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Key Points:

- The skill of September sea ice extent (SIE) forecasts over 2008–2022 is modest. The multi-model forecast has the highest skill
- Sea ice forecast initial conditions are variable. Forecasts initialized with more sea ice volume forecast greater September SIE
- Summer atmospheric circulation has an impact on forecast error

Supporting Information:

Supporting Information may be found in the online version of this article.

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Forecast Skill of the Arctic Sea Ice Outlook 2008–2022

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Abstract We assess the skill of forecasts of Arctic September sea ice in the Sea Ice Outlook over 2008–2022. The multi-model median June initialized forecast of September sea ice extent (SIE) is slightly more skilled (RMSE = 0.48 million km^2) than a damped anomaly forecast, but July and August initialized forecasts (RMSE = 0.52 and 0.36 million km^2 respectively) do not beat this benchmark. The skill of individual dynamical and statistical SIE forecasts is lower than the multi-model median forecast skill. Overall skill is lower than expected from retrospective forecasts. Several forecasts initialized in early September 2021 and 2022 imply physically improbable values. Spatial forecasts of sea ice concentration show multi-model forecast skill and an improvement in individual forecast skill in recent years. Initial conditions show large spread in sea ice volume and a positive correlation between initialized sea ice volume and September SIE forecast. Summer weather has an impact on forecast error.

Plain Language Summary We have collected, analyzed, and disseminated seasonal forecasts of September sea ice over 2008–2022. Here, we analyze the skill of these forecasts. We show that individual forecasts of September sea ice extent (SIE) have limited skill, but the median forecast shows skill that is at least as good as a statistical benchmark. Overall the skill is lower than expected from existing retrospective forecasts. Shorter-term forecasts produced in early September show that many forecasts imply physically unprecedented rates of SIE change. The skill of spatial forecasts from individual models is also limited, but the multi-model forecast is twice as skilled, showing the value of a multi-model forecast ensemble. To explore the spread across forecasts we have assessed sea ice initial conditions and found large differences in the sea ice volume used to initialize forecasts, which has an impact on the forecast. We also find that summer weather has a modest impact on forecast error, which tends to underpredict September SIE during summers with circulation patterns that favor high September SIE and vice versa.

1. Introduction

As Arctic sea ice extent (SIE) has declined and socio-economic activity in the Arctic has increased over recent decades, forecasts of Arctic sea ice have become increasingly relevant. The Sea Ice Outlook (SIO) is a seasonal forecast effort of September Arctic sea ice that emerged from a meeting of Arctic researchers in autumn 2007 following the first extreme September SIE low in the satellite record, with the goal of galvanizing the community to explore seasonal forecasts of Arctic sea ice. Since 2008, the SIO has collected, analyzed, and disseminated seasonal forecasts of September Arctic sea ice initialized in the preceding summer months (early June, July, and August over 2008–2022, and early September since 2021). The SIOs attract contributions spanning diverse methods and models and have advanced our understanding by identifying the nature of the errors in seasonal sea ice forecasts. Early estimates showed that the multi-model median SIO forecast skill was limited (Blanchard-Wrigglesworth et al., 2015; Hamilton & Stroeve, 2016; Stroeve et al., 2014) and only slightly better than a benchmark forecast produced by a linear trend climatology. Predicting extreme states, when observed SIE is much greater or lower than expected from the long-term trend, has proven challenging. These early estimates of SIO forecast skill were however conditioned by the short record available and the presence of 2 years with extreme forecast errors (2012 and 2013).

While the low skill could be due to inherent predictability limits associated with unpredictable summer Arctic weather or other factors, such as errors in the model initialization fields, input observations, ensemble construction, coupled model biases, or a relatively small sample size, the SIO skill over 2008–2014 was lower than the skill in retrospective forecasts (forecasts initialized in the past, e.g., Chevallier et al., 2013; Msadek et al., 2014; Sigmond et al., 2013; Wang et al., 2013), and in potential (perfect-model) predictability studies (e.g., Blanchard-Wrigglesworth et al., 2015; Bushuk et al., 2018; Tietsche et al., 2014).

To coincide with the end of the second phase of the Sea Ice Prediction Network (SIPN2), which currently hosts and organizes the SIO, here we update our skill assessment of September SIE forecasts over the full 15 yr 2008–2022 period. We also explore the skill of forecasts of spatial fields over 2014–2022, the impact of initial conditions on SIO forecasts, and the impact of summer weather on forecast error.

2. Data

Two types of forecasts are submitted to the SIO. The first type is a September pan-Arctic SIE forecast (i.e., one value per contributor for a given year and initialization), which has been regularly submitted to the SIO since 2008. Figure 1a shows the multi-model SIO forecast median (hereafter referred to as SIO median) over 2008–2022 using all initialization months, and Figure S1 in Supporting Information S1 shows the total number of forecast contributions per year. The forecasts are classified according to forecast method: dynamical (produced by dynamical models), statistical, mixed (forecasts produced by a combination of dynamical and statistical), and heuristic (such as expert estimates and pools). The total number of forecasts over 2008–2022 is 1,294 forecasts (about 85 per year on average), with a gradual increase in the number of forecasts over 2008–2015 and over 100 forecasts per year over 2015–2022. Recognizing that for most stakeholders pan-Arctic SIE is a metric of limited use, the SIO has encouraged forecasts of Sea Ice Probability (SIP) since 2014, which is the second type of forecast. SIP is defined as the fraction of ensemble members in an ensemble forecast with September ice concentration in excess of 15%. Over 2014–2022, the SIO received 233 forecasts of SIP (Figure S2 in Supporting Information S1), of which 179 are from dynamical models and 60 from statistical models. To evaluate the forecasts with observations, we use the NSIDC Sea Ice Index for SIE from 1979 to present (Fetterer et al., 2017, updated 2022), the NSIDC sea ice concentration (SIC) CDR product (Meier et al., 2021b) for 2008–2021 and the NSIDC Near-Real-Time SIC product (Meier et al., 2021a) for 2022. For atmospheric geopotential data, we use the ERA-5 reanalysis (Hersbach et al., 2020).

3. Skill of September Extent Forecasts

The root-mean-square errors (RMSEs) for SIO forecasts from 2008 to 2022 as well as two benchmark forecasts (a linear trend climatology forecast and a damped anomaly forecast) are shown in Figure 1b. Benchmark forecasts are used to assess how well forecasts perform against simple alternatives, a bare-minimum level of skill expected in environmental forecast systems (e.g., Collins, 2002). The linear trend climatology forecast ($\mathrm{SIE}_{\mathrm{trend}}$) is constructed by projecting the long-term trend of past observed September SIE (from 1979 to 1 yr previous to the one being predicted) to the year being predicted. A second, slightly more sophisticated benchmark forecast that takes advantage of the seasonal memory of SIE anomalies (Blanchard-Wrigglesworth et al., 2011) is a damped anomaly (auto-regressive of order 1) forecast produced by multiplying the detrended SIE anomaly at the initialization time (the 1st of each month) with the correlation of SIE anomalies at the initialization time with September SIE anomalies, weighted by the ratio of the standard deviation of September SIE to the standard deviation of SIE on the initialization date. This anomaly is added to $\mathrm{SIE}_{\mathrm{trend}}$ to construct the AR-1 damped anomaly forecast as shown in Equation 1. To forecast each year we only use past years' SIE from 1979 onwards and all SIE timeseries are detrended prior.

$$\mathrm{SIE}_{t,yr=n} = \mathrm{SIE}'_{t,yr=n} \times r\left(\mathrm{SIE}'_{t,yr<n}, \mathrm{SIE}'_{sep,yr<n}\right) \times \frac{\sigma\left(\mathrm{SIE}'_{sep,yr<n}\right)}{\sigma\left(\mathrm{SIE}'_{t,yr<n}\right)} + \mathrm{SIE}_{trend}, \tag{1}$$

where t is forecast initialization time (1st of the month), sep is September, n is the year being forecast, σ is the standard deviation operator, and primes represent detrended anomalies.

Figure 1b reveals that the SIO median forecast skill is comparable to that of a damped anomaly forecast for July and August initialized forecasts, and slightly better for the June forecasts. This skill metric shows a slight improvement as compared to the early SIO record, 2008–2014 (Blanchard-Wrigglesworth et al., 2015). Forecasts

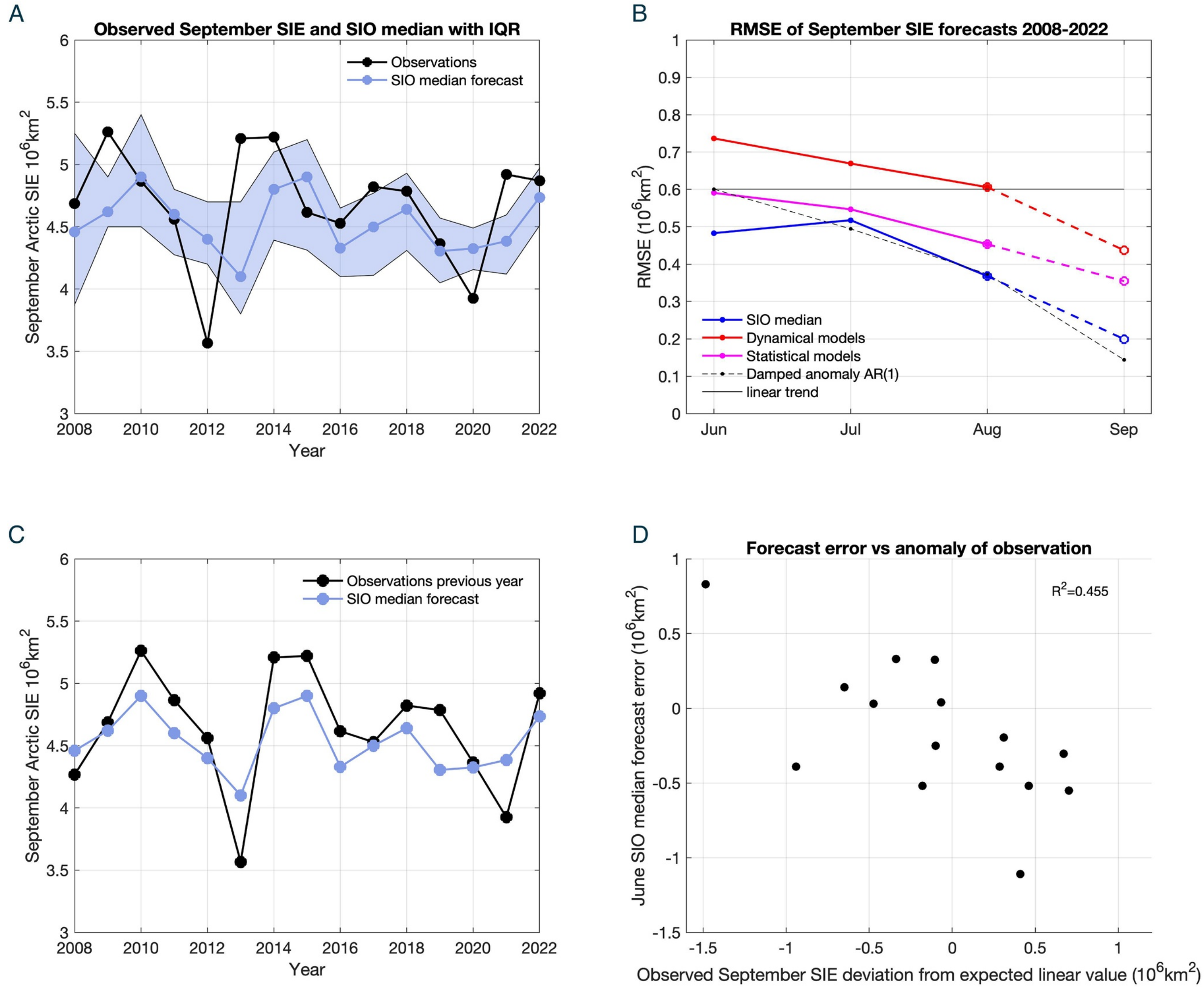

Figure 1. (a) September sea ice extent (SIE) and Sea Ice Outlook (SIO) median and Interquartile Range (IQR) forecasts for all initialization months, 2008–2022, (b) RMSE values of SIO forecasts for June through August initializations (2008–2022), and September initialized forecasts (2021–2022) for the SIO median forecast (blue), dynamical models (red), statistical models (magenta), a damped anomaly (AR-1) forecast (dashed black) and a linear trend forecast (solid black). (c) as in (a), but showing observed September SIE in previous year, and (d) observed September SIE deviation from the expected linear trend value (x-axis) and June SIO median forecast error (y-axis).

from the complete record are not able to consistently beat the damped anomaly benchmark. Individually, statistical forecasts show slightly better skill than dynamical forecasts, yet neither method beats damped anomaly forecasts for all lead times. The RMSE of September initialized forecasts in 2021–2022 was lower than forecasts initialized earlier in the summer, yet greater than that expected from the damped anomaly forecast (see below).

Comparison of the observed September SIE and the SIO median forecasts shows a relationship between 1 yr observed value and the following year's SIO median forecast (Figures 1a and 1c), as suggested for earlier SIO periods (Lukovich et al., 2021). The correlation between same-year observed September SIE and SIO median forecasts is $r = 0.27$ and increases to $r = 0.86$ when comparing 1 yr lagged SIO median forecasts to observations. This is unexpected, as there is no significant correlation in observations between one year's September SIE and the next (the detrended 1 yr lag correlation of September SIE is $r = 0.13$), and suggests forecasts are pre-conditioned by the previous year's observed SIE. We find this to also be the case across dynamical and statistical models (not shown), and when 2013/2014 forecasts (2012/2013 observations) are removed from the analysis (1 yr lagged correlation of $r = 0.77$). No satisfactory explanation has been found yet to explain this unexpected behavior.

Figure 1d shows the June SIO median forecast error against the observed SIE deviation relative to SIE_{trend}. A significant negative correlation exists ($r^2 = 0.46$), showing that SIO forecasts struggle to predict anomalous years: SIO errors are larger when observations deviate far from the long-term trend, as found in the first half of the SIO period (Hamilton & Stroeve, 2016).

In 2021, the SIO began inviting forecasts of September SIE anomalies, calculated relative to models' adopted baseline trend (e.g., the trend in historical observations, model hindcasts, etc.), motivated by the prospect of reducing SIO forecast uncertainty and error that may originate from models having different trends, mean states, and post-processing methodologies. Figure S3 in Supporting Information S1 shows the September SIE and SIE anomaly forecasts for the SIO models that provided both forecasts in 2021 and 2022, together with the forecast error, forecast spread, and RMSE. While the sample size is small, SIE anomaly forecasts are no more accurate than SIE forecasts, and the forecast spread is not reduced.

3.1. September 2021 and 2022 Extent Forecasts

To test whether forecasts of September SIE would converge to a higher skill at shorter lead times, the SIO began inviting forecasts initialized in early September 2021. Figures 2a and 2c show the distribution of forecasts in 2021 and 2022 for all four initialization months, clustered by forecast method (dynamical and statistical). SIO forecasts in 2021 showed comparable levels of skill compared to the full SIO period (Figure 1b), and only showed modest improvement from June through August (RMSEs of 0.59, 0.58, and 0.52 million km^2 SIE for June, July, and August SIOs respectively, with little difference across forecast methods). September SIO forecasts were slightly more skillful (RMSE for the SIO median of 0.34 million km^2 SIE), yet the forecast spread was still significant (ranging from 3.8 to 5.17 million km^2 SIE), with several forecasts of September SIE below 4.5 million km^2. To further assess these forecasts, we show an additional benchmark forecast of September 2021 SIE based on the observed 31 August 2021 SIE and past (1987–2020) daily changes of SIE between 31 August and 30 September (Figure 2b). These forecasts (shown as timeseries from which we obtain monthly SIE averages in Figure 2b) show that, on 31 August 2021, one could have expected September 2021 SIE values to be in the 4.9–5.4 million km^2 range. September forecasts below these values imply record rates of sea ice loss during September and can be regarded as physically improbable. We emphasize that 15 of 20 September 2021 SIO forecasts were below the benchmark forecasts, illustrating that even at short lead times SIO forecasts are struggling to show the expected skill from simple yet physically robust statistical relationships in the observed record of SIE.

The same analysis for the September 2022 SIO forecasts (Figures 2c and 2d) shows better skill overall, despite the near identical September SIE (4.91 million km^2 in 2021 and 4.87 million km^2 in 2022) and 31 August SIE in both years. Focusing on the September 2022 SIO forecasts shows a narrower spread (4.49–5.12 million km^2) compared to September 2021 SIO, although several forecasts are still lower than the benchmark forecast range.

3.2. Spatial Skill Forecasts

To assess the skill of SIP forecasts, we calculate the Spatial Probability Score (SPS, Goessling & Jung, 2018), defined as the spatial integral of the local Brier Score. We calculate the SPS of each SIP submission over 2014–2022 and the SPS of the multi-model mean SIP forecast for each forecast solicitation. Since models submit SIP forecasts on native grids, all forecasts and observations are regridded to a common 1° × 1° latitude-longitude grid. To provide a benchmark forecast, we produce a linear trend climatology SIP forecast by projecting at each grid cell the linear trend of past September SIC to the year being forecast. Figure 3 shows the SPS for all SIP submissions, the model-mean forecast SPS and the benchmark SPS. Overall, individual submission SPS ranges between 0.5 and 1.8 million km^2, which are significantly higher than the RMSE values shows in Figure 1. This is expected due to compensating positive and negative regional errors of SIC in the SIP forecasts that cancel out when calculating a pan-Arctic SIE, and has been seen in previous studies comparing forecasts of pan-Arctic SIE with spatial field forecasts (e.g., Goessling & Jung, 2018). The multi-model mean SPS forecast is consistently among the more skilled, or most skilled forecasts. The linear trend climatology SPS forecast varies in skill between 0.5 and 1 million km^2. In some years, over half of the individual models beat the linear climatology benchmark (e.g., 2018, 2020, 2021), whereas in other years few individual models beat the benchmark (e.g., 2017, 2019). Considering the mean SPS forecasts over 2014–2022, the multi-model SPS forecast amply beats linear trend climatology, yet the individual forecasts do not. Nevertheless, there is an increase in the number of

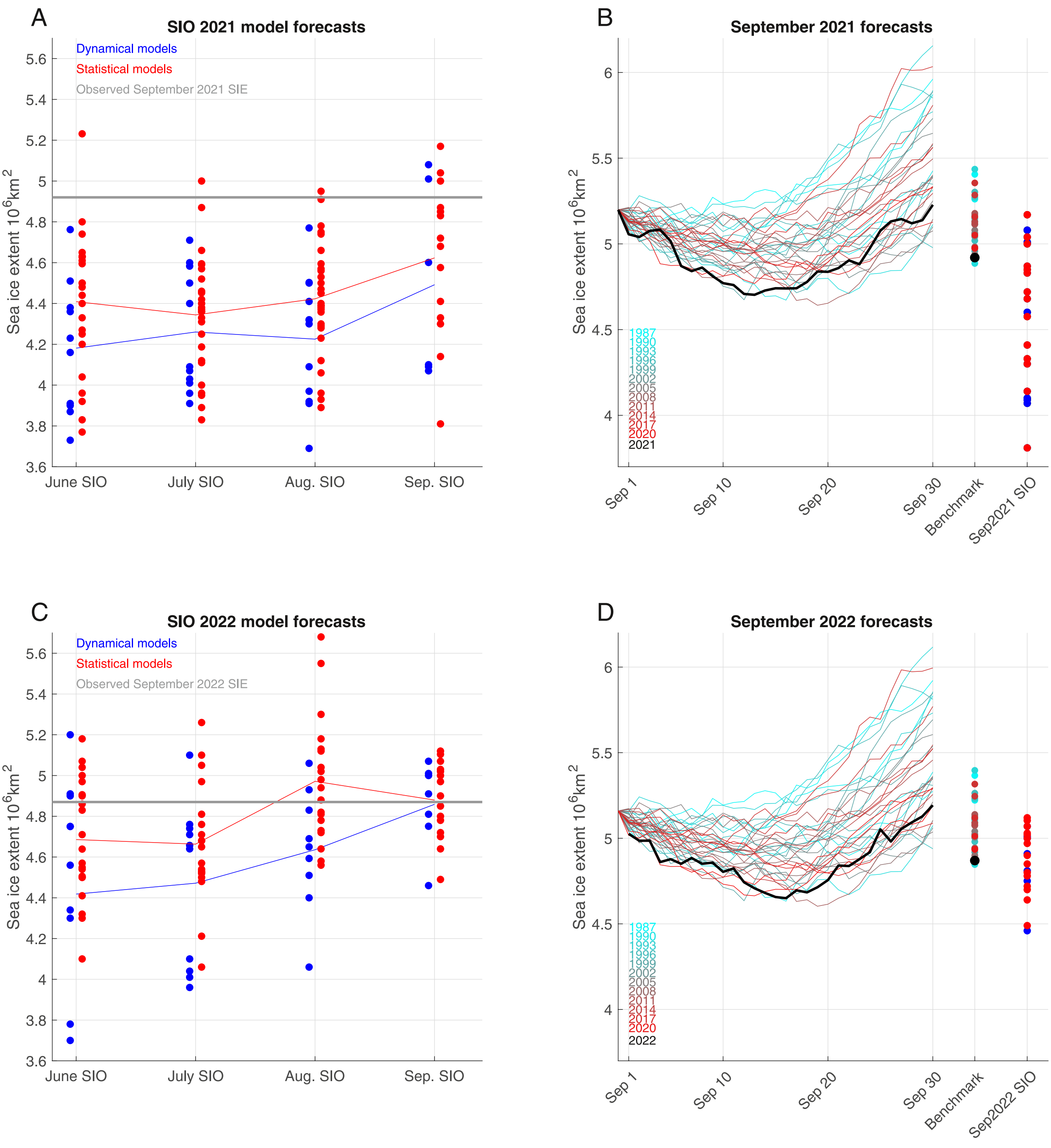

Figure 2. (a, c) Sea Ice Outlook (SIO) forecasts in 2021 and 2022, the dots represent individual forecasts, and the thin lines the median forecast for each forecast method, and (b, d) forecasts of September 2021 and September 2022, showing the benchmark forecasts that use the observed sea ice extent (SIE) on 31 August and past sea ice extent tendencies between 31 August and 30 September, represented by the cyan-through-red timeseries (the labeled years indicate the year from which the September tendencies are sampled, note all previous years from 1987 onwards are used). The benchmark September SIE forecasts are shown by the cyan-red circles ("Benchmark"), with the observed 2021 and 2022 SIE values in black. September SIO forecasts for each year are shown in the rightmost column.

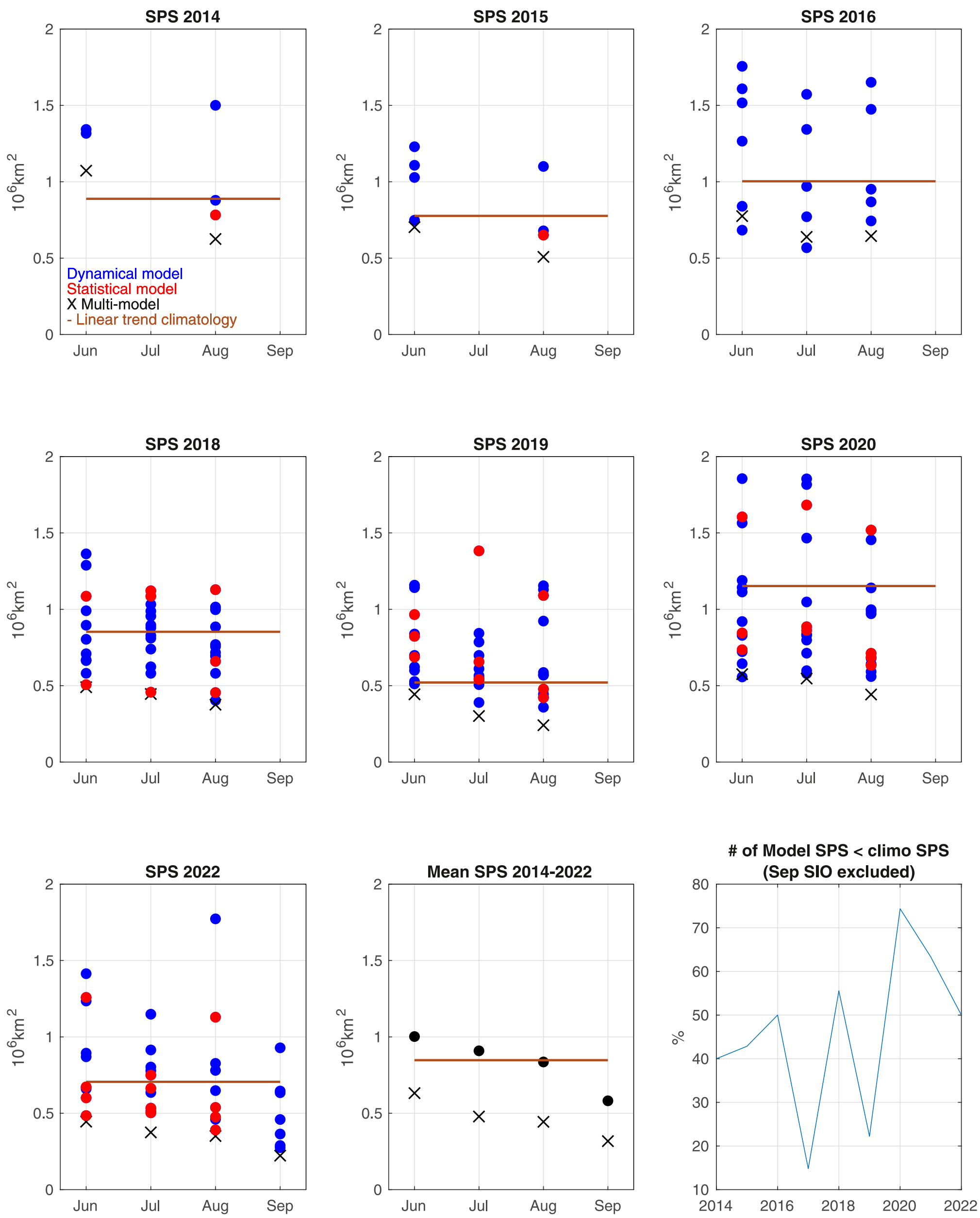

Figure 3. SPS of Sea Ice Probability (SIP) forecasts 2014–2022. Each round dot represents a single forecast (blue dynamical model, red statistical model), the black Xs represents the model-mean SIP forecast skill, and the maroon line represents the skill of a linear climatological SIP forecast for each year. The bottom right panel shows the percentage of individual model forecasts (excluding the September initialized forecasts in 2021 and 2022) that beat climatology each year.

forecasts that beat the benchmark each year over 2014–2022, which may evidence an improvement in the true skill of the forecasts over time.

3.3. The Role of Initial Conditions

Poor forecast skill may be due to poor initial conditions and/or biased model physics. To further explore the spread and skill of SIO forecasts, the SIO has in recent years invited submissions of sea ice forecast initial conditions (SIC and sea ice thickness - SIT), motivated by the known predictor value of these variables for seasonal sea ice forecasts (e.g., Day et al., 2014; Lindsay et al., 2008). Figure S3 in Supporting Information S1 and Figures 4a and 4b show the initial conditions for SIC and SIT and for total sea ice volume (SIV) as a function of initialization date in 2020 and 2021 (note that SIO contributors may initialize their forecasts on different days, even

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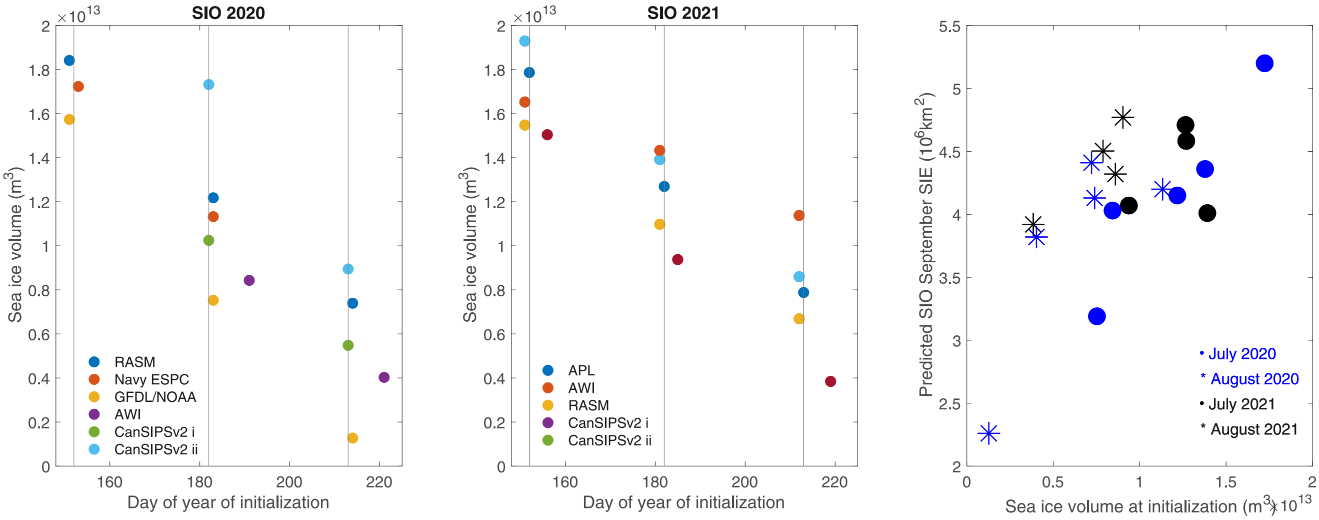

Figure 4. (a, b) Total sea ice volume on the date of initialization for Sea Ice Outlook (SIO) forecasts that shared their initial conditions in 2020 and 2021, the three vertical lines are 1 June, 1 July, and 1 August, and (c) the relationship between sea ice volume at initialization and predicted September sea ice extent (SIE), clustered by July and August SIO contributions in 2020 and 2021.

if all contributions have the same early summer month submission deadlines). Figure 4c shows the relationship between initialized SIV and the September extent SIO forecasts for the models that provided initial conditions. These figures show two main results: (a) SIO models generally agree in their SIC initial conditions, yet show large spread in their SIT (and thus SIV) initial conditions, and (b) there is a positive correlation between the forecasts' initialized SIV and their September SIE forecasts.

3.4. Is There a Relationship Between Summer Weather and Forecast Error?

Throughout the SIO effort, it has been hypothesized that (a) summers with anomalous atmospheric circulation result in anomalous September SIE, (b) that these summers' anomalous circulations are generally unpredictable at seasonal lead times, and (c) that the SIO sea ice forecast error (especially for forecasts in early June or July) is larger during these summers, as the SIO forecasts are not able to skillfully forecast the anomalous atmospheric circulation. We address this question by comparing the SIO error from June forecasts to the mean summer atmospheric circulation. To characterize the state of the summer circulation that impacts September SIE, we first regress June through September (JJAS) mean 500 hPa geopotential heights on the September SIE over 1979–2021 after detrending both data sets. This atmospheric pattern (Figure 5a) shows that after summers with anomalously low 500 hPa heights over the Arctic (i.e., cyclonic circulation), September SIE tends to be anomalously high, and vice versa, as previously found in the literature (e.g., Ding et al., 2017; Ogi et al., 2008). Next, we characterize each summer's circulation pattern over 2008–2022 by calculating the area-weighted pattern correlation and regression coefficient of each summer's 500 hPa anomalies with the atmospheric pattern in Figure 5a. These metrics characterize the sign and amplitude of the atmospheric circulation anomalies in terms of the pattern that optimally impacts September SIE. Finally, we correlate the pattern correlations and regression coefficients with the SIO error from June forecasts (Figures 5b and 5c). We find a relationship between JJAS atmospheric circulation and June SIO error. Summers when the pattern favored a positive sea ice anomaly (represented by a positive pattern correlation or regression coefficient, such as 2013, 2016, or 2017) tend to show negative SIO errors, as expected if the forecasts cannot predict the JJAS circulation patterns, and vice versa (positive June SIO errors when the JJAS atmospheric circulation favors sea ice loss, such as 2015 or 2020). Nevertheless, the correlations between the atmospheric circulation patterns and the SIO error are modest ($r = 0.4$ and $r = 0.54$ for the pattern correlation and regression coefficients respectively, only the latter is significant at the 95% level), illustrating that other factors beyond unpredictable summer atmospheric circulation—such as initial conditions and model physics—play a role in the SIO forecast errors.

4. Discussion and Conclusions

The SIO has created an active sea-ice seasonal forecasting network over 2008–2022, and has collected and distributed over 1,200 forecasts of September SIE. We have found that the forecast skill of September SIE is modest.

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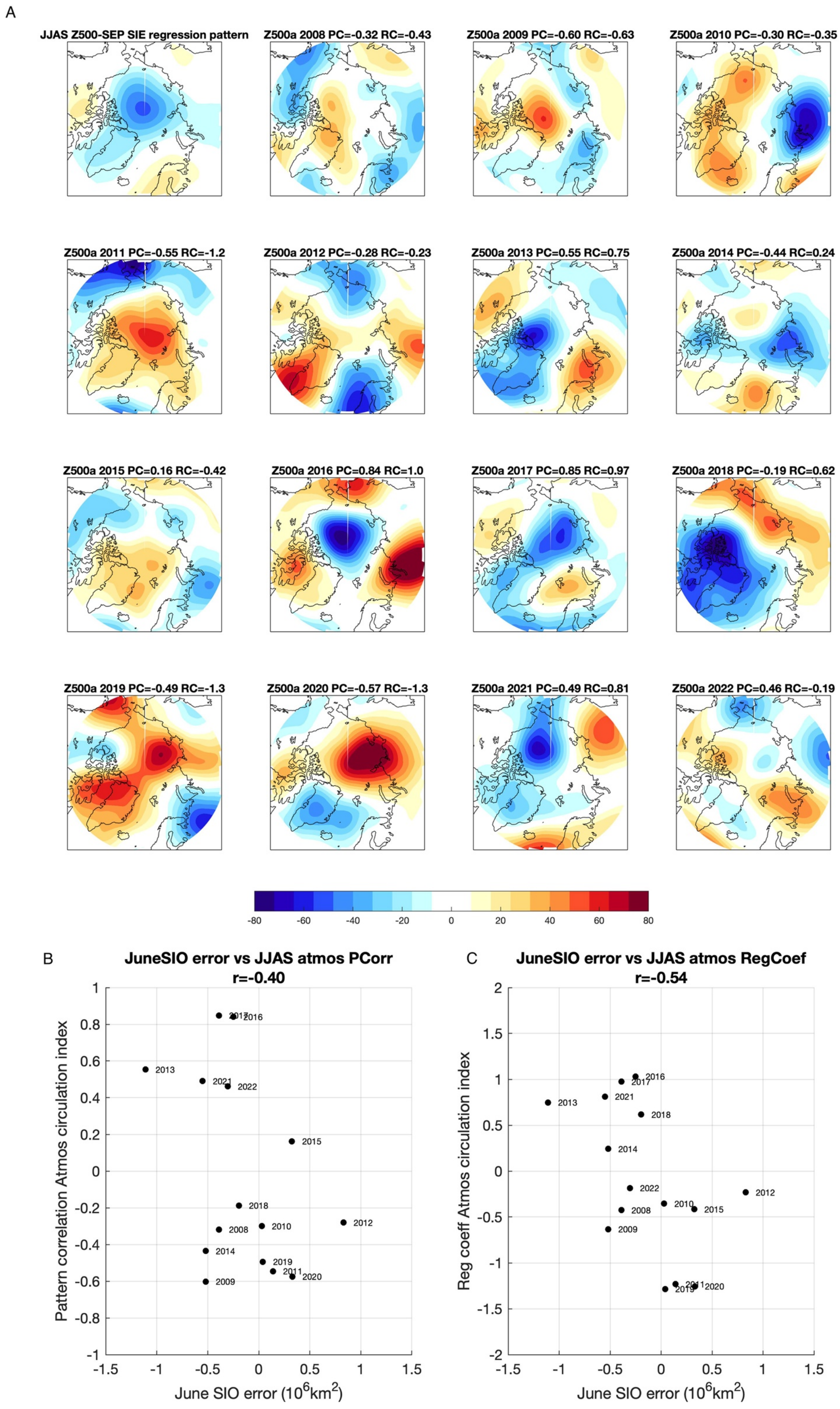

Figure 5. (a) The regression of June through September (JJAS) 500 hPa heights on September sea ice extent over 1979–2022 (in m per 10^6 km^2), anomalous JJAS 500 hPa heights (in m) over 2008–2022, the titles show the pattern correlation (PC) and regression coefficient (RC) with the regression pattern in the top left panel. Only values north of 60°N are shown. (b, c) Scatter plots of the June Sea Ice Outlook (SIO) median error (*x*-axis) and the JJAS anomalous atmospheric circulation, characterized by pattern correlation (b) and regression coefficient (c).

Individual dynamical and statistical forecasts show RMSEs of 0.7–0.5 million km^2 in forecasts submitted from early June to early August, which are less skillful than a damped anomaly (AR-1) benchmark forecast, and whose RMSE is 0.6 million km^2 on 1 June and 0.4 million km^2 on 1 August. The SIO median forecast is slightly more skilled than individual forecasts—likely due to error cancellations—and is as skilled or slightly more skilled than a damped anomaly forecast. Some individual September SIE forecasts initialized in early September in 2021 and 2022 are physically improbable and imply unprecedented rates of sea ice loss during September. These findings suggest that some dynamical SIO models are making notable errors in their initialization of SIE and statistical models may not be using the latest daily SIE observations when producing their forecasts and/or may be poorly calibrated.

As in past studies assessing the skill of the first half of the SIO (Blanchard-Wrigglesworth et al., 2015), we find that these skill scores are lower than expected from existing retrospective forecasts (hindcasts) of Arctic September SIE (e.g., Chevallier et al., 2013; Msadek et al., 2014; Sigmond et al., 2013; Wang et al., 2013), and illustrate known gaps between operational and potential sea ice forecast skill (Bushuk et al., 2018). Why this is the case is unclear. It is not possible to use the SIO data set to assess the skill of individual forecast model systems throughout the SIO period, since forecast models and initialization methods are updated regularly, and thus even forecasts from the same modeling centers are produced by different forecast systems in different years. In order to assess the skill of individual forecast model systems that submit to the SIO and to compare forecast skill across individual models an SIO retrospective forecast effort is needed. We are currently producing such an effort.

We have also assessed the skill of spatial forecasts by calculating the SPS of September SIP forecasts. The mean SPS of SIO forecasts is 1 million (0.8 million) km^2 for June (August) SIOs, which is no more skilled than the SPS of a linear trend climatology benchmark forecast (0.8 million km^2). The SPS of the multi-model SIP forecast (0.6 million km^2 for the June SIO, 0.4 million km^2 for the August SIO) is significantly more skilled, illustrating the value of producing multi-model ensemble forecast system in which the ensemble-mean offers significant skill over a linear trend climatology forecast. While individual forecasts can fail to beat a linear trend climatology forecast benchmark, it is encouraging to see an increase over 2014–2022 in the proportion of forecasts that beat the benchmark.

A limited number of forecast initial conditions of SIC and SIT have been submitted to the SIO, which show a large spread in the SIV of the initial conditions that is positively correlated with their September SIE forecasts. It is likely that some of the forecast spread across the SIO is due to different initial conditions used by different modeling centers. In addition, the spread in the initialized SIV is dominated by spread in SIT (rather than SIC), which is likely due to SIC being better observed by remote sensing platforms than SIT and more sophisticated schemes for assimilating SIC into forecast models compared to SIT. Nevertheless, even when SIO models are initialized with the same SIT in controlled experiments, September SIE forecasts can show large spread (Blanchard-Wrigglesworth et al., 2017), and it is likely that different model physics and forecast post-processing methods are also contributing to forecast spread across models in the SIO.

Finally, we also find that the error in the SIO is affected by summer atmospheric circulation patterns. In years when the summer circulation patterns favor high (low) September SIE, SIO errors tend to be negative (positive). The relationship is significant yet modest and shows that other aspects discussed above, such as initial conditions, model physics, and forecast post-processing are leading to SIO forecast error.

Data Availability Statement

NSIDC SIC data (Meier et al., 2021a, 2021b) are available at https://doi.org/10.7265/efmz-2t65 and https://doi.org/10.7265/tgam-yv28, NSIDC Sea Ice Index (Fetterer et al., 2017, updated 2022) data are available at https://doi.org/10.7265/N5K072F8, ERA-5 data (Hersbach et al., 2020) are available at https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5, SIO forecast data are available at https://www.arcus.org/sipn/sea-ice-outlook/archive.

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