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Predictability of Arctic climate variability

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This issue of *Variations* is dedicated to the predictability of Arctic climate, its interaction with the climate of lower latitudes, and how climate change may impact such interactions. The dramatic retreat of perennial Arctic sea ice has become the poster child of climate change. Such a large and visible change to the Arctic system has been a wake up call to the climate community that climate change may not necessarily be slow and steady nor its impacts only of consequence in the far off future. The newly revealed open waters of the Arctic ocean and the less discussed collapse of warm season spring snow cover are known to have profound impacts on the energy balance of the Arctic at the surface and in the lower troposphere. And just as heating anomalies in the tropics can influence weather around the globe, it is plausible that large heating anomalies in the Arctic can have ripple effects at lower latitudes, especially across the industrialized countries and population centers of the Northern Hemisphere.

(Cont. pg. 2)

Arctic–lower latitude coupling: What is the forcing and what is the response?

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Recent Arctic changes are expected to, and may already be, impacting middle latitudes and the rest of the globe. For the first time, the US National Climate Assessment (Melillo et al. 2014) has called attention to a possible role of the Arctic in variations of the jet stream (now referred to as the "polar vortex") over the contiguous United States (http://nca2014.globalchange.gov/report/our-changing-climate/melting-ice). As evidence of the increased public awareness of this topic, Hamilton and Lemcke-Stampone (2013) have recently reported results showing that a clear majority (60%) of surveyed members of the public now accepts that there is a connection between Arctic warming and mid-latitude weather. Yet the Arctic's connection with middle latitudes represents a challenge to scientific diagnosis because the forcings and responses of the two regions are intertwined. Hence a key question about Arctic–lower latitude coupling is: What is the forcing and what is the response to Arctic warming?

Drivers of the amplified warming in the Arctic

There is indisputable evidence that the Arctic has warmed over the past several decades at more than double the global rate of warming. There are at least four factors that contribute to the polar amplification:

- A temperature feedback by which a warming surface leads to a more radiative loss to space in the warmer lower latitudes than in the colder polar regions;
- The albedo-temperature feedback associated with a reduction of sea ice and snow;
- Increased atmospheric humidity and the associated increase of downwelling longwave radiation; and
- Increased poleward transports by the ocean and atmosphere.

While these drivers are not independent (e.g., the loss of sea ice can be driven by warming associated with increased humidity or poleward transports), the following sequential summary enables a more structured presentation.

IN THIS ISSUE

Though the entire globe is warming, the rate of warming in the Arctic is two to three times faster than the rest of globe. Why the Arctic is warming quickly is not obvious. Walsh discusses the causes and implications of Arctic amplification of warming. Though the snow and ice albedo feedback is thought by most as responsible for Arctic amplification, it is hard to reconcile the timing and pattern of warming simply with an albedo feedback. Feldstein and Lee argue that much of the Arctic warming can be explained by tropical variability. One direct cause of Arctic amplification is a weaker meridional temperature gradient. Francis and Overland discuss how changes in the meridional temperature gradient may be influencing mid-latitude weather. And given the possible growing influence of Arctic variability on our weather, Riddle and Scaife and Peings et al. discuss new sources of predictability on seasonal to decadal timescales. Finally, given large sea ice melt and increased sea ice variability, societal interest in sea ice predictability has grown, and Bitz and Stroeve summarize the prospects for long range forecasts.

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Latitudinal dependence of efficiency of re-radiation of energy

Pithian and Mauritsen (2014) have recently shown that polar amplification is a prominent feature of global climate warming even without changes in snow and ice. In the absence of a decrease of surface albedo, the Arctic still warms more than lower latitudes because the cold shallow near-surface layer, often characterized by temperature inversions, is relatively inefficient at re-radiating the additional energy. This inefficiency can be explained by the smaller increase of emitted blackbody radiation per unit warming at lower temperatures. Pithian and Mauritsen find that this "Planck feedback" is stronger than even the albedo feedback in shaping the latitudinal pattern of externally forced warming.

The albedo-temperature feedback

The warming since 1980, shown in Figure 1 as a function of calendar month and latitude, is strongest over the Arctic Ocean (70-90°N) during the period September-December. This period coincides with the greatest loss of sea ice. The reduction of the reflective sea ice cover during the season of strong solar radiation enables the upper ocean to absorb heat for release back to the atmosphere during the autumn and early winter (Perovich and Richter-Menge 2009), when cooling would be most rapid in the presence of sea ice. The signature of this release of stored heat by the high-latitude ocean is unmistakeable in Figure 1, which also shows a secondary maximum of warming in the northern high latitudes during spring. This maximum is consistent with the earlier disappearance of snow over northern land areas. Snow cover on land has decreased over the past several decades (Shi et al. 2013), especially in spring (Derksen and Brown 2012). As with the loss of sea ice over the ocean, the loss of springtime snow cover enables the less reflective land surface to absorb greater amounts of incoming solar radiation, thereby contributing to warmer spring conditions in the northern high latitudes. Because land has a smaller heat capacity than the ocean, there is less seasonal lag in the warming relative to the loss of terrestrial snow cover compared to the loss of sea ice.

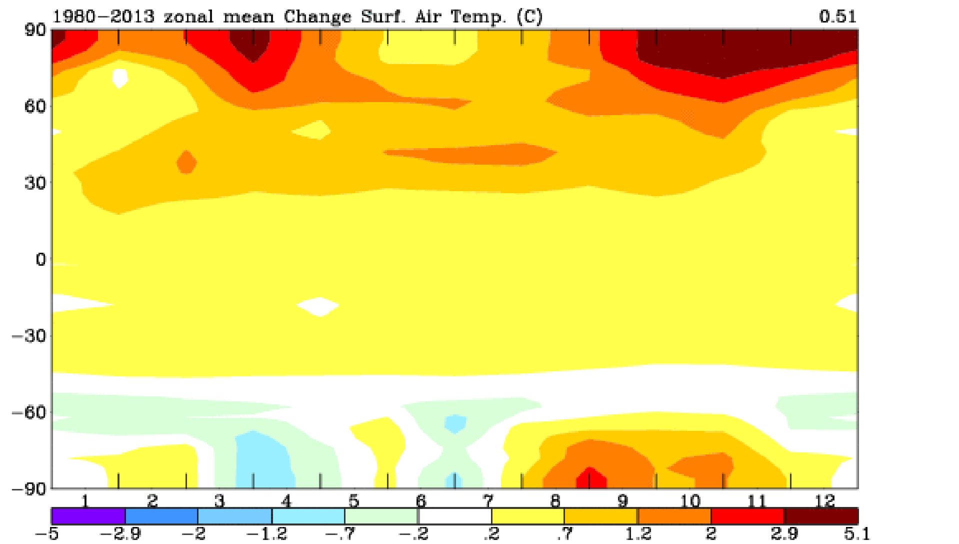


Figure 1. Change of temperature (°C) over 1980-2013 as a function of calendar month and latitude. Values are differences between end point and starting point of linear trend lines. Source: NASA Goddard Institute for Space Studies, http://data.giss.nasa.gov/gistemp/.

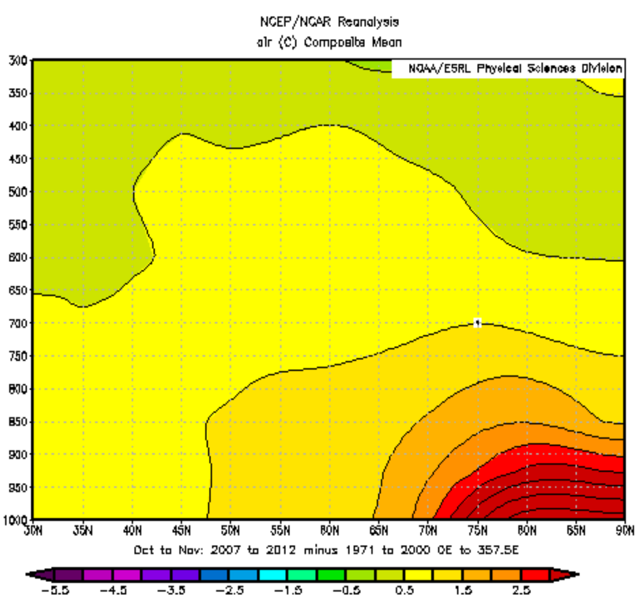
Increased atmospheric humidity and associated downwelling radiation

Water vapor is a strong greenhouse gas. Increases in humidity can therefore be expected to result in additional trapping of the infrared radiation emitted by the Earth. The corresponding increase in downwelling radiation will then enhance the warming of the surface. Even before the recent decline of sea ice, Francis and Hunter (2006) showed that variability of downwelling radiation was associated with sea ice variations on interannual timescales. Since a loss of sea ice leads to increased atmospheric moisture, which then increases the downwelling radiation and warming of the surface, the Arctic is a prime candidate for a manifestation of the so-called "water vapor feedback" and amplification of surface warming. Moreover, because the Arctic atmosphere is very dry, especially in winter, even a small increase in moisture can have a relatively large impact on the downwelling longwave radiation reaching the surface.

Several recent studies confirm increases of humidity in the Arctic. Screen and Simmonds (2010) present evidence that the increase of humidity in recent decades has arisen largely from the reduction of sea ice and has contributed to the Arctic warming, especially during summer and early autumn. The increases of humidity reported by Screen and Simmonds have been largest over the Arctic Ocean. Serreze et al. (2012) used a set of three atmospheric reanalyses as well as rawinsonde data to document humidity changes poleward of 60°N. While the increases varied by season and location, all sources showed increases of precipitable water in the surface-500 hPa layer over the period 1979-2010. Cohen et al. (2013) show that the recent increase is especially large in September-October.

While the water vapor feedback appears to have emerged as a contributor to Arctic amplification, changes in cloudiness are also considered to be candidates for feedbacks to climate change in high latitudes. However, Screen and Simmonds (2010) concluded that changes in cloudiness have played a much smaller role than changes in sea ice and atmospheric water vapor in the recent Arctic warming, and this conclusion is supported by the more recent results of Ghatak and Miller (2013). Given the tenuous nature of the evidence to date (and the difficulty of systematically documenting changes in Arctic clouds and their radiative properties), the jury still appears to be out in the assessment of the role of clouds in the recent and future Arctic amplification.

Impacts of increased water vapor are intertwined with increases in downwelling longwave radiation resulting from warmer air temperatures in the lower troposphere. The recent warming of the Arctic is strongest near the surface and diminishes upward, as shown in Figure 2. Since most of the downwelling longwave radiation that reaches the surface is emitted in the lowest



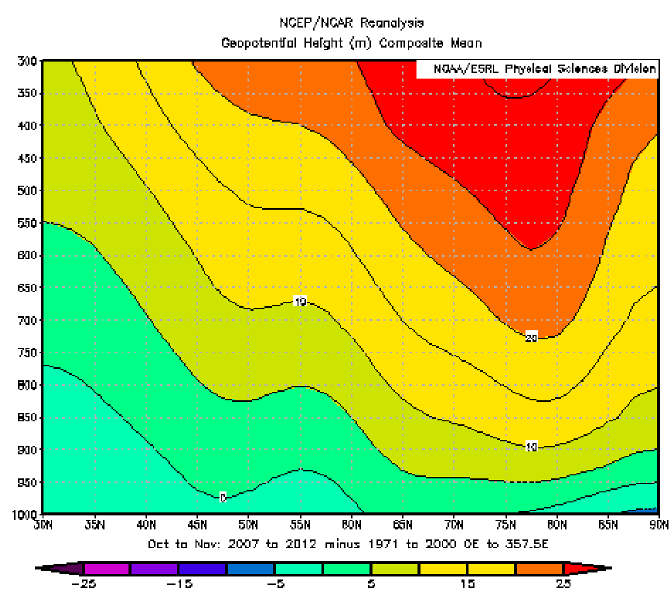


Figure 2. Left panel: The vertical cross-section composite plot of October to November zonally-averaged air temperature anomalies (ºC) for 2007-2012 relative to the 1971-2000 base period. Right panel: Same as upper panel, but for geopotential heights (m). Source: NOAA Earth Sciences Research Laboratory, http://www.esrl.noaa.gov/psd/cgi-bin/data/composites/printpage.pl.

kilometer of the atmosphere, warming of this layer will increase the downwelling longwave radiation at the surface. Bintanja and van der Linden (2013) show that the combined effect of a warmer lower troposphere and increased water vapor, which together comprise their "infrared feedback," outweigh the ice-albedo feedback by about 3:1 in amplifying Arctic winter warming. However, Pistone et al. (2014) have used satellite data to show that the recent decrease of albedo in the Arctic is considerably larger than previous estimates; when averaged globally, the impact of the Arctic albedo decrease is equivalent to about 25% of the direct radiative forcing from the increase of CO_2 over the past 30 years.

Increased poleward transports by the ocean and atmosphere

Poleward transports of heat and moisture are key components of the Arctic's energy budget (Serreze and Barry 2005). These transports are achieved by the ocean and atmosphere through their respective circulations (currents and winds). Variations of the North Atlantic/Arctic heat exchanges are largely the result of the varying temperature of North Atlantic Ocean inflow to the Arctic Ocean. This inflow occurs in two main branches, one west of Svalbard and the other through the Barents Sea. It is characterized by decadal and multidecadal variations superimposed on a warming trend (Polyakov et al. 2010). The combination of variability and the underlying trend leads to increasingly warm inflow pulses, one of which occurred in 2005-2006, immediately prior to the extreme ice retreat of 2007 (Alexeev et al. 2013). Because the Atlantic water circulates in a counterclockwise sense at depths of 100-400 m around the Arctic Basin, with a timescale of several years, measurements of abrupt warming of the Atlantic layer north of Siberia during 2007-2009 are consistent with the inflow pulse of 2005-2006 (Polyakov et al. 2011).

The corridor for Pacific Ocean water entering the Arctic is the Bering Strait. This water has also warmed over the past decade (Woodgate et al. 2012). Moreover, there are indications that the introduction of this warmer water reduces the thickness and coverage of sea ice in the Beaufort, Chukchi, and East Siberian Seas. The thinner ice, in turn, is more mobile and responsive to winds that drive the Beaufort gyre, enabling transports of the warmer Pacific water from the continental shelves to the deeper Arctic Ocean (Shimada et al. 2006). The further melt of sea ice then contributes to the albedo-temperature feedback discussed earlier. The fact that the recent retreat of sea ice has been largest in this sector attests to the importance of Pacific water inflow for the Arctic and its recent warming.

Atmospheric transports of heat and moisture into the Arctic can also be expected to increase as the atmosphere in lower latitudes becomes warmer and more moist. Zhang et al. (2013) point to a recent increase in poleward moisture transports into some areas of the terrestrial subarctic, although more complete assessments of moisture transports to the higher latitudes are required in order to place this process into the context of other drivers of Arctic warming.

Response to the Arctic warming

The preceding section has shown that the recent Arctic warming is not uniform throughout the year. Because the air normally tends to cool in autumn, the impact of the heat released from the ocean is greatest in the September-November period. This heat release from the ocean continues even after freeze-up, because the ice is thinner and less insulating than in previous decades. This ocean-to-atmosphere heat transfer affects the distribution of atmospheric pressures that, in turn, drive atmospheric circulation (Overland and Wang 2010).

Figure 2 shows the warmth of 2007-2012, relative to the 1971-2000 "normal" as a function of latitude and calendar month. The pattern in Figure 2 highlights the polar amplification discussed earlier, but it also shows that the relative increase in Arctic warming is strongest near the surface, consistent with the idea that such changes are driven by changes in the sea ice.

The fact that the warming is strongest in autumn directly above the Arctic Ocean surface is consistent with the delayed freeze-up noted above. The delayed freeze-up means that an ice-free ocean underlies the atmosphere at a time of the year when reduced solar radiation favors strong atmospheric cooling. The expanded areas of open water during autumn and early winter represent not only a source of heat to the lower atmosphere, but also a source of moisture. This additional moisture increases the amount of precipitation falling over the Arctic Ocean and adjacent land areas during autumn and early winter. Not surprisingly, recent decades have seen a highly significant increase in autumn snow cover over Eurasia, particularly in October. The increase since the late 1980s has been more than 1.4 million square kilometers of snow cover per decade (Cohen et al. 2012). The correlation between autumn ice extent in the Arctic and winter snow cover over the Northern Hemisphere is even more noteworthy. Reduced Arctic sea ice extent in autumn is associated with increased winter snow cover in large areas of eastern Asia, central Europe, and the northern half of the United States (Liu et al. 2012). But why should sea ice in autumn affect wintertime snow cover in middle latitudes? The proposed explanation for this relationship is based on reasoning about the pressure field that drives the primary feature of the Northern Hemisphere atmospheric circulation – the west-to-east flow at middle and upper levels of the mid-latitude atmosphere. This airflow includes the jet stream, with its wave-like meanders around the hemisphere. Further discussions of the midlatitude manifestations of Arctic warming are presented in other papers in this issue.

Acknowledgments

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The influence of tropical convection on Arctic climate variability

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For the past several decades, it has been widely accepted that Arctic climate variability, especially that of surface air temperature (SAT), is driven by midlatitude baroclinic (synoptic-scale) eddies over a wide range of time scales and by local ice-albedo feedback (e.g., Budkyo 1969) on interannual and longer time scales. In this paper, our aim is to show that the Rossby wave response to tropical convection is a major driver of climate variability in the Arctic SAT, perhaps even more so than that by baroclinic eddies and ice-albedo feedback. This process has been referred to as the tropically-excited Arctic warming (TEAM) mechanism (Lee 2012). The basic picture is that an intensification and localization of warm pool tropical convection can warm the Arctic during the winter (Lee et al. 2011; Yoo et al. 2011, 2012; Lee 2012, 2014) via the convective excitation of poleward propagating waves, which transport heat and moisture poleward, leading to enhanced downward infrared radiation (IR) and the inducement of sinking motion (adiabatic warming) over the Arctic. We will show that tropical convection influences the Arctic over a very broad range of time scales, including the intraseasonal, interannual, and interdecadal.

The TEAM mechanism is motivated by considering the global energy balance (Figure 1). The energy gain (deficit) at low (high) latitudes through radiative processes must be balanced by a poleward eddy heat flux. For baroclinic eddies, this heat flux is typically expressed by the flux-gradient relationship, which states that the baroclinic eddy heat flux is proportional to the meridional temperature gradient of the background flow. However, when this is applied to Arctic warming a difficulty arises. According to the flux-gradient relationship, as the Arctic warms the baroclinic eddy heat flux must decline. This implies that some other mechanism, not involving baroclinic eddy heat fluxes, must warm the Arctic. In this paper, we explore the Arctic warming that occurs via the TEAM mechanism.

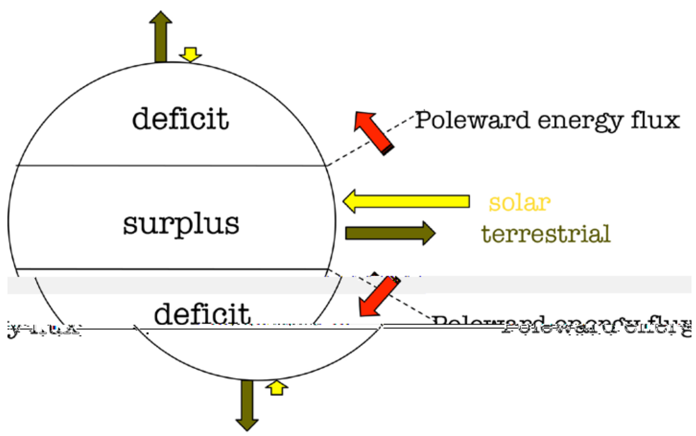

Figure 1. Schematic of the global energy budget. Radiation surplus and deficits are indicated along with the poleward energy flux.

Intraseasonal time scale (MJO)

The Madden-Julian Oscillation (MJO) is the most prominent mode of intraseasonal variability in the tropics. The MJO has been divided into eight different phases (Wheeler and Hendon 2004), based on a combined empirical orthogonal function (EOF) analysis of the outgoing longwave radiation (OLR) and 200- and 850-hPa zonal winds in the tropics. As is shown in Yoo et al. (2011), MJO phase 1 is characterized by weak tropical convection that extends over a broad range of longitudes and MJO phase 5 shows more localized and intense tropical convection (Figure 2).

The results from a lagged-composite calculation of the 250-hPa geopotential for these two MJO phases are shown in Figure 3, expressed as the difference between the phase 5 and phase 1

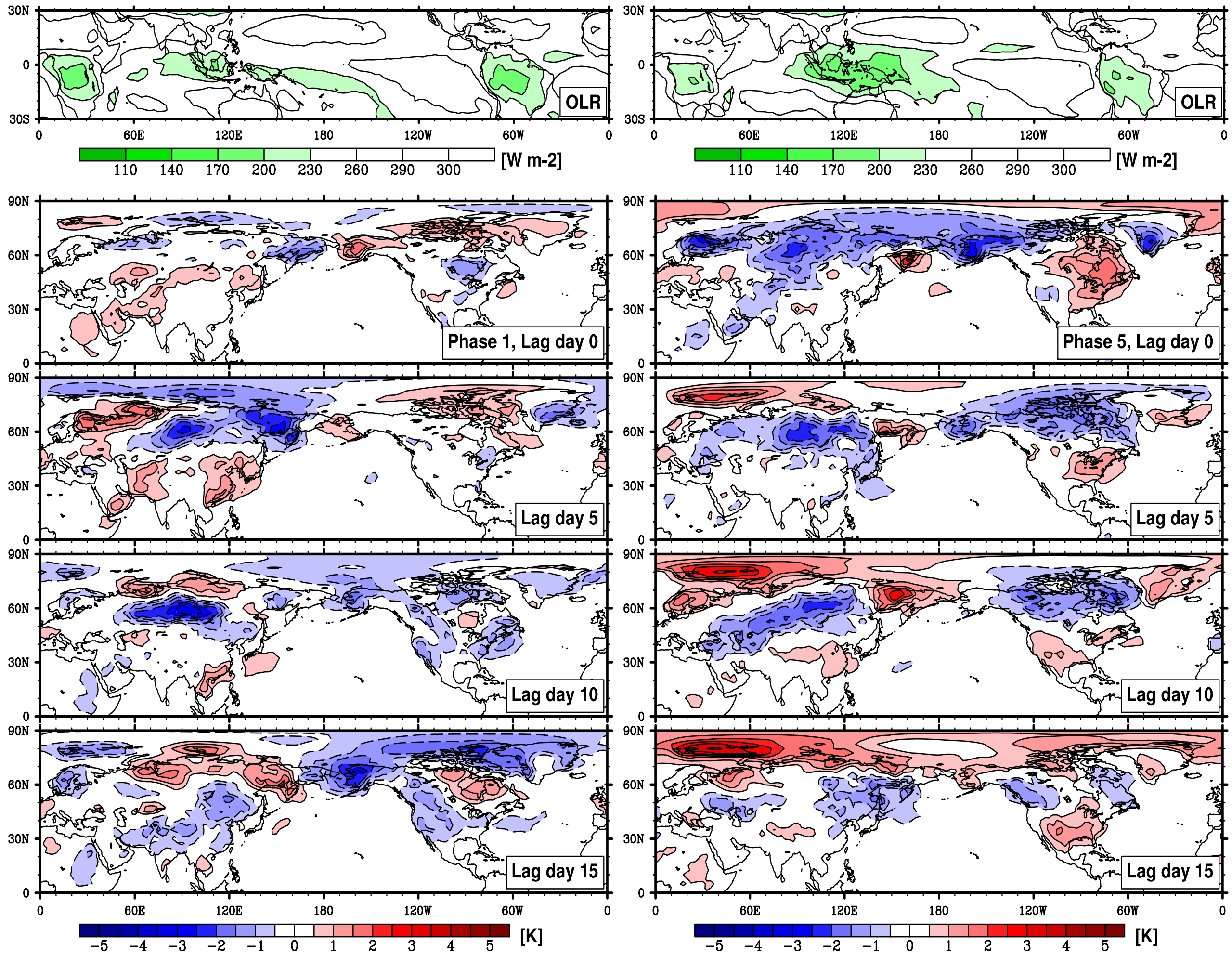

Figure 2. Total OLR composite (Wm^{-2}) on lag day 0 (first panels), with lagged composites of ERA-40 SAT (°C) on lag days 0, 5, 10, and 15 for MJO phases 1 (left) and 5 (right). Solid contours are positive, dashed contours negative, and the zero contours are omitted. Adapted from Yoo et al. (2011).

composites. At lag days 10 and 15, following the MJO convection, a wave train resembling the positive phase Pacific/North American (PNA) teleconnection pattern (three of the four centers of the canonical PNA can be seen) is observed (Yoo et al. 2012).

The corresponding anomalous composite SAT (Yoo et al. 2011) shows that when associated with the PNA-like wave train, there is a cooling over the Arctic for MJO phase 1 and a warming for MJO phase 5 (Figure 2). An examination of the terms in the thermodynamic energy equation finds that the downward IR and horizontal thermal advection, associated with this wave train, are the largest contributors to the Arctic SAT warming (Yoo et al. 2012).

Interannual time scale (El Niño Southern Oscillation)

We next examine the composite anomalous SAT associated with La Niña and El Niño (Lee 2012). For La Niña, with its relatively narrow and intense tropical convection, the composite SAT was found to show an anomalously warm Arctic. For El Niño, with its broader and less intense tropical convection, opposite Arctic SAT changes were found. These results are consistent with the above TEAM mechanism findings for the MJO. Findings also show that La Niña is associated with an increased poleward moist static energy transport in midlatitudes, with El Niño showing opposite features.

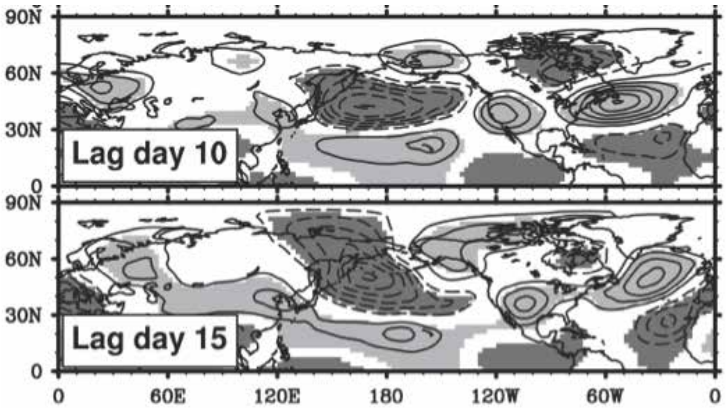

Figure 3. Lagged composites of the difference between the MJO phase 5 and MJO phase 1 ERA-Interim 250-hPa geopotential. The contour interval is 200 $m^{-2}s^{-2}$. Solid contours are positive, negative contours dashed, and the zero contour is omitted. Shaded values indicate statistical significance ($p<0.05$). Adapted from Yoo et al. 2012.

Decadal Arctic SAT trend

To the extent that the TEAM operates on all times scales, it is to be expected that much of the recent decadal Arctic warming trend is driven in part by tropical convection. Consistently, the decadal trend in tropical OLR, Global Precipitation Climatology Project (GPCP), and Climate Prediction Center merged analysis of precipitation (CMAP) indicate an increased intensity and localization of tropical convection over the past few decades (Lee et al. 2011). In analogy with the MJO, decadal trends in downward IR and horizontal thermal advection (primarily by stationary eddies) contribute to the Arctic warming (Lee et al. 2011). The results of that study also show that surface sensible and latent heats fluxes play a minor role in the decadal warming trend over the Arctic Ocean during the winter. These findings contrast with the long held view that Arctic warming trends are due to ice albedo feedback.

In Lee et al. (2011), this trend was further examined with self-organizing map (SOM) analysis, a type of cluster analysis. In that study, 20 combined 250-hPa geopotential height/convective precipitation cluster patterns were obtained. These patterns were dominated by the PNA, North Atlantic Oscillation (NAO), and circumglobal (a zonal wave number 5 pattern; Branstator 2002) teleconnection patterns. Each of the 20 patterns has an e-folding time scale of less than 10 days.

The decadal trend in the frequency of occurrence of these 20 patterns is illustrated in Figure 4a. It can be seen that patterns 4-5 and 11-14 dominate in early years, whereas patterns 1, 7-8, and 17-19 dominate in later years. This corresponds to a trend from negative phase PNA-like and negative circumglobal patterns, to positive phase PNA-like and positive circumglobal patterns. These results imply that the majority of the Northern Hemisphere 250-hPa decadal trend arises from decadal trends in the frequency of occurrence of intraseasonal teleconnection patterns. These findings also suggest that the decadal Arctic warming trend can also be explained to a large extent by the decadal trend in the frequency of occurrence of the intraseasonal teleconnection patterns, along with the heat transported poleward by these patterns.

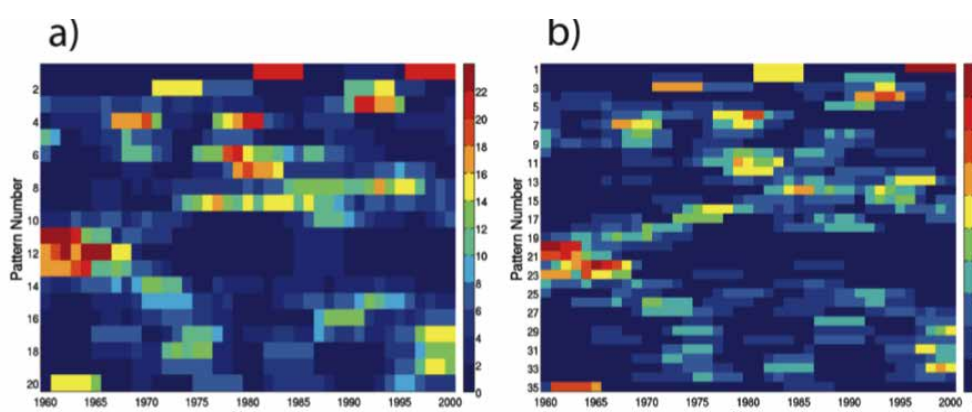

Figure 4. Time evolution of the frequency of occurrence (expressed in percentage of days within each year) for **a)** 20-pattern SOM and **b)** 35-pattern SOM array. ERA-40 reanalysis data is used. The ordinate identifies the SOM pattern number. Panel **b)** shows that the SOM analysis is not sensitive to the number of SOM patterns. Adapted from Lee et al. 2011.

Stratospheric sudden warmings

Tropical convection has also been shown to impact the Arctic stratosphere. Garfinkel et al. (2012) showed that particular phases of an active MJO occur with increased frequency ($p<0.10$) prior to stratospheric sudden warmings. Their finding suggests that an active MJO is followed by constructive interference between the Rossby wave train excited by the MJO and the climatological stationary eddies. This interference leads to enhanced vertical wave activity propagation, and a deceleration of the stratospheric polar vortex along with the stratospheric sudden warming event. This coincides with the excitation of the negative phase Northern Annular Mode (NAM) in the stratosphere, and a descent of the NAM into the troposphere, along with a warming over the Arctic.

Possible role played by moisture fluxes

More recent, not yet published studies by S. Lee and S. Feldstein find that poleward moisture transport into the Arctic, which increases the downward IR over the Arctic, is the key driver of both Arctic SAT warming and the loss of Arctic sea ice. They find that the condensation of water vapor transported into the Arctic by Rossby wave trains leads to the increase in downward IR. This occurs because liquid water and ice are much more effective emitters of IR than water vapor.

Implications for climate models

The results from the above studies suggest that tropical convection has a large impact on Arctic climate for a broad range of time scales. The linkage between tropical convection and decadal climate warming is of particular interest as the area of Arctic sea ice has been undergoing a dramatic decline over the past two decades. All modern day climate models have failed to simulate this large loss of sea ice, alluding to the fact that these models may be missing or misrepresenting some key process. Also, there are large differences in the simulation of tropical convection between climate models.

Furthermore, the simulation of convection in climate models is least accurate in the tropics (Stevens and Bony 2013). Thus, the results from the papers presented in this article suggest the possibility that an insufficiently accurate representation of tropical convection is contributing to the inability of climate models to simulate recent Arctic climate change, and that a better simulation of the recent Arctic climate change may require improvement in the manner in which climate models treat tropical convection.

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Implications of rapid Arctic change for weather patterns in northern mid-latitudes

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A variety of positive feedbacks – processes that amplify an original change – cause the Arctic to be more sensitive to global temperature change than anywhere else on Earth. Consequently, the Arctic's lower tropospheric air temperature has continued to rise at three times the rate exhibited by Northern Hemisphere mid-latitudes during the recent slowdown in the global temperature increase (Figures 1 and 2), resulting in substantial losses of sea ice, land ice (glaciers and ice sheets), permafrost, and snow cover in spring (Jeffries et al. 2013). Recent studies suggest that the rapidly warming Arctic is associated with an increase in extreme weather events, such as cold spells (Tang et al. 2013a; Cohen et al. 2013) and heat waves (Tang et al. 2013b) in Northern Hemisphere continents, as well as wet summers in western Europe (Screen 2013). Identifying the mechanism(s) underlying the linkage is a focus of active research, including an assessment of the relative roles of forced versus random natural variation in these events. Evidence for complicating weather linkages includes observed asymmetrical surface temperature trends that vary by season. Winter continental regions, for example, have cooled during 1979-2011 (Cohen et al. 2012).

One hypothesis for a mechanism linking rapid Arctic warming with changing mid-latitude weather patterns is as follows. Arctic amplification (AA) – the heightened sensitivity of the Arctic to global temperature change – has reduced the Arctic/mid-latitude temperature contrast in recent decades, particularly during autumn in response to sea ice loss (Figure 1). Because this gradient is a fundamental driver of the jet stream's westerly wind speed, the weaker temperature contrast leads to weakened upper-level winds (Overland and Wang 2010; Francis and Vavrus 2012). A weaker jet stream tends to take a more meandering path as it encircles the Northern Hemisphere (Thompson and Wallace 2001; Palmén and Newton 1969). In highly meandering flows, the north-south waves in the jet stream tend to travel eastward more slowly, which increases the likelihood of persistent weather patterns that can cause a variety of extreme events (Screen and Simmonds 2014). This new manifestation of global warming is of great potential importance, as more frequent extreme weather events in mid-latitudes will affect billions of people directly through damage to property and infrastructure and indirectly through agriculture and water supplies. Moreover, even though they may not contribute to hemispheric temperature trends, the

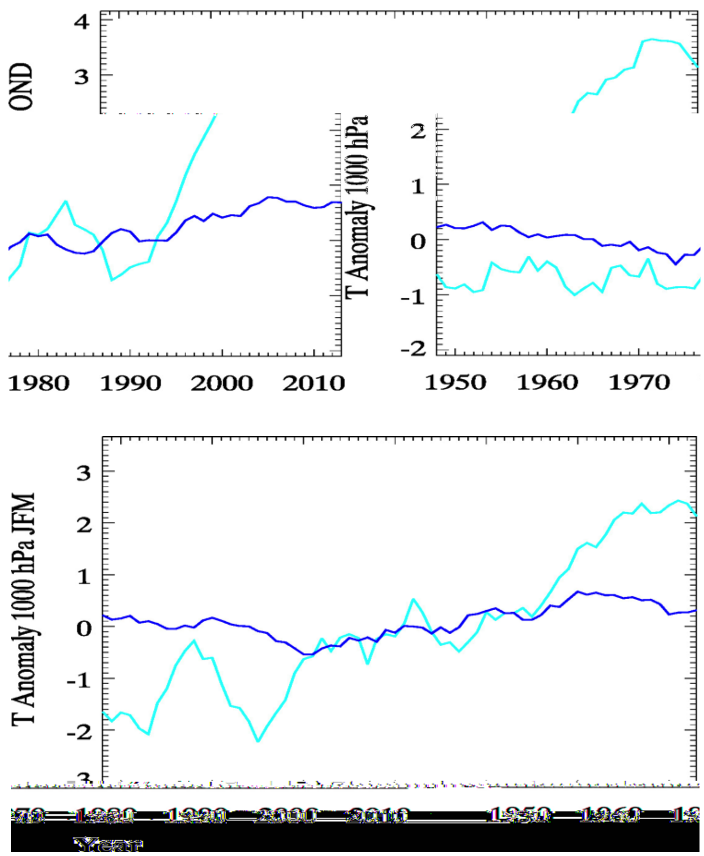

Figure 1. Five-year running means of near-surface air temperature anomalies (°C, relative to 1970-1999) during autumn (Oct.-Dec., top) and winter (Jan.-Mar., bottom) for the Arctic (70°N to 90°N, cyan) and for the Northern Hemisphere mid-latitudes (30°N to 60°N, blue). Data were obtained from the NOAA/ESRL Physical Sciences Division, Boulder CO, http://www.esrl.noaa.gov/psd/.

amplified patterns do exhibit regional preferences for anomalies in temperature and precipitation; thus it may be possible to predict which types of extreme events will be more likely to occur in certain areas, and in turn assist decision-makers in preparing for the future.

Because the atmosphere is inherently chaotic and the signal of AA has emerged so recently, it is a challenge to detect robust changes in the character of the jet stream (Barnes 2013; Screen and Simmonds 2013) and separate the various influences on its behavior. Here we briefly outline two new efforts to elucidate the issue.

The probability (P) of detecting a signal amid a noisy system can be estimated using Bayes Theorem (Silver 2012), which relates a known forcing (X) to the natural variability of the system:

$$P = \frac{XY}{XY + Z(1 - X)}$$

In this application, we assume the known forcing is the present (0.4) and future (0.9) estimates of open-water fraction in the Arctic Ocean at the time of minimum sea ice extent, as increased open water heats the atmosphere and is a primary driver of AA. The probability that a signal is detectable, if the hypothesized linkage is true, is represented by Y. For this value we use the fraction of variance in sea level pressure between 20°N and 90°N explained by the Arctic Oscillation (AO) index, as determined through an empirical orthogonal function (EOF) analysis (Overland et al 2008): Y = 0.23. Finally, the probability of detecting a signal if the hypothesized linkage is false is represented by Z, which we estimate to be of order 0.5, as the unexplained fraction of variability in sea level pressures, i.e., the chaotic noise.

The results of this Bayesian analysis suggest that under present conditions, the probability of detecting an atmospheric response (measured as a change in the AO index) to AA is approximately 0.21, meaning that natural variability (the noise) exceeds the signal. Although this is a simple calculation with approximate values, it is consistent with the current state of the science, i.e., that proposed linkages are provisional episodes and "unproven" in terms of statistical significance (e.g., Screen et al. 2013). In the future, as sea ice loss continues and the open water fraction approaches 0.90, the probability of signal detection increases to 0.78. With most sea ice researchers are expecting the Arctic Ocean to become nearly ice-free during summer within a few decades (Overland and Wang 2013), a robust change in the large-scale circulation should be evident in the future. However, other measures of inherent variability may produce different results, and certain regions may exhibit a detectable response sooner than others. New research suggests that the signal may already be emerging.

AA is largest in fall and winter, thus the atmospheric response should become evident first and be largest in cold seasons. In fall the signal is approximately concentric around the pole, but in other seasons the pattern is highly spatially variable (see Figure 2, Francis and Vavrus 2012). In all seasons, the northwest Atlantic appears to be a "hot spot" of AA, thus the circulation in this area should exhibit a more robust response than elsewhere. While previous studies investigated a change in amplitude of planetary waves, as hypothesized by Francis and Vavrus (2012), here we instead shift the focus to measure a changing frequency of highly amplified jet stream patterns. As in Francis and Vavrus (2012), our analysis is based on single height contours in the 500 hPa field such that the selected contours best represent the trajectory of the jet stream: 5600 m for cold months (October – April), and 5700 m for warm months (May – September). We use daily-mean data from 1979 to 2013 obtained from the NCEP/NCAR reanalysis (Kalnay et al. 1996).

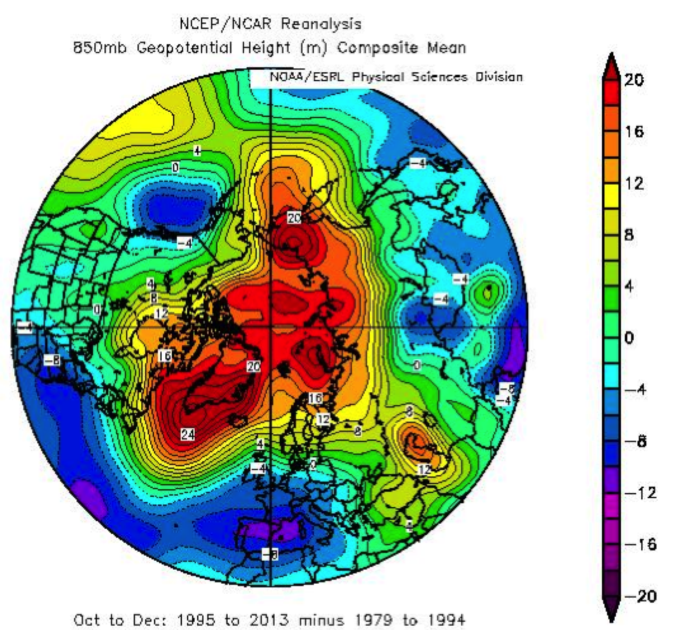

Figure 2. Difference in mean autumn (Oct.-Dec.) 850 hPa heights (m) between the period of recent Arctic amplification (after 1995) and earlier years (1979 to 1994). Data were obtained from the NOAA/ESRL Physical Sciences Division, Boulder CO, http://www.esrl.noaa.gov/psd/.

A highly amplified jet stream pattern is identified when the difference between the daily maximum and minimum latitudes of a single contour in a particular region exceeds 35°. This threshold is selected to obtain approximately 20 events per season, but the main conclusions are not sensitive to small variations in the threshold or to using other height contours within 100 m. In Table 1, we compare seasonal mean frequencies of high amplitude configurations during the period prior to the emergence of AA (1980-1994) to frequencies during recent years (1995-2013). Varying the division between these periods by five years earlier and later makes no appreciable difference to the results presented. Values and cell color indicate percentage differences in six regions and in each season.

Substantial increases in the occurrence of high amplitude jet stream patterns have occurred during autumn in all regions, with large increases evident over North America and the Atlantic during winter and summer. The results for fall and winter are consistent with the expected response to large AA in these seasons and support the hypothesis proposed by Francis and Vavrus (2012). We speculate that increased frequencies in summer may result in part from the rapid decline in late spring snow cover on high latitude land areas, which is collocated with the pattern of AA during summer (Francis and Vavrus 2012). Because highly amplified jet stream patterns have been linked with a variety of extreme weather types (Screen and Simmonds 2014), our findings suggest that the recent increase in extreme events throughout the Northern Hemisphere mid-latitudes (Coumou and Rahmstorf 2012) may be partly due to the rapid pace of Arctic warming.

Clearly much additional research is needed to understand better the mechanisms by which mid-latitude weather patterns will respond to the changing climate system, and particularly if and how they may be influenced by AA. There is also much to learn about the interplay among AA and modes of natural variability (such as the El Niño Southern Oscillation, the Pacific Decadal Oscillation, and the Atlantic Multidecadal Oscillation). The recent flooding in the UK (winter 2014) and the North America "Snowmageddon" (February 2010), for example, were apparently caused by a combination of Arctic and tropical influences on the jet stream's configuration. Progress can be made by assessing the behavior and trends in weather patterns by region and season, as the globe – and particularly the Arctic – continue to warm in response to unabated emissions of greenhouse gases.

Region	JFM	AMJ	JAS	OND
Atlantic -75 – 0E	38	7	133	64
North America 220 – 290E	26	12	49	41
Europe -15 – 45E	1	-6	32	39
Asia 30 – 150E	2	-5	-21	113
Pacific 150 – 240E	-14	13	-5	43
Northern Hemisphere	3	1	-9	30

< -40%	-39 to 30%	-29 to 20%	-19 to 10%	-9 to 0%
0 to 9%	10 to 19%	20 to 29%	30 to 39%	> 40%

Table 1. Percentage change in seasonal frequency of extreme waves from the pre-AA period (1979-1994) to the AA-era (1995-2013). Extreme waves are identified when the difference between the maximum and minimum latitude of the 500 hPa height contour (selected to correspond with mean height of strongest westerly winds) within a specified region exceeds 35° latitude. Height data were obtained from the NCEP/NCAR reanalysis, NOAA/ESRL Physical Sciences Division, Boulder CO, http://www.esrl.noaa.gov/psd/.

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Recent evidence for skill in model forecasts of Northern Hemisphere winter climate

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Recent record-breaking winters in North America and Europe have piqued interest in whether winter climate extremes are predictable on seasonal timescales. The answer is closely tied to the predictability of leading modes of Northern Hemisphere interannual variability, the Arctic Oscillation (AO) and North Atlantic Oscillation (NAO), which control the position and strength of the Northern Hemisphere jet streams and impact near-surface winds and temperatures across the northern mid-latitude continents. Swings in these indices often dominate over other factors influencing Northern Hemisphere winter climate. For example, the exceptionally negative AO and NAO during the winter of 2009/2010 (L'Heureux et al. 2010; Fereday et al. 2012) caused widespread cold anomalies across the eastern and central United States and Northern Europe, overshadowing the impacts of El Niño and other climate indicators (Figure 1).

While some statistical techniques have shown promise in forecasting the AO and NAO several months in advance (e.g., Cohen and Fletcher 2007; Cohen and Jones 2011), recent operational seasonal forecast systems based on dynamical models show only modest levels of skill (Arribas et al. 2011; Kim et al. 2012). This is because models have shown little extratropical atmospheric response to slowly varying components of the climate system, such as the ocean (Kushnir et al. 2006). Instead, variability in the AO/NAO appears in the models to be mostly due to internal atmospheric dynamics and feedbacks (e.g., Lorenz and Hartmann 2003), with predictability of these modes decreasing rapidly at lead times beyond two weeks. These results have led to the conclusion that little predictability exists for key extratropical events such as extreme winters (Jung et al. 2011) at longer lead times.

However, three recent papers (Riddle et al. 2013; Scaife et al. 2014; Kang et al. 2014) suggest that the newest state-of-the-art seasonal forecast systems have usable skill in predicting the AO/NAO several months in advance. Moreover, recent results indicate that the predictability of the AO/NAO may be greater in the real world than suggested by signal-to-noise ratios observed in the models (Scaife et al. 2014; Eade et al. 2014). In other words, surface and/or atmospheric precursors in October and November may have a more important influence on Northern Hemisphere extratropical winter climate than previously thought.

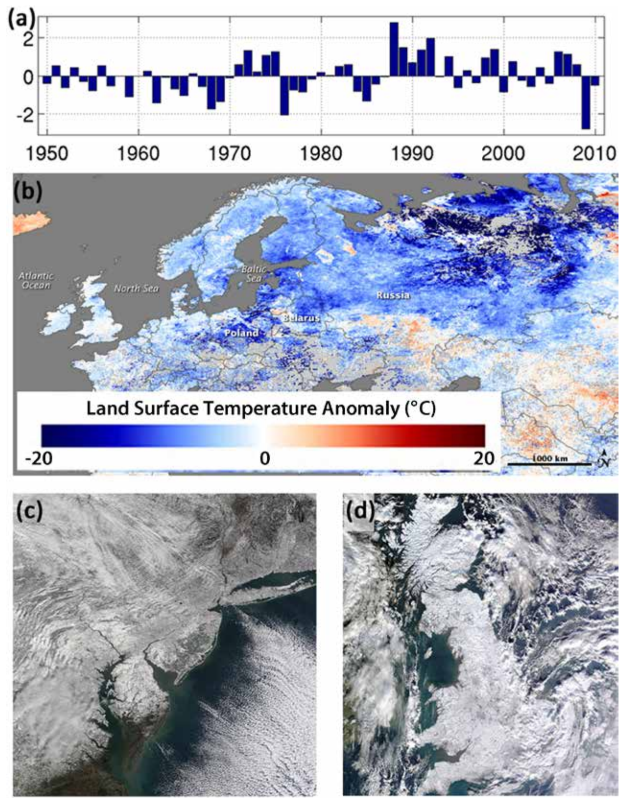

Figure 1. Depiction of cold air outbreak and record snowfall over northern Europe and the eastern US occurring during the extreme negative phase of the AO during the winter of 2009/2010. **a)** Time series of the December - February AO Index from the winters of 1950/1950 through 2010/2011 showing the extreme negative AO value during the winter of 2009/2010. **b)** Temperature anomalies (°C) over Eurasia for December 7-9, 2009. **c)** Snow cover during a severe winter storm that hit the US mid-Atlantic region on December 21, 2009. **d)** Great Britain and Ireland covered with snow on January 7, 2010. Figures **b)**-**d)** are from the NASA Earth Observatory, based on MODIS satellite imagery.

Diagnosing model skill

Diagnosing skill in a dynamical forecast system requires the use of a "hindcast" or "reforecast" over an extended historical period. For operational seasonal forecast systems, running the most recent operational version of the model retrospectively – to simulate forecasts of seasons that have already occurred – creates such a record. For example, to recreate a forecast of wintertime (DJF) climate, ensembles of coupled simulations initialized with November initial conditions are run for a range of previous years. Model output for the winter season in a given year can then be compared with the conditions that actually occurred. Both the ensemble-mean model forecast and the spread between ensemble members can be used to assess the skill of the forecast, the signal-to-noise ratio in the model, and the forecast uncertainty.

While the reforecast approach is simple enough, a variety of different forecast configurations are possible. The "lead time" of a forecast refers to the time between the date that a forecast was issued and the start date of the "target" period. For a forecast of the winter (DJF) season, the target period begins on December 1, so a forecast issued on November 1 would have a one-month lead time. In general, a larger number of ensemble members provides a higher quality forecast. However, the computational power needed to run a large number of ensemble members over many reforecast years, lead times, and seasons is non-trivial. Therefore, often only a few ensemble members are initialized every few days, and a "lagged ensemble" is used that includes a suite of ensemble members with staggered start dates. Alternatively, a larger number of ensemble members may be produced less frequently (e.g., at the start of each month).

Skillful forecasts of the AO / NAO

Figure 2 shows forecasts of leading modes of Northern Hemisphere surface variability from the UK Met Office Global Seasonal Forecast System version 5 (GloSea5) and the US National Centers for Environmental Prediction (NCEP) Climate Forecast System version 2 (CFSv2). The forecast years and configurations are different between the two models, and the GloSea5 forecast is for the single location NAO index, while the CFSv2 forecast is for the hemispheric AO. However, both show lagged ensemble forecasts with 24 members and lead times of around one month (i.e., the latest members in the lagged ensembles are initialized in early November). The GloSea5 NAO forecast shows anomaly correlations (AC) between the predicted and observed time series of 0.62, which is statistically significant at the 99% confidence level (Scaife et al. 2014). For comparison, a persistence forecast only yields an AC value of 0.15. The CFSv2 forecast shown is for a longer time series and shows AC skill of 0.46, which is statistically significant at the 95% confidence level (Riddle et al. 2013). Riddle et al. (2013) also report skill for lead times ranging from zero to

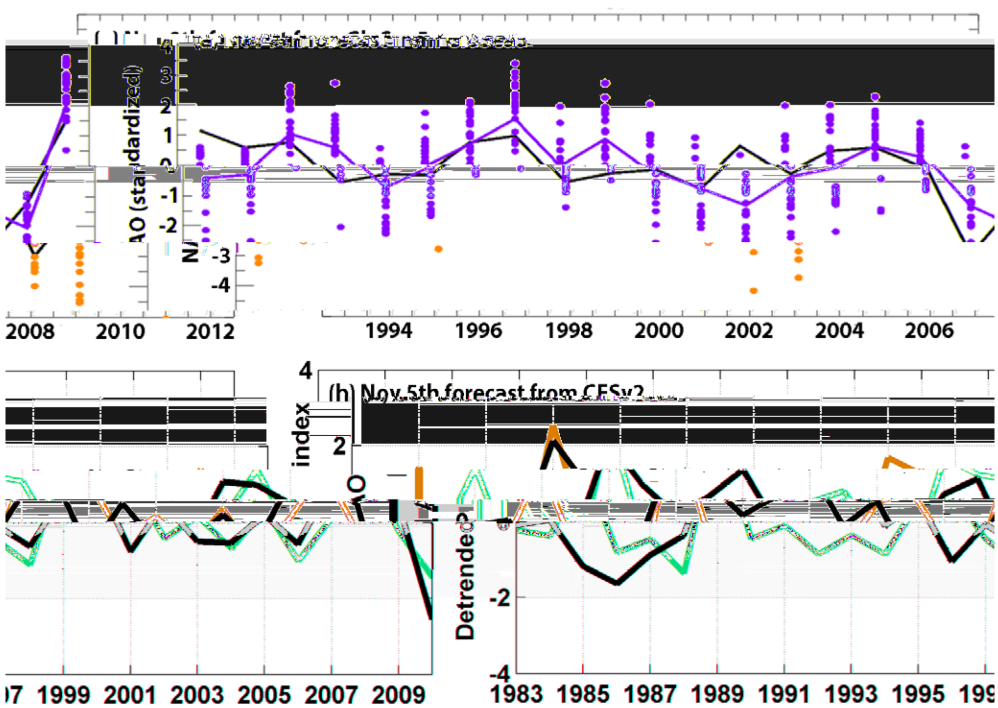

Figure 2. Model forecasts of the leading modes of Northern Hemisphere climate variability. **a)** GloSea5 ~one-month lead standardized forecasts of the DJF NAO, showing 24 individual ensemble members (orange dots), the ensemble mean (orange line), and the observed NAO (black line). Ensemble member initialization dates range from October 25 - November 9 (reproduced from Scaife et al. 2014). **b)** CFSv2 ~one-month lead standardized forecast of the DJF AO based on a 24-member ensemble mean (orange), compared with the NCEP Climate Forecast System Reanalysis AO index (black). The CFSv2 ensemble member initialization dates range from October 13 - November 7 (based on results from Riddle et al. 2013).

five months (not shown). They find a large degree of sampling variability in the AC skill (Kumar 2009), however statistically significant correlations are consistently found at up to two months lead if a large enough ensemble is used.

Results from a third study (Kang et al. 2014) suggest that these results might extend to other models as well. The authors analyze forecasts for 1983-2010 in five models (CFSv2, GEOS-5, CanCM3, CanCM4, CM2.1), with lagged ensemble members initialized between November 1 and December 2. Because of the shorter lead time, skill is expected to be higher than for the results shown in Figure 2. All five models show correlations that are statistically significant at the 95% confidence level for the 1983-2010 period, and three models show AC exceeding 0.65 ($p<<0.01$). As also reported in Riddle et al. (2013), skill in the second half of the record (1997-2010) is higher than in the earlier portion of the record, with correlation skill measures in the most recent 14 years exceeding 0.79 in three of the models.

Predictability in models versus the real world

In principle, the individual forecast members that make up an ensemble each represent an alternative, yet viable evolution of the seasonal climate. If this is the case, then each forecast member will contain the same predictable signal as in the real world but a different realization of the unpredictable "noise" due to the inherent chaotic nature of the climate system (Lorenz 1963). However, even the newly developed and skillful systems described above appear to fall short of this ideal. The interannual correlation between pairs of individual forecast members is systematically lower than the correlation between forecast members and the real world. This important discrepancy suggests that the predictable component in the forecasts is smaller than the predictable component of the real climate (Eade et al. 2014). Therefore, it appears that while these new systems are beginning to represent processes that give rise to predictability of the NAO and AO, they are only weakly represented.

In this situation, so called 'perfect model' estimates of predictability – where a single forecast member is used as a proxy for observations – will provide a misleading estimate of forecast skill. It will underestimate the forecast skill (Kumar 2014; Eade et al. 2014) rather than estimate the maximum achievable skill, as is sometimes assumed. Similarly, in this situation, probabilistic verification scores can miss the small forecast signal and again give a misleading estimate of skill.

There is a further consequence of the small signal-to-noise ratio in these seasonal forecast systems. As shown in Figure 3, the large proportion of chaotic 'noise' in the forecasts means that many forecast members are required to eliminate the noise and thereby provide skillful forecasts (Riddle et al. 2013; Scaife et al. 2014). In the example shown, the correlation skill of the forecast rises with the number of forecast members from very modest values for single forecasts (~0.15) to potentially useful values (~0.6) for the 24 members run in this particular hindcast set. However, more than 80 members would be needed to get close to the maximum achievable skill. Yet, current forecast systems use much less than this number, especially for hindcasts where 10-15 members are commonly employed. Skill estimates from these hindcasts are therefore not representative of the forecast ensemble skill, and ensemble size needs to be accounted for before estimating skill.

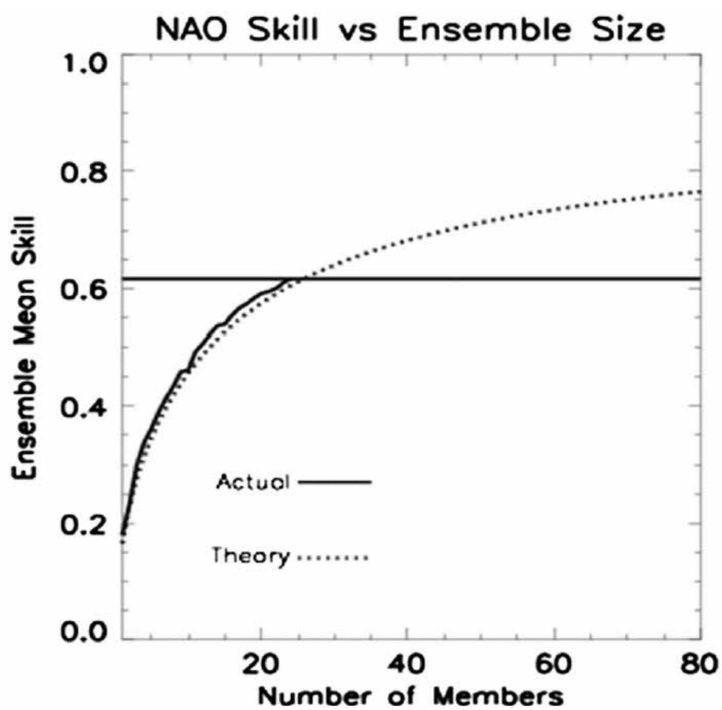

Figure 3. Correlation skill score for winter predictions of the NAO over the 20-year period, 1992/93-2011/12, as a function of ensemble size for the GloSea5 forecast system. Solid line depicts the actual correlation for the 24-member hindcast set. Dashed line depicts theoretical correlation based on simple statistical theory using the average inter-member correlation and the average member-observation correlation (Murphy et al. 1990). Figure reproduced from Scaife et al. (2014).

Where does the model skill come from?

Given the skill observed in CFSv2, GloSea5, and other models, a natural next question arises concerning its source. Over the past decade, studies have identified several factors that may influence variability in the wintertime AO and NAO. Some that have been proposed include: (1) Pacific sea surface temperatures (SSTs), (2) North Atlantic SSTs, (3) October Eurasian snow cover, (4) the quasi-biennial oscillation (QBO), (5) solar variability, and (6) late summer Arctic sea ice extent. Is it possible to isolate which of these processes in the models are most responsible for the model skill?

Scaife et al. (2014) and Riddle et al. (2013) investigated how some of these relationships are represented in the GloSea5 and CFSv2 hindcasts, respectively. Scaife et al. (2014) examined relationships between DJF surface pressure, and November Pacific SSTs, North Atlantic Ocean heat content, Kara sea ice and the QBO. The observed teleconnections between these factors and DJF North Atlantic surface pressure were all reproduced in the GloSea5 ensemble mean, though the signals were generally only weakly represented, consistent with the skillful but weak signals in forecasts. Of the factors tested, the strength of the Pacific SST teleconnection was the most robust in the model and observations. Riddle et al. (2013) performed a mechanistic study focusing on stratosphere/troposphere coupling in CFSv2 and on relationships between the DJF AO and October Eurasian snow cover. The model lacked (or represented weakly) several important links between the stratosphere and troposphere and did not show a relationship between Eurasian snow cover and the DJF AO, leaving the question open as to the source of skill in CFSv2.

To truly diagnose the sources of model skill, further simulations will be needed that test how skill measures respond to degradation of various initial conditions. Interestingly, preliminary results using the European Centre for Medium-Range Weather Forecasts (ECMWF) model suggest that the atmospheric initialization appears to be more important to November forecasts of the DJF AO than the initialization of the surface (T. Stockdale, personal communication). These results will need to be investigated further using other models.

Summary

Three recent studies (Riddle et al. 2013; Scaife et al. 2014; Kang et al. 2014) have demonstrated predictability of the AO/NAO in seasonal forecast models. All models in the three studies are able to forecast important excursions in the NAO/AO index, including the very negative index values during the winter of 2009/2010, previously thought to be unpredictable at seasonal timescales (Jung et al. 2011). While the results from these studies are interesting in their own right, together they provide stronger evidence that state-of-the-art models may be more skillful than previously thought for seasonal forecasts of Northern Hemisphere winter climate variability.

These results open the door to promising new research directions and applications. Results indicate that models may just be beginning to weakly represent key processes leading to the potential predictability of the AO/NAO. Further work is needed to understand what processes are governing these weak signals and determine whether noise levels in the models can be further reduced (e.g., with increased model resolution). In addition, the observed decadal shift in skill identified in these studies requires further investigation. Given the relatively short hindcast records available for these studies (28 years at most), some uncertainty inevitably remains as to whether the skill observed will remain robust into the coming decade. Given that the AO/NAO indices govern the risk of extreme winter weather events across much of Europe and North America, answers to these questions and others will be of wide societal interest.

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Can high latitude boundary forcings (ocean-ice-snow) improve predictability on seasonal and decadal time scales?

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Potential predictability of the atmosphere arises from slowly varying boundary components of the climate system such as the oceans and the cryosphere. Surface climatic anomalies that are more persistent than the atmosphere represent a potential source of predictability at different time scales and are therefore exploited in seasonal to decadal forecasting. The role of sea surface temperature (SST) anomalies was first identified due to early availability of SST measurements (late 19th century). The ocean surface not only responds to atmospheric variability, it in turn influences climate through heat flux exchanges with the overlying atmosphere (Bjerknes 1964). In the tropics, warm SST anomalies induce a local heat source due to increased evaporation and precipitation. Under certain conditions, the atmospheric perturbation has an impact in remote regions through teleconnections associated with large-scale Rossby waves in the atmosphere (Hoskins and Karoly 1981). While the potential of different tropical SST patterns in forcing the atmosphere has long been recognized, the influence of extratropical SST anomalies is less evident. For example, the North Atlantic Oscillation (NAO), a large-scale atmospheric mode of variability of the Northern Hemisphere, induces an Atlantic SST-tripole pattern that feedbacks on it (e.g., Czaja and Frankignoul 1999), but this feedback is weak (Kushnir et al. 2002). However, recent studies show that long-term basin-wide SST anomalies associated with the Atlantic Multidecadal Oscillation (AMO) can drive significant NAO-like responses in winter (Msadek et al. 2011; Peings and Magnusdottir 2014a; Omrani et al. 2014) leading to a non-negligible source of predictability at decadal timescales. In addition to the open oceanic surface, Arctic sea ice concentration anomalies and snow-cover extent anomalies over the continents are two other major sources of predictability in northern high latitudes. Like SST, sea ice and snow cover anomalies exhibit some persistence (up to several months) that can be exploited in seasonal forecasting. Natural and anthropogenic driven trends in sea ice and snow cover are also a source of predictability for the 21st century climate.

Short and long-term predictability associated with the Arctic sea ice

Sea ice strongly modifies the ocean-atmosphere heat exchange and the amount of solar radiation that is absorbed in the upper ocean. Numerous modeling studies have explored the predictability associated with the sea ice dipole variability on interannual time scales (e.g., Magnusdottir et al. 2004; Deser et al. 2007; Strong and Magnusdottir 2010). The sea ice dipole is a NAO-driven pattern of sea ice concentration anomalies with oppositely-signed centers of action over the Labrador and Barents Seas. Observational studies have also explored interactions between atmospheric modes of variability (NAO and West Pacific (WP) patterns, both local manifestations of the northern annular mode, NAM) and modes of variability in sea ice on the intraseasonal time scale (Deser at al. 2000; Strong et al. 2009; Matthewman and Magnusdottir 2011). These studies demonstrate that while the NAO/WP patterns force modes of sea ice variability there is a feedback from the sea ice onto the atmospheric modes that is negative in the North Atlantic basin and weakly positive in the Pacific part of the Arctic in winter. At longer time scales, the potential predictability associated with Arctic sea ice anomalies is difficult to deduce from observations given the shortness of the record (satellite data of sea ice concentration starts in 1978). However, the fast retreat of the Arctic sea ice in summer is a strong climate signal that may significantly impact the atmospheric circulation. Several papers have suggested a linkage between the Arctic amplification (i.e., the recent rapid and large warming of the Arctic compared to other regions of the globe) and the increase in the occurrence of extreme weather events in mid-latitudes, including cold spells in winter (see Vihma 2014 for a review).

In our recent paper (Peings and Magnusdottir 2014b), we revisit this question using the latest version of the Community Atmospheric Model (CAM5). CAM5 is forced with recent sea ice anomalies (2010C experiment, based on the 2007-2012 average annual cycle of sea ice) and "future" sea ice anomalies (2090C experiment, 2080-2099 period average annual cycle from simulations performed for the Coupled Model Intercomparison Project 5, CMIP5). In each case, the perturbation consists of an overall reduction in the Arctic sea ice extent compared to a control simulation forced by climatological SST and sea ice concentration for the 1979-2000 period. Each experiment consists of a 50-member ensemble, where each ensemble member has different initial conditions, in order to isolate the response due to the forcing from the internal variability of the atmosphere. Figure 1 shows the daily response in geopotential height for the polar cap (geopotential for each level area-averaged north of 65°N) using a time versus pressure plot for the two experiments. This variable is a good proxy for the daily NAM anomalies in the vertical. The response of the 500 hPa geopotential height field (Z500) is also depicted. For 2010C it is averaged over February when the signal is significant. For 2090C, the Z500 response is averaged over winter (DJF). In 2010C, the signal is weak when averaged over the entire winter. However, a significant weakening of the polar vortex is found in late winter (positive anomalies of Z500 in the stratosphere, representative of a negative NAM anomaly) that propagates downward and briefly reaches the surface in mid-February (Figure 1a). This signal is associated with an anomalous upward propagation of stationary waves in mid-latitudes that penetrate into the stratosphere and weaken the stratospheric polar night jet (Peings and Magnusdottir 2014b). The Z500 response is quite asymmetric in that it is stronger over the North Pacific (Figure 1b), probably because of the influence of the sea ice anomalies in the Sea of Okhotsk that have a strong impact on the surface energy budget due to their mid-latitude location. When a larger decrease of sea ice is imposed, the negative NAM response is more persistent in the troposphere in winter, but it is weaker in the stratosphere (Figure 1c). The Z500 response is more annular in shape (Figure 1d) since in this case a large warming of the lower troposphere over the Arctic drives the atmospheric response. The latter experiment suggests that the continued retreat of Arctic sea ice into the future may promote the negative polarity of the NAO/NAM. These experiments only include the impact of Arctic sea ice loss, and some other climate forcings (that are not included) may counter or enhance this effect in the real climate system. Nevertheless, considering the state of Arctic sea ice – both for seasonal and decadal forecasting of the Northern Hemisphere climate – is important given its non-negligible influence on the NAO/NAM.

location of the North Atlantic baroclinic zone that feeds back on the NAO as well as a perturbation of the Hadley cell by tropical SST anomalies. A stratospheric pathway has been also identified in Omrani et al. (2014). They find a negative-NAO response to warm North Atlantic SST imposition (Figure 2b) only when the stratosphere is resolved (high-top model), suggesting that the stratosphere-troposphere interaction acts to reinforce the direct tropospheric response (Keenlyside and Omrani 2014).

In Peings and Magnusdottir (2014a), we use the 20th Century Reanalysis (20CR) to investigate the AMO-NAO relationship and compare to results from numerical experiments. A significant inverse AMO-NAO relationship is found in 20CR, as illustrated in Figure 2c that shows the difference in sea level pressure between positive AMO years and negative AMO years (shading). A clear negative NAO signal is visible, albeit the period of analysis only includes two cycles of the AMO and the statistical relationships have to be interpreted with caution. When the AMO SST and sea ice anomalies are prescribed in CAM5, a negative NAO response is found in winter, and the frequency of cold extreme days increases over Europe and the eastern United States (Figure 2d). It is therefore plausible that the recent resurgence of severe winter weather over these regions is partially driven by the current positive polarity of the AMO, with smaller than expected contribution from Arctic amplification. The AMO-NAO linkage is encouraging and gives intriguing possibilities for decadal forecasting, especially as the North Atlantic SST is predictable (Keenlyside et al. 2008). However, a requirement for fully exploiting this source of predictability for decadal forecasting is that the representation of the AMO and AMO-NAO relationship in coupled climate models is significantly improved (Ba et al. 2014).

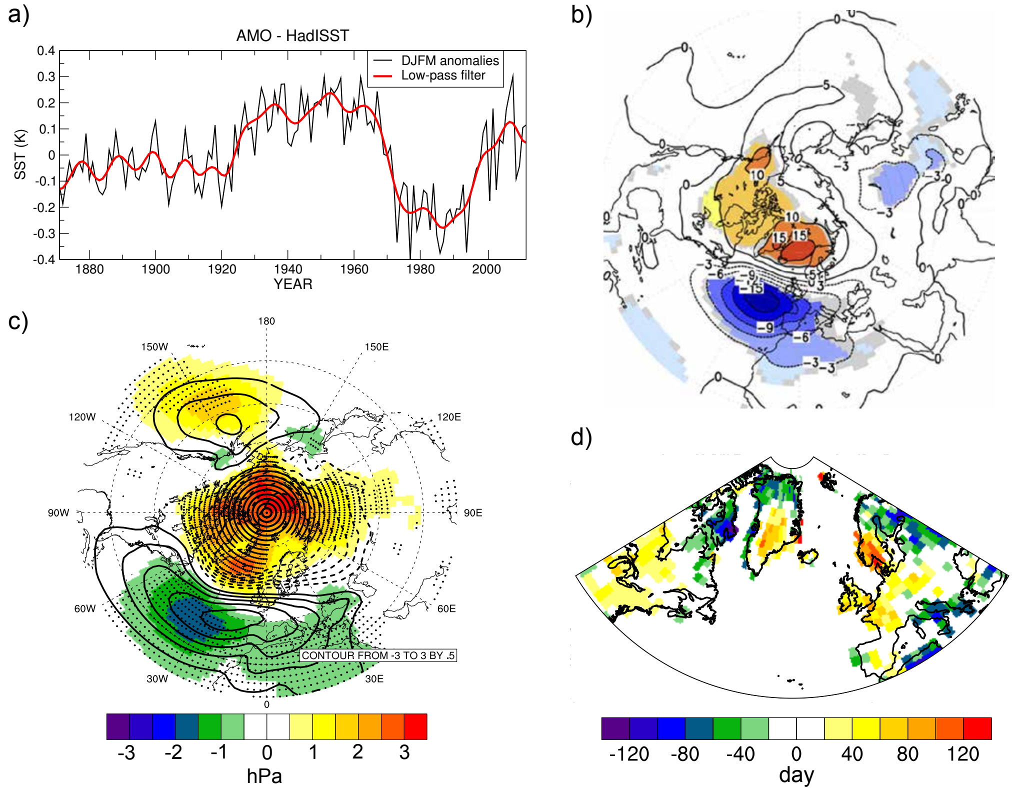

Figure 2. **a)** Winter (DJFM) AMO time series from the HadISST dataset (red). Seasonal anomalies are shown in black. **b)** Response of the winter (JFM) 1000 hPa geopotential height (m) to warm-AMO conditions when using the high-top version of ECHAM5. Anomalies significant at the 95% (90%) level are colored (grey). **c)** Winter (DJFM) sea level pressure (SLP) anomalies associated with the AMO signal (57 AMO+ years minus 53 AMO- years) in 20CR over 1901-2010 (shading in hPa). The NAM pattern computed from an EOF analysis using the 20CR SLP is shown in contours (hPa). Anomalies significant at the 95% level are stippled. **d)** Response of the number of wintertime cold spell days (on 50 years) when the AMO forcing (positive minus negative) is prescribed to CAM5. **a)**, **c)**, and **d)** are adapted from Peings and Magnusdottir (2014a); **b)** is adapted from Omrani et al. (2014).

The Siberian snow cover as a skillful predictor of the wintertime NAO/NAM

There is an inverse relationship between Siberian snow cover and the NAO/NAM, such that an excess of snow over Siberia tends to be followed by the negative NAO/NAM and vice versa (Cohen and Entekhabi 1999). This climatic teleconnection is probably one of the more intriguing due to the time lag and the distance between the location of forcing and response. Several observational and modeling studies have confirmed the statistical link and helped to identify the physical mechanism (e.g., Gong et al. 2003). The snow cover anomalies lead to surface flux anomalies that excite Rossby waves that can interact with the climatological stationary waves through constructive linear interference. A hemispheric response is induced when upward planetary waves penetrate into the stratosphere and weaken the stratospheric polar vortex. As found with a sea ice perturbation in Peings and Magnusdottir (2014b, see Figure 1a of the present letter), the annular mode anomaly then propagates downward in the following weeks and induces significant NAM anomalies at the surface.

Siberian snow is one of the best predictors of the wintertime NAO/NAM and is therefore routinely used in statistical forecasting of the Northern Hemisphere winter climate (Cohen and Fletcher 2007). However, assessing the robustness of this teleconnection is limited by the shortness of the observational record of snow cover (satellite data are available since 1967). Peings et al. (2013) try to overcome this limitation by using the snow cover of the 20CR reanalysis that they find in good agreement with in situ measurements of snow depth. Despite uncertainties in the 20CR snow, their analyses suggest that the snow-NAM relationship is not stationary over the 1891-2010 period. Indeed, the snow-NAM correlation is not statistically significant prior to the 1970's, for unknown reasons (Figure 3). Still, the fall Siberian snow cover represents an important source of predictability of the Northern Hemisphere wintertime circulation, and a realistic snow initialization can increase the skill of dynamical seasonal forecasting models (Orsolini et al. 2013). Cohen et al. (2012) suggest that the recent trend of the NAO/NAM towards negative values is driven by the increase of snow cover over Siberia in fall. They also argue that the positive trend in snow cover is related to the loss of Arctic sea ice in summer/fall that causes more evaporation and a moistening of the atmosphere that lead to increased snowfall over high-latitude continents. If this mechanism is confirmed, the potential predictability associated with the retreat of sea ice in the coming decades might be reinforced by its influence on Siberian snow cover.

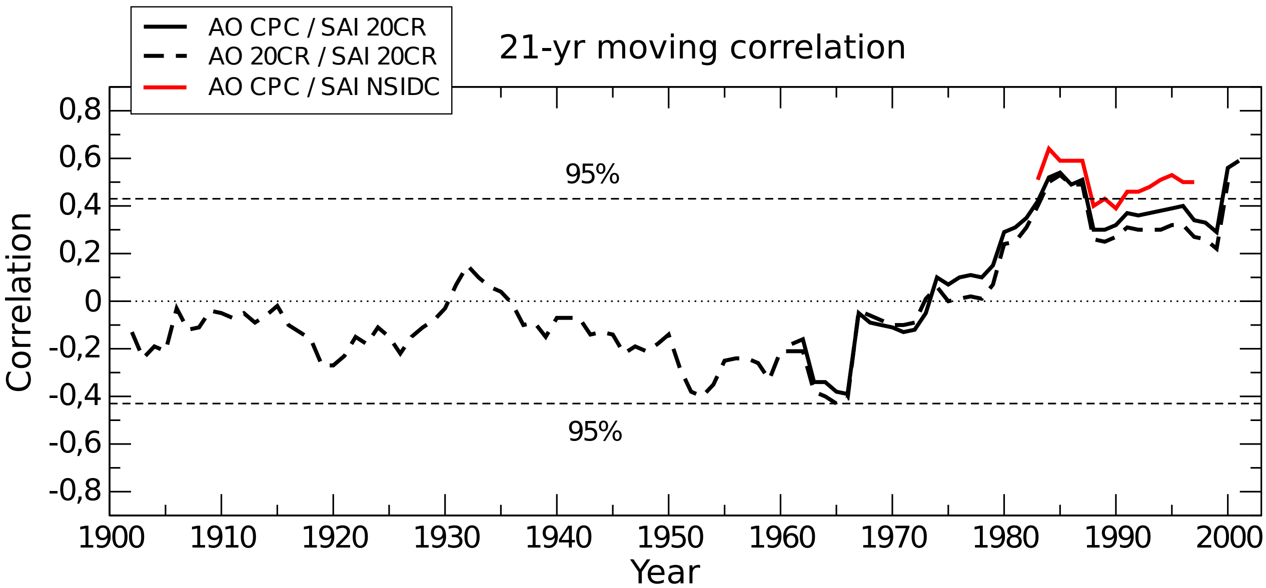

Figure 3. Correlations on a 21-year moving window between the Arctic Oscillation (equivalent to the surface NAM) and the October Snow Advanced Index (SAI) of Cohen and Jones (2011). Two different indices are used for the AO: the CPC (Climatic Prediction Center) AO index (1950-2010) and the 20CR AO index (1891-2010). Similarly, two different indices are used for the SAI: the NSIDC SAI (National Sea Ice Data Center, satellite data over 1972-2010) and the 20CR SAI (1891-2010). The 95% confidence level for correlations is indicated by the horizontal dashed lines. Adapted from Peings et al. (2013).

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Arctic sea ice predictability

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After the jaw-dropping low Arctic sea ice extent (SIE) in September 2007 there has been a growing effort to develop methods to predict the summer minimum SIE from a few months to a year in advance. The effort has been galvanized by a grassroots project to collect and synthesize sea ice "outlooks" of the pan-Arctic (or hemispheric total) September SIE starting each year in June since 2008. The original Sea Ice Outlook (SIO) project was organized through the Study of Environmental Arctic Change (SEARCH), and this year[1] the management was adopted by the new Sea Ice Prediction Network project as a contribution to SEARCH.

The SIO project refers to the forecasts as "outlooks" because all contributions are accepted and methods can be either heuristic or from a statistical and/or dynamical model (either sea ice–ocean coupled or fully-coupled with sea ice, ocean, and atmosphere components). Figure 1 shows the most recent outlook issued in June 2014 for September SIE, partitioned by method type. Note that the distributions tend to be narrower among quantitative methods. The number of contributions to the pan-Arctic SIO has increased steadily from about 15 in the first few years of the project to 28 in 2014. At first only a couple of contributors employed dynamical models, while this year the number reached 10. Interest in the SIO synthesis is substantial, with over 1900 unique views on the SIO website in the first month after the June 2014 report was published.

The contributions to the SIO from 2008-2013 are examined in a study by Stroeve et al. (2014), which shows that the median prediction of the contributions tended to be accurate in years when the SIE is near its long-term trend. In years when the observed extent departs from the trend, the median and most individual predictions are less accurate. On a more positive note, however, other studies show that high skill scores for retrospective predictions of pan-Arctic September SIE are possible a half year in advance (Msadek et al. 2014; Massonnet et al. submitted). Investigations using idealized methods have indicated that predictability at longer lead times may be possible (Blanchard-Wrigglesworth et al. 2011a; Day et al. 2014). There is also good reason to expect that model improvements and/or better observations in the Arctic could raise predictive skill (Lindsay et al. 2012; Msadek et al. 2014; Massonnet et al. submitted). In other encouraging developments, studies are evaluating predictions at the local scale (Tietsche et al. 2014; Day et al. 2014), and in some regions the SIE is equally or even more predictable than at the pan-Arctic scale.

Sea ice predictability studies are in their early years and lag meteorological prediction studies by several decades. However, the Sea Ice Prediction Network has ambitious plans to advance sea ice predictability and make the SIO more scientific and of greater value to stakeholders, including the general public. This article reviews these plans and some of the recent research developments.

A short history of sea ice predictability studies

Users of sea ice forecasts want accurate information at the local to regional scales year round. Many countries have forecasting services that provide ongoing short-term (typically up to two weeks) sea ice predictions. The short-term products are generally prepared using a combination of current ice conditions (derived from satellite imagery, ship reports, and aerial reconnaissance) and meteorological predictions with experts judging how the sea ice will respond to the anticipated air temperature and winds. These "now-cast" methods are not suitable for accurately forecasting sea ice conditions beyond a few weeks. Some centers also provide long-range outlooks that are typically based on heuristic and statistical models.

Research on sea ice predictability has shown that forecast skill arises primarily from persistence of sea ice thickness and sea surface temperature and salinity anomalies, including the transport of these anomalies, accurate knowledge of sea ice conditions at melt

[1]The new home for the SIO is http://www.arcus.org/sipn/sea-ice-outlook.

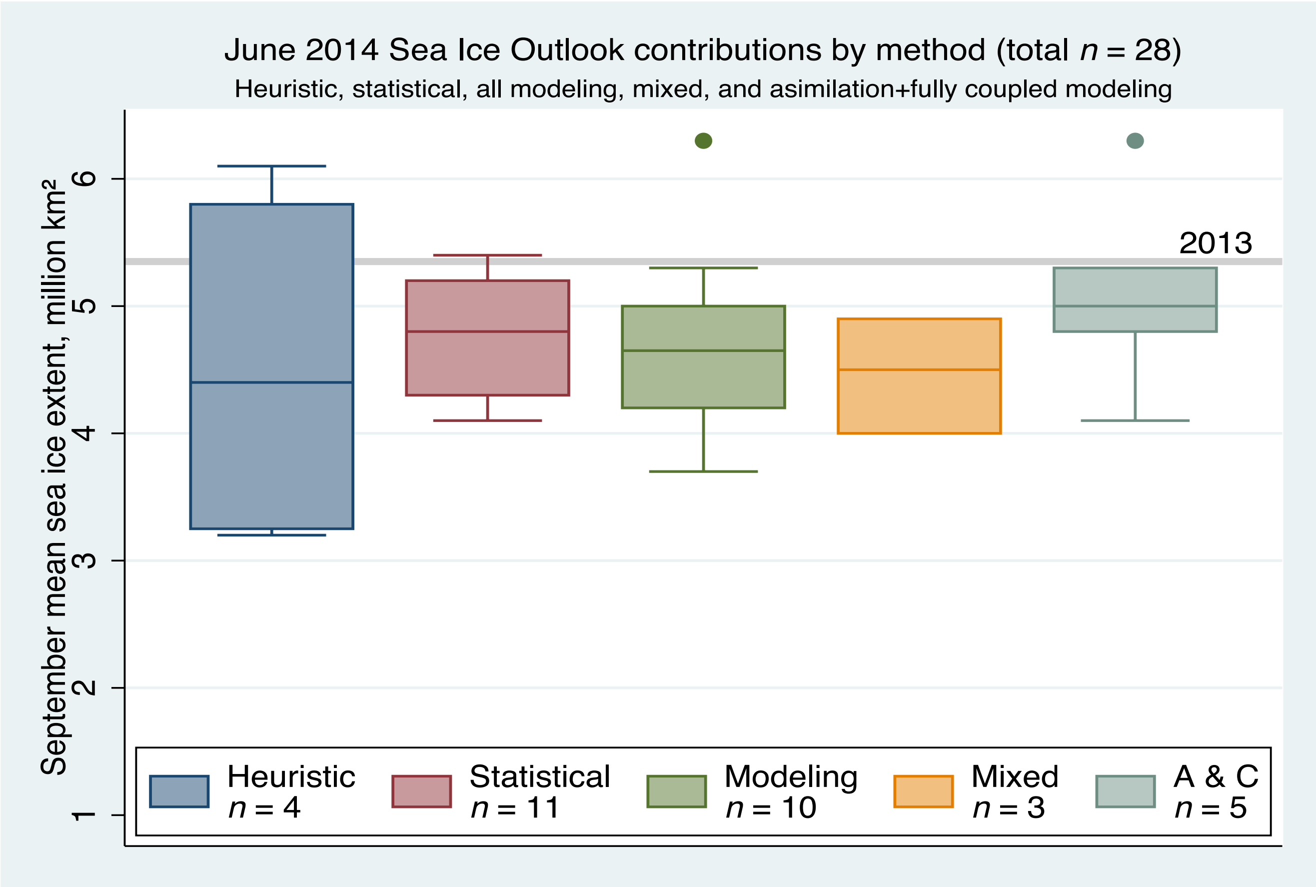

Figure 1. June 2014 predictions of September pan-Arctic sea ice extent (million km^2). Boxes show the inner quartile range of the distribution for each set of prediction methods, grouped by type. The median prediction is 4.7 million km^2 with quartiles of 4.2 and 5.1 million km^2. Observed September 2013 extent of 5.3 million km^2 is indicated by the grey line. The dots near the top of the figure indicate statistical outliers. Figure by Lawrence Hamilton for the Sea Ice Prediction Network synthesis of the June 2014 Sea Ice Outlook.

onset, and coupled interactions of sea ice with the atmosphere and ocean (Blanchard-Wrigglesworth et al. 2011b; Schröder et al. 2014; Guemas et al. 2014a). Owing to the complexity of these behaviors, dynamic, fully-coupled (i.e., coupled atmosphere-ice-ocean) models ought to be the best tool for prediction on subseasonal timescales and beyond. However, accurately modeling Arctic climate system dynamics is challenging for many reasons, including the parameterization of feedbacks and small-scale processes, capturing coupled interactions, and the sparsity of observations. The first dynamic models used for ensemble predictions were ice-ocean only models (e.g., Zhang et al. 2008), and much has been learned from them about how to design forecast systems and initialize models with observational constraints (e.g., Kauker et al. 2009; Massonnet et al. submitted). Fortunately, a number of modeling centers are making an effort to examine sea ice in their fully-coupled seasonal forecast systems and to achieve the skill that could be useful to stakeholders. The retrospective forecast skill of pan-Arctic September SIE in at least six models has been published (Wang et al. 2013; Sigmond et al. 2013; Chevallier et al. 2013; Merryfield et al. 2013; Peterson et al. 2014; Guemas et al. 2014b; and Msadek et al. 2014). Among these published results, half of the models produced forecast skill that exceeded estimates of skill based purely on extrapolating the long-term trend in September SIE or the persistence of monthly SIE anomalies in observations.

Advances have been made in the area of model parameterizations. A new statistical method has shown that a model-based estimate of melt pond coverage in May is an accurate predictor of pan-Arctic September SIE (Schröder et al. 2014). Moreover, the study also suggests that the earliest stages of ponding contribute more to predictive skill than their evolution later into the season. Others had found a barrier to predictability in early summer, which they attributed to sea ice-albedo feedback and a strong sensitivity to weather at that time of the year (Blanchard-Wrigglesworth et al. 2011b; Day et al. 2014). The strong correlation found by Schröder et al. may result from pinning down a quantity (melt ponds) that is indicative of the albedo state in early summer. While this is an exciting development, it is unclear how the method would predict the spatial pattern of sea ice cover since melt pond coverage is not well correlated in space with where sea ice loss occurs. An important conclusion to draw from this work is that there is a potential benefit from observations that can improve initialization of the sea ice albedo and successful parameterizations of melt ponds and early melt processes in forecast systems with dynamical models.

Finally, given the strong sensitivity of sea ice forecasts to the initial conditions, it is no surprise that there is clear evidence of the value of expanding observations in the Arctic. A rise in sea ice predictability over a 40-year retrospective forecast period led Msadek et al. (2014) to suspect that the increase in Arctic upper-ocean temperature observations over the same period contributed to improved forecasts. Additionally, the sea ice thickness measured in spring from aircraft flight tracks during the IceBridge campaigns was shown to reduce the forecast bias of the 2012 September pan-Arctic SIE in Lindsay et al. (2012) by 20%.

The Sea Ice Prediction Network

With the recent surge of interest in seasonal sea ice forecasts, we expect the accuracy of the SIO contributions to rise, especially from the subset of contributions from dynamical models. Moreover, new opportunities will emerge as researchers better understand sources of predictability and identify skill in new models and methods.

In April this year, over 50 scientists attended a workshop of the Sea Ice Prediction Network. A detailed set of recommendations arose from the workshop, a few of which are described here. First, participants wanted to expand the SIO call for contributions to include spatial distributions of the sea ice predictions, of the probability of sea ice occurrence, and of the first ice-free date each year, with an uncertainty estimate. In response, the Sea Ice Prediction Network made this an optional item for submissions this year and gave notice that spatial distributions (figures and forecast data) would be requested in future years. Workshop participants also expressed a desire for the Sea Ice Prediction Network to solicit outlooks for July and August in addition to the standard request for September.

Workshop participants expressed a great deal of interest in undertaking intercomparison studies to investigate sources of predictability and to identify the most beneficial observations to improve predictions, such as through sensitivity analysis with multivariate initialization methods. Participants recognized a need to construct better metrics to meet stakeholder's needs, understand predictability, and evaluate skill at the spatial scale. Finally, there was a call to carefully articulate the limitations and uncertainties of sea ice predictions and strengthen ties with forecast users.

The Sea Ice Prediction Network welcomes participants who wish to work together to tackle these and other recommendations from the community.

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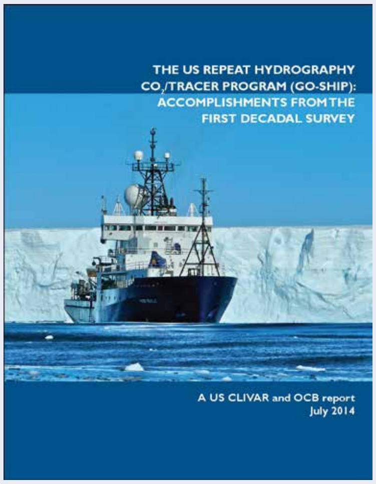

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