CHAPTER

10

The Role of Sea Ice in Sub-seasonal Predictability

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OUTLINE

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1 INTRODUCTION

The polar regions, the Arctic and the Antarctic, are the scene of a number of unique weather and climate phenomena and conditions, such as polar lows, stable boundary layers, tip jets, katabatic winds, sea and land ice, snow, and mixed-phase clouds. Polar regions are also characterized by their remoteness, which makes them naturally undersampled by conventional observation systems, although they are currently well covered by polar-orbiting satellites. The Arctic is home to >4 million people, including an increasing majority of nonindigenous settlers with growing economic activity. The Antarctic has no permanent human habitation, but it does host a number of permanent research stations.

Sea ice is arguably one of the most iconic features of the polar system. Due to its insulating properties, it regulates exchanges between the atmosphere and ocean. Its high albedo has a direct impact on the Earth's energy balance. Sea-ice growth and melting affect the upper-ocean stratification, possibly feeding back on the thermohaline circulation. It is also a central player in the process of polar amplification, which affects the meridional structure of the atmosphere. Therefore, the recent trends observed in many sea ice parameters, which are often interpreted as early-warning signals of climate change, also may have far-reaching consequences for the whole climate system.

Along with its key role in the Earth's climate system, sea ice is at the center of several socioeconomic, geopolitical, and operational concerns. Rapid sea ice changes unlock invaluable opportunities for the shipping, tourism, and offshore industries (Smith and Stephenson, 2013; Lloyd's, 2012; COMNAP, 2015). At the same time, sea ice inevitably poses a serious threat to all types of marine operations, regardless of their purpose. In this context, the need for sea ice (and, more generally, polar environmental) prediction on timescales ranging from hours (tactical) to months (operational) and years (strategic) has become pressing (e.g., Jung et al., 2016).

The scientific community has eagerly responded to the need for sea ice predictions, focusing mainly on seasonal to decadal timescales (e.g., Guémas et al., 2016). After initiating research for operational purposes, especially for predicting marine accessibility in the Beaufort Sea along the Alaskian coast (Barnett, 1980), this area has become well established for research. Since 2008, interests in seasonal sea ice predictability and predictions also have benefited from the momentum generated by the Sea Ice Outlook (SIO; Stroeve et al., 2014; https://www.arcus.org/sipn/seaice-outlook), a forum of Arctic sea ice prediction providers with the purpose of liaising with a growing stakeholder community. However, research on seasonal sea ice predictability in the Southern Ocean is far less advanced.

Sea ice lies between the atmosphere, which has a memory of about 1–4 weeks, and the ocean, which is known to have persistence at timescales longer than a few seasons (Frankignoul and Hasselmann, 1977), especially in the tropical oceans (e.g., Latif et al., 1998). The oceanic origin of sea ice provided the hope that it could hold a considerable memory, like many components of the Earth's cryosphere (e.g., snow and land ice). However, its relative thinness (only a few meters thick, compared to a few hundreds of meters or kilometers for land ice) and the fact that it is strongly driven by the atmosphere, especially on synoptic timescales, drastically limit its predictability beyond months compared to the ocean. By acting as an effective insulator, the presence of sea ice (and snow on top) transforms the surface such that from an atmospheric perspective, it behaves less like an open ocean and more like land, allowing atmospheric near-surface temperatures to vary more strongly and rapidly. The location of the sea ice edge, therefore, is not only of particular interest to potential forecast users, but it also has a pronounced impact on the overlying atmosphere. The marginal ice zone and adjacent regions, hence, are places where the predictability of the second kind of the atmosphere—that is, the influence of slow variations in ocean-surface characteristics on weather statistics (discussed further in Chapter 1)—can be particularly pronounced. Combined with growing evidence that a substantial fraction of nonseasonal variations in the ice-edge location are potentially predictable at sub-seasonal to seasonal (S2S) timescales, there is the potential for trustworthy predictions of the atmosphere on S2S timescales as well.

The critical role of sea ice in forcing atmospheric variability, as will be discussed later in this chapter, is one of the main reasons why prediction systems used for shorter-term forecasts increasingly account for it, either to improve the forcing of weather forecasting models or to provide dedicated forecasts (Pellerin et al., 2002). The focus has been primarily on sea ice concentration—the fraction of an area covered with sea ice, which is the quantity that (1) primarily determines how air-sea fluxes are modulated by sea ice, and (2) provides the basic information on the presence of sea ice in an area. Stakeholders, however, require information on other variables, including sea ice thickness.

The goal of this chapter is to present sea ice in relation to S2S prediction. The field of S2S prediction attempts to bridge the gap between numerical weather prediction (NWP) and climate prediction. Interestingly, thus far, the role of sea ice on sub-seasonal climate predictability is not well understood. From the existing literature, which mostly deals with seasonal-to-interannual timescales, we will review the sources of sea ice predictability at timescales from 2 weeks to 1 year. Based on this analysis, we will characterize the predictability of the second kind as related to sea ice and provide an overview of our understanding of the possible role of sea ice as a source of S2S atmospheric predictability, in the polar regions and beyond.

2 SEA ICE IN THE COUPLED ATMOSPHERE-OCEAN SYSTEM

2.1 Sea Ice Physics

The process of sea ice formation and subsequent growth is a complex topic that is beyond the scope of this chapter (for a comprehensive review, see Petrich and Eicken, 2017). Sea ice initially forms through the freezing of the surface ocean. While sea ice forms, it captures only a fraction of sea salt (from 2 to about 10 g/kg), which is dissolved in brine pockets. The remaining salt is released to the ocean, thereby modifying the density profile of the water column. As sea ice grows, its salinity keeps decreasing though drainage. After the initial ice formation, thermodynamic ice growth is sustained by thermal imbalance as a consequence of air-sea temperature differences. The thermodynamical growth rate is rapidly damped as sea ice thickens; thicker ice grows more slowly than thin ice (e.g., Bitz and Roe, 2004). Sea ice can reach up to 2–3 m only through thermodynamical growth (e.g., Maykut and Untersteiner, 1971). During sea ice growth, snow plays a significant role. It is a powerful insulator, limiting the loss of heat in the ocean to the atmosphere during winter (e.g., Semtner Jr, 1976). Furthermore, the thermal conductivity of snow is lower than that of sea ice by one order of magnitude. The presence of a thick layer of snow is one of the reasons why Antarctic sea ice is on average thinner than its Arctic counterpart. Note that when the snow load is sufficient to depress the ice-snow interface below the sea surface, snow ice may form. Again, this process is mostly observed to occur in the Southern Hemisphere.

Dynamical processes play an important role in shaping the space-time variability of sea ice thickness. Sea ice floes—discrete elements of the sea ice cover—drift in response to atmospheric winds and ocean currents. Sea ice motion is not a free drift, and part of the kinetic energy input is dissipated in the sea ice interior. Sea ice deformation occurs under ridging (e.g., collision and accumulation of ice along a ridge) and rafting (e.g., sliding of ice floes above one another) in areas of convergence. Under mechanical deformation, sea ice can form a pile of up to 10–20 m. In areas of divergence, leads open within the sea ice pack.

As temperatures rise in the spring, sea ice undergoes top, bottom, and lateral melting. Similar to its central role during the growth season, snow plays a key role in modulating surface melt. If present, snow delays the ice melt onset due to its relatively high albedo. And when snow melts, ponds of liquid water—known as *melt ponds*—form at the surface of the ice, significantly lower the surface albedo, and deepen to reach the bottom of the ice eventually.

2.2 Sea Ice Observations

Satellite-based retrieval of sea ice concentration has been done on a regular basis since the early 1970s using passive microwave sensors. Brightness temperatures from Scanning Multichannel Microwave Radiometer (SMMR), Special Sensor Microwave Imagers (SSMI), and Special Sensor Microwave Imager/Sounder (SSMI/S) are used to estimate sea ice concentration using a variety of retrieval algorithms. For instance, the Bootstrap algorithm (Comiso, 1995) is used to determine sea ice concentration at a resolution of 25 km on a daily basis since 1987 (every other day since 1979), as well as to calculate various sea ice indices, such as the total sea ice extent provided by the National Snow and Ice Data Centre (NSIDC; Fetterer et al., 2002).

Direct or indirect measurements of sea ice thickness are more scarce. In the Arctic, sources of in situ data include measurements from in situ drillings and submarine and moored, upward-looking sonar and airborne electromagnetic freeboard measurements (e.g., Lindsay, 2010). The only comprehensive and long-term, in situ data set on ice thickness in the Southern Ocean is provided by the Antarctic Sea-ice Processes and Climate (ASPeCt) group (Worby et al., 2008), a compilation of visual, ship-based observations of ice thickness. More recently, spatial altimetry provides enhanced coverage of both poles (ICESAT, CryoSat-2).

Other parameters are monitored from space or buoy data, such as sea ice drift, deformation, snow, surface temperature, albedo, or melt pond fraction. Since the remainder of this chapter focuses on sea ice concentration and thickness, the interested reader is referred to more detailed studies (e.g., Leppäranta, 2011; Kwok, 2011; Heygster et al., 2012; Meier and Markus, 2015) for more information on how these other sea ice parameters are retrieved.

2.3 Sea Ice in Models and Reanalyses

Due to the relatively short observational records on sea ice concentration, and the scarcity of sea ice thickness observations, our knowledge of sea ice variability and predictability relies mostly on modeling studies. Most sea ice models now include all the dynamics and thermodynamics processes described thus far, as well as reasonable formulations for coupling with the atmosphere and the ocean (e.g., Notz and Bitz, 2017). State-of-the-art sea ice models include representations of subgrid-scale physics (Hunke et al., 2010). Historically, sea ice models have been developed in the context of climate modeling, and their formulations are based on assumptions that are believed not necessarily valid at fine space scales and timescales (i.e., a few kilometers and a few hours), which are usually of interest in operational short-term prediction. For example, sea ice is assumed to act as a continuous viscous-plastic medium (i.e., a viscous behavior under low-stress forcing and a plastic behavior under intense-stress forcing) in most sea ice models, an assumption that is not supported by careful examination of observations from drifting buoys (Rampal et al., 2008). Most of these models also lack a proper representation of wave-ice interactions.

In general, ocean-sea ice models forced by atmospheric reanalyses provide reasonable estimates of the position of the sea ice edge, especially in winter. This is largely due to the strong constraints imposed by prescribed atmospheric forcing; atmospheric reanalyses are produced with atmospheric models using prescribed sea ice concentrations as lower boundary conditions (e.g., Lindsay et al., 2014). However, even under the same atmospheric conditions, forced ocean-sea ice models differ significantly in their simulated ice-thickness distribution in the Arctic (e.g., Danabasoglu et al., 2014; Wang et al., 2016) and the Antarctic (Downes et al., 2015), due to a combination of factors.

Sea ice mean state and variability in fully coupled atmosphere-ocean-sea ice climate models differ considerably from one model to another, and there are substantial biases (e.g., Flato et al., 2013; Day et al., 2016). Model shortcomings in atmospheric and oceanic physics, as well as inaccurate formulation of atmosphere-sea ice-ocean couplings, contribute to biases in sea ice models (e.g., Notz and Bitz, 2017).

A good representation of sea ice in ocean reanalyses is key, especially for S2S prediction purposes. First, for poorly observed properties like sea ice thickness, reanalyses provide unique sources of information regarding long-term trends and variability. Second, reanalyses are widely used for predictions, such as boundary conditions for atmosphere-only or regional simulations and predictions, or as initial states of sub-seasonal and seasonal hindcasts (Guémas et al., 2016). Up to now, none of the current operational reanalyses assimilates sea ice thickness data directly, and most ocean-sea ice reanalyses have shown significant biases in the sea ice thickness fields, at least in the Arctic Ocean (Chevallier et al., 2017).

Among all the various reanalyses, the Panarctic Ice-Ocean Model Assimilation System (PIOMAS) is an ocean-sea ice reanalysis dedicated to the Arctic Ocean; it uses an ocean-sea ice model driven by atmospheric reanalyses, with assimilation of sea surface temperature and sea ice concentration. PIOMAS estimates of sea ice thickness and volume have been evaluated through comparisons with observations from U.S. Navy submarines, oceanographic moorings, and satellites (Schweiger et al., 2011). A few global ocean-sea ice reanalyses show similar performance in their Arctic sea ice simulations as PIOMAS, such as ORAP5 (Zuo et al., 2015), from the European Centre for Medium-range Weather Forecasts (ECMWF). Recent intercomparisons suggest that ORAP5 provides reasonable solutions for Arctic (Chevallier et al., 2017) and Antarctic sea ice. The PIOMAS and ORAP5 reanalyses will be used in the following discussion to assess sea ice volume variability.

3 SEA ICE DISTRIBUTION, SEASONALITY, AND VARIABILITY

In both hemispheres, sea ice cover has its maximal extension at the end of the winter and its minimal extension at the end of the summer. The amplitude of the seasonal cycle however, is different in each hemisphere.

The mean seasonal cycle of Arctic sea ice extent (i.e., the area covered with sea ice having a concentration higher than 15%) has an amplitude of about 9.2 million km^2, with a climatological maximum of 15.5 million km^2 and a minimum of 6.3 million km^2 over the reference period 1979–2015. The spatial distribution of sea ice concentration is primarily constrained by the presence of land. In winter, sea ice expands in the northern North Atlantic and Pacific oceans roughly to the mean position of the ocean thermal front, as reflected in Fig. 1. Ocean heat advection plays an important role in shaping the sea ice edge in the winter (Bitz et al., 2005), as evidenced in the east-west asymmetry in both the Atlantic and Pacific (e.g., approximately 45°N offshore North America versus northward 80°N in the Barents Sea). Sea ice motion is also responsible for the sea ice presence along the eastern coast of Greenland. Within the interior Arctic basin, the ice motion is constrained by coastlines. As a result, ice piles up to thicknesses well above 10 m (Thorndike, 1992). A large fraction of this ice can survive the melt season in the Arctic Ocean, this latter fraction being the basis of the ice cover that would grow over the next year. The spatial distribution of sea ice thickness in the Arctic Ocean, with the thickest ice located against the northern coast of Greenland and the Canadian Arctic archipelago, partially reflects large-scale atmospheric and oceanic circulation in the Arctic (e.g., Bourke and Garrett, 1987).

The seasonal cycle of sea ice extent in the Southern Ocean is larger than in the Arctic Ocean, which is due to both a larger maximum sea ice extent and a smaller minimum sea ice extent than in the Arctic. The position of the winter sea ice edge is mostly thermodynamically driven (Bitz et al., 2005). In the winter, the sea ice extent is limited by the westerly winds and the position of the Antarctic Circumpolar Current, which has surface temperatures above the freezing point and acts as a permanent heat source. In the summer, sea ice survives only in the Weddell and Ross seas. As a consequence, the Antarctic winter sea ice cover is mostly ice that forms during the same freezing season, with an average thickness below 2 m. Although mechanical deformation seems less possible there than in the Arctic Ocean, instances of sea ice thickness larger than 10 m can be found (Williams et al., 2015).

Interannual variability of sea ice extent and sea ice volume is different in the two hemispheres as well. In the Arctic Ocean, the variability of sea ice extent is much greater in the summer than in the winter. In the Southern Ocean, sea ice extent variability is greater during the transition seasons (spring and fall) and lower at the February minimum and September maximum. The summer Arctic sea ice extent variability is 2–3 times larger than the summer Antarctic sea ice extent variability. According to a reanalysis, the interannual variability of sea ice volume is larger in the Arctic than in the Antarctic at all months.

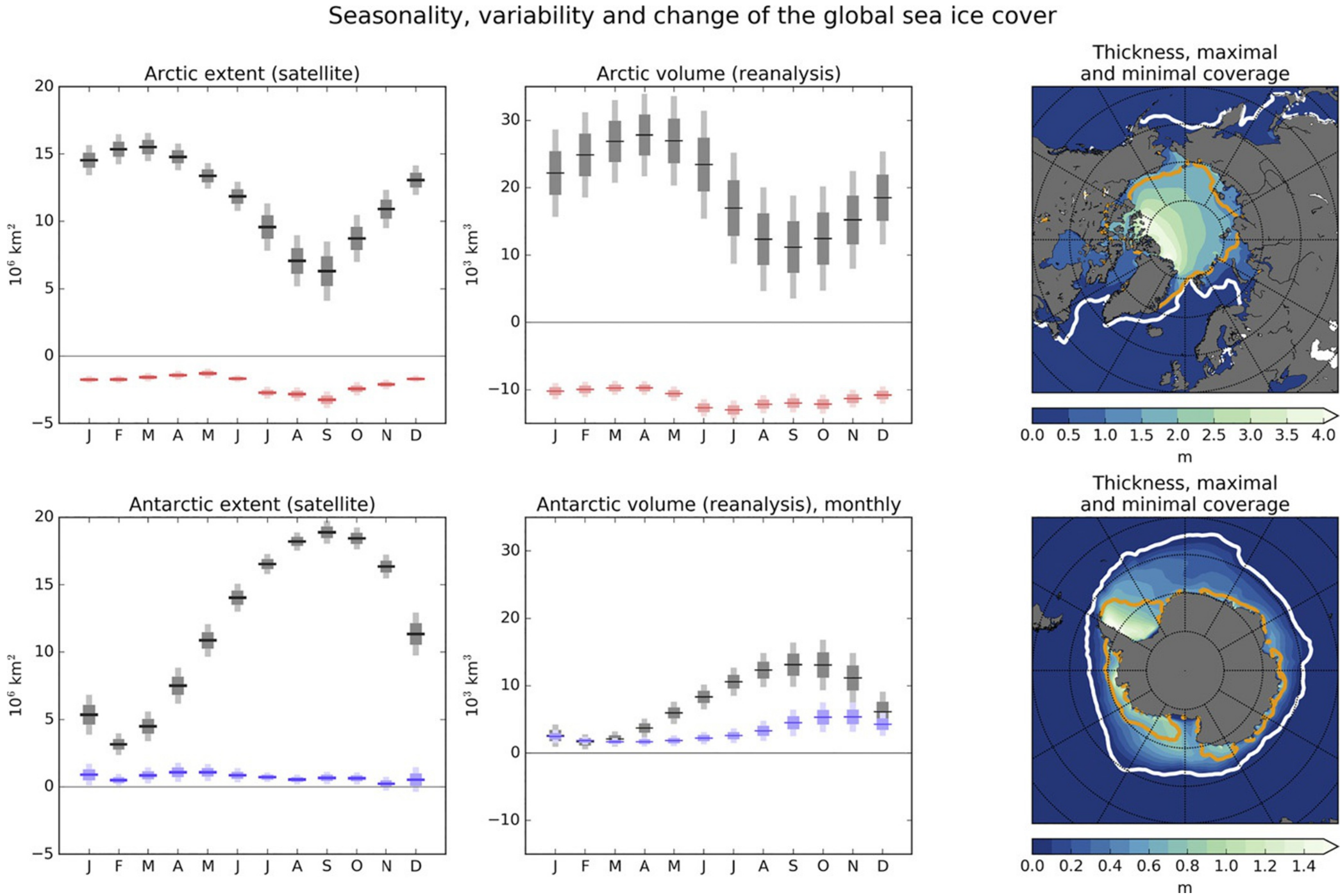

FIG. 1 Arctic (top) and Antarctic (bottom) sea ice mean state and variability. The left column displays annual cycles of 1979–2015 monthly sea ice extent (gray; data: NSIDC sea ice index) and changes in sea ice extent estimated from a quadratic fit over 1979–2015 (the *shadings* denote one and two standard deviations around the estimated quantities, respectively). The central column displays the same statistics for sea ice volume (from the PIOMAS reanalysis for the Arctic, 1979–2015, and the ORAP5 reanalysis for the Antarctic, 1979–2012). The right column displays the annual mean sea ice thickness from PIOMAS (1979–2015) and ORAP5 (1979–2012), together with the positions of the ice edge at the annual minimum and maximum (September and March in the Arctic, February and September for the Antarctic; data: NASA Bootstrap).

Over the recent decades, sea ice has undergone significant changes. Fig. 1 shows estimates of long-term trends over the last four decades (1979–2012 or 1979–2015) for the Arctic and Antarctic sea ice extent and volume in all months. The picture is remarkably different in each of the two hemispheres. There has been a strong and significant decrease (negative trend) in Arctic sea ice extent and volume in every month of the year. The negative trends reached their maximum in September for sea ice extent (Stroeve et al., 2012), and June–July for sea ice volume. The rate of thinning, however, seems more consistent year round. Kwok and Rothrock (2009) documented a 40% reduction of sea ice thickness in an interior Arctic basin based on submarine measurements and recent altimetry data.

Trends for total Antarctic sea ice extent are positive in all months, though they are small and not always significant; in addition, regional trends may differ substantially from each other (Holland, 2014). The origin of the positive trend in Antarctic sea ice extent is a topic of particular interest. Recent studies highlight regional discrepancies, as well as a possible role played by natural variability and feedback (e.g., Polvani and Smith, 2013; Goosse and Zunz, 2014). However, there is some evidence, based on early proxy, satellite, or whaling records, of an abrupt decline in sea ice extent between the 1930s and the beginning of the satellite era in the late 1970s (Curran et al., 2003; Edinburgh and Day, 2016; Gagné et al., 2015).

4 SOURCES OF SEA ICE PREDICTABILITY AT THE SUB-SEASONAL TO SEASONAL TIMESCALE

4.1 Persistence

The term *persistence* was originally introduced in meteorology to describe a series of several days with similar weather characteristics. The extension of that concept to climate scales and other components than the atmosphere has been natural since then. In this regard, the case of sea ice is of particular interest. Dynamically and thermodynamically forced by the relatively fast atmosphere (i.e., short persistence) and the relatively slow ocean (i.e., long persistence), a complex situation can be expected, especially because sea ice evolution also is governed by internal processes with their own characteristic timescales. This section reviews the typical timescales at which sea ice exhibits significant memory associated with persistence, as well as some physical processes that provide the source of this memory.

Persistence is loosely defined as the time necessary for a time series to decorrelate from itself. While seemingly simple in its formulation, this definition is more complicated in its implementation. First, *decorrelation* must be properly defined, and various approaches exist for doing so (e.g., Flato, 1995). Second, as shown in the previous section, contemporary sea ice signals are highly seasonal and bear the imprint of background climate change. The imprint of these two external drivers must be accounted for (and possibly removed) if the goal is to study the inherent persistence of the system itself, not the persistence offered by these external drivers. This implies the adequate estimation and removal of these forced contributions, which are far from trivial (Mudelsee, 2014). Third, there is evidence of nonstationarity in sea ice properties (e.g., Holland and Stroeve, 2011; Goosse et al., 2009), which makes the choice of the baseline period important to estimate autocorrelations. Similarly, memory properties are likely to be season dependent (Chevallier and Salas-Mélia, 2012; Day et al., 2014). Finally, most sea ice parameters are difficult to monitor accurately, further challenging the idea that robust estimates of persistence can be retrieved accurately from observationally based estimates only.

For all these reasons, it is not surprising that estimates of sea ice anomaly persistence vary from study to study. In the following discussion, we refer to persistence as *persistence of anomalies* with respect to the long-term linear trend. Arctic sea ice areal properties are found to exhibit persistence from 1 to 5 months, depending on the product, the methods, and the season in question (Walsh and Johnson, 1979; Lemke et al., 1980; Blanchard-Wrigglesworth et al., 2011a; Guémas et al., 2016). This range of 1–5 months tends to be generally overestimated by climate models (Day et al., 2014; Blanchard-Wrigglesworth et al., 2011a), possibly due to the lack of representation of important physical processes in these models. Estimates of sea ice volume persistence are more uncertain, owing to the lack of reliable observational thickness estimates. Early modeling studies by Flato (1995) and Bitz et al. (1996) estimated the total Arctic sea ice volume as persisting for up to 6–7 years, although more recent estimates point to values closer to 2–4 years (Bushuk et al., 2017; Blanchard-Wrigglesworth et al., 2011b; Day et al., 2014), possibly as a consequence of using more advanced and fully coupled models in those latter studies. Antarctic sea ice persistence has largely been disregarded in the literature.

Fig. 2 offers an updated estimation (following a consistent definition) of the persistence of various dynamic and thermodynamic sea ice parameters in the Arctic and the Antarctic. Three remarkable points must be noted. First, persistence ranges from synoptic (about 1 day) to annual and even interannual timescales. This gives full justification for considering sea ice as a key source of S2S predictability in the polar regions and even beyond (see Section 6). Second, Antarctic sea ice generally exhibits less persistence than Arctic sea ice. This is likely due to the difference in geographical configurations (see Section 3 and Fig. 1, earlier in this chapter). Antarctic sea ice variability has a strong regional component (e.g., Parkinson and Cavalieri, 2012) and hence is characterized by strong decouplings (e.g., Lemke et al., 1980) that reduce the persistence of the hemispheric quantities. Besides, Antarctic sea ice is on average much thinner than the Arctic and almost entirely seasonal (Fig. 1). In an Arctic study based on coupled climate models, Blanchard-Wrigglesworth and Bitz (2014) suggested that thinner ice is generally associated with shorter-lived anomalies. Finally, and as expected, persistence is shorter at the local than the global scale. Still, the persistence of sea ice concentration and thickness, on the order of weeks and seasons, respectively (see Fig. 2, but also Lukovich and Barber, 2007, and Blanchard-Wrigglesworth and Bitz, 2014), indicate the potential for climate information based solely on the intrinsic memory of the ice, provided that the initial state is estimated accurately.

Persistence of sea ice area depends on the season. Using monthly mean observational and model data of Arctic sea ice area, Blanchard-Wrigglesworth et al. (2011a) noticed that correlations were lower between successive months when the initial sea ice is most rapidly advancing or retreating. Fig. 3 presents these results differently for both polar oceans based on daily data. The longest persistence (between 5 and 60 days) is found when the correlation varies the least, which happens in the summer of both hemispheres, before the annual minimum. It coincides with a slowing of seasonal ice loss during the melt season. Shorter persistence can be found during the spring in both hemispheres, shortly after the annual maximum, and during the fall in the Arctic. During these seasons, anomalies of sea ice extent are anticorrelated with those 1–2 months later.

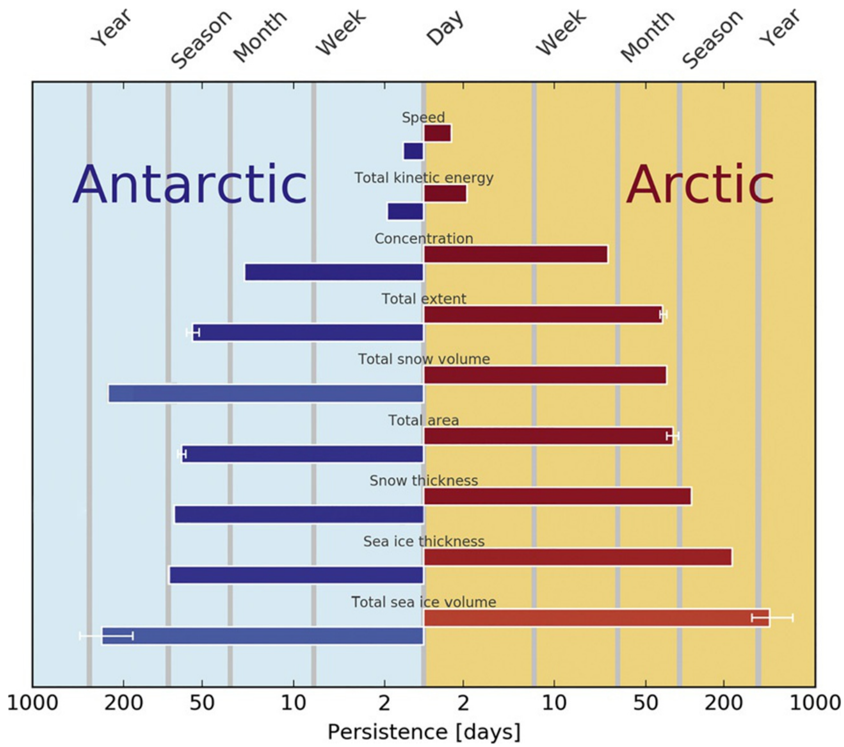

FIG. 2 Persistence of common sea ice parameters. From top to bottom: Sea ice speed at a point in the Beaufort Sea (P1: 81 N, 145°W) and at a point in the Ross Sea (P2: 74°S, 165°W); hemispheric average of kinetic energy per unit mass; concentration at points P1 and P2; hemispheric sea ice extent; hemispheric snow-on–sea ice volume; hemispheric sea ice area; snow-on–sea ice thickness at points P1 and P2; sea ice thickness at points P1 and P2; hemispheric sea ice volume. Persistence is primarily estimated from a 1979–2015 ocean-sea integration. When possible, other data sources are used (e.g., sea ice reanalyses and satellite-based retrievals), and whiskers are displayed to reflect the range between these sources. Persistence is estimated as the time necessary for the autocorrelation function of the daily mean, quadratically detrended time series to reach $1/e$.

4.2 Other Mechanisms

Several physical mechanisms can offer other sources of predictability besides persistence. These mechanisms can be split into two types: those related to the sea ice itself and those related to other agents (e.g., the atmosphere or the ocean). We provide a few examples in the following discussion.

The sea ice cover is far from uniform. At horizontal scales of about 10 m, sea ice thickness can vary substantially, by as much as a few meters (Thorndike et al., 1975). The way that sea ice thickness is distributed in a given area (e.g., a grid box typically employed in climate models) has a significant impact on the amount of energy, mass, and momentum exchanged with the atmosphere and the underlying ocean. This is because many fluxes depend nonlinearly on the ice thickness. Therefore, it has been hypothesized that the wintertime ice thickness distribution (ITD) could carry predictability over to the area during the next

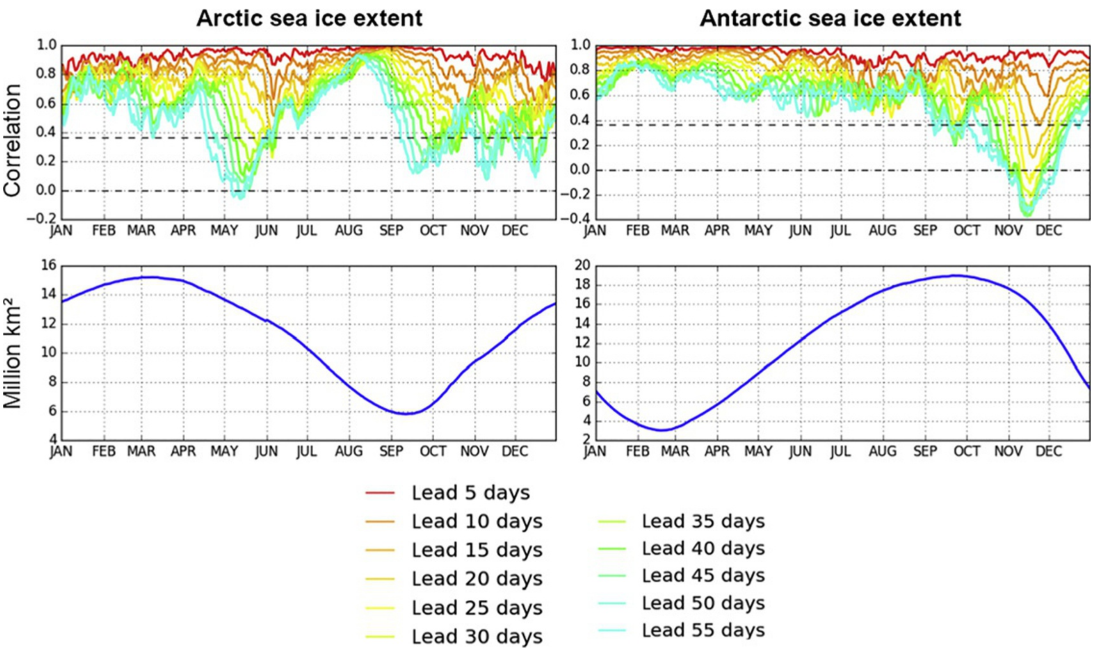

FIG. 3 Top row: lagged correlation for lead times from 5 to 60 days for sea ice area in the Arctic (left) and Antarctic (right) oceans. Bottom row: annual cycle of sea ice area. The dotted lines in the top row indicate 95% significance and null correlation. *Source: NSIDC Bootstrap sea ice concentration (daily data).*

summer because thicker ice has less propensity to melt away than thin ice. Blanchard-Wrigglesworth et al. (2011a) first identified a mechanism of summer-to-summer reemergence of Arctic sea ice area as follows: An anomaly of sea ice area in summer causes ice thickness to become anomalous in winter, which eventually causes a summer sea ice area anomaly; that is, sea ice partly "remembers" its summer area from year to year, even though the summer-to-winter link is nonsignificant (hence the term *reemergence*). Chevallier and Salas-Mélia (2012) explored this mechanism further and determined that the anomalous summer ice area is significantly determined by the area of ice thicker than 0.9–1.5 m up to 6 months earlier. The tight coupling between wintertime sea ice thickness and summertime sea ice area has been confirmed in other studies in various setups (Guémas et al., 2016; Day et al., 2014; Massonnet et al., 2015) and appears to be a robust feature. Owing to the lack of long-term and reliable sea ice thickness observational data, this proposed mechanism has not yet been assessed with observational data.

The low albedo of melt ponds in spring is thought to be a source of predictability for summer sea ice extent, although modeling and observational estimates differ in the range at which this process operates. Using melt pond fractions reconstructed with a stand-alone sea ice model, Schroeder et al. (2014) showed that the amount of melt ponds in May explained up to 64% of the variance of the September Arctic sea ice extent over the period 1979–2013. However, Liu et al. (2015) found no evidence of such predictive skill in May using satellite retrievals of melt ponds over the period 2000–2010. Nevertheless, greater predictability arises when the amount of melt ponds is integrated from May to late July, suggesting that the relationships may be robust for sub-seasonal prediction. The possible role of melt pond fraction as a precondition of summer melting can be explained by a positive feedback mechanism and a larger melt pond fraction, leading to more absorbed solar radiation and thus more melting.

Because sea ice is interacting with the atmosphere and the ocean, these two media may have an imprint on sea ice predictability. A number of studies suggest that the ocean is the main source of sea ice predictability on interannual and longer timescales (e.g., Guémas et al., 2016, for a comprehensive review). It also plays a role at S2S timescales. Woodgate et al. (2010), for example, emphasized the role played by anomalous warm water inflow through the Bering Strait in the summer of 2007 and showed that it accounted for one-third of sea ice melt in that year, leading to the then-record-breaking September sea ice minimum.

Sea ice drift results from the integration by sea ice of forcing from the atmosphere and the ocean. As shown in Fig. 2, the memory of sea ice speed is very low, which is consistent with the predominance of wind forcing, which has a very limited memory. However, sea ice advection has long been considered as a potential source of predictability at various timescales (e.g., Koenigk and Mikolajewicz, 2009). More recently, Holland et al. (2013) showed an eastward-propagating signal of potential predictability arising in the fall and continuing into the winter following the initial January, providing predictability beyond initial persistence. In the Arctic Ocean, advection during May–June acts as a key driver of September sea ice distribution through a redistribution of winter sea ice thickness anomalies (Kauker et al., 2009). It is thus likely that sea ice advection may play a role in S2S timescales at a regional scale, especially in the marginal ice zone.

Past studies have documented a modulation of the sea ice extent by the El Niño–Southern Oscillation (ENSO) in the Arctic (Liu et al., 2004), and possibly in both hemispheres (Gloersen, 1995). Guémas et al. (2016) showed the major role played by the atmosphere in the Arctic Ocean. The Arctic surface circulation is primarily wind-driven (Gudkovich, 1961). The North Atlantic Oscillation (NAO) is thought to drive a seesaw in sea ice conditions between the Labrador Sea and the Greenland and Barents seas, with sea ice area in the former positively correlated with the NAO index (e.g., Deser et al., 2000) and a maximum correlation at a lag of about 2 weeks in the sea ice response to NAO. In the Southern Ocean, the Antarctic Dipole, characterized by out-of-phase sea ice concentration anomalies between the South Atlantic and the South Pacific, persists 3–4 months after being triggered by ENSO (e.g., Yuan, 2004). Fluctuations in the polarity of the Southern Annular Mode (SAM) are also thought to affect sea ice area. Positive Southern Annular Mode induces an overall sea ice expansion (though with regional differences) of sea ice at the short timescale through enhanced northward surface Ekman drift (Hall and Visbeck, 2002; Lefebvre et al., 2004), but sustained positive Southern Annular Mode conditions eventually may lead to a decrease of sea ice area due to the upwelling of warm water from below the mixed layer (Ferreira et al., 2015; Holland et al., 2016).

Henderson et al. (2014) studied the response of winter and summer Arctic sea ice concentration to specific phases of the Madden-Julian Oscillation (MJO), which is the leading mode of atmospheric intraseasonal variability. Building on previous studies showing the modulation of high-latitude climate by the MJO (e.g., Cassou, 2008; Lin and Brunet, 2009), the authors show coherent regions of ice concentration variability in the Atlantic (phases 4 and 7), and in the Pacific sectors (phases 2 and 6) during January, and for the North Atlantic (phases 2 and 6) and Siberian sectors (phases 1 and 5) during July. These active regions are coherent with corresponding anomalies in surface wind. The authors argued that the MJO still could project onto the Arctic ice margins in the future, while specific phase relationships may change.

5 SEA ICE SUB-SEASONAL TO SEASONAL PREDICTABILITY AND PREDICTION SKILL IN MODELS

5.1 Potential Sea Ice Predictability

The term *predictability* is sometimes used loosely as a synonym for *predictive skill.* In the following section, we use it specifically to refer to the inherent or potential predictability of sea ice; that is, the theoretical limit for the predictive skill of a sea ice forecast system that would be achieved with a model that perfectly resembles reality and with close-to-perfect knowledge of the initial state of the atmosphere-sea ice-ocean system. For classical weather forecasts, this definition is somewhat vague, as the obtained predictability limits depend strongly on how exactly the initial state is known. The definition is better constrained when it comes to assessing the predictability of the ocean and sea ice (and the associated predictability of the second kind) on S2S and longer timescales. The increasingly uncorrelated atmospheric forcing is the main factor driving ice/ocean states apart. However, whether atmospheric states diverge within 5 or 10 days does not much affect the subsequent speed of ice/ocean state divergence on longer S2S timescales (e.g., Juricke et al., 2014); therefore, the obtained estimates of potential predictability should be more robust.

Obviously there will never be a model perfectly resembling reality, so estimates of potential predictability can be obtained only in the so-called perfect-model world, using a model itself as a surrogate reality. Boer (2000) termed this type of predictability “prognostic potential predictability” (in contrast to diagnostic approaches that estimate predictability based on the temporal characteristics of a time series, as described in Section 4). In this framework, one can conduct pseudoforecast experiments, where one just slightly perturbs the initial state and investigates how quickly different system trajectories diverge. Following numerous studies of this kind with individual models (Koenigk and Mikolajewicz, 2009; Blanchard-Wrigglesworth et al., 2011b; Holland et al., 2011; Tietsche et al., 2013; Day et al., 2014), recently a number of global climate modeling groups contributed to the Arctic Predictability and Prediction on Seasonal to Inter-annual Timescales (APPOSITE) project, following a common perfect-model-type experimental protocol. More specifically, initial conditions for the forecast ensembles were taken from a long control simulation under constant present-day forcing (greenhouse gas concentrations, etc.), with minute perturbations added to the SSTs (Tietsche et al., 2014; Day et al., 2016).

Studies following the perfect-model approach under constant conditions have the advantage that there are no uncertainties in observations or reanalyses because the model’s surrogate reality is perfectly known. Even more so, there are no secular trends that are hard to separate from long-term variability in the real world. While limitations accompanying this strongly idealized approach, such as neglecting model biases and unrealistic forcing, need to be kept in mind, these circumstances considerably facilitate the clean quantification of the potential predictability of a given system.

To quantify the predictability of sea ice also requires the specification of what characteristic of the sea ice precisely is to be assessed (see also Fig. 2). For Arctic sea ice, the most commonly addressed quantities are simple scalar quantities such as the pan-Arctic sea ice extent and volume (also compare Fig. 1). For such scalars, one meaningful way to quantify potential predictability is to compute a root-mean-squared error (RMSE) based on all possible pairs of ensemble members, and to derive a normalized root-mean-squared error (NRMSE) by dividing this error by a climatological error that is obtained when the procedure is repeated with pairs of sea ice states from different years (but from the same time of year). The NRMSE quantifies the degree to which ensemble members are more similar to each other than states randomly chosen from a long time series. To give an example, in the APPOSITE simulations, initialized July 1, the NRMSE in September ranges from about 0.3–0.6 for pan-Arctic sea ice extent, and from about 0.1–0.3 for volume. Here, a value of zero implies perfect predictability, whereas a value of 1 implies a complete loss of predictability (see Day et al., 2016, Fig. 5). Thus, the APPOSITE results imply that roughly half the interannual variations in September sea ice extent are potentially predictable from July 1, and even about 80% of the variations in sea ice volume, consistent with the longer memory associated with volume compared to extent as mentioned previously.

Potential predictability could be estimated locally (e.g., to sea ice concentration or thickness). For sea ice concentration, however, this is not very meaningful, as the climatological RMSE will be close to zero in most places, which is trivial because significant variability occurs only around the marginal ice zone. A reasonable alternative is to sum up all areas where a forecast disagrees with the observations on whether sea ice is present (e.g., using the typical 15% sea ice concentration threshold); such an approach, called the Integrated Ice Edge Error (IIEE), has been proposed by Goessling et al. (2016).

Fig. 4 illustrates the predictability of the Arctic sea ice cover at S2S timescales. The ice edges in the four forecast ensembles (Fig. 4A–D) exhibit a clear coherency even after 2.5 months when atmospheric states have diverged completely due to internal atmospheric variability. For example, at 150°E, all ice edges are far north of 80°N in the ensemble depicted in Fig. 4B, but all edges are south of 80°N in Fig. 4D, meaning that this information resided already in the difference in initial states on July 1. This qualitative assessment is confirmed by the quantitative estimates provided in Fig. 4E (where the gray dashed vertical line corresponds to the situation shown in Fig. 4A–D); measured by the IIEE, about 50% of the ice-edge variations in September can potentially be predicted from July 1.

While such perfect-model estimates give rise to optimism that sea ice can be predicted at S2S timescales with some useful skill, we cannot rule out that coupled climate models might systematically overestimate potential predictability compared to the real world. Indeed, there is some indication that sea ice may be less predictable in the real world (Day et al., 2014). The abovementioned limitations, however, make it difficult to diagnose the potential predictability in the real world. In summary, previous work on potential predictability provides room for optimism when it comes to predicting sea ice on S2S timescales.

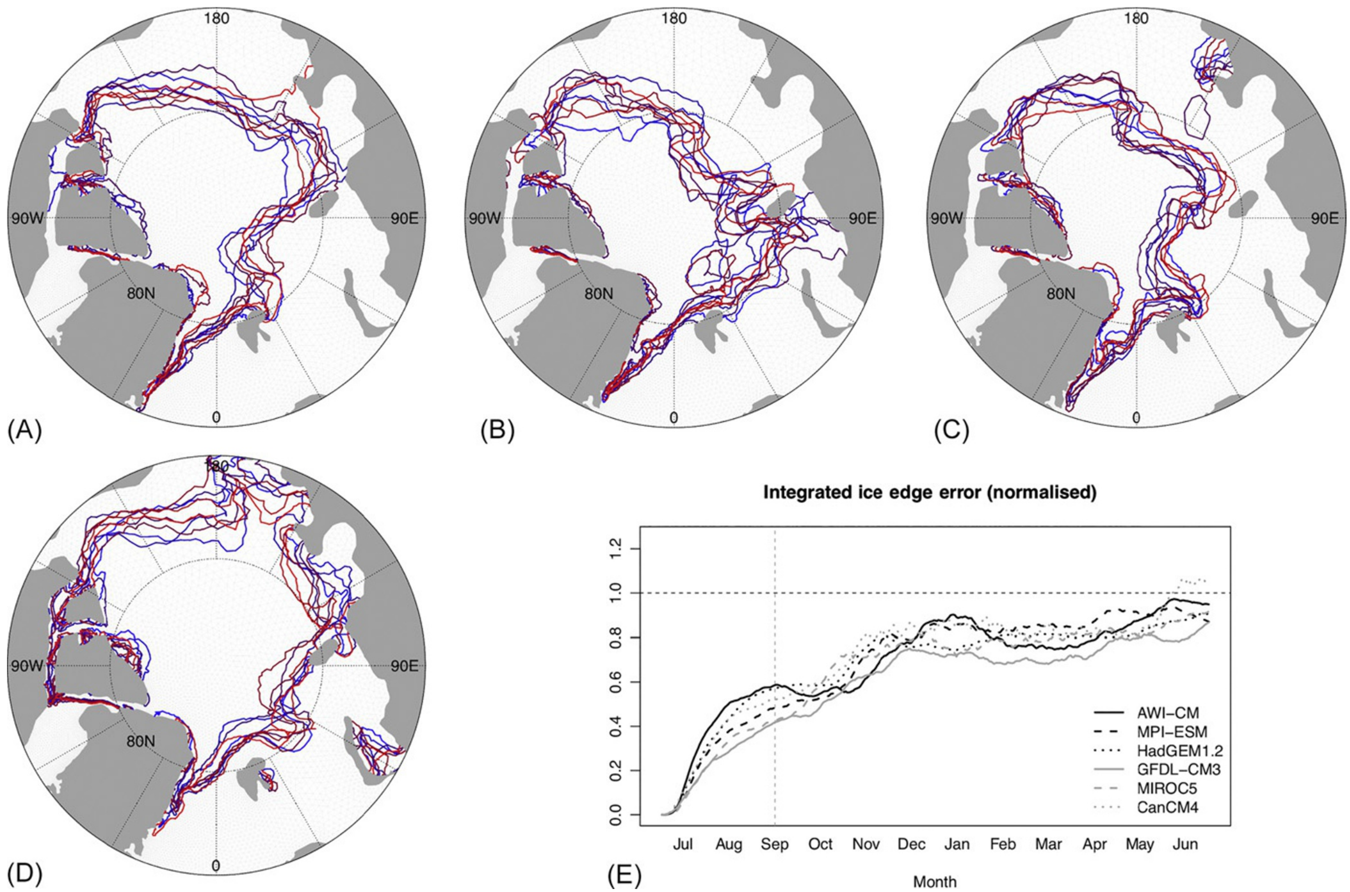

FIG. 4 Potential predictability of the Arctic sea ice edge in coupled climate models. (A)–(D) Ice edge locations (15% concentration contours) in 9-member idealized (perfect-model) forecast ensembles on September 14 in four different years from one of the models (AWI-CM). Ensemble members are shown in different colors. The ensembles were started 2.5 months earlier on July 1, with initial conditions taken from a long control simulation with minute perturbations added to the SSTs. (E) The IIEE, the total area of mismatch, averaged over all possible pairs of ensemble members and over a number of cases for six climate models following the same protocol. Errors are normalized by a climatological error, such that IIEE = 0 indicates perfect predictability and IIEE = 1 indicates the complete loss of predictability (for details, see Goessling et al., 2016).

5.2 Skill of Sea Ice Prediction Systems at Sub-seasonal Timescales

5.2.1 Short-Term Predictions

Sea ice models were originally developed as part of climate models. While climate models now all include a dynamic-thermodynamic sea ice model, most forecasting systems used for short- to medium-range predictions still use a persisted sea ice cover (Jung et al., 2016). Recently, ECMWF upgraded its operational forecasting system by incorporating a fully dynamic-thermodynamic sea ice model. Such a choice was motivated by the belief that accounting for sea ice in prediction matters, both for prediction skill itself and for users of forecast products.

Accounting for interactive sea ice cover, rather than persisting sea ice throughout the forecast, has been shown to improve predictions on short timescales (e.g., Jung et al., 2016, their Fig. 7). Sea ice predictions at lead times from a few days to 2 weeks are typically done using ocean-sea ice models forced with operational weather forecasts. This two-tier approach has some inconsistencies because operational atmospheric forecasts often used a persisting sea ice cover. Since Van Woert et al. (2004), the added value of model-based forecasts of sea ice concentration in the Arctic Ocean has been assessed relative to the persistence forecasts[1] in areas where sea ice concentration changed by >5% over the forecast. In the Polar Ice Prediction System, Van Woert et al. (2004) showed that the skill of 24-h forecasts of sea ice concentration is higher than that of persistence in all months except during the freeze-up period, when a combination of persistence and climatology offers a better estimate.

More recently, in the Canadian Global Ice-Ocean Prediction System (GIOPS; Smith et al., 2014), improved skill of sea ice concentration forecasts up to 7 days into the forecast compared to persistence were reported for the Arctic and Antarctic oceans. Errors present at such lead times arise from inconsistencies between GIOPS forecasts and atmospheric fields in areas where sea ice concentration evolves rapidly. Using pseudoforecasts in which the ice-ocean model is forced with a new forecast every day (instead of a single, 7-day-long forecast), Smith et al. (2014) showed that the error relative to persistence is even more reduced in both polar oceans. This suggests that more accurate atmosphere fluxes could provide better forecasts, which could be the case in fully coupled atmosphere-sea ice-ocean forecasting systems (e.g., Faucher et al., 2010).

5.2.2 Sub-seasonal to Seasonal Predictions

Sea ice forecasts aiming at timescales longer than a few days have classically used empirical models that tried to exploit statistical relations between the state of the sea ice at the target time and the state of the sea ice and other physical quantities at earlier times. For example, Barnett (1980) used the intensity of the Siberian High to predict ice conditions off Alaskian coasts in August. Walsh (1980) used similar methods to forecast the sea ice extent north of Alaska in all months based on sea level pressure, air temperature, and sea ice concentration. Along similar lines, Johnson et al. (1985) generalized the use of periodic regression coefficients to predict sea ice anomalies in various sectors of the Arctic and Antarctic oceans. These early empirical models suggested that using "internal" sea ice predictors such as sea ice concentration or lateral advection improve forecasts compared to persistence, whereas using

[1] This technique assumes that the information on an initial sea ice anomaly is maintained during the forecast.

"external" predictors such as sea level pressure, air temperature, and SST can even deteriorate forecasts. Overall, significant forecast skill up to 2 months in advance was reported.

Drobot and Maslanik (2002) found for the period 1979–2001 that 85% of the variance in Beaufort Sea summer ice extent is explained jointly by spring total ice concentration, winter multiyear ice concentration, the October East Atlantic Index, and the March North Atlantic Oscillation Index. In a follow-up study, Drobot et al. (2006) showed that February sea ice concentration, surface skin temperature, surface albedo, and downwelling longwave radiation jointly explain 46% of September Arctic sea ice extent variance over the 1984–2004 period. However, once again, most of the skill originates from the sea ice concentration—that is, through persistence—which is also the case for regional forecasts (Drobot, 2007). While the latter studies were based on observational data, Lindsay et al. (2008) followed a similar statistical approach to predict pan-Arctic sea ice extent based on a variety of atmospheric, oceanic, and sea ice predictors derived from atmosphere and ocean-sea ice reanalyses, finding that apparent skill for lead times of 3 months or more derives only from the long-term trend.

Similar statistical approaches have been used to predict sea ice in the Antarctic, such as by Chen and Yuan (2004), who conducted principal component analysis (PCA) with seven atmospheric and sea ice variables. Remarkably, significant skill for Antarctic winter sea ice conditions has been achieved up to 1 year in advance. This forecast skill seems to be due to linkages between the variability of the Bellingshausen/Weddell seas dipole and tropical modes of variability (Yuan and Martinson, 2001; Yuan, 2004; Holland et al., 2005).

Coming back to the Arctic, for which more studies exist but where there is also a much stronger long-term trend to cope with, Lindsay et al. (2008) and Holland and Stroeve (2011) highlighted the limitation of statistical approaches in the presence of nonstationarity. This is one motivation to move from statistical approaches toward dynamical forecasts for seasonal timescales. Another argument in favor of dynamical systems is that any statistical approach condenses the information contained in the initial state (and earlier states) to a reduced set of state variables. To provide a simple example, forecasts based solely on current (and past) sea ice anomalies neglect any information that other state variables, such as ocean temperature anomalies or modes of atmospheric circulation, may contain about the future sea ice evolution. Forecasts based on dynamical models that capture the physics of the climate system as comprehensively as possible largely overcome this limitation. Nevertheless, statistical methods are still useful benchmarks for forecast skill (e.g., Chevallier et al., 2013).

Dynamical forecasts of the sea ice extent include the use of (1) ocean-sea ice models forced by atmospheric reanalyses (e.g., Zhang et al., 2008); and (2) fully coupled atmosphere-ocean-sea ice models. Skill assessment of these techniques has been made in hindcast mode, which means a set of reforecasts over the past, typically from the 1990s to the 2010s, initialized with sea ice reanalyses (Peterson et al., 2015) or reconstruction (Chevallier et al., 2013). Recent studies have shown that the forecast skill varies significantly among systems. Guémas et al. (2016) showed that anomaly correlation for the reforecast of September sea ice area initialized in May can vary from 0.2 to 0.7. Forecast skill seems to depend on the initialization of sea ice thickness (Dirkson et al., 2017) or sea ice concentration (Bunzel et al., 2016; Msadek et al., 2014). Combining forecasts by several models seems to improve forecast skill (Merryfield et al., 2013).

A community effort that since 2008 has coordinated S2S predictions of the September Arctic sea ice extent, based on statistical as well as dynamical methods and allowing even heuristic estimates, is the SIO of the Sea Ice Prediction Network (SIPN). Stroeve et al. (2014) concluded for the SIO predictions, which are initialized at the beginning of the months of June, July, and August, that (1) the prediction error for the September sea ice extent is only slightly better than predictions based on linear trends, and (2) there is no indication yet of fully coupled models yielding better sea ice predictions compared to other methods. The apparent gap between real-world forecast skill and potential predictability estimates from perfect-model studies suggests that there is strong potential for improved sea ice predictions, although one cannot preclude that the reality might be less predictable. Blanchard-Wrigglesworth et al. (2015) also showed that the skill of forecasts submitted to SIO is lower than in the hindcasts, which suggest that summer sea ice extent could have been even less predictable in recent years compared to previous decades.

While the SIO will continue to provide interesting data to document and advance our ability to forecast sea ice, a new data set of high relevance in this context, rooted in the operational NWP community, is the S2S data set (Vitart et al., 2017). While some of the systems still prescribe the sea ice cover (e.g., by persisting the ice edge at the beginning and relaxing toward climatology after some time), seven of the contributing forecast systems include a dynamic sea ice component, recently including the abovementioned ECMWF system. A systematic assessment of the sea ice forecast skill of these systems will allow the approach to the sea ice prediction problem to be from a really seamless perspective.

6 IMPACT OF SEA ICE ON SUB-SEASONAL PREDICTABILITY

Skillful predictions of sea ice, discussed in previous sections of this chapter, are also potentially important for predicting the atmosphere and ocean, both in the polar regions and in midlatitudes. Over its lifetime, sea ice acts as a unique boundary condition for the atmosphere. From an atmospheric perspective, it is a highly variable surface, both in time and space (Persson and Vihma, 2017). Sea ice surface properties (e.g., albedo, temperature, and roughness) can change rapidly in time as a result of dynamic and thermodynamic processes. The presence of a mixture of sea ice (possibly snow-covered) and open waters has a strong impact on surface-air turbulent heat fluxes. As a consequence, near-surface temperatures may vary by 30 K (or even more) across relatively short distances depending on whether sea ice is present. For instance, in a large-eddy simulation model, Lüpkes et al. (2008) showed that a 1% variation in sea ice concentration resulting from opening leads could change the surface air temperature by 3.5 K in winter. The presence of sea ice also affects the stratification in the lower atmosphere: the atmospheric boundary layer over sea ice has a stable or near-neutral stratification over most of the year, while over open waters (leads, polynyas), localized convection takes place. Furthermore, sea ice can influence the stratification of the upper ocean through changes in salinity and heat, with implications for deep convection in the ocean. Therefore, there are strong reasons to believe that skillful forecasts of sea ice are a source of predictability for atmospheric and oceanic parameters on the timescales considered here.

The rapid decline of Arctic sea ice and its possible impact on Northern Hemisphere weather and climate have triggered a large number of scientific studies aimed at understanding the influence of sea ice on the atmosphere. Although most of these studies target the climate change problem, it can be argued that the lessons learned apply equally well to shorter S2S timescales, given the relatively fast atmospheric response to an external forcing (e.g., Semmler et al., 2016a,b).

6.1 Impacts in the Polar Regions

For the Arctic, there is consensus that reduced sea ice leads to a warming of the lower atmosphere due to increased heating from the ocean. This low-level warming goes along with a large-scale baroclinic atmospheric response, which is reflected by reduced sea level pressure and increased geopotential height at the 500-hPa level (e.g., Semmler et al., 2016a). It can be expected that a similar robust baroclinic response can be found in the Antarctic, should similar ice retreat occur.

Changes in sea ice also accompany oceanic changes, most notably the heat content of the upper ocean. A reduction of Arctic sea ice, for example, leads to lower turbulent heat fluxes out of the ocean in the vicinity of the ice edge, which results in positive SST anomalies. It has been argued that these anomalies south of the Arctic sea ice edge are instrumental in triggering an midlatitude response (Blackport and Kushner, 2017). Furthermore, it is plausible that thinner sea ice leads to larger momentum transport from the atmosphere into the ocean, thereby influencing the strength of the wind-driven ocean circulation in sea ice–covered regions (e.g., Roy et al., 2015).

6.2 Impacts Outside Polar Regions

The impact of sea ice anomalies on the atmosphere outside of the polar regions is much more controversial. In fact, numerous recent workshops have concluded that we are in a preconsensus state, not unlike with ENSO global impacts in the 1980s (Overland et al., 2015; Jung et al., 2015). The controversy arises from the fact that various modeling studies have found different atmospheric responses to similar imposed sea ice perturbations. Several possible explanations for these differences have been proposed, such as a weak atmospheric response, which leaves the results prone to sampling variability, and the importance of nonlinearity, which makes the results sensitive to small details in the imposed forcing and used numerical protocol (e.g., coupled versus atmosphere-only experiments).

It is accepted, however, that in principle, there are physical mechanisms through which sea ice *can* influence midlatitude weather. A good summary of these mechanisms is given by Barnes and Screen (2015). It turns out that the most robust midlatitude response to sea ice change is thermodynamic in nature, owing to advection of warmer (colder) air masses for low (high) sea ice years; this effect may even offset dynamical temperature changes associated with atmospheric circulation regimes (Screen, 2017). The atmospheric circulation response over the Northern Hemisphere is less certain, although there is some agreement among modeling studies, suggesting that low sea ice winters go along with a strengthened Siberian high pressure system (Deser et al., 2010), which may be explained by an external forcing of the atmosphere in the Barents Sea (Petoukhov and Semenov, 2010). For the wintertime NAO, observational studies suggest a strong link to sea ice anomalies in the Arctic (Cohen et al., 2014). This link involves the impact of SST anomalies in the Barents-Kara seas, snow anomalies in

Siberia, and stratosphere-troposphere interaction. Modeling studies strongly disagree on the degree (and even the sign) to which the NAO is influenced by Arctic sea ice anomalies. A similar situation is found for the Aleutian low-pressure system in the North Pacific.

A completely different approach to studying the impact of the Arctic on midlatitude weather and climate was employed by Jung et al. (2014). They carried out sub-seasonal prediction experiments with the ECMWF model (atmosphere-only) with and without relaxation of the Arctic troposphere toward ERA-Interim reanalysis data (see also Semmler et al., 2017). By studying linkages from a prediction perspective, Jung et al. (2014) identified two main pathways out of the Arctic—one over Eurasia and one over North America. A relatively small impact was found over the North Pacific and North Atlantic, where it was argued that midlatitude dynamics and tropical forcing are more important. They also highlighted the fact that midlatitude prediction skill may benefit only intermittently from Arctic processes due to the strongly flow-dependent nature of these linkages. Strong flow dependence calls for using ensemble prediction systems to exploit the potential of linkages between the Arctic and midlatitudes in operational S2S prediction.

A similar study, employing the relaxation approach for the Southern Hemisphere, has found a smaller impact of the Antarctic troposphere on midlatitude weather; and it was argued that this has to do with the fact that planetary waves in the Southern Hemisphere are weaker than those in the Northern Hemisphere (Semmler et al., 2016c).

7 CONCLUDING REMARKS

This chapter has reviewed various aspects of sea ice, following mainly two directions: (1) the sources and mechanisms of sea ice S2S predictability and (2) the role played by sea ice on atmospheric S2S predictability.

The key concepts to remember about sea ice predictability may be summarized as follows:

(1) Sea ice is part of a *coupled* system. Sea ice physics is driven by forcing from the atmosphere and the ocean. Thus, sea ice predictability is influenced (enhanced or damped) by the two media. Additionally, from a prediction perspective, sea ice exemplifies the added value of using coupled models even for short timescales, showing the importance of coupled processes right from day 1.

(2) Sea ice is present in *both* polar regions. However, different geographical configurations, climates, and physical processes (at the large and small scales) lead to differences in mean state, seasonality, and variability (see Fig. 1). As a result, predictability mechanisms differ in both polar oceans. Noteworthy, research on seasonal sea ice predictability in the Southern Ocean is far less advanced than in the Arctic.

(3) Sea ice has *memory* at the S2S timescale. In observations and models, persistence is identified as the primarily source of predictability for sea ice area properties at the S2S timescale (see Fig. 2). This is a promising result that provides hope for skillful predictions based on the knowledge of sea ice concentration, but also physical grounds on an impact of sea ice on atmospheric predictability in the polar regions. Other sea ice properties have memory at longer (sea ice thickness) and shorter (sea ice speed) timescales, and reemergence mechanisms provide further predictability at longer timescales.

(4) Sea ice has a strong *seasonal* component. As a result, persistence properties are season dependent (see Fig. 3). Sea ice extent anomalies observed in the summer have longer memory than in the spring and fall. This, along with the intrinsic coupled nature of sea ice, argues for the use of fully coupled models for S2S predictions.

(5) Like other components of polar climate, sea ice exhibits *transiency*. In the relatively short observational records, it is difficult to disentangle actual predictability from the signal due to the negative or positive trends. Model studies can partially help, for instance in providing information on unobserved variables, in examining predictability under stable forcing (e.g., preindustrial conditions) or in extrapolating the climate system behavior under future conditions.

This chapter is an invitation to explore the world of sea ice predictability further. We would like to stress the value of coordination in advancing knowledge on sea ice predictability and improving sea ice predictions in the Arctic and Antarctic. Such coordination has been successful for the Arctic, as exemplified by the momentum gained by SIO since 2008. There is a strong demand for a similar initiative in the Southern Ocean. As already mentioned, a systematic assessment of the hindcasts and forecasts available from the S2S database would allow significant progress in many areas, with a seamless perspective. We also encourage further investigations using the Year Of Polar Prediction (YOPP) data portal (Jung et al., 2016; https://yopp.met.no/), which will host coordinated model experiments designed to explore sea ice predictability and polar to lower-latitude connections in weather and climate, run during the YOPP core phase (2017–19) and consolidation phase (2019–22).

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