A Regional Seasonal Forecast Model of Arctic Minimum Sea Ice Extent: Reflected Solar Radiation versus Late Winter Coastal Divergence

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ABSTRACT: Thinning sea ice cover in the Arctic is associated with larger interannual variability in the minimum sea ice extent (SIE). The current generation of forced or fully coupled models, however, has difficulty predicting SIE anomalies from the long-term trend, highlighting the need to better identify the mechanisms involved in the seasonal evolution of sea ice cover. One such mechanism is coastal divergence (CD), a proxy for ice thickness anomalies based on late winter ice motion, quantified using Lagrangian ice tracking. CD gains predictive skill through the positive surface albedo anomalies, mirrored in reflected solar radiation (RSR), during melt season. Exploring the dynamic and thermodynamic contributions to minimum SIE predictability, RSR, initial SIE (iSIE), and CD are compared as predictors using a regional seasonal sea ice forecast model for 1 July, 1 June, and 1 May forecast dates for all Arctic peripheral seas. The predictive skill of June RSR anomalies mainly originates from open water fraction at the surface; that is, June iSIE and June RSR have equal predictive skill for most seas. The finding is supported by the surprising positive correlation found between June melt pond fraction (MPF) and June RSR in all peripheral seas; MPF anomalies indicate the presence of ice or open water, which is key to creating minimum SIE anomalies. This contradicts models that show correlation between melt onset, MPF, and the minimum SIE. A hindcast model shows that for a 1 May forecast, CD anomalies have better predictive skill than RSR anomalies for most peripheral seas.

KEYWORDS: Arctic; Albedo; Climate change; Feedback; Ice loss/growth; Ice thickness; Radiative fluxes; Shortwave radiation; Forecasting; Seasonal forecasting

1. Introduction

Since the beginning of the satellite era, the Arctic has witnessed large changes in the minimum sea ice extent (SIE), area, and mean thickness with long-term trends approximately equal to −12%, −14%, and −11% decade^{-1}, respectively (Rigor and Wallace 2004; Kwok 2018; Maslanik et al. 2011; Comiso 2012). Superimposed on these trends are large interannual variations (Serreze et al. 2007) that make seasonal and decadal forecasting of the minimum SIE a challenge (Stroeve et al. 2012, 2014). The changes in minimum SIE have been largest in the Pacific sector, with the largest trends found in the East Siberian (22%) and Chukchi (17%) Seas since 1979 (Onarheim et al. 2018). Variability in the minimum SIE is projected to increase during the transition from a perennial to a seasonal ice cover (Holland et al. 2011), making seasonal forecasts and decadal projections of the minimum SIE both more challenging, and more important in mitigating the political, economic, environmental, and social consequences of a changing Arctic climate (Blanken et al. 2017; Newton et al. 2017; Stephen 2018; DeRepentigny et al. 2020).

In an effort to improve SIE forecasting under a rapidly changing Arctic climate, the Study of Environmental Arctic Change (SEARCH) Sea Ice Outlook (SIO) was initiated in 2008—1 year after the drastic all-time record minimum of 2007—to assess the predictive skill of forecasting models currently in use in the community. These include statistical, heuristic, coupled sea ice–ocean and fully coupled sea ice–ocean–atmospheric models. An assessment report by SEARCH SIO covering the 2008–15 time period shows that the ensemble skill of the models is good when the minimum SIE lies on the long-term trend, but have difficulty forecasting the minimum SIE when large anomalies are present (Hamilton and Stroeve 2016).

Model studies also highlight the importance of sea ice thickness and sea surface temperature anomalies in the initialization of seasonal predictions of the minimum SIE (Blanchard-Wrigglesworth et al. 2011; Chevallier and Salas-Mélia 2012; Msadek et al. 2014; Guemas et al. 2016). For instance, two models with similar ice and ocean components but with different atmospheric components show similar skill in summer SIE forecasts (Msadek et al. 2014). Bushuk et al. (2017b) find a May “barrier of predictability” in the Geophysical Fluid Dynamics Laboratory global climate model; that is, forecasts initialized with May or earlier sea ice thickness anomalies in the peripheral seas do not demonstrate skill in predicting the minimum SIE. Rather, sea ice thickness anomalies present in May or later are amplified after melt onset by the ice albedo feedback (Bushuk et al. 2017a, 2020).

This link between sea ice thickness and surface albedo anomalies strengthens as the Arctic transitions from a perennial to a seasonal ice cover because a larger fraction of the ice pack consists of thinner, saltier, weaker, and more mobile first-year ice (FYI), which has a lower melting point and a lower surface albedo (Rigor et al. 2002). A simplified coupled ice–ocean model showed an increased sensitivity in ice–ocean albedo feedback since 2000 because of a thinner, more mobile ice cover.
and increased early summer offshore ice motion (Kashiwase et al. 2017). Similarly, Perovich et al. (2008) report a fivefold increase in the heat input to the upper ocean from positive anomalies in early summer open water fraction. Flatter FY1 ice also leads to a larger melt pond area compared to ridged multiyear ice (Perovich and Polashenski 2012). For instance, simulated melt pond fraction (MPF) from an ice–ocean coupled model was found to significantly correlate with the minimum SIE as early as May (Schröder et al. 2014). However, the fact that MPF in Baffin Bay, the Canadian Archipelago, and the central Arctic beyond the seasonal ice zone contributes to the correlation suggests that MPF may be correlated with a third parameter physically related to the minimum SIE (e.g., the Arctic Oscillation; Williams et al. 2016).

Sea ice thickness anomalies in peripheral seas, caused by anomalous late winter offshore ice motion (something that is not well resolved in current models) and later amplified by ice-albedo feedback during summer, may be useful in predicting the minimum SIE from observations. For instance, June reflected solar radiation (RSR) anomalies are significantly correlated with the September minimum SIE for the pan-Arctic area (Zhan and Davies 2017; Choi et al. 2014; Huang et al. 2019). As such, the skill of minimum SIE predictions from top-of-atmosphere (TOA) RSR is closely related to the contribution from surface anomalies (open water and melt ponds) rather than atmospheric anomalies (clouds, water vapor, aerosols, etc.) in June. This link, however, is not as robust for earlier forecast dates (Kapsch et al. 2016; Zhan and Davies 2017). The summer cloud effects are also debated. Choi et al. (2014) and Huang et al. (2019) attribute June RSR anomalies to both the cloud shielding effect and surface albedo anomalies, while Francis et al. (2005) find no cloud shielding effect with respect to sea ice melt and argue instead that downwelling longwave anomalies in the summer explain approximately 40% of the variability in the minimum SIE in Arctic peripheral seas.

Ultimately, dynamical processes are key to the generation of sea ice thickness anomalies that are amplified later in summer by thermodynamical processes. The mobility of the ice cover and sea ice drift speeds increased dramatically after the mid-1990s, following large positive Arctic Oscillation index anomalies and the associated flushing of multiyear ice out of the Arctic. Since then, late winter coastal divergence has been a more skillful predictor of the minimum SIE (Rigor et al. 2002; Rigor and Wallace 2004; Maslanik et al. 2007; Spreen et al. 2011). The area covered by thin ice after late winter (February–May) coastal divergence will grow to a thickness similar to the climatological summer melt (1.15–1.45 m) (Nikolaeva and Sesterikov 1970), leaving it vulnerable to thermodynamic retreat. This mechanism has been used to predict the minimum SIE at regional and pan-Arctic scales (Nikolaeva and Sesterikov 1970; Chevallier and Salas-Mélia 2012; Bushuk et al. 2017a; Williams et al. 2016; Brunette et al. 2019). Chevallier and Salas-Mélia (2012) report a similar critical sea ice thickness of 0.9–1.5 m as a useful metric to predict the minimum SIE up to 6 months in advance using a coupled global climate model. Williams et al. (2016) used late winter dynamic preconditioning area (or coastal divergence) in a Lagrangian ice model forced with observed sea ice drift to develop a skillful statistical model of the minimum pan-Arctic SIE. Nikolaeva and Sesterikov (1970), Brunette et al. (2019), and Krumpen et al. (2013) used a similar Lagrangian approach to skillfully predict the minimum SIE in the Laptev Sea from late winter coastal divergence area.

Other factors with potential predictive skill include cloud longwave forcing and ocean heat transport. Winter cloud forcing anomalies integrated from November to February using reanalysis data explain approximately 25% of the variance in the minimum SIE at a 90% confidence level in the East Siberian and Kara Seas, suggesting a potential predictive skill of winter radiative flux anomalies for the minimum SIE (Letterly et al. 2016). Liu and Key (2014) and Letterly et al. (2016) report on similar links between September SIE anomalies and integrated winter cloud anomalies from January to February and from November to February (respectively) advected until September. These results, however, may be circumstantial as both studies look at only one signature year, 2013 and 2007, respectively. Cao et al. (2017) merge in situ observation and reanalysis data to find similar spatial patterns between winter downward longwave anomalies and SIC anomalies during melt onset (mid-May–early June) but only looks at two anomalously low (1990, 2006) and high (1999, 2013) melt onset years without considering a link with the minimum SIE. Kapsch et al. (2016) use a fully coupled global climate model to report that winter cloud forcing has negligible influence, but spring and early summer cloud forcing impact the following September SIE. King et al. (2020) connect observed March longwave downwelling radiation and June/July longwave cloud radiative forcing with sea ice volume loss between March and October. However, no correlation is found between cloud forcing on shortwave radiation and computed sea ice volume for June and July, so the link between longwave cloud radiative forcing and sea ice volume loss remains unclear. Finally, ocean heat transport through the Bering Strait is suggested to influence late summer anomalous sea ice conditions by triggering the onset of sea ice melt (Woodgate et al. 2010). The sea ice retreat date in the Chukchi Sea correlates most strongly with Bering Strait ocean heat transport from April to June (Serreze et al. 2016). On decadal time scales, a study from the Community Earth System Model Large Ensemble showed that rapid declines in SIE were mainly correlated with ocean heat transport through the Bering Strait and the Barents Sea Opening where shallow continental shelves allow ice–ocean interaction to dominate (Auclair and Tremblay 2018).

The main goal of this study is to develop a regional and seasonal forecast and hindcast models of the minimum SIE for each peripheral sea using observations of RSR, initial SIE (iSIE), late winter coastal divergence, and ocean heat transport as predictors. In doing so, we also shed light on the sources of June RSR’s predictive skill of the minimum SIE (i.e., late winter dynamics preconditions surface albedo anomalies that are amplified with melt onset) using observed sea ice concentration (open water fraction), MPF, and longwave downwelling (atmosphere).

Results show that June iSIE anomalies are as good as or more skillful than June RSR anomalies for the seasonal forecast of the minimum SIE for all seas. Counterintuitively, we find that
while June MPF is negatively correlated with RSR in the central Arctic and landfast ice area (high MPF, low RSR), it is positively correlated in the peripheral seas (high MPF, high RSR). Finally, we find that lead time for minimum SIE forecasting can be extended by 2 months using late winter coastal divergence for three of the five peripheral seas compared to that from June RSR. In the Chukchi and East Siberian Seas, neither RSR nor late winter coastal divergence is skillful for earlier forecast dates.

This paper is structured as follows: section 2 describes the observational data used in this study. The Sea Ice Tracking Utility (SITU) used for quantifying late winter coastal divergence is described in section 3. In section 4, we identify and quantify the sources—open water fraction (sea ice concentration), MPF, and atmospheric components (longwave downwelling)—of RSR’s predictive skill of the minimum SIE. Finally, we present hindcast models using the linear trend, RSR, late winter coastal divergence, and spring ocean heat transport as predictors for each peripheral sea. Conclusions and future work are summarized in section 5.

2. Data

a. Sea ice concentration

We use the Daily NOAA/NSIDC Climate Data Record (CDR) of Passive Microwave Sea Ice Concentration (SIC) version 3 from January 1979 to December 2019 regridded on the 25 km × 25 km Equal-Area Scalable Earth (EASE) Grid (Meier et al. 2017; Peng et al. 2013). SIC from January 1979–July 1987 is obtained by including three other products that are not officially a part of the CDR as they are processed under different standards. SIC is the percentage of ocean area covered by sea ice. The data are derived using brightness temperatures from the Defense Meteorological Satellite Program (DMSP) Special Sensor Microwave/Imagers (SSM/I) and DMSP Special Sensor Microwave Imager/Sounder (SSMIS). We calculate the weekly and monthly SIC from the daily SIC data. The error is approximately 5% and up to 20% in winter and summer, respectively, compared to airborne or satellite remote sensing data of higher resolution than SSM/I and SSMIS instruments (Steffen et al. 1992; Meier et al. 2017). The higher error in summer is due to clouds and sea ice surface melt effects on the measured brightness temperatures (Meier et al. 2011). We define sea ice extent (SIE) as the total area of all grid cells with SIC ≥ 15%.

b. Radiative flux

We use the gridded monthly mean top-of-atmosphere (TOA) all-sky and clear-sky reflected solar radiation (RSR) and all-sky surface longwave downwelling (LWD) flux from the Clouds and the Earth’s Radiant Energy System (CERES) Energy Balanced and Filled (EBAF) Edition 4.1 (CERES Science Team 2019a,b; Kato et al. 2018; Loeb et al. 2018). CERES instruments are on the Terra and Aqua satellites and provide daily data coverage at a global scale with a spatial resolution of 1° × 1° from March 2000 to present (CERES Science Team 2018). TOA all-sky radiative fluxes are corrected using global mean energy budget constraints derived from in situ Argo observations (Loeb et al. 2009). CERES EBAF clear-sky TOA fluxes are corrected using a radiative transfer model that removes clouds but is initialized with identical properties to all-sky conditions such as surface temperature, temperature/humidity profiles, aerosols, and surface albedo. Satellite-based clear-sky fluxes are derived from cloud-free regions within a grid box and are weighted according to the cloud fraction identified by applying a cloud mask of higher resolution (Loeb et al. 2020). TOA-RSR is chosen over surface RSR since TOA irradiance is directly derived from satellite measurements with uncertainties of 2.5 and 5.4 W m⁻² for all sky and clear sky, respectively. Surface irradiance has a higher uncertainty of 11 W m⁻² (all sky and clear sky) as errors are introduced from input sources of satellite-derived cloud and aerosol properties, and temperature and specific humidity profiles from reanalysis (Kato et al. 2018; Loeb et al. 2020). Moreover, Choi et al. (2014) compare the previous version of CERES TOA and surface radiative flux anomalies and report that absorption and scattering by the atmosphere have minor effects on the absorbed solar radiation.

Monthly mean all-sky surface LWD fluxes are derived from gridded CERES SYN 1-deg-Month monthly mean surface fluxes, calculated from cloud properties derived from MODIS and geostationary satellites (CERES Science Team 2020). Errors in the surface LWD fluxes—associated with a bias in the cloud fraction viewed from the surface—are corrected using CALIPSO/CloudSat, MODIS, and geostationary satellites (CERES Science Team 2020). The degradation of the Terra MODIS water vapor channel that affects the nighttime cloud mask over polar regions (60°–90°N), causing a downward trend in LWD anomalies, is also corrected starting in January 2003 to match the cloud fraction derived from the Aqua satellite (CERES Science Team 2020). The overall uncertainty of the surface LWD is 9 W m⁻² (Loeb et al. 2020) and is larger for polar regions (12 W m⁻²; CERES Science Team 2020).

c. Melt pond fraction

We use version 2 of the Integrated Climate Data Center (ICDC) “clear-sky” melt pond fraction (MPF) data available in 8-day composites from 9 May to 13 September for the time period 2000–11 at a spatial resolution of 12.5 km × 12.5 km (Rösel et al. 2012). Note that the MPF is defined as the fractional area of a grid cell covered by melt ponds, as opposed to the fractional area of ice (SIC). In principle, the MPF relative to SIC could be used instead (i.e., MPF/SIC); however, the two datasets are not internally consistent (so that, e.g., MPF can be larger than SIC) and for this reason, we use MPF alone. MPF is derived using an artificial neural network algorithm on MODIS data at frequency bands 1, 3, and 4 in a grid cell size of 500 m. The neural network uses different surface reflectance values for snow, sea ice, melt ponds, and open water. “Almost clear-sky” MPF is defined as 12.5-km grid cells derived from more than 90% usable 500-m grid cells (Rösel et al. 2012). We use clear-sky MPF since all-sky MPF includes grid cells derived from a low fraction of usable 500-m grid cells and are flagged for increased uncertainty (if less than 10%) (Rösel et al. 2012). The
uncertainty of MPF is 6% (Rösel et al. 2012). The derived dataset was also compared with aerial photos from the Beaufort Sea in 2000, 2001, and 2008 NSIDC data from four sites located in the pan-Arctic and ship observations from the trans-Arctic Healy–Oden Trans-Arctic Expedition (HOTRAX) cruise in 2005. The approximate RMSE values are 11%, 10.7%, and 3.8%, respectively (Rösel et al. 2012).

d. Sea ice drift

We use the Weekly Polar Pathfinder (PPF) Sea Ice Motion Vectors, version 4 of NSIDC on the 25 km \( \times \) 25 km EASE grid from 1993 to 2019 (Tschudi et al. 2019b) together with the Sea Ice Tracking Utility (SITU; http://icemotion.labs.nsidc.org/SITU/), formerly known as the Lagrangian Ice Tracking System (DeRepentigny et al. 2016; Williams et al. 2016; Brunette et al. 2019). Weekly mean fields are calculated by averaging daily motion vectors. Daily motion vectors are derived using an optimal interpolation scheme to merge the Advanced Very-High-Resolution Radiometer (AVHRR), the Advanced Microwave Scanning Radiometer–Earth Observing System (AMSR-E), the Scanning Multichannel Microwave Radiometer (SMMR), the Special Sensor Microwave Imager/Sounder (SSMIS), and the Special Sensor Microwave Imager (SSM/I) passive microwave sensors, International Arctic Buoy Program (IABP) buoy data, and freestream estimates derived from the NCEP–NCAR geostrophic wind reanalysis (Tschudi et al. 2019b). The daily ice motion from satellite imagery is derived using a maximum-cross-correlation method (Emery et al. 1995). The optimal interpolation scheme uses weight for each sea ice motion vector based on input source’s accuracy and distance, and takes the average of the 15-highest-weighted ice motion vectors. This merged sea ice motion dataset is temporally and spatially complete (Tschudi et al. 2019a). Sea ice motion vectors were merged without buoy data to compare the two for accuracy assessment. Mean difference and RMS error between the daily merged vector and buoy data are 0.1 and 3.36 cm s\(^{-1}\), respectively, in the \( u \) component and 0.4 and 3.40 cm s\(^{-1}\) in the \( v \) component—with larger errors in the summer compared with the winter due to surface melt and increased cloud cover (Tschudi et al. 2019b). While a low bias can be observed in areas of lower temporal sampling of SMMR (Tschudi et al. 2019b), this study uses sea ice drift data from 1993 onward for all analyses presented and the bias does not affect the results. Lastly, a sea ice mask with a threshold of SIC\( \geq 15\% \) and a land mask are applied to sea ice motion fields to retrieve motion estimates from ice-covered ocean only and eliminate cells near coast and within the Canadian Archipelago as motion retrieval is unreliable in these areas due to mixed land, ocean, and ice cells (Tschudi et al. 2019a).

e. Ocean heat transport

We use monthly mean Bering Strait ocean heat transport (OHT) data for the time period 1998–2015 (Woodgate 2018). The monthly mean OHT is derived from a mooring identified as A3, which was deployed 35 km north of the Bering Strait at a depth of 57 m (Woodgate 2018). The A3 mooring was chosen according to its observation quality, completeness throughout the record period, and proximity to the Bering Strait (Woodgate 2018). However, the Alaskan Coastal Current is not sampled in the mooring, and this omission results in an underestimation of the Bering Strait transport by approximately 25% (Woodgate 2018). Despite the underestimation, the Bering Strait OHT data show a strong correlation in the velocity and temperature measurements with the A4 mooring deployed near the Alaskan coast and hence provide an accurate measure of the Bering Strait OHT anomalies (Woodgate 2018). The uncertainty in the OHT estimates is lower than 5% (Woodgate 2018).

3. Methods

We present a regional seasonal forecasting model of the minimum SIE for each peripheral sea of the Arctic Ocean. Following Nikolaeva and Sesterikov (1970), Krumpen et al. (2013), Williams et al. (2016), and Brunette et al. (2019), we use late winter coastal divergence area, referred below as coastal divergence (CD), as a predictor of the September minimum SIE. We use SITU to calculate CD. At an initial time (week X, from here WX), we place tracers in every sea ice–covered grid cell in the 25 km \( \times \) 25 km EASE-grid. Using sea ice motion vectors from the PPF dataset, we advect tracers at a weekly time step from start week WX until the week of 1 May (W18), 1 June (W22), and 1 July (W26), for each year, from 1993 to 2019. At each time step, advected sea ice tracers lying outside the SIC\( \leq 15\% \) threshold are flagged as inactive and no longer advected. At the end of the integration, we quantify the area of CD with the number of grid cells that are free of tracers in each Arctic peripheral sea (Fig. 1). These time series of regional CD (integrated over different lengths of the winter–spring season) are used to produce 1 May, 1 June, and 1 July forecasts of the regional minimum SIE. The error estimate on the CD area is therefore 625 km\(^2\) (25 km \( \times \) 25 km) multiplied by the characteristic length (parallel to the coast) of a peripheral sea.

DeRepentigny et al. (2016) compared sea ice drift simulations from the PPF dataset with IABP buoy data to quantify tracking error in SITU. For a weekly temporal resolution, the median error in trajectories is 7% and the upper-quartile error is 16% of the total distance traveled. The trajectory error is about 25 km and 36 km for a 12-week (from the first week of March to the first week of June) and 17-week (from the first week of February to the first week of June) advection, respectively.

Predictability of the minimum SIE is analyzed for each of the Arctic peripheral seas, as defined in NSIDC (ftp://sidads.colorado.edu/DATASETS/NOAA/G02186/ancillary/; see also Fig. 2). The Barents and East Greenland Seas are not included in this study as sea ice is not present in late summer. We also note that while we study the surface conditions using SIC and MPF, we do not consider snow morphology, which is also a contributing factor, as it is beyond the scope of our study and stands as one of the limitations.

All datasets are interpolated using the bilinear method on the EASE-grid with a 25-km resolution. We subtract the climatological mean and linearly detrend the datasets to remove seasonal and secular trends in order to focus on the interannual variability. From here on, SIC, initial SIE (iSIE, as a predictor of the minimum SIE), SIE, RSR, LWD, MPF, and OHT refer
to monthly anomalies and CD refers to integrated coastal divergence area anomalies unless specified otherwise. Monthly anomalies of June, May, and April refer to 1 July, 1 June, and 1 May forecasts, respectively. The Pearson correlation coefficients presented in this study are significant at the 95% confidence level, unless specified otherwise.

4. Results and discussion

a. RSR predictive skill: Atmosphere versus surface contributions

We first aim to quantify sources of RSR’s predictive skill of the minimum SIE from the atmosphere (LWD) and surface conditions (melt pond, open water) for each peripheral sea and forecast lead time. To this end, we calculate the Pearson correlation coefficients between clear-sky RSR and all-sky RSR (surface), all-sky surface LWD and all-sky RSR (atmosphere), SIC and clear-sky RSR (open water) and clear-sky MPF and clear-sky RSR for April, May, and June (Fig. 3). The clear-sky RSR and all-sky surface LWD correlation maps indicate the fraction of variance explained by the surface (melt ponds, open water, sea ice thickness, snow morphology) and the atmosphere (water vapor, clouds), respectively. The SIC and clear-sky MPF correlation maps indicate the fraction of variance explained by open water and melt pond, respectively. All aforementioned correlations are computed over the 2000–19 period, with the exception of the clear-sky MPF/clear-sky RSR correlation, which is computed over the 2000–11 period due to the availability of the MPF data. The correlations are not sensitive to the choice of the period except for the central Arctic—a region of low SIC variability—where the explained variance by all-sky surface LWD in all-sky RSR increases from 26%–30% (2000–19) to 33%–50% (2000–11) for April–June. However, the larger atmospheric contribution to the variability of all-sky RSR in the central Arctic supports the finding that atmospheric and surface effects are both important in low SIC variability regions (discussed below). We use the 2000–19 period where applicable in Fig. 3 to achieve more robust statistics. The explained variance is computed from the mean correlations that are within the 95% confidence level and within the regions with SIC variability larger than 5%.

Clear-sky RSR explains between 60% and 71% of the variance in all-sky RSR in the peripheral seas for all forecast dates (Fig. 3, first column). All-sky LWD is negatively correlated in the Kara Sea, indicating a positive feedback from the presence of clouds (i.e., low SIC, low RSR, and high cloud/LWD). In the central Arctic where SIC variability is low, all-sky LWD

![Fig. 1. (a) Initial and (b) final positions of sea ice tracers (green dots) advected from early November 2006 (W45) until the first week of June 2007 (W22) using the Sea Ice Tracking Utility (SITU). Blue shading shows the SIC in the background. Note that most of the coastal divergence, inferred from the area with no green dots, in each peripheral sea occurs in late fall and early winter when the pack is more mobile. We show an early November start week as an example instead of a late winter start week for the sake of clarity as the signal in coastal divergence is larger.](image)

![Fig. 2. Arctic map including the definitions of peripheral seas: the Beaufort, Chukchi, East Siberian, Laptev, and Kara Seas. The jagged edges along each peripheral sea give an indication of the spatial resolution of the EASE-grid used in this study.](image)
explains 26%–30% of the variance in all-sky RSR (positively correlated: high cloud, high RSR/LWD), indicating that both surface and atmospheric effects are important in regions of low SIC variability (Fig. 3, second column). We conclude that the surface conditions ($r^2 = 0.60–0.71$) dominate the variability in TOA-RSR signal and that the atmosphere, while being non-negligible in certain regions and months, is of less importance, in accord with Zhan and Davies (2017).

The surface conditions can be broken into two parts: melt pond and open water fraction. In the peripheral seas open water fraction explains 51%–64% of the variance of clear-sky RSR for all forecast dates while clear-sky MPF explains 4%, 29%, and 0% in clear-sky June, May, and April RSR, respectively (see Fig. 3). Note that MPF derived under all-sky conditions does not correlate with all-sky RSR for any of the peripheral seas. The fact that MPF and RSR are only significantly correlated under clear-sky conditions implies that the effects of the atmosphere and MPF on all-sky RSR are comparable in magnitude. Given that the effect of the atmosphere on RSR is of second order compared to the surface (Fig. 3, first column), we conclude that MPF’s effect on RSR is also of secondary importance when compared to that of the open water/ice signal. While open water fraction (SIC) explains most of the variance in clear-sky RSR for all months, the area over which the variability of SIC is above the threshold ($s > 0.05$) decreases from June (when it covers most of the peripheral seas) to May and April when it covers much smaller areas limited to coastal water polynyas (Morales Maqueda et al. 2004; Preußer et al. 2019).

We note that clear-sky MPF in June is positively correlated with clear-sky RSR in all peripheral seas except over land fast ice (in the Laptev and western East Siberian Seas) and in the central Arctic (Fig. 3d), where SIC variability is low. This is
Table 1. Uncertainties in Pearson correlation coefficients between detrended June RSR, June SIE, and the minimum SIE anomalies for the time period 2000–19 for each Arctic peripheral sea. Uncertainties are calculated from a bootstrap analysis of 1000 resampling of n = 20 elements.

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<thead>
<tr>
<th></th>
<th>June RSR</th>
<th>June SIE</th>
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<tbody>
<tr>
<td>Beaufort</td>
<td>0.10</td>
<td>0.05</td>
</tr>
<tr>
<td>Chukchi</td>
<td>0.20</td>
<td>0.14</td>
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<tr>
<td>East Siberian</td>
<td>0.19</td>
<td>0.20</td>
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<tr>
<td>Laptev</td>
<td>0.09</td>
<td>0.10</td>
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<tr>
<td>Kara</td>
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Because in the peripheral seas, where both open water and sea ice are present, MPF anomalies are synonymous with the presence or absence of sea ice (no sea ice, no melt ponds, less RSR: positive correlation), whereas in the central Arctic where sea ice is always present, MPF anomalies are a more accurate description of the fractional cover by melt ponds (more melt ponds over sea ice, less RSR: negative correlation). This suggests again that open water fraction rather than MPF is key for the predictability of the minimum SIE. The positive correlation in the peripheral seas is counterintuitive and contradictory to previous studies arguing that May or May–June MPF is a skillful predictor of the minimum SIE (Schröder et al. 2014; Liu et al. 2015).

In the central Arctic, June MPF still explains 42% of the variance in clear-sky RSR where correlation is significant, but SIC variability is less than 5%. At high latitudes, between 80° and 88°N, SIC is typically higher, ice is fresher and thicker and therefore less permeable to surface runoff from melt ponds, leading to a maximum MPF per grid cell despite the sun being lower on the horizon (Tschudi et al. 2008; Rösel et al. 2012). Below, we compare predictors (iSIE, RSR, and CD) of their predictive skill of the minimum SIE in light of the results above for all peripheral seas of the Arctic and for all forecast dates.

b. Predictive skill of RSR, iSIE, and CD

For the most part, the predictive skill of RSR and iSIE (or equivalently, sea ice area; results not shown) is similar (within uncertainty; see Table 1) and explain between 27% and 62% of the variance in the minimum SIE for peripheral seas where correlation is significant for the month of June (Figs. 4a,b).

In May and April, they mostly lose their predictive skill in agreement with previous studies showing a loss of early summer iSIE’s predictability for detrended minimum SIE when forecast lead times are greater than 3 months (Figs. 4d,e.g,h; Lindsay et al. 2008; Blanchard-Wrigglesworth et al. 2011). CD has similar skill as RSR and iSIE for a 1 July forecast and remains skillful for 1 June and 1 May forecasts except for the Chukchi and East Siberian Seas, where other dynamical and thermodynamical factors are important [see sections 4b(2) and 4b(3) below]. We note that 1 July is past the melt onset date; as such, a 1 July CD forecast is in part due to a summer dynamic loss, or ice advected offshore leaving open water behind, and in part due to sea ice thickness anomalies from CD occurring before the melt onset. The increased skill for a 1 July forecast is present despite increased error in summer sea ice drift estimates. Lastly, CD and RSR have similar skill (within uncertainty) whenever they are both significant (Table 1; see also Fig. A1 in the appendix), whether we consider the 1993–2019 or the 2000–19 time period (results not shown).

We now discuss regional predictability for each peripheral sea separately and for all forecast dates.

1) Beaufort Sea

In the Beaufort Sea, iSIE and RSR’s predictive skill of the minimum SIE is high ($r^2 = 0.61; 0.52$) and significant for the month of June. In May, iSIE and RSR have lower predictive skills with $r^2 = 0.15$ and 0.36 (significant at the 90% and 95% confidence level, respectively). iSIE and RSR both show no predictive skill for the month of April. CD, however, remains skillful ($r^2 = 0.52, 0.41, 0.30$) for 1 June, 1 May, and 1 April forecast dates, respectively (Fig. 4). The comparable skill between June RSR and 1 July CD supports the idea that the predictive skill of June RSR comes from sea ice thickness anomalies at the onset of the melt season (Nikolaeva and Sesterikov 1970; Chevallier and Salas-Mélia 2012; Bushuk et al. 2017a; Williams et al. 2016; Brunette et al. 2019).

The predictive skill of iSIE and RSR in the Beaufort Sea is linked with the presence of open water in June and with the spatial extent of the Amundsen Gulf polynya in May (Figs. 3c,g). In May, RSR shows higher predictive skill than iSIE (see Fig. 4). This is in agreement with the fact that SIC explains 56% of the variance in clear-sky RSR, presumably because other surface components (e.g., snow depth/morphology, ice thickness) also play a role (Fig. 3g). Lastly, the predictive skill of May iSIE is lower than that of June as the area of open water decreases earlier in the season (Figs. 3c and 4d). In April when the area of SIC variability greater than 5% is nearly zero, both iSIE and RSR lose skill.

In this sea, while both coastal convergence and divergence are present in winter, late winter CD gives predictability for the entire study period. For instance, a large fraction (55%) of tracers were advected out of the Beaufort Sea between the third week of March (W12) and 1 May 2008, a year with one of the lowest SIE minima (regionally) in the historical records (see also Hutchings and Rigor 2012). Our results are in accord with the findings of Kimura et al. (2013), who observe a steady divergence of sea ice tracers in the Beaufort, Laptev, and Kara Seas from 1 December to 30 April in 2003–11 with a similar ice tracking system using daily ice velocity from the satellite passive microwave sensor AMSR-E data. Finally, we note that CD remains a skillful predictor of the minimum SIE for a 1 June forecast (although with a smaller correlation coefficient, $r = –0.52$) for the entire satellite record (1979–present), when a thicker and less mobile ice cover was present.

2) Chukchi Sea

In the Chukchi Sea, iSIE, RSR, and CD have similar (within uncertainty) predictive skill of the minimum SIE ($r^2 = 0.35$, 0.27, and 0.14) for the month of June and lose skill for the months of May and April (Fig. 4). This suggests that other processes govern the interannual variability in the minimum SIE in this sea. For instance, Bering Strait OHT in spring is a
skillful predictor of June and July SIE through anomalies in sea ice melt (Woodgate et al. 2010; Lenetsky et al. 2021) and is responsible for rapid sea ice declines in forced climate simulations (Auclair and Tremblay 2018). Francis et al. (2005) used LWD, winds, and sensible heat data derived from the TIROS Operational Vertical Sounder (TOVS) and report that the variance in minimum SIE anomalies in the Chukchi Sea is primarily explained by summer processes—that is, LWD from June to September (~20%–55%), advective heat in the month before the maximum SIE retreat (~10%), and meridional winds early in the melt season (~25%). The fact that CD integrated until 1 July has predictive skill indicates that summer
dynamics influence the variability in SIE in the Chukchi Sea (Fig. 4c). Results from a multivariate model that include Bering Strait OHT are presented in section 4c below.

Finally, clear-sky RSR shows no predictive skill for a 1 July forecast in the Chukchi Sea, contrary to all-sky RSR (and all other peripheral seas). This suggests that early summer atmospheric radiative fluxes (i.e., clouds) also play a role in this peripheral sea (results not shown).

3) EAST SIBERIAN SEA

In the East Siberian Sea, iSIE and RSR have similar predictive skill for the minimum SIE in June ($r^2 = 0.31, 0.42$) and lose all predictive skill in May and April. In May, iSIE no longer has predictive skill because SIC is highly and significantly correlated with clear-sky RSR only in small regions along the flaw-lead polynya (see Figs. 4d and 3g). In the East Siberian Sea, sea ice motion is mostly parallel to the shore along the circumpolar flaw lead polynya (Kwok et al. 2013), and is therefore less likely to produce sea ice thickness anomalies over extended areas (as in the neighboring Laptev Sea). We hypothesize that this, combined with low SIC variability at this time of year, potentially explains the loss of skill in May iSIE. This is in line with the fact that CD has low (significant at the 90% confidence level) predictive skill for the minimum SIE for a 1 July forecast, and no predictive skill for 1 June and 1 May forecasts (Figs. 4c,f,i; see the appendix for more discussion).

In general, there is more sea ice convergence in the East Siberian Sea—assessed from our tracer advection—compared to other peripheral seas despite some interannual variability (results not shown). This is consistent with findings from Kwok (2006) and Kimura et al. (2013), who also report convergent winter ice motion in this peripheral sea from a similar satellite-based ice tracking algorithm. An anecdotal evidence of large sea ice convergence in the East Siberian Sea occurred in the winter of 2017 when Russian ice breakers Kapitan Dranitsyn and Admiral Makarov were beset on their way to Arkhangelsk in the East Siberian Sea from thick ridged ice while on a mission to test the northern sea route in a warming Arctic (Staalesen 2017). For this reason, June RSR and iSIE are better predictors of the minimum SIE in this peripheral sea.

Finally, while there is little offshore ice motion in late winter in the East Siberian Sea, Francis et al. (2005) report on summer LWD anomalies explaining approximately 35% of the variance in the minimum SIE with southerly wind anomalies also having some influence on the maximum retreat (~10%) through sea ice advection (Rigor et al. 2002).

4) LAPTEV SEA

In the Laptev Sea, iSIE and RSR show similar and high predictive skill in June ($r^2 = 0.62, 0.45$). Earlier forecasts using iSIE decrease in skill from May ($r^2 = 0.14$; significant at the 90% confidence level) to April ($r^2 = 0.09$; nonsignificant) while RSR remains skillful ($r^2 = 0.36$ and $r^2 = 0.45$; Figs. 4d,e,g,h). This loss of iSIE’s predictive skill occurs despite the fact that May SIC anomalies explain 53% of mean variance in clear-sky RSR (mostly at the northern edge of the coastal polynya); however, the areal extent where SIC variability is greater than 5% is much smaller compared to June (Fig. 3g). The fact that clear-sky RSR has similar predictive skill of the minimum SIE to that of all-sky RSR suggests that the atmosphere is not responsible for this difference in predictive skill between iSIE and RSR, leaving MPF and/or sea ice thickness anomalies as the potential source of May RSR predictive skill in the Laptev Sea (results not shown).

We observe a significant correlation between May RSR and 1 June CD in the Laptev Sea (results not shown). RSR is a function of the surface albedo; surface albedo, in turn, is affected by both open water area and sea ice thickness (Light et al. 2015). The fact that SIC and MPF only explain a fraction of clear-sky RSR variance (Figs. 3g,h) suggests that sea ice thickness is responsible for this correlation. Another interpretation is simply that uncertainties and the short length of the MPF time series are responsible, as opposed to the lack of skill of MPF.

In April, we argue that RSR remains a skillful predictor (contrary to iSIE) because of atmospheric contribution; that is, clear-sky RSR explains a small fraction of the variance in all-sky RSR (44%), compared with May (72%) and June (72%) (Figs. 3, first column). Moreover, clear-sky RSR shows lower predictive skill of the minimum SIE than all-sky RSR, further supporting the idea that atmospheric radiative fluxes play a role (results not shown).

The increased surface air temperature associated with the ubiquitous presence of a polynya at the northern edge of the Laptev Sea may explain why RSR remains skillful in April contrary to iSIE (see polynya signature in Figs. 3g,k; Barber and Massom 2007; Bareiss and Görgen 2005). In April, the net ocean–atmosphere heat flux, including shortwave radiation, can cause a surface ocean warming (Willmes et al. 2011), despite the high zenith angle (Morales Maqueda et al. 2004; Wang et al. 2009); this increases the water vapor content in the atmosphere and clouds (Bareiss and Görgen 2005). While surface albedo increases dramatically with increasing solar zenith angle under clear-sky conditions, the presence of clouds increases diffuse radiation that lowers surface albedo (i.e., high polyynas, high clouds, low RSR, low minimum SIE; Hartmann 2016; Gardner and Sharp 2010). Choi et al. (2014) also attribute the positive correlation found between cloud fraction and absorbed solar radiation in April and May to the cloud effect at higher solar zenith angles.

CD is a skillful predictor in the Laptev Sea for all forecast dates because of the ubiquitous offshore ice motion in late winter. Results from the Lagrangian tracer experiment also show the largest percentage of tracers lost due to CD (and ice melt for a July forecast) in this peripheral sea. These results are in accord with the findings of Brunette et al. (2019) and Kimura et al. (2013), who report a significant predictive skill in the Laptev Sea for a 1 May forecast and a steady divergence of sea ice tracers integrated from 1 December to 30 April.

5) KARA SEA

In the Kara Sea, iSIE and RSR both have low predictive skill of the minimum SIE for June (at the 90% confidence level; Fig. 4). This is in agreement with Choi et al. (2014), who report
Table 2. Correlation coefficients ($r^2$), adjusted correlation coefficients ($r^2$) and standard deviation of hindcast error ($\sigma_{\text{err}}$) in millions of square kilometers for hindcast models of the minimum SIE from 2000 to 2019 for each peripheral sea using linear trend (M1), linear trend and 1 May coastal divergence area anomalies (CD, M2), and linear trend and April reflected solar radiation (RSR) anomalies (M3). Bold characters indicate significant improvement in predictability using an additional predictand.

<table>
<thead>
<tr>
<th>Model</th>
<th>Predictors</th>
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<th>$r^2$</th>
<th>$\sigma_{\text{err}}$</th>
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</tr>
<tr>
<td></td>
<td>M2 Linear trend, 1 May CD</td>
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<tr>
<td></td>
<td>M3 Linear trend, April RSR</td>
<td>0.43</td>
<td>0.36</td>
<td>0.14</td>
</tr>
<tr>
<td>Chukchi</td>
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<td>0.32</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>M2 Linear trend, 1 May CD</td>
<td>0.50</td>
<td>0.44</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>M3 Linear trend, April RSR</td>
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<td>0.30</td>
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</tr>
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</tr>
<tr>
<td></td>
<td>M2 Linear trend, 1 May CD</td>
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<tr>
<td></td>
<td>M3 Linear trend, April RSR</td>
<td>0.46</td>
<td>0.40</td>
<td>0.09</td>
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</tbody>
</table>

For May and April, both iSIE and RSR lose skill. This is due to the significant and negative correlation found between May MPF and clear-sky RSR in this sea ($r = -0.71$; Fig. 3h). As discussed above, this is due to open water anomalies having a larger impact on the minimum SIE anomalies as opposed to melt pond fraction. In April, predictive skill is lost due to lack of surface albedo anomalies.

CD is a skillful predictor of the minimum SIE for all forecast dates. The Kara Sea also shows consistent CD (as for the Laptev Sea) and the highest percentage of tracers lost due to coastal divergence and melt (for 1 July forecasts) for all forecast dates (results not shown), in line with the steady divergence of sea ice tracers reported by Kimura et al. (2013). This confirms the hypothesis that open water anomalies created by offshore advection of sea ice dominate the predictability in this sea.

In summary, RSR and iSIE have similar predictive skill in most peripheral seas and their predictive skill is mainly due to open water at the surface. Since open water anomalies are preconditioned by CD, most of the predictive skill in RSR and iSIE is explained by CD. For a 1 June forecast, RSR is a more skillful predictor than iSIE in the Beaufort and Laptev Seas, as RSR appears to reflect other surface conditions like ice thickness anomalies preconditioned from CD and snow morphology through surface albedo. For a 1 May forecast (i.e., before melt onset), RSR and iSIE are both nonskillful predictors of the minimum SIE in the peripheral seas. One exception is the Laptev Sea where RSR shows significant skill, most likely from coastal polynyas and associated atmospheric contribution. Overall, for most peripheral seas, RSR and iSIE’s predictive skill that relies on summer thermodynamics is capped at a lead time of 3 months (1 July forecast) and CD remains skillful at a longer lead-time for the Beaufort, Laptev, and Kara Seas. Lastly, sea ice signal dominates the variability in RSR and MPF’s effect is of secondary importance in the peripheral seas. This result contradicts studies stating that spring/early summer MPF is a skillful predictor of the minimum SIE (Schröder et al. 2014; Liu et al. 2015). Consequently, MPF is not considered as one of the predictors in the hindcast models in the following section.

c. Minimum SIE hindcasts

We develop three hindcast models M1, M2, and M3 for the minimum SIE for 2000–19 in each peripheral sea based on the linear trend (M1), linear trend + CD integrated from start week WX (see Table A1) to 1 May (M2), and linear trend + April RSR (M3). The 2000–19 period is selected based on availability of RSR data. A forecast date of 1 May is chosen for our hindcast models based on the longest lead time CD offers for most regional seas. We chose CD as a reference since our goal is to show that CD—a proxy for sea ice thickness anomalies—is at the origin of RSR’s predictive skill through the amplification of surface albedo anomalies after melt onset.

The simplest model (M1) is written mathematically as $\text{SIE}_p = a + C$, where $\text{SIE}_p$ is the predictand, $t$ is time (year), and $C$ is a constant. M2 is based on the linear trend and 1 May CD ($X_1$) as predictors: $\text{SIE}_p = a + bX_1 + C$. M3 is based on the linear trend and April RSR ($X_2$) as predictors: $\text{SIE}_p = a + cX_2 + C$. All constants ($a$, $b$, and $c$) are determined from the method of least squares. We use the adjusted coefficient of determination ($r^2$) to take into account the fact that increasing the number of predictors in a statistical model increases the correlation even if the new predictor is not correlated with the predictand.

The linear trend in M1 explains 32%, 32%, 21%, 32%, and 39% of the variance in the minimum SIE ($r^2$) in the Beaufort, Chukchi, East Siberian, Laptev, and Kara Seas, respectively.
In general, the fraction of variance explained by the linear trend is related to the relative magnitude of the interannual variability in the minimum SIE compared to the trend (Fig. 5). For instance, the linear trend explains the smallest fraction of the variance in the East Siberian Sea where the interannual variability is large and explains the largest fraction of the variance in the Kara Sea where the interannual variability is small and the trend is large (see Fig. 5). The large interannual variability in the East Siberian Sea shows that winter (strong convergence event related to persistence of ice thickness anomalies) and summer mechanisms explain the rest of the variance in minimum SIE.

For the East Siberian Sea, the interannual variability of the minimum SIE is small relative to that in 2007 and 2012 when two all-time record low minima in SIE occurred (black dashed line in Fig. 5c). The Beaufort and Chukchi Seas also show large negative SIE anomalies for those two record minimum years (black dashed line in Figs. 5a,b); however, those anomalies are not significantly larger than the general interannual variability in these peripheral seas. It is interesting to note that the East Siberian Sea is responsible for the all-time record minima, while the Laptev, Beaufort, and Kara Seas show systematic CD. In summer 2007, a semipermanent high over the Beaufort Sea and a strong positive dipole anomaly (Wang et al. 2009) led to sustained winds exporting sea ice out of the Arctic and large solar radiation anomalies in the largely ice-free Beaufort Sea with summer sea surface temperature anomalies reaching up to 5°C (Steele et al. 2008). In summer 2012, an extreme storm that formed over the East Siberian Sea in August led to surface divergence and facilitated summer melt (Simmonds and Rudeva 2012; Parkinson and Comiso 2013).

Hindcast model M3 (linear trend + April RSR) does not significantly improve the skill of a 1 May forecast compared to that based on only the linear trend (M1), except for the Laptev Sea (see Table 2). The Laptev Sea experiences a significant increase from M1 to M3 by 28% (\(r^2_{M1} = 0.32\) to \(r^2_{M3} = 0.48\)) and is also higher than that of M2 (\(r^2_{M2} = 0.46\)).

Finally, we find that \(\hat{F}\) from a hindcast model based on linear trend and June RSR (Beaufort: 0.65, Chukchi: 0.48, East Siberian: 0.52, Laptev: 0.60, Kara: 0.46) are comparable (within 10%) to a hindcast model based on linear trend and June iSIE.
models (Williams et al. 2016). are expected to perform equally well in theory as the hindcast tive skill of the minimum SIE, we note that forecasting models over the deep Canadian Basin where ocean heat flux and sea dynamical processes and the sea ice edge retreating northward Chukchi Sea, but loses significance with August and September SIE. The loss of significance after July is attributed to summer

5. Conclusions

This study compares a regional seasonal sea ice forecasting model of the minimum sea ice extent (SIE) using satellite-derived reflected solar radiation (RSR), initial SIE (iSIE), and sea ice drift to show that late winter coastal divergence area (CD) is the best predictor over the shelf seas, and in fact explains most of the predictive skill in RSR and iSIE. The key conclusions are as follows:

- RSR’s predictive skill of the minimum SIE mainly arises from open water anomalies and is essentially equivalent to iSIE.
- In June, melt pond fraction (MPF) is negatively correlated with RSR in the central Arctic; however, it is positively correlated (counterintuitively) in the peripheral seas. This is because large MPF in June in the peripheral seas implies the “presence of sea ice” at the surface and low MPF implies absence of sea ice or open water. We find that June RSR has predictive skill in all the peripheral seas because the signal from open water is larger than the signal from the “presence of ponded sea ice.”
- RSR and iSIE have similar predictive skill of the minimum SIE for all peripheral seas for a 1 July forecast. RSR has better skill than iSIE in the Beaufort and Laptev Seas for a 1 June forecast, and in the Laptev Sea for a 1 May forecast. For the Beaufort and Laptev Seas, May iSIE has lower predictability as it does not reflect the albedo variability from other surface anomalies (e.g., snow depth, sea ice thickness). April RSR has predictive skill from atmospheric contribution due to high concentration of polynyas.
- CD has similar predictive skill of the minimum SIE compared to RSR for most peripheral seas for a 1 July forecast. For longer lead times, CD and RSR both lose skill in the East Siberian and Chukchi Seas. In the Beaufort and Kara Seas, only CD remains skillful for all forecast lead times.
- The predictive skill of the minimum SIE in the East Siberian and the Chukchi Seas is dominated by summer processes. In the Kara Sea, CD remains always skillful for all forecast dates while RSR never shows significant predictive skill. This confirms the hypothesis that open water anomalies created by coastal divergence of sea ice dominates the predictability in this sea.
- A simple hindcast model for 2000–19 using the linear trend (M1) explains 32%, 32%, 21%, 32%, and 39% of the variance in the minimum SIE ($r^2$) in the Beaufort, Chukchi, East Siberian, Laptev, and Kara Seas, respectively. The largest explained variability in the Kara Sea highlights the strong trend toward a seasonal ice cover. The lowest explained variance in the East Siberian Sea show that other seasonal processes explain the rest of the variance to varying degrees.
- The largest improvement in predictive skill from adding 1 May CD to the linear trend was surprisingly found in the Beaufort Sea (from $r_{M1}^2 = 0.32$ to $r_{M2}^2 = 0.48$ and from $\sigma_{errM1} = 0.15$ to $\sigma_{errM2} = 0.13$) and the Kara Sea (from $r_{M1}^2 = 0.39$ to $r_{M2}^2 = 0.55$ and from $\sigma_{errM1} = 0.09$ to $\sigma_{errM2} = 0.08$). For the Beaufort Sea, CD remains a skillful predictor of the minimum SIE for the entire satellite record (1979–present) and adds more predictive skill of the minimum SIE than in the Laptev Sea, where it is an ice factory due to the presence of steady offshore ice motion throughout winter. The Laptev Sea gains skill from 1 May CD (from $r_{M1}^2 = 0.46$ and from $\sigma_{errM1} = 0.13$), slightly less than the 21% reported by Brunette et al. (2019). While 1 May CD adds predictive skill in the Kara Sea, the implication of the minimum SIE predictability in this sea is minor due to its fast transition to a seasonal ice cover. In fact, the predictive skill ($r_{M2}^2$) is better for the time period of 1993–2019 than for 2000–19 when summer SIE in this sea was greater.
- Besides the Laptev Sea (where April RSR shows higher improvements in skill than 1 May CD) and the East Siberian Sea (where neither 1 May CD nor April RSR shows improved skill), 1 May CD has better predictive skill of the minimum SIE than April RSR for the same lead time in all peripheral seas.
- Bering Strait ocean heat transport (OHT) does not improve predictive skill in the Chukchi and the East Siberian Seas. In the two peripheral seas, the ocean–sea ice interaction with OHT is lost further into the summer as the SIE retreats farther north with summer melt and advection.

Our study identified key dynamic and thermodynamic mechanisms that govern the minimum SIE for each Arctic peripheral sea. CD is skillful for 1 May and 1 June seasonal forecasts in the Beaufort, Laptev, and Kara Seas. We note that latency of RSR and the Polar Pathfinder (PPF, for CD) data-sets makes it unrealistic to produce seasonal forecasts in real-time. However, the Pan-Arctic Ice Ocean Modeling and Assimilation System (PIOMAS) is updated in near real time twice a month and can be an alternative to the PPF dataset. It is the authors’ hope that this study will encourage near real time production of these datasets by demonstrating the potential of improving seasonal forecasts of the minimum SIE. Minimum SIE is, after all, a critical parameter in operational management of coastal infrastructure, transportation, habitat protection, and subsistence hunting for Arctic communities. Future
work includes identifying sources of correlation between longwave downwelling (LWD), CD, and the minimum SIE. This is based on the hypothesis that LWD and CD may be correlated with a tertiary variable (i.e., large-scale atmospheric circulation) that affect the minimum SIE.

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Data availability statement. All sea ice concentration data used or created during this study are openly available from NSIDC, the National Snow and Ice Data Center, at https://doi.org/10.7265/N59P2ZT as cited in Meier et al. (2017). All CERES radiative flux data used during this study are available by order from https://ceres.larc.nasa.gov/data/. MODIS Arctic melt pond cover fractions (v02) were obtained for 9 May 2000–13 September 2011 from the Integrated Climate Data Center (ICDC; icdc.cen.uni-hamburg.de/), University of Hamburg, Hamburg, Germany, at ftp://ftp-icdc.cen.uni-hamburg.de/arctic_meltponds/ as cited in Rösel et al. (2012). All Polar Pathfinder sea ice drift data used during this study are openly available from the NASA National Snow and Ice Data Center Distributed Active Archive Center at https://doi.org/10.5067/INAWUW07QH7B as cited in Tschudi et al. (2019b). Monthly ocean heat transport data are openly accessible at http://psc.apl.washington.edu/HLD as cited in Woodgate (2018).
Table A1. Start week (WX) for peak Pearson correlation coefficients between detrended anomalies of coastal divergence (CD) area integrated from start week WX to 1 July, 1 June, and May, and the minimum SIE for each Arctic peripheral sea. The peak correlations are shown in parenthesis next to the optimal start week. Common start week WX for each peripheral sea is shown in bold; |Δr| is the difference in the correlation coefficients between the common start week and start week with peak correlation. The |Δr| is smaller than the computed correlation uncertainties for all peripheral seas (see Fig. A1).

<table>
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<tr>
<th>Forecast date</th>
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<td>1 July</td>
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<td>W15 (−0.65)</td>
<td>W12 (−0.55)</td>
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<td>W15 (−0.35)</td>
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<td>W5 (−0.24)</td>
<td>W5 (0)</td>
</tr>
<tr>
<td>Common start week (</td>
<td>Δr</td>
<td>)</td>
<td>W5 (−0.73)</td>
<td>W5 (−0.53)</td>
</tr>
</tbody>
</table>

APPENDIX

Regional Seasonal Forecast Based on Coastal Divergence: Lead Time and Predictive Skill of the Minimum Sea Ice Extent

Following Williams et al. (2016) and Brunette et al. (2019), we present a regional analysis of late winter coastal divergence area anomalies (CD) for 1 July, 1 June, and 1 May forecast dates. CD is a proxy for ice thickness anomaly before the melt onset and a skillful predictor for the Laptev Sea and pan-Arctic. To this end, we present the correlation coefficients between CD integrated from start week WX (W3–W25) to forecast dates of 1 July, 1 June, and 1 May for all peripheral seas (see Fig. A1). The optimal start week WX for the Beaufort, Chukchi, East Siberian, Laptev, and Kara Seas is taken to be W12, W15, W5, W5, and W10, respectively, irrespective of the forecast date (see Table A1).

Different seas are expected to be affected differently by late winter dynamical processes. For instance, in the Laptev Sea, where the ice flow is mostly offshore, CD as early as February is believed to have an impact on the following September SIE (Brunette et al. 2019). This is the time scale required to thermodynamically grow 1.0–1.2 m of ice (i.e., the climatological melt in a given summer) (Nikolaeva and Sesterikov 1970). In the Beaufort Sea, where the pack can periodically move toward or away from the coastline in late winter, sea ice thickness anomalies caused by CD that occurs midwinter can be erased by a subsequent coastal convergence event. For this reason, dynamical processes that occur later in the winter are expected to govern the predictive skill in this sea. Regardless, CD was shown to have predictive skill of the minimum SIE for instance, anomalous divergence in the ice pack in February and April in the Beaufort Sea in 2016 lead to an ice-free cover in the region the following summer (Babb et al. 2019). In the East Siberian Sea, offshore ice motion is not obviously dominant over onshore or parallel-to-shore ice motion (Miles and Barry 1998; Kimura et al. 2013; Kwok 2006). Onshore ice motion erases the thin ice signal from the previous offshore motion. For that reason, the peak correlation in CD is lost in spring, the signal is smaller, and the correlation is significant at the 90% confidence level.

The maximum correlations between CD and the minimum SIE in the Laptev (−0.53) and Kara (−0.62) Seas for a 1 June forecast are comparable to that of Williams et al. (2016), who find a maximum correlation of −0.58 using a proxy for CD estimated by backtracking a synthetic ice edge located at 77.5°N from 1 June until the third week of April. The predictive skill was hypothesized to come from the Laptev Sea where offshore ice motion is a semipermanent feature. This hypothesis was tested by Brunette et al. (2019), who report a maximum correlation of −0.63 ± 0.1 for a 1 May forecast (compared to −0.48 ± 0.1 in this study) for a slightly larger Laptev Sea domain (70°–85°N, 90°–155°E) and a different time period of 1992–2016.

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