

Persistence and Inherent Predictability of Arctic Sea Ice in a GCM Ensemble and Observations

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ABSTRACT

The temporal characteristics of Arctic sea ice extent and area are analyzed in terms of their lagged correlation in observations and a GCM ensemble. Observations and model output generally match, exhibiting a red-noise spectrum, where significant correlation (or memory) is lost within 2–5 months. September sea ice extent is significantly correlated with extent of the previous August and July, and thus these months show a predictive skill of the summer minimum extent. Beyond this initial loss of memory, there is an increase in correlation—a reemergence of memory—that is more ubiquitous in the model than observations. There are two distinct modes of memory reemergence in the model. The first, a summer-to-summer reemergence arises within the model from the persistence of thickness anomalies and their influence on ice area. The second, which is also seen in observations, is associated with anomalies in the growth season that originate in the melt season. This reemergence stems from the several-month persistence of SSTs. In the model memory reemergence is enhanced by the sea ice albedo feedback. The same mechanisms that give rise to reemergence also enhance the 1-month lagged correlation during summer and winter. The study finds the least correlation between successive months when the sea ice is most rapidly advancing or retreating.

1. Introduction

Sea ice has long been recognized as a key player in global climate (e.g., Budyko 1969). Through its high albedo, it reflects large amounts of incident solar radiation to outer space that would otherwise be absorbed, thus cooling the surface. It regulates the fluxes of turbulent heat between the ocean and atmosphere, acting as an insulating cap between both mediums (Maykut 1982). It also plays an important role in the makeup of ocean currents by modulating the production of North Atlantic Deep Water (NADW; Dickson et al. 1988). Reduced sea ice volume (thickness and areal extent) is expected to contribute to the polar amplification of twenty-first-century greenhouse warming (e.g., Manabe and Stouffer 1980), and thus it has long been suggested that trends in the extent and thickness of sea ice are

likely to be among the early indicators of greenhouse warming (Walsh 1983).

The unique aspects of sea ice that are important for Arctic climatology and the greenhouse warming problem also ought to influence climate variability at seasonal to interannual time scales. Such effects on the atmosphere have been investigated by, for example, Alexander et al. (2004) and Bhatt et al. (2008). Nonetheless, predicting seasonal to interannual variability of the sea ice cover has only recently received much attention by the scientific community (e.g., Drobot 2007; Lindsay et al. 2008), and little work has been done to explore the inherent predictability of Arctic sea ice (e.g., Döscher et al. 2010; Mikolajewicz et al. 2005). Using a linear empirical model of sea ice with a range of predictors, including atmospheric circulation indices, ocean temperature, and sea ice data, Lindsay et al. (2008) found that, except for the trend, much of the predictive information in the ice–ocean system is lost for lead times greater than about 3 months.

Predicting sea ice cover on seasonal time scales in the Arctic may be of use to many, and the cumulative gains in observing sea ice and advances in modeling are

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making it possible to assess how predictable sea ice is at seasonal to interannual time scales. For example, advanced knowledge of the opening of the northwest and northeast passages could offer faster and cheaper shipping between the Atlantic and Pacific Oceans (Hassol 2004). Growing ecotourism in the Arctic is also likely to benefit.

Climate change has proven problematic for local Inuit communities, whose elders are no longer able to reliably predict the weather and sea ice for hunting from traditional means, thus having an effect on those communities' hierarchical systems (Fox 2003). This raises the question of how predictability might change with greenhouse warming. One might reason that thinner ice is more variable in areal coverage and thickness. Indeed Holland et al. (2008) and Goosse et al. (2009) found the variability of sea ice area increased significantly over the twenty-first century, which suggests predictability may decline.

Persistence of Arctic sea ice can offer some degree of predictability even without the use of a numerical model. High persistence may also indicate times when predictability with numerical models is most promising. Lemke et al. (1980) found that the main patterns of Arctic sea ice area variability showed a decorrelation time scale (or loss of persistence) of 2–5 months, yet they did not specify whether these relaxation times varied throughout the year. This time scale was found to be associated with heat storage in the marginal ice zone mixed layer. Subsequent work has focused on calculating relaxation times for sea ice volume (and by proxy thickness) using sea ice models. Flato (1995) calculated a relaxation time of 7 yr for total Arctic sea ice volume in a model forced by observed monthly air temperature anomalies. Bitz et al. (1996), using a single column stochastic model of sea ice, found relaxation time scales fell from 15 to 6 yr for Arctic sea ice volume when accounting for ice export through Fram Strait.

Lindsay et al. (2008) note the importance of properly predicting thickness to improve predictions of area. The lack of consistent observations of ice thickness (Kwok and Rothrock 2009) point to a role for climate modeling to extend predictions of ice area beyond the initial 2–5-month decorrelation time scale found by Lemke et al. (1980).

In this study we reexamine the persistence properties and inherent predictability of Arctic sea ice in both observations and one advanced climate model. Satellite observations of sea ice extent and area exist now for slightly more than 30 yr. Prior measurements are available from ship records, yet they are of questionable spatial and temporal resolution for meaningful statistical studies in the context of this study. We evaluate mechanisms for

persistence with the more comprehensive sea ice model output and evaluate their plausibility by comparing their character with observations. Given the key influence of Arctic sea ice on climatically relevant time scales, it is of paramount importance for climate models to successfully characterize such mechanisms that give rise to sea ice persistence so models may be used to make seasonal to annual forecasts.

2. Data

We use output from the Community Climate System Model, version 3 (CCSM3) Large Ensemble Experiment, a 30-member ensemble run for the period 2000–61 under the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) A1B. The CCSM3 in general is described by Collins et al. (2006), and the sea ice component and polar climate are described by Holland et al. (2006). The atmospheric component of the model employs T42 spectral truncation, consisting of a roughly $2.8^\circ \times 2.8^\circ$ latitude–longitude grid. The ocean component is simulated with the Parallel Ocean Program (POP), which is run on a nominally 1° grid with the grid pole displaced into Greenland, leaving a smooth, singularity-free grid in the Arctic Ocean of substantially higher resolution than the T42 grid. The sea ice component employs the same grid as the ocean.

At T42, the resolution of the atmosphere is half that of the majority of CCSM3 integrations in the World Climate Research Programme's Coupled Model Intercomparison Project phase 3 (CMIP3; Meehl et al. 2007) data archive, which were run at T85 (e.g., see analysis of Arzel et al. 2006; Gerdes and Köberle 2007). Compared to the T85 integrations, the sea ice in the T42 integrations is thicker on average by approximately 0.75 m and more extensive by approximately 1 million km^2 (Holland et al. 2006). The thickness and extent at T85 in the Climate of the Twentieth-Century Climate in Coupled Model (20C3M) integrations were found to compare well with observations by Stroeve et al. (2007) and Gerdes and Köberle (2007). Thus, the bias in the T42 model makes the output from 2000 to 2030 be in fairly good agreement with the observed sea ice over last three decades (see Fig. 1).

There remains in the model, however, a positive bias in sea ice thickness along the East Siberian shelf, where ice thicker than 3 m is found. We find that our results are not influenced by this spatial bias, given its comparatively small area (when considering the whole of the Arctic) and the fact that this area has little variability, because it remains mostly frozen throughout the year.

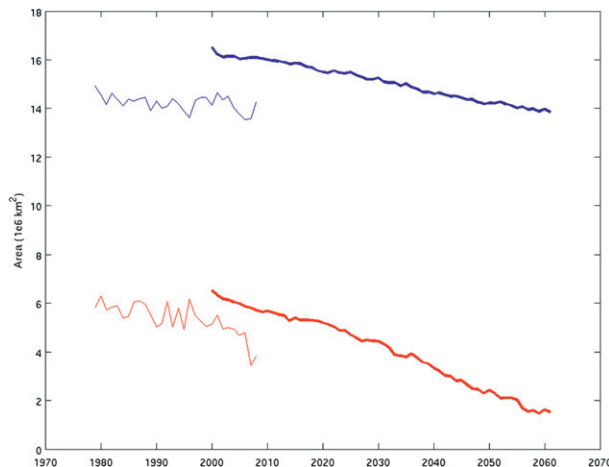


FIG. 1. Mean sea ice area in September (red) and March (blue) in observations (thin line) and the ensemble mean (thick line).

Each ensemble member is initialized from the same sea ice, land, and ocean conditions, which are taken from the end of a 20C3M integration with the same coupled model. The initial conditions of the atmosphere are different for each ensemble member and correspond to the state of the atmosphere at 12 a.m. on days drawn from 1 December 1999 to 15 January 2000 of the 20C3M integration.

Monthly output from the large ensemble is used for this study. We calculate the total Arctic sea ice area by integrating the ice concentration over Northern Hemisphere grid cells. Sea ice extent is calculated as the sum of gridcell areas wherever the sea ice concentration is greater than 15%. Both area and extent are analyzed because they offer slightly different information about the system. Sea ice area is a useful index of the Arctic climate (Flato 1995) and arguably more relevant than extent when considering the influence of sea ice on surface albedo and heat fluxes. However, sea ice extent in observations is arguably of better quality than area (Parkinson and Cavalieri 2008). We discard the first year of model output data in the ensemble (2000) to allow for spinup of the sea ice component (to achieve consistency between the state of the atmosphere and sea ice concentration). Monthly anomalies are calculated for each ensemble member by subtracting the ensemble mean from each ensemble member, which effectively detrends the data. For example, the anomaly for January 2001 for each member has the 30-member ensemble mean for January 2001 removed. The large number of ensemble members allows us to satisfactorily estimate and eliminate the anthropogenically forced response from the variability. We compare the two halves of the period to determine if the variability depends on the forced response.

We use monthly observed Arctic sea ice extent and area from the satellite period (November 1978–December 2008), which we obtained from the National Snow and Ice Data Center (NSIDC; Fetterer et al. 2002). Sea surface temperature (SST) data are obtained from the Met Office Hadley Centre Sea Ice and Sea Surface Temperature (HadISST) dataset (Rayner et al. 2003) over the period 1978–2008. Anomalies in the observations are calculated by taking each month of data and removing the mean and the long-term linear trend in that month's time series.

3. Results

a. Lagged correlation of total ice area and extent

We begin with an analysis of the persistence of Northern Hemisphere total sea ice area and extent. Figure 2 shows the monthly lagged correlation of total Northern Hemisphere sea ice area for all ensemble members for the first half of the run period (2001–30), the average of all 30 members, and observations from 1978 to 2008. Figure 2a shows all Januaries correlated with themselves at 0 lag, Januaries correlated with Februaries at lag 1, and Marches at lag 2, and so on up to a lag of 15 months. We assess the significance of the lagged correlations using a Student's t distribution statistic.

1) INITIAL DECLINE OF MEMORY

In each panel the lagged correlation coefficients drop rapidly within the first few months in the model and in observations. The ensemble mean drops below 0.3 (when the original anomaly explains less than 9% of subsequent anomalies) within 3–6 months. For at least the first 6 months, the lagged correlation plots roughly decay exponentially, and thus approximate a red-noise process, with an e -folding time that varies seasonally from 2 to 5 months both for ensemble mean and observations. The extent to which they depart from an exponential decay will be explained in section 3. This initial e -folding (or relaxation) time scale is thus comparable to that found by Lemke et al. (1980). Lagged correlations of the observations are generally within the envelope of all ensemble runs or slightly outside, yet they also tend to drop faster than the ensemble mean of the lagged correlation values and often lose all memory within a few months.

2) REEMERGENCE OF MEMORY

After the initial drop in correlation with increasing lag, the correlation rises again in every panel of Fig. 2 in the ensemble mean of the lagged correlation from the model. Such an increase in correlation after some time has been described as a reemergence of memory

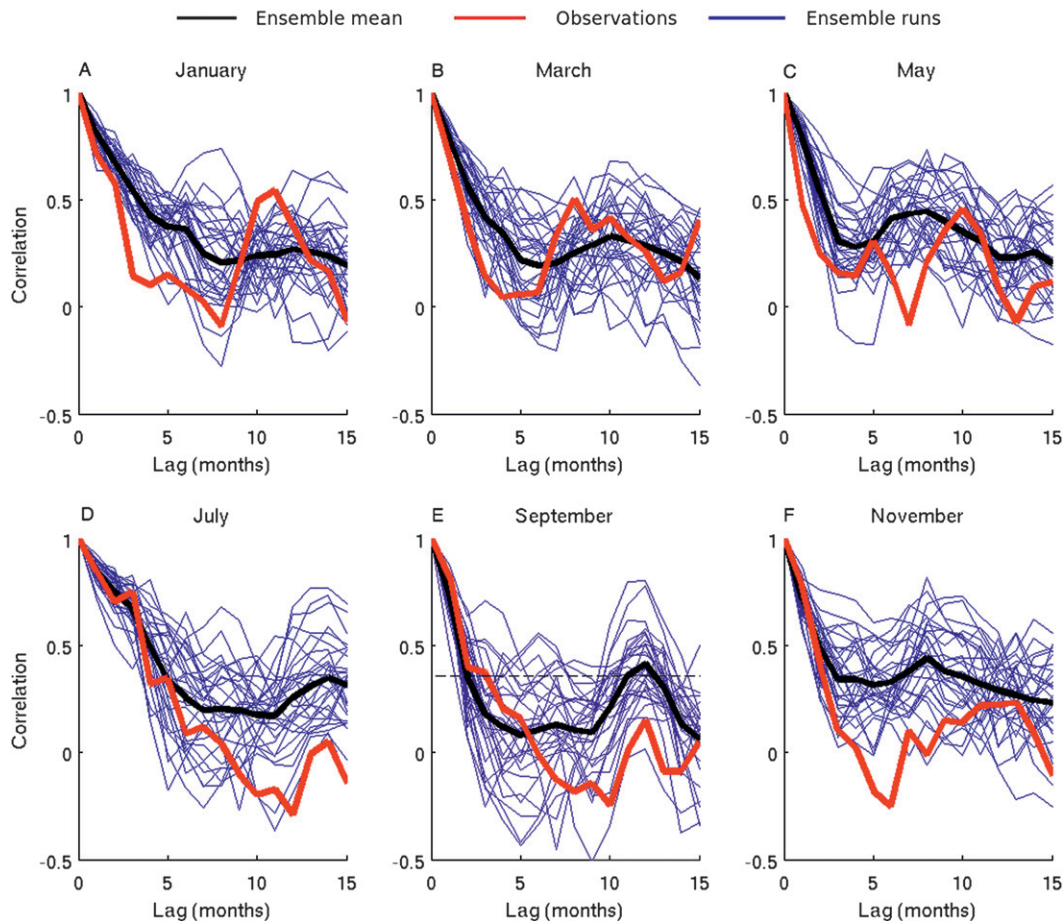


FIG. 2. Monthly lagged correlations of total sea ice area for every other month for the Northern Hemisphere in the observational record and CCSM ensemble. The ensemble mean (thick black curve) is the mean of the individual ensemble members (blue curves). The broken line in (e) indicates the 95% significance level for a single 30-yr run.

(Alexander et al. 1999), and it signals a return of persistence after a gap. Hence, the reemergence is manifest as a secondary peak in the lagged correlation. Reemergence is seen only in winter month anomalies in observations. Beyond 15 months' lag, all correlations drop to values near zero (not shown).

This secondary (or reemergence) peak is significant following anomalies that originate in every month in the model ensemble mean. The time when the peak occurs varies seasonally in roughly two repeating patterns. First, following anomalies that originate in late winter and spring (January–May), the reemergence peak is weakest and latest (lagged up to 12 months) following anomalies that originate in January. The reemergence peak then occurs progressively earlier following anomalies that originate in March and May. This pattern is nearly repeated following anomalies that originate in summer and fall (July–November) and that reemerge about a year later. A noteworthy feature in the ensemble mean

following these anomalies that originate in summer and fall is the reemergence always peaks in September, yielding a summer-to-summer persistence. The reemergence peak is largest for September-to-September persistence in the model. Mechanisms to describe these patterns of reemergence are offered below at which time the seasonally distinct behaviors will become more apparent.

In observations the reemergence is significant following anomalies that originate in January and March and peak in the following late fall. Although the September-to-September lagged correlation is slightly peaked (Fig. 2e) mirroring the reemergence seen in the model, the peak is not statistically significant at the 95% threshold. While the period for which this analysis is performed is not the same (1979–2008 in the observations versus 2001–30 in the model), and the overlap is just 8 yr, there are two reasons we believe our comparison is valid. First, as explained in the data section, there is a positive bias in sea ice extent and thickness in the T42 CCSM3 model,

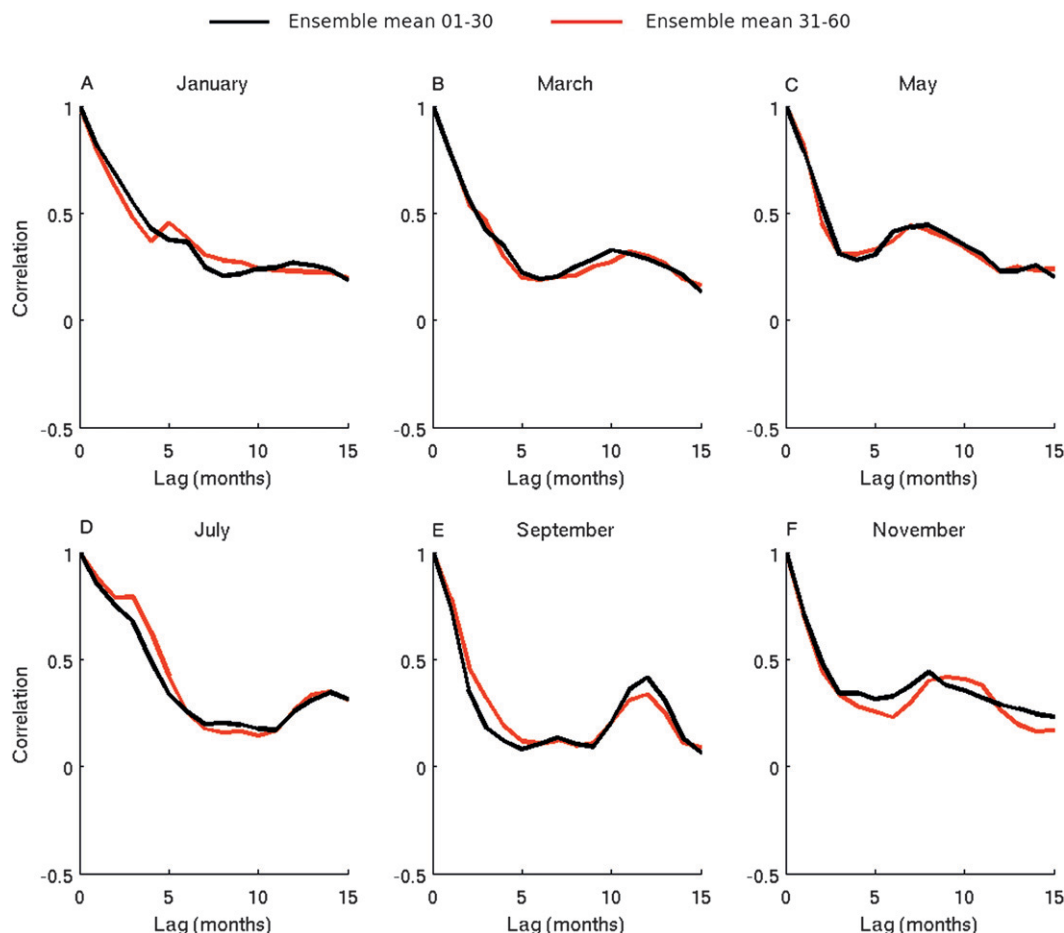


FIG. 3. As in Fig. 2, but for ensemble mean of the first half (2001–30; black) and second half (2031–60; red) of the model run.

such that the average September sea ice extent in the early twenty-first century in the model is comparable to that in observations in the late twentieth century. Second, Fig. 3 shows results for the same analysis as Fig. 2 but for the ensemble means of the periods 2001–30 and 2031–60. Despite a diminished sea ice environment, both in terms of area and thickness in the second half of the model ensemble—summer sea ice area is reduced by 50% with respect to the first half—the model shows similar patterns of lagged correlation. This result is discussed further below. Additionally, the 20C3M control run also shows similar patterns of lagged correlation (not shown).

Our analysis shows that extent anomalies (not shown) for both model and observations generally have even shorter initial persistence and weaker reemergence. For example, spring and early summer (April–June) sea ice extent yields no information on the following summer's minimum extent in September, and July is the earliest month in the melt season that is significantly correlated with the late-summer minimum.

Figure 4 shows lagged correlations for anomalies that originate in every month (predictor) up to and including a lag of 23 months (predictand). In the model ensemble mean (Figs. 4a and 4b), two main features appear that correspond to reemergence of memory. One is a “summer limb” of relatively high lagged correlation values extending out from the initial 1-month-lag primary correlation peak in late summer and representing predictor–predictand persistence pairs from August to September, July to October, June to November, and May to December. The second feature is a “winter limb” of relatively high lagged correlation extending out from the initial 1-month-lag primary correlation peak in late winter. Anomalies that originate in late fall/early winter reemerge at increasingly shorter lags and smaller magnitude, while anomalies that originate in late-summer/early-fall months are seen to reemerge in the following September. The winter limb is considerably longer than the summer limb. This presentation of the lagged correlation (in Fig. 4) highlights the timing of the

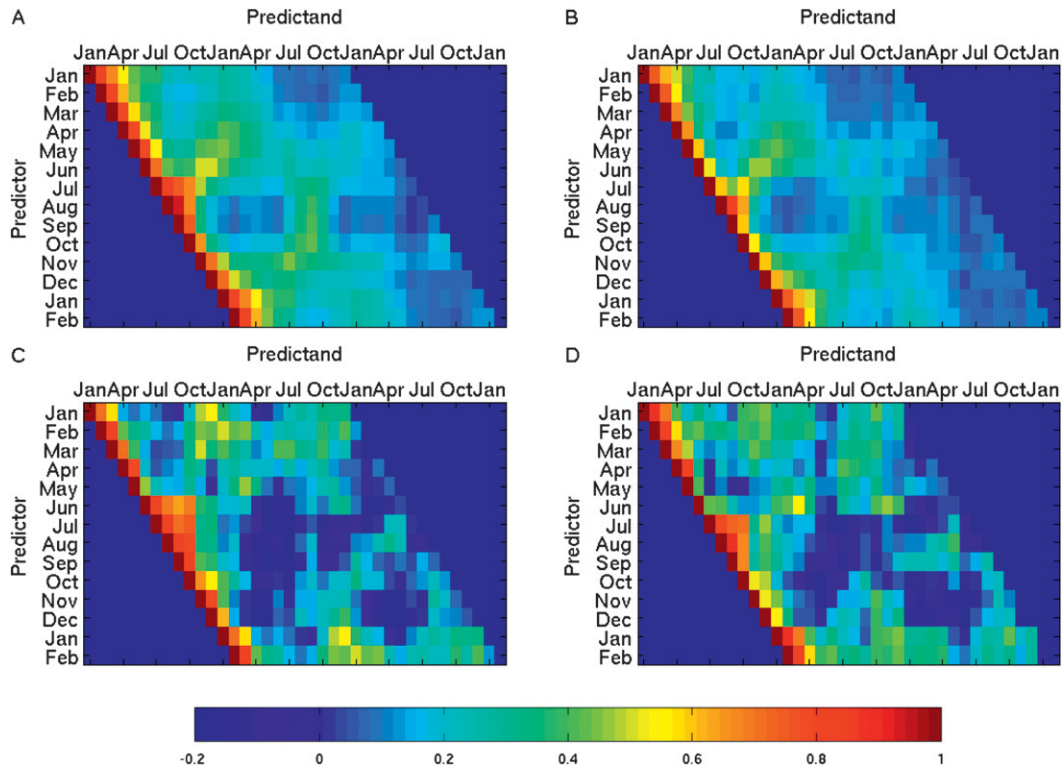


FIG. 4. Correlations values for all months and all lags. Months along the x axis indicate the month whose anomaly (predictand) is correlated with the month's anomaly along the y axis (predictor), from lags of 0 months (thus values of 1 along the diagonal) to 23 months. Shown are (a) model sea ice area, (b) model sea ice extent, (c) observed sea ice area, and (d) observed sea ice extent. The model results are the ensemble mean correlation of the individual ensemble members. January and February data have been duplicated for ease of following structures through winter. Figure repeats what is shown in Fig. 2 for lags up to and including 15 months.

reemergence and confirms the distinct behaviors that were noted in Fig. 2. It further illustrates that the reemergence branches into “limbs” from the initial decline of memory, and hence we can expect the same mechanisms that give rise to reemergence to also enhance the initial persistence during certain seasons, namely, at the peak and trough of the seasonal cycle of sea ice area. We examine in detail the seasonality of the initial persistence in the following section. Sea ice extent in the model ensemble has consistently lower lagged correlation values than sea ice area (Fig. 4b versus Fig. 4a), yet the same patterns of memory reemergence are present.

The observational data, while much noisier, have similar patterns to the model data where the limbs branch from initial 0-lag primary peak correlation (especially for extent). Thus, both the summer limb and winter limb may only be present for short lags (August–September and July–October for the summer limb and January–March for the winter limb). However, there is a significant reemergence of winter anomalies originating in January, February and March at 1-yr lags that is subtler

in the model. As discussed by Bitz et al. (2005), the location of the mean winter ice edge is strongly related to ocean heat flux convergence, which owing to its relatively long time scales causes a significant winter-to-winter memory in the location of the winter ice edge and thus the total Arctic sea ice area and extent.

3) THE CONNECTION BETWEEN THE INITIAL DECLINE OF MEMORY AND MEMORY REEMERGENCE

The peak values of lagged correlation in the summer limb of memory reemergence correspond to pairs of months that share a similar amount of mean sea ice cover. For the winter limb, this relationship is not as strong. Figure 5 shows the annual cycle of mean sea ice area in the CCSM3 ensemble for the period 2001–30. The arrows indicate predictor–predictand persistence pairs that share a high degree of lagged correlation relative to other pairs of months with identical lag. The black arrows indicate months that represent the summer limb of high lagged correlation values, whereas the gray

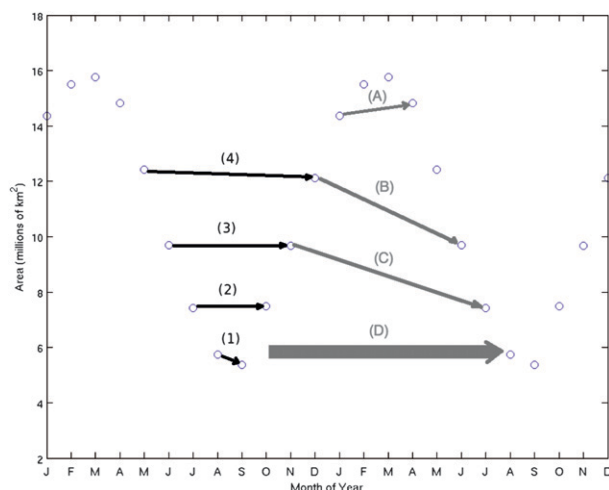


FIG. 5. Mean annual cycle of sea ice area in millions of square kilometers in the CCSM ensemble run for 2001–30. The arrows are used to illustrate pairs of months that show high correlation values in their sea ice area (and extent) anomalies. The black arrows show pairs of months during the summer limb of memory seen in Fig. 4: (1) August–September, (2) July–October, (3) June–November, and (4) May–December. The gray arrows represent pairs of months with memory reemergence in the winter limb: (A), January with April; (B), December with June; (C), November with July; and (D) late summer (July–October) with the following September.

arrows indicate months that represent the winter limb of high lagged correlation values in Fig. 4. The results from Fig. 4 hint that the degree of similarity in the expanse of the Arctic sea ice, and likely the collocation of the sea ice edge between certain months, is one of the main factors driving the overall memory in the sea ice.

To investigate this further we have calculated the correlation between absolute change in sea ice area and extent for both model and observations and the 1-month lag correlation for all months. In the model the absolute change in month-to-month sea ice extent explains 63% of the 1-month lagged correlation (32% for area). The relationship in observations is not significant at the 95% level, yet the sign of the correlation agrees with the model. This behavior is even clearer at lags of 2–3 months. For a 3-month lag, absolute value of the 3-month change in mean area (extent) explains 70% (72%) of the 3-month lagged correlation in the model and extent explains 35% of the 3-month lagged correlation in the observations. Thus, during the part of the annual cycle in which there is a rapid change (freeze up in fall, melt in spring) 1-month lagged correlations tend to be lower. Therefore, the seasonality in the initial decline of persistence is driven by the seasonal cycle in sea ice area.

Figure 6 shows the 1-month-lag squared correlations of sea ice area and extent for all months of the year (January correlated with February, February with March,

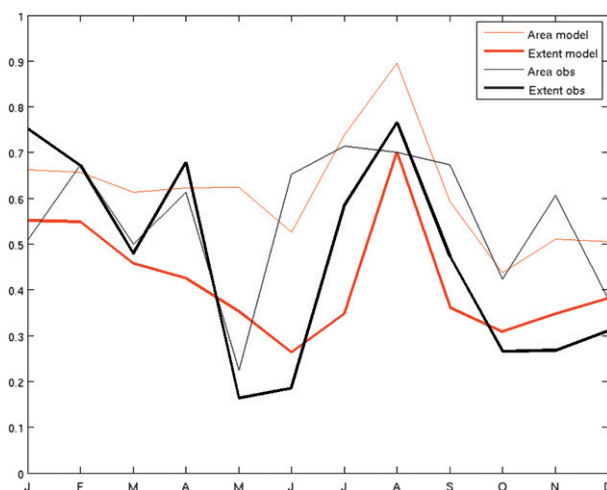


FIG. 6. Squared correlation at 1-month lag for area and extent in observations and the CCSM3 ensemble for 2001–30. Along the x axis, “J” refers to January correlated with February, “F” refers to February correlated with March, and so on.

and so on) in both model and observations. In the model, area and extent have similar annual cycles of 1-month-lag squared correlations: low values occur during spring and fall, separated by a peak during late summer, with August having the highest 1-month-lag squared correlation in the annual record. During winter, values are halfway between the summer peak and spring/fall valley. The same measure of near-term persistence in observations of sea ice is in reasonable agreement with the model ensemble mean outside the winter months, although the summer peaks are broader. In all four curves in Fig. 6, the difference between the high (August) and low values (spring and fall) in 1-month-lag squared correlation is significant at the 95% confidence level [assuming an first-order autoregressive (AR1) model; e.g., von Storch and Zwiers 1999]. The 1-month-lag squared correlation is consistently higher for area than extent in the model, and the same is true for most months in the observations. Our results suggest that extent is not as valuable as area for predicting sea ice behavior, and thus we focus on area as we attempt to identify mechanisms of persistence and reemergence. Later we discuss why. In the next two sections, we describe in detail the physical mechanisms driving this seasonally varying pattern in persistence and the reemergence of memory.

b. SSTs as source of persistence and reemergence in sea ice area

A possible mechanism for the increased lagged correlation and persistence between months in the melt and growth season with similar ice area comes from persistence within the ocean. Our hypothesis is that SST

anomalies that accompany sea ice coverage anomalies, and their characteristic behavior in terms of time and spatial scales, are the key player in the context of the summer limb of memory in Fig. 4. In this case SST anomalies provide the memory from the months during the melt season to the subsequent months during the growth season with similar mean sea ice coverage (see Fig. 5). SST anomalies extend throughout the oceanic mixed layer, which gives rise to a relatively large heat capacity compared to sea ice or the atmosphere (White and Walker 1974). As a result, SST anomalies are rather persistent, with a typical e -folding time of 3–6 months (e.g., Frankignoul and Hasselmann 1977), although this persistence is scale dependent, being longer for large-scale patterns of SST variability. Additionally it has been shown that SST anomalies may reemerge at later times than their initial relaxation time (e.g., Alexander et al. 1999).

A negative (positive) sea ice anomaly at a certain location during the melt season is associated with positive (negative) SST anomalies in that vicinity, which persists for a number of months. If within this timeframe the sea ice edge returns to this vicinity, the SST anomaly “inherited” from the original sea ice area anomaly will have an influence on the rate at which sea ice forms again in that vicinity.

The total July sea ice area for all ensemble members for the first half of the model run is correlated in Fig. 7 with SSTs at each grid cell during July and the following months. The SSTs in the Barents and Beaufort Seas from July to October are negatively correlated with July sea ice area (high area is correlated with low SSTs). The regional pattern of variability in sea ice concentration changes little from July to October (a consequence of being in the “trough” of the seasonal cycle of Arctic sea ice area). The regions of high variability are collocated with high correlations between SST and July total sea ice area. The SST remains highly correlated with the previous July sea ice area for at least 3 months, which provides a means of maintaining the initial sea ice anomaly. After October, the regions of SST that were highly correlated with July sea ice area experience freeze up (note especially the Beaufort sea) and thus the SST correlation signal disappears, leading to a fast decline in persistence of July sea ice area anomalies beyond the month of October (see Fig. 4).

The persistence of SST anomalies and its influence on sea ice area is more peculiar following sea ice/SST anomalies initiated in May. This is easily seen when the total May sea ice area is correlated in Fig. 8 with SSTs at each grid cell during the subsequent months. As in Fig. 7, SSTs correlations are especially negative in the Barents and Bering Seas but now for a much longer period. May sea ice area anomalies in the model are mainly a result of

variability in the ice concentration of the Barents and Bering Seas. From May to September, the sea ice edge retreats and with it the region of maximum variability in the sea ice concentration moves poleward, beyond the vicinity where the SST anomaly persists. By the time of the sea ice area minimum in September, the region of large variability in the sea ice concentration is almost entirely within the Arctic Ocean Basin, well separated from the anomalous SSTs in the Bering and Barents Seas. During the autumn freeze up, the sea ice edge advances southward and returns to the region of anomalous SSTs where the sea ice edge advance is modulated by the SST anomaly, thus giving rise to memory reemergence of sea ice area anomalies.

In summary, an anomaly in the sea ice area in May will, on average, be followed by an anomaly of the same sign in fall. The memory of the May sea ice area anomaly persists over the summer as an SST anomaly. The sea ice edge retreats poleward of the SST anomalies at the height of summer but returns to feel its influence in fall, and so the previous May’s anomaly reemerges.

This mechanism to explain the correlation, and hence reemergence of memory between melt and growth months in CCSM3 is supported by results found using the same atmosphere and sea ice component models but with the dynamic ocean replaced by a slab mixed layer (see section 3d).

In observations, evidence for the SST-driven persistence and reemergence of sea ice area anomalies can be seen at two different times. First, October sea ice area anomalies are correlated with the previous July sea ice area anomalies, which explains a greater part of the variance in October sea ice area anomalies than August or even September sea ice area anomalies do (see section 4b). Second, we find that the reemergence of winter sea ice area anomalies in the following fall/winter (indicated by the strengthening of the lagged correlation at 10–12 months’ lag in January and March in Fig. 1) is produced by the reemergence of SST anomalies in the Barents and Okhotsk regions (these are the two regions in which sea ice concentration is highly correlated with total Arctic sea ice area, and thus variability of sea ice area in these regions accounts for a large fraction of the variability of total Arctic sea ice). Anomalous SSTs in these regions in late winter correlated with the original sea ice anomaly reemerge in the following late fall (not shown) in a manner analogous to the reemergence of late winter/spring SST anomalies in the following fall/winter found by Alexander et al. (1999).

Given the key role played by the persistence of SST anomalies in forcing the reemergence of sea ice area anomalies, we have compared the SST e -folding times in the CCSM3 and in the HadISST datasets and found them to be of similar magnitude (not shown). We note,

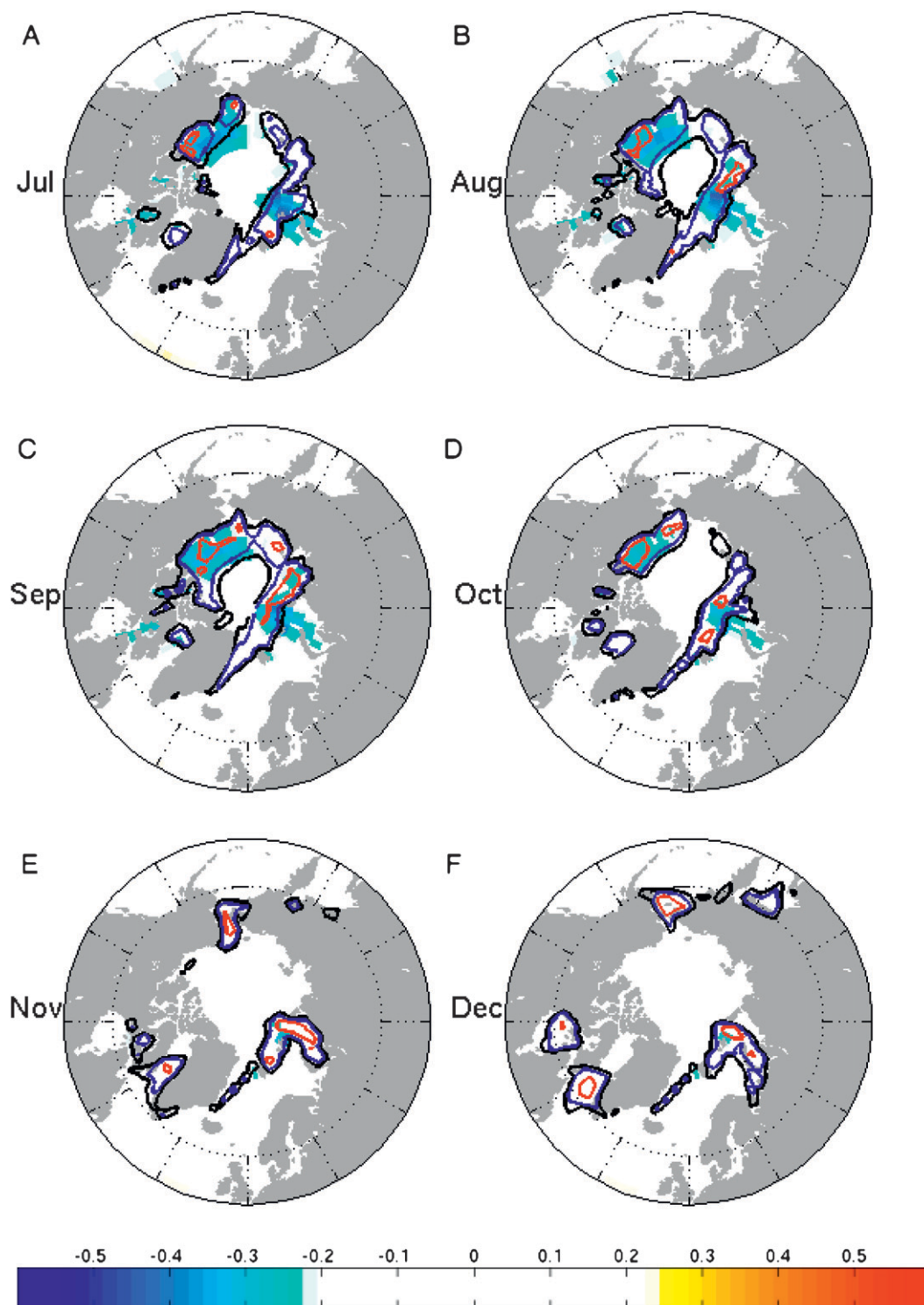


FIG. 7. Correlation (colored above 95% significance levels, values are shown in color bar at bottom of figure) of total July sea ice area with SSTs by grid cell in July and subsequent months. The standard deviation of sea ice concentration is shown (contours, black are 10%, blue are 20%, and red are 30%) for the same months. All panels are ensemble averages of the statistics of individual ensemble members in CCSM3 for 2001–30.

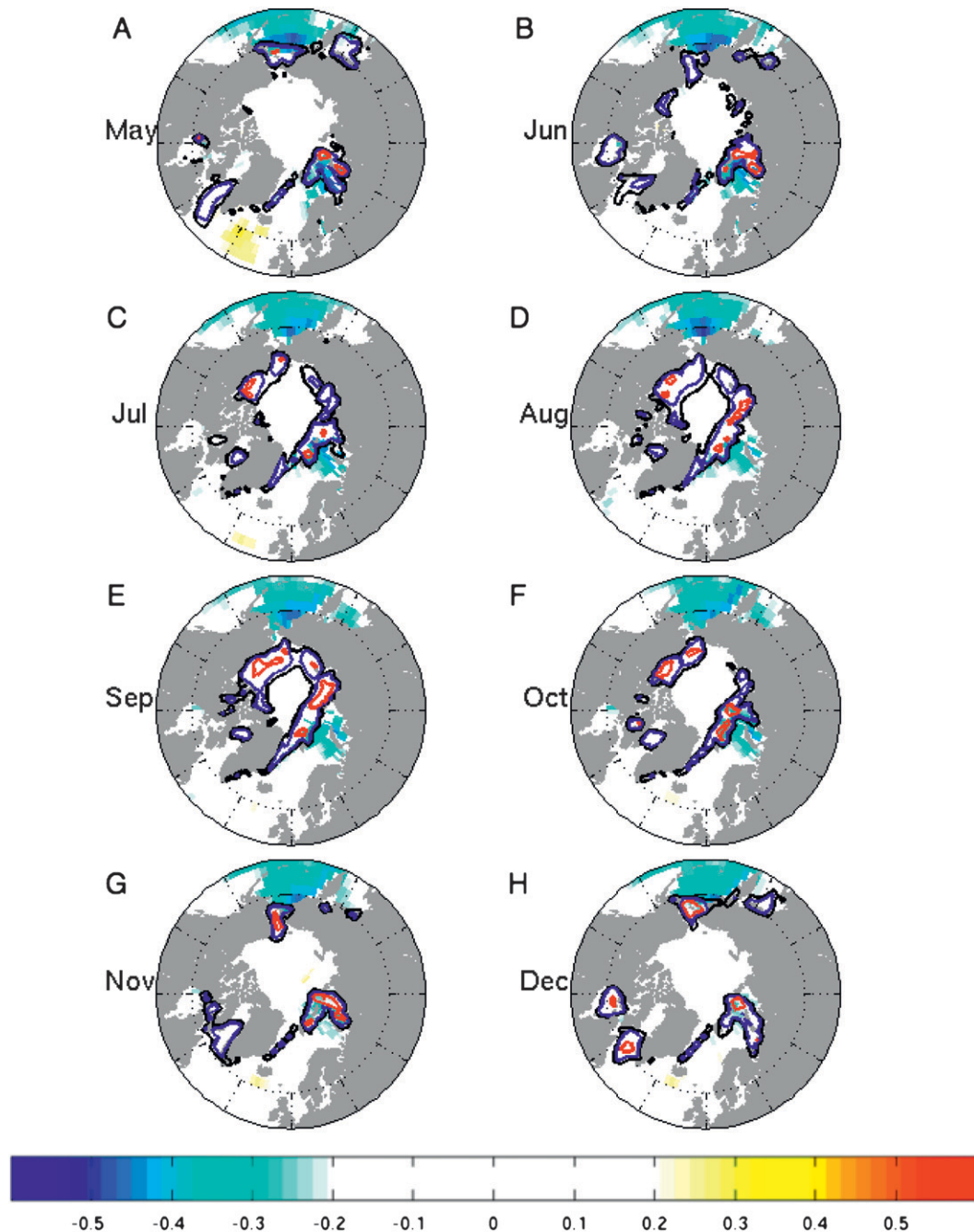


FIG. 8. As in Fig. 7, but correlation (colored, values are shown in color bar at bottom of figure) of total May sea ice area with SSTs by grid cell in May and subsequent months.

however, that there are important discrepancies in the autocorrelation of SST anomalies across different observational datasets (Rayner et al. 2003).

c. Sea ice thickness as source of persistence and reemergence in sea ice area

The SST anomaly cannot persist in winter past freeze up, and hence the SST persistence mechanism cannot

explain the correlation from growth to melt months or the summer-to-summer memory reemergence of the winter limb. An alternative mechanism to explain reemergence is for area anomalies to impart thickness anomalies that persist in the seasonal ice zone through spring. The timing of freeze up (i.e., sea ice edge advance) at a certain location alters sea ice thickness at that location through the following spring, particularly where sea

ice velocities are low. For example, a positive sea ice area anomaly in January is associated with an earlier date of freeze up, creating anomalously thick ice in the vicinity of the climatological sea ice edge. The sea ice edge subsequently advances toward its March maximum, its rate of advance not significantly affected by the anomalously thick ice in the region of the January ice edge. As the sea ice edge starts to retreat poleward in spring, it will slow anomalously in April, when the edge reaches the anomalously thick ice in the vicinity of the January ice edge. The thicker sea ice imparted by a positive sea ice anomaly in January will tend to create a positive sea ice area anomaly in April.

The negative feedback between ice growth and ice thickness [thinner ice grows faster than thick ice, see, e.g., Bitz and Roe (2004)], however, ensures that thickness anomalies tend to decay in time.

The role of sea ice thickness on the persistence of area in CCSM3 is illustrated in Fig. 9, which shows January total sea ice area correlated with sea ice thickness by grid cell during January and the following months. Thickness anomalies persist in the Barents and Okhotsk regions for several months after January. The spatial and temporal distribution of thickness anomalies imparted by earlier area anomalies varies throughout the year. Analysis similar to Fig. 9 indicates that only sea ice area in late-summer months (August, September, and to a lesser extent October) is correlated with sea ice thickness at subsequent lags of up to 12 months. These highly persistent thickness anomalies occur in the central Arctic Basin. For example, Fig. 10 shows total September sea ice area correlated with sea ice thickness by grid cell in September through the following August. One can see that although sea ice thickness anomalies remain within the central Arctic, the sea ice edge expands southward (shown by the regions of high variability in sea ice concentration shifting southward), and only during the following summer does the sea ice edge return into the region of thickness anomalies that were imparted in September of the previous year. This interchange between sea ice area and thickness anomalies provides a mechanism for the 1-yr summer-to-summer memory seen in the model. During the rest of the year (i.e., at times of greater mean sea ice coverage than August–October), total sea ice area and thickness are correlated over the marginal sea ice zones, and these correlations generally are indistinguishable from 0 within ~6 months.

Given the key role played by ice thickness anomalies in the reemergence of sea ice area anomalies, we next investigate the temporal characteristics of ice thickness anomalies across the Arctic. Figure 11 illustrates ice thickness in the central Arctic has an e -folding time of

approximately a year, while ice in the seasonal ice zone has an e -folding time of a few months. We find that the e -folding time at the regional scale (i.e., at the gridcell level) is significantly shorter than the e -folding time of the total Arctic sea ice volume, which is ~4 yr (not shown). This is likely a result of advection moving floes in and out of a region and disrupting the persistence of anomalies. We also find that the e -folding times at the regional scale are nearly identical during the first and second half of the runs (Fig. 11a versus Fig. 11b), despite a 40% reduction in the mean sea ice thickness. Interestingly, the e -folding time of the total Arctic sea ice volume is reduced significantly in the second half compared to the first (not shown). These results are reminiscent of Bitz et al. (1996), who found a strong thickness dependence on the e -folding time of total Arctic volume anomalies. Their estimates were generally much longer, as they were from a one-dimensional model that lacked explicit transport. When Bitz et al. parameterized divergent transport out of the Arctic Basin, the e -folding time fell considerably.

Our results suggest that the regional pattern of e -folding time in sea ice thickness anomalies is dictated primarily by thickness gradients and advection, and it is therefore little affected by the overall sea ice thinning. It is important to recognize that summer-to-summer persistence in total Arctic sea ice area anomalies depends on the regional-scale thickness anomalies, not on the total Arctic sea ice volume; thus, the summer-to-summer area persistence is also only modestly influenced by thinning. Modest as it is, the difference in September-to-September area persistence between the first and second half of the runs (see Fig. 3e) is significant. Further, we find this same measure in 10-yr intervals of the runs (2001–10, 2011–20, and so on) decreases monotonically.

Significant biases in atmospheric circulation in the CCSM3 model have been shown to occur over the Arctic Basin in all seasons (DeWeaver and Bitz 2006). In particular, anticyclonic (convergent) surface flow is common over the central Arctic about the North Pole as opposed to more cyclonic circulation seen in observations. Biases in surface winds yield biases in ice thickness and ice velocities. We note that in the model, the mean annual ice velocities in the Beaufort region are just 1–2 cm⁻¹, which amounts to ~500 km of advection annually. In observations, however, ice velocities are estimated at 5–10 cm⁻¹ (e.g., Fig. 1 of Lindsay and Zhang 2005), making it possible for sea ice in nature to be advected away from regions where the ice thickness is overly persistent in the model. Thus, we speculate that wind and subsequent sea ice motion biases might be a source of the discrepancy in summer-to-summer memory between the model and observations.

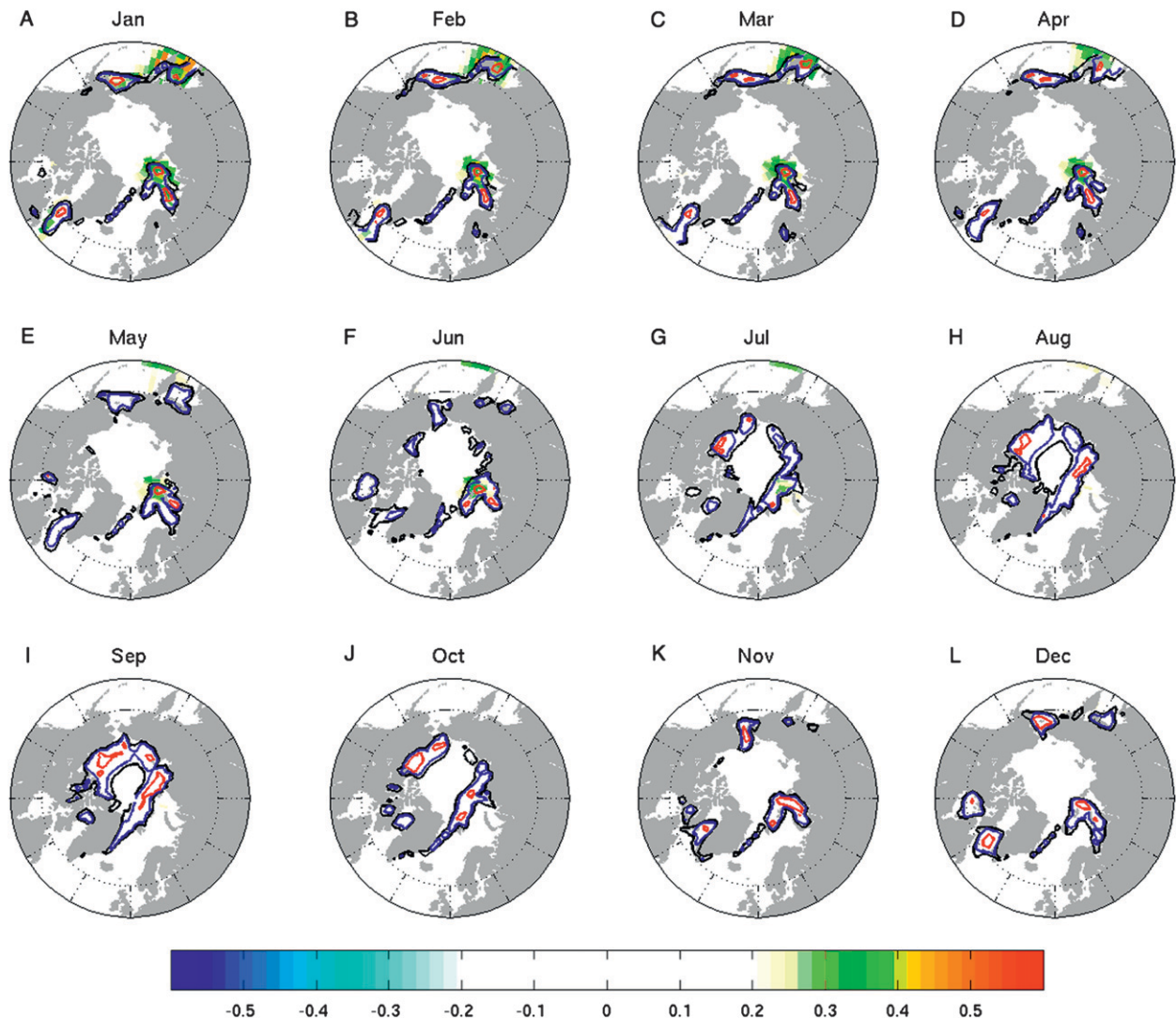


FIG. 9. As in Fig. 7, but correlation (colored, values are shown in color bar at bottom of figure) of anomalous total January sea ice area with sea ice thickness by grid cell in January–December.

d. The role of sea ice albedo and ocean dynamical feedbacks in the reemergence mechanism

An additional factor that may account for the increase in memory throughout the summer may be the sea ice albedo feedback (SIAF; e.g., see Curry et al. 1995). To investigate the effect of the SIAF on memory, we ran a sensitivity experiment with the CCSM3 model with the surface albedo within the sea ice zone held fixed to a climatological value (i.e., climatological SIAF). Specifically, a positive (negative) sea ice concentration anomaly is compensated with a reduction in sea ice albedo (increase in ocean albedo) to maintain the climatological mean annual cycle of ice and ocean surface albedo. This way the deviation from climatology in the climatological SIAF run does not experience a sea ice albedo

feedback. The atmosphere, land, and sea ice components were otherwise identical to the CCSM3 version of the large ensemble, while for efficiency the ocean was a slab mixed layer rather than the full ocean general circulation model. The ocean heat transport was prescribed from a climatological monthly-mean annual cycle taken from the fully coupled run. A run with variable SIAF in this model configuration is used for comparison. The fixed and variable SIAF runs are 200 yr long. For our analysis we discard the first 50 yr of output to allow for spinup in the model. These runs, which we refer to as slab ocean CCSM3 runs, are discussed further in Bitz (2008).

Figure 12 shows the monthly lagged correlations of total sea ice area in the slab ocean runs as in Fig. 4. Both runs have the summer-to-summer memory reemergence

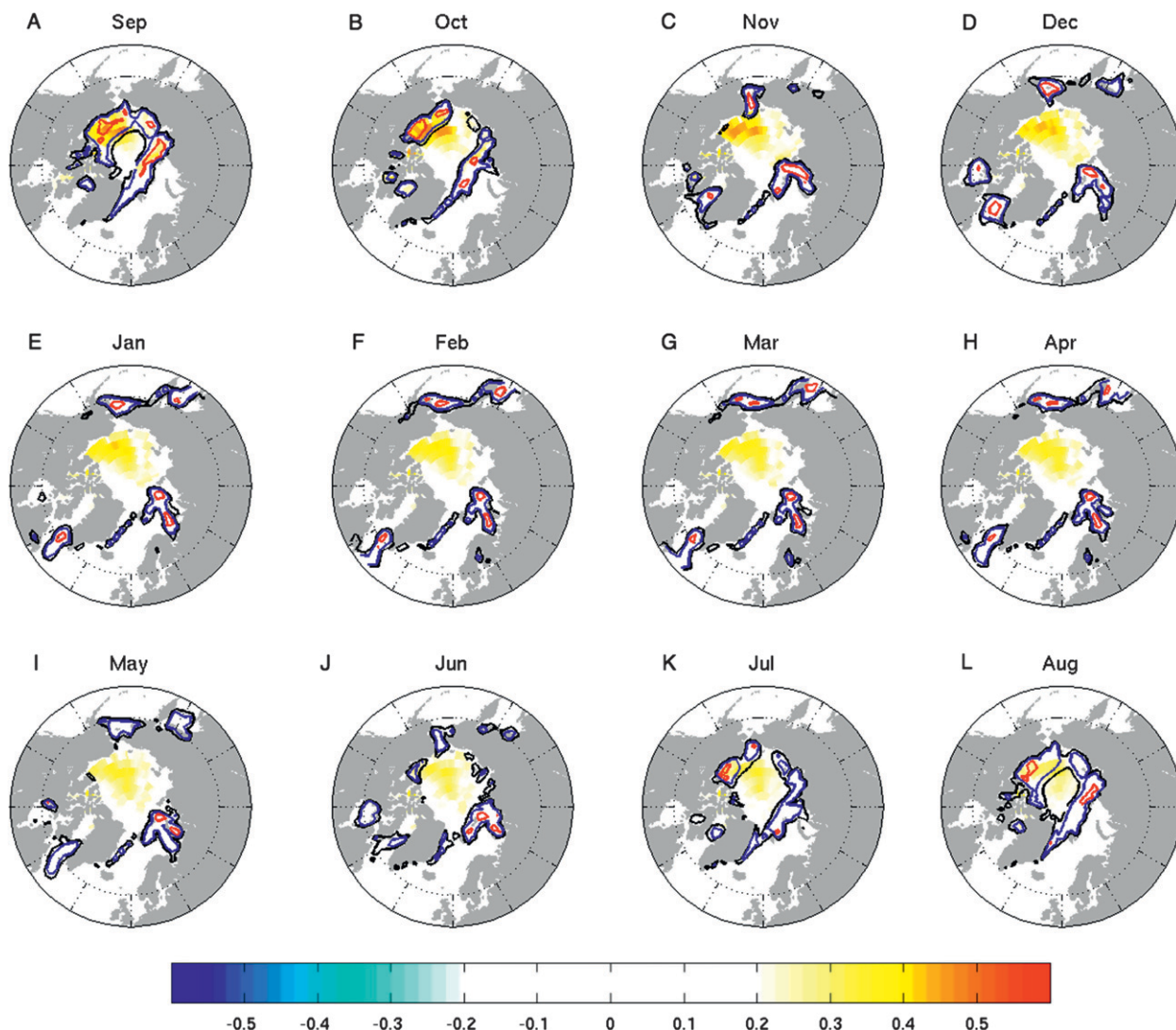


FIG. 10. As in Fig. 7, but correlation (colored, values are shown in color bar at bottom of figure) of anomalous total September sea ice area with sea ice thickness by grid cell in September–August. Statistics are as in Fig. 9.

in lagged correlations, as seen in Fig. 4, indicating that SIAF is not solely responsible for the reemergence associated with thickness persistence. However, the summer-to-summer reemergence is significantly weaker with climatological SIAF in almost every predictor–predictand month pair in Fig. 11, so clearly SIAF is a factor. In addition, the initial decline in persistence of anomalies in the summer is more rapid in the climatological SIAF run, indicating that SIAF contributes to the high persistence during the summer months.

We note that the summer limb in the slab ocean runs in Fig. 12 appears only as strengthening in persistence following anomalies in July. This indicates that SST persistence is diminished in the slab ocean configuration of CCSM3. Analysis of these runs in the same manner

as Fig. 8 is illustrative. Figure 13 shows the correlation of total sea ice area in May with SST by grid cell in November (the first month that shows reemergence of May sea ice area anomalies) in the CCSM3 ensemble and in the slab ocean runs. Compared to the ensemble, the SST anomalies in the slab ocean CCSM3 are shorter lived in the Barents region (one of the two regions of memory storage for this reemergence mechanism; see Fig. 8); therefore, by freeze up, the SSTs in the Barents are uncorrelated with total sea ice area in the previous spring. Additionally, sea ice area variability in the Labrador Sea gains importance in driving total Arctic sea ice area variability in autumn in the slab ocean CCSM3 runs. However, Labrador Sea SSTs are not correlated with May total sea ice area, which precludes much possibility

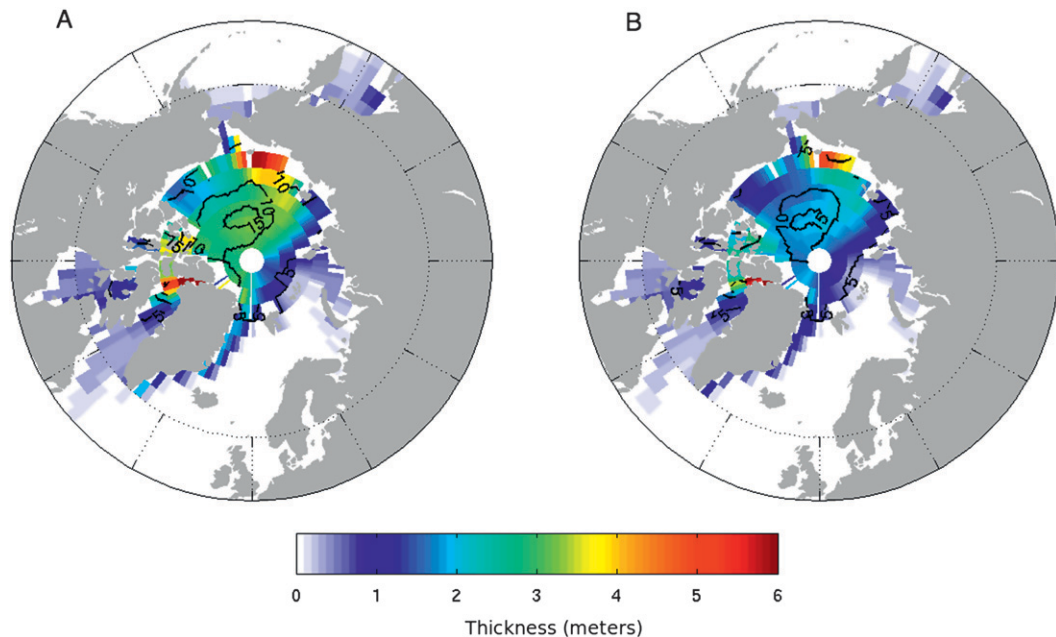


FIG. 11. Ensemble mean sea ice thickness (m, colored) and e -folding times of sea ice thickness anomalies in months (months, contours) for (a) 2001–30 and (b) 2031–60.

for reemergence. Conversely, Bering Sea SSTs are correlated with May total sea ice area; however, the sea ice concentration varies too little there to cause reemergence of total Arctic sea ice area anomalies.

e. Sea level pressure persistence

Sea ice concentration responds to winds on the weekly to monthly time scale (Fang and Wallace 1994), and recent studies (e.g., Ogi et al. 2008) have shown that summer sea level pressure (SLP) in the Arctic may account for a large degree of the variability in the summer minimum sea ice. If the atmospheric patterns that force sea ice area anomalies persist, then one could expect this atmospheric persistence to cause persistence in the sea

ice. There is some evidence that atmospheric patterns of circulation in the Arctic may have some persistence at the monthly time scale. For example, Ogi et al. (2004) showed that the persistence of their seasonally varying northern annular mode (SV-NAM) was significant in adjacent months in winter and summer but not in spring and early fall.

Motivated by these findings, we have calculated the 1-month lag correlation of the time series that characterizes the atmospheric SLP pattern that best explains the loss in sea ice extent in the satellite record between May and September found by Ogi et al. (2008) (see their Fig. 3a). The squared correlation of this time series for May with June, June with July, and July with August is

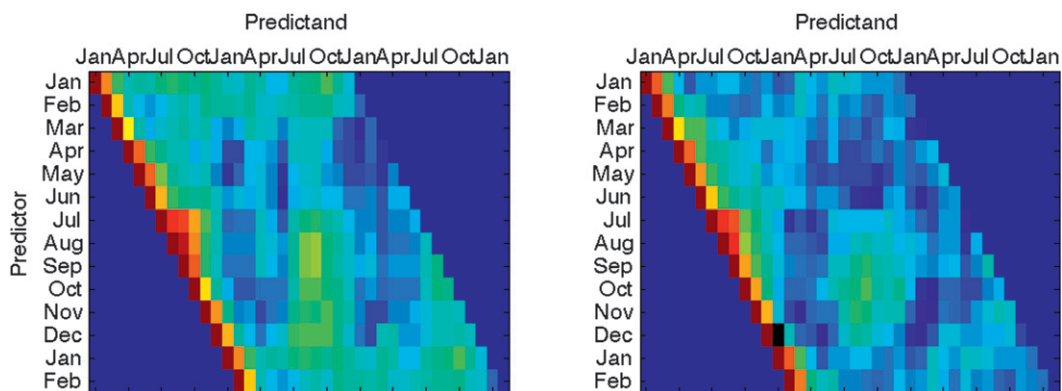


FIG. 12. As in Fig. 4, but for (left) total sea ice area in CCSM3 slab ocean with variable SIAF and with (right) climatological SIAF.

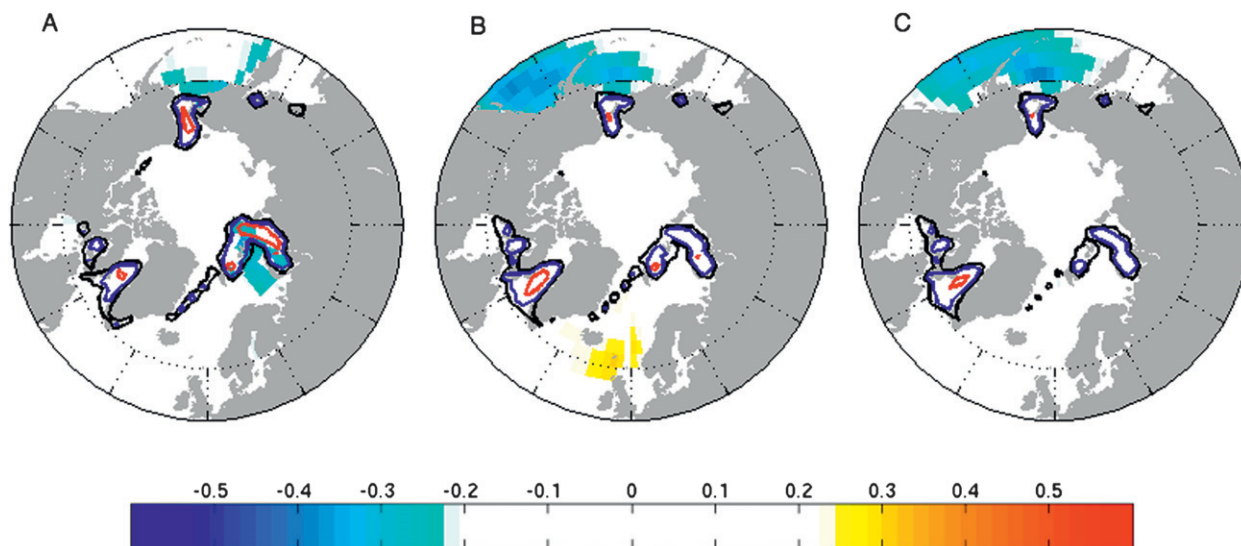


FIG. 13. Correlation (colored, values are shown in color bar at bottom of figure) of anomalous total May sea ice area with November SSTs by grid cell. The standard deviation of sea ice concentration (contours, black are 10%, blue are 20%, and red are 30%) is shown for November. (a) Repeat of Fig. 7e. From integration with the slab ocean version of CCSM3, with (b) variable SAIF and (c) climatological SAIF.

small ($r^2 = 0.09\text{--}0.15$) and varies little over summer. This leads us to dismiss this SLP pattern as a source for the significant increase in persistence of sea ice between May and August (see Fig. 6). We have performed the same analysis on the GCM data and found that there is no robust SLP signal that forces summer sea ice loss—unlike in observations. This makes it even less likely for hypothetical patterns of SLP persistence to have an imprint on patterns of sea ice persistence.

4. Discussion of sea ice predictability

Even though the reemergence of sea ice area anomalies is much clearer in the 30-member ensemble of the CCSM3 model than it is in observations, we present an in-depth analysis of the reemergence mechanisms in the model for three reasons. First, it is possible that the observations of sea ice *area* are too inaccurate to reliably exhibit reemergence. Because sea ice *extent* is thought to be more accurately observed than area, we have also shown results for sea ice extent in Figs. 4 and 6. We have noted that extent tends to be less persistent than area, so extent cannot serve as a substitute. We return to this issue below to explain why this may be. Second, a more compelling motivation for examining the reemergence mechanism in CCSM3 is that we found the same mechanisms also enhance persistence during the initial relaxation of sea ice area anomalies, when model and observations agree quite well. We end this section with a discussion of whether measurements of thickness might improve predictability of area and the prospect for

future predictability. And third, we note that nearly all models from CMIP3 (Meehl et al. 2007) have significant September-to-September correlation in sea ice area (not shown). This analysis developed herein is thus a constructive way to diagnose behavior common among models and will be the subject of a future study.

a. Sea ice area versus extent

The differences in persistence and reemergence behavior for sea ice area and extent arise from the different response of these two variables to dynamical forcing. Conceptually, under a divergent wind field, sea ice floes are likely to diverge without any change in total area but decreasing concentration and increasing extent. Under a convergent wind field, leads may close, again without any change in total area but increasing concentration and decreasing extent. If the sea ice should deform, then area will decrease as well but often at a lesser rate than the extent. These behaviors argue that sea ice extent is more sensitive to high-frequency wind forcing than sea ice area and is thus more variable and less persistent, as our results show.

b. Seasonal predictability of total Arctic sea ice area

We have shown that persistence of total sea ice area anomalies for the 1–5-month time scale in the model agrees well with observations. The correlation of sea ice area between months in this time range also tends to be largest (see Figs. 2 and 4). We are thus motivated to ask how well the area in a given month can be predicted from knowledge of the area in earlier months, which

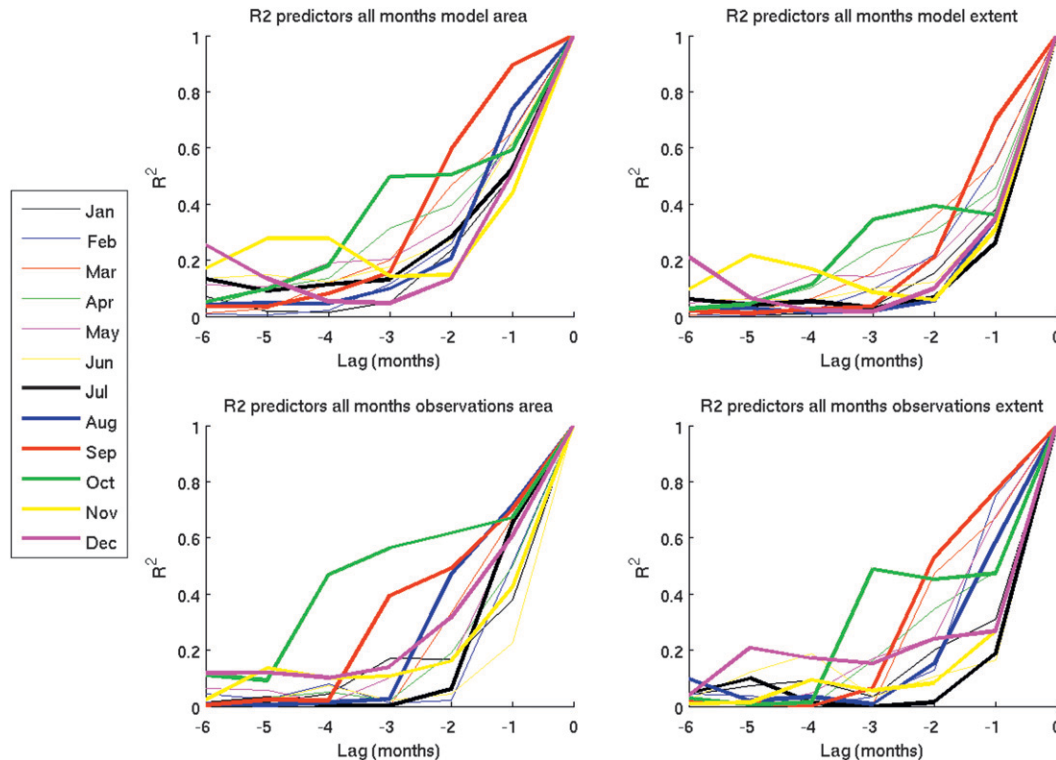


FIG. 14. Squared correlation value for a given month at lags shown in the x axis for model and observed sea ice area and extent.

months are predictable the earliest in advance, and which months offer the most value for predicting later months. These questions are most easily answered by reformatting the results in Figs. 2 and 4 so that the 0-lag correlation is lined up for every month. We also square the correlations to give the explained variance r^2 and emphasize shorter lags and higher correlations. This presentation of predictability for both area and extent in the model and observations is given in Fig. 14.

Many of the curves in Fig. 14 bear a strong resemblance to an exponential decaying away from 0 lag, which is characteristic of red noise (AR1 process). However, significant departures occur in the explained variance for September and October. It can be seen that area anomalies in July explain as much of the variance in the following October as the area anomalies in August or September. This is a result of the SST persistence mechanism described in section 3b, and the fact that this mechanism not only affects reemergence but also enhances the near-term persistence in summer months. It further suggests that intensive accurate measurements of July area would offer the most value for predicting future months, with a bonus that it is also a good predictor of the September area minimum, which has captured so much attention. Anecdotal evidence of the value

of July occurred in 2007 and 2008, years with similar anomalies in July and October. There was an unusually early episode of high melt back in late June 2007, leading to large negative sea ice area and positive SST anomalies by July. Unusually high SSTs and low sea ice area continued through fall 2007, whereas in 2008, the main episode of anomalous melt back occurred during August, which did not allow the SSTs to warm up as much as in the previous summer, and thus July and October sea ice areas were closer to normal. In both years, however, August and September had anomalously low areas.

Figure 14 also shows March–June sea ice area anomalies are largely uncorrelated with September values, and alone they are not useful predictors of the summer area minimum, in agreement with Lindsay et al. (2008).

c. Interseasonal to interannual predictability of total Arctic sea ice area

The reemergence mechanisms invite the possibility of predicting sea ice area anomalies beyond approximately 4 months in the future. The persistent SST anomalies induced by area anomalies in spring and summer yield significant predictability in the model up to approximately 10 months (deductible from the summer limb in

Fig. 4). The persistent sea ice thickness anomalies induced by area anomalies in summer and fall yield significant predictability in the model for even longer, up to approximately 15 months (deductible from the summer-to-summer memory in Fig. 4). Even though reemergence is not significant in observations, we found evidence to suggest that these mechanisms influence seasonal predictability in observations. Therefore, we suspect that these mechanisms also influence longer time-scale predictability in nature, even though the observations are unable to verify it.

The summer-to-summer reemergence of area anomalies via memory that is stored in the sea ice thickness in the central Arctic raises the possibility of using thickness as a predictor of the summer area minimum. Again, we turn to the model output for our analysis because detailed spatial and temporal observations of sea ice thickness are lacking. The model may yield insights applicable to future observational thickness-based approaches for predicting the summer area minimum.

Figure 10 shows that sea ice thickness in the Beaufort Sea holds most of the memory of sea ice area anomalies from one September to the next. Based on this result, we created an index of sea ice thickness over the Beaufort sector (75° – 90° N, 180° – 90° W). Figure 15a shows the lead-lag squared correlation of the thickness index and the September sea ice area. The correlation is significant from when the thickness index leads by 4 months through a lag of 12 months. Included in Fig. 15 is the lead-lag squared correlation of total Arctic sea ice area in each month, with September and the multiple regression using both variables (thickness index and total Arctic sea ice area) to explain the variance of September sea ice area. While sea ice thickness offers some degree of predictability during the winter and spring months prior to September when extent or area are not useful metrics, the values obtained ($r = 0.4$ – 0.5) indicate that September sea ice coverage is weakly dependant on the previous winter's thickness and coverage. These results generally agree with those of Lindsay et al. (2008), who found no skill (r^2 values below 0.5) in predicting detrended September total sea ice extent from a range of atmospheric, oceanic, and sea ice variables (including total sea ice extent and thickness) for lead times greater than about 3 months.

d. Changes in predictability in a greenhouse warming climate

Recent work (e.g., Holland et al. 2008; Goosse et al. 2009) has shown that the natural variability of simulated summer sea ice extent increases in the twenty-first century because of the thinning ice cover. Holland et al. (2008) speculate that higher variability will cause

a reduction in predictability. This increase in variability of summer sea ice extent (and area) is seen in the CCSM3 large ensemble used in this study. Additionally, Holland et al. (2010) found that ice extent in a thicker sea ice regime generally exhibited higher potential predictability by comparing experiments initialized with different mean ice conditions.

We find that the September-to-September persistence of total Arctic area anomalies does decline as the ice thins over from 2001 to 2060, in broad agreement with Holland et al. (2010). However, we characterize the decline as modest—especially in contrast with the strong decline in persistence of the total Arctic ice volume.

e. September lagged correlation and the extended observational sea ice record

The brief satellite record of Arctic sea ice is one of the obvious shortcomings in the present work. One of the more interesting aspects of the satellite record—both for its scientific and societal effects—is the evolution of the summer minimum extent. A longer sea ice record has been constructed by the Hadley Centre (Rayner et al. 2003) by combining ship- and airborne-based observations with the satellite record. We use the adjusted Hadley time series of total September sea ice area since 1953 following the analysis and modification by Meier et al. (2007) of the dataset. This shows a somewhat strengthened September-to-September correlation ($r = 0.22$), yet still not significant at the 95% level.

5. Conclusions

Arctic sea ice area decorrelates exponentially over a time scale of 2–5 months in observations and in the CCSM3 model. This persistence time scale is variable throughout the year, with longer values in winter and summer and shorter values during the spring and fall. To a large degree, this range is accounted for by the rate of ice edge retreat/advance, with a longer decorrelation time scale at the peak/trough of the seasonal cycle of area. We find that sea ice area at the summer minimum (September) is only significantly correlated with area in the previous two months, July and August, both in the model and observations.

We found that the persistence of SST and sea ice thickness anomalies is a means of storing memory of Arctic sea ice area anomalies, even at times when the area anomalies themselves appear uncorrelated. Therefore, memory of an area anomaly can return after a period when all memory appears to have been lost. We borrow the term reemergence from the midlatitude mixed layer ocean dynamics literature to describe this phenomena.

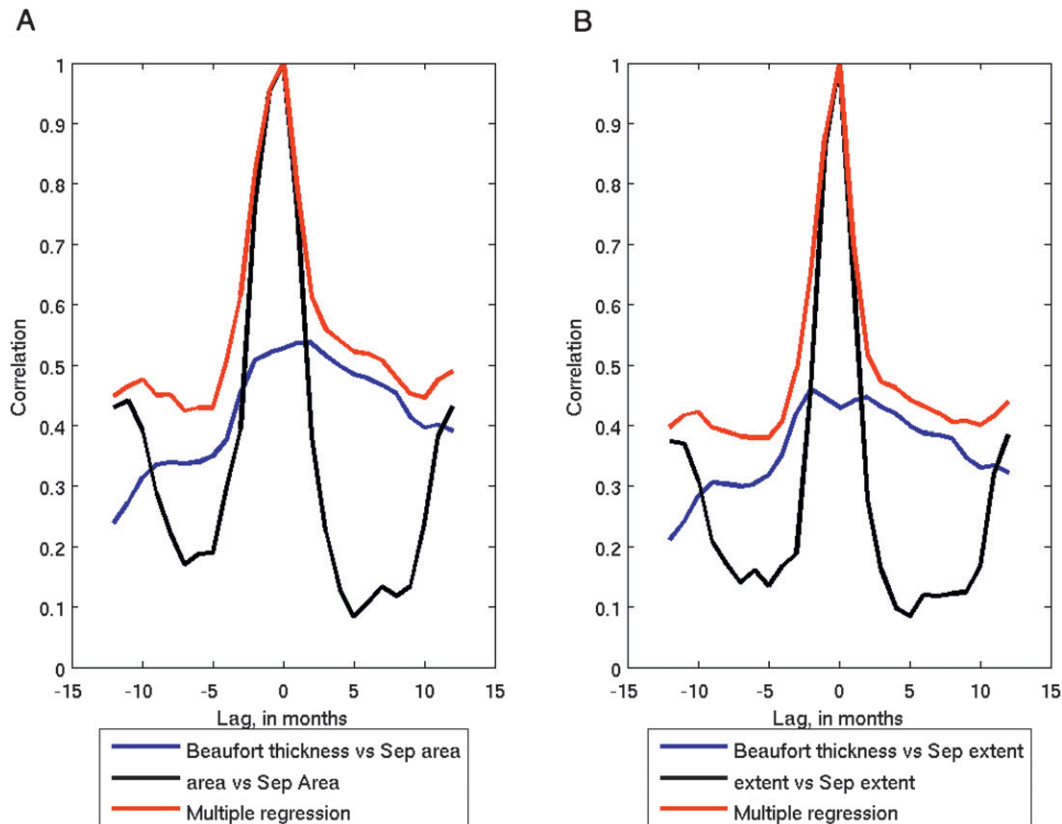


FIG. 15. Mean correlation of Beaufort sea ice thickness and total Arctic sea ice (a) area and (b) extent with respective September values in the ensemble, and multiple regression using both variables in each panel for lags from -12 to $+12$ months.

There are two modes of reemergence of memory in the Arctic sea ice area in the model and at least one in observations. These reemergence modes are intrinsically linked with the seasonal variability in the initial persistence. The first reemergence mode common to model and observations is between pairs of months that share a similar mean sea ice coverage from melt-to-growth seasons (i.e., August–September, July–October, June–November, and so on), while the second one is reemergence from one summer to the next. The melt-to-growth season reemergence patterns can be explained through the imprint of sea ice anomalies on SST in the vicinity of the sea ice edge. The anomaly persists in the SST after the sea ice edge moves away to the north, and it is regained by sea ice area when the sea ice edge returns to the vicinity in the fall. A similar exchange of anomalies between area and thickness gives rise to the summer-to-summer reemergence.

We find little change in the persistence of Arctic sea ice area anomalies as the ice thins in a future greenhouse warming scenario. There is only a weak, albeit significant, loss in correlation of September-to-September area.

This is in striking contrast to a substantial reduction in the persistence of total Arctic sea ice volume anomalies in the future scenario. The former relationship is weak because area anomalies depend on the persistence of regional sea ice thickness anomalies, which changes little in the future scenario.

A sensitivity study with sea ice albedo feedback eliminated from the models shows that sea ice albedo feedback lengthens the persistence of SST and sea ice area anomalies in summer. Our diagnostic analysis finds little persistence in the atmospheric circulation patterns most correlated with the ice area.

Our results are relevant to the Sea Ice Outlook Project (available online at <http://www.arcus.org/search/seaiceoutlook/index.php>), which gathers and summarizes estimates of the September sea ice extent 1–3 months in advance. We note, for example, that winter sea ice extent has been used as a predictor for the 2010 outlook by a number of working groups. In this work we show that winter sea ice extent is uncorrelated with the following summer sea ice extent minimum and thus should not be used. Our results indicate the summer minimum area

may be predictable from regional thickness anomalies up to a year in advance.

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