A new index for more accurate winter predictions

Judah Cohen[1] and Justin Jones[1]

Received 8 September 2011; revised 5 October 2011; accepted 9 October 2011; published 5 November 2011.

[1] Seasonal climate prediction remains a challenge. During Northern Hemisphere (NH) winter the large-scale teleconnection pattern the Arctic Oscillation (AO) explains the largest fraction of temperature variance of any other known climate mode. However the Arctic Oscillation is considered to be a result of intrinsic atmospheric dynamics or chaotic behavior and therefore is unpredictable. Here we develop a snow advance index (SAI) derived from antecedent observed snow cover that explains a large fraction of the variance of the winter AO. The high correlation between the SAI and the winter AO demonstrates that the AO is most likely predictable and that this index can be exploited for skillful seasonal climate predictions. **Citation:** Cohen, J., and J. Jones (2011), A new index for more accurate winter predictions, *Geophys. Res. Lett.*, *38*, L21701, doi:10.1029/2011GL049626.

1. Introduction

[2] The most important advance in seasonal climate prediction has been the linkage of the dominant mode of tropical atmosphere and ocean variability (El Niño-Southern Oscillation or ENSO) with surface temperatures and precipitation patterns across the globe. However, predictive skill for temperature forecasts outside of the tropics, including the U.S., has been mixed [*Spencer and Slingo*, 2003; *Cohen and Fletcher*, 2007]. The most commonly employed tool in seasonal forecasting at the operational forecast centers is general circulation models or global climate models (GCMs). These highly complex dynamical models represent many of the major processes in the ocean-land-atmosphere climate system; however, at present nearly all of their seasonal forecast skill can be attributed to variability in ENSO alone [*van Oldenborgh et al.*, 2005a, 2005b; *Quan et al.*, 2006; *Delsole and Shukla*, 2006; *Saha et al.*, 2006]. But, the fact that ENSO variability offers only limited atmospheric predictability away from the tropics [*Kumar et al.*, 2007] has proven a natural constraint on improving seasonal prediction skill in the extratropics. In light of limited extratropical predictability associated with ENSO, a question remains as to what are the prospects for skillful seasonal and longer forecasts in the extratropical latitudes.

[3] A dominant mode of Northern Hemisphere (NH) winter climate variability is the North Atlantic Oscillation (NAO) or the Arctic Oscillation (AO). The surface-temperature and surface-circulation signatures of the N/AO are strongest in the North Atlantic sector [*Ambaum et al.*, 2001; *Cohen and Saito*, 2002]. It has been argued that a better understanding of the N/AO variability could lead to improved extratropical predictability, and is often recognized as the most important anticipated advance in seasonal climate forecasting [*Cohen*, 2003] especially for the eastern U.S. and Europe, regions where temperature forecasts based on ENSO have little or no skill [*O'Lenic et al.*, 2008; *Livezey and Timofeyeva*, 2008].

[4] The harsh winters of 2010/11 but especially 2009/10 across the NH mid-latitudes coupled with a record minimum value in the N/AO index focused greater attention on the N/AO and its strong relationship with NH winter climate anomalies. Studies of that winter have mostly concluded that internal atmospheric dynamics drive the phase and amplitude of the N/AO and that it is therefore unpredictable [*Seager et al.*, 2010; *Jung et al.*, 2011]. In contrast one study argues that the record low AO observed that winter was at least partially attributed to above normal snow cover across Eurasia during the preceding October [*Cohen et al.*, 2010]. To what extent is the N/AO variability predictable and is it related to varying boundary conditions? Linking the N/AO to varying boundary conditions could therefore provide greater predictability for seasonal climate variability in the extratropics.

[5] In the NH, snow cover is the most variable land surface condition in both time and space [*Cohen*, 1994] making it a viable candidate for amplifying climate and atmospheric anomalies. An early study demonstrated from the observations that the time series of fall Eurasian snow cover is significantly correlated with the winter (December–February) AO [*Cohen and Entekhabi*, 1999]. Therefore snow cover is a potentially useful and important modulator of winter climate, especially for those lands areas in the North Atlantic sector, including the eastern US and Europe, where the influence of the N/AO are the strongest.

[6] Follow-up observational studies have established a statistically significant link between fall snow cover extent (SCE) and the winter AO and numerical modeling experiments forced with varying Eurasian SCE, reproduce an atmospheric AO response in winter similar to the observations [*Gong et al.*, 2003; *Cohen et al.*, 2007; *Fletcher et al.*, 2009; *Orsolini and Kvamstø*, 2009; *Allen and Zender*, 2010; *Mote and Kutney*, 2011; *Peings et al.*, 2011]. However during October 2009 it was not the mean SCE that was exceptional but rather the rapidity of the snow cover advance that was exceptional [*Cohen et al.*, 2010].

[7] Therefore rather than creating an index from monthly SCE we created an index from the mean rate of change of SCE from daily snow cover data [*Ramsay*, 1998], which we refer to as the snow advance index or SAI.

2. Data and Methods

[8] For all climate data we used the National Center for Environmental Protection (NCEP)/National Center for

[1]Atmospheric and Environmental Research, Lexington, Massachusetts, USA.

0094-8276/11/2011GL049626

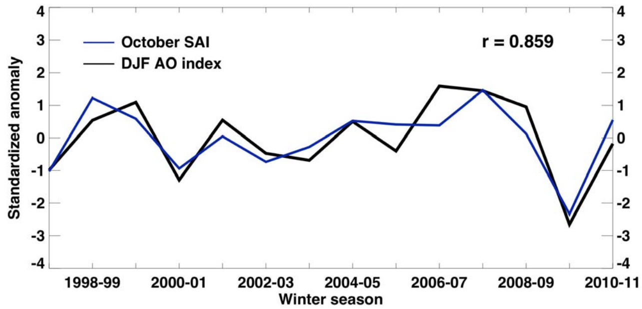

Figure 1. Time series of the October daily snow advance index (SAI in blue) and the December–February (DJF) Arctic Oscillation (AO in black) for the years 1997/98 through 2010/11. Both time series are detrended and are shown as standardized anomalies. The SAI index is multiplied by −1 for ease of comparison. Correlation coefficient for the two time series is 0.86, which is statistically significant at the $p < 0.01$ level. The correlation coefficient is 0.75 when 2009 is removed.

Atmospheric Research (NCAR) Reanalysis Project [*Kalnay et al.*, 1996]. Monthly and weekly SCE from 1973–2010 was derived from NOAA's satellite-sensed observations [*Robinson et al.*, 1993]. Daily snow cover data from 1997-2010 was taken from the Interactive Multisensor Snow and Ice Mapping System (IMS), which generates daily 4km and 24km maps of snow, and ice cover derived from visible and microwave satellite imagery [*Ramsay*, 1998]. The system has incorporated new products as they have become available, including the Advanced Very High Resolution Radiometer (AVHRR) channel 4A in February 2001 and the moderate resolution imaging spectroradiometer (MODIS) channel 1 in February 2004 [*Helfrich et al.*, 2007]. We only computed snow cover for Eurasia, which we define as 25–85°N and 0–180°E. The winter (December, January and February) AO index was computed from the monthly AO values published on the Climate Prediction Center website (http://www.cpc.ncep.noaa.gov/products/precip/CWlink/daily_ao_index/ao.shtml).

[9] Correlation and linear regression analysis are the two statistical techniques employed throughout the study. Statistical significance of correlation coefficients were computed using a Student two-tailed *t*-test. The snow advance index (SAI) is the regression coefficient of the least square fit of the daily Eurasian SCE equatorward of 60°N calculated for the month of October. The units of the SAI index are million km^2/day. A plot of the October SAI for Eurasia correlated with the winter AO at each latitude shows that the highest correlations exist equatorward of 60°N (Figure S1 of the auxiliary material).[1] In the remainder of the Letter the SAI index will be limited to all latitudes equatorward of and including 60°N. In Figure S2 of the auxiliary material we show the daily Eurasian snow cover equatorward of 60°N for Octobers 2007, 2009 and the 14-year mean with the trend line associated with both years (and the mean) as examples of two years with a low and high SAI value respectively.

3. Results and Discussion

[10] In Figure 1 we plot the October SAI for Eurasian SCE equatorward of 60°N correlated with the following winter AO. The correlation between the two time series is ~0.86. Daily snow cover has only been available for 14 years. Over that time period the SAI has significantly outperformed the SCE as a predictor of the winter AO. However because the SAI time series is only available for a relatively short period, therefore in Figure 2 we computed

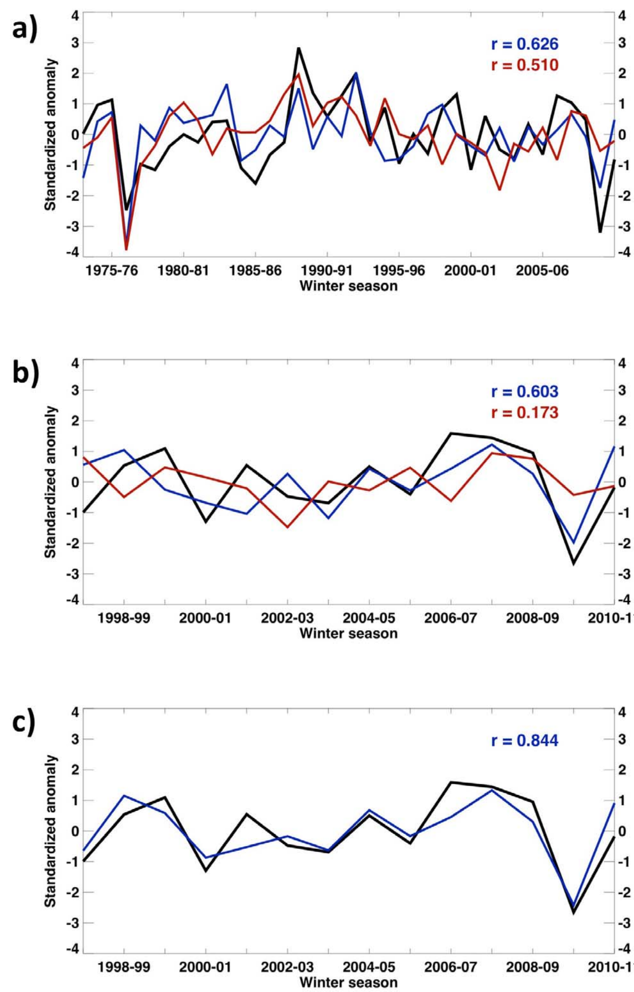

Figure 2. Time series of the October SAI using weekly data (blue) and the December–February AO (black) and the October-mean Eurasian snow cover extent (SCE in red) for the years (a) 1973/74-2010/11 and (b) 1997/98-2010/11. (c) Time series of the SAI using daily data for weeks 40–44 (blue) and the December–February AO (black) for the years 1997/98 through 2010/11. All values are shown as standardized anomalies. Correlation coefficients shown in blue are for SAI and the AO while correlation coefficients shown in red are for SCE and the AO. The snow indices are multiplied by −1 for ease of comparison. All correlations between the SAI and the AO are significant at the $p < 0.01$ level.

[1]Auxiliary materials are available in the HTML. doi:10.1029/2011GL049626.

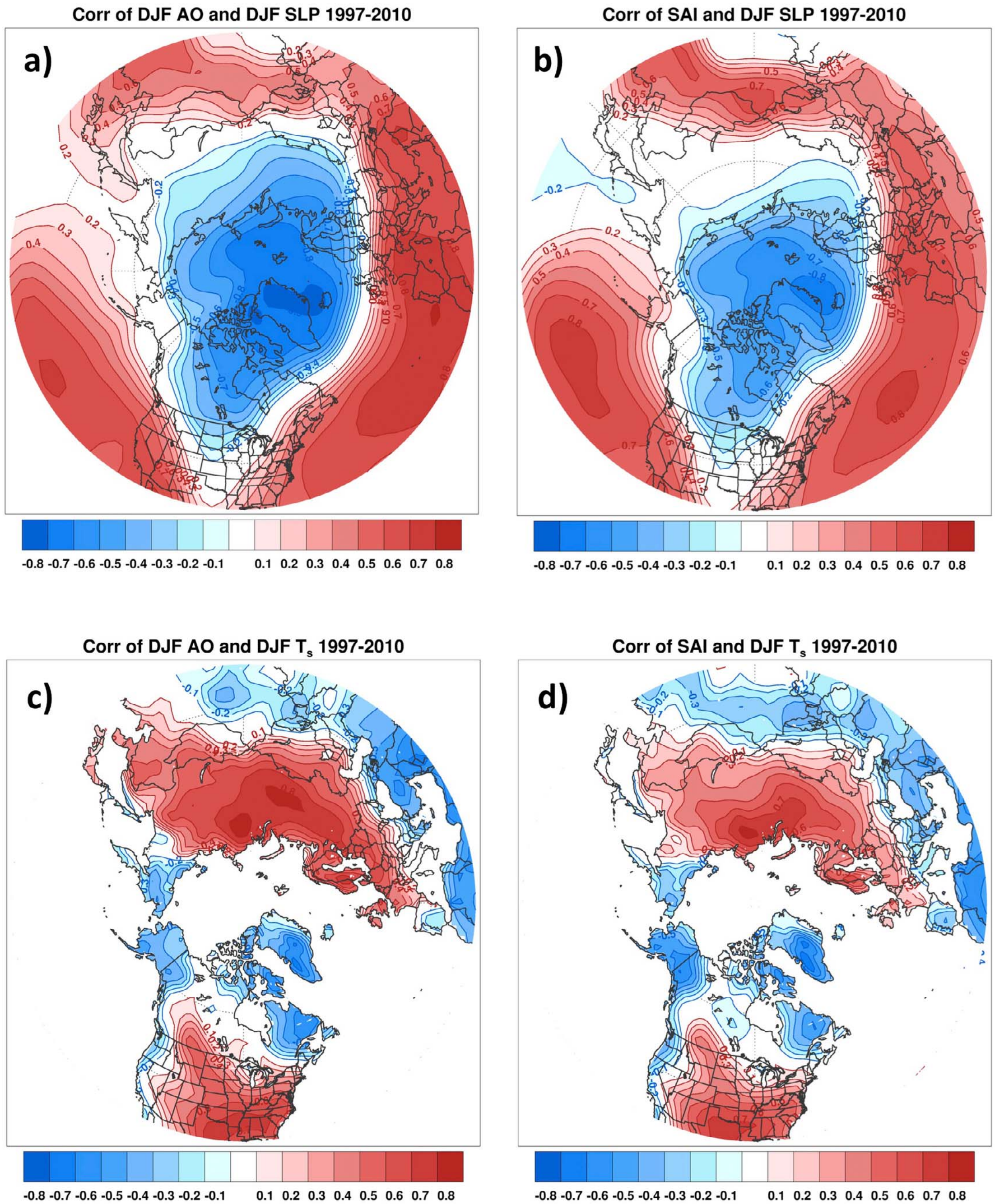

Figure 3. (a) Correlation of DJF AO and DJF SLP. (b) Correlation of October SAI and DJF SLP. (c) Correlation of DJF AO and DJF land surface temperatures. (d) Correlation of October SAI and DJF land surface temperatures.

the SAI using weekly SCE for weeks 40-44, which most closely corresponds to October and correlated the time series with the following winter AO. For comparison we included the October SCE index going back to 1973 and the overlap period of 1997–2010. Even the highly degraded weekly SAI outperforms the October SCE index as a predictor of the winter AO over the period of 1973–2010 and especially the period of 1997–2010 (0.60 vs. 0.17). And importantly the correlation remains above 0.6 for all time periods, which is considered the minimum value required for skillful predictions.

[11] In Figure 3 we correlate the SAI with winter sea level pressure (SLP) and for comparison we correlate the winter AO with winter SLP. Given the strong coupling between the surface AO and the stratospheric AO [*Baldwin and Dunkerton*, 2001], we repeated the same analysis with the geopotential height field at 50 hPa (Figure S3 of the auxiliary material). Remarkably similar patterns are revealed in both the SLP and 50 hPa height fields. The canonical AO pattern can be seen when both variables are correlated with SLP and 50 hPa geopotential heights, with one signed anomaly over the Arctic and a ring of opposite signed anomalies over the mid-latitudes especially over the oceans. The pattern correlation when correlating the AO and the SAI with SLP and 50 hPa heights are both 0.94. Also shown in Figure 3 are the values of the SAI and the AO correlated with land surface temperatures (T_s). In the T_s field for both

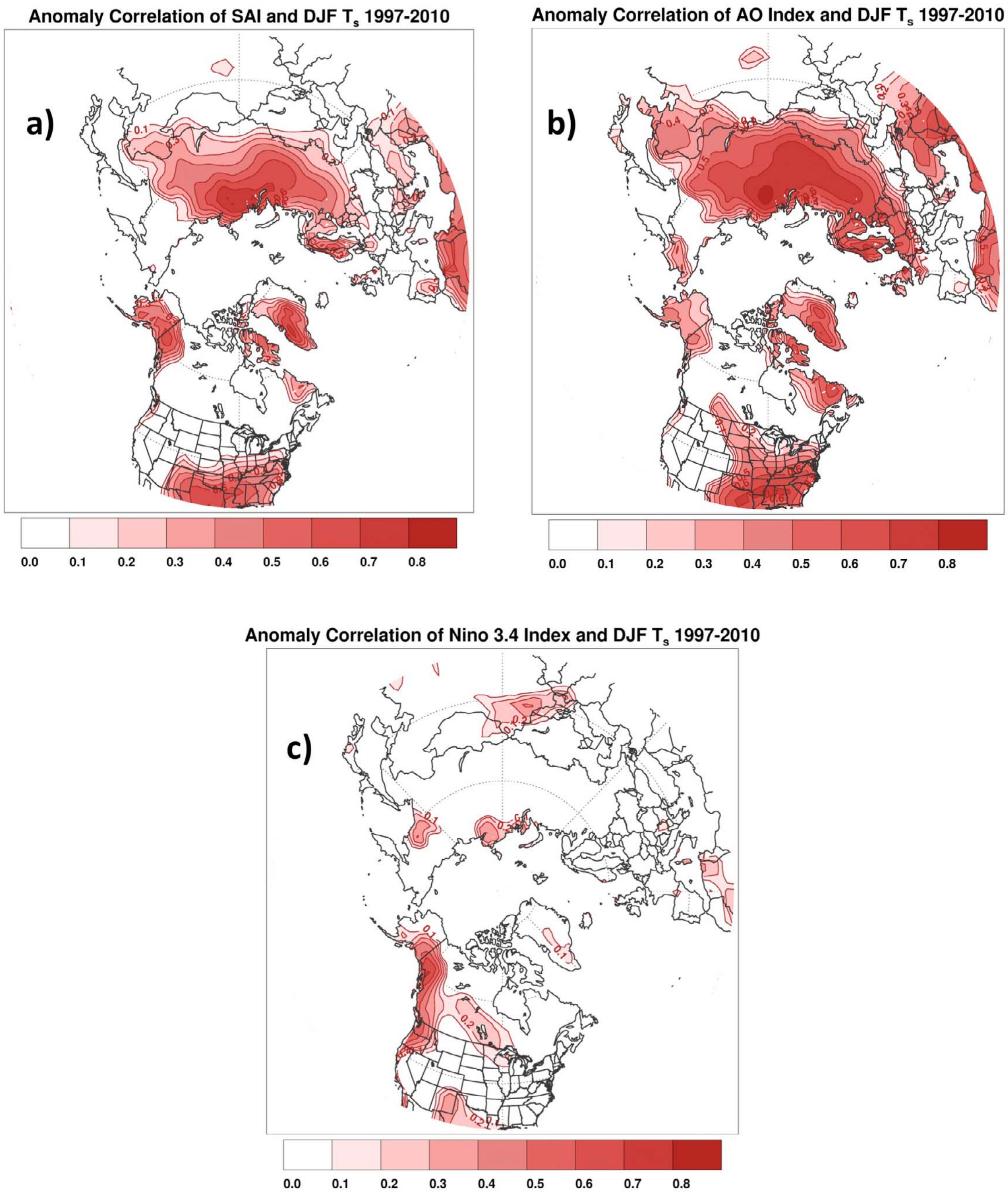

Figure 4. The anomaly correlation coefficient for cross-validated hindcasts of DJF land surface temperatures using as a predictor the (a) October SAI, (b) the DJF AO, and (c) the DJF Niño 3.4 index. Only positive values are shown.

plots the canonical quadropole pattern is seen with one signed anomaly across Northern Eurasia and the United States, east of the Rockies and an opposite signed anomaly across the Mediterranean, North Africa and the North American Arctic.

[12] One immediate potential benefit of the development of this new index is improved seasonal climate predictions. The ability to predict the winter AO is considered the single most important advance in achieving successful winter forecasts. We created cross validated hindcasts of winter land T_s using as predictors the SAI, the winter AO and the winter Niño 3.4 index; the anomaly correlation of all three predictors are shown in Figure 4 (only positive values shown). Even exact knowledge of the winter Niño 3.4 index provides no forecast skill for the Eastern US and virtually all of Eurasia. Instead, exact knowledge of the winter AO and the SAI demonstrates positive forecast skill for the Eastern US and large portions of Northern Eurasia. And considering that the SAI index is known four months prior to the winter AO, yet matches the skill of the winter AO so closely, demonstrates great potential for improved real-time winter forecasts.

4. Conclusions

[13] The implications of this discovery are potentially significant. Currently the AO is considered a product of the stochastic behavior of internal atmospheric dynamics and

therefore chaotic. The fact that we discovered a single predictive index that explains close to 75% of the variance of the winter AO (though the period is short and the degraded SAI over a longer time period explains less of the AO variance) is inconsistent with this thinking and demonstrates that the AO, while thought to be unpredictable, may in fact be one of the most easily predicted phenomenon known in the climate system. Even the most sophisticated GCMs achieve only marginal skill on the seasonal time scale in the extratropics (for examples see Figure S4 of the auxiliary material). Implementation of the SAI in winter seasonal forecasts could potentially be a sea change in operational seasonal forecasts (compare Figure 4a with Figure S4 of the auxiliary material).

[14] Even on longer time scales these results have important implications. Based on the presented results snow-atmosphere coupling is fundamental to winter climate dynamics. Currently the state of the art GCMs are deficient in simulating snow atmosphere coupling on seasonal time scales [*Hardiman et al.*, 2008]. Furthermore GCMs simulate the variance in SCE more poorly than they simulate mean SCE [*Frei et al.*, 2003] and as we show here it is the variability in fall SCE that is more important than the mean fall SCE in predicting the winter AO. Large improvements are needed in simulating land-atmosphere coupling before we can be confident in numerical seasonal to interannual winter climate predictions for the NH extratropics.

[15] An important question that we have not answered is why the October SAI is more highly correlated with the DJF AO than the October SCE index. One likely reason is that the SAI is limited to latitudes equatorward of 60°N while the SCE index includes all of Eurasia, which has a significant amount of snow cover north of 60°N. Assuming that the high albedo of snow cover is one if not the most important snow characteristic that influences the overlying atmosphere, this would favor the SAI, which is limited to regions that are exposed to a higher sun angle more so than the SCE, in predicting the atmospheric response to snow cover variability. Another possibility is that the SAI is sensitive to the timing of snowfall, where snowfall at the end of the month contributes to higher values of the SAI and snowfall at the beginning of the month contributes to lower SAI values while the monthly-mean SCE is insensitive to the timing of snowfall. A rigorous answer to the question is beyond the scope of this concise Letter and will require more in-depth analysis.

[16] **Acknowledgments.** J.C. is supported by the National Science Foundation grants ARC-0909459 and ARC-0909457 and NOAA grant NA10OAR4310163. Weekly snow cover extent data was provided by the Rutgers Global Snow Lab.

[17] The Editor thanks the anonymous reviewer.

References

Allen, R. J., and C. S. Zender (2010), Effects of continental-scale snow albedo anomalies on the wintertime Arctic oscillation, *J. Geophys. Res.*, *115*, D23105, doi:10.1029/2010JD014490.

Ambaum, M. H. P., B. J. Hoskins, and D. B. Stephenson (2001), Arctic Oscillation or North Atlantic Oscillation?, *J. Clim.*, *14*, 3495–3507, doi:10.1175/1520-0442(2001)014<3495:AOONAO>2.0.CO;2.

Baldwin, M. P., and T. J. Dunkerton (2001), Stratospheric harbingers of anomalous weather regimes, *Science*, *294*, 581–584, doi:10.1126/science.1063315.

Cohen, J. (1994), Snow cover and climate, *Weather*, *49*, 150–156.

Cohen, J. (2003), Introducing sub-seasonal spatial and temporal resolution to winter climate prediction, *Geophys. Res. Lett.*, *30*(1), 1018, doi:10.1029/2002GL016066.

Cohen, J., and D. Entekhabi (1999), Eurasian snow cover variability and northern hemisphere climate predictability, *Geophys. Res. Lett.*, *26*(3), 345–348, doi:10.1029/1998GL900321.

Cohen, J., and C. Fletcher (2007), Improved skill for Northern Hemisphere winter surface temperature predictions based on land-atmosphere fall anomalies, *J. Clim.*, *20*, 4118–4132, doi:10.1175/JCLI4241.1.

Cohen, J., and K. Saito (2002), A test for annular modes, *J. Clim.*, *15*, 2537–2546, doi:10.1175/1520-0442(2002)015<2537:ATFAM>2.0.CO;2.

Cohen, J., M. Barlow, P. Kushner, and K. Saito (2007), Stratosphere-troposphere coupling and links with Eurasian land-surface variability, *J. Clim.*, *20*, 5335–5343, doi:10.1175/2007JCLI1725.1.

Cohen, J., J. Foster, M. Barlow, K. Saito, and J. Jones (2010), Winter 2009–2010: A case study of an extreme Arctic Oscillation event, *Geophys. Res. Lett.*, *37*, L17707, doi:10.1029/2010GL044256.

DelSole, T., and J. Shukla (2006), Specification of wintertime North American surface temperature, *J. Clim.*, *19*, 2691–2716, doi:10.1175/JCLI3704.1.

Fletcher, C., S. C. Hardiman, P. Kushner, and J. Cohen (2009), The dynamical response to snow cover perturbations in a large ensemble of atmospheric GCM integrations, *J. Clim.*, *22*, 1208–1222, doi:10.1175/2008JCLI2505.1.

Frei, A., J. A. Miller, and D. A. Robinson (2003), Improved simulations of snow extent in the second phase of the Atmospheric Model Intercomparison Project (AMIP-2), *J. Geophys. Res.*, *108*(D12), 4369, doi:10.1029/2002JD003030.

Gong, G., D. Entekhabi, and J. Cohen (2003), Modeled Northern Hemisphere winter climate response to realistic Siberian snow anomalies, *J. Clim.*, *16*, 3917–3931, doi:10.1175/1520-0442(2003)016<3917:MNHWCR>2.0.CO;2.

Hardiman, S. C., P. J. Kushner, and J. Cohen (2008), Investigating the ability of general circulation models to capture the effects of Eurasian snow cover on winter climate, *J. Geophys. Res.*, *113*, D21123, doi:10.1029/2008JD010623.

Helfrich, S. R., D. McNamara, B. H. Ramsay, T. Baldwin, and T. Kasheta (2007), Enhancements to, and forthcoming developments in the Interactive Multisensor Snow and Ice Mapping System (IMS), *Hydrol. Processes*, *21*, 1576–1586, doi:10.1002/hyp.6720.

Jung, T., F. Vitart, L. Ferranti, and J.-J. Morcrette (2011), Origin and predictability of the extreme negative NAO winter of 2009/10, *Geophys. Res. Lett.*, *38*, L07701, doi:10.1029/2011GL046786.

Kalnay, E., et al. (1996), The NCEP/NCAR 40-year reanalysis project, *Bull. Am. Meteorol. Soc.*, *77*, 437–471, doi:10.1175/1520-0477(1996)077<0437:TNYRP>2.0.CO;2.

Kumar, A., J. Bhaskar, Q. Zhang, and L. Bounoua (2007), A new methodology for estimating the unpredictable component of seasonal atmospheric variability, *J. Clim.*, *20*, 3888–3901, doi:10.1175/JCLI4216.1.

Livezey, R. E., and M. M. Timofeyeva (2008), The first decade of long-lead U.S. seasonal forecasts, *Bull. Am. Meteorol., Soc.*, *89*, 843–854, doi:10.1175/2008BAMS2488.1.

Mote, T. L., and E. R. Kutney (2011), Regions of autumn Eurasian snow cover and associations with North American winter temperatures, *Int. J. Climatol.*, doi:10.1002/joc.2341, in press.

O'Lenic, E. A., D. A. Unger, M. S. Halpert, and K. S. Pelman (2008), Developments in operational long-range climate prediction at CPC, *Weather Forecast.*, *23*, 496–515, doi:10.1175/2007WAF2007042.1.

Orsolini, J. Y., and N. G. Kvamstø (2009), Role of Eurasian snow cover in wintertime circulation: Decadal simulations forced with satellite observations, *J. Geophys. Res.*, *114*, D19108, doi:10.1029/2009JD012253.

Peings, Y., D. Saint-Martin, and H. Douville (2011), A numerical sensitivity study of the Siberian snow influence on the northern annular mode, *J. Clim.*, doi:10.1175/JCLI-D-11-00038.1, in press.

Quan, X., M. Hoerling, J. Whitaker, G. Bates, and T. Xu (2006), Diagnosing sources of U.S. seasonal forecast skill, *J. Clim.*, *19*, 3279–3293, doi:10.1175/JCLI3789.1.

Ramsay, B. H. (1998), The interactive multisensory snow and ice mapping system, *Hydrol. Processes*, *12*, 1537–1546, doi:10.1002/(SICI)1099-1085(199808/09)12:10/11<1537::AID-HYP679>3.0.CO;2-A.

Robinson, D. A., F. Dewey, and R. Heim Jr. (1993), Global snow cover monitoring: An update, *Bull. Am. Meteorol. Soc.*, *74*, 1689–1696, doi:10.1175/1520-0477(1993)074<1689:GSCMAU>2.0.CO;2.

Saha, S., et al. (2006), The NCEP climate forecast system, *J. Clim.*, *19*, 3483–3517, doi:10.1175/JCLI3812.1.

Seager, R., Y. Kushnir, J. Nakamura, M. Ting, and N. Naik (2010), Northern Hemisphere winter snow anomalies: ENSO, NAO and the winter of 2009/10, *Geophys. Res. Lett.*, *37*, L14703, doi:10.1029/2010GL043830.

Spencer, H., and J. M. Slingo (2003), The simulation of peak and delayed ENSO teleconnections, *J. Clim.*, *16*, 1757–1774, doi:10.1175/1520-0442(2003)016<1757:TSOPAD>2.0.CO;2.
van Oldenborgh, G. J., M. A. Balmaseda, L. Ferranti, T. N. Stockdale, and D. L. T. Anderson (2005a), Did the ECMWF seasonal forecast model outperform statistical ENSO forecast models over the last 15 years, *J. Clim.*, *18*, 3240–3249, doi:10.1175/JCLI3420.1.
van Oldenborgh, G. J., M. A. Balmaseda, L. Ferranti, T. N. Stockdale, and D. L. T. Anderson (2005b), Evaluation of atmospheric fields from the ECMWF seasonal forecasts over a 15 year period, *J. Clim.*, *18*, 3250–3269, doi:10.1175/JCLI3421.1.

J. Cohen and J. Jones, Atmospheric and Environmental Research, Lexington, MA 02421, USA. (jcohen@aer.com; jjones@aer.com)