Added value of assimilating springtime Arctic sea ice concentration in summer-fall climate predictions

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Added value of assimilating springtime Arctic sea ice concentration in summer-fall climate predictions

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Abstract
Prediction skill of continental climate in the Northern Hemisphere (NH) midlatitudes is generally limited throughout the year in dynamical seasonal forecast systems. Such limitations narrow the range of possible applications by different stakeholders. Improving the predictive capacity in these regions has been a challenging task. Sea ice is a central component of the Arctic climate system and a local source of climate predictability, yet its state is often not fully constrained in dynamical forecast systems. Using the EC-Earth3 climate model, we study the added value of assimilating observed Arctic sea ice concentration on the NH extratropical climate in retrospective forecasts of summer and fall, initialized every spring over 1992–2019. Predictions in the North Atlantic and Eurasia benefit from better initialization of sea ice in the Atlantic sector of the Arctic in a two-step mechanism. Initially, sea ice influences the central North Atlantic Ocean through an atmospheric bridge that develops in the first forecast weeks, subsequently leading to preserved skill in the sea surface temperatures (SSTs) throughout summer and early fall. Secondly, these long-lasting SST improvements provide better surface boundary conditions for the atmosphere and lead to more skillful predictions of circulation and surface climate in the Euro-Atlantic and Asian regions. In addition, our findings suggest that fully coupled ocean-atmosphere-sea ice models are likely necessary to study linkages between Arctic sea ice and midlatitudes, by better representing the interactions and feedbacks between the different components of the climate system.

1. Introduction
The primary goal of seasonal climate prediction is to generate useful climate information for the coming months up to a year. This relatively young scientific endeavor has enormous potential to benefit a broad range of stakeholders, by assisting the development of climate services for agriculture, insurance, power generation, and others (Buontempo et al 2018, Ceglar and Toreti 2021). Despite progress in the past decades, a wider use of seasonal predictions produced with dynamical forecast systems is still hindered by important forecast skill limitations. Predictive capacity of user-relevant climate variables (e.g. sea level pressure, precipitation, wind) is low in many extratropical land regions in the Northern Hemisphere (NH, Yuan and Wood 2013, Dutra et al 2014, Johnson et al 2019), where billions of people live. Seasonal climate predictability largely stems from the predictable evolution of slowly varying components of the climate system, such as ocean temperature, soil moisture, snow or sea ice (Doblas-Reyes et al 2013). Tropical oceans are the largest source of seasonal predictability and the most prominent example is the El Niño-Southern Oscillation, a highly predictable mode of variability that affects weather and climate patterns worldwide through large-scale atmospheric teleconnections, including areas in the NH midlatitudes (Díaz et al 2001).

NH midlatitudes are also affected by Arctic sea ice changes (e.g. Ye et al 2018, Acosta Navarro et al 2019). Due to its slow variability and the predominant role it plays in the Arctic climate system, sea ice is an important source of predictability at sub-seasonal to
annual timescales (Day et al 2014, Guemas et al 2016, Acosta Navarro et al 2020). Arctic sea ice acts as an insulator of the ocean and atmosphere, significantly affecting the exchange of energy, momentum and mass. First order local climate effects of sea ice extent reduction and thinning include larger solar energy absorption, further ice melt and additional ocean heat storage in the warm season (~May–October), and a larger sea-to-air latent and sensible heat release in the cold season (~November–April), delaying the ice formation, accelerating the water cycle and further warming the lower Arctic troposphere (Serreze and Barry 2011, Previdi et al 2021). Sea ice extent growth and thickening leads to opposite effects. In the satellite era, the Arctic lower troposphere has warmed much faster than the global average, and the warming has been strongest in the fall and winter (Ballinger et al 2020).

This strongest warming in the fall and winter has motivated the majority of studies aiming to link Arctic sea ice changes and midlatitude climate in that part of the year, yet a consensus is still elusive due to divergent conclusions on whether and how sea ice can influence midlatitude atmospheric circulation (see Overland et al 2021 for a review). Studies focusing on the remaining parts of the year are scarce. A few studies focusing on the summer months partially attribute higher heat wave frequency in Europe (Zhang et al 2020) and higher precipitation (Screen 2013) in northwestern Europe to diminishing sea ice. Sea ice retreat is also associated with Arctic amplification, hence contributing to reducing the meridional temperature gradient, something that has been observed in summer but not in winter. A reduced meridional temperature gradient affects both the intensity and position of the jet stream and storm tracks, and amplifies quasi-stationary waves in the summer months which can have an impact on persistent weather patterns such as heat waves (Coumou et al 2015, 2018, Tang et al 2014). Here we follow an alternative approach to study how Arctic sea ice impacts midlatitude climate in the summer and fall by comparing two sets of retrospective seasonal predictions, respectively initialized with and without assimilating Arctic sea ice concentration (SIC) from satellite observations (SIC-ASSIM and NOSIC-ASSIM). Our strategy allows for an objective quantification of forecast improvements when sea ice is better constrained at initialization by systematically confronting the two sets of climate predictions against observational products.

2. Methods

2.1. Model experiments

Two sets of 30 member, seven month long seasonal retrospective forecasts (or hindcasts) were carried out with the Coupled Model Intercomparison Project - phase 6 (CMIP6) version of the climate model EC-Earth3 (Doblas-Reyes et al 2018) previously employed to make decadal predictions (Bilbao et al 2021). In each experiment the forecast system is initialized every 1st of May in the reforecast period 1992–2019. Both experiments share an identical initialization of the atmosphere, using initial conditions from ECMWF Atmospheric Reanalysis ERA5 (Hersbach et al 2020) after performing a spatial interpolation to match the atmospheric model grid. White noise is added to the initial atmospheric temperature field to generate 30 different atmospheric states, one for each member of the hindcast. The ocean and sea ice initial conditions are generated from in-house ocean-sea ice assimilation ensemble simulations or ‘reconstructions’ with the same ocean–sea ice version of the fully coupled model used for the hindcasts.

In the NOSIC-ASSIM reconstructions, the model is driven by ERA5 surface fluxes and only ocean data from the Ocean Reanalysis System 5 (ORASS, Zuo et al 2019) is assimilated through Newtonian relaxation or ‘nudging’. Surface temperature and salinity are nudged everywhere except under sea ice, with restoring coefficients of $-200$ W m$^{-2}$ K$^{-1}$ and $-750$ W m$^{-2}$ psu$^{-1}$, respectively. Subsurface relaxation of temperature and salinity is performed under the mixed layer and excludes the tropical band 15°–15°N to avoid spurious effects (Sanchez-Gomez et al 2016). The relaxation time scale decreases with depth, its value is about three days at the surface and one year at the bottom. Surface restoring is not applied under sea ice, but subsurface relaxation is. We note that sea ice in NOSIC-ASSIM is only constrained through the ocean conditions and atmospheric forcing, and no information from sea ice observations is used. SIC-ASSIM ocean and sea ice initial conditions are generated identically to those in NOSIC-ASSIM, except that in this case, SIC observations are additionally assimilated through a surface heat flux adjustment. Three independent datasets of SIC were considered to generate different members of the ocean–sea ice reconstructions of SIC-ASSIM that take into account the underlying observational uncertainty: CERSAT (Girard-Ardhuin and Piolé 2018), OSISAFv2 (Lavergne et al 2019) and ORASS (Zuo et al 2019).

The sea ice assimilation scheme implemented in EC-Earth3 and applied in the ocean–sea ice reconstructions, introduces an additional surface heat flux to the sea ice module (LIM3) and is similar to the ‘ghost flux’ (Sun et al 2018) or ‘ice-flux’ (McCusker et al 2017) techniques (see Sun et al 2020 for a review of ice-constraining approaches). Note that there is no artificial energy source in the free running model (predictions) at any moment. With this method SIC is not directly relaxed to the target values as is the case for temperature and salinity damping in the ocean. Rather at each time step the scheme calculates and applies the nudging heat flux based on the enthalpy needed to convert the sea ice volume in the grid cell to
the target value. Hence, melting (freezing) is achieved by adding (removing) heat at the sea ice-atmosphere (ocean-sea ice) interface with a rate defined as the product of the restoring coefficient of 1200 W m$^{-3}$ and the difference in model and observed SIC, which is only activated if this difference is larger than 0.15 at a given timestep. The sea ice restoring coefficient roughly translates to the relaxation timescale of three days. The 0.15 threshold was the optimal value identified in several sensitivity simulations.

In total 15 members of SIC-ASSIM ocean-sea ice reconstructions were generated (five for each reference sea ice dataset) and five accompanying NOSIC-ASSIM reconstructions were produced. Each ocean-sea ice reconstruction has a different initial state in 1992 and is forced by ERA5 fields. Spread in the ocean-sea ice reconstructions is generated by applying random perturbations to the near surface temperature, longwave and shortwave radiation forcings. The SIC-ASSIM and NOSIC-ASSIM hindcasts are then initialized from the available members of each one of the ocean/sea ice reconstructions (15 for NOSIC-ASSIM and 5 for SIC-ASSIM) and the 30 different atmospheric initial conditions. A first inspection of the differences between SIC-ASSIM and NOSIC-ASSIM and their respective ocean-sea ice reconstructions from which initial conditions were taken, confirms that any difference at initialization is confined to the Arctic region (figure S1 available online at stacks.iop.org/ERL/17/064008/mmedia).

### 2.2. Forecast verification metrics

Two main forecast verification metrics have been considered in this study. The anomaly correlation coefficient (ACC) is one of the most widely used verification metrics in weather and climate forecasting. It measures the linear association (Pearson correlation) between the ensemble mean and observations, after removing the lead-time dependent climatology in the hindcasts. Estimates of statistical significance of the differences in ACC between two sets of hindcasts are computed following the approach by Siegert et al (2017), which accounts for statistical dependence between the hindcasts.

In addition, the integrated ice edge error (IIEE; Goessling et al 2016) measures the ensemble mean absolute error in the position of the sea ice edge after simple bias correction of the hindcasts (Batté et al 2020). It is defined as the sum of areas where the presence of sea ice is overestimated or underestimated with respect to reference data. Sea ice presence is defined with a 0.15 SIC threshold.

### 3. Results

#### 3.1. Added value of SIC assimilation on Arctic sea ice forecasts

A comparison between the hindcasts SIC-ASSIM and NOSIC-ASSIM reveals an overall added value of SIC assimilation on the skill to predict it during the first (May), second (June) and third to fifth (JAS) forecast months for most of the Arctic region (figures 1(a)–(c), S2(a)–(c) and S3). The largest improvements are generally located in the vicinity of the observed climatological sea ice edge, suggesting a better representation of the ice margins when SIC is assimilated, something that is especially marked in the Atlantic sector, particularly in the Greenland Sea. These improvements are confirmed by a lower pan-Arctic (figures S2(a)–(c)) and Atlantic (not shown) IIEE in SIC-ASSIM as compared to NOSIC-ASSIM hindcasts. The assimilation of SIC improves the representation of the ice edge for the months of May and June in the Labrador-Baffin, Greenland-Iceland-Nordic (GIN), and Barents Seas (figures 1(d)–(f)). Additionally IIEE in the GIN and Barents seas shows improvement in October and November in SIC-ASSIM, most likely as a result of the well known spring-fall reemergence mechanism of sea ice, which is mediated by the persistence of sea surface temperatures (SSTs; Bushuk and Giannakis 2017). The added value of SIC assimilation is robust and not sensitive to the SIC product assimilated (figures S2(a)–(c)) or the observational reference chosen for forecast verification (figure S3).

#### 3.2. Added value of SIC assimilation on Arctic and extra-Arctic climate forecasts

Besides improving the forecast quality of Arctic sea ice, SIC assimilation also leads to improved local SST skill within the Arctic in May, June and JAS (figures 2(a)–(c)). This is expected since the SIC assimilation applies heat flux corrections that impact SSTs in the sea ice areas (see section 2). More remarkably, SIC assimilation also leads to an improvement in SST skill in the central North Atlantic from May to October (figures 2(a)–(c)). The skill improvements due to SIC assimilation, calculated for the monthly mean, area-averaged SSTs in the central North Atlantic (purple box in figures 2(a)–(c)), are small but statistically significant in May, and peak from June to September (figure 2(d)). Similar to SIC, the North Atlantic SST skill gain is robust and not sensitive to the SIC product assimilated (figure S2), giving more confidence to the results.

Skill differences in near surface air temperature (T2m) show an overall similar behavior than SSTs in the central North Atlantic, both for the spatial maps (figures 2(e)–(g)) and area-averaged values (figure 2(h)). However, in May the differences in skill between SIC-ASSIM and NOSIC-ASSIM are larger for T2m than for SST, which is clearly illustrated when averaged in the central North Atlantic (figure 2(h)). This suggests the existence of a possible atmospheric bridge from the sea ice to the ocean developing during the first forecast month (May). This bridge is further supported by large skill increases in geopotential height at 500 mb
Figure 1. Difference in SIC skill (anomaly correlation coefficient) between SIC-ASSIM and NOSIC-ASSIM in (a) May, (b) June and (c) JAS. Mean 1992–2019 integrated Arctic sea ice edge error (IIEE) in SIC-ASSIM (light blue) and NOSIC-ASSIM (light red) hindcasts in (d) Labrador and Baffin, (e) GIN and (f) Barents Seas. The observational reference is NSIDC (Cavalieri et al. 1996). Dots on the maps (a)–(c) and on lines (d)–(f) indicate statistically significant differences (95% confidence level) between SIC-ASSIM and NOSIC-ASSIM. Purple boxes in (a), (b) and (c) indicate the regions of Labrador and Baffin, GIN and Barents Seas, respectively. Symbols on the left hand side in (d), (e) and (f) indicate the IIEE values in the initial conditions (1 May).

Figure 2. Difference in SST skill (anomaly correlation coefficient) between SIC-ASSIM and NOSIC-ASSIM in (a) May, (b) June and (c) JAS. (d) Monthly SST skill (anomaly correlation coefficient) in the central North Atlantic (50–20 W, 35–55 N) in SIC-ASSIM (blue) and NOSIC-ASSIM (red). (e)–(h) and (i)–(l) as (a)–(d) but for T2m and GPH500, respectively. The box in (l) is defined for the eastern North Atlantic (35–10 W, 40–55 N). The observational reference is the mean of ERA5 (Hersbach et al. 2020), JRA55 (Kobayashi et al. 2015) and NCEP (Saha et al. 2010) reanalyses for T2m and GPH500, and HadISSTv1.1 (Rayner et al. 2003) for SST. Dots on lines and on the maps indicate statistically significant differences (95% confidence level) between SIC-ASSIM and NOSIC-ASSIM.
Figure 3. Difference in (a) GPH500 and (b) T2m skill (anomaly correlation coefficient) between SIC-ASSIM and NOSIC-ASSIM in the North Atlantic during forecast weeks 2–4. (c) GPH500 skill (anomaly correlation coefficient) in the eastern North Atlantic (35–10 W, 40–55 N) of running bi-weekly (14 days) averages in May from SIC-ASSIM (blue), NOSIC-ASSIM (red), and SIC-ASSIM without the sea ice influence in Labrador + Baffin (yellow), GIN (purple) and Barents (green) hindcasts. (d) as (c), but for T2m in the central North Atlantic (50–20 W, 35–55 N). The observational reference is the mean of ERA5, JRA55 and NCEP reanalyses. Dots on lines indicate statistically significant differences (95% confidence level) between SIC-ASSIM (blue) and the given hindcast. Values in the x-axis represent the central day in the bi-weekly average.

(GPH500) over the eastern North Atlantic in May (figures 2(i)–(k), purple box in figure 2(l)) with SIC assimilation, increases that are higher than for T2m and SST. These local GPH500 skill differences disappear in June, but are evident again in JAS. The improved GPH500 skill in JAS, unlike the suggested fast sea ice—atmosphere—ocean response in May, is most likely a direct atmospheric response driven by better simulation of SSTs on longer timescales. Note that box definitions for computing GPH500 and SST/T2m averages (figures 2(d), (h) and (l)) are slightly different to adjust to the areas in which each variable exhibits skill gains in May in the spatial maps (figures 2(a), (e) and (i)).

3.3. Atmospheric linkage between Arctic sea ice and the ocean leading to better SST forecasts

To gain deeper insight into the fast sea ice-atmosphere-ocean pathway suggested above, which could explain the skill gain in central North Atlantic SSTs due to SIC assimilation, a submontly analysis of skill for T2m and GPH500 is shown in figure 3. ACC differences between SIC-ASSIM and NOSIC-ASSIM for forecast weeks 2–4 show a fast and positive impact of SIC assimilation in the eastern and central North Atlantic for GPH500 (figure 3(a)) and T2m (figure 3(b)), respectively. Note that these three-weekly averages show larger skill improvements than the monthly means (figures 2(e) and (i)), most likely due to the exclusion of the first forecast week in which the pathway is still not set up. This is further supported in a skill assessment of biweekly averages of GPH500 for different sliding windows, which shows significantly higher skill in SIC-ASSIM than in NOSIC-ASSIM for the eastern North Atlantic (purple box in figures 3(a) and 2(i)–(k)) already by the second to third weeks of the forecast (figure 3(c), red dots). Similarly, T2m improvements in the adjacent central North Atlantic region (purple box in figures 3(b) and 2(e)–(g)) are visible about a week later (figure 3(d)), indicating a possible directional causality and suggesting that a better representation of atmospheric circulation in the region leads to better near surface temperatures and SSTs. Note that the difference in
Figure 4. Lag-lead linear regression between SST in the central North Atlantic (purple box, 50–20 W, 35–55 N) in June and turbulent heat flux in (a) May, (d) June and (g) JAS from SIC-ASSIM hindcasts. (b), (e) and (h) as (a), (d) and (g), but for the mean of ERA5, JRA55 and NCEP turbulent heat flux and HadISST1.1 SST index. (c), (f) and (i) Difference between the regression coefficients in SIC-ASSIM and NOSIC-ASSIM. Dots indicate statistically significant values (95% confidence level). The regression coefficients in SIC-ASSIM and NOSIC-ASSIM are estimated after concatenating the ensemble members along the temporal dimension.

Figure 4. Lag-lead linear regression between SST in the central North Atlantic (purple box, 50–20 W, 35–55 N) in June and turbulent heat flux in (a) May, (d) June and (g) JAS from SIC-ASSIM hindcasts. (b), (e) and (h) as (a), (d) and (g), but for the mean of ERA5, JRA55 and NCEP turbulent heat flux and HadISST1.1 SST index. (c), (f) and (i) Difference between the regression coefficients in SIC-ASSIM and NOSIC-ASSIM. Dots indicate statistically significant values (95% confidence level). The regression coefficients in SIC-ASSIM and NOSIC-ASSIM are estimated after concatenating the ensemble members along the temporal dimension.

skill between SIC-ASSIM (blue lines) and NOSIC-ASSIM (red lines) hindcasts is exclusively caused by SIC assimilation. This already points to the conclusion that better initialization of Arctic SICs is behind the improved skill in the North Atlantic atmospheric circulation and surface temperature.

Additional evidence of the sea ice effect on atmospheric circulation is also seen by comparing the skill in SIC-ASSIM hindcasts with synthetic SIC-ASSIM hindcasts in which the GPH500 and T2m signals explained by previous variations in the sea ice areas of Labrador-Baffin (yellow line), GIN (purple line) and Barents (green line) Seas are removed (figures 3(c) and (d), respectively). The synthetic hindcasts are generated by computing the residual of the linear regression between the SIC-ASSIM fields and the given sea ice area indices (which corresponds to the signal that is independent of the indices). This process is done for each member separately (for more details see Acosta Navarro et al 2020). The sea ice area indices are taken for the 1st of May so that the sea ice always precede the biweekly atmospheric means analyzed. Removing the sea ice signal from SIC-ASSIM reveals that both, GIN (not statistically significant) and Labrador-Baffin Seas degrade GPH500 skill in the North Atlantic in the second half of May with skill levels more similar to those of NOSIC-ASSIM. In the case of T2m skill in the central North Atlantic, only Labrador-Baffin Sea ice has a noticeable and statistically significant impact on hindcast skill at the end of the month. The skill degradation caused on one hand by the lack of SIC assimilation, and on the other by the statistical removal of sea ice signal from the selected regions, supports the conclusion that the initial state of sea ice in GIN Seas, and more especially the Labrador and Baffin Seas, affects the atmospheric circulation in spring and affects surface temperature predictability from late spring to early fall.

Figure 4. Lag-lead linear regression between SST in the central North Atlantic (purple box, 50–20 W, 35–55 N) in June and turbulent heat flux in (a) May, (d) June and (g) JAS from SIC-ASSIM hindcasts. (b), (e) and (h) as (a), (d) and (g), but for the mean of ERA5, JRA55 and NCEP turbulent heat flux and HadISST1.1 SST index. (c), (f) and (i) Difference between the regression coefficients in SIC-ASSIM and NOSIC-ASSIM. Dots indicate statistically significant values (95% confidence level). The regression coefficients in SIC-ASSIM and NOSIC-ASSIM are estimated after concatenating the ensemble members along the temporal dimension.

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3.4. Direction of causality diagnosed by surface turbulent heat flux

The turbulent (latent + sensible) heat flux (THF) represents an important fraction of the total energy exchange between the ocean and the atmosphere and dominates air-sea interaction in the extratropics (Frankignoul 1985, Kushnir et al 2002). To explore in more detail the physical mechanisms responsible for the improved SST skill in the central North Atlantic, linear regressions of THF (upward is positive) in May (figures 4(a)–(c)), June (figures 4(d)–(f)) and JAS (figures 4(g)–(i)) onto the central North Atlantic SST index in June (figure 4, purple boxes) are shown for the SIC-ASSIM hindcast (figures 4(a), (d) and (g)) and observational data (figures 4(b), (e) and (h)). The impact of SIC assimilation on the link between North Atlantic SSTs and THF is additionally addressed by computing the difference between the regression coefficients in the SIC-ASSIM and NOSIC-ASSIM hindcasts (figures 4(c), (f) and (i)). Note that THF dominates the net surface heat flux (see figure S4 with the analysis of turbulent plus radiative heat fluxes). In qualitative terms, SIC-ASSIM displays very similar results than the observational estimates. In the lagged relationship (figures 4(a) and (b)), there is a negative THF anomaly (i.e. ocean heat uptake) in May preceding positive SST anomalies in June over the central North Atlantic, which supports an atmospheric influence on the ocean. The contemporary relationship (June–June) between SST and THF (figures 4(d) and (e)) shows a less uniform direction of the flux and reduced agreement between hindcasts and observational estimates. When SST anomalies lead (June–JAS; figures 4(g) and (h)), the sign of the regressions is consistently reversed over the central North Atlantic, showing a positive THF anomaly (i.e. ocean heat release), indicating in this case an oceanic influence on the atmosphere. Interestingly, the difference between SIC-ASSIM and NOSIC-ASSIM (figures 4(c), (f) and (i)) regression coefficients displays similar spatial patterns than both, SIC-ASSIM and observational estimates in May–June and June–JAS. This better agreement translates into more skillful predictions of central North Atlantic THF in SIC-ASSIM than in NOSIC-ASSIM (figure 5). Hence, these results provide physical evidence of how, through more realistic THF, the atmosphere leads to skill improvement in June SSTs, and that improved June SSTs exert a better-captured influence on the overlying atmosphere in the subsequent months.

3.5. Atmospheric circulation skill improvement in JAS due to more skillful SST forecasts over the central North Atlantic

In figure 6 we diagnose how much of the JAS GPH500 skill gain with SIC assimilation can be explained by central North Atlantic SST. This is performed by comparing the difference in skill of the original set of SIC-ASSIM hindcasts and a synthetic set in which the signal of central North Atlantic SSTs is removed from SIC-ASSIM. As in figure 3, the synthetic forecast is computed by retaining the residual of the JAS GPH500 field when regressing it...
Figure 6. Difference in GPH500 skill (anomaly correlation coefficient) in JAS between SIC-ASSIM and SIC-ASSIM without the influence of central North Atlantic SSTs in June (a) and JAS (b). The observational reference is the mean of ERA5, JRA55 and NCEP reanalyses. Dots in (a) and (b) indicate statistically significant differences (95% confidence level) between SIC-ASSIM and SIC-ASSIM without the North Atlantic SST signal. The influence of SSTs in (a)–(b) is removed for each member separately. Linear regression between SST in the central North Atlantic (purple boxes in figures 2(a)–(c) and 3(b), 50–20 W, 35–55 N) in JAS and GPH500 in JAS in the observational references (c) and SIC-ASSIM hindcasts (d). Dots in (c) and (d) indicate statistically significant values (95% confidence level). The regression coefficients in SIC-ASSIM (d) are estimated after concatenating the ensemble members along the temporal dimension.
this waveguide pattern to extratropical SST forcing (e.g. Garcia-Serrano et al 2013), which is thus consistent with our interpretation that improved prediction of central North Atlantic SSTs can cause a downstream influence on the Eurasian atmospheric circulation. We indeed note that the improved SST prediction in the North Atlantic extend further into fall and lead to concomitant improvements in sea level pressure and GPH500 in the Euro-Atlantic region (figures S6 and S7).

4. Discussion

Using the EC-Earth3 fully-coupled dynamical forecast system, we have investigated the impact of SIC assimilation on NH summer and fall climate prediction skill. Assimilation of observed SIC in retrospective forecasts initialized on May 1st improves Arctic sea ice predictions in May-June, and October-November. The largest improvements in the sea ice edge representation are found in the Greenland-Norwegian-Iceland (GIN) Seas, a region where EC-Earth3 is known to have important systematic sea ice biases (Cruz-García et al 2021, Tian et al 2021). Better skill in SIC also leads to improved central North Atlantic SST forecasts already in May via a fast (sub-monthly scale) atmospheric pathway, evidenced by increased prediction skill of GPH500 and T2m in the first weeks of May over the North Atlantic. These skill gains translate into long-lasting improved skill in SST from late spring to early fall. Analysis of THF confirms that positive (negative) June SST anomalies are preceded by downward (upward) heat flux anomalies in May, which indicates heat uptake (release) by the ocean, helping preserve SST skill in the model. The SST skill improvement peaks in summer and early fall, and leads to better climate forecasts in the Euro-Atlantic and Eurasian mid-latitudes through a slow (seasonal scale) mechanism involving a direct forcing of the overlying atmosphere, through heat release (uptake).

Despite using a simple assimilation strategy and a single forecast system, we have shown predictive skill benefits in the midlatitude climate resulting from better Arctic sea ice initialization. To our knowledge, this study is the first one to show a positive effect of Arctic SIC assimilation beyond the Arctic. Further, the positive impact on skill is robust, as it is present in all three sub-ensembles with different sea ice product assimilation. We believe there is still room for improvement, as it has been shown that assimilating sea ice thickness leads to better Arctic sea ice forecasts in a limited period of time (Blockley and Peterson 2018, Balan-Sarojini et al 2021) and using perfect model predictions (Day et al 2014). Due to the reported positive impact on seasonal climate prediction, future efforts should additionally aim at assimilating sea ice thickness information, for which decadal and longer datasets are becoming available.

Our results have shown that the state of sea ice in spring may affect midlatitude climate up to half a year later and that the mechanisms connecting them involve interactions between different components of the climate system (i.e. ocean, atmosphere and sea ice) across different timescales. For this reason, we call for caution in all studies exclusively based on atmosphere-only modeling experiments looking at sea ice—midlatitudes linkages at seasonal timescales, as they may be omitting key processes and feedbacks present in the system.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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