CHAPTER

9

The role of sea ice in subseasonal to seasonal predictability

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1 Introduction

The polar regions, the Arctic and the Antarctic, are the scene of several 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 several 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 the ocean. Its high albedo has a direct impact on the Earth's energy balance. Sea ice growth and melt 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

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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 (Jung et al., 2016; Bromwich et al., 2020).

The scientific community has eagerly responded to the need for sea ice predictions, focusing mainly on seasonal to decadal timescales (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 Prediction Network's (SIPN) 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. Research on seasonal sea ice prediction in the Southern Ocean is less advanced, although progress has been made since 2016 with an Antarctic counterpart of the SIO by the SIPN-South initiative (Massonnet et al., 2023).

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 (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 intrinsic 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 subseasonal 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 (SIC)—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 subseasonal 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 through gravity drainage and brine expulsion. 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 (Bitz and Roe, 2004). Sea ice can reach up to 2–3 m only through thermodynamical growth (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 (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 (the other reason being that the bottom ocean-to-ice flux is usually larger in the Antarctic than in the Arctic). 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 SIC has been done on a regular basis since the early 1970s using passive microwave sensors. Brightness temperatures from scanning multichannel microwave radiometer, special sensor microwave imagers (SSMI), and special sensor microwave imager/sounder (SSMI/S) are used to estimate SIC using a variety of retrieval algorithms. For instance, the Bootstrap algorithm (Comiso, 1995) is used to determine SIC at a resolution of 25 km on a daily basis since 1987 (every other day between 1979 and 1987), as well as to calculate various sea ice indices, such as the total sea ice extent (SIE) provided by the National Snow and Ice Data Centre (Fetterer et al., 2002).

Observations of Arctic sea ice thickness with high accuracy but limited spatial and temporal coverage are available from drillings, ice mass balance buoys, from the draft of the sea ice as detected from stationary or submarine-borne upward-looking sonars, and from airborne electromagnetic detection of the sea ice interfaces. Several efforts have been undertaken to compile these different types of observational data into comprehensive and long-term databases (Lindsay and Schweiger, 2015). For the Southern Ocean the only comprehensive and long-term in situ data set on ice thickness in the Antarctic is provided by the Antarctic Sea-Ice Processes and Climate group (Worby et al., 2008), a compilation of visual, ship-based observations of ice thickness.

Satellite-based observations of Arctic sea ice thickness with dense spatial and temporal coverage are available from around 2010 from two sources: L-band passive microwave radiometry for ice thinner than about 1 m (e.g., SMOS and SMAP satellites) and radar altimetry for thick ice (CryoSat 2, Sentinel-3). Observational products are available that combine data from the two different approaches, exploiting their complementary characteristics (Ricker et al., 2017). Research is ongoing into overcoming several limitations of the current sea ice thickness observational records: an extension of the record to cover the Southern Ocean and to go back to 2002 by merging the CryoSat 2 data with data from the Envisat RA-2 altimeter has been proposed using machine-learning techniques to allow sea ice thickness observations from radar altimetry during the summer months, which is not possible with the currently mature data sets; Bocquet et al. (2023) propose a reconstruction of sea ice freeboard back to 1995.

Other parameters are monitored from space or buoy data, such as sea ice drift, deformation, snow, surface temperature, albedo, or melt pond area fraction. Since the remainder of this chapter focuses on SIC and thickness, the interested reader is referred to more detailed studies (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

Most sea ice models now include all the dynamic and thermodynamic processes described thus far, as well as reasonable formulations for coupling with the atmosphere and the ocean (Notz and Bitz, 2017). State-of-the-art sea ice models include representations of subgrid-scale physics (Hunke et al., 2010; Blockley et al., 2020). 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 always supported by careful examination of observations from drifting buoys (Rampal et al., 2008). However, continuum-based models cannot be readily invalidated using observation-based metrics (Blockley et al., 2020), and to date, it is not straightforward to link model performance to a specific rheological framework (Bouchat et al., 2022). 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 SICs as lower boundary conditions (Lindsay et al., 2014). However, even under the same atmospheric conditions, forced ocean–sea ice models differ significantly in their simulated ice-thickness distribution (ITD) in the Arctic (Danabasoglu et al., 2014; Wang et al., 2016; Chassignet et al., 2020; Lin et al., 2021) and the Antarctic (Downes et al., 2015; Lin et al., 2021), 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 (Flato et al., 2013; Day et al., 2016; Notz et al., 2020; Roach et al., 2020). 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 (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 subseasonal and seasonal hindcasts (Guémas et al., 2016). Until the 2020s, SIC (i.e., the fraction of a given area that is covered by ice) was the main variable assimilated, and substantial spread existed in the various reanalyses (Uotila et al., 2019; Shi et al., 2021) as well as in the simulated budget terms (Nie et al., 2022). A growing number of operational reanalyses now assimilate sea ice thickness in addition to SIC (Balan-Sarojini et al., 2021).

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, differs between the two hemispheres.

The mean seasonal cycle of Arctic SIE (i.e., the area covered with sea ice having a concentration higher than 15%) has an amplitude of about 9.3 million km^2, with a climatological maximum of 15.2 million km^2 and a minimum of 5.9 million km^2 over the reference period 1979–2023. The spatial distribution of SIC 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. 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 vs 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 circulations in the Arctic (Bourke and Garrett, 1987).

The seasonal cycle of SIE in the Southern Ocean is larger than in the Arctic Ocean, which is the consequence of both a larger maximum SIE and a smaller minimum SIE than in the Arctic. The position of the winter sea ice edge is mostly thermodynamically driven (Bitz et al., 2005). In the winter the SIE 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 common 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 SIE and sea ice volume is different in the two hemispheres as well. In the Arctic Ocean the variability of SIE is much greater in the summer than in the winter. In the Southern Ocean, SIE variability is greater during the transition seasons (spring and fall) and lower at the February minimum and September maximum. The summer Arctic SIE variability is 2–3 times larger than the summer Antarctic SIE variability. According to a reanalysis the interannual variability of sea ice volume is larger in the Arctic than in the Antarctic in all months (Fig. 9.1).

Over the recent decades, sea ice has undergone significant changes. Fig. 9.1 shows estimates of long-term trends over the last four decades (1979–2023) for the Arctic and Antarctic SIE 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 SIE and volume in every month of the year. The negative trends reached their peak in September–October for SIE, and in June–July for sea ice volume. The rate of thinning, however, seems more consistent year-round. Based on altimeter mission data and in situ submarines and moorings data, Lindsay and Schweiger (2015) documented a 65% decrease in ice thickness in the central Arctic between 1975 and 2012, dropping from 3.59 to 1.25 m.

Trends for total Antarctic SIE are, for most months of the year, not significantly different from zero. These close-to-zero trends mask pronounced subdecadal variability: during the period 1979–2014, Antarctic SIE showed a net positive gain that was offset since 2015–16 by a significant decrease in all seasons (Parkinson, 2019). This sudden decrease since 2015–16 is suggestive of a regime shift in Antarctic sea ice (Purich and Doddridge, 2023; Hobbs et al., 2024), although more evidence is needed to qualify this reversal of trends as a state change. According to early proxy, satellite, or whaling records, such a large variability in decadal or multidecadal trends and such rapid changes are not unusual, since other instances have likely happened before the satellite era (Curran et al., 2003; Edinburgh and Day, 2016; Gagné et al., 2015; Fogt et al., 2022).

4 Sources of sea ice predictability at the subseasonal 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

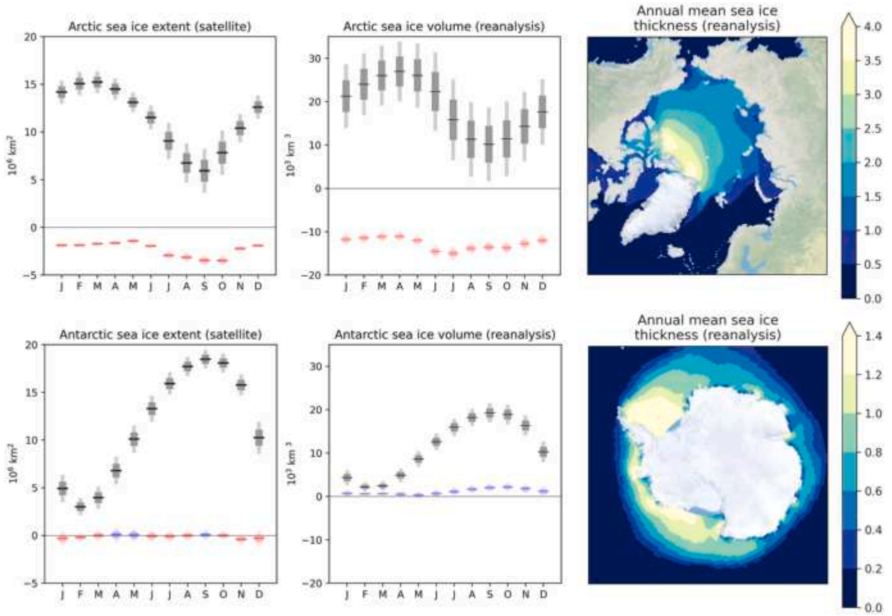

FIG. 9.1

Arctic (top) and Antarctic (bottom) sea ice mean state and variability. The left column displays annual cycles of 1979–2023 monthly sea ice extent (gray; data: National Snow and Ice Data Centre sea ice index) and changes in sea ice extent estimated from a quadratic fit over 1979–2023 (the shadings denote one and two standard deviations around the estimated quantities, respectively; the red colors indicate negative trends, while the blue colors indicate positive trends). The central column displays the same statistics for sea ice volume (from the Pan-Arctic Ice Ocean Modeling and Assimilation System (PIOMAS) reanalysis for the Arctic, 1979–2023, and the **Global Ice-Ocean Modeling and Assimilation System** (GIOMAS) reanalysis for the Antarctic, 1979–2023). The right column displays the annual mean sea ice thickness from PIOMAS (1979–2023) and GIOMAS (1979–2023).

thermodynamically forced by the relatively fast atmosphere (i.e., with a short persistence) and the relatively slow ocean (i.e., with a long persistence), a complex situation can be expected, especially because sea ice evolution is also 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 (typically, when the autocorrelation drops below 1/e). 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 (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 and mean-state dependence in sea ice properties (Holland and Stroeve, 2011; Goosse et al., 2009; Massonnet et al., 2018), 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 persistence vary from study to study. In the following discussion, we refer to "persistence" as the persistence of anomalies with respect to the long-term linear trend. Arctic sea ice area 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. 9.2 offers an 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. 9.1, earlier in this chapter). Antarctic sea ice variability has a strong regional component (Parkinson and Cavalieri, 2012) and hence is characterized by strong decouplings (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. 9.1). In an Arctic study based on coupled climate models, Blanchard-Wrigglesworth and

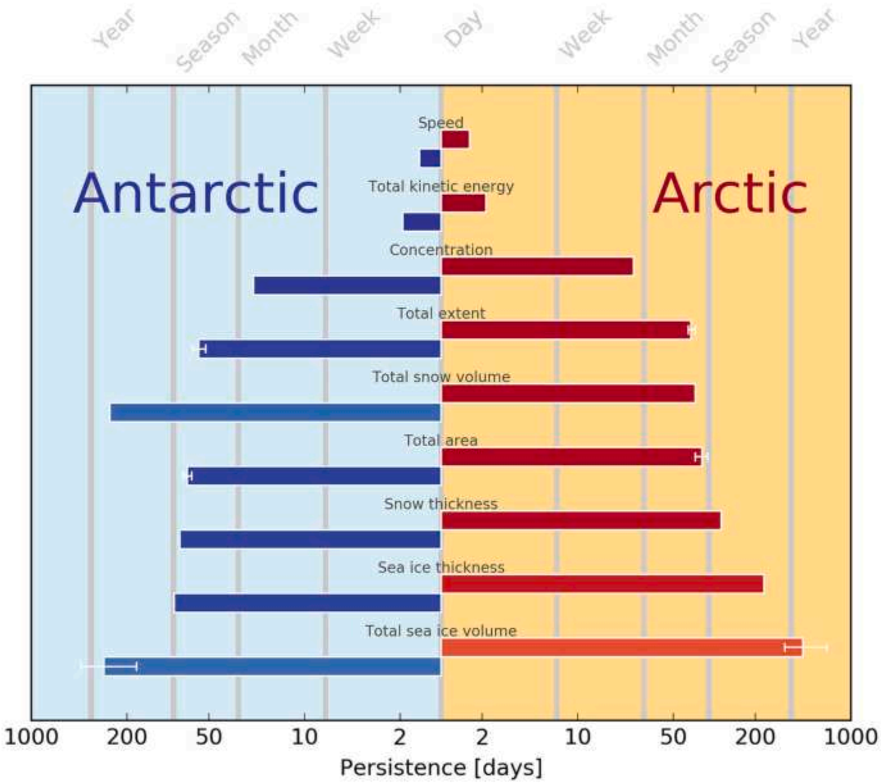

FIG. 9.2

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.

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 SIC and thickness, on the order of weeks and seasons, respectively (see Fig. 9.2; Lukovich and Barber, 2007; and Blanchard-Wrigglesworth and Bitz, 2014), indicates the potential for climate information based solely on the intrinsic memory of the ice, provided that the initial state is estimated accurately.

The 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. 9.3 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 SIE are anticorrelated with those 1–2 months later.

There is evidence that persistence is also state dependent. For example, the persistence of sea ice thickness anomalies is dependent on the thickness of the sea ice, as a result of the negative feedback between ice thickness and ice growth rate (Bitz and Roe, 2004; Massonnet et al., 2018), and as a result climate change may change thickness error growth (Holland et al., 2019). There is also evidence that sea ice persistence properties in the Southern Ocean changed after the recent dramatic shift in the ocean state (Purich and Doddridge, 2023; Hobbs et al., 2024).

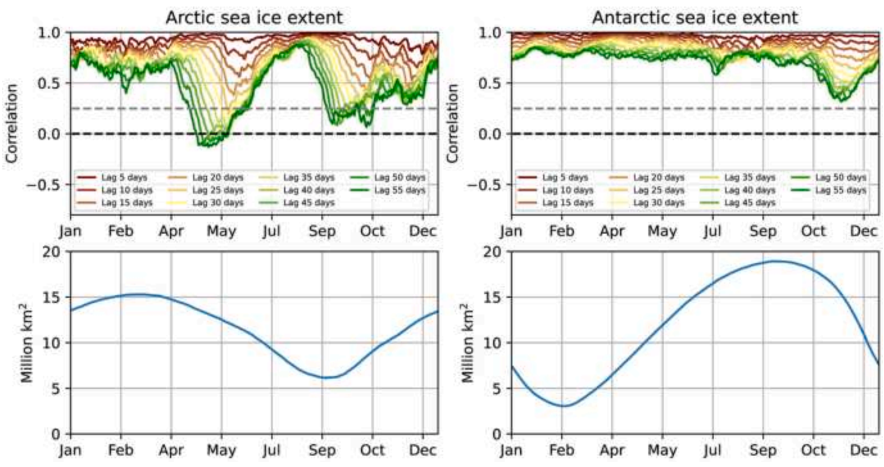

FIG. 9.3

Top row: lagged correlation for lead times from 5 to 60 days of linearly detrended sea ice extent anomalies (1979–2024) in the Arctic (left) and Antarctic (right) regions. Bottom row: annual cycle of sea ice extent over 1979–2024. The dotted lines in the top row indicate 95% significance and null correlation.

OSI-SAF sea ice index (daily, data from https://osi-saf.eumetsat.int/products/osi-420).

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 ITD could carry predictability over to the area during the next 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; Zhang et al., 2023) and appears to be a robust feature. Due to thinner sea ice conditions in the Antarctic, it has been suggested that this mechanism plays less of a role there (Holland et al., 2013; Ordoñez et al., 2018; Marchi et al., 2019). 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, but possibilities offered by recent progress in satellite altimetry (see Section 2.2) may well unlock this possibility in the near future.

The low albedo of melt ponds in spring is thought to be a source of predictability for summer SIE, 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 SIE 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 2000–10. 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 subseasonal 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 (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. At seasonal timescale, Sea Surface Temperature (SST) is a critical predictor in linear statistical models for Arctic sea ice predictions (Yuan et al., 2016; Wang et al., 2022). It is also likely that interactions with the ocean play a larger role in the Antarctic, where sea ice is thinner, and the impact of ocean heat content anomalies on the position of the sea ice edge plays an important role (Marchi et al., 2019; Libera et al., 2022).

Sea ice drift results from the integration by sea ice of forcing from the atmosphere and the ocean. As shown in Fig. 9.2 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 a potential source of predictability at various timescales (Koenigk and Mikolajewicz, 2009). 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 SIE 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 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 (Deser et al., 2000) and a maximum correlation at a lag of about 2 weeks in the sea ice response to the NAO. In the Southern Ocean the Antarctic Dipole, characterized by out-of-phase SIC anomalies between the South Atlantic and the South Pacific, persists 3–4 months after being triggered by ENSO (Yuan, 2004). This tropical forcing provides additional seasonal (Chen and Yuan, 2004) and subseasonal (Wang et al., 2023) predictability for sea ice. Fluctuations in the polarity of the Southern Annular Mode (SAM) (Fogt and Marshall, 2020) are also thought to affect sea ice areas. Positive SAM induces an overall sea ice expansion (though with regional differences) at the short timescale through enhanced northward surface Ekman drift (Hall and Visbeck, 2002; Lefebvre et al., 2004), but sustained positive SAM 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). Such an effect, along with the phase change in the Interdecadal Pacific Oscillation, is believed to have contributed to the abrupt decline of the Antarctic SIE in 2015–16, ending its 3-decade increasing trend (Meehl et al., 2019).

The interplay between remote and regional forcings often results in either constructive or destructive influences on sea ice. When ENSO and SAM are out of phase (e.g., positive SAM with La Niña or negative SAM with El Niño), they provide a constructive influence on sea ice and vice versa (Stammerjohn et al., 2008). Moreover, SAM and the wavenumber-3 pattern (another extratropical mode in the Southern Ocean) are circumpolar phenomena. However, they exert a more pronounced impact on sea ice in the West Antarctic, where ENSO's influence predominantly exists (Yuan and Li, 2008), indicating an amplified effect from remote and regional climate variability interactions.

Henderson et al. (2014) studied the response of winter and summer Arctic SIC to specific phases of the Madden-Julian Oscillation (MJO), which is the leading mode of atmospheric intraseasonal variability (see Chapter 4). Building on previous studies showing the modulation of high-latitude climate by the MJO (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. Similar relationships were examined for the Southern Hemisphere (Yoo et al., 2012; Flatau and Kim, 2013; Lee and Seo, 2019).

5 Sea ice subseasonal 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 (Juricke et al., 2014); therefore the obtained estimates of potential predictability are robust.

Estimates of potential predictability can be obtained in the so-called perfect-model framework, using a model itself as a surrogate reality. Boer (2000) termed this type of predictability "prognostic potential predictability" (in contrast to diagnostic approaches that explore the temporal characteristics of time series, as in Section 4). In this framework, initial states are just slightly perturbed, and the subsequent divergence of ensemble members is analyzed. Simplifications such as stationary forcing and the neglection of model biases need to be kept in mind, but at the same time, they considerably facilitate the quantification of the potential predictability of a given system. 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), several global climate modeling groups contributed to the Arctic Predictability and Prediction on Seasonal to Interannual Timescales (APPOSITE) project, following a common experimental protocol (Tietsche et al., 2014; Day et al., 2016).

Quantifying the predictability of sea ice also requires the specification of what characteristic of the sea ice precisely is to be assessed (see also Fig. 9.2). For Arctic sea ice the most commonly addressed quantities are simple scalar quantities such as the pan-Arctic SIE and volume (also compare Fig. 9.1). 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 to 0.6 for pan-Arctic SIE, and from about 0.1 to 0.3 for volume. Here, a value of zero implies perfect predictability, whereas a value of 1 implies a complete loss of predictability (Day et al., 2016, Fig. 9.5). Thus the APPOSITE results imply that roughly half the interannual variations in September SIE 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 SIC or thickness). For SIC, 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% SIC threshold). Such an approach is underlying the integrated ice-edge error (IIEE) (Goessling et al., 2016) and, generalized to probabilistic forecasts, the spatial probability score (Goessling and Jung, 2018), which have become standard metrics to assess sea ice forecast skill.

Fig. 9.4 illustrates the potential predictability of the Arctic sea ice cover at S2S timescales. The ice edges in the four forecast ensembles (Fig. 9.4A–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. 9.4B, but all edges are south of 80°N in Fig. 9.4D, 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. 9.4E (where the gray dashed vertical line corresponds to the situation shown in Fig. 9.4A–D); measured by the IIEE, about 50% of the ice-edge variations in September can potentially be predicted from July 1.

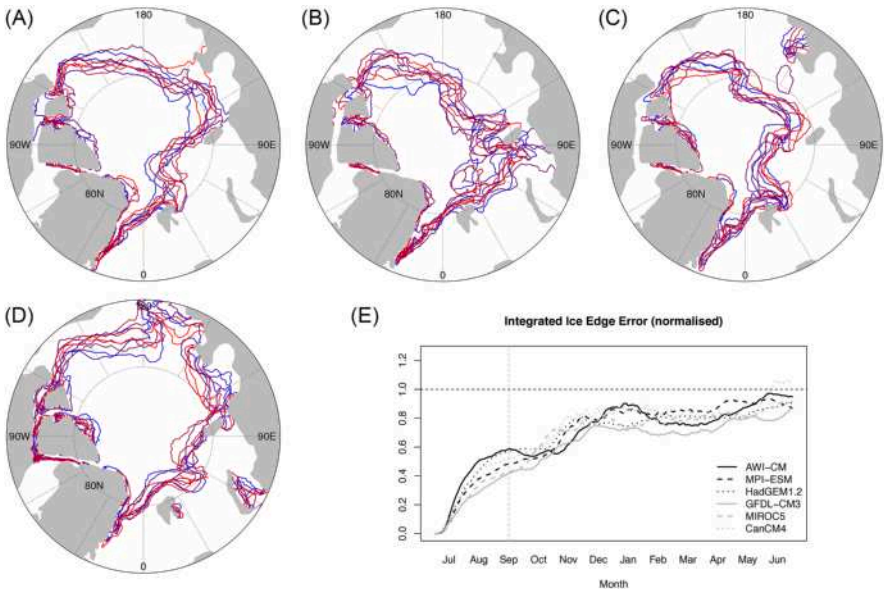

FIG. 9.4

Potential predictability of the Arctic sea ice edge in coupled climate models. (A)–(D) Ice-edge locations (15% concentration contours) in nine-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 integrated ice-edge error (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]). Map lines delineate study areas and do not necessarily depict accepted national boundaries.

APPOSITE data has also been used to assess the potential predictability of sea ice drift, suggesting that there is only little predictability of drift beyond the limited predictability of near-surface winds (Reifenberg and Goessling, 2022). While 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; Blanchard-Wrigglesworth and Bushuk, 2019). The earlier mentioned limitations, however, make it difficult to diagnose the potential predictability in the real world. In summary, earlier work on potential predictability demonstrated considerable potential for skillful sea ice prediction on S2S timescales, which has already materialized to some degree over the recent years (see later).

5.2 Skill of sea ice prediction systems at subseasonal timescales

5.2.1 Short-term predictions

Sea ice models were originally developed as part of climate models. While climate models have included a dynamic-thermodynamic sea ice model for many years, forecasting systems for short- to medium-range predictions have long relied on a persisted sea ice cover (Jung et al., 2016). ECMWF, ECCC, and the UK Met Office upgraded their operational forecasting systems by incorporating full dynamic-thermodynamic sea ice models (Smith et al., 2018; Vellinga et al., 2020; Keeley and Mogensen, 2018). This 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 (Jung et al., 2016, their Fig. 7), with the benefit over persistence being particularly large during periods of rapid ice advance or retreat (Day et al., 2022).

Despite recent advances in coupled NWP, sea ice predictions at lead times from a few days to 2 weeks are still typically done using ocean–sea ice models forced with operational weather forecasts. This two-tier approach has some inconsistencies because operational atmospheric forecasts often use a persisting sea ice cover. Nevertheless, already two decades ago, Van Woert et al. (2004) demonstrated the added value of model-based forecasts of SIC in the Arctic Ocean relative to persistence forecasts in areas where SIC changed by $>5\%$ over the forecast. They showed that the skill of 24-hour SIC forecasts from the polar ice prediction system 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.

In the meantime, improved skill of Arctic and Antarctic SIC forecasts up to 7 days into the forecast compared to persistence was reported for the Canadian Global Ice-ocean Prediction System (GIOPS) (Smith et al., 2014), with similar efforts ongoing that are driven partly by National Ice Services (Carrieres et al., 2017) and Marine Services (Bertino and Xie, 2020). Some of the errors present in GIOPS arise from inconsistencies between forecasts and atmospheric fields in areas where SIC evolves rapidly, suggesting that fully coupled atmosphere–sea ice–ocean forecasting systems are required for more accurate forecasts. The transition to fully coupled systems at NWP (see earlier) and other centers (Barton et al., 2021) thus has the potential for significant progress.

5.2.2 Subseasonal to seasonal predictions

The first sea ice forecasts aiming at timescales longer than a few days have classically relied on 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, early studies by Barnett (1980) and Walsh (1980) used atmospheric variables and SIC to sea ice in the Alaska region. 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 SIC or lateral advection improved forecasts compared to persistence, whereas using “external” predictors such as sea level pressure, air temperature, and SST could 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 the 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 NAO Index. In follow-up studies, Drobot et al. (2006) showed that February SIC, surface skin temperature, surface albedo, and downwelling longwave radiation jointly explain 46% of September Arctic SIE variance over the 1984–2004 period. However, once again, most of the skill originated from the SIC—that is, through persistence. Lindsay et al. (2008) followed a similar statistical approach to predict pan-Arctic SIE based on a variety of atmospheric, oceanic, and sea ice predictors, finding that apparent skill for lead times of 3 months or more derives only from the long-term trend. On the contrary, more recent statistical models, such as principal component analysis (PCA) based linear Markov models, can achieve considerable skills at the 6–9-month leads for the summer and fall predictions in the East Siberian, Chukchi, and Beaufort Seas. These models deliver reasonable skills at a 3-month lead even after linear trends are removed (Yuan et al., 2016; Wang et al., 2022).

Similar statistical approaches have been used to predict sea ice in the Antarctic, such as by Chen and Yuan (2004), who conducted 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 has been also a much stronger long-term trend to cope with since at least the 2000s, Lindsay et al. (2008) and Holland and Stroeve (2011) highlighted the limitation of statistical approaches in the presence of nonstationarity.

The nonstationarity of predictor–predictand statistical relationships has been one of the main reasons for the push of process-based dynamical alternatives to statistical approaches. Dynamical forecasts of the SIE include the use of (1) ocean–sea ice models forced by atmospheric reanalyses (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 onward, initialized with sea ice reanalyses (Peterson et al., 2015) or reconstruction (Chevallier et al., 2013). Guémas et al. (2016) showed that anomaly correlation for reforecasts 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 SIC (Bunzel et al., 2016; Msadek et al., 2014). Combining forecasts by several models seems to improve forecast skill (Merryfield et al., 2013). A more recent study based on 17 dynamical and 17 statistical models generally confirmed these results but also documented considerable progress (Bushuk et al., 2024), finding that dynamical models tend to outperform statistical methods for regional and local predictions. By contrast, for the Antarctic, it was found in the SIPN-South set of real-time forecasts that the dynamical models perform worse than the statistical models at the regional scale (Massonnet et al., 2023); in the Southern Hemisphere, promising results were reported from machine-learning approaches as demonstrated for the Antarctic Weddell Sea (Wang et al., 2023). This study suggests that more advanced AI modeling has the potential to achieve significant skill at the skill gap of the subseasonal timescale.

A community effort that, since 2008, has coordinated S2S predictions of the September Arctic SIE, based on statistical as well as dynamical methods and allowing even heuristic estimates, is the SIO of the SIPN. Stroeve et al. (2014) concluded for the SIO predictions, which are initialized at the beginning of the months of June, July, August, and September that (1) the prediction error for the September SIE 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 the reality might be less predictable (Blanchard-Wrigglesworth and Bushuk, 2019). Blanchard-Wrigglesworth et al. (2015) and Bushuk et al. (2024) also showed that the skill of forecasts submitted to the SIO is considerably lower than in the hindcasts reported in individual studies, although improvements have been documented recently (Blanchard-Wrigglesworth et al., 2023).

While the SIO will continue to provide interesting data to document and advance our ability to forecast sea ice, a more recent data set of high relevance in this context, rooted in the operational NWP community, is the S2S data set (Vitart et al., 2017). While initially some of the systems prescribed the sea ice cover (e.g., by persisting the ice edge at the beginning and relaxing toward climatology after some time), dynamic sea ice components are now standard. Systematic assessments of the sea ice forecast skill of these systems have shown promising potential for both the Arctic (Zampieri et al., 2018) and the Antarctic (Zampieri et al., 2019). Forecasts still suffer from initial-state errors as well as biases and thus drift at longer lead times, so that an observation-based benchmark method utilizing spatial damped anomaly persistence is difficult to beat (Fig. 9.5; Niraula and Goessling, 2021). However, with appropriate calibration, the ECMWF and ECCC systems have been shown to clearly outperform similar benchmarks at a broad range of lead times (Dirkson et al., 2022).

6 Impact of sea ice on atmospheric 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

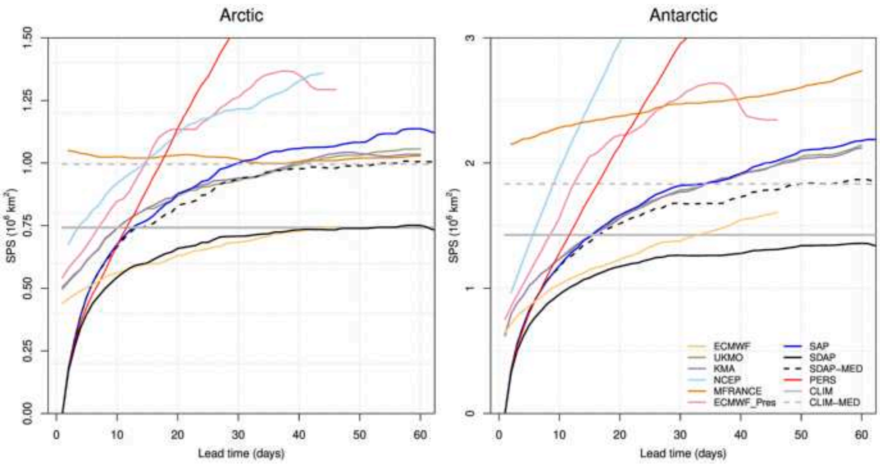

FIG. 9.5

Sea ice edge forecast error (spatial probability score) of uncalibrated forecasts from the subseasonal to seasonal data set, alongside some statistical benchmarks (*CLIM*, climatology; *PERS*, initial-state persistence; *SDAP*, spatial damped anomaly persistence), averaged across all seasons and years between 1999 and 2010.

Reproduced from Niraula, B., Goessling, H.F., 2021. Spatial damped anomaly persistence of the sea ice edge as a benchmark for dynamical forecast systems. J. Geophys. Research: Ocean. 126e2021JC017784, https://doi.org/10.1029/2021JC017784.

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 because 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. Consequently, 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 SIC 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 (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 (Semmler et al., 2016a). However, Woollings et al. (2023) argue that the potential to trigger a Rossby wave response from local heating is lower than in midlatitudes. 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 enhanced turbulent heat fluxes out of the ocean in the vicinity of the ice edge, which results in negative SST anomalies (Deser et al., 2010; Day et al., 2022). It has been argued that these anomalies south of the Arctic sea ice edge are instrumental in triggering a midlatitude response (Barton et al., 2021; Blackport et al., 2019). 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 (Roy et al., 2015).

6.2 Impacts outside the polar regions

The impact of sea ice anomalies on the atmosphere outside of the polar regions is much more controversial. 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, the importance of nonlinearity, which makes the results sensitive to small details in the imposed forcing and used numerical protocol (e.g., coupled vs atmosphere-only experiments), and the fact that climate models largely underestimate the fraction of predictable variability at the seasonal timescale (Weisheimer et al., 2024).

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) and in Cohen et al. (2020). 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). However, Blackport and Screen (2019, 2020) argue that the influence of the sea ice is small and that anomalies of the Siberian high precede sea ice anomalies in the Barents Sea.

For the wintertime NAO, observational studies suggest a strong link to sea ice anomalies in the Arctic (Cohen et al., 2014), although no trend in winter extremes was detected at midlatitudes despite Arctic sea ice loss and Arctic Amplification (Cohen et al., 2023). 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 subseasonal prediction experiments with the ECMWF model (atmosphere-only) with and without relaxation of the Arctic troposphere toward ERA-Interim reanalysis data (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, 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. 9.1). 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, although research on Antarctic sea ice is gaining momentum.
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. 9.2). This is a promising result that provides hope for skillful predictions based on the knowledge of SIC, 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. 9.3). SIE 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 transience. 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 the SIO, the S2S, and the SIPN-South projects. A few success stories of S2S sea ice prediction can be pointed out, powered in part by the success of the Year of Polar Prediction (Jung et al., 2016): Sir Ernest Shackleton's endurance wreckage was located on March 5, 2022, by an expedition that was partly supported by the real-time prediction of Antarctic sea ice drift thanks to the SIDFEx project. Likewise, operations during the MOSAiC expedition (Shupe and Rex, 2022; Nicolaus et al., 2022) were informed by drift forecasts generated within SIDFEx. The Copernicus Climate Change Service (Buontempo et al., 2020) routinely publishes sea ice forecasts from several centers.

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