ABSTRACT: Investigation of the predictability of sea ice cover in the Barents Sea is of paramount importance since sea ice changes in this part of the Arctic not only affect local marine ecosystems and human activities but may also influence weather and climate in northern midlatitudes. Here, observational data from the period 1981–2018 are used to identify statistical linkages of wintertime sea ice cover in the Barents Sea region to preceding sea surface temperature (SST) and Atlantic Water temperature anomalies in that region. We find that the ocean temperature anomalies formed by local air–sea interactions during the winter-to-spring season are a significant source of predictability for sea ice area (SIA) in the Barents Sea region the following winter. Optimal areas for constructing SST predictors of Barents Sea SIA and skill scores from retrospective statistical forecasts are shown to differ between the periods up to and since the onset of rapid sea ice decline in the region. In the EARLY period (1982–2003), springtime SSTs in the western Barents Sea predicted 44% of the variance of the following winter Barents Sea SIA. In the LATE period (2003–17), springtime SSTs in the southern Barents Sea predicted 70% of the variance of the following winter Barents Sea SIA. Regression analysis suggests that feedbacks from anomalous winds may be important for the predictability of wintertime sea ice cover in the Barents Sea region.

KEYWORDS: Arctic; Sea ice; Seasonal forecasting; Statistical forecasting; Interannual variability; Oceanic variability

1. Introduction

Through the past few decades, the Arctic Ocean sea ice has undergone spectacular changes (Serreze et al. 2007; Kwok and Rothrock 2009; Comiso and Hall 2014; Stroeve et al. 2014). Climate warming has led to a prolonged and more intense melt season, resulting in diminished sea ice cover at the end of summer. In September, the linear trend in Arctic sea ice extent estimated from satellite passive microwave data over the period 1979–2017 amounts to −13% decade$^{-1}$ (Serreze and Meier 2019). Climate models predict that the Arctic will be free of sea ice in summer by the middle of the twenty-first century (Wang and Overland 2009; Notz and Stroeve 2016). Even though the Arctic Ocean refreezes during the ice-growth season, a significant recent decline in Arctic sea ice cover has been observed in all seasons (Stroeve and Notz 2018; Onarheim et al. 2018; Serreze and Meier 2019). This decline has contributed to a faster surface atmospheric warming in the Arctic than over the rest of our planet, observed mainly in autumn and winter (Screen and Simmonds 2010b; Dai et al. 2019). In summer, most of Arctic sea ice change and variability occurs in the perennial ice-covered seas. However, in winter, most of sea ice change and variability appears in the seasonally ice-covered peripheral seas (Onarheim et al. 2018). The onset time of rapid recent sea ice loss is a function of both the geographical location and the season (Close et al. 2015). In winter, recent changes in Arctic sea ice cover are dominated by sea ice decline in the Barents Sea (Onarheim et al. 2018; Schlichtholz 2019). In this shelf sea, located north of Europe between the northern area of the Nordic seas (Greenland–Iceland–Norwegian Seas) to the west and the Kara Sea to the east (see Fig. 1a for its location and Fig. 2a for its bathymetry), a pronounced decline started in the mid-2000s (Herbaut et al. 2015; Lind et al. 2018; Barton et al. 2018).

Variations in Arctic sea ice conditions not only alter the regional surface energy budget and atmospheric temperature (Screen and Simmonds 2010a; Lee et al. 2017; Schlichtholz 2014) but also influence the circulation and thermohaline structure of the Arctic Ocean (Krishfield et al. 2014; Polyakov et al. 2017), including the Barents Sea shelf (Lind et al. 2018). These variations affect the functioning of marine ecosystems (Oziel et al. 2017) and create new opportunities for human activities, including fisheries, shipping, exploration of natural resources, and tourism (Meier et al. 2014). The recent Arctic sea ice decline and variability are also likely to affect remote components of the Earth system (Bhatt et al. 2014), including weather and climate over Northern Hemisphere continents (Petoukhov and Semenov 2010; Cohen et al. 2014; Schlichtholz 2018; Blackport and Screen 2019; Mori et al. 2019) as well as the Atlantic meridional overturning circulation (Sévèllec et al. 2017). It is therefore essential to identify sources and understand physical mechanisms of sea ice predictability in different geographical areas of the Arctic region, on different time scales, and in different seasons (Yeager et al. 2015; Cruz-Garcia et al. 2019; Bushuk et al. 2019a). Here, the focus is on linkages of wintertime sea ice concentration (SIC) in the Barents Sea region to preceding ocean temperature anomalies over the era of satellite observations (ESO period) from 1981 to 2018.

Sea ice in the Barents Sea responds to several driving agents, such as wind-driven anomalies of sea ice export from the central Arctic Ocean and the Kara Sea (Kwok 2009; Lind et al. 2018), local variability in surface winds, surface heat fluxes and
sea surface temperature (SST) (Sorteberg and Kvingedal 2006; Schlichtholz 2011, 2019; Bushuk et al. 2017, 2019b), local subsurface ocean temperature variations (Schlichtholz 2011, 2019; Onarheim et al. 2015; Li et al. 2017; Lien et al. 2017), and remote effects of oceanic and atmospheric variability in the North Atlantic region (Vinje 2001; Nakanowatari et al. 2014; Jung et al. 2017). The thermal memory of the ocean (large heat capacity of seawater) and a relatively long (1–2.5-yr) residence time of Atlantic Water within the Barents Sea (Smedsrud et al. 2010) should result in some predictability of Barents Sea ice cover. Retrospective forecasts based on simple statistical models applied to observations (Schlichtholz 2011, 2019; Onarheim et al. 2015) as well as complex coupled climate models (Bushuk et al. 2017, 2019b) show that skillful seasonal-to-annual predictions of Barents Sea ice cover are feasible. Winter-centered annual mean heat fluxes through the BSO are skillful predictors of sea ice area (SIA) in the Barents Sea the following year (Onarheim et al. 2015). Summertime anomalies of subsurface Atlantic Water temperature (AWT) in the BSO area are skillful predictors of Barents Sea SIA the following winter (Schlichtholz 2011, 2019).

The warm and salty Atlantic Water is transported toward the Arctic Ocean by the Norwegian Atlantic Current (see Fig. 1 for a summertime climatology of subsurface temperature and a schematic of subsurface ocean circulation in the Barents Sea–Nordic seas region). This current feeds warm water pathways across the Barents Sea via the North Cape Current (Loeng 1991; Ingvaldsen 2005) and through Fram Strait via the West Spitsbergen Current (Beszczynska-Möller et al. 2012; Walczowski et al. 2017). The Atlantic Water entering the Barents Sea through the BSO feeds the major outflow from this sea through the Novaya Zemlya–Franz Josef Land passage (Gammelsrød et al. 2009) and partly recirculates westward as a topographically trapped current (Gawarkiewicz and Plueddemann 1995), hereafter referred to as the Hopen-Bjørnøya Recirculation. The recirculated Atlantic Water leaves the Barents Sea along the slope to the south of Bear Island (Bjørnøya) in southern Svalbard (Ingvaldsen 2005; Skagseth 2008). Since the water column in the southern Barents Sea is weakly stratified, the

![FIG. 1. DJF mean SST in the Barents Sea–Nordic seas region in the winter of (a) 1981/82 and (b) 2016/17. In (a) and (b) the red lines show the mean position of the sea ice edge (15% SIC contour) in the winters of 1981/82 and 2016/17, respectively. (c) JJA mean subsurface ocean temperature in the Barents Sea–Nordic seas region constructed from scattered observations north of 65°N (see the appendix). The temperature is averaged between 50 and 200 m depths and over the summers 1981–2003. Grid cells with missing data or shallower than 100 m are dark shaded. The black contours are the 300 and 1000 m isobaths. The black box corresponds to the SSS box in Fig. 2. The arrows with acronyms depict the Norwegian Atlantic Current (NwAC), North Cape Current (NCaC), West Novaya Zemlya Current (WNZC), Hopen-Bjørnøya Recirculation (HBR), West Spitsbergen Current (WSC), and East Greenland Current (EGC). (d) Time series of DJF mean sea ice area (SIA) in the Barents Sea region [green box in (b)] over the ESO period (solid blue curve), its linear trend (red line), and its continuous piecewise linear trend with the breakpoint in the winter of 2003/04 (dashed line). Each year on the horizontal axis includes January of the DJF season.](1566 JOURNAL OF CLIMATE VOLUME 34)

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Atlantic Water loses most of its heat to the atmosphere en route to its exit north of Novaya Zemlya (Smedsrud et al. 2010). A net surface heat loss to the atmosphere, caused by large turbulent heat fluxes and longwave radiation, occurs from October through April (Håkkinen and Cavalieri 1989). In summer, the warming by solar radiation and the freshening of the surface layer by lateral expansion of melt and coastal waters create a seasonal pycnocline at 20–50 m depth. With the onset of autumnal cooling, thermal convection combined with wind-driven mixing erode the seasonal pycnocline and deepen the surface mixed layer by entraining Atlantic Water from below. At the end of winter, the mixed layer extends down to (or nearly to) the seafloor (Harris et al. 1998; Smedsrud et al. 2010). The heat content anomalies present at the end of winter in the deep ocean surface mixed layer are, in summer, sequestered below the shallow seasonal pycnocline. They are subsequently re-entrained into the deepening surface mixed layer during the autumn-to-winter ocean ventilation (Bushuk et al. 2017). Such an SST re-emergence mechanism has long been known to operate in the midlatitudes (Namias and Born 1970; Deser et al. 2003). However, its impact on wintertime Arctic sea ice advance has not been noted until recently (Schlichtholz 2011, 2013). Its importance for sea ice predictability has been corroborated by an up-to-date dynamical forecast system (Bushuk et al. 2017, 2019b).

Variability in ocean temperature can influence sea ice cover in the Barents Sea region in several ways. In areas where there is direct contact between Atlantic Water and sea ice, such as the eastern Barents Sea (Árthun et al. 2012) or north of Svalbard (Piechura and Walczowski 2009; Onarheim et al. 2014), a warmer-than-normal ocean column lengthens the time of cooling to the freezing point and enlarges the area where sea ice cannot form. Another mechanism may be related to a fixed position of the polar front separating the Atlantic Water in the south from the Arctic water on the northern Barents Sea shelf along topographic features. Warmer Atlantic Water would strengthen SST gradients across the front, preventing sea ice advance to the south. This mechanism was proposed as a driver of the recent wintertime sea ice decline in the Barents Sea by Barton et al. (2018). Another mechanism was proposed by Lind et al. (2018), who linked the wintertime sea ice loss in the Barents Sea to a reduced freshwater supply to the Arctic layer on the northern Barents Sea shelf. The lowered stratification of the water column would prevent sea ice formation by enhanced vertical mixing of the Arctic water with the underlying (modified) Atlantic Water.

The present paper expands upon results from a recent study that examined linkages of wintertime surface climate variability in the Barents Sea–Nordic seas region to subsurface ocean thermal conditions the previous summer using observations from the ESO period (Schlichtholz 2019). Among other results, that study showed a somewhat tighter relation of wintertime Barents Sea ice cover to summertime AWT anomalies in the area of the westward outflow from the Barents Sea through the northern BSO (black box in Fig. 1c) in the LATE period since the onset of rapid sea ice loss in the Barents Sea than in the EARLY period up to that onset. The selection of the breakpoint between the EARLY and LATE periods in the winter of 2003/04 (see also Fig. 1d) was based on the same technique for detection of nonlinear changes as employed by Close et al. (2015) and confirmed by the regime shift detection

![Figure 2](https://example.com/figure2.png)

**Fig. 2.** (a) Bottom topography in the Barents Sea region. The yellow, red, and blue boxes mark the southern Svalbard slope (SSS), central Barents Sea (CBS), and southern Barents Sea Opening (sBSO) areas, respectively. Named geographic features are SBD = Svalbard, FJL = Franz Josef Land, NZ = Novaya Zemlya, BIT = Bear Island Trough, HT = Hopen Trench, CBk = Central Bank, and CBn = Central Basin. (b) Time series of the anomalies of JJA mean Atlantic Water temperature (AWT) in the SSS area (AWT$_{JJA}^{SSS}$; blue curve) and SON mean AWT in the CBS area (AWT$_{SON}^{CBS}$; red curve) in the ESO period. The anomalies are centered in order to have zero mean. The dashed blue and red lines show their linear trends. (c) DJF mean sea ice concentration (SIC) in the Barents Sea region regressed onto the preceding summer AWT$_{JJA}^{SSS}$ index over the ESO period. The contour interval (CI) is 5% per 1 standard deviation (SD) of AWT$_{JJA}^{SSS}$. Shading marks anomalies statistically significant at the 95% confidence level.
method devised by Rodionov (2004). If the recent tight relation of wintertime Barents Sea SIA to summertime AWT anomalies primarily reflects local climate feedbacks resulting from re-emerging SST anomalies, springtime SSTs could be used to extend the lead time of skillful SIA forecasts. Another advantage of SSTs as a potential SIA predictor is that they are available continuously on regular grids from satellite observations. In contrast, time series of observed subsurface ocean temperature in the Barents Sea are based on hydrographic measurements that are irregular in time and space due to high survey costs and harsh field conditions, which may hamper operational forecasts from such series. In any case, it is important to know what types of observations, from what areas, and of what lead time are critical for initialization of dynamical prediction systems to improve their performance (Bushuk et al. 2019b). The present study aims to address the question to what extent do springtime SST anomalies rival isolated subsurface ocean temperature anomalies during summer stratification in skillful predictions of wintertime Barents Sea SIA. For this purpose, regression/correlation analysis, maximum covariance (MC) analysis and retrospectiveleave-one-out forecasting are applied to observations from the ESO period and its EARLY and LATE subperiods. The study also investigates relations of ocean temperature variations to local atmospheric variability, which may not only drive re-emerging SST anomalies but also participate in feedbacks contributing to the sea ice response to these anomalies (Schlichtholz 2013; Herbaut et al. 2015).

This paper is organized as follows. Data and methods are described in section 2. The SIC–AWT–SST linkages and their relation to atmospheric variability during the ESO period are analyzed in section 3. The results confirm the importance of re-emerging SST anomalies for wintertime sea ice variability in the Barents Sea. First, in section 3a, the relation of this variability to different indices of earlier AWT anomalies is investigated. It is shown that wintertime Barents Sea SIA is linked more tightly to summertime AWT anomalies in the area of the outflow from the Barents Sea through the northern BSO than to AWT anomalies in the area of the inflow to the Barents Sea through the southern BSO in any season. Then, in section 3b, the relation of summertime AWT anomalies to air–sea interactions during the previous winter-to-spring season is analyzed. Regression patterns demonstrate that atmospheric variability in the Barents Sea region should leave an imprint on ocean temperatures via anomalous heating through the surface. Summertime AWT variability is shown to be highly predictable from springtime SSTs and surface air temperature (SAT) anomalies in the southern Barents Sea region. Finally, in section 3c, the structure of time-lagged cross-correlations between seasonal mean Barents Sea SIA and area-averaged SSTs in the southern Barents Sea is examined. For the SIA in seasons with large sea ice extent, two distinct maxima in correlation are found, one with the concurrent SSTs and the other one with the previous spring SSTs. Relations of wintertime SIC variability to re-emerging SST anomalies and atmospheric variability during the EARLY and LATE periods are investigated in sections 4 and 5, respectively. Notable differences between these periods are found in the scores of SIA forecasts from SSTs, in the location of significant springtime SST anomalies and wintertime SIC anomalies, and in the timing and patterns of the associated surface wind anomalies. These differences and other results are summarized and discussed in section 6.

2. Data and methods

a. Surface climate and subsurface ocean data

The variability of SST and SIC is investigated using monthly mean fields on a 1° latitude × 1° longitude grid from the NOAA Optimum Interpolation (OI) Sea Surface Temperature version 2 dataset (Reynolds et al. 2002). These fields (downloaded via https://www.esrl.noaa.gov/psd/) are derived from remote and in situ observations since December 1981. The SST monthly fields are produced from weeklyOI fields. The OI mapping procedure combines in situ SSTs with bias-adjusted satellite SSTs and proxy SSTs derived from SICs. The proxy SSTs are generated using a quadratic equation with coefficients obtained from a climatological least squares fitting procedure applied to collocated data (Reynolds et al. 2002). Therefore, the SST data in the marginal ice zone are uncertain. It is assumed that this uncertainty does not bias considerably the results presented in this study.

The SST/SIC fields are supplemented by monthly mean fields of the surface (10-m height) wind velocity (\( \mathbf{u} \)), surface wind stress (\( \mathbf{\tau} \)), surface (2-m height) air temperature (\( T_s \)), and total (turbulent plus radiative) surface heat flux (SHF; positive upward) from the NCEP–NCAR reanalysis (Kalnay et al. 1996). These fields are provided on a ~2° latitude × ~2° longitude grid and downloaded via https://www.esrl.noaa.gov/psd/. The zonal and meridional components of \( \mathbf{u} \) are employed to compute the surface wind convergence (\( -\nabla \cdot \mathbf{u} \)), where \( \nabla \) is the horizontal gradient operator) and SAT advection by the surface wind, as explained later. The corresponding components of \( \mathbf{\tau} \) are used to calculate the wind stress curl (\( \mathbf{k} \cdot \nabla \times \mathbf{\tau} \), where \( \mathbf{k} \) is a vertical unit vector).

A 3-month running mean is applied to compute seasonal mean fields of SST, SIC, and atmospheric variables. The four basic seasons (i.e., DJF, MAM, JJA, and SON) are referred to as winter, spring, summer, and autumn, respectively. The seasons starting one month earlier and later than the basic seasons are referred to as “early” and “late”, respectively. For instance, the January–March (JFM) season is referred to as late winter. For all selected seasons, indices of variability are constructed using either averaging over selected boxes (listed in Table 1) or the MC methodology (described below). The only index of sea ice variability used throughout the study is the SIA\(_{BS}\) index defined as seasonal mean SICs integrated over the Barents Sea region (BS box in Fig. 1b). The region includes the Barents Sea itself and an adjacent area of the Arctic Ocean in which considerable recent SIC changes have been observed (e.g., Ivanov et al. 2016). The selection of other boxes is made upon inspection of regression/correlation patterns. In particular, “optimal” SST predictors of wintertime Barents Sea SIA
are obtained by averaging SSTs over areas that on the one hand maximize the correlation with the predictand and, on the other hand, remain relatively large.

Analysis of subsurface ocean temperature variability is based on time series and anomaly maps constructed using scattered temperature profiles from the Unified Database for Arctic and Subarctic Hydrography (UDASH) north of 65°N (Behrendt et al. 2018) supplemented with temperature profiles provided by the International Council for the Exploration of the Sea (ICES 2019) and the Institute of Oceanology, Sopot, Poland (Walczowski et al. 2017). Details of temperature data processing are given in the appendix. The time series of JJA mean AWT anomalies in the southern Svalbard slope area (SSS box in Fig. 2a) based on these data (the AWTJJA index) is derived from temperature data averaged between 100 and 300 m depths (T_{50–200}). It is nearly identical (correlates at 0.97) with its version computed from temperature data averaged between 50 and 200 m depths (T_{50–200}). Complete time series of T_{50–200} are also constructed for other boxes and seasons. A time series is considered as complete if, for each year in the ESO period, at least three profiles per year are found in the given box for the given season. The minimum (N_{min}) and median (N_{med}) numbers of profiles per year for all boxes with complete summertime series of T_{50–200} within a regular array of adjacent boxes covering the area 69°–77°N, 6°–34°E and including the SSS box are listed in Table 2. The values of N_{min} and N_{med} for other selected predictors, for each basic season for which these predictors could be constructed, are included in Table 3. One of these predictors (the AWT_{SON}^{nBS} index) is based on autumn data from the central Barents Sea (cBS box in Fig. 2a). The cBS box was “optimized” by adjusting its boundaries to maximize the correlation of the resulting time series with SIA_{nBS}^{DIFF}. Since the AWT_{SON}^{{cBS}} index is dominated by measurements taken in September, it represents subsurface conditions at the end of summer. Another predictor is based on data from the area of Atlantic Water inflow to the Barents Sea north of Norway (the sBSO box in Fig. 2a).

b. Statistical techniques

The retrospective forecasts performed in this study employ ordinary linear regression with the leave-one-out cross-validation technique (Michaelsen 1987). This technique consists of removing one data point from the observed predictand–predictor time series of length N, generating a linear model from the remaining N – 1 data points, and predicting the omitted value of the predictand (target T_i) from the model. This step is repeated for each data point so that a set of N predicted values (forecasts F_i) and forecast residuals (F_i – T_i) is obtained. Accuracy of the forecasts is measured using the correlation skill score (CSS) and the proportion of explained variance (PEV). The CSS is defined as the correlation coefficient between the forecasts and their targets. The PEV is defined as

$$\text{PEV} = 1 - \frac{\text{SSR}}{\text{SSA}} = 1 - \frac{\sum_{i=1}^{N} (F_i - T_i)^2}{\sum_{i=1}^{N} (T_i - \bar{T})^2},$$

Table 1. Definition of areas over which climate variables are averaged for constructing indices of their variability.

<table>
<thead>
<tr>
<th>Area</th>
<th>Acronym</th>
<th>Coordinates</th>
<th>Figure</th>
<th>Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Barents Sea</td>
<td>BS</td>
<td>67°–83°N, 10°–65°E</td>
<td>1b</td>
<td>Sea ice area (SIA)</td>
</tr>
<tr>
<td>Southern Svalbard slope</td>
<td>SSS</td>
<td>73°–75°N, 13°–20°E</td>
<td>2a</td>
<td>Atlantic Water temperature (AWT)</td>
</tr>
<tr>
<td>Southern Barents Sea</td>
<td>sBS</td>
<td>70°–75°N, 15°–50°E</td>
<td>4a</td>
<td>Sea surface temperature (SST)</td>
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<td></td>
<td>5c</td>
<td>Surface air temperature (SAT)</td>
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<td></td>
<td></td>
<td></td>
<td>7b</td>
<td>Eastward surface wind velocity (u)</td>
</tr>
<tr>
<td>Northern Barents Sea</td>
<td>nBS</td>
<td>75°–83°N, 10°–65°E</td>
<td>11e</td>
<td>Northward surface wind velocity (v)</td>
</tr>
<tr>
<td>Western Barents Sea</td>
<td>wBS</td>
<td>72°–78°N, 20°–40°E</td>
<td>4b</td>
<td>SST, SAT</td>
</tr>
<tr>
<td>Central Barents Sea</td>
<td>cBS</td>
<td>73.5°–77.5°N, 30°–45°E</td>
<td>2a</td>
<td>AWT</td>
</tr>
<tr>
<td>Southern Barents Sea Opening</td>
<td>sBSO</td>
<td>71°–73°N, 16°–23°E</td>
<td>2a</td>
<td>AWT</td>
</tr>
</tbody>
</table>

Table 2. Correlation r (×100) of winter mean sea ice concentration integrated over the Barents Sea region (the SIA_{nBS}^{DIFF} index from Fig. 1d) with the previous summer (JJA mean) temperature anomalies averaged over the 50–200-m-depth layer (T_{50–200}) and over 2° latitude × 7° longitude boxes in the region 69°–77°N, 6°–34°E and the minimum (N_{min}) and median (N_{med}) numbers of temperature profiles per year used for constructing the T_{50–200} averages (not given if N_{min} < 3) in the ESO period. The values for the SSS box from Fig. 2a are in boldface. All correlations are significant at the 95% confidence level.

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</tr>
<tr>
<td>N_{min}</td>
<td>-64</td>
<td>-63</td>
<td>-86</td>
<td>-72</td>
</tr>
<tr>
<td>N_{med}</td>
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<td>N_{med}</td>
<td>28</td>
<td>14</td>
<td>30</td>
<td>30</td>
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where SSR is the sum of the squared forecast residuals, and SSA is the sum of the squared departures of the target values from their mean value $T$.

The MC analysis is carried out to detect dominant modes of covariability between two space–time fields, say $A$ and $B$. This statistical method is a generalization of the empirical orthogonal function (EOF) technique used to extract dominant modes of variability from a single time–space field (von Storch and Zwiers 1999). In contrast to the individual EOF analysis of $A$ and $B$, the MC analysis identifies only those modes in which $A$ and $B$ are strongly coupled. Here, the MC analysis is based on the singular value decomposition (SVD) of the temporal cross-covariance matrix of $A$ and $B$ (Bretherton et al. 1992). Before constructing the matrix, the anomalies of $A$ and $B$ are multiplied by the square root of the cosine of latitude, which gives equal areas equal weights in the analysis. The analysis produces pairs of orthogonal spatial patterns (singular vectors) and associated time series of temporal coefficients (TCs). The first pair of singular vectors (the leading MC mode) explains the largest time series of temporal coefficients (TCs). The first pair of orthogonal spatial patterns (singular vectors) and associated weights in the analysis. The analysis produces pairs of or-

$3. SIC$–$AWT$–$SST$ linkages in the ESO period

a. Relation of wintertime SIC variability to preceding AWT anomalies

In the Barents Sea–Nordic seas region, the coldest and warmest wintertime SSTs and the corresponding maximum and minimum sea ice extent during the ESO period were observed in the winters of 1981/82 and 2016/17, respectively (see

\begin{table}
\begin{center}
\begin{tabular}{|l|l|l|l|l|l|}
\hline
Index & Variable & $N_{\text{min}}$ & $N_{\text{med}}$ & Lag(SIA$_{\text{BS}}$) (months) & \multicolumn{2}{l|}{\begin{tabular}{l}
$r$(SIA$_{\text{BS}}$) \tabularnewline Raw & Det \end{tabular}} & \multicolumn{2}{l|}{\begin{tabular}{l}
$r$(AWT$_{\text{SSS}}$) \tabularnewline Raw & Det \end{tabular}} & \multicolumn{2}{l|}{\begin{tabular}{l}
$r$(AWT$_{\text{ASS}}$) \tabularnewline Raw & Det \end{tabular}} \\
\hline
AWT$_{\text{BS}}^{\text{FA}}$ & $T_{50-200}$ & \textbf{4} & \textbf{22} & \textbf{15} & \textbf{89} & \textbf{89} & \textbf{80} & \textbf{80} & \textbf{80} & \textbf{80} \\
AWT$_{\text{BS}}^{\text{FA}}$ & $T_{50-200}$ & \textbf{8} & \textbf{22} & \textbf{15} & \textbf{79} & \textbf{80} & \textbf{79} & \textbf{80} & \textbf{80} & \textbf{80} \\
AWT$_{\text{BS}}^{\text{FA}}$ & $T_{50-200}$ & \textbf{3} & \textbf{18} & \textbf{12} & \textbf{71} & \textbf{71} & \textbf{69} & \textbf{69} & \textbf{69} & \textbf{69} \\
AWT$_{\text{BS}}^{\text{FA}}$ & $T_{50-200}$ & \textbf{9} & \textbf{29} & \textbf{9} & \textbf{79} & \textbf{79} & \textbf{80} & \textbf{80} & \textbf{80} & \textbf{80} \\
AWT$_{\text{BS}}^{\text{FA}}$ & $T_{50-200}$ & \textbf{8} & \textbf{38} & \textbf{6} & \textbf{71} & \textbf{71} & \textbf{80} & \textbf{80} & \textbf{80} & \textbf{80} \\
AWT$_{\text{BS}}^{\text{FA}}$ & $T_{50-200}$ & \textbf{3} & \textbf{18} & \textbf{0} & \textbf{72} & \textbf{72} & \textbf{80} & \textbf{80} & \textbf{80} & \textbf{80} \\
\hline
\end{tabular}
\end{center}
\caption{Correlation $r$ ($\times 100$) of indices of Atlantic Water temperature (AWT) with winter mean sea ice concentration integrated over the Barents Sea region (the SIA$_{\text{BS}}$ index from Fig. 1d), summer mean temperature anomalies averaged over the 100–300-m-depth layer ($T_{(100-300)}$) in the southern Svalbard slope area (the AWT$_{\text{BS}}$ index from Fig. 2b; blue curve), and autumn mean temperature anomalies averaged over the 50–200-m-depth layer ($T_{50-200}$) in the central Barents Sea (the AWT$_{\text{BS}}$ index from Fig. 2b; red curve) in the ESO period. In the first column, the subscript and superscript of the given AWT index indicate the area (box) and the season for which the index is calculated, respectively. The boxes are marked in Fig. 2a, and their geographical coordinates are given in Table 1. Columns $N_{\text{min}}$ and $N_{\text{med}}$ give the minimum and the median number of temperature profiles in the given season per year used for constructing the given AWI index, respectively. Column “Lag(SIA$_{\text{BS}}$)” indicates the number of months by which the SIA$_{\text{BS}}$ index lags the given AWT index. The correlations are for the raw (columns “Raw”) and linearly detrended (columns “Det”) time series. Correlations significant at the 99% (99.99%) confidence level are in boldface (boldface and italic).}
\end{table}
Figs. 1a,b for the SST distribution and the ice edge location in these winters). These extremes reflect both a long-term change and strong interannual variability. The time series of winter SIA in the Barents Sea (the SIA_{DJF} index) exhibits a downward trend of −10.9% decade⁻¹ (Fig. 1d, red line). Consistent with other studies (e.g., Onarheim et al. 2018), the trend is significant (p < 0.01) and explains 40% of the variance of SIA_{DJF}. It is accompanied by ocean warming (Lind et al. 2018; Barton et al. 2018), here illustrated by the time series of subsurface temperature anomalies on the southern Svalbard slope in summer (the AWTS_{SSS} index; blue curve in Fig. 2b) and in the central Barents Sea in autumn (the AWTS_{DJF} index; red curve in Fig. 2b). The linear trend is about 0.36°C decade⁻¹ (p < 0.01) in both indices and explains 42% (53%) of the variance of AWTS_{DJF} (AWTS_{SSS}). The two indices are strongly related one to the other regardless of whether the long-term trend is removed (r = 0.80) or not (r = 0.89). They correlate with Barents Sea SIA the following winter approximately at the same high level (r = −0.88 for the raw data).

The SIA_{DJF} index is related more tightly to the previous summer AWT anomalies on the southern Svalbard slope than to the corresponding AWT anomalies averaged over any box of the same size as the SSS box for which a complete time series could be constructed (see the correlations in Table 2). Since all these boxes but one are located in or west of the BSO, the AWTS_{SSS} index might not be the most skillful summer AWT predictor of SIA_{DJF}. In any case, it is a more skillful predictor of SIA_{DJF} than either its spring version (the AWTS_{MAM} index) or AWT anomalies in the area of the inflow to the Barents Sea through the southern BSO (the AWTS_{wBS} index) in any season (see the correlations in Table 3). The anomalies of AWT_{wBS} are linked most tightly to the following winter SIA_{DJF} in spring. SIA_{DJF} correlates equally highly (r = −0.79) with the spring AWT_{wBS} and AWTS_{SSS} indices but considerably lower with the summer AWTS_{wBS} index than with the summer AWT_{SSS} index, especially for the detrended data (Table 3). This striking feature indicates that the strong SIA_{DJF}-AWTS_{SSS} linkage should to a large extent reflect a close relation of AWT anomalies outflowing from the Barents Sea along the southern Svalbard slope in summer to AWT anomalies generated within the Barents Sea during preceding seasons and then influencing sea ice formation on the Barents Sea shelf during the following winter. In summer, AWT anomalies in the southern BSO may have an independent contribution (e.g., coming from the south).

The anomaly pattern of winter SICs associated with the preceding summer AWT_{wBS} index (Fig. 2c) suggests that ocean temperature anomalies generated in the Barents Sea influence sea ice formation not only on the Barents Sea shelf but also north/northeast of Svalbard via their advection along the Svalbard slope. This scenario is consistent with a sequence of seasonal patterns of temperature anomalies in the 50–200-m-depth layer (T_{50–200}; Fig. 3) between warm (AWT') and cold (AWT') years defined according to the value of AWTS_{SSS} in the EARLY period (see the appendix). In winters preceding the AWT' summers, significant positive differences of T_{50–200} reaching up to −1°C appear in the western Barents Sea (Fig. 3a). In spring, they locally grow to nearly 1.5°C and spread eastward around the southern rim of the Central Basin toward Novaya Zemlya (Fig. 3b). Further spreading in this direction occurs in summer (Fig. 3c) and autumn (Fig. 3d).

Further, in the LATE period, the data coverage is insufficient to investigate seasonal evolution of the anomalies of T_{50–200} either along the Svalbard slope or on the Barents Sea shelf.

b. Relation of AWT anomalies to preceding air–sea interactions

The top panels in Fig. 4 show anomaly patterns of spring SSTs in the Barents Sea–Nordic seas region regressed onto the following summer AWT_{wBS} index based on the raw and linearly detrended data over the ESO period. These patterns indicate that summertime AWT anomalies on the southern Svalbard slope are preceded by widespread regional SST anomalies. The pattern based on the raw data exhibits the largest anomalies in the southern Barents Sea and the West Spitsbergen Current (Fig. 4a). The spring SSTs in the southern Barents Sea averaged over the wBS box in Fig. 4a (the SST_{wBS} index) predict 70% of the variance of AWT_{wBS} the following summer (see Fig. 4c for comparison of the observed and predicted time series). In the SST anomaly pattern based on the detrended data, large anomalies appear at the ice edge in the Barents and Greenland Seas (Fig. 4b). The most significant anomalies are found in the western Barents Sea. The detrended spring SSTs averaged over the wBS box in Fig. 4b (the SST_{wBS} index) are a skillful predictor of the detrended AWT_{wBS} anomalies the following summer (PEV = 0.64) and the detrended AWT anomalies in the central Barents Sea the following autumn (PEV = 0.68; see Fig. 4d for comparison of the observed and predicted anomalies of AWT_{wBS}^{SO}).

Figure 5 displays anomaly patterns of early spring wind stress curl and significant surface wind velocity (top panels), SAT (middle panels), and SHF (bottom panels) associated with the following summer AWT_{SSS} index. The patterns based on the raw data (Fig. 5, left panels) are generally similar to the corresponding patterns based on the detrended data (Fig. 5, right panels). Warm AWT anomalies are preceded by a cyclonic wind anomaly around Svalbard, with a maximum positive wind stress curl anomaly in the Hopen Trench area of the western Barents Sea (Figs. 5a,b). The anomalous Ekman
transport off the Svalbard shelf corresponding to the positive wind stress curl anomaly should induce an anomalous barotropic along-slope current that weakens the westward transport of Atlantic Water in the Hopen-Bjørnøya Recirculation (Lien et al. 2013). Besides, westerly wind anomalies in the BSO (Figs. 5a,b) should drive anomalous Ekman transport toward the Norwegian coast, which should then intensify the southern branch of the North Cape Current (Ingvaldsen et al. 2004) and lead to downstream ocean warming (Lien et al. 2017).

Wind variability may also drive ocean temperature anomalies via thermodynamic processes. In the AWT$_{\text{SSS}}$-related pattern, westerly wind anomalies over the southwestern Barents Sea turn into southerly wind anomalies over the central Barents Sea (Figs. 5a,b). Warm air advection by such anomalous on-ice winds should contribute to positive SAT anomalies over the open water and in the marginal ice zone (Schlichtholz and Houssais 2011). In the latter, the sea ice retreat forced dynamically by the anomalous on-ice winds should cause additional atmospheric warming via upward SHF anomalies. Consistent with this scenario, significant AWT$_{\text{SSS}}$-related SAT anomalies appear over the entire Barents Sea region (Figs. 5c,d). In the open water, anomalous advection of warm air combined with anomalous eddy heat flux convergence leads to anomalous diabatic cooling of the atmosphere at the surface (Schlichtholz and Houssais 2011). This cooling is accomplished by reduced heat loss from the ocean, as indicated by a lobe of downward SHF anomalies in the southern Barents Sea with a maximum magnitude in the Hopen Trench area (Figs. 5e,f). The downward SHF anomalies should then contribute to ocean warming manifested in the widespread positive springtime SST anomalies (Figs. 4a,b). The predictability of the AWT$_{\text{SSS}}$ and AWT$_{\text{SON}}$ indices from the previous early spring or spring SATs averaged over the southern Barents Sea (sBS box in Fig. 5c) is approximately as high as their predictability from the SST$_{\text{MAM}}$ index (see Table 4 for comparison of the CSS scores for the MAM predictors).

c. Lagged SIC–SST coupling

Summer and autumn AWT anomalies in the Barents Sea are tightly related not only to Barents Sea SIA the following winter (Table 3) but also to SSTs and SATs in the Barents Sea open water the previous spring (Table 4). These linkages are consistent with the scenario in which wintertime Barents Sea ice cover responds to locally formed re-emerging SST anomalies (Schlichtholz 2011). This scenario is also supported by the cross-correlations between seasonal mean SIA$_{\text{BS}}$ and SST$_{\text{BS}}$ indices displayed in Fig. 6 for the raw (left panel) and detrended (right panel) data in the ESO period. Similar cross-correlation patterns for SIA$_{\text{BS}}$ are found using the SST$_{\text{wBS}}$ index instead of the SST$_{\text{BS}}$ index (not shown). In Fig. 6, the
SIABS index is stratified according to the seasons marked on the vertical axis. The SSTs index leads for the negative lags on the horizontal axis. As shown in Schlichtholz (2019), winter Barents Sea SIA is tightly linked to the concurrent SSTs in the southern Barents Sea. Figure 6 demonstrates that SIABS is highly anticorrelated ($r < 0.90$ for the raw data and $r < 0.85$ for the detrended anomalies) with the concurrent SSTs index in all seasons from early winter to late spring (correlations along the vertical black line at lag 0). For SIABS in these seasons, the maximum negative correlation with SSTs at lag 0 is preceded by a summer/late summer minimum when seasonal stratification is present (correlations along the red line are for the SSTs index). This minimum is preceded by a spring maximum before seasonal stratification sets in (correlations along the magenta line are for the SSTs index). For SIABS in the coldest seasons (DJF to FMA), the magnitude of the correlation with the previous spring SSTs index exceeds 0.75 for the raw data and 0.65 for the detrended data. These correlations are comparable to the corresponding correlations of SIABS with SSTs leading by three months (correlations along the vertical blue line). The highest of these correlations ($r = -0.85$ for the raw time series) is for SIABS in winter (the SIADJF index) with SSTs in autumn (the SSTSON index). Therefore, both springtime and autumnal SSTs should be useful predictors of wintertime sea ice cover in the Barents Sea.

The SSTMAMsBS index predicts 55% of the total variance of Barents Sea SIA the following winter and 37% of its interannual variance. The corresponding scores for the SSTSONsBS index as the predictor are 67% and 51%, respectively. Slightly higher scores are obtained in the forecasts of SIADJF from AWT indices (see Table 5 for comparison of the CSS and PEV scores for selected predictors). In particular, the AWTJaSSS index predicts 73% of the total variance of SIADJF the following winter and 61% of its interannual variance.

4. SIC response to re-emerging SST anomalies during the EARLY period

a. SIC–SST linkages

To investigate the spring-to-winter coupling between SSTs in the Barents Sea over the EARLY period, the MC analysis is performed on the cross-covariance matrix of the MAM mean

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**Fig. 4.** Relation between springtime SSTs and AWT anomalies in the following seasons during the ESO period. (a) MAM mean SSTs (thin contours) in the Barents Sea–Nordic seas region regressed onto the following summer AWTTSSS index [blue curve in (c)]. The red (blue) contours represent positive (negative) anomalies. The CI is 0.1°C per 1 SD of AWTTSSS. The zero contour is omitted. Pink (aquamarine) shading marks positive (negative) anomalies statistically significant at the 95% confidence level. The thick black lines are the 15% and 85% contours of the springtime SIC climatology. (b) As in (a), but for the linearly detrended data. (c) Observed (blue curve) and predicted (red curve) time series of the AWTTSSS anomalies. The predicted series is from the leave-one-out forecast with the preceding spring SSTs averaged over the sBS box in (a) as the predictor. (d) Observed (blue curve) and predicted (red curve) time series of the detrended AWTTSON anomalies. The predicted series is from the leave-one-out forecast with the preceding spring detrended SSTs averaged over the wBS box in (b) as the predictor. In (a) and (b) the SSS and cBS boxes show the area over which the AWT anomalies were averaged to construct the AWTTSSS and AWTTSON indices, respectively.
SSTs (from 1982 to 2003) and the following DJF mean SSTs in the BS box in Fig. 7a. The leading MC mode explains 80% of the total square covariance of the coupled variations, and the temporal coefficient time series of this mode (TC1MAM and TC1DJF) correlate one with the other at the 99% confidence level (r = 0.72; see Fig. 7c for comparison of the time series). The regression maps of spring SST anomalies associated with the following winter TC1DJF and winter SIC anomalies associated with the previous spring TC1MAM are displayed in Figs. 7a and 7b, respectively. These maps reveal that wintertime SIC anomalies in the eastern Barents Sea are significantly related to SST anomalies at the ice edge in the western Barents Sea the previous spring via oceanic processes.

The linkage of wintertime SICs to SSTs the previous spring is further illustrated in Fig. 7d, which displays time-lagged correlations of the seasonal mean SIABS index with spring SSTs averaged over the western Barents Sea (wBS box in Fig. 7a). The correlations are practically the same for the raw (blue curve) and detrended (red curve) data. They indicate that a significant sea ice response to the springtime SSTs (from 1982 to 2003) and the following DJF mean SSTs in the BS box in Fig. 7a. The leading MC mode explains 80% of the total square covariance of the coupled variations, and the temporal coefficient time series of this mode (TC1MAM and TC1DJF) correlate one with the other at the 99% confidence level (r = 0.72; see Fig. 7c for comparison of the time series). The regression maps of spring SST anomalies associated with the following winter TC1DJF and winter SIC anomalies associated with the previous spring TC1MAM are displayed in Figs. 7a and 7b, respectively. These maps reveal that wintertime SIC anomalies in the eastern Barents Sea are significantly related to SST anomalies at the ice edge in the western Barents Sea the previous spring via oceanic processes.
anomalies occurs from the following winter (lag +9 months) to early spring (lag +11 months). A maximum negative correlation ($r = -0.78$) is attained by SIABS in late winter (lag +10 months). Consequently, the SSTsBS index explains a slightly higher fraction of the cross-validated variance of SIABS in late winter (54%) than winter (44%).

b. Relation to atmospheric variability

The leading mode of coupled spring-to-winter SST variability is associated with regional air–sea interactions. This is demonstrated by the patterns of significant spring anomalies of the surface wind velocity regressed onto the following winter TC1MAM and winter anomalies of the surface wind velocity regressed onto the preceding spring TC1MAM (arrows in Figs. 7a,b, respectively). These patterns are quite different. Over the Barents Sea, the springtime pattern exhibits southerly wind anomalies while westerly wind anomalies prevail in the wintertime pattern. The springtime pattern suggests that the SST anomalies that are present at the ice edge in the western Barents Sea at the end of winter and influence sea ice cover during the following winter are, in their positive phase, to a large extent generated by the reduced open water heat loss to the atmosphere in response to warm advection by the anomalous southerlies. This scenario is corroborated by the patterns of SAT advection by the surface wind ($-\mathbf{u}_{\text{MAM}} \cdot \nabla T^\text{FMA}$), SAT itself, and SHF in early spring regressed onto the following late winter Barents Sea SIA (shown in Figs. 8a–c for the negative phase of the SIABS index). Significant positive anomalies of SAT advection appear in the eastern Barents Sea (Fig. 8a), in the area of significant positive SAT anomalies (Fig. 8b). They achieve a maximum amplitude near the ice edge, at the location of a maximum downward SHF anomaly in the Hopen Trench area (Fig. 8c). The maximum negative correlation of SIABS with SATs averaged over the western Barents Sea (wBS box in Fig. 8b) in the preceding early spring (lag −10 months) is nearly as high as the corresponding maximum springtime correlation for the seasonal mean SSTs (Fig. 8d).

The winter westerly wind anomalies associated with the preceding spring TC1MAM and SIABS (Fig. 7b) should induce anomalous surface ocean Ekman transport toward Norway, which should drive anomalies of geostrophic current into the Barents Sea along the shoreline (Ingvaldsen et al. 2004). These current anomalies may in turn increase the Atlantic Water transport along the downstream negative thermal gradient (Fig. 1c) and thus contribute to the reduction of sea ice extent in the eastern Barents Sea on a time scale of about one month (Lien et al. 2017). To support this scenario, an index of the seasonal mean zonal wind in the southern Barents Sea ($u_{\text{ABS}}$) is defined by averaging the zonal component of the surface wind velocity ($u$; positive eastward) over the sBS box in Fig. 7b. Time-lagged correlations of $u_{\text{ABS}}$ with the previous spring SSTs in the

![Fig. 6. Cross-correlation between the year-round seasonal mean SIABS index and the year-round seasonal mean SSTsBS index for the (a) raw and (b) linearly detrended data. The SIABS and SSTsBS indices are defined as SICs integrated over the Barents Sea region (BS box in Fig. 1b) and SSTs averaged over the southern Barents Sea (sBS box in Fig. 4a), respectively. The seasonal means are running averages over 3 months with a step of 1 month. The seasons of the SIABS index are indicated on the ordinate. The negative (positive) numbers on the abscissa indicate the number of months by which the SIABS index leads (lags) the SSTsBS index. Blue (red) contours represent negative (positive) correlations plotted with the CI of 0.05. The zero contour is omitted. Correlations statistically significant at the 99% confidence level are shaded. Simultaneous (lag 0) correlations are based on data from the summer (JJA) of 1982 to the early summer (MJJ) of 2018. Lag-0 correlations for the seasons from NDJ to AMJ are marked by a thick black line. The correlations of SIABS in these seasons with SSTsBS preceding by 3 months are marked by a thick blue line. Thick red and magenta lines mark the correlations of SIABS in the NDJ to AMJ seasons with SSTsBS the preceding late summer (JAS) and spring (MAM), respectively.](image-url)
western Barents Sea are significant from winter (lag +9 months) to early spring (lag +11 months) for both the raw and detrended data (Fig. 7e). A maximum correlation \( r = 0.78 \) is attained in winter, and most significant SIC anomalies associated with the \( \sigma_{\text{DB}}^{\text{diff}} \) index are found in the eastern Barents Sea in late winter (see Fig. 7f for the late winter SIC anomaly pattern).

5. SIC response to re-emerging SST anomalies during the LATE period

a. SIC–SST linkages

To examine the spring-to-winter coupling between SSTs in the Barents Sea over the LATE period, the MC analysis is applied to the cross-covariance matrix of the MAM mean SSTs (from 2003 to 2017) and the following DJF mean SSTs in the BS box in Fig. 9a. The leading MC mode accounts for 97% of the total square covariance of the coupled variations and is characterized by a strong link between its TC time series \( r = 0.84 \); see Fig. 9c for their comparison). In the anomaly pattern of spring SSTs associated with the following winter TC1DJFBS (Fig. 9a), the largest SST anomalies appear at the ice edge in the southeastern Barents Sea. Their significant lobe extends from this area westward through the BSO to the West Spitsbergen Current. In the anomaly pattern of winter SICs associated with the previous spring TC1MAMBS (Fig. 9b), the largest SIC anomalies appear in the marginal ice zone from the southern tip of Svalbard to the northern tip of Novaya Zemlya and north/northeast of Svalbard.

The strong linkage of wintertime SICs to SSTs the previous spring is further documented in Fig. 9d, which shows time-lagged correlations of the seasonal mean SIABS index with spring SST anomalies averaged over the southern Barents Sea (sBS box in Fig. 9a). For the raw data (blue curve), the magnitude of the negative correlation drops from a lag-0 maximum \( r = -0.94 \) to a minimum in early autumn (lag +5 months). It takes a maximum the following early winter and winter \( r = -0.87 \) at lags +8 and +9 months). For the detrended data (red curve), the correlation has slightly lower extremes at lag 0 and +9 months. Consequently, the SISTBS index explains a higher fraction of the cross-validated variance of SIABS for the raw (70%) than detrended (52%) anomalies.

b. Relation to atmospheric variability

There is no clearly recurrent pattern of spring or early spring surface wind anomalies in the Barents Sea associated with the leading mode of coupled SST variability (see the arrows in Fig. 9a for significant anomalies of the MAM mean winds associated with the following winter TC1DJFBS). However, the patterns of SHF and SAT in early spring regressed onto the following winter Barents Sea SIA (shown in Figs. 10a–d for the negative phase of the SIABS index) indicate that springtime SST anomalies in the Barents Sea should to a large extent be generated by local air–sea interactions. A lobe of downward SHF anomalies in the open water, with maxima in the Hopen Trench area and at the ice edge in the southeastern Barents Sea for either the raw (Fig. 10a) or detrended (Fig. 10b) data, coincides with significant positive SAT anomalies (Figs. 10c,d). A maximum negative correlation of seasonal mean SATs averaged over the southern Barents Sea (sBS box in Fig. 10c) with winter Barents Sea SIA is found just for the preceding early spring (lag −10 months) SATs. For both the raw and detrended anomalies, this maximum is nearly as high as the corresponding springtime maximum correlation for the seasonal mean SSTs (Figs. 10c,f).

Significant winter surface wind anomalies associated with the previous spring TC1MAMBS related wind anomalies, with significant southerlies in the Barents Sea region, is found in the following late autumn (Fig. 11b, arrows). The anomalous winds converge in the marginal ice zone, mainly in the northeastern Svalbard area (see Fig. 11a, contours, for the OND mean anomalies of −u · u, associated with the previous spring TC1MAMBS). In this area, the TC1MAMBS-related SIC anomalies in late autumn (Fig. 11b) are already as large as in the following winter (Fig. 9b). The wind convergence in this area may therefore represent a direct atmospheric response to heating from below caused by the sea ice retreat in an early stage of the sea ice response to oceanic forcing.

The anomalous southerlies in late autumn should restrain southward sea ice advance via wind-induced anomalies of ice drift (Kimura and Wakasuchi 2000). By warm air advection, they should also generate atmospheric warming south of the ice edge, as indicated by the pattern of late autumn SAT anomalies associated with the previous spring SISTBS index (Fig. 11c). A high late autumn maximum negative correlation of winter Barents Sea SIA with time-lagged seasonal mean SATs averaged over the southern Barents Sea \( r = −0.87 \) at lag −2 months; Fig. 10e, red curve) supports this conclusion.

Table 5. Correlation skill score (CSS; \( \times 100 \)) and proportion of explained variance (PEV; in %) in the leave-one-out forecasts of the raw and linearly detrended time series of the SIA\(_{\text{DB}}^{\text{diff}}\) index in the period 1982/83–2017/18 (see Fig. 1d for the raw index). The predictors are the preceding spring (MAM mean) SSTs averaged over the southern Barents Sea (sBS box in Fig. 4a) and the western Barents Sea (wBS box in Fig. 4b), the preceding summer AWTSON index (Fig. 2b, blue curve), the preceding autumn AWTBS index (Fig. 2b, red curve), and the preceding autumn SSTs averaged over the southern Barents Sea. The CSS values significant at the 99% (99.99%) confidence level are in boldface (boldface and italic).

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The atmospheric warming may in turn positively feed back to the re-emerging SST anomalies and in this way contribute to a maximum sea ice response a month or two later. Such feedback is consistent with a lobe of large late autumn SST anomalies south of the ice edge associated with the previous spring TC1MAM SST2BS (Fig. 11d) and a high correlation of winter Barents Sea SIA with the preceding late autumn SSTs averaged over the southern Barents Sea ($r = -0.93$ at lag $-2$ months; Fig. 10e, blue curve). Such feedback is also indicated by a strong resemblance of the patterns of late autumn wind anomalies associated with the previous spring TC1MAM SST2BS (Fig. 11a) and the following winter Barents Sea SIA.
To further support the likely importance of late autumn wind feedbacks to the ocean for wintertime sea ice response, a late autumn wind index ($v_{\text{OND}}^{nBS}$) is defined as the meridional component of the OND mean surface wind velocity ($v$; positive northward) averaged over the northern Barents Sea ($nBS$ box in Fig. 11e).

There is a striking similarity of the patterns of wintertime SIC anomalies associated with the previous late autumn $v_{\text{OND}}^{nBS}$ (Fig. 11f) and previous spring $\text{TCI}_{\text{SON}}^{\text{BS}}$ (Fig. 9b) indices. The $v_{\text{OND}}^{nBS}$ index correlates nearly as highly with $\text{SIADJF}^{\text{BS}}$ ($r = 0.72$) as with $\text{SSTMAM}^{\text{sBS}}$ ($r = 0.79$).

### 6. Summary and discussion

A strong linkage of wintertime Barents Sea ice cover to the preceding summer subsurface ocean temperature anomalies in the area of the westward outflow from the Barents Sea through the northern BSO was previously reported based on observations during the ESO period from 1981 to 2018 (Schlichtholz 2019). The primary purpose of the present study was to determine whether this linkage may reflect the sea ice response to re-emerging SST anomalies, and to estimate the predictability of wintertime Barents Sea ice cover from different indices of AWT and SST variability. Relationships between SIC, AWT, SST, and atmospheric variables were examined over the full ESO period and its EARLY and LATE subperiods to and since the onset of rapid sea ice loss in the Barents Sea in the mid-2000s, respectively. Correlation analysis over the full ESO period revealed equally strong linkages of the total sea ice cover in the Barents Sea region during winter (the $\text{SIADJF}^{\text{BS}}$ index) to the preceding summer AWT anomalies on the southern Svalbard slope (the $\text{AWT}_{\text{JJA}}^{\text{SSS}}$ index) and the preceding autumn AWT anomalies in the central Barents Sea (the $\text{AWT}_{\text{SON}}^{\text{BS}}$ index). Weaker linkages to $\text{SIADJF}^{\text{BS}}$ were found for AWT anomalies in the area of the inflow to the Barents Sea through the southern BSO. Leave-one-out retrospective forecasts showed that, over the ESO period, the $\text{AWT}_{\text{JJA}}^{\text{SSS}}$ index accounted for 73% (61%) of the cross-validated variance of the raw (detrended) Barents Sea SIA the following winter. The corresponding forecast correlation scores (0.86 for the raw data and 0.78 for the interannual anomalies) are higher than the recently reported correlation scores from retrospective state-of-the-art dynamical forecasts over the period 1997–2016 for the target months January and February in experiments...
initialized 6 and 7 months earlier, respectively (Bushuk et al. 2019b, Figs. 7 and 8 therein). The prediction skill of \( SI_{ADJ} \) from \( AWT_{JJA} \) over the ESO period is also higher than the prediction skill of winter-centered annual mean Barents Sea SIA from the ocean heat transport through the BSO the preceding year (50%–55% of the variance explained) reported by Onarheim et al. (2015) from observations over the period 1997–2015 and from a model simulation over the period 1948–2007.

A study based on detrended data over the period 1982–2006 showed that summertime AWT anomalies in the BSO are linked to air–sea interactions in the Barents Sea region during the preceding winter-to-spring season (Schlichtholz and Houssais 2011). Regardless of whether or not the data are detrended, regressions of early spring (February–April mean) atmospheric variables with the following summer \( AWT_{JJA} \) index over the ESO period indicate that warm summertime AWT anomalies in the northern BSO are preceded by a cyclonic surface wind anomaly around Svalbard. They are also preceded by reduced surface heat loss to the atmosphere in the Barents Sea open water. Both the \( AWT_{JJA} \) index and the following autumn \( AWT_{SSS} \) index were shown to be highly predictable from area-averaged springtime SSTs (the \( SSTMAM_{sBS} \) index) and SATs in the southern Barents Sea (correlation scores above 0.8 for the raw data and above 0.7 for the interannual anomalies). These relations do support the scenario in which the strong \( SI_{ADJ} \)–\( AWT_{JJA} \) linkage mainly reflects the sea ice response to re-emerging SST anomalies driven by atmospheric forcing over the Barents Sea shelf at the end of winter. Similarly, generation of Barents Sea heat content anomalies by anomalous local surface heat fluxes was reported by Bushuk et al. (2019b) in a modeling study. This scenario is however not in line with the findings of Årthun et al. (2012) based on annual mean variables, according to which variations in the Barents Sea heat content are primarily driven by anomalous volume transport through the BSO.

Further support for the importance of the SST re-emergence mechanism for the predictability of Barents Sea ice cover during the ESO period was provided by time-lagged cross-correlation analysis between the seasonal mean \( SIA_{BS} \)
This analysis showed that a high maximum anticorrelation of SIABS in cold seasons with the concurrent SSTs is preceded by a significant secondary maximum anticorrelation with the previous spring SSTs. The same analysis revealed considerable predictability of winter (DJF mean) and late winter (JFM mean) sea ice cover in the Barents Sea from the preceding autumn (SON mean) and late autumn (OND mean) SSTs, respectively. However, this predictability was significant only in the LATE period (see Table 6 for comparison of the skill scores of the SIADJFBS and SIAJFMBS forecasts from selected predictors in the EARLY and LATE periods). This result stands somewhat in contrast with a significant linkage of JFM mean SIA in the northern Barents Sea to OND mean SSTs in the southern/central Barents Sea found by Herbaut et al. (2015) for the EARLY period (extended back to 1979) in a model simulation.

Similarly, springtime SSTs in the southern Barents Sea were not skillful predictors of wintertime Barents Sea SIA in the EARLY period. Compared to that period, in the LATE period, the cross-validated variance of SIADJFBS explained by the previous spring SSTMAMBS index increased from 15% to 70% and that explained by the previous summer AWTJJA SSS index from...
46% to 85%. Both increases are significant, as indicated by \( p \) values from the Monte Carlo test (see column \( p_{Dr} \) in Table 6). In the EARLY period, wintertime Barents Sea SIA was to some extent predictable from springtime SSTs averaged over the western Barents Sea (the \( SSTMAM_{BS} \) index). The largest 

**FIG. 11.** Relation of late autumn surface climate variability to springtime SSTs and wintertime SICs in the LATE period. (a) OND mean surface wind convergence (thin contours and color shading) and surface wind velocity (arrows) in the Barents Sea–Nordic seas region regressed onto the previous spring TC time series from the leading MC mode of coupled spring-to-winter SST variability in the Barents Sea region (red curve in Fig. 9c). The CI is \( 2 \times 10^{-7} \) s\(^{-1}\) per 1 SD of \( TC_{SST-BS}^{MAM} \). The zero contour is omitted. The thin contour and shading colors are explained in the caption to Fig. 4. The anomalies of \( u \) are per 1 SD of \( TC_{SST-BS}^{MAM} \), subsampled and masked if both components are nonsignificant at the 95% confidence level. (b)–(d) The thin contours and color shading are as in (a), but for OND mean SIC, SAT, and SST, respectively. The CI is 5%, 0.5\(^\circ\), and 0.1\(^\circ\) C per 1 SD of \( TC_{SST-BS}^{MAM} \), respectively. In (e) and (d) the thick black lines are the 15% and 85% contours of the late autumn SIC climatology in the LATE period. (e) The arrows are as in (a), but for OND mean surface wind velocity regressed onto the following winter Barents Sea SIA (with reversed sign). (f) As in (b), but for DJF mean SIC regressed onto the previous late autumn meridional wind velocity (positive northward) averaged over the northern Barents Sea [nBS box in (e)].

Land passage into the Barents Sea at that time (Kwok et al. 2005). Diminished inflows of multiyear ice might have contributed to the recent increase of Barents Sea SIA predictability from ocean temperature anomalies.

To illustrate recent changes in the spring-to-winter coupling of surface climate variations in the Barents Sea region, the leading MC mode of SST variability in this region was computed for the EARLY and LATE periods from MAM and DJF means of SST. In the EARLY period, the coupled mode linked
wintertimic SIC anomalies in the eastern Barents Sea to springtime SST anomalies in the western Barents Sea. In the LATE period, the coupled mode linked wintertime SIC anomalies across the northern Barents Sea shelf and north/northeast of Svalbard to widespread springtime SST anomalies in the southern Barents Sea. Regressions of wintertime Barents Sea SIA with SAT and SHF anomalies the previous early spring revealed that, in both periods, local thermodynamic atmospheric forcing should have contributed to the ocean temperature anomalies that induced the delayed sea ice ice response. In the EARLY period, the most significant SAT/SHF anomalies were found in the western Barents Sea, where they were related to SAT advection by anomalous meridional winds. In the LATE period, the most significant SAT/SHF anomalies appeared in the southeastern Barents Sea, in the area of large springtime SST anomalies at the ice edge.

The delayed wintertime sea ice response to locally driven ocean temperature anomalies in the EARLY period is consistent with the results obtained by Herbaut et al. (2015) from their numerical model. However, Herbaut et al. (2015) emphasized significant linkages of wintertime SICs in the northern Barents Sea to AWT anomalies in the southern Barents Sea one year earlier and attributed these AWT anomalies to locally driven variability in the ocean circulation rather than thermodynamic forcing at the surface. Wind-driven ocean circulation variability might have also contributed to interannual AWT anomalies in the LATE period. For the detrended data, lobes of significant correlations of the wind stress curl in winter with the following summer AWT$_{SBS}^\text{SON}$ index are found over the Barents and Greenland Seas in both periods (Fig. 12). Compared to the EARLY period, in the LATE period, they are displaced northeastwards, the Barents Sea lobe from the Svalbard Bank area (Fig. 12a) to the central part of the northern Barents Sea shelf (Fig. 12b). Anomalous divergence of the surface Ekman transport corresponding to the positive wind stress curl anomaly over the northern Barents Sea shelf, as in the positive phase of the AWT$_{SBS}^\text{SON}$ index in the LATE period, should drive a barotropic circulation anomaly around this shelf enhancing penetration of Atlantic Water into the Barents Sea via a route along the Polar Front (Lien et al. 2013). Such an enhancement might have led to more widespread ocean temperature anomalies in the Barents Sea in the LATE than in the EARLY period. Besides, the convergence of the interior flow compensating anomalous water suction into the surface Ekman layer on the northern Barents Sea shelf favors enhanced penetration of Atlantic Water onto this shelf through the Svalbard/Franz Josef Land passage (Lind and Ingvaldsen 2012). Temperature anomalies generated in this way could, because of the recently reduced stratification of the Arctic domain of the Barents Sea (Lind et al. 2018), mix upward at a later time and possibly contribute to the widespread SIC anomalies in the Barents Sea region the following winter.

According to Nakanowatari et al. (2014), Barents Sea SIC variability at the beginning of winter is mainly driven by a combination of ocean temperature anomalies advected from the North Atlantic and quasi-simultaneous local wind forcing. This scenario is inconsistent with the concept of sea ice predictability from the locally formed ocean temperature anomalies. However, feedbacks from anomalous local winds driven by re-emerging SST anomalies could play a key role in establishing a prolonged sea ice response to ocean temperature anomalies. In the EARLY period, the springtime SST anomalies were linked to anomalous zonal winds over the southern Barents Sea the following winter. These winds might have contributed to the sea ice variability in the eastern Barents Sea via subseasonal feedbacks between self-sustaining anomalies of ocean temperature, sea ice cover, winds, and wind-driven ocean currents, as proposed in an earlier study (Schlictholz 2013). In the LATE period, the springtime SST anomalies were related to anomalous meridional winds and SATs over the Barents Sea the following late autumn. Numerical models should elucidate possible feedbacks from these winds and SATs to the ocean and their role in the sea ice response to oceanic forcing.

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APPENDIX

Processing of Subsurface Ocean Data

The UDASH dataset contains quality-controlled temperatures profiles from the ESO period up to 2015 and includes data from the ICES (Behrendt et al. 2018). The analysis of summertime AWT variability in Schlichtholz (2019) included additional data from cruises of R/V Oceania in the period 1991–2017 (Walczowski et al. 2017) and, for the summers of 2016 and 2017, from the ICES. Here, data from the same sources are utilized for analysis of subsurface ocean temperature variability also in other seasons. Since the UDASH dataset contains a limited number of profiles in 2015, and additional data from that year could have been added to the ICES database after the release of the UDASH dataset, the present analysis also includes the ICES data from 2015 if not present in the UDASH dataset.

Before averaging over selected boxes or gridding, some preprocessing is applied to the vertically averaged temperature $T_{av}$ ($T_{50–200}$ or $T_{100–300}$) at the hydrographic stations. First, to account for month-to-month variability, $T_{av}$ is referenced to the middle of the given season using a correction based on monthly mean temperature distributions from the PHC 3.0 global ocean climatology updated from Steele et al. (2001). Then, for any given season, mean values of $T_{av}$ are computed for a base (EARLY) period at the locations of all stations in the ESO period by averaging $T_{av}$ data found inside a circular domain around the given station with a radius corresponding to the distance of half a degree of latitude. Next, local anomalies of $T_{av}$ at all stations are calculated by subtracting the base period climatology from the original data.

To construct the time series, the anomalies of $T_{av}$ in the given season of each year are averaged over the given box using the procedure previously employed in Schlichtholz and Houssais (2011). The stations from the box are assumed to lie on the same meridian. The anomalies of $T_{av}$ are then linearly interpolated between the southern and northern boundaries of the box before taking the meridional average. The values at the southern and northern boundaries are obtained by extrapolating data from the closest station inside the box. The final time series is obtained by averaging estimates from Monte Carlo simulations in which the interpolation and meridional averaging is repeated 500 times using a randomly selected subset (50%) of the stations in each year.

The maps of composite mean differences of subsurface ocean temperature in the Barents Sea–Nordic seas region between “warm” and “cold” years for the four basic seasons in the EARLY period (1981–2003; Fig. 3) are obtained using the $T_{50–200}$ variable. This variable is also used for constructing the map of the summer mean temperature in the EARLY period (Fig. 1c). The maps are constructed on a 0.5° latitude by 1.5° longitude grid. Local inverse distance weighting is applied for computation of the temperatures and their anomalies at the grid points. The weighting factors $w$ are defined as $w(r) = (R^2 - r^2)/(R^2 + r^2)$, where $r$ is the distance between the grid point and the station, and $R$ is the “radius of influence” at which $w$ goes to zero ($R$ is set to the distance of one degree of latitude). The weighting factors are normalized so that their sum equals unity. The composites are built on the AWT$_{SSS}$ index (Fig. 2b, blue curve). The positive (negative) composites are computed using the data from the years in which the AWT$_{SSS}$ index is greater (smaller) than one (minus one) standard deviation over the EARLY period. The warm years are 1983, 1984, 1990–92, and 2000. The cold years are 1981, 1986–88, 1997, and 1998.

![FIG. 12. Correlation coefficient of winter (DJF mean) surface wind stress curl in the Barents Sea–Nordic seas region with the following summer AWT$_{SSS}$ index (Fig. 2b, blue curve) for the linearly detrended anomalies in the (a) EARLY and (b) LATE periods. Pink (aquamarine) shading marks positive (negative) correlations significant at the 95% confidence level. In (a) and (b) the thick black lines are the 15% and 85% contours of the winter SIC climatology in the EARLY and LATE periods, respectively.](image)


