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Coupled ice-ocean modeling and predictions

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ABSTRACT

We review the coupled ice-ocean modeling activities aimed at predictions, both in the near term (days to a week) and in the long term (seasonal to decadal) of the polar oceans. First the state of the knowledge of potential predictability is exposed, then an overview is given of the tools available for carrying out such predictions: the observations that can be used to initialize actual predictions, the coupled ice-ocean–modeling, including the fully-coupled Earth System Models for long-term predictions, and data-assimilation techniques. Finally, the performance of existing prediction systems is reviewed, showing that, although more predictive capability remains than what is presently achieved, both the near- and long-term forecasts show skill over trivial predictors. Parallel efforts should therefore be invested into acquiring more observations of the ocean and sea ice, developing new models both in standalone and coupled mode, and improving the data-assimilation techniques.

Keywords: Polar predictability, polar prediction, ice-ocean modeling, coupled data assimilation

1. Introduction

Polar regions have changed dramatically over the historical record. In the Arctic, this includes sea-ice loss in all seasons with the largest reductions occurring in September (Figure 1). Although this ice loss is large and significant, with a September linear trend of greater than 10% per decade, year-to-year variability is also considerable. Arctic sea-ice loss is consistent with other large-scale changes in the region, including a general warming, decreased terrestrial snow cover (Derksen and Brown 2012), and thawing permafrost (e.g., Romanovsky, Smith, and Christiansen 2010). In the Antarctic, an increase in sea ice has been observed, but this masks large and partially compensating trends in different regions (Figure 2). Changing ocean conditions have also occurred with a warming of the subsurface Southern Ocean since the 1950s (Gille 2008). Some of these changing Antarctic ice and ocean conditions appear related to a poleward shift and increasing strength of the westerly winds that have been driven largely by reductions in stratospheric ozone (e.g. Arblaster and Meehl 2006; Stammerjohn et al. 2008).

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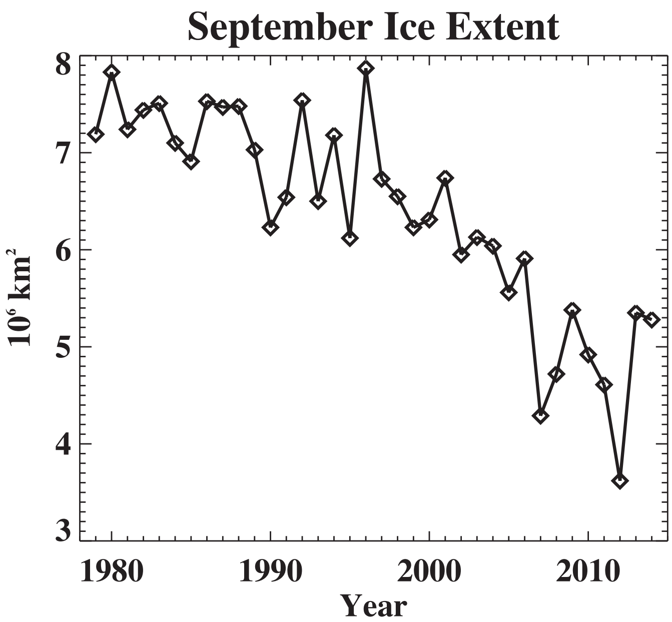

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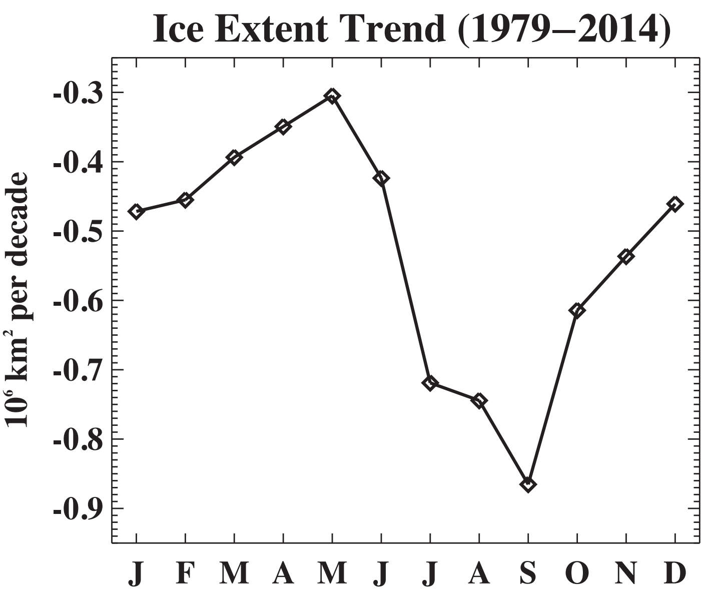

Figure 1. Observed Northern Hemisphere sea-ice conditions including (a) the timeseries of September ice extent in millions of square kilometers and (b) monthly ice-extent trends from 1979 to 2014. Analysis uses data from the sea ice index (Fetterer et al. 2002, updated).

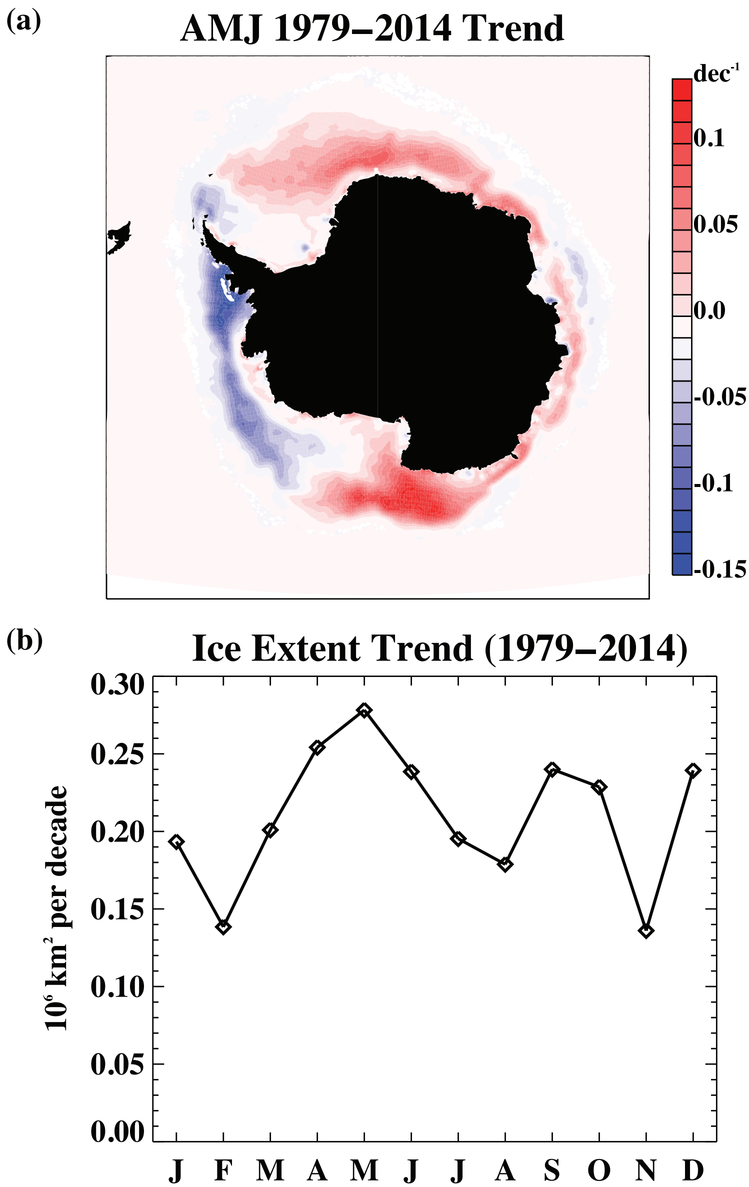

Figure 2. Observed Southern Hemisphere sea ice conditions including (a) April–June averaged ice concentration trends from 1979 to 2014 in ice concentration change per decade and (b) monthly ice extent trends from 1979 to 2014. Analysis uses data from Cavalieri et al. (1996, updated) and Fetterer et al. (2002, updated).

The changing polar climate conditions have provided a new impetus for reliable predictions in these regions on timescales of days to decades. With increasing Arctic marine access, many stakeholders are in increasing need of coupled ice-ocean predictions to support, for example, shipping operations, resource extraction, and wildlife-management concerns. Different stakeholder interests imply a need for forecasts on different temporal and spatial scales. For example, offshore operations require near-term (less than a week) and local predictions of ice and ocean conditions for operators working in the region but also require longer-term (seasonal to decadal) information to inform future shipping routes and new port infrastructure needs.

Coupled ice-ocean and ice-ocean-atmosphere models are being used to forecast polar conditions. These models underwent intense numerical developments in the early 1990s and became more widely used in the 20 following years. Initially aimed at the Arctic sea ice, they have been applied to the Southern Ocean but with less success (Massonnet et al. 2013; Barth et al. 2015). The sea ice–areal coverage has been monitored on a daily basis on both Poles since 1978. The first fully multivariate assimilation of sea ice concentration data into a coupled ice-ocean model has been demonstrated by Lisæter, Rosanova, and Evensen (2003) and then ported to a real-time, short-term forecasting system TOPAZ (Towards Operational Predictions of the North Atlantic Ocean and the Coastal Zone) the same year. Similar initialization methods are now being implemented in seasonal-to-decadal climate forecast systems (Guemas et al. 2014). End of the story? Well, unfortunately no. First because the operational community has only just begun to use current model predictive skills, which may not be suited to all operational purposes, second because the ice concentrations only give a “top view” of the sea ice but no information about its thickness, nor its movements, leaving high uncertainties in the total sea-ice volume and fluxes of momentum, heat, and moisture across it. Additionally, over the course of the last decade, the Arctic Ocean has already become quite a different place and the properties of the sea ice have already changed dramatically, making the Arctic ice to some extent more similar to the seasonal and thinner Antarctic sea ice. Because data assimilation is not meant to correct model biases, the predictions it produces suffer from these biases in complex ways.

Here we will address polar ice-ocean predictions from days out to decades. We will consider two aspects of prediction: first, the potential predictability that can indicate what and why we may hope to be able to predict (section 3), and, second, the actual prediction skill of forecasting systems providing forecasts to the public (section 7). As discussed further, potential predictability is generally assessed from theoretical studies, and insights into mechanisms giving rise to predictability are informed by observational analysis. Realizing this predictability in a forecasting system is then dependent on the skills of a given data-assimilation system, merging a set of incomplete observations and a single dynamical model, all of them suffering from various imperfections. In order to make the link from potential predictability to actual prediction skill, we will discuss relevant aspects of the observations (section 4), models (section 5), and data assimilation systems (section 6).

We will show that some aspects of numerical ice-ocean predictions are undergoing rapid changes. The models and satellite detection algorithms developed a few decades ago need to be refreshed, which will again have profound implications on data-assimilative sea-ice prediction systems. The implications for our understanding of long-term prediction will also be discussed.

2. The purposes of ice-ocean predictions

The Arctic is getting hotter, in all ways, with temperatures rising at approximately twice the rate of the global average (Overland et al. 2016). The natural resources of the Arctic are becoming available for exploitation and transport for the first time in our history. This includes about 13% of the world's oil and gas resources as estimated by the U.S. Geological Survey (2008), gold and other metals, and 5.5% of the freshwater resources stored on Greenland (UNEP [United Nations Environment Programme]). Changing environmental conditions are modifying ecosystems in diverse ways. In the Barents Sea, the cod are thriving in part because of warming conditions (Kjesbu et al. 2014). This migration behavior of boreal generalist fishes is also observed in the Bering Sea (Mueter and Litzow 2008). These changes have implications for fisheries management and more generally for the Arctic ecosystem.

The Northern Sea Route (NSR) along the Russian coast of the Arctic, which was heavily used by the Soviet Union until the 1990's, could again become an attractive alternative to reach East Asia from Western Europe. The route is indeed shorter than the one crossing Suez Passage (17,000 km instead of 22,000 km for a Rotterdam–Shanghai voyage) and would save fuel, although not time, so it would be considered a reasonable alternative only for bulk shipping including transport of oil and fertilizers. In case of accidents, the goods would pose serious threats for the Arctic environment. So, the coastguards and navies of the Arctic nations must be prepared to assist vessels, perform search and rescue operations, and remediate oil spills in ice-infested waters. A ship captain navigating the NSR needs to know the location of large leads (larger than 100 m), and will tend to use the lead at the exterior of landfast ice, which is immobile along the coast. Because communications are poor in high latitudes, a ship may not be able to obtain updated information and may use information that is already three days old (typically an interpreted synthetic aperture radar [SAR] image). Because of delays in obtaining real-time information, the decision on routing an ice-going vessel can be made onshore and communicated to the ship captain, who will adjust the course depending on observations from the deck.

The oil and gas exploration in the Arctic has been declining in the recent years but may take off again depending on oil-price variations and changing environmental regulations. An offshore platform cannot adjust its position and will need forecasts of sea-ice conditions at its precise location. In case of serious threats, for example, the approach of a large drifting iceberg or ice ridge, the platform may need to be disconnected and reconnected later when the risk is gone, incurring operational risks and astronomical costs. The oil industry would therefore need sea-ice forecasting both on local scales, to simulate individual ice floes on the theater of their operations, and on large scales to predict the time of the freeze-up and break-up of the ice. It is also expected that the oil and gas exploration and production activities will be more active in relatively mild ice conditions than in severe ice conditions, which means that forecasts of the marginal ice zone (MIZ) will have higher value than the ice pack. Because the MIZ is under the influence of surface waves from the open ocean, it requires particular forecasts of, for example, the ice-floe projections under the influence of waves.

Both the shipping and oil industry also have need for information on climate timescales. Strategic choices for a harbor, a shipping fleet, and the exploitation of an oil field incur the planning of infrastructure of a lifetime of 40 years, so those industries need to gather information about future climate change and the related uncertainties. Wildlife-management decisions are also increasingly taking into account information on predicted changes in polar conditions and their potential implications for wildlife in the region. For example, the decision to list polar bears as a threatened species under the U.S. Endangered Species Act used information on future sea ice loss, and its implications for polar bear habitat, as predicted by coupled climate models (e.g., Durner et al. 2009).

With reduced commercial activities in the region, there are fewer stakeholder interests in the Southern Ocean. However, ice-ocean predictions can provide information for tourism or scientific operations in the region, including access to Antarctic research stations and support for scientific research vessels. The complex rescue of a joint tourist-research vessel stuck within the Antarctic sea ice in December 2013 (Luck-Baker 2014), requiring assistance from two icebreakers and a helicopter, highlights the need for reliable predictions even in the most remote regions. On longer timescales, changing sea ice conditions have implications for ice-dependent wildlife in the region, such as emperor penguins (e.g., Jenouvrier et al. 2012), which raises associated wildlife management concerns.

Although the shipping industry is primarily concerned with ice concentration and ice thickness (and marginally snow depths, because deep snow can also impede the progression of an icebreaker), search and rescue operations and forecasting in ice-infested waters in the aftermath of oil spills are both dependent on ice motion and their diffusive properties that increase the search radius with time. The question of spatial and temporal resolution is especially critical for the latter case because of the strong scale-dependence of sea-ice deformation rates (Rampal et al. 2008). In addition, the diffusion is higher in the chaotic MIZ than in the ice pack. The oil industry would ultimately need a detailed forecast of the position of each ice floe surrounding their operations for the day-to-day management of their activities, which can be only delivered by discrete-element models (Herman 2015, Rabatel, Labbé, and Weiss 2015). How to nest discrete element models into the continuum sea-ice models considered in this chapter remains an open question.

3. Potential predictability in the polar oceans

Predictability in the earth system arises from 1) knowledge of the initial state of the system (initial value predictability) and 2) changes in external forcing (for example, greenhouse gas concentrations, solar input at the top of the atmosphere, or volcanic emissions). Lorenz (1975) referred to these as predictability of the first and second kinds, respectively. There are inherent limits of initial-value predictability due to the chaotic nature of the system. This limits the timescale of skillful forecasts. Predictability arising from changing forcing requires a sufficiently large forced signal to be predictable above the inherent variability (or noise) within the system. The timescales at which these predictability mechanisms are active differ for the various earth-system components. For example, the atmosphere has an inherent initial-value predictability on the order of weeks, whereas the ocean has longer initial-value timescales because of its higher heat capacity, which results in enhanced "memory". Sea-ice deformations also follow specific multifractal scaling laws, which exhibit intermittency and localization (Weiss and Marsan 2004), and their predictability is thus relatively limited across all spatial and temporal scales. Because of the need for an adequate signal-to-noise ratio, changes in external forcing, for example, those associated with rising greenhouse gases, typically provide predictive skill on longer timescales of decades to centuries. Here we discuss potential predictability of the sea ice system and the mechanisms that give rise to this predictability.

a. Near-term predictability

Manned ice camps noticed early on that the ice drift direction could change within the same day, either following a change of the wind direction or when readjusting after deformation events. They also found that a crack could open overnight right under their camp, rushing a move of all the equipment. The essence of intermittency is that large deformations occur suddenly, after long quiet periods, in similar ways to earthquakes (Weiss and Marsan 2004). These deformations are strongly dependent on both spatial and temporal scales, so that the resulting motions are more predictable in daily average than as instantaneous values, and an average on a model grid cell of 10 km on a side is likewise more predictable than a small individual ice floe. For short-term predictions (from hours to a week), the focus of the user is generally more on predictions of local conditions—those relevant to a ship, an ice camp, or an oil spill—than of large scales.

The sea ice dynamics are characterized by the sea ice velocity $\boldsymbol{u}$, its thickness h, and areal concentration and internal stress $\boldsymbol{\sigma}$. The evolution of sea-ice velocity comes from the (vertically averaged) momentum equation

$$m\frac{du}{dt} = \boldsymbol{\tau}_a + \boldsymbol{\tau}_w + \boldsymbol{\tau}_b + \Delta.(\boldsymbol{\sigma}h) - \mathcal{F} \tag{1}$$

where m is the ice mass, external forces are the air drag $\boldsymbol{\tau}_\mathrm{a}$, water drag is $\boldsymbol{\tau}_\mathrm{w}$ and the basal stress is $\boldsymbol{\tau}_\mathrm{b}$ in case of grounded ice. The internal stress is the main counteraction to the external forces and represents the rheological sea-ice model. It depends on the ice thickness but also on the ice areal concentration. Other—less important—forces such as the Coriolis force and the slope of the ocean surface are gathered in the last term, $\mathcal{F}$. From equation (1), it appears that the predictability of the ice motions depends primarily on the predictability of winds and ocean surface currents, but also on the choice of the model rheology and the sea-ice thickness. The internal stress $\boldsymbol{\sigma}$ also depends on the state of damage of the ice (the presence of cracks, leads, and ridges accumulated in past deformations) and can also include the flexural stress by waves coming in the MIZ (Squire, Williams, and Bennetts 2013). Because of the sparseness of validation data, it is difficult to set numbers to each of the terms above. The winds are changing rapidly in polar areas and, as an example, polar lows are particularly unpredictable, so weather forecasts older than 3 days are usually not trusted. The temporal variability of ocean currents is slower than that of winds and in principle more predictable, but because ocean currents are unobserved under sea ice, except for a few moorings, their predictability is unknown. The basal stress provides a better case for predictability because the bottom topography is known and the ice will be landfast if the depth of the keels is sufficient to scour the sea bottom, so that knowledge of ice thickness can be sufficient to predict when the ice is landfast, although not necessarily where it stops. Even if the winds and ocean currents were accurately forecast, the rheology term would introduce some chaotic behavior with unpredictable cracks and ridges. Because the ice deformations are intermittent, one can expect variability of ice drift at timescales shorter than the frequency of the forcing fields (Rampal et al. 2009).

Thermodynamics are a secondary contribution to the near-term sea ice predictability. Melting and freezing of the sea ice generally occurs on slower scales than the sea ice motions (weeks to months). However, abrupt changes of the sea ice properties due to thermodynamics have been reported, such as a sudden (overnight) melting of the sea ice following the upwelling of warmer waters, for example, during the Office of Naval Research (ONR) cruise in the Beaufort Sea in October 2015 (Thompson 2015). This event is still rather exceptional. Melt ponds, because of their darker surface, can also accelerate the surface melt of sea ice but are still more a concern for seasonal predictions than for near-term predictions.

As such, information on ice concentration, thickness, and drift are important starting points for sea-ice forecasts, as well as the history of past deformations of the sea ice. In addition, high quality information on surface-wind forcing and ocean currents is of utmost importance.

b. Longer-term predictability

Insights into the mechanisms that give rise to predictability on monthly-to-yearly timescales have been obtained through idealized coupled-model studies and by observational analysis of precursors and lagged relationships. At these timescales, which are discussed further as follows, sea-ice predictability is an initial value problem (predictability of the first kind). For timescales longer than about five years, anthropogenic forcing (predictability of the second kind) provides some predictive capability (Blanchard-Wrigglesworth, Bitz, and Holland 2011).

Guemas et al. (2014) have reviewed Arctic sea-ice predictability on timescales from months to decades. Figure 3 shows the autocorrelation of ice-area anomalies for different

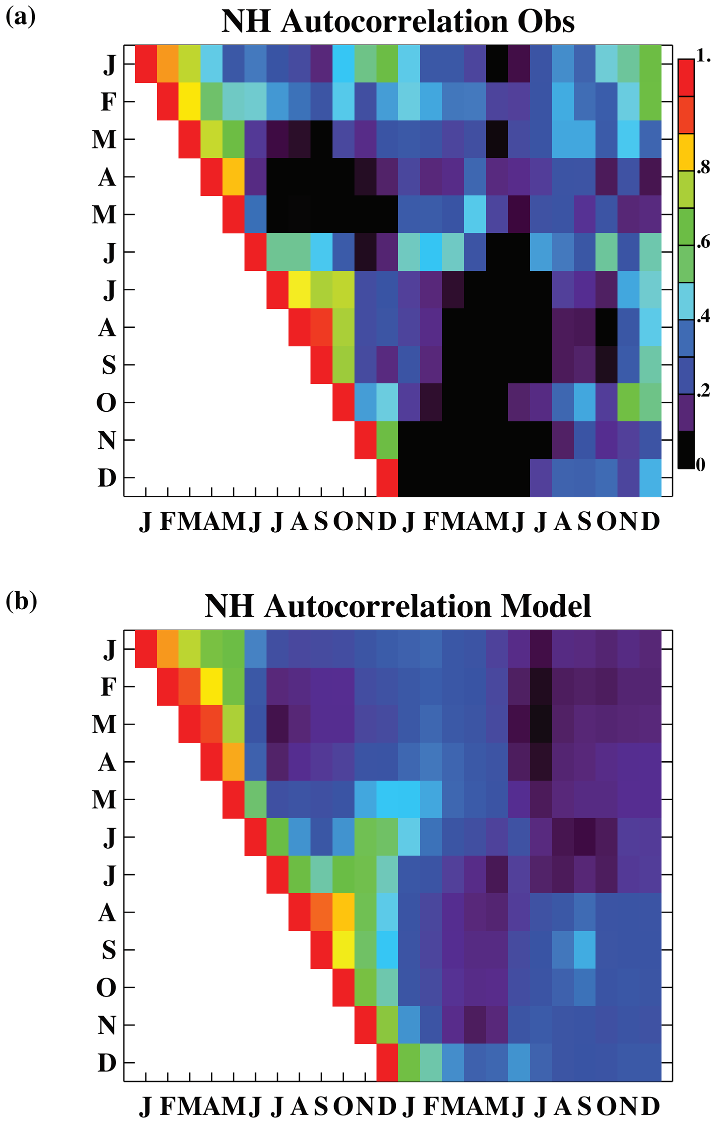

Figure 3. The autocorrelation of monthly Northern Hemisphere sea-ice extent from (a) observations (Fetterer et al. 2002, updated) and (b) the Community Earth System Model Large Ensemble (CESM-LE) (Kay et al. 2015). The y-axis shows correlations beginning in different start months (January through December) with values along the x-axis indicating the autocorrelation for following months. Analysis uses detrended ice-extent data from 1979 to 2014. For the CESM-LE, correlations are computed separately for 38 ensemble members and then averaged together. This follows analysis by Blanchard-Wrigglesworth et al. (2011).

start months for both coupled climate-model simulations and the observations. This autocorrelation analysis suggests that there is predictability in the total Arctic sea-ice area on seasonal-to-interannual timescales. Blanchard-Wrigglesworth et al. (2011) showed that Arctic ice-area anomalies typically persist for several months with high autocorrelation. The anomalies then become decorrelated before again exhibiting significant correlation at longer lags (approximately 5 to 12 months). This property has been termed a "reemergence of memory". For summer anomalies, this appears as a summer-to-summer ice-area autocorrelation, which is associated with long-lived anomalies in ice thickness and the influence these anomalies have on ice area during summer. Results from an adjoint of an ice-ocean coupled model are consistent (Kauker et al. 2009). However, the summer autocorrelation appears stronger in climate-model simulations than in observations (Figure 3b). Another mechanism causes ice-area anomalies in the ice-growth season to be significantly correlated with variations in the previous melt season. This is associated with the persistence of ocean heat content anomalies that are influenced by the timing of ice retreat from a region, survive the summer melt season, and then affect the advancement of ice into the region during the following autumn (Blanchard-Wrigglesworth et al. 2011; Bushuk and Giannakis 2015). For the Antarctic, a similar mechanism seems to be at play. In particular, the timing of ice advance is significantly correlated to the previous timing of ice retreat about five months earlier (Stammerjohn et al. 2008). As discussed by Gloersen and White (2001), a "reemergence" of ice-area anomalies likely occurs because of ocean heat content anomalies that retain a signal of ice conditions over summer months when ice is not present.

Many "perfect model studies" have been used to further explore the sources of seasonal-to-interannual initial–value predictability in the ice-ocean system of both the Arctic (e.g., Koenigk and Mikolajewicz 2008; Holland, Bailey, and Vavrus 2011; Blanchard-Wriggelsworth Bitz, and Holland 2011; Chevallier and Salas-Melia 2012; Tietsche et al. 2014; Day, Tietsche, and Hawkins 2014) and Antarctic (e.g. Holland et al. 2013; Zunz, Goosse, and Dubinkina 2015). These studies use an ensemble of coupled climate-model simulations to predict simulated reference conditions from the same model. The ensemble is initialized with information from the coupled model with very small errors (usually at a round-off level value) introduced. Because of the chaotic nature of the system, these errors grow over time and the ensemble of forecast simulations diverge. By assessing the forecast skill of these simulations, information on the potential predictability of the system can be gained. Within the context of the model climate, these experiments provide an upper bound of what predictive skill can be realized in that the initial condition information is known nearly perfectly and the predictive model is, by design, consistent with the reference conditions. However, the application of "perfect model" results to the real system is uncertain given that model biases are present and representation of potentially relevant processes, such as wave or tidal influences, may be lacking (e.g. Kumar, Peng, and Chen 2014).

The aspects of the persistence and reemergence of Arctic sea ice area anomalies identified by Blanchard-Wrigglesworth et al. (2011) have also been identified in perfect model studies (e.g., Blanchard-Wrigglesworth, Bitz, and Holland 2011; Chevallier and Salas-Melia 2012)

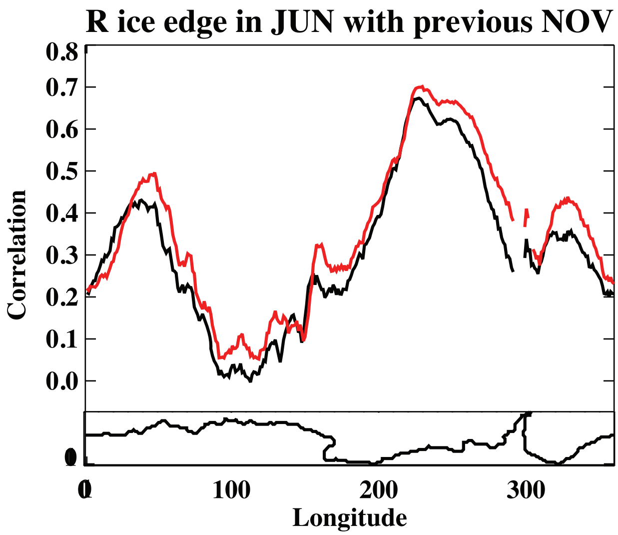

Figure 4. The correlation of the latitude of the June Antarctic sea-ice edge with the ice-edge latitude in the previous November as a function of longitude. Correlations are computed from 38 simulations of the Community Earth System Model Large Ensemble (CESM-LE) over 1979 to 2014 using detrended data. The Antarctic continental outline is shown at the bottom for reference. The black line shows correlations for June and November data at the same longitude, whereas the red line shows correlations in which the November data is shifted about 5 degrees westward.

although differences do exist across different models (Tietsche et al. 2014). These studies have also assessed the relative importance of dynamic and thermodynamic influences on ice predictability (e.g., Holland, Bailey, and Vavrus 2011; Tietsche et al. 2014), the dependence on initialization month (Day, Tietsche, and Hawkins 2014), how seasonal prediction skill may change with large-scale climate change (Holland, Bailey, and Vavrus 2011), the potential to predict extreme ice anomalies (Tietsche et al. 2013), issues with ensemble design and skill metrics (Hawkins et al. 2016), and the importance of certain aspects of model uncertainty for predictions (Juricke, Goessling, and Jung 2014). Perfect model experiments have also been used to assess Antarctic sea ice and indicate, as shown in Figure 4, that the location of the ice edge during the austral fall is related to its location in the previous spring (Holland et al. 2013). Consistent with observations (Gloersen and White 2001), this occurs because ocean heat content retains a signal of the ice conditions over the summer months. These studies provide an indication that skillful seasonal-to-interannual sea ice predictions may be possible. However, this is dependent on having an adequate knowledge of initial condition information and adequate models.

Studies assessing seasonal sea-ice predictability characteristics have also analyzed precursors (or potential predictors) of sea-ice conditions at different times of year. These have used both information from the historical record, such as atmospheric reanalysis data and its relation to following satellite-derived sea ice conditions, or similar information from fully coupled simulations. For example, Rigor, Wallace, and Colony (2002) used observational data to assess the influence of winter Arctic Oscillation (AO) variability on subsequent sea-ice conditions and found significant correlation with the following summer's ice-area anomalies. This occurred because wintertime wind-driven ice-thickness anomalies, associated with AO variability, influenced potential summer melt-out during the following summer season. Observational studies have also suggested that springtime atmosphere-ice surface fluxes (Drobot, Maslanik, and Fowler 2006; Kapsch et al. 2014) and sea ice surface conditions, such as melt-pond coverage (Schroder et al. 2014; Liu et al. 2015) or melt onset (Petty et al. 2017), may provide predictive skill for the Arctic September ice area. Spring surface properties can provide predictive skill because they influence the initiation of the melt season and associated surface albedo reductions that affect melting and ice loss throughout the summer season. Other precursors appear important for specific regions. For example, Steele et al. (2015) find that spring wind variations are associated with anomalies in the timing of ice retreat in the Beaufort Sea. Skillful seasonal-prediction statistical models have been designed that make use of these types of relationships (e.g., Yuan et al. 2016; Stroeve, Crawford, and Stammerjohn 2016). However, as discussed by Holland and Stroeve (2011), these predictor relationships may not be robust on longer timescales, especially with large-scale sea-ice loss.

Idealized studies indicate that ocean-temperature and ice-thickness anomalies may allow for some predictive skill. This has been quantified further by Day, Hawkins, and Tietsche (2014), who performed experiments in a perfect-model framework with degraded ice-thickness initialization (see also Guemas et al. 2016). They found that the use of ice-thickness information considerably improves Arctic ice-area prediction skill up to eight months in advance, particularly in summer. Results from initial-condition perturbation experiments (Blanchard-Wrigglesworth et al. 2015) also indicate that model physics plays an important role in forecast uncertainty. To assess the role of ocean conditions for sea-ice prediction, the National Center for Atmospheric Research (NCAR) and other scientists have performed integrations using the Community Earth System Model (version CESM1-CAM5) (Hurrell et al., 2013). The simulations include two sets of model ensembles, both initialized using output from the CESM1 Large Ensemble (Kay et al. 2015) for 1 January 2000. Each ensemble set has 17 members and is integrated for two years in length. The first ensemble set is a standard "perfect model" experiment with near-perfect initial conditions; a round-off level perturbation of order 10^{-14} K is applied to the initial air-temperature field to create the ensemble spread. The second ensemble set is identical to the first except that the ocean initial conditions are replaced with the model-simulated climatology. With a lack of initial ocean information, the Arctic MIZ regions have a quick and significant degradation in predictive skill, as can be seen from, for example, the spread across ensemble members in the ice edge location in the Greenland–Iceland–Norwegian seas (Figure 5). For the Antarctic, the potential prognostic predictability (PPP) (Pohlmann et al. 2004) is commonly used to compare the variance across the initialized ensemble members with the variance from natural variability.

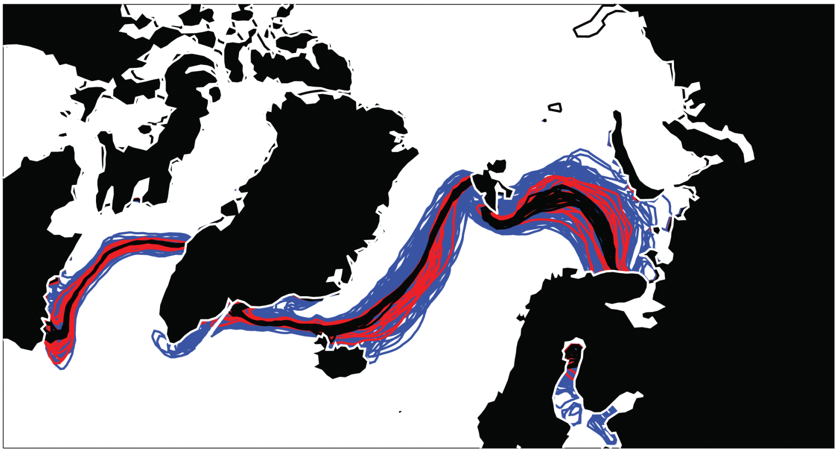

Figure 5. The location of the January average ice edge, defined as the 15% ice-concentration contour for noninitialized Community Earth System Model Large Ensemble (CESM-LE) simulations (blue), initialized perfect model experiments (black), and initialized perfect model experiments in which the ocean conditions are initialized with climatology (red).

A PPP value of one means that conditions are perfectly predictable, whereas a value of zero means that the initialized ensemble spread is equal to that from natural variability and no initialized predictability exists. As shown in Figure 6, ice-edge predictability is retained for several months regardless of the degradation in ocean initialization. However, with climatological initial-ocean conditions, the ice-edge prediction loses skill as ice advances away from the continent from May onward, in contrast to simulations with "perfect" initial conditions. This indicates the importance of ocean initial-state information for sea-ice forecast skill in both hemispheres. However, as discussed further as follows, there are challenges in obtaining reliable polar observations of ice and ocean conditions for use in operational forecasts.

4. Observations in the polar oceans

Initialized forecasts are critically dependent on the observations used for their initialization. To be useful for operational systems, observations are needed in near real-time for short-term forecasts and with limited time lag for seasonal and longer forecasts. There are unique challenges involved in polar observations owing to the remoteness, harsh conditions, and long polar night. However, forecasting systems are making use of satellite observations for initialization, most routinely for ice concentration. Additionally, new products, such as ice thickness, are becoming available and may ultimately improve our predictive capabilities.

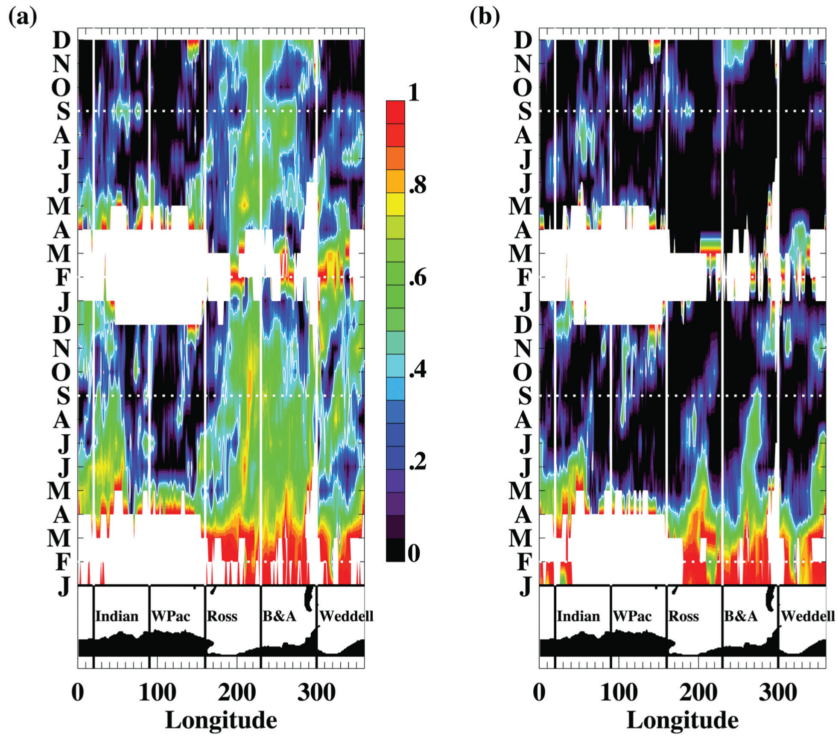

Figure 6. Potential prognostic predictability (PPP) of the ice edge latitude from initialized perfect model experiments. The values are shown as a function of longitude around the Antarctic continent (x-axis) and for months following initialization (y-axis). The simulations are initialized on 1 January using conditions from year 2000 of the Community Earth System Model Large Ensemble (CESM-LE) and then integrated two years forward in time. Panel (a) shows simulations with perfect initial conditions with only a small round–off level perturbation to the initial surface air temperature, whereas panel (b) shows simulations in which the ocean initial conditions are replaced with climatology. The white areas on the figure are missing data that occur when no ice is present at those longitudes.

a. Observations of sea ice

Sea-ice reconnaissance flights were mostly occasional until after the Second World War, with the exception of the USSR, which started systematic flights with the polar aviation as early as 1929 to monitor the Northern Sea Route. The U.S. and Japan gradually increased the frequency of their flights at the turn of the 1950s and adopted the World Meteorology Organization (WMO) sea-ice charting standard proposed in 1952 (Arctic Sea Ice 1958). These flights are still used, nowadays mostly in Canada, but have elsewhere been superseded by satellite data. The longest satellite record to cover the whole Arctic, which started in 1978, comes from polar-orbiting passive microwave sensors onboard the satellites SSMR, SSM/I, AMSR-E, and AMSR2 (Cavalieri and Parkinson 2012). Their main advantage is that they can see through clouds, although a few issues still remain, especially with the Summer ice, because the sensor does not discriminate between open water and signatures from wet snow or ice surface (including melt ponds). This and other technical issues are accommodated differently in a multitude of algorithms that calculate sea-ice concentrations from the raw passive-microwave retrievals (Ivanova et al. 2014, 2015). This is an important matter for data assimilation, as we will see in Section 6. The resolution of passive-microwave ice–concentration data is between 6 km and 25 km, which is consistent with current operational models of the whole Arctic but still coarse with respect to the needs of any operational users navigating in ice-infested waters. SAR and satellite data in the visible channels (Moderate Resolution Imaging Spectroradiometer [MODIS], Système Pour l'Observation de la Terre [SPOT]) provide much more detail at resolutions higher than 1 km, which is the level of detail that a ship captain would need, for example, in order to sail along a lead. But both types of data suffer from poor coverage: SAR images because the acquisition frequency is limited, and visible data because they are impaired by the frequent cloud coverage and by winter darkness.

For short-term forecasts, it is important to assess how the ice is moving. Various ice-drift products are obtained from different satellites and can be split in two types: 1) the coarse-resolution, full-coverage products using passive microwave radiometers and scatterometers (full spatial coverage, but most of them are only available during winter because of the aforementioned limitations of passive microwave data in the summer [see Sumata et al. 2014 for a review], and 2) the high-resolution but low-coverage SAR-based products (Kwok 2004). The latter use or a combination of both (Korosov and Rampal 2017). The coverage by SAR images has recently been improved by the launch of the Sentinel 1A and 1B missions by the European Space Agency and offer full daily coverage in high latitudes. Drifting buoys on sea ice still provide the longest data record, with more than 30 years of the International Arctic Buoy Program (IABP), but are limited in their spatial coverage.

Until model forecasts have reached a comparable level of detail and accuracy, operators working in the Arctic will continue to rely primarily on ice charts. These are produced manually by experts using available satellite and aerial data of the day and starting from the previous day's chart as a first guess. Operators also keep track of the type of ice for young ice (less than a month) and multi-year ice that has survived the September minimum. The "egg code" of ice charts contains a mass of information (See Figure 7), but only the overall ice concentration (the number on the top of the egg) can be informed quantitatively from satellite images and numerical predictions. The other information (thickness and floe size for each ice type found locally) still relies on onsite measurements and local knowledge. Most navigators will use the charts conservatively to remain safely out of ice-infested waters. Experienced navigators can venture closer to the ice, or into the ice, depending on the type of ship and will use their intuition to match the ice chart to their own observations. For example, tourist operators use the ice charts to find wildlife on its favorite feeding grounds.

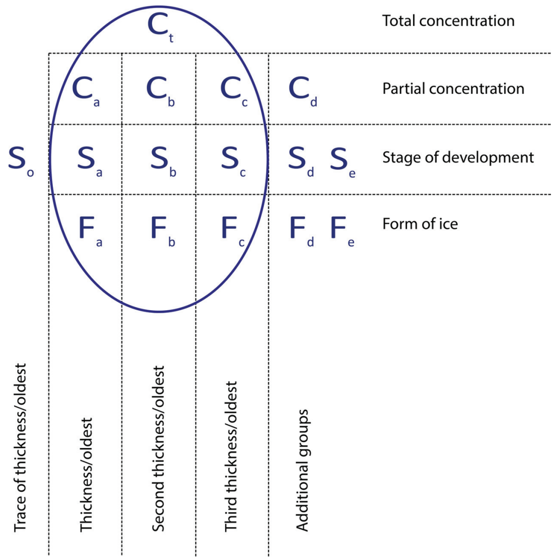

Figure 7. The "egg code" adopted by World Meteorology Organization (WMO), adapted from Environment Canada. Stages of development implicitly link the age of the ice to its thickness. For example, code 9 stands for second-stage thin first-year ice (50–70 cm). Form of ice is related to the floe size, medium floes (100–500 m) are code number 4.

For predictions on seasonal and longer timescales, other observations are likely to play an important role. Ice thickness observations from satellite have recently become available. These use different principles to obtain either sea ice freeboard of thick ice, for example, from IceSAT (Ice, Cloud, and land elevation Satellite; e.g., Kwok et al. 2007) or CryoSat (e.g., Laxon et al. 2013), or the thickness of thin ice (from SMOS, the Soil Moisture and Ocean Salinity Mission) (Tian-Kunze et al. 2014). These observations are quite complex and come with relatively high uncertainties (Zygmuntowska et al. 2014; Tian-Kunze et al. 2014). However, as discussed previously, thickness is an important source of sea-ice predictability on seasonal and longer timescales because thickness anomalies are quite long-lived. Other aspects of the sea ice such as its snow cover, snow thickness, and melt pond characteristics may also be important for sea-ice forecasts on seasonal and longer timescales. Remote sensing is being used to characterize these aspects of the sea ice. For example, snow-depth information is being provided through the NASA (National Aeronautics and Space Administration) Operation IceBridge airborne campaign (Kurtz et al. 2013) and melt-pond fractions have been derived from satellite data in the visible channels (Rösel, Kaleschke, and Birnbaum 2012). Ice-mass buoys are also providing in situ measurements of snow depth and other sea-ice characteristics (Richter-Menge et al. 2006; Perovich et al. 2008). However, only limited work has been done to quantify the possible influence of these types of observations on forecasting systems. More studies are needed to understand where, what,

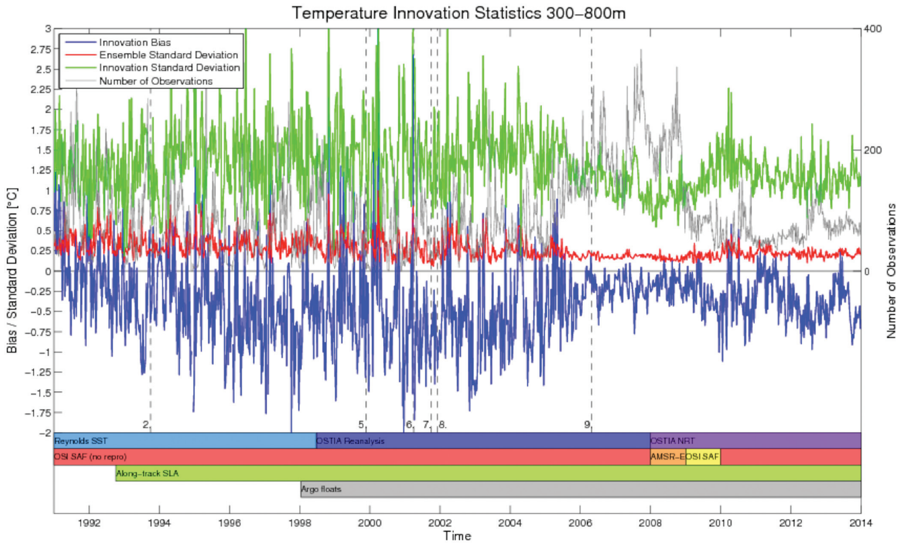

Figure 8. Different assimilation statistics extracted from the weekly in situ temperature innovations (observations minus corresponding model values) in the TOPAZ4 reanalysis, averaged from 300 m to 800 m depths. The number of profiles (grey line) augments drastically during the IPY from 2007 to 2009 and the bias (blue line) reduces from 0.5 K to 0.2 K; this reduction seems to be sustained in a few years after the end of the IPY. From http://marine.copernicus.eu/.

and with what accuracy measurements are needed to improve the forecast skill of sea ice on seasonal to interannual timescales.

b. Observations of the ocean

Information from under the ice is also important for constraining ocean model predictions. In situ observations can be made under ice: moorings have been used in the Arctic-Subarctic Ocean Fluxes (ASOF), Nansen and Amundsen Basins Observational System (NABOS) and Canadian Basin Observational System (CABOS) programs, but the main breakthrough from the modeling point of view occurred during the 2007 to 2009 International Polar Year (IPY) with the Ice-Tethered Profilers (Toole et al. 2011; Krishfield et al. 2008) that carry a yo-yo taking temperature and salinity profiles. These observations are very useful for assimilation in ice-ocean models, which usually have a hard time maintaining correct water masses over long spinup times (see Figure 8, for example, how the appearance of IPY data from 2007 to 2009 has reduced the temperature bias and root mean square [RMS] errors in the TOPAZ4 reanalysis). As suggested by idealized studies, ocean temperature information is also important for longer-timescale sea ice predictability in both hemispheres, particularly in the MIZ during the ice-advance period. The ocean salinity should be monitored as well because the upper cold halocline layer isolates the sea ice from warm waters below. The freshwater fluxes are also anticipated to increase and influence the circulation in the Arctic and the subpolar North Atlantic (Nummelin et al. 2016). Sea surface temperature (SST) and sea level anomalies (SLA) from satellite altimeters are also major inputs for initialization in the open ocean, the assimilation of SST alone has some potential to benefit seasonal-to-decadal forecasts of Arctic ice concentrations (Counillon et al. 2014).

Other observations can be collected under ice by acoustic tomography (Mikhalevsky et al. 2013), which provide integrated sound speed over large distances but must be calibrated to mooring data to be inverted to temperature integrals. The ability to fly gliders below the sea ice would open tremendous opportunities to study the small-scale ocean processes but, so far, is limited by the issues of communication with and localization of the glider. Poor telecommunications in general are a bottleneck for data transmission in the polar oceans as long as Iridium is the only network covering the poles.

5. Coupled ice-ocean models

To perform forecasts of the polar oceans, observations such as those discussed in the previous section are used to obtain initial conditions for numerical models that then forecast forward in time. This is often done using an ensemble of simulations to provide insights on forecast uncertainty. The numerical modeling systems used for forecasting can include fully coupled ocean, sea-ice, atmosphere, and land components or some combination of these.

The sea ice is between the atmosphere and the ocean, but its solid state requires a specific model, similar to waves being modeled separately from the ocean and the atmosphere. The slow exchanges of heat, salt, and momentum with the ocean mixed layer justify a coupling to the ocean, but the fast changes of sea-ice surface properties (temperature, albedo) could as well justify the coupling of the sea ice to a weather-prediction model. Still, weather-forecast models are often run using a sea-ice boundary condition based on recent sea-ice observations, whereas an ocean model without the coupling to a dynamic sea-ice model would lose critical features, like the cold and saline water masses generated by the freezing of leads and coastal polynyas and the East Greenland Current, driven by the Southward export of sea ice through the Fram Strait. These may not appear as highly relevant for short-term forecasting out to ten days ahead, but because an ocean model needs at least ten years of spinup to equilibrate, these timescales are the ones that need to be considered for the success of an ocean forecast. So, ocean forecasting systems, even those not specifically designed for forecasting sea ice, should use a coupled ice-ocean system, whereas the need is not as obvious for weather forecasting. Predictions out to months and years ahead go beyond the predictability limit of atmosphere-only weather forecasts and require, in principle, the representation of coupled processes with the atmosphere. Some hints can however be obtained using coupled ice-ocean models only (Massonnet, Goosse, and Fichefet 2015).

Examples of systems using an ice-ocean coupled model for forecasting include Zhang et al. (2008), Sakov et al. (2012), Posey et al. (2015), and Smith et al. (2015) (see also a review in Tonani et al. 2015), although most of them are coupled without the use of a coupling framework simply by including the sea-ice model code as part of the ocean model and running it on the same horizontal grid used by the ocean model. These models need prescribed atmospheric forcing information that can be obtained from historical data or numerical weather prediction systems. This can be problematic for remote environments like the Southern Ocean, which has fewer in situ measurements and generally suffers from poorer quality of the weather models in the decades when satellite coverage was poor. Numerical models used for forecasting have been configured in both global and regional configurations. For regional configurations, information is needed at the regional boundaries to drive the model. Recently, full earth system models, which can include marine and terrestrial biogeochemistry, have been used for initialized decadal forecasts under the auspices of the Coupled Model Intercomparison Project (CMIP5) (Taylor et al. 2012). Note that there is not one optimal model configuration for forecasts but depends instead on the timescales and products of interest. In general, for short-term forecasts, issues of sea-ice dynamics and factors influencing regional characteristics are important. On longer timescales, the representation of feedback processes that influence the system evolution play a critical role, which also implies a need for coupling to atmospheric components. Computational constraints are also a consideration and may require compromises in the model configuration and its complexity.

In general, the sea-ice models used in these forecasting systems are built on thermodynamic and dynamic modules. Originally developed for Arctic process studies and climate modeling (Maykut and Untersteiner 1971; Hibler 1979; Hunke and Dukowicz 1997; Bitz and Lipscomb 1999), the same sea-ice models have also been used for short-term predictions. Model developments have largely focused on Arctic sea ice, although the models are also used in the southern oceans. The Arctic-climate focus means that some processes of relevance for shorter timescales, regional characteristics, or Antarctic ice cover have received less attention. For example, wave interactions, which are not typically included in current forecasting systems, are likely to influence Antarctic sea ice conditions (Kohout et al. 2014) and may well become more relevant in the Arctic as the ice retreats and the wind fetch over large areas of open water generates longer and more powerful waves (Squire, Williams, and Bennetts 2013). The waves have a mechanical effect on the sea ice and also influence the thermodynamics of lateral freezing and melting. Landfast ice, which is the ice that is immobile in coastal regions and an important regional consideration, is not included in most current models, although Lemieux et al. (2015) have recently developed a parameterization of these processes. Snow conditions on sea ice have also received relatively little development, although recent work by Lecomte et al (2011) has improved this. Antarctic sea ice is subject to heavy snow loading and snow-ice formation, making these aspects particularly important for Southern Ocean predictions. As noted in section 3, the initiation of melt onset and pond formation and coverage appears to influence sea-ice predictions on seasonal timescales. Snow processes and their interactions with melt ponds (e.g., Polashenski, Perovich, and Courville 2012; Lecomte et al. 2015), which are not currently included in most models, may be important aspects of capitalizing on these relationships to advance sea-ice prediction.

In terms of sea-ice dynamics, most sea-ice models have a common ancestor based on the Arctic Ice Dynamics Joint EXperiment (AIDJEX), the elastic-plastic rheological model (Coon et al. 1974), later superseded by the viscous-plastic model (VP) (Hibler 1979) and then again by the elastic-viscous-plastic model (EVP) (Hunke and Dukowicz 1997). The evolution between these successive models was largely pragmatic and associated with the available computing power (imposing a coarse model resolution of the order of 100 km) and the simplicity of coupling the ocean and the sea-ice models on the same Eulerian grid. However, Coon et al. (2007) pointed out that the approximations once valid at 100 km scales are less relevant now that models afford to run at resolutions below 10 km. The advent of coupling software eventually alleviates the need to run the sea-ice model on the horizontal grid of the ocean model and allows more freedom in the design of sea-ice models. At high resolution, maintaining deformation features at the smallest scale can be challenging for diffusive advection schemes, so that it becomes attractive to consider a Lagrangian grid (Sulsky et al. 2007; Bouillon and Rampal 2015), which also constitutes a convenient framework for calibration against observations from—Lagrangian—ice camps. It should also be noted that ocean and sea-ice models may not need to run at the same resolution to perform best because they are meant to resolve different horizontal scales.[4] But the resolution of the sea-ice model is not the only parameter to have in mind: the choice of rheology and damage mechanisms is another key aspect of correctly resolving deformations. The Maxwell elasto-brittle rheologies have successfully reproduced the scaling laws (Dansereau et al. 2016; Rampal et al. 2016). The accuracy of numerical solvers has also been identified as an area of improvement for the EVP and VP models (Bouillon et al. 2013; Lemieux et al. 2014; Mehlmann and Richter 2017).

Ocean models were also originally designed for process studies and then used in climate simulations and operational forecasting (Tréguier et al. 2017). The immense majority of ocean models used for polar operational forecasting and climate predictions is expressed in finite differences horizontally and differs by the choice of vertical coordinate system: z-level models have been used extensively in polar regions such as the MIT General Circulation Model (MITgcm) (Nguyen et al. 2011, Fenty, Menemenlis, and Zhang 2015), Modular Ocean Model (MOM) (Kauker et al. 2009), and Nucleus for European Modelling of the Ocean (NEMO) models (Smith et al. 2015), and the hybrid vertical coordinate model, HYCOM, in which isopycnic layers are used below the mixed layer (Posey et al. 2015, Sakov et al. 2012), also now adopted in the 6th version of MOM. Although the treatment of the top levels in contact with sea ice requires special attention (Campin, Marshall, and Ferreira 2008), in the Arctic, those various ocean models show common weaknesses in the representation of the warm Atlantic layer and the Pacific water masses, possibly due

4. The ocean model needs to resolve the Rossby radius of deformation, see Nurser and Bacon (2014) for values in the Arctic.

to problems in correctly simulating the flow across the Fram and Bering Straits, as well as in St. Ana Trough (Ilıcak et al. 2016). The representation of the upper cold halocline layer is another challenge because it requires the sources and pathways of this water to be well simulated and well preserved in the top layers of the ocean model. Finite-element ocean models, like the Finite Element Sea Ice-Ocean Model (FESOM) (Wang et al. 2014) and the Model for Prediction Across Scales (MPAS), present an advantage for simulating the Canadian Archipelago because the elements can be made small enough locally to resolve its many narrow straits. The Southern Ocean represent additional challenges for these ocean models because of aspects like the critical roles of eddies (Thompson et al. 2014), ice shelf interactions (Bintanja et al. 2013; Swart and Fyfe 2013; Pauling et al. 2016), and strong surface forcing such as surface waves (Kohout et al. 2014) and katabatic winds (e.g., Zhang et al. 2015).

It is also worth noting that the ocean and sea-ice models used for short-term forecasting are often very much the same as those used for climate predictions. Because of computational considerations, Lagrangian approaches and adaptive meshes may be applicable first for short-term, high-resolution forecasting. However, short- and long-term predictions share similar concerns with physical ice-ocean processes and their numerical implementation. Although climate predictions have a stronger focus on conserving heat and water, there are obvious benefits to collaborating on model developments that will improve predictions across timescales.

New developments in support of polar forecasting should focus on model aspects that appear to have an important influence on forecast skill. For example, Arctic sea-ice research has highlighted processes at the initiation of the melt season as providing some seasonal predictive skill (e.g., Kapsch et al. 2014). Upper-ocean heat content anomalies are long-lived and influence seasonal sea ice–area anomalies. This provides a source of sea ice–predictive skill in both hemispheres (e.g., Blanchard-Wrigglesworth et al. 2011 for the Arctic; Holland et al. 2013 for the Antarctic). As such, improvements in parameterizations that target these aspects of the system are likely to improve sea ice forecasting skill. Some of these areas are being addressed in recent model developments, for example, in melt pond parameterizations (e.g., Flocco, Feltham, and Turner 2010; Holland et al. 2012; Hunke, Hebert, and Lecomte 2013). A better understanding of other factors that influence predictive skill would be useful for prioritizing model developments and should be the subject of future work. For example, Rampal et al. (2011) showed that if Intergovernmental Panel on Climate Change (IPCC) models did reproduce the acceleration of the ice-drift speed across the Fram Strait, their predictions of an ice-free Arctic in Summer would probably occur decades earlier than forecast. This motivates the improvement of the sea ice rheological model.

6. Assimilation of sea-ice observations

Assimilation of sea-ice observations must be coupled in the sense that it should update both the sea ice and the ocean properties consistently. In the case in which the ocean mixed layer is too warm to sustain sea ice, but observations show the presence of sea ice, a data assimilation system that would update only sea ice would add ice on top of the warm waters, but the huge heat capacity of the ocean would then melt the added ice almost immediately. Repeating this operation at each assimilation cycle for long enough will eventually sustain sea ice on top of the water: not because the ocean model would have lost enough heat, but because the repeated melt of added ice would have released enough fresh water to the ocean surface as to create a new mixed layer, able to cool down and freeze. This simple example can be extended to other situations (water too cold, too saline, or any combinations of those) and in most cases assimilating sea-ice properties in the sea-ice component only would lead to a worse ocean simulation. This suggests that the sea-ice observation should be projected to the ocean column using a multivariate forecast error covariance matrix, in which the covariance values linking ice to ocean parameters are nonzero. Dynamical model ensembles are a practical way to estimate those values. In data-assimilation terminology, the state vector must include all prognostic variables of the coupled model (ocean and sea-ice variables) and the ensemble of model runs can be used to empirically calculate the cross-covariances between ice and ocean variables. Similarly, observations of the ocean are used to update sea-ice variables, although this situation is less common. So, using an Ensemble Kalman Filter (EnKF), Lisæter, Rosanova, and Evensen (2003) demonstrated that the coupled assimilation of sea-ice properties can modify the ocean-surface temperatures in rather systematic ways (adding ice cools down the water), but not ocean salinities. According to sea-ice halodynamics, however, the freezing of sea ice injects salty brines to the ocean mixed layer, and the melting releases fresher water. But these simple relationships would only explain part of the ice-salinity cross-covariances and a relationship may arise in other situations without the intervention of sea-ice thermodynamics: the wind may occasionally blow the ice on top of more saline water. Sakov et al (2012) further showed how the ice-salinity cross-covariance can change sign on either side of the ice edge in the Barents Sea: the ice-salinity correlation turns negative on the ocean side because the main process responsible for melting is the advection of warm and saline Atlantic Water near the surface; thus, the ice-salinity correlation is made through the intermediate of the surface temperature variable. The latter finding is of course not to be generalized to locations where the ice is isolated from the Atlantic Water, but such isolation may not remain forever if the open-water mixing reaches these warm waters (Rippeth et al. 2015). The assimilation of ice concentrations with the EnKF described in Lisæter, Rosanova, and Evensen (2003) was included in the near real–time TOPAZ forecasts in 2003.

An alternative to ensemble methods is the use of an adjoint model, as in the 4D-variational (4DVAR) data assimilation method. The adjoint model and the tangent linear model calculate the sensitivity of observed variables to the control variables within the duration of the assimilation window. If tangent linear and adjoint models are available both for the ocean and the sea-ice models, they can exchange information about the interface variables like heat, salt, and momentum fluxes. Because these correlations are usually monovariate at the beginning of the assimilation window, the length of the assimilation window should be as long as possible. The most recent experiments report successful applications of the 4DVAR in an Arctic regional configuration for durations of one year or longer (Fenty and Heimbach 2013; Fenty, Menemenlis, and Zhang 2015), even though these applications include an adjoint of the sea ice–thermodynamical model, and they still miss the adjoint of the sea ice–dynamical model. The advantage of the 4DVAR method is that it returns one optimized model trajectory, which is very useful for oceanographic interpretation (Kauker et al. 2009) and quantitative network design (Kaminski et al. 2015), although 4DVAR is not used for operational ice-ocean forecasting to our knowledge.

Coupled multivariate covariances do not necessarily cure all the troubles of assimilating sea-ice observations. Another source of problems is the lack of respect for the traditional Gauss-linear assumptions underlying classical data-assimilation methods. Sea-ice concentrations, by definition, have bounded values between zero and one, and other sea ice variables (thickness, snow depth) have positive values. Ocean temperatures are not allowed below the freezing point. Although it would be easy for a monovariate assimilation method based on a heuristic covariance function to preserve monotonicity and therefore the bounds of variables (Wackernagel 2003), an ensemble-based covariance (or a tangent linear model) may generate values out of bounds. Honoring the bounds can be forced by different means, either by nonlinear transformations of the variables (a method called Gaussian anamorphosis in geostatistics) (Bertino, Evensen, and Wackernagel 2003; Barth et al. 2015) or by including inequality constraints in the cost function (Lauvernet et al. 2009; Janjic et al. 2014; Simon et al. 2012). Altogether, the benefits of multivariate flow-dependent covariances still outweigh the inconvenience of values out of bounds.

There are continuous improvements to data-assimilation methods in chaotic high-dimensional systems such as coupled ice-ocean models. But new models and new observations always call for further developments in data assimilation. In particular, sea ice models expressed in Lagrangian grids with automatic remeshing are uncommon targets for data assimilation. Ensemble Kalman filtering techniques rely on cross-covariances between observed and nonobserved variables, which implies that the grid cells have to be uniquely identified across different members of the ensemble. This also becomes difficult when adaptive remeshing is turned on, unless the Lagrangian model output is interpolated on a fixed grid, at the risk of smoothing the very localized kinematic features (long cracks, ridges, and leads) that they are meant to simulate. Lagrangian models do not offer any easy differentiation/automatic adjoint capabilities, thus preventing the use of variational techniques. Particle filters however could be well-suited to Lagrangian sea-ice models because they do not compute any cross-covariances provided that the number of particles can be reasonably small. It should also be noted that a coupling framework such as CESM is sufficiently flexible to allow running several instances of one model component (e.g., the atmosphere) for each instance of another (e.g., the ocean), thus allowing the use of a particle filter for the sea ice and other data-assimilation methods for the ocean, land, and atmosphere. One important aspect of viewing coupled data assimilation and ensemble forecasting is that the uncertainties should be consistent across these components: the error statistics at the base of the atmosphere are consistent with those at the surface of the sea ice and similar between the bottom of the sea ice and the ocean surface. This is generally easy to enforce if all components of the coupled system use an ensemble to represent the errors.

7. Present predictions, fit for purpose?

a. Short-term predictions

Most present day short–term forecast systems assimilate sea-ice concentration and are therefore expected to perform well at forecasting the ice edge, including the following: the Canadian Global Ice-Ocean Prediction System (GIOPS) (Smith et al. 2015), the U.S. Arctic Cap Nowcast/Forecast System (ACNFS) (Hebert et al. 2015) and the European Copernicus Arctic Marine Forecasting System (TOPAZ) (Sakov et al. 2012). Standalone sea-ice models are also used for forecasting purposes, like the Canadian Regional Ice Prediction System (RIPS) (Lemieux et al. 2016). Because their control vector excludes the ocean, they can be initialized more accurately than coupled ice-ocean systems.

Because a measure of RMS errors of ice concentrations has little physical meaning (these errors also diminish as more open ocean is included in the validation area) we will concentrate on the skill expressed as distance from the forecast to the observed ice edge. In the Arctic, the skill of the 24-hour forecast of the location of the ice edge is about 50 km for the TOPAZ (including both seasonal biases and RMS errors [Melsom et al. 2015], updated in real-time on http://cmems.met.no/ARC-MFC/V2Validation/timeSeriesResults/index.html), and 40 km down to 30 km depending on the input data sources in the ACNFS systems (Hebert et al. 2015). This number is a rough indication because the methods used to calculate the distance between modeled and observed ice edges have not been standardized yet. Contingency tables are also a valuable approach to the validation of sea-ice concentrations (Smith et al. 2015). The latter indicate that the Canadian forecast system beats persistence more often in the Arctic than it does in the Southern Ocean.

The forecast skill for ice drift has received much less attention, but long climate simulations hint at the seasonal dependence of the forecast skill. Severe ice-drift biases have been revealed in IPCC AR4 simulations (Rampal et al. 2011): the seasonal cycle of ice drift is shifted by months and its amplitude is too small; the accelerating trend revealed by IABP buoys over the last 30 years is also not reproduced. There are, to our knowledge, no signs that these shortcomings are corrected in recent forecast models (Xie et al. 2017 for the TOPAZ system; Hebert et al. 2015 for the ACNFS), although a review of global reanalysis systems shows that some models correctly simulate the minimum ice drift in March (Chevallier et al. 2015). Hebert et al. (2015) also note that the forecast of drifters' positions beats persistence, whereas the forecast of drift speed does not, indicating that the drift direction is better forecast than the drift speed. How can these shortcomings be remedied? Although adjusting the mean speed of sea ice can be easily achieved by tuning the drag coefficients, there is no simple tuning that can make the sea ice accelerate over years

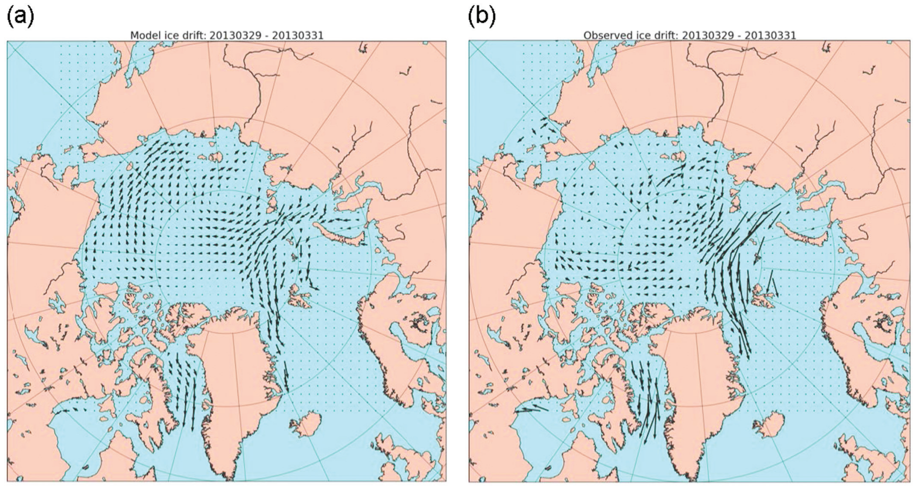

Figure 9. Example of 3–day ice-drift vectors in the TOPAZ4 model (a) vs the Ocean and Sea Ice Satellite Application Facility (OSI-SAF) satellite product (b). From http://cmems.met.no.

or shift its seasonal cycle. The assimilation of ice-drift data has so far been less successful than that of ice concentrations: Sakov et al. (2012) indicate a low sensitivity of the ice drift to external perturbations in the wind forcing, which points to a shortcoming of the TOPAZ4 version of the EVP sea-ice rheology. Qualitatively, the large-scale patterns of ice drift can be reproduced by such a model (see Figure 9 for a typical situation) but the observed gradients between areas of low ice drift (North of Greenland) and strong ice drift (North of the Barents Sea) are smoothed by the model that tends to simulate intermediate values of the ice drift speed. The forecast of 24-hour ice trajectories' end locations exhibits an RMS error of 6.3 km in TOPAZ4 (Melsom et al. 2015), which does not seem to beat a simple free-drift predictor (5 km in Grumbine 1998). Note that the validation is done against different data sources (ice drift from satellite SAR images versus IABP buoys) and on different periods (years 2012–2015 versus the 80s and 90s decades). Errors in ice drift are important both for their contribution to the forecast errors of the ice edge and for their cumulative contribution to the ice-thickness distribution and its export through the Fram Strait and Nares Strait. This is also relevant for climate models (Rampal et al. 2011).

The forecast of ice thickness also suffers from excessive smoothness: the thick ice is too thin and thin ice is too thick (Johnson et al. 2012) by values one to two meters. The dynamical contributions to these errors are quite likely because the too-high ice–drift speed North of Greenland will inevitably simulate a transport of thick ice away into the Beaufort Gyre, but the thermodynamical contributions cannot be excluded (in particular, from snow, melt ponds). More generally, any error in the model inputs or parameters will eventually accumulate in ice-thickness biases, which means that different errors can cancel off and yield a correct ice thickness for the wrong reasons. It is worth stressing the important role of snow on ice as an effective insulator; its presence can inhibit both the growth and melt of sea ice. Snow predictions in ice-ocean models are very dependent on the quality of precipitation from weather forecasts and analyses that are difficult to validate and vary from one product to another (Lindsay et al. 2014).

b. Longer term predictions

Dynamical model forecast systems in use for seasonal sea ice prediction include both ice-ocean models that are driven with retrospective atmospheric reanalysis information (Zhang et al. 2008) and fully coupled model systems (e.g. Wang et al. 2013; Sigmond et al. 2013; Chevallier et al. 2013; Msadek et al. 2014; Peterson et al. 2015). These systems differ in their initialization method and model structure. Some initialize using a system that assimilates satellite-derived ice concentration and other observations (e.g., Wang et al. 2013; Msadek et al. 2014), whereas others use initialization fields from hindcast-forced ice–ocean model integrations (e.g. Chevallier et al. 2013). As discussed by Massonnet, Goosse, and Fichefet (2015), sea-ice seasonal forecast systems benefit from a more realistic sea-ice initialization (see also Massonnet et al. 2013 for Antarctic ice conditions). At these longer timescales, model drift and bias become important concerns and methods are needed to account for this (e.g., Krikken et al. 2016). A source of predictability in the retrospective forecasts comes from the long-timescale trends. Indeed, a synthesis of forecasts submitted to the Sea Ice Outlook (SIO) (Stroeve et al. 2014; Hamilton and Stroeve 2016) indicates that, for the SIO ensemble, forecast skill is only marginally better than that of a linear trend. However, some individual forecasting systems do have sea ice–prediction skill on seasonal timescales, extending up to 6 or 7 months ahead, that are separate from the trend. This skill is associated with the initial value information, presumably the influence of long-lived ice-thickness anomalies and/or ocean heat-content anomalies consistent with the studies on potential predictability reviewed in section 3.2.

On multiyear-to-decadal timescales, changes in boundary forcing (such as rising greenhouse gases) may provide some predictive skill. From idealized studies, Blanchard-Wrigglesworth, Bitz, and Holland (2011) suggest that recent greenhouse gas–concentration increases provide predictive capability for Arctic sea-ice area on timescales longer than 5 years. Several studies have assessed sea ice–forecast skill in decadal prediction experiments that have been performed under the protocols of CMIP5 (e.g., Yang et al. 2016). For example, Yeager, Karspeck, and Danabasoglu (2015) show skillful prediction of decadal trends in winter sea ice in the Atlantic sector of the Northern Hemisphere. This is due in part to the changing external forcing and in part to initial conditions that influence ocean heat-transport variations with an impact on sea ice. This is in agreement with results from Germe et al. (2014), who assessed decadal predictions from a different model that also followed the CMIP5 decadal prediction protocol. They found that predictability of summer Arctic sea ice was weak and had skill for less than two years. Winter sea–ice extent and thickness had longer predictability, largely owing to conditions in the Atlantic sector and to forecast initialization.

For the Antarctic, Zunz, Goosse, and Massonnet (2013) assessed CMIP5 decadal-prediction experiments and found negligible predictive skill at interannual-to-decadal timescales. This is consistent with results from Yang et al. (2016). The Southern Ocean is particularly challenging for initialized predictions given the sparse observations available for assimilation. As discussed by Zunz, Goosse, and Dubinkina (2015), the density of observations and the assimilation method are important for realizing the potential predictability in Antarctic sea ice conditions.

In general, the initialized forecasting systems have skill on shorter timescales than what potential predictability studies suggest may be possible. As mentioned previously, this is to be expected given the design of "perfect model" studies. Results from these idealized studies can provide information on possible avenues to improve the forecasting systems, for example, by highlighting particular processes of interest or initial information that provide predictive capability. Most studies to date have assessed skill for Arctic basin–wide metrics such as total ice area. Some more recent work has provided regional metrics (e.g. Posey et al. 2015; Dukhovskoy et al. 2015; Goessling et al. 2016). Additional work is needed to better match stakeholder needs with forecast variables in both idealized and operational systems.

c. Summary

Ice and ocean models have transitioned from separate component models to operational coupled-prediction systems that are being used for both short- and long-term forecasting. Although they are able to beat trivial predictors for ice-edge forecasts in the short term and winter sea ice on decadal scales, there are still several user needs that remain unfulfilled, in particular for the representation of ice thickness and ice drift. These can safely be blamed on shortcomings of the numerical models, both for short- and longer-term forecasting. Idealized studies suggest more predictive capability than is currently achieved in seasonal-to-interannual forecasting systems. As such, it appears that enhancements in models, observations, and data-assimilation systems could allow for improved predictive skill.

Significant progress has been attained in the past decades thanks to the increase of computational power. However, technological limitations are likely to put a more stringent requirement on code scalability (Bauer, Thorpe, and Brunet 2015), which is compatible with high scientific standards of sea-ice and ocean models. The new, main driver of progress in ice-ocean forecasting is more likely to be the increased availability of observations, both in situ and from remote sensing, not only as direct food for data assimilation but, more importantly, for the development of new models. For example, systematic observations of ice drift at smaller scales allow a better evaluation of the physics simulated by rheological models and stimulate the development of new rheological models. The new models should in turn become more efficient at assimilating observations.

Priority for model developments should be given to the processes that have documented virtues for predictability (i.e., melt ponds and other surface properties) and to those with known biases that have cascading effects on many other properties (i.e., ice deformations and drift). Further work is needed to explore how other properties, such as the snow conditions, may influence predictive capability. This will inform future development needs. Additionally, new capabilities within the models are required to further enhance predictive skill. For example, waves and wave-ice interactions are not currently included in most forecasting systems but are likely to play an important role for some ice-covered regions.

Regarding observational needs, given the remoteness of polar regions, prioritization of what measurements are critical for initialized predictions is also required. These priorities may differ depending on the timescales and forecast products of interest. In general, though, information is needed on what to measure, where to measure, and what measurement accuracy is required for sufficient initialization of forecasting systems. Observing network–design studies can help to determine this information and should be pursued to elucidate ice- and ocean-forecasting needs. Model-development priorities will also be important for determining process-level observations that will be useful in making model improvements.

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