Early Student Support to Investigate the Role of Sea Ice-Albedo Feedback in Sea Ice Predictions

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LONG-TERM GOALS

The overarching goals of this project are to understand the role of sea ice-albedo feedback on sea ice predictability, to improve how sea-ice albedo is modeled and how sea ice predictions are initialized, and then to evaluate how these improvements influence inherent sea ice predictability.

OBJECTIVES

The sources of errors in a model forecast are from initial conditions and the model itself. Both can be evaluated with observations and potentially improved. We will use observations and field studies to improve how sea-ice albedo is modeled. We will use methods to quantify feedback in models, and thereby directly relate feedback to predictability.

We will use initial conditions from the model itself in idealized, perfect model studies, and from other models with data assimilation. Soon the modeling system we use will have its own sea ice data assimilation scheme (it has data assimilation in the atmosphere and ocean already) and we can investigate how model improvements influence the initialization procedure as well.

We anticipate that stakeholders will value sea ice predictions of the summer season most, especially if they are skillful for lead times at least a season in advance (i.e., a forecast initialized in spring or earlier). This means models must be initialized prior to the melt season and must forecast through the time of strongest ice-albedo feedback, when sea ice anomalies grow most rapidly. Therefore, we propose to scrutinize the model behavior precisely at this time by examining the model physics and parameters that control the sea-ice albedo.

APPROACH

This project supports Brandon Ray, who just completed his second year of graduate studies. Cecilia Bitz, the PI, manages the project and supervises the graduate student. During the past academic year, Brandon split his time taking classes, doing research, and serving as a teaching assistant. He spent the summer entirely on research. He attended the Polar Predictability Workshop at University of Reading, UK.

For our project, we are using the Community Earth System Model version 1 (CESM1), which can be run in various configurations, such as fully-coupled, with slab-ocean, or ice-ocean only. We are investigating predictability in the most advanced version of the model, known as CESM1-CAM5 because it uses the Community Atmosphere Model Version 5 (CAM5). We are using a developmental version (CESM1.3) with the latest version of the Los Alamos sea ice model, known as CICE5, which has options to investigate the sensitivity to three melt pond schemes. All previous integrations with CESM1-CAM5 were done with CICE4, which only has the simplest melt-pond scheme that remains an option in CICE5.

The simplest melt-pond parameterization keeps an account of all the snow meltwater starting each spring and assumes some fraction is captured at the surface. A fixed volume to depth ratio is assumed based on SHEBA data. Upon freeze-up, the meltwater account is depleted with an assumed decay rate. The newer detailed physics scheme is described in Hunke et al. (2013) that is in CICE5 and is now coupled to CESM1.3. The new scheme has ponds develop on level-sea ice. Ponds drain through permeable ice or through cracks and leads, and refreezing eliminates ponds. The new CICE5 model also has more sophisticated sea ice thermodynamics, which treats the sea ice as a mushy-layer.

We are currently running a pair of control simulations with CESM1.3 using these two melt-pond schemes, with all other options otherwise identical. We are using the slab ocean model so we are assured that the model is in equilibrium. Once the control runs are finished, we will run double CO2 perturbation experiments so we can evaluate feedback strength. We will compute shortwave radiative feedback and climate response in two ways: (1) from the kernel feedback method (e.g., Soden et al, 2008; Shell et al, 2008; Bitz et al, 2012) and (2) from the top of atmosphere absorbed shortwave radiation sensitivity to a climate forcing (e.g., Kay et al, 2012).

Once we have quantified the feedback strength, we shall first run a perfect-model ensemble study to identify how predictability depends on feedback strength in an idealized experimental framework. A perfect-model method is used first because it requires a more limited number of integrations compared to a hindcast, which is otherwise needed to test predictability. We can use the perfect-model technique to test a range of sea ice model formulations and link feedback to predictability.

While waiting for the output from our new runs, we are diagnosing predictors of September sea ice cover, focusing especially on surface albedo and ponds, using the CESM1-CAM5 large-ensemble (LENS) project. The LENS offers an opportunity to scrutinize the robustness of relationships to natural variability. It is also available immediately, while output from our specially designed integrations with CESM1.3 is forthcoming. Of note, the CESM1-CAM5 LENS used CICE version 4.0, which has the simpler melt pond scheme, Bitz and Lipscomb thermodynamics, and elastic-viscous-plastic dynamics.

Model output was obtained for 30 ensemble members for sea ice variables for the Northern Hemisphere. To examine the influence of the base-state, monthly output was taken from four different 36-year time periods: 1925-1960, 1970-2005, 2015-2050, and 2060-2095. Model runs from the first two time periods had historical radiative forcing, whereas the runs from the last two time periods had RCP 8.5 radiative forcing. For each variable, the 30-member ensemble mean was computed as an estimate of the forced signal. This ensemble mean was removed from each ensemble, leaving a detrended monthly timeseries of anomalies that contain the natural variables for the 30 ensemble members.

Correlations of each detrended variable with the detrended September ice area were investigated at lead/lag periods of up to eight months, for each ensemble member. Months that exhibited statistically significant correlation coefficients were used for further analysis. These variables were then used in a stepwise multivariate linear regression, again performed on each ensemble member, in which the first regression was performed on only those variables that were statistically significant for the month of January (i.e. eight month lead period). Subsequent regressions were performed in which variables were added for the next longest lead month (i.e. the second regression would include all the variables for January and February that were statistically significant). The variables that remained statistically significant were included for a further round of analysis. To avoid overfitting biases in the results, the time period was divided in half, and a further round of stepwise multivariate linear regressions was performed (in a similar manner) on each half of the data to cross-validate. This entire process was performed on the entire range of variables, as well as a subset of variables considered to be observables (i.e. if a stakeholder needed to base decisions on variables that are observed and collected or reanalyzed in nature): ice thickness, snow thickness, air temperature at 10m, reference air temperature at 2m, melt-pond area, and thin ice (<1.4 m). Finally, the correlation analysis informed variable choices that we then studied further with maximum covariance analysis (MCA) to examine relationships at the local scale. In addition, skill scores were calculated for all the observable variables to determine the ensemble spread of skill.

WORK COMPLETED

Brandon completed his second academic year of advanced graduate coursework in atmospheric sciences and oceanography, with several courses in marine policy as well. His diagnostic analysis of the CESM1-CAM5 LENS is nearly complete and he is in the process of writing a paper and the first half of his masters thesis on this work. He completed the setup of the CESM1.3-CAM5 using CICE5 and has integrations with this version are underway.

RESULTS

Our in-depth analysis of the robustness across ensemble members of predictors for September sea ice area and extent is illustrated for pond area (Figure 1) and thin ice area (Figure 2). We find for the 1970-2005 period, total pond area in July is generally a reasonably good predictor of September sea ice area (R=-0.55 for ensemble mean). However, no ensemble member has a correlation with magnitude as large as that found by Schröder et al. (2014). We also examined the sensitivity of our results to time period, as the mean sea ice conditions are dramatically different among the time periods, with the correlation generally decreasing. To better understand this result, correlation maps of pond fraction and total sea ice extent was examined (Figure 3). We see that the correlation is not uniformly negative. Regions of positive correlation occur because the pond fraction diminishes when the sea ice concentration is low. Thus near the ice edge pond coverage has the opposite correlation with September sea ice extent. We are exploring MCA analysis as a means of creating a predictor based on this pond coverage pattern, as opposed to the simplistic prediction of total pond area that gave the modest results in Figure 1.

Thin ice area is another variable that has been argued to be a good predictor of September sea ice extent (Boe et al. 2009). However, Boe et al. showed it was useful for predicting model uncertainty in the long-term trends in the 21st century among CMIP3 models. Boe et al. suggest that the more thin ice, the more quickly the ice can retreat. We examine this behavior on the seasonal timescale in Figure 2. We find that thin ice area in July has a weak but significant correlation with September sea ice area.

At shorter lead times, approaching September, the correlation flips sign, which is probably why the correlation in July is so small. This simultaneous correlation is an indication that when the sea ice in September is anomalously expansive, the ice that lingers in the normally ice-free areas is at-least rather thin. Further, we find the larger magnitude correlation (a negative correlation) occurs at 2 months lag, indicating low September sea ice extent is a good predictor of higher than normal December thin ice area, as the ice-free areas in September fill in. Hence, thin ice area has a complicated relationship with September sea ice extent that suggests it is not a variable of much use for seasonal prediction.

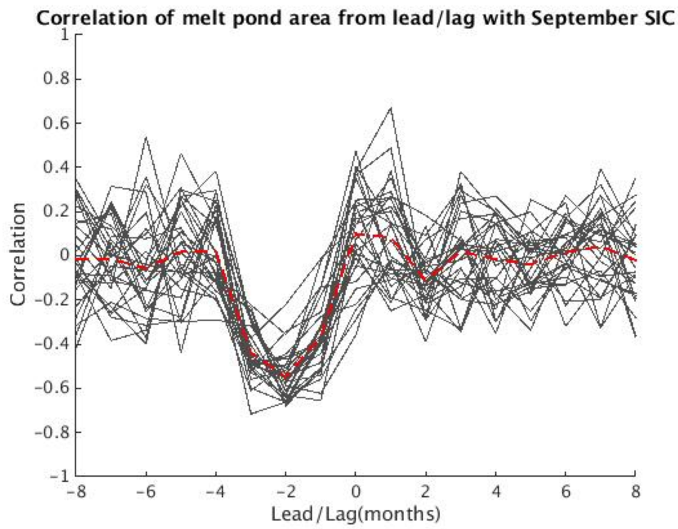

Figure 1: Correlation of the total Arctic melt pond area with total September sea ice area as a function of lead/lag for CESM1-CAM5 LENS output from 1970-2005. The most negative correlation occurs at 2 months lead, indicating high melt pond area in July is the best predictor of low September sea ice extent. There is a black line for each of the 30 ensemble members of the LENS. The red line is the ensemble mean of the black lines.

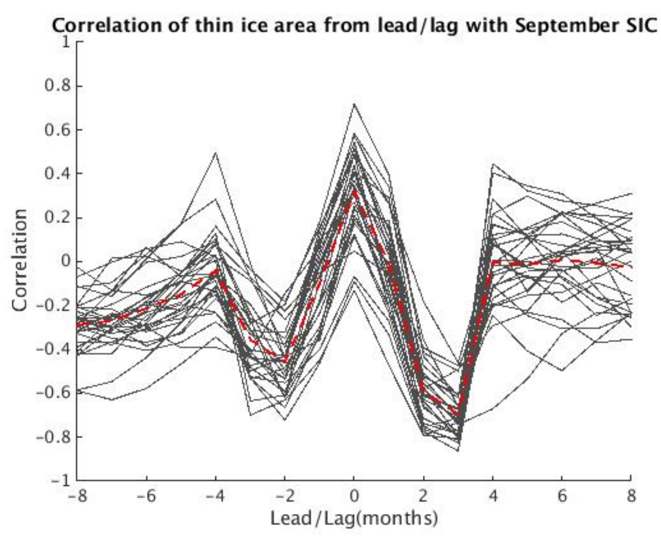

Figure 2: Correlation of the total Arctic thin ice (<1.4m) area with September sea ice area as a function of lead/lag for CESM1-CAM5 LENS output from 1970-2005. Black and red lines are as in Figure 1.

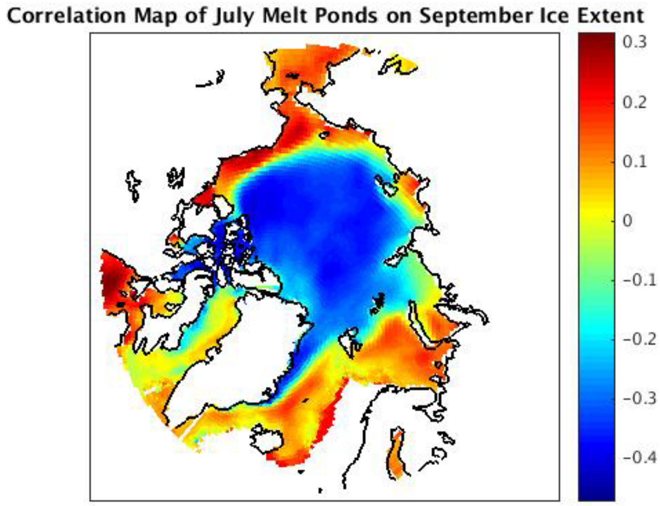

Figure 3: Map of the correlation of melt pond area in July at each point with the September sea ice extent for CESM1-CAM5 LENS output from 1970-2005. Negative values indicate that higher pond area at that point precede lower extent in September. Ponds area can be only be high if there is sufficient sea ice concentration. Positive values tend occur where lower ponds fractions are synchronous with lower ice concentration. Hence, this map shows that only ponds in the central Arctic are a reasonably good predictor of future ice extent, while near the ice edge, ice concentration is more important.

Summary of Results

- Correlation of July melt pond area with September sea ice area (as in Figure 1) increases over time, becoming less negative near the end of the 21st century. The only areas with negative correlations remain tightly concentrated around the Canadian archipelago and Greenland. Thus later in the 21st century, as the sea ice becomes mostly seasonal, much of the Arctic exhibits the relationship seen near the sea ice edge in the late 20th century.
- Between 2015-2050 and 2060-2095, there is a regime shift from a dominant negative correlation in the central Arctic to a dominant positive correlation (i.e., if melt ponds are present, there will still likely be ice in those areas – as the remainder of the sea ice has melted away)
- The amount of cross-covariance explained by the leading modes in the maximum covariance analysis increases with time (caveat – as time progressed, fewer grid points were included in the analysis as they did not have sea ice).
- Melt pond fraction increases and becomes less variable with time
- Overall sea ice area decreases (though trend doesn't start until ~1980). Ice-free summers are not found until 2060s.
- From the linear regressions, air temperatures decrease in importance over time as good predictors, whereas snow and ice thickness become better predictors. Melt ponds are not robust in predictive capacity.

- Similarly, the spread in skill scores generally increased with time for sea ice thickness, snow depth, pond area, and thin ice area; whereas the skill score spread generally narrowed for surface air temperature and surface temperature.
- As far as months are concerned, the closer to September – generally, the better predictive quality. However, June appears to decrease in importance over time while August and July tend to remain either constant or increase in their predictive capability.

IMPACT/APPLICATIONS

Loss of sea ice in recent decades has opened the Arctic Ocean to increasing access of wide-ranging vessels and activities. The Navy is concerned about the potential for conflict and need for search and rescue on the Arctic Ocean. Each year the sea ice cover is different owing to natural variability and forced change. Forecasts of Arctic sea ice and atmospheric conditions have high societal value if they predict when ship transit lanes will be open and where low ice cover might lead to dangerous coastal erosion or ice shelf break-up. Sea ice forecasts have scientific value as they could inform scientists of locations that should be instrumented to monitor large anomalies. This project aims to improve Arctic sea ice prediction of the natural variability and forced change, which is a benefit to society, scientists, and Naval operations. We also seek to improve the simulation of sea ice-albedo feedback in models in general.

RELATED PROJECTS

ONR Project N00014-13-1-0793 An Innovative Network to Improve Sea Ice Prediction in a Changing Arctic is also about investigating sea ice predictability. The project website http://www.arcus.org/sipn

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PUBLICATIONS

Notz, D. and C.M. Bitz, Sea Ice in Earth System Models in "Sea Ice", 3rd Edition, Ed. by D. Thomas [in press].

HONORS/AWARDS/PRIZES

Cecilia Bitz of University of Washington in 2015 was elected a member of the Washington State Academy of Sciences.

Cecilia Bitz of University of Washington in 2015 was listed on the Highly Cited Researchers of 2015 by Thomson Reuters.