Changing seasonal sea ice predictor relationships in a changing Arctic climate

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[1] Seasonal predictions of Arctic sea ice conditions often rely on statistical relationships of a set of predictors that have shown skill for historical conditions. However, with rapid changes occurring in the Arctic climate, it is unclear whether these statistical relationships will remain valid. Here, preindustrial control, present-day control, and 20th–21st century climate model integrations are used to assess predictors for end-of-summer sea ice extent under various and changing climate conditions. Of importance for future forecasting systems, we find that the variance of September extent anomalies explained by winter-spring sea ice predictors, such as the area of Arctic basin thin ice cover, increases during the transition to a seasonally ice-covered Arctic. In contrast, summer atmospheric circulation variability plays a decreasingly important role in explaining the end-of-summer ice cover anomalies. These changes are primarily related to climate-dependent changes in the location of summer sea ice anomalies.


1. Introduction

[2] Seasonal forecasts of Arctic sea ice are used for maritime operations and are likely to become increasingly important as marine access increases with continued sea ice loss. Many seasonal forecasting systems use statistical models that rely on lagged-correlations of a set of predictors with future ice conditions [e.g., Drobot et al., 2006; Lindsay et al., 2008]. These have been a necessary and useful tool given limitations in physically-based models and the observations needed to initialize them. Statistical predictors include prior information on sea ice and atmospheric conditions that play a role in sea ice evolution [e.g., Maslanik et al., 2007; Rigor et al., 2002]. These relationships are physically based. For example, large-scale sea level pressure (SLP) variations affect winds and ice motion, which can produce ice anomalies [e.g., Rigor et al., 2002; Ogi et al., 2010]. In addition, winter and spring pre-conditioning, in the form of an anomalously thin ice pack, is more prone to melt out the following summer [Holland et al., 2006; Lindsay et al., 2009].

[3] The physical basis of these relationships increases their reliability. However, they have been diagnosed from relatively short-term observational records (generally 1979 to near present) and there is little reason to expect that they are stationary. Rapid and widespread Arctic climate changes have occurred and are projected to continue [e.g., Serreze et al., 2007a]. Statistical relationships that provide ice-forecasting skill over the historical record may not remain valid in a rapidly changing Arctic environment.

[4] Here we discuss observed relationships used in sea ice forecasting systems and assess them in model integrations with changing climate conditions. We examine the robustness of these relationships in the climate model context, determining how and why they change as the Arctic transitions to a seasonally ice-free state.

2. Data

[5] Historical data are used to illustrate relationships that have been employed in ice forecasting systems. NCEP Reanalysis [Kalnay et al., 1996], a retrospective form of numerical weather prediction, provides information on atmospheric variables of interest. While there are known biases in some high latitude NCEP fields [e.g., Curry et al., 2002], the variations in near surface air temperature and SLP since 1979 are thought to be reasonable [Makshtas et al., 2007; Screen and Simmonds, 2011]. Unless otherwise noted, we examine detrended time-series to focus on seasonal relationships.

[6] Historical anomalies of monthly sea ice extent (the area where ice concentration exceeds 15%) are obtained from the National Snow and Ice Data Center (NSIDC) sea ice index [Fetterer et al., 2002]. This uses satellite passive microwave data with the NASA Team algorithm [Cavalieri et al., 1984]. First-year ice extent is obtained from ice age data [Fowler et al., 2004] that assesses the history of sea ice by advecting it as independent Lagrangian particles using satellite and buoy derived ice motion. The ice age data has been updated to use a 15% threshold for ice concentration [Maslanik et al., 2011] rather than the 40% threshold used originally. Here we limit the ice age analysis to an Arctic Ocean Domain, previously defined by Serreze et al. [2007b].

3. Model Experiments

[7] We analyze 300 years of multi-century preindustrial (PI; 1870 forcing) and present-day (PD; 1990 forcing) control runs from the Community Climate System Model 3 (CCSM3) run with an atmospheric resolution of T85 (nominally 1.4 degrees) and ocean resolution of 1-degree [Collins et al., 2006]. These have constant external (e.g., solar, greenhouse gas, volcanic) forcing. This is complemented by an analysis of eight 20th and 21st century ensemble runs [Meehl et al., 2006]. The 20th century runs have prescribed external forcings based on observations. The 21st century runs use the SRES A1B emission scenario.
[10] For 1979–2010, spring first-year ice extent and September ice extent are highly correlated (R = -0.78). This is due to the linear trend in the two time-series. For detrended data, the correlation is near-zero. Of note, Maslakík et al. [2011] suggest that the survivability of multiyear ice over the summer has changed in recent years. Hindcast model experiments [Lindsay et al., 2008] suggest that other spring variables, such as thickness and thin ice area, are correlated to subsequent September extent even when detrended. However, observation of these variables is problematic, although methods to derive ice thickness from satellite show promise [e.g., Kwok and Cunningham, 2008; Laxon et al., 2003].

[11] Atmospheric circulation also influences sea ice variability and trends. The Arctic Oscillation (AO) [Thompson and Wallace, 1998] is the leading mode of northern hemisphere SLP variability, with a positive index associated with a weak Beaufort High and strong Icelandic Low. Rigor et al. [2002] showed that a positive winter AO pattern promotes anomalous cyclonic sea ice motion with resulting ice redistribution and thinner ice in the eastern Arctic. This allows greater melt-out there, leading to low summer sea ice area. Enhanced ice export also occurs during a positive AO phase [Kwok, 2000]. However, the winter AO/summer ice extent correlation has weakened in recent years (Figure 1a). For detrended data, the correlation is only marginally significant throughout the record length and so may be of limited use for seasonal prediction. There is also evidence that the character of the AO may be changing [e.g., Wang et al., 2009; Overland and Wang, 2010; Stroeve et al., 2011], which together with sea ice change may have contributed to a weakened winter AO/September sea ice relationship.

[12] Summer atmospheric circulation affects the September ice cover with low summer Arctic SLP and associated winds generally preceding positive September ice anomalies [Ogi and Wallace, 2007] (Figure 1b), although exceptions have occurred [e.g., Serreze et al., 2003; Stroeve et al., 2005]. Because this relationship occurs with a lead-time of only 1–3 months, it can limit predictability gained by winter/spring ice preconditioning.

[13] Air temperature has also been used as a predictor and extensive September sea ice is associated with a cold Arctic during the previous winter (Figure 1c). This suggests that anomalous ice growth associated with cold conditions precedes the ice pack, influencing summer open water formation. Summer temperatures show a similar albeit stronger relationship (Figure 1d). Cause and effect are not clear however since ice conditions both respond to and affect surface temperatures.

5. Simulated Sea Ice Predictor Relationships From Control Integrations

[14] Analysis of multiple simulated variables shows that thin (<1.4 m) ice area and mean thickness provide the strongest correlations with subsequent September ice extent for both PI and PD climates. Correlations of winter/spring (JFMA) thin ice area and the following September extent are significant over large regions, indicating potential predictive capability for up to a nine month lead-time (Figures 2d and 2e). However the nature of the relationship does significantly change for the different climate states (Figure 2f). In the thinner ice regime of the PD control, anomalies across the Arctic are important, whereas for the PI climate, Eurasian basin anomalies are most influential. This is not surprising given that the location of September ice anomalies is different for the two climates (Figures 2a–2c) and largely co-located with the regions of high correlations.

[15] The relationship of atmospheric conditions and subsequent September ice anomalies also varies for the PI and PD climates. As in observations, cold surface air temperature anomalies typically lead high September ice extent (not shown). These simulated temperature anomalies are co-located with the region of maximum September ice extent variance and as such the character of the relationship changes.

Figure 1. Correlations from observationally based records of the timeseries of September ice extent and: (a) the winter (JFMA) AO index for different length timeseries, starting in 1979 and running through the end year listed on the x-axis; (b) gridded JJA average SLP; (c) gridded JFMA 10-meter air temperature; (d) gridded JJA air temperature. Figure 1a shows correlations for the raw timeseries (solid), detrended timeseries (dashed), and the 95% significant level (dotted). Figures 1b–1d use detrended data from 1979–2006. The contour interval is 0.1, the zero contour is omitted, negative (positive) values are shown in blue (red), and values that are significant at the 95% level are shaded.

[Nakicenovic et al., 2000], which reaches 720 ppm CO₂ by 2100.

[8] Previous work suggests that CCSM3 simulates realistic Arctic sea ice, including the mean late-20th century state [Holland et al., 2006; Gerdes and Koberle, 2007] and trends over the historical record [Stroeve et al., 2007]. This gives confidence that they can provide a useful analogue for the real system in the context of this study.

4. Observed Sea Ice Predictor Relationships

[9] Predictors used in ice forecasting systems include the area of ice of different ages, ice thickness, atmospheric temperatures and circulation. Some predictions have also relied on ocean variables [e.g., Tivy et al., 2007], although we do not focus on those here. The predictor variables are strongly associated with each other and not generally independent. Here we review observed relationships to provide context for the model analysis.

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[15] The relationship of atmospheric conditions and subsequent September ice anomalies also varies for the PI and PD climates. As in observations, cold surface air temperature anomalies typically lead high September ice extent (not shown). These simulated temperature anomalies are co-located with the region of maximum September ice extent variance and as such the character of the relationship changes.
In both climate regimes anomalously low summer (JJA) Arctic SLP generally precedes high September ice cover (Figures 2g and 2h) similar to observations. Correlations are weaker in the PD compared to the PI climate and, as for other variables, the location of relevant SLP anomalies differs. In the PI climate, high summer ice extent is associated with low East Siberian Sea (ESS) SLP with corresponding high SLP in the Barents Sea. Based on this, a SLP index equal to the JJA average Barents Sea—ESS SLP difference was designed. This explains about 19% of the PI run September ice extent variance (R = 0.44). Consistent with the SLP gradient characterized by this index (Figure 2g), regression analysis reveals basin-wide summer ice motion anomalies associated with September extent in the PI climate (not shown). In the PD climate, the SLP-ice relationship weakens and ESS SLP anomalies (Figure 2h) are no longer significantly related to the September ice extent. The correlation of September ice extent with the Barents Sea—ESS SLP difference exhibits a significant drop to R = 0.16. In the PD climate, ice often melts out along the ESS coast making ice motion anomalies affecting that region (earlier in the year when ice is present) of little importance for September ice area.

[17] CCSM3 simulates an AO-like leading mode of winter SLP variability [Teng et al., 2006]. However, its relationship to the following September ice extent is weak and variable over time in the control runs. Correlation maps (not shown) indicate ice redistribution associated with AO variability and winter ice motion anomalies are related to the September ice extent. However, the relationships are regional and mainly isolated to the Fram Strait/Barents Sea. There are biases in the CCSM3 Arctic SLP distribution [Chapman and Walsh, 2007], which may influence these relationships. However, hindcast studies [Hilmer and Jung, 2000] and more recent observations (Figure 1a) also suggest the AO-sea ice relationship may vary over time. This is due to the fact that ice motion responds to the position of SLP anomalies, which can differ for a given AO index [e.g., Stroeve et al., 2011]. Whether the weak CCSM3 relationship is due to model bias or instead reflects a non-robust relationship also present in the real system is not clear.

6. Changing Predictor Relationships in a Changing Climate

[18] CCSM3 simulates large ice cover reductions in the late 20th–early 21st century, reaching near ice-free Septembers by mid 21st century [Holland et al., 2006] and increased summer
Figure 3. The correlation of JFMA thin ice concentration with the subsequent September ice extent for (a) 1950–1980, (b) 1980–2010 and (c) 2010–2040 using model simulated output from eight 20th–21st century CCSM3 ensemble member integrations. The contour interval is 0.1, the zero contour is omitted, significant negative (positive) values are shaded blue (red), and hatching denotes where a significant change in correlation from Figure 3a is present. (d) The correlation of the CCSM3 JFMA Arctic mean thin ice area and September ice extent for running 30-year timeseries. The x-axis denotes the final year from each timeseries. The dotted line shows the 95% confidence interval and diamonds denote where a significant change from the initial running correlation values (for 1950–1980) are present. All timeseries are detrended.

Figure 4. (a–c) As in Figure 3 but for the correlation of CCSM3 simulated September sea ice extent with the preceding gridded JJA SLP. (d) The correlation of CCSM3 September ice extent with the difference in JJA averaged SLP between an average Barents Sea (15E–100E and 66–80N) and East Siberian Sea (100–192E and 68–80N) domain for running 30-year timeperiods. The dotted line shows the 95% confidence interval and diamonds denote where a significant change from the initial running correlation values (for 1950–1980) are present. The x-axis denotes the final year from each timeseries. All timeseries are detrended.

7. Discussion and Conclusions

[21] Seasonal forecasting of the Arctic sea ice cover is important for assessing marine access to the region. The applications of these forecasts are likely to grow with expected increases in marine activity. In light of this, the Study of Environmental Arctic Change (SEARCH) program (http://www.arcus.org/search/seaiceoutlook/index.php) synthesizes September ice extent outlooks at several months lead-time. To date, seasonal ice forecasting has often relied on statistical relationships determined from historical records. Given rapid Arctic change, it is unclear that these relationships will continue to provide useful information.

[22] Predictor relationships for the September sea ice extent show important changes for preindustrial, present-day, and transient 20th–21st century climate model runs. Winter–Spring air temperature and ice anomalies that provide potential predictive capability show a strong dependence on the location of resulting September ice extent variations. This causes Arctic basin variations in the winter–spring ice conditions to become increasingly important for the following September ice extent as the system transitions to a thinner and more seasonal ice pack. In contrast, summer atmospheric circulation variations become less important for September ice variability in a warmer climate and the location of relevant SLP anomalies changes. This is related
to how ice transport anomalies modify ice volume in seasonal sea ice loss areas that change with the climate state. Given the possibility for rapid ice loss events [Holland et al., 2006], the decrease in skill associated with an individual predictor may not be gradual but could instead change rather abruptly (as in Figure 3d). This has implications for how frequently statistical models should be re-trained with new information. Finally we expect that other variables that affect seasonal sea ice evolution, such as snowfall and related ice growth/melt anomalies, will also undergo important transformations in the changing Arctic environment that can affect their utility as potential sea ice predictors. [25] This general lack of stationarity in sea ice predictor relationships suggests that forecasting based on historical relationships may have limited utility in the future. More physically based models [e.g., Zhang et al., 2008] may provide an alternative. However, these need adequate observations for initialization and, given important feedbacks, should include coupling to an atmosphere. Finally, there is still a limited understanding of inherent Arctic sea ice predictability [Koenigk and Mikolajewicz, 2008; Holland et al., 2011]. As such, a multi-pronged approach of basic research into predictability, innovating forecasting system design, and an observing network that can provide relevant model initial conditions is needed if we are to reliably produce useful sea ice forecasts on seasonal timescales.

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