variables, and for which the coupled land-atmosphere model must be initialized from a previously existing scheme (e.g. in this case from a set of snow variables from a single-layer scheme, hereinafter “SL”). In the case of the multi-layer snow developments for IFS, having such a warm-start initialization procedure is important for two major applications:

1) To enable using the snow data assimilation methodology that is currently used in IFS, which modifies only the bulk snow-accumulations by adding or removing snow;
2) To ensure compatibility between the ML5 snow forecasts and the SL snow forecasts produced in the ERA-Interim and ERA5 reanalyses and used for the re-forecasts of the monthly and seasonal forecasting systems.

To satisfy both requirements, a warm-start procedure for the ML5 snow scheme has been developed and tested at ECMWF in the framework of Task 4.3.3, taking advantage of the snow profile observations from the Sodankyla supersite and the ESM-snow Model Intercomparison Project (ESM-snowMIP). This consists of a parameterization routine called at the initial step of each forecast which uses the single-layer snow fields, the skin temperature and the upper soil temperature fields to generate the vertical profiles of the fields needed by the multi-layer snow scheme. The warm-start is compared to a “cold-start” procedure in which no assumption is made to disaggregate the snow temperature and snow density along the vertical (i.e. isothermal and isodensity initialisation across the 5 layers).

2.2 EC-Earth system: sea ice initialization strategies

In Task 4.3.1, we aim at evaluating the benefits in forecast skill of using improved sea ice initial conditions over the Arctic. The analyses are carried out with the EC-Earth Earth System Model in its seasonal climate prediction configuration (Doblas-Reyes et al., 2018). The bulk of this analysis is still in process, as it first needs the generation of different sets of initial conditions of increasing complexity. Three approaches of increasing complexity will be investigated to produce initial conditions:

Approach 1 Oceanic and atmospheric data obtained from reanalyses will be interpolated to the model grid to generate initial states;

Approach 2 An ocean-sea ice standalone reconstruction using the NEMO3.6-LIM3 model (that is part of EC-Earth) forced by an atmospheric reanalysis will be produced, from which initial states will be drawn;

Approach 3 Same as Approach 2 but the ocean-sea ice reconstruction will also be nudged towards reanalysed ocean conditions, and satellite-derived Sea Ice Concentrations (SIC) data will be assimilated with an Ensemble Kalman Filter (EnKF; Sakov and Oke, 2008).

The three streams of data generated will be used to initialize three different seasonal forecast systems with EC-Earth in its CMIP6 version (3.2.3). Additionally, we will consider two complementary approaches that could be placed between Approaches 2 and 3 in terms of their complexity: an Approach 2 with ocean nudging only, and an Approach 2 with EnKF assimilation of SIC only. In this report, we present results from this latter sensitivity experiment and compare them with the initial states obtained from Approach 2.

2.3 GloSea system: sea ice thickness initialization

The initialization of sea ice thickness is a promising avenue for seasonal sea ice prediction, as several studies have found that winter sea ice thickness provides important preconditioning for the evolution of Arctic sea ice through the summer melt season (Blanchard-Wrigglesworth and Bitz, 2014; Holland et al., 2011; Kauker et al., 2009; Day et al., 2014). Sea ice thickness is not yet routinely used to initialise these systems (Martin et al., 2015; Tonani et al., 2015). There have been several recent studies that have sought to improve the representation of Arctic sea ice thickness using satellite thickness products. What has not been investigated is the impact that assimilation of sea ice thickness may have in seasonal forecasts made using fully coupled models. Here we do so for the first time by initializing the Met Office GloSea coupled seasonal prediction system using sea ice thickness derived from CryoSat-2 (CS2) measurements provided by the Centre for Polar Observation and Modelling (CPOM; Laxon et al., 2013).

We use the latest development version of the GloSea coupled seasonal prediction system, which employs the CMIP6 version of the Met Office coupled model architecture (Williams et al., 2017). Evaluation of this GloSea system has been performed (outside of APPLICATE WP4), using reanalysis and hindcast simulations covering the period 1992-2015. Here we use these simulations, which do not use sea ice thickness initialisation, as our control experiments ("CTRL" hereafter), and focus on the period from October 2010 to the end of 2015 – when both the CS2 and the CTRL data are available. To test the impact of sea ice thickness initialisation we perform a parallel set of experiments ("ThkDA" hereafter) using CS2 thickness data to initialise the sea ice. The CTRL ocean-sea ice reanalysis was re-run for the period 2010-2015 using identical ocean and sea ice data, but using CS2 observations to constrain the model sea ice thickness fields. CS2 thickness observations are included within the analysis using a nudging technique – an approach that is similar to a climatological relaxation but using gridded monthly CS2 thickness observations. Ocean and sea ice initial conditions obtained from this reanalysis are then used to initialise an ensemble of GloSea seasonal predictions of September Arctic sea ice made from the start of May. The ThkDA seasonal predictions run here comprise an ensemble of 24 seasonal forecasts, made from start dates in late April and early May, for each year from 2011-2015. This approach exactly mirrors the structure of the existing CTRL ensemble, meaning that each of the CTRL and ThkDA experiments used in this study consist of a total of 120 seasonal predictions of September Arctic sea ice over the 5-year period 2011-2015.

3. RESULTS AND DISCUSSION

3.1 Snow-on-land initialization and assimilation in a multi-layer scheme (ECWMF)

Following the experimental setup described in Sec. 2.1, the initialization routine for the multi-layer snow scheme has been implemented as a first step for (coupled) forecast experiments, without any assimilation cycle. Fig. 1 shows a comparison of the temporal evolution of surface and 2-meter temperature at Dome C, Antarctica, for two experiments with the multi-layer snow scheme; one using the parameterized snow profiles at initial time (warm-start) and one with constant-value profiles (cold-start, in which the initial snow vertical layers have same temperature and density).

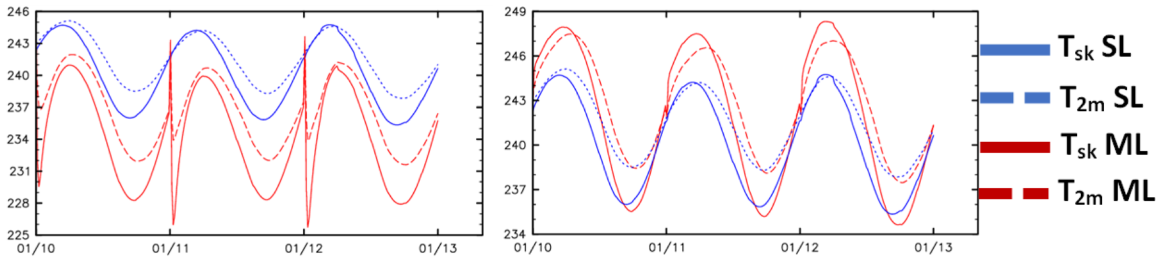

Figure 1. Time-series from 10th to 13th January 2017 at Dome C, Antarctica, of surface temperature (continuous lines) and 2-meter temperature (dashed lines) for forecast experiments using the multi-layer snow scheme (red colours) without the initialization routine for the multi-layer snow fields (cold-start, left) and with the initialization routine (warm-start, right); results for an experiment using the single-layer snow scheme are also shown for comparison (blue colours). The individual forecasts are initialized every day at 00UTC and concatenated from t+0h to t+24h (output every time-step) to create a continuous time-series.

The individual forecasts are initialized every day at 00UTC and concatenated from t+0h to t+24h (with output every time-step) to create a continuous time-series, to diagnose instabilities at the beginning of the forecasts. The cold-start experiment (Fig. 1, left) shows large instabilities of the surface temperature at the beginning of each forecast (00UTC), which are reduced for the warm-start experiment (Fig. 1, right).

As a second step, the warm-start procedure will enable to use the ML5 snow scheme also in analysis experiments without further adaptation of the current data assimilation methodology.

In order to use the ML5 snow scheme with the current OI snow analysis in the coupled forecasts, the multi-layer snow fields are aggregated at each assimilation cycle into a single-layer value containing the bulk information of the snowpack. Hence, the snow depth assimilation can be performed using the aggregated single-layer snow field of the forecast model and the available observations of snow depth and cover. The warm-start routine is then used to initialize in the next forecast the multi-layer snow fields from the analyzed (single-layer) snow fields.

3.2 Impact of sea ice initialization approach (EC-Earth)

A couple of preliminary analyses have already been performed to illustrate the impact that initial conditions can exert on the predictive skill. In the first analysis, we used a preliminary version of EC-Earth to produce two sets of retrospective seasonal predictions (10 member each) over the period 1993-2008, initialized the 1st of November using forced NEMO3.6-LIM3 stand-alone reconstructions performed successively with and without EnKF assimilation of the SIC products of the European Space Agency (ESA) (ocean nudging was not activated in either case). Comparison of both ensembles shows an improvement in the skill of the North Atlantic Oscillation for sea ice initial conditions produced by EnKF assimilation (See Fig. 2). However, caution must be taken due to the small ensemble size and the relatively short period analyzed. A set of physical analyses is currently conducted to trace the origin of these improvements.

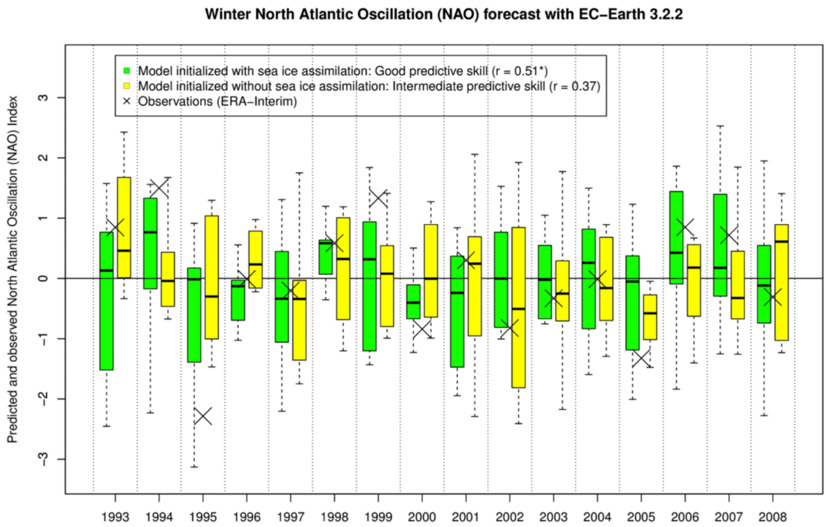

Figure 2. Winter (DJF) North Atlantic Oscillation Index skill in 10-member seasonal forecast initialized with (green) and without (yellow) Ensemble Kalman filter assimilation of ESA sea-ice concentrations from the period 1993-2008. The skill score is statistically significant at a 95% confidence only in the simulations initialized with sea-ice concentration assimilation.

In the second analysis, we show that the EnKF reconstruction is far from perfect, and that further improvements in skill can be expected. Here we focus on the EC-Earth seasonal forecast system initialized from the EnKF Sea Ice Reconstruction (hereinafter EnKF-SIR) as for our first analysis described above. An analysis of the forecast bias reveals that this bias develops really fast, and is particularly strong during the first day of the forecast (Figure 3a). This bias seems to be related to inherent limitations in the EnKF assimilation, which become evident when the EnKF-SIR is compared with the assimilated ESA SIC data the day before the forecasts start (Figure 3b). This bias in the SIR introduces an inconsistency between the sea ice initial conditions and those of the ocean (that come from ORAS4), which produces a strong initial shock in pan-Arctic sea ice during the first 3 weeks of the forecast. Indeed, Figure 3c shows that the initial Integrated Ice Edge Error (Goessling et al., 2016 for more details), a metric that measures the mismatch between simulated and observed ice edge, calculated over the Arctic for each start date (evaluated between ORAS4 and EnKF-SIR SICs the day before the forecasts start) is significantly correlated from the second to the 20th forecast day with an equivalent index evaluated between the forecasts and NSIDC data. The initial shock happens because the SIR has too much sea ice in regions like the Greenland Sea, which is melted by the relatively warm oceanic conditions imposed underneath and does not manifest in the first day because it requires some for the warm oceanic conditions to erode the sea ice.

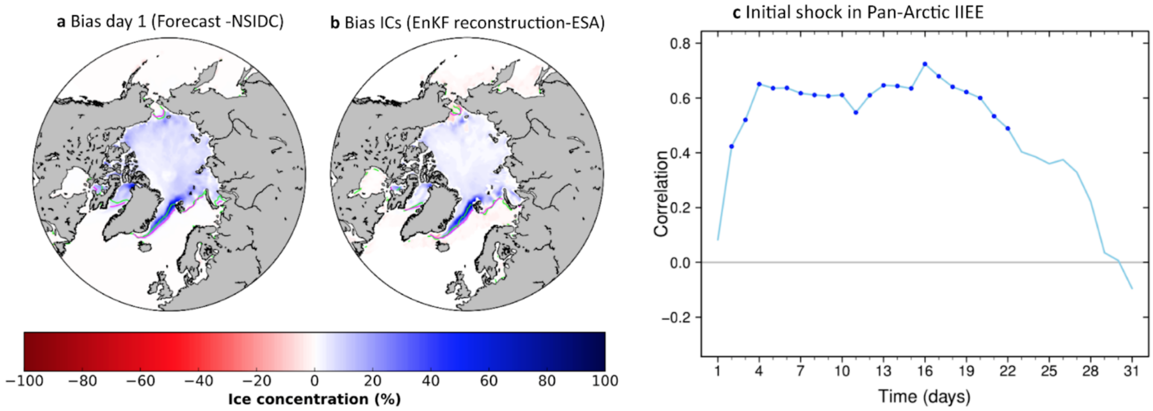

Figure 3. a SIC bias during the first day of a 1st November initialized forecasts from an EnKF sea ice reconstruction (EnKF-SIR). **b** 1st November SIC difference between EnKF-SIR and the target observational data (from ESA). **c** Evolution of the correlation between the Integrated Ice Edge Error (IIEE) of EnKF vs ORAS4 in the day before initialization for all start dates, and the IIEE during the first 31 days of the forecasts evaluated against NSIDC. Dots represent the significant correlations at 95 %, estimated from a one-sided student-T distribution.

3.3 Sea ice thickness assimilation (GloSea)

The thickness-initialized seasonal predictions (ThkDA, see Sec. 2.3) have been compared with the predictions made without sea ice thickness initialization (CTRL, see Sec. 2.3). The impact of using initialized sea ice thickness fields, from the ThkDA reanalysis, for seasonal predictions of Arctic sea ice is illustrated, for 2011 and 2012, in Fig. 4 – which shows the probability of sea ice at each model grid-cell (the fraction of ensemble members that predict ice of concentration >15%) from the CTRL and ThkDA experiments. The ensemble-mean 15% concentration contour – as a proxy for sea ice edge location – is overlain in orange, and compared with the equivalent derived using OSI-SAF data (in black). Fig. 4 clearly shows that seasonal predictions made using CS2 thickness initialization (ThkDA; right-hand plots) are much closer to observations; the ice edge (orange contours) are much closer to those observed (black contours) – particularly in the Atlantic Sector and near Fram Strait.

To quantify the improvement in our seasonal predictions of sea ice cover and ice edge location, we use the Integrated Ice-Edge Error (IIEE) metric introduced by Goessling et al. (2016). This metric is essentially the area integral of all model grid cells where the forecast and observations disagree about whether sea ice is present or not – defined here as whether the ice concentration is at least 15% (see Goessling et al., 2016). The IIEE analysis shows that using CS2 thickness initialization, the ice-edge error is significantly reduced; the 2011-2015 mean IIEE is reduced from 3.20 x10^6 km^2 (CTRL) to 2.02 x10^6 km^2 (ThkDA) – a reduction of 37% (not shown). To illustrate this, the IIEE for each of 2011 and 2012 have been added to Fig. 4 (pink boxes), along with the modelled and observed sea ice extent (i.e., the total area of Arctic sea ice with concentration of at least 15%).

Sea ice concentration and extent in the CTRL predictions is generally under-estimated in the Atlantic Sector (Greenland, Barents, Kara, Laptev, and East Siberian Seas), and over-estimated in the Pacific Sector (Beaufort and Chukchi Seas), whilst the ThkDA predictions more closely match observations (Fig. 4).

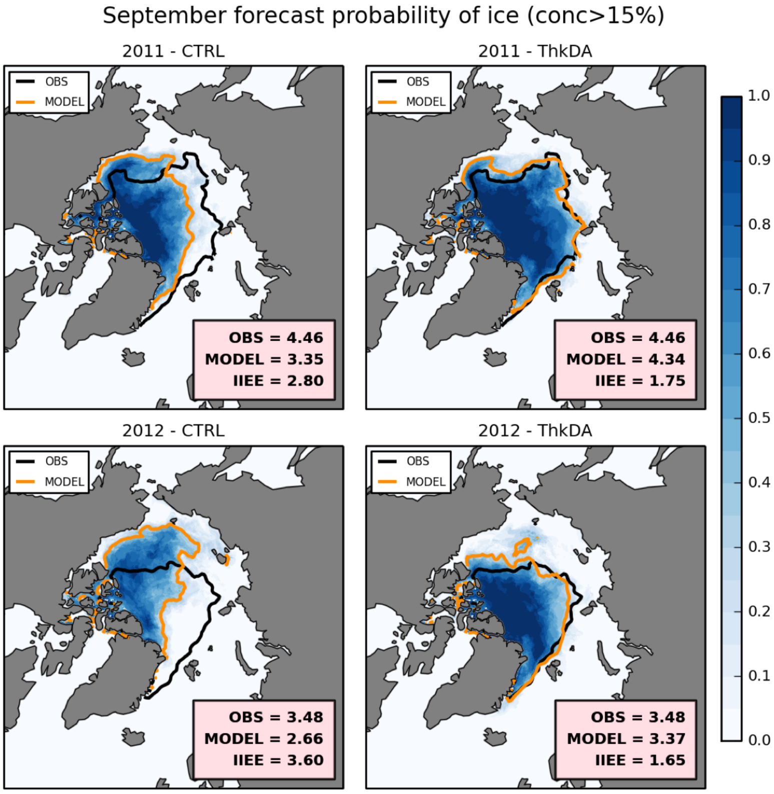

Figure 4. September mean probability of sea ice for the CTRL (left) and ThkDA (right) seasonal predictions for 2011 (upper) and 2012 (lower). Contours of 15% concentration are overlain to represent the sea ice edge for the ensemble mean (orange) and OSI-SAF observations (OBS: black). Probability is defined at each point as the proportion of ensemble members that have at least 15% ice concentration. The OBS extent, modelled extent and corresponding Integrated Ice Edge Error (IIEE) are included, for each plot, in the lower-right corner (units: 10^6 km^2).

Fig. 5 shows that there is a strong relationship between sea ice thickness errors at the start of the melt season and sea ice concentration errors at the end of the melt season. In areas where the sea ice cover predicted by the CTRL ensemble (grey contour) is too extensive, the CS2-initialised sea ice thickness fields tend to be thinner (blue shading); conversely, where the CTRL ensemble predicts an ice cover that is not extensive enough, the CS2-initialised sea ice tends to be thicker (red shading). In both cases these changes to the initial ice thickness lead to an ice edge prediction (pink contour) that more closely matches observations (black contour).

The relationship between modelled winter thickness biases and summer extent errors shown in Fig. 5, along with the improved ice cover obtained using thickness initialization (Fig. 4), supports the theory that Arctic winter thickness provides some predictive capability for summer ice extent, and highlights the importance that modelled winter thickness biases can have on the evolution of forecast errors through the melt season.

4. CONCLUSIONS AND OUTLOOK

Work conducted in WP4 Task 3 has so far allowed exploring the benefits of various types of assimilation schemes and the use of new data sets for the initialization of the Arctic state. Results demonstrate the high potential of these new data sets for improving sub-seasonal to seasonal forecast skill, but also emphasize that a careful treatment in the update of non-

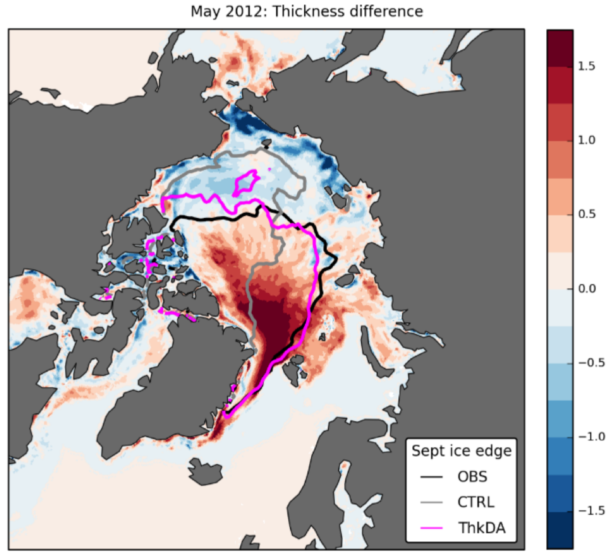

Figure 5. Thickness difference (m) between ThkDA and CTRL experiments (ThkDA – CTRL; contour shading) for the reanalysis fields used to initialise the seasonal predictions on 1st May 2012. Overlain are September-mean contours of 15% ice concentration, to represent the sea ice edge, for the CTRL (grey) and ThkDA (pink) experiments along with OSI-SAF observations (OBS: black).

observable fields should be taken, in order to avoid initial shocks and model drift during the initial stages of the predictions.

Regarding snow-on-land assimilation, a new initialization routine for a multi-layer snow scheme (ML5) is developed both to enable using the current snow data assimilation methodology used at ECMWF and to ensure compatibility with the previous single-layer snow scheme. The use of this initialization procedure in coupled forecasts was shown to impact the mean diurnal cycle of near-surface air temperatures and to reduce initial shocks in the forecasts. The adaptation of the initialization scheme for data assimilation experiments (in which the ML5 would be used both in the 4D-Var trajectories and in the non-linear model) is work in progress. The future developments will consider the use of multi-layer snow (or a simplified physics version) also in atmospheric data assimilation experiments, in order to ensure a consistent representation of the snow-atmosphere interactions also within the assimilation window. This will require the adaptation of the tangent linear and adjoint snow schemes in the atmospheric analysis (4D-Var), which are currently coded to work with a single snow layer.

Preliminary results indicate that the assimilation of sea ice concentration may positively impact the skill of the North Atlantic Oscillation, for reasons that are yet to be investigated. While improvements are modest as measured by the slight increase in correlations between retrospective seasonal forecasts and observations, they confirm other independent work (Scaife et al., 2014) and support the notion that the knowledge of late-summer sea ice conditions can be useful for predicting lower latitude atmospheric circulation anomalies, a topic of direct relevance for WP3 and WP5.

Finally, sea ice thickness assimilation was tested and evaluated in the GloSea coupled climate prediction system. It was shown that spring sea ice thickness initialization acts to significantly reduce systematic biases in late-summer sea ice extent, a result supported by the notion that sea ice thickness anomalies during the melting season are a strong predictor of sea ice concentration anomalies at the end of this season. We therefore recommend that initialization of sea ice thickness should be included within seasonal prediction systems such as GloSea. However we note that reduction of modelled winter thickness biases should also be prioritized.

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