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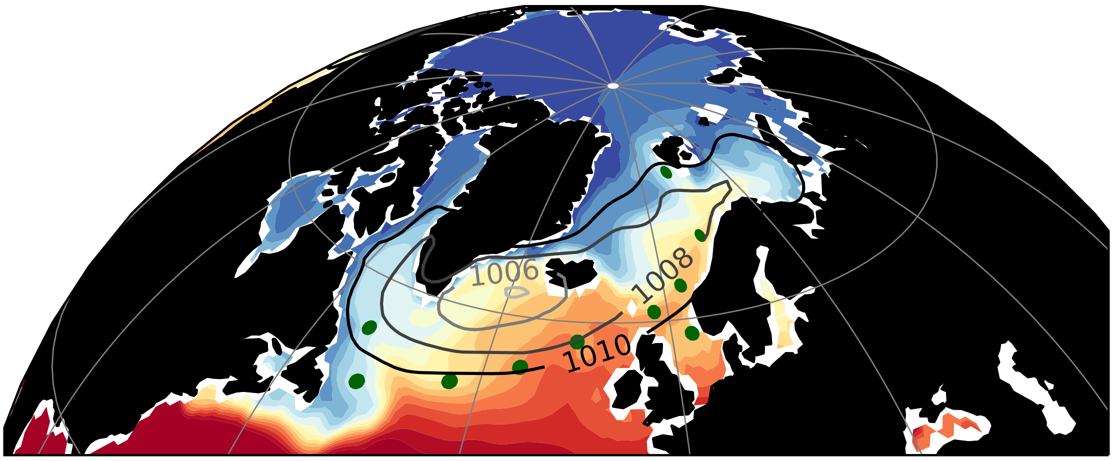
Subdecadal Variability and Predictability of the Subarctic Atlantic Ocean



Hongdou Fan

Hamburg 2024

Berichte zur Erdsystemforschung
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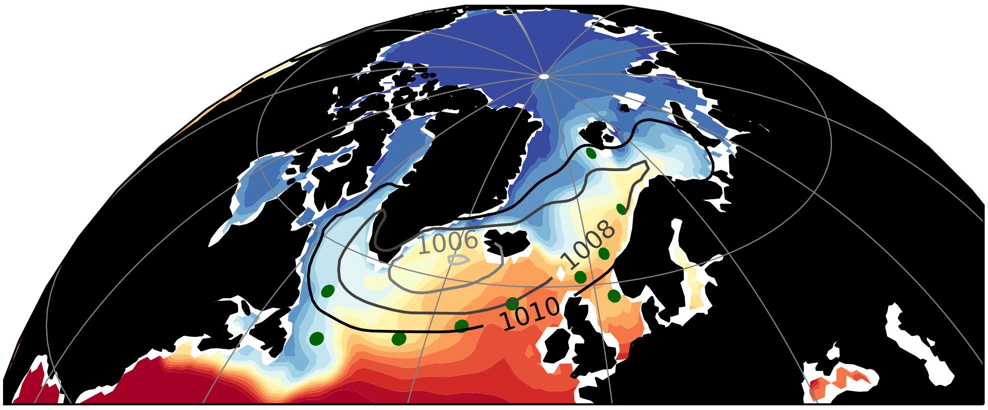

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ABSTRACT

Slowly varying large-scale ocean circulation can provide climate predictability on decadal time scales. It has been hypothesized that the North Atlantic subpolar gyre (SPG) exerts substantial influence on ocean predictability in the Subarctic Atlantic. However, a clear identification of the downstream impact of the SPG variations is still lacking. In this dissertation, I demonstrate that along the Atlantic water pathway, a dynamical link to the SPG causes salinity to be considerably better predicted than temperature in the MPI-ESM-LR1.2 decadal prediction system. By modulating the slow northward ocean propagation, the subsurface memory of SPG variations enables salinity to be skillfully predicted up to 8 years ahead. In contrast, the SPG loses influence on temperature before Atlantic water penetrates into the Nordic Seas, and in turn limits temperature to be predicted only 2 years ahead. I identify the key role of SPG signals in downstream prediction and highlight how SPG signals determine prediction time scales for salinity and temperature.

I further investigate the low predictability of temperature in the Subarctic Atlantic, and disentangle the roles of the North Atlantic Oscillation (NAO) and the SPG in the subdecadal variability of the Norwegian Sea upper ocean temperature. With emphasis on the subdecadal time scale, I detect the lagged and transient impacts of the NAO on the Norwegian Sea temperature. By inducing temperature anomalies in the subpolar North Atlantic via buoyancy forcing, the lagged impact of the NAO manifests itself through the oceanic pathway. The resulting temperature anomalies in the subpolar North Atlantic show a poleward propagation and spread across the Norwegian Sea in the following 4-5 years. The NAO also exerts a transient impact on the Norwegian Sea temperature by modulating turbulent heat flux and wind-driven transport into the Norwegian Sea. The positive NAO elevates sea surface height along the Norwegian continental shelf and enhances temperature transport into the Norwegian Sea simultaneously. While the negative NAO lowers sea surface height and reduces temperature transport into the Norwegian Sea. This twofold, lagged and transient impact of the NAO, limits the predictability of the Norwegian Sea temperature. Although the lagged impact of the NAO stores as ocean memory and emerges 4-5 years later in the Norwegian Sea, the transient impact may damp and counteract the lagged oceanic signal, leading to only 1-year predictability of the Norwegian Sea temperature. I argue that the lagged impact of the NAO via slow ocean dynamics is potentially predictable, and the emergence of ocean memory reveals the possibility to improve subdecadal prediction of the Norwegian Sea temperature with postprocessing tools.

Overall, this dissertation disentangles the roles of the SPG and the NAO in variability and predictability of upper Subarctic Atlantic Ocean. It reveals the challenge in predicting the Norwegian Sea temperature and sheds light on the possible directions

to improve decadal prediction, opening the door for investigating potentially associated predictions in the Subarctic Atlantic for the earth system.

ZUSAMMENFASSUNG

Langsam schwankende großräumige Ozeanzirkulationen können die Klimavorhersage auf dekadischen Zeitskalen ermöglichen. Es wurde die Hypothese aufgestellt, dass der subpolare Wirbel des Nordatlantiks (SPG) einen erheblichen Einfluss auf die Vorhersagbarkeit des subarktischen Atlantiks hat. Die Auswirkungen der SPG-Variationen auf die downstream gerichteten Prozesse sind jedoch noch nicht eindeutig geklärt. In dieser Dissertation zeige ich, dass entlang des Nordatlantikstroms eine dynamische Verbindung zum SPG dazu führt, dass der Salzgehalt im dekadischen Vorhersagesystem MPI-ESM-LR1.2 wesentlich besser vorhergesagt wird als die Temperatur. Durch die Modulation der langsamen nordwärts gerichteten Ozeanausbreitung ermöglicht das Gedächtnis der SPG-Variationen eine Vorhersage des Salzgehalts bis zu 8 Jahre im Voraus. Im Gegensatz dazu verliert der SPG seinen Einfluss auf die Temperatur, bevor atlantisches Wasser in die nordischen Meere eindringt, was wiederum dazu führt, dass die Temperatur nur 2 Jahre im Voraus vorhergesagt werden kann. Ich ermittle die Schlüsselrolle der SPG-Signale bei der Vorhersage und zeige auf, wie SPG-Signale die Vorhersagezeitskalen für Salzgehalt und Temperatur bestimmen.

Deweiteren untersuche ich die geringe Vorhersagbarkeit der Temperatur im subarktischen Atlantik und entflechte die Rolle der Nordatlantischen Oszillation (NAO) und des SPG in Bezug auf die subdekadische Variabilität der Meerestemperatur in den oberen Schichten der Norwegischen See. Mit Schwerpunkt auf der subdekadischen Zeitskala ermittle ich die verzögerten sowie die instantanen Auswirkungen der NAO auf die Temperatur der Norwegischen See. Durch die Induzierung von Temperaturanomalien im subpolaren Nordatlantik über Änderungen im Auftrieb manifestiert sich der verzögerte Einfluss der NAO über den ozeanischen Pfad. Die daraus resultierenden Temperaturanomalien im subpolaren Nordatlantik breiten sich in den folgenden 4-5 Jahren polwärts über die Norwegische See aus. Die NAO übt auch einen instantanen Einfluss auf die Temperatur der Norwegischen See aus, indem sie den turbulenten Wärmefluss und den windgetriebenen Transport in die Norwegische See moduliert. Die positive NAO erhöht die Höhe der Meeresoberfläche entlang des norwegischen Kontinentalschelfs und verstärkt gleichzeitig den Temperaturtransport in die Norwegische See. Die negative NAO senkt die Meeresoberflächenhöhe und verringert den Temperaturtransport in die Norwegische See. Diese doppelte Auswirkung der NAO, verzögert und zeitgleich, schränkt die Vorhersagbarkeit der Temperatur in der Norwegischen See ein. Obwohl die verzögerte Auswirkung der NAO als ozeanisches Gedächtnis gespeichert wird und 4-5 Jahre später in der Norwegischen See auftritt, kann die instantane Auswirkung das verzögerte ozeanische Signal dämpfen und ihm

entgegenwirken, was zu einer nur einjährigen Vorhersagbarkeit der Temperatur der Norwegischen See führt. Ich zeige, dass die verzögerte Auswirkung der NAO durch die langsame Ozeandynamik potenziell vorhersagbar ist, und das Vorhandensein des Ozeangedächtnisses zeigt die Möglichkeit auf, die subdekadische Vorhersage der Temperatur der Norwegischen See mit Post-processing zu verbessern.

Insgesamt wird in dieser Dissertation die Rolle des SPG und der NAO für die Variabilität und Vorhersagbarkeit der oberen Schichten des subarktischen Atlantiks entschlüsselt. Sie zeigt die Herausforderung bei der Vorhersage der Temperatur in der Norwegischen See auf und beleuchtet die möglichen Richtungen zur Verbesserung der dekadischen Vorhersage, was die Tür zur Untersuchung potenziell damit verbundener Vorhersagen im subarktischen Atlantik für das Erdsystem öffnet.

ACKNOWLEDGEMENTS

Immersing in the unknown, having a breakthrough in the darkness, uncovering patterns from the seemingly ‘noise’ background, to me, this is the essence and beauty of research. This incredible journey has been far more than earning a PhD, it has been an exploration of myself and uncovering life. Throughout this process, I have built a great deal of confidence, while also realizing how much more there is to learn. I am eager to grow. I would like to extend my deepest gratitude to people who supported me. Without you, I wouldn’t have made this precious journey.

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PUBLICATIONS

Appendix A:

Fan, H., L. F. Borchert, S. Brune, V. Koul, and J. Baehr, 2023: North Atlantic subpolar gyre provides downstream ocean predictability. *Npj Clim. Atmospheric Sci.*, **6**, 145, https://doi.org/10.1038/s41612-023-00469-1.

Appendix B:

Fan, H., L. F. Borchert, S. Brune, A. Drews, and J. Baehr, 2024: Lagged and transient impacts of the NAO on subdecadal variability of the Norwegian Sea temperature. *J. Clim* (under review).

CONTENTS

Unifying Essay

Appendices

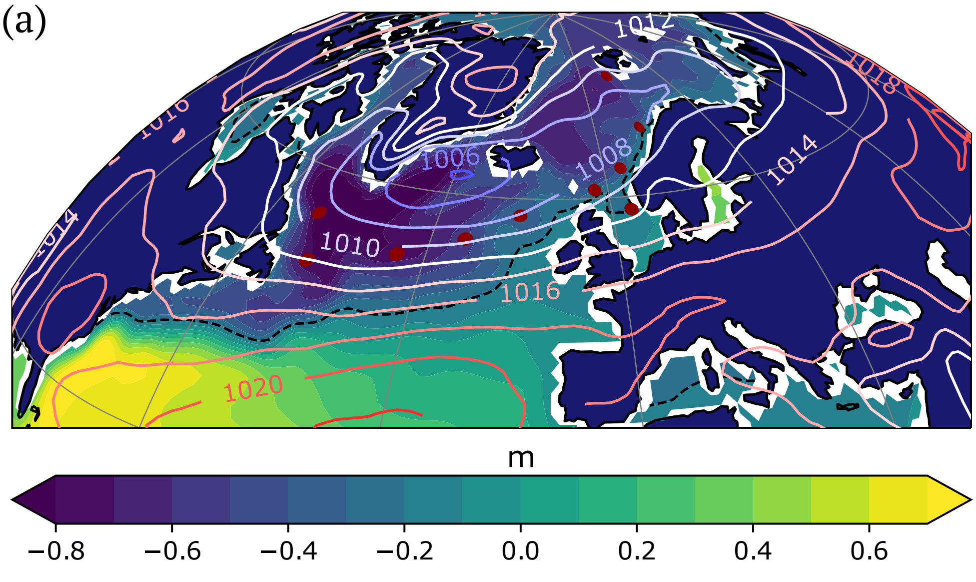
Unifying Essay

1 Introduction

1.1 Overview of the Subarctic Atlantic Sector

A broad consensus has been reached on the crucial role of the North Atlantic Ocean in modulating European and global climate (e.g., Yeager and Robson 2017). One iconic phenomenon is the Gulf Stream and its extensions, which carry heat salt and nutrients from tropics to the subpolar North Atlantic and Subarctic Atlantic Ocean (**Fig. 1**a). The inflow of warm and saline water into the Subarctic Atlantic Ocean has significant impacts on the northern climate and biological production. The warm ocean currents in the subpolar North Atlantic and Subarctic Atlantic transfer heat to the overlaying cold atmosphere, which results in a warmer climate in northern Europe compared with regions in similar latitude such as Russia. Understanding and predicting ocean conditions in the Subarctic Atlantic where large population of marine species live, have great social and economic impacts and therefore are important. Predicting changes of water properties in the Subarctic Atlantic Ocean from interannual to decadal time scales (from 1 year up to 10 years) years is useful to assess long-term risk and avoid huge socio-economic loss for relevant stakeholders and governments. Particularly, predicting ocean temperature and salinity is essential for predicting habitats of marine species in the Subarctic Atlantic, and therefore is beneficial to fisheries and aquaculture (Hollowed et al. 2013).

(a)



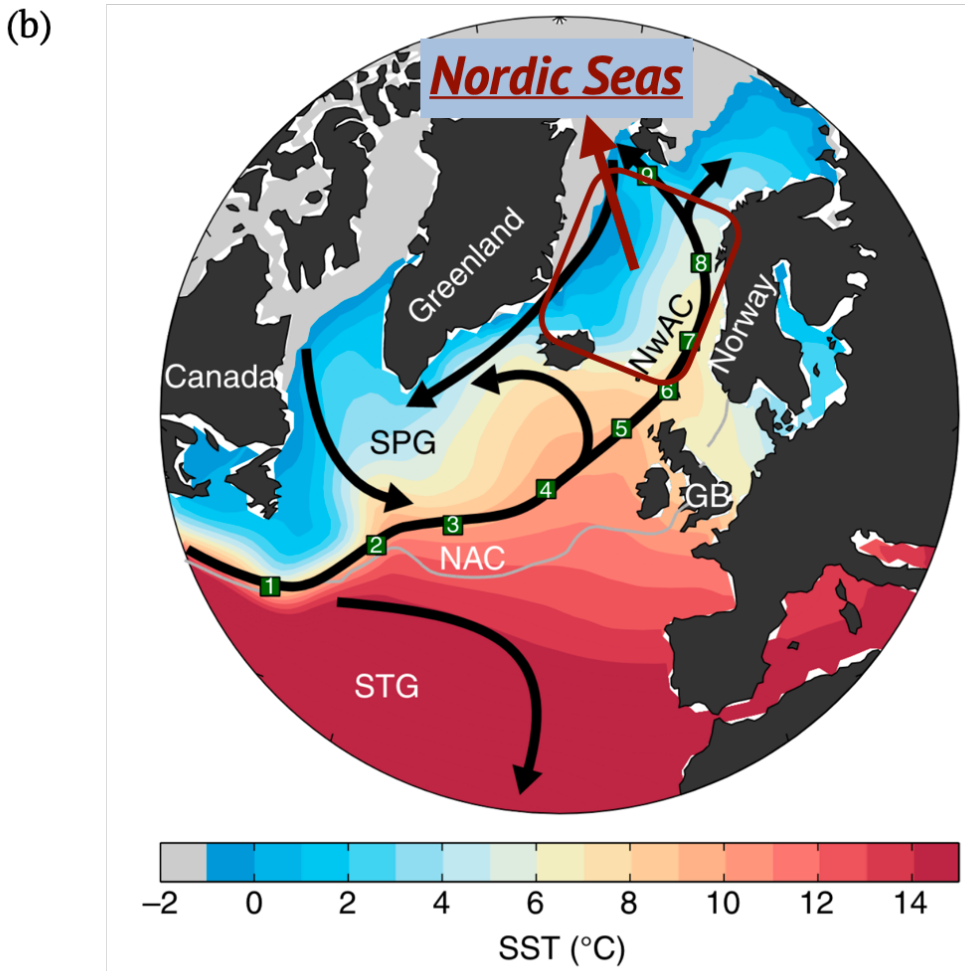


Fig. 1 Overview maps of the North Atlantic sector. (**a**) Climatological sea surface height (SSH; shading; m) and sea level pressure (SLP; contour; hPa) for the period 1970-2019 in assimilation based on MPI-ESM-LR1.2. The SSH with values of -0.2m is highlighted by a black dashed contour. Dark red dots show positions along the SPG, the North Atlantic Current (NAC) and the Norwegian Atlantic Current (NwAC). (**b**) Conceptual map of the North Atlantic showing the SPG and main surface currents: NAC, NwAC, and the counterclockwise circulation in the Nordic Seas. Adapted from Årthun et al. 2017.

The skillful predictions of temperature and salinity in the Subarctic Atlantic Ocean are not only important for northern European climate and fish industries, but also are of great scientific interest. Understanding the variability and predictability of temperature and salinity in the Subarctic Atlantic Ocean is important for investigating ocean dynamics and understanding mechanisms of interactions in climate systems. In the Subarctic Atlantic sector, the Nordic Seas are the main focus of this dissertation (Fig. 1b), which consist of the Greenland Sea, Iceland Sea, and the Norwegian Sea. As a transition zone between the northern North Atlantic Ocean and the Arctic Ocean, Nordic Seas import warm and saline water to the Arctic and export cold and fresh water into North Atlantic. In deep Nordic Seas, the dense overflows across the Greenland-Scotland Ridge are part of the Atlantic Meridional Overturning Circulation (AMOC). The AMOC is perceived as a prominent system modulating climate in the North Atlantic on the decadal time scale and provides decadal predictability. Temperature variability and salinity variability in the Nordic Seas are closely associated with density variability and ocean convection, thus in turn influence the variability and predictability of the AMOC. However, simulations and predictions of magnitude for temperature and salinity variability are still far from satisfactory, which lead to incorrect density variability therefore unrealistic convection. The inaccurate prediction of convection may result in wrong drivers for AMOC thus limited performance in decadal prediction systems (Menary et al. 2016). Moreover, ocean variability in the Subarctic Atlantic exerts impact on sea ice extent in the Arctic via heat exchange. The sea ice extent is much more sensitive to greenhouse gas than other regions due to the positive albedo-climate feedback (Ding et al. 2014), and sea ice in turn can affect global climate (e.g., Fan et al. 2020). Hence, understanding the variability of temperature and salinity and improvements of their predictions hold the key to understand mechanisms in complex earth system and to improve the decadal prediction in the North Atlantic.

Understanding how water properties change in the Subarctic Atlantic Ocean is important. However, the climate variability is not simple and linear. Instead, it is involved with many influencing factors in earth systems and its dominant mechanisms changes on across spatial scales and time scales. Therefore, climate perdition up to 10 years is a big challenge in scientific community. Climate prediction is different from weather forecast, which forecasts weather condition from a few hours to 2 weeks. The numerical weather forecast model depends on current weather conditions and integrates partial differential equations based on fluid dynamics. Besides initial conditions, climate prediction has to take interactions among different components in earth systems such as atmosphere, ocean, sea ice, snow, soil and so on into consideration. Climate prediction is also different from climate projection, which copes with long-term climate trends such as global warming. Climate projection mostly relies on forcings outside climate systems such as greenhouse gas concentration, solar radiation, volcano eruption and so on. The climate predictions into next 1 year up to 10 years are a combination of initial value problem and boundary value problem, and are produced by decadal prediction systems. Different components in climate system including atmosphere, ocean, land and so on, have different response timescales and they interact with each other. This fact exacerbates the difficulty of climate prediction.

The predictability of the Subarctic Atlantic Ocean is still a challenge to tackle. On the one hand, the ocean heat content in the Subarctic Atlantic is largely govern by ocean heat transport along Atlantic water inflow. On the other hand, ocean circulations in the Subarctic Atlantic are also significantly influenced by the overlaying atmosphere via heat, momentum, and water vapor exchanges. Ocean and atmosphere respond to stimulations on different time scales. Atmosphere changes fast with time scales from hourly to annually, while it takes seasons up to

1000 years for ocean to react to external forcing. The distinguishable response time scales of atmosphere and ocean decide that they play different roles in climate prediction. In terms of the climate predictability, atmospheric circulation is perceived as noise and the main source of uncertainties due its chaotic dynamics (Lorenz 1963). In contrast, the slowly varying ocean circulation gives rise to the feasibility of interannual to decadal predictions (e.g., Langehaug et al. 2022; Fan et al. 2020). The interactions of different components can also serve as memory and therefore provide decadal climate predictability. The questions come: if atmosphere and ocean these two factors compete and interact with each other, which dominates water properties in the Subarctic Atlantic and when it dominates? How do atmosphere and ocean together play roles in governing water properties in the Subarctic Atlantic? What decides the predictability of the Subarctic Atlantic ocean?

With the development of global climate models in recent years, North Atlantic climate prediction has improved significantly from seasonal to decadal time scales. It is documented that decadal North Atlantic Ocean variability contributes to climate predictability to a large extent (Årthun et al. 2021; Menary et al. 2021). Recently, many studies indicated that the poleward propagation of thermohaline anomalies in the North Atlantic provides potential climate predictability on decadal time scale (e.g., Årthun et al. 2017; Langehaug et al. 2022). Much attention has been drawn to the predictability of sea surface temperature (SST) along the Atlantic water pathway particularly the subpolar North Atlantic (e.g., Borchert et al 2018). In contrast, predictions of temperature and salinity in depth layers in the Subarctic Atlantic Ocean are less documented. In fact, simulations of magnitude particularly for temperature variability in the Nordic Seas are still far from satisfactory. The predictability of subsurface water properties and associated mechanisms along the Atlantic water pathway are still not fully understood, and are the gap I aim to fill.

This dissertation focuses on changes of water properties in the Subarctic Atlantic Ocean from interannual to decadal time scales. On these time scales, the atmosphere and ocean are two key components driving the climate variability in the Subarctic Atlantic sector. The atmospheric component is featured by an atmospheric pressure see-saw across the North Atlantic (**Fig. 1**a). This pressure difference between Azores high and Icelandic low is represented by the North Atlantic Oscillation (NAO; Hurrell 1995). The NAO is the predominant mode of atmospheric variability in the North Atlantic, governing the intensity and location of westerlies in the North Atlantic. The NAO + (–) phase represents stronger (weaker) westerlies and more (less) frequent storms across the northern North Atlantic, modulating the northern climate (e.g., Hurrell 1995; Smith et al. 2020).

The ocean component is closely coupled with atmosphere via energy and material exchanges at the air-sea interface. The upper ocean circulation is predominantly driven by wind-forcing via momentum exchange. The westerlies prevail to the south of 60°N and the polar easterlies prevail to the north of 60°N, resulting in a positive wind stress curl in the subpolar North Atlantic. The distribution of wind stress curl together with the conservation of potential vorticity of water columns (i.e., Sverdrup balance; Talley et al. 2011) leads to a wind-driven quasi-cyclonic ocean circulation north of 50°N, identified as the North Atlantic subpolar gyre (SPG; **Fig. 1**b). To the southern boundary of the SPG, the North Atlantic Current (NAC) transports warm and saline water from the subtropics to the subpolar North Atlantic. As the poleward extension of the NAC, the Norwegian Atlantic Current (NwAC) advects across the Faroe-Iceland Ridge and the Faroe-Shetland Channel, and flows in a counterclockwise direction in the Nordic Seas (Årthun and Eldevik 2016; Chepurin and Carton 2012).

It has been documented that both large-scale ocean circulation, the SPG and large-scale atmospheric circulation, the NAO contribute to upper ocean variability in the Nordic Seas (Asbjørnsen et al. 2019). This brings us to the central focus of my dissertation: if atmosphere and ocean these two factors compete and interact with each other, which dominates water properties in the Subarctic Atlantic? How atmosphere and ocean together play roles in governing water properties in the Subarctic Atlantic? What decides the predictability of the Subarctic Atlantic ocean?

Overall, the main incentive for this dissertation is to illuminate the imprint of ocean and atmospheric dynamics in predictability of the Subarctic Atlantic Ocean. To tackle challenges in decadal predictions, it is essential to understand mechanisms driving the climate variability, and how they manifest in predictability. For this goal, Chapter 1 provides an overview of large-scale atmospheric and ocean circulation in the Subarctic Atlantic sector, then illustrates purpose of my dissertation: disentangle the roles of large-scale ocean and atmospheric circulations in variability and predictability of upper Subarctic Atlantic Ocean. Chapter 2 and Chapter 3 explores the impact of large-scale ocean circulation and atmospheric circulation on the Subarctic Atlantic Ocean, respectively. Chapter 4 summarizes key findings of my dissertation and gives an outlook for future investigations.

1.2 The Impact of Large-scale Ocean Circulation on Predictability of the Subarctic Atlantic Ocean

Several studies indicated that the SPG dominates properties of the Atlantic Inflow into the Nordic Seas by modulating the proportion of subpolar and subtropical waters in the NAC and NwAC on interannual to decadal time scales (e.g., Asbjørnsen et al. 2019; Hátún et al. 2005; Koul et al. 2019; Sarafanov et al. 2008). A strong SPG feeds cold and fresh subpolar water to the Atlantic Inflow, while a weak SPG allows the northward extension of warm and saline subtropical water. It takes 3-7 years for the upper ocean anomalies progressing from the eastern SPG to the Fram Strait and Barents Sea (Holliday et al. 2008; Koul et al. 2022). The well identified high predictability of SPG (e.g., Borchert et al. 2021) together with its prominent influence on the slow northward advection of thermohaline anomalies implies potential high decadal predictability in the downstream ocean.

Efforts have been taken to explore the impact of the SPG on the predictability of downstream sea surface temperature (SST) in dynamical prediction systems (e.g., Langehaug et al. 2017), but the manifestation of SPG signals in the downstream upper ocean prediction has not been clearly identified. Significant SST skill along the Atlantic water pathway is limited to 1-2 lead years in dynamical prediction systems (e.g., Langehaug et al. 2022), rather than a decade as demonstrated in observation-based study (Årthun et al. 2017). Research from a forced ocean model indicated that SST along the Atlantic water pathway is more dominated by the overlaying atmospheric interannual variability than subsurface variability (Langehaug et al. 2019), implying that the impact of the SPG may manifest in the prediction of subsurface ocean. Recent studies revealed a close linkage between the SPG and subsurface salinity in the Barents Seas (Koul et al. 2022), and showed that SPG signals can lead to skillful statistical prediction of fish stocks in the Barents Seas a decade in advance (Koul et al. 2021). The evident impact of SPG on the downstream salinity prediction, but unclear impact on SST prediction, agrees well with notions that conservative tracers such as salinity properties along the Atlantic water pathway mostly remain unchanged, while temperature anomalies are modified by the atmosphere through heat loss (e.g., Hátún et al. 2005). This motivates me to ask the first research question of my dissertation:

How do the SPG signals manifest in the downstream (Nordic Seas) upper ocean prediction?

1.3 The Impact of Large-scale Atmospheric Circulation on Variability of the Subarctic Atlantic Ocean

As introduced in chapter 1.1, besides the SPG, large-scale atmospheric circulation may also play a role in variability and predictability of Subarctic Atlantic Ocean. Abundant papers investigated hydrographic anomalies in the Norwegians Sea, reporting on their connection to the NAO forcing (e.g., Lien et al. 2014; Chafik et al. 2015). But how the temperature variability and predictability in the Norwegians Sea is impacted by the NAO has not been fully understood. From monthly to decadal timescales, previous studies have hinted but not identified the role of the NAO in temperature variability in the Norwegian Sea. On the monthly time scale, Lien et al., 2014 claimed that the NAO can affect simultaneous Atlantic Water depth via wind-induced Ekman transport, but the influence on heat transport is only seen in the Svinøy section, not other sections in southern Norwegian Sea (Richter et al. 2012). On the interannual time scale, the covariability between the NAO and heat transport at Svinøy is insignificant (Fig. 10 in Chafik et al. 2015). On interannual to decadal time scales, closed heat budget diagnostics indicated that ocean heat content anomalies in the Norwegian Sea are largely controlled by ocean heat transport (Årthun and Eldevik 2016; Asbjørnsen et al. 2019), and the roles of the NAO and wind-driven transport were not clearly depicted. On the decadal time scale, the NAO was not identified as a vital contributor to the Norwegian Sea temperature changes (Årthun et al. 2017). This brings us to the second research question of my dissertation:

Is the impact of the NAO on the Norwegian Sea temperature variability detectable and predictable?

2 Large-scale Ocean Circulation Provides Downstream Ocean Predictability

To answer the first question that whether and how the SPG signals manifest in the downstream (Nordic Seas) upper ocean prediction, I use the retrospective initialized decadal predictions (hindcasts) which are based on the Max-Planck-Institute Earth System Model version 1.2, low-resolution set up (MPI-ESM-LR1.2). And the corresponding assimilation experiment (ASSIM) is employed as observational reference (see Appendices A). For the period 1970-2019, each year is predicted 1 year ahead (1 lead year) up to 10 years ahead (10 lead year). To disentangle the connection of SPG variations with downstream temperature and salinity prediction, I carry out a comparison of prediction between salinity and temperature along the Atlantic water pathway. Then I examine the propagation of SPG signals based on lag correlation and composite analysis, and investigate the impact of SPG signals on prediction skill at individual forecast lead years.

I find that along the Atlantic water pathway, a dynamical link to the SPG causes salinity to be considerably better predicted than temperature (Fan et al. 2023). Measured by anomaly correlation coefficient (ACC), the prediction skill of sea surface salinity (SSS) is significantly higher than the skill of sea surface temperature (SST) over the eastern and western Nordic Seas, where the Atlantic water anomalies move northward and southward, respectively (**Fig. 2**a-c). The ACC of subsurface temperature especially over 50-400 meter from hindcasts is even lower than ACC from persistence forecast (**Fig. 2**d). The discrepancy of prediction skill of downstream salinity and temperature is caused by a dynamical link to the SPG. The SPG plays a stronger role in salinity prediction than that in temperature prediction along the Atlantic water pathway.

I use a density based SPG index which captures the connection between SPG variability and water properties in the eastern subpolar North Atlantic (Koul et al.

2020) to investigate the impact of SPG variations on subsurface salinity and subsurface temperature (over 150-310 meter) changes. A lead-lag correlation analysis between the salinity anomalies along the Atlantic water pathway (boxes in Fig. 3a) and the SPG index further supports the different downstream influence of the SPG. The hindcasts reproduce the salinity signals, propagating from the subpolar region to the Nordic Seas with increasing time lag (Fig. 3b). Benefiting from the poleward propagation and persistence of SPG signals, the salinity in the northernmost Nordic Seas is still skillfully predicted at forecast lead year 8 (Fig. 3c). There is no clear poleward propagation of the temperature signal (Fig. 3d). Consequently, the ACC of temperature along the ocean currents is generally lower than ACC of salinity and the ACC of temperature in the Nordic Seas becomes negative after 2 or 3 lead years. (compare Fig. 3c and e). The decomposition of temperature and salinity transport anomalies at the Faroe-Shetland Channel (Fig. A. 7) suggests that they are both dominated by the ocean component, confirming the key role of ocean advection in volume transport anomalies (Langehaug et al. 2022; Arthun et al. 2021). However, the contribution of temperature component to total transport anomalies is comparable with that of velocity component in some years, indicating possible effects from atmosphere. Temperature variability plays a subdominant role in heat transport anomalies, which explains why the link of the SPG to downstream salinity is stronger than that to downstream temperature.

In summary, the SPG provides downstream ocean predictability via modulating volume transport anomalies along the Atlantic water pathway. By modulating the slow northward ocean propagation, the subsurface memory of SPG variations enables salinity to be skillfully predicted up to 8 years ahead. In contrast, the SPG loses influence on temperature before Atlantic water penetrates into the Nordic Seas, and in turn limits temperature to be predicted only 2 years ahead. The SPG signals are damped more in temperature than in salinity, probably because temperature anomalies tend to be modified by the negative feedback of air-sea flux (Frankignoul and Hasselmann 1977). The results motivate me to investigate the role of atmosphere in the variability and predictability of temperature in the Nordic Seas.

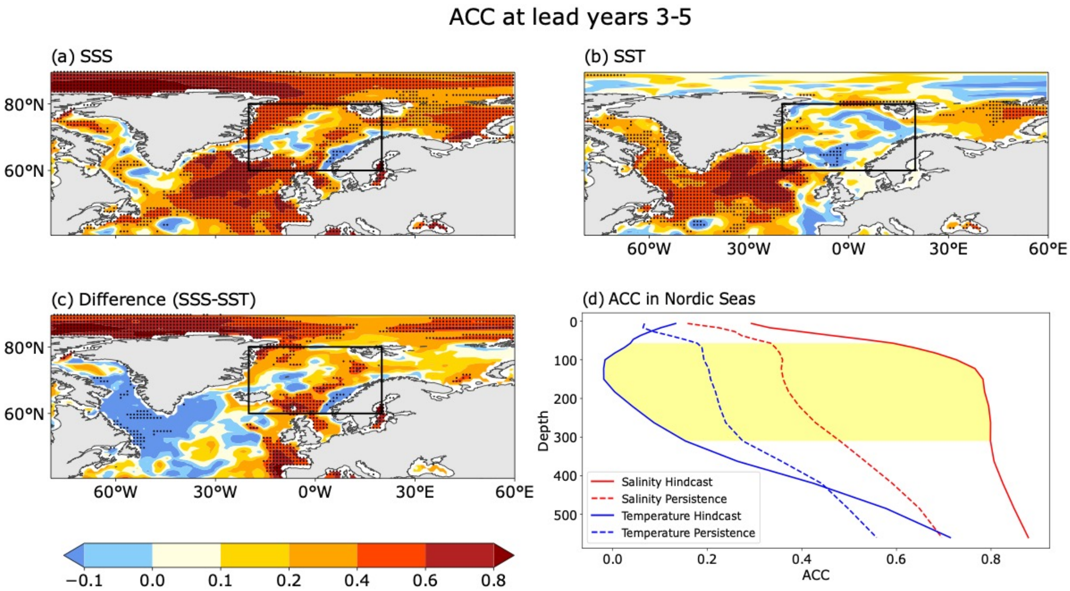


Fig. 2 The anomaly correlation coefficient (ACC) and ACC difference for detrended annual mean salinity and temperature at lead years 3-5. ACC between hindcast and ASSIM for (**a**) sea surface salinity (SSS), (**b**) sea surface temperature (SST) for the period 1970-2019. (**c**) ACC difference between SSS and SST in hindcast. **(d)** ACC in hindcast (solid line) and persistence (dash line) for salinity (red) and temperature (blue) at different depths in the Nordic Seas for the period 1975-2019. Stippling in (**a**)-(**c**) denotes the ACC or ACC difference is significant at 95% confidence level based on block bootstrapping. Yellow shading in (**d**) denotes the ACC difference between salinity and temperature in hindcast is significant at 95% confidence level based on block bootstrapping. The box outlined in black in (**a**)-(**c**) shows the area used to calculate the ACC in the Nordic Seas. Adapted from Fan et al. 2023.

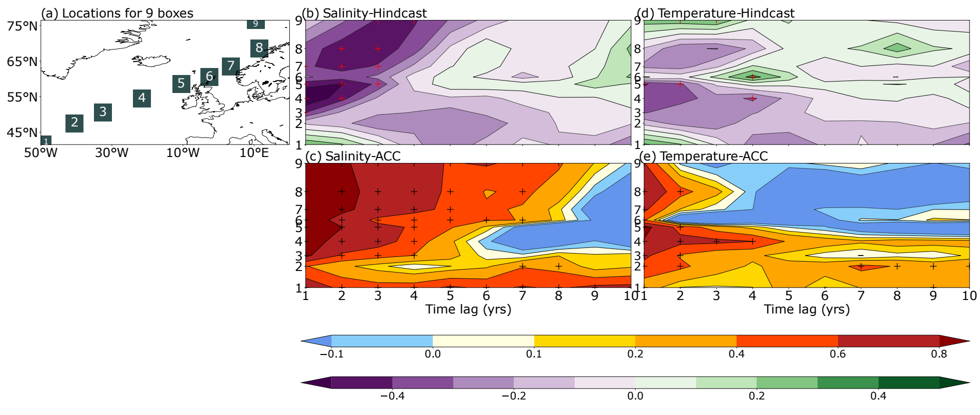


Fig. 3 Cross-correlation coefficients and ACC along the Atlantic water pathway. (**a**) Cross-correlation between the SPG index and subsurface salinity along the Atlantic water pathway (green boxes in Fig. 3a) in hindcast. The x-axis in (**b**) denotes the lag years for cross-correlation (salinity lags the SPG) and the hindcast lead years for salinity. (**c**) ACC for salinity at different hindcast lead years. (**d**) and (**e**) As in (**b**) and (**c**), but for subsurface temperature. Stippling in (**b**) and (**d**) denotes 90% confidence level based on Student's t test. Stippling in (**c**) and (**e**) denotes 95% confidence level based on block bootstrapping. Adapted from Fan et al. 2023.

3 Large-scale Atmospheric Circulation Limits Downstream Temperature Predictability

I demonstrate above that poleward ocean propagation plays a role in connecting salinity variability in the Nordic Seas with upstream variations in the SPG. It remains unclear why the impact of the SPG variations on downstream temperature is limited and why the downstream (Nordic Seas) temperature is poorly predicted. In this chapter, I investigate whether the NAO, the representative of large-scale atmospheric circulation plays a role in the downstream temperature. I focus on upper ocean temperature in the eastern Nordic Seas (i.e., Norwegian Sea), since this region is significantly influenced by ocean advection and potentially influenced by the NAO. I find that the NAO dominates variability of the Norwegian Sea temperature on the subdecadal time scale. With emphasis on the subdecadal time scale, I detect that the NAO exerts impacts in a twofold way, lagged and transient impacts. The lagged impact of the NAO originates in the SPG region via buoyancy forcing. The westerlies are suppressed due to the negative NAO (NAO –) pattern (**Fig. 4**a, d). The negative zonal wind stress anomalies in the SPG leads to positive turbulent heat flux anomalies (**Fig. 4**b, e). As a result, ocean responds as warm anomalies in the SPG (**Fig. 4**c, f). The induced SPG variation is carried by poleward ocean currents and leads to consequent changes in the Norwegian Sea temperature 4-5 years later. The transient NAO exerts influence on the Norwegian Sea temperature by modulating heat flux (**Fig. 5**c, g) and wind-driven transport (**Fig. 5**b, f) into the Norwegian Sea. Consequently, 4-5 years later, the superimposed NAO + pattern leads to the prominent enhancement of warm anomalies in the Norwegian Sea (**Fig. 5**d, h).

These impacts of the NAO illuminate the low prediction skill of temperature in Chapter 2, where I find the temperature in the Norwegian Sea is only predicted 1-2 years in advance. The twofold impact of the NAO holds the key to the low predictability of the Norwegian Sea temperature. The 1-year predictability of Norwegian Sea temperature is is to a large extent derived from the initialized NAO + via the transient impact (**Fig. 6**b). However, the transient impact may counteract the lagged oceanic signal and rapidly modify ocean temperature, thus limit subdecadal predictability. The lagged impact of the NAO via the ocean dynamics constrains Norwegian Sea temperature 4-5 years after NAO events (**Fig. 6**a). However, this lagged impact is limited and not reproduced in hindcasts, thus providing limited predictability for the Norwegian Sea temperature.

These results highlight that the challenge of predicting the Norwegian Sea temperature goes hand in hand with predicting the NAO (Smith et al. 2020), which is only predicted 1 year in advance in MPI-ESM decadal prediction system. Nevertheless, the lagged impact stored in ocean dynamics can constrain the

Norwegian Sea temperature a few years later and therefore may provide windows of opportunity for prediction. The ocean memory can be potentially harnessed to improve subdecadal prediction of the Norwegian Sea temperature. To make use the information of ocean memory, one potential approach is to employ the Ensemble Empirical Mode Decomposition method (EEMD; see Appendices B) to decompose prediction time series and 'correct' the subdecadal component statically. The EEMD method has been applied in wind speed prediction and proved to be efficient in hybrid prediction models (Yan et al. 2022). Machine learning is also becoming a powerful tool in incorporating oceanic signals to improve predictions (Carvalho-Oliveira et al. 2022). On the other hand, recently it was claimed that skillful predictions of the NAO are feasible with large ensemble sizes and postprocessing technique (Smith et al. 2020). Therefore, enhancement the predictability of the Norwegian Sea temperature is promising in the future.

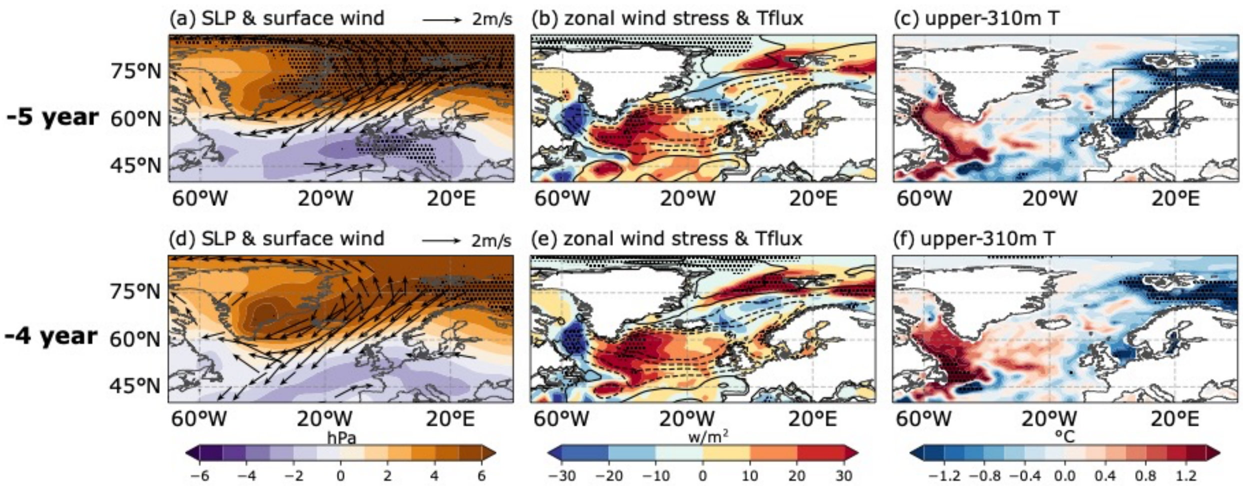


Fig. 4 Regression coefficients of annual anomaly fields onto the subdecadal component of the Norwegian Sea temperature at lag year 5. (**a**) SLP (shading; hPa) and surface wind (arrow; m/s), (**b**) turbulent heat flux (shading; w/m^2) and zonal wind stress (contour; N/m^2), and (**c**) upper 310m temperature (°C) The subdecadal component of the Norwegian Sea temperature lags by 5 years. (**d**)-(**f**) As in (**a**)-(**c**), but when the subdecadal component of the Norwegian Sea temperature lags by 4 years. Stippling in shading fields indicates 95% confidence level based on block bootstrapping. The arrows whose magnitude are smaller than 1m/s are masked out in (**a**) and (**d**). The area outlined in black (0°-20°E, 60°-76°N) in (**c**) is used to calculate the area-averaged temperature in the Norwegian Sea.

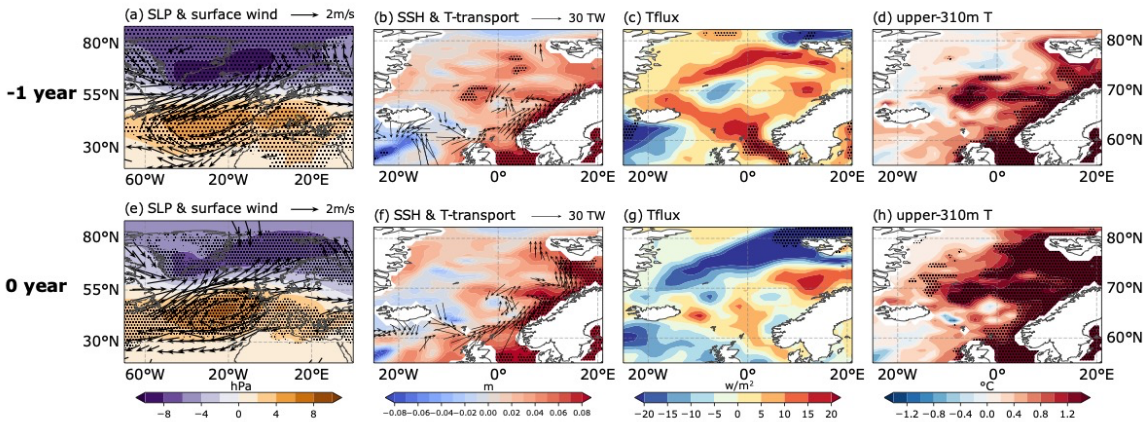


Fig. 5 As in Fig. 4 but onto (**a**) SLP (shading; hPa) and surface wind (arrow; m/s), (**b**) SSH (shading; m) and temperature transport (arrow; W), (**c**) turbulent heat flux (w/m^2), and upper 310m temperature (°C) at (**a**)-(**d**) lag year 1 and (**e**)-(**h**) lag year 0, respectively. The arrows whose magnitude are smaller than 10TW are masked out in (**b**), (**f**).

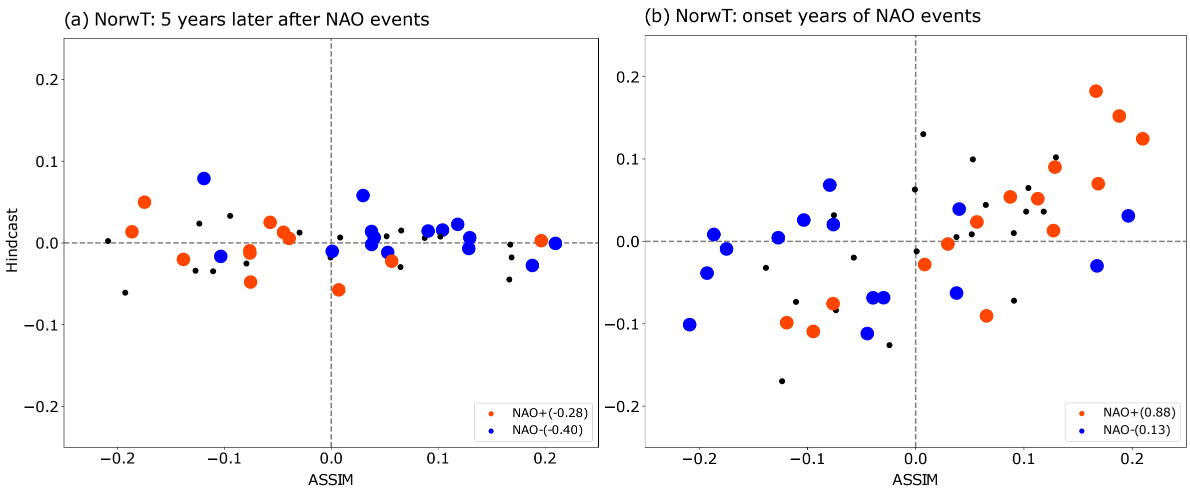


Fig. 6 Norwegian Sea temperature anomalies after NAO events in ASSIM and in Hindcast. (**a**) 5 years after and (**b**) at onset years of NAO events. The temperature anomalies from Hindcast are at forecast lead year 6 in (**a**) and forecast lead year 1 in (**b**), respectively. Red (blue) dots denote NAO + (–) events at onset years. Brackets give the prediction skill for Norwegian Sea temperature anomalies according to NAO + (–) events at onset years.

4 Conclusions and Outlook

In this dissertation, I start with the question that how the SPG signals manifest in the downstream Subarctic ocean prediction. I find that the SPG provides downstream ocean predictability by modulating volume transport anomalies along the Atlantic water pathway. The SPG signal can manifest itself differently in downstream salinity and temperature, which leads to different prediction skill for temperature and salinity in the MPI-ESM-LR1.2 decadal prediction system. The link of the SPG to downstream salinity is stronger than that to downstream temperature, and therefore salinity is better predicted than temperature. The significant SPG-induced salinity anomalies persist into the Nordic Seas significantly for 6 years, and are skillfully predicted up to 8 years ahead. In contrast, SPG-induced temperature anomalies persist up to the eastern Nordic Seas only for 2-3 years, and are skillfully predicted up to 2 years ahead.

I attribute the low predictability of upper ocean temperature in the eastern Nordic Seas to the influence and the low predictability of the NAO, which dominates subdecadal variability of the Norwegian Sea temperature in a twofold way. The lagged impact of the NAO originated in the subpolar region via buoyancy forcing, is carried by poleward ocean currents and leads to consequent changes in the Norwegian Sea temperature 4-5 years later, while the transient NAO exerts influence on the Norwegian Sea temperature by modulating heat flux and wind-driven transport into the Norwegian Sea. The transient impact may counteract the lagged oceanic signal and rapidly modify ocean temperature, thus limit subdecadal predictability. I further find the asymmetric impact of the NAO phase on temperature predictability and this asymmetry is probably inherent to the periodicity and dynamics of the NAO.

In summary, I disentangle the roles of large-scale ocean circulation, represented as the SPG and large-scale atmospheric circulation, represented as the NAO in variability and predictability of upper ocean properties in the Subarctic Atlantic. Although temperature and salinity covary in the same water parcel and are both modulated by the SPG and the NAO. They exhibit differently in terms of the governing mechanisms and the corresponding predictability. Salinity as a passive tracer is driven by the ocean dynamics (i.e., the SPG variations), resulting in high predictability up to 8 years in the Subarctic Atlantic. The upper ocean temperature in the Subarctic Atlantic communicates with atmosphere and is dominated by the NAO especially on the subdecadal time scale, which limits the predictability to 1-2 years. My dissertation reveals that the manifestation and persistence of the SPG signals play a key role in determining the prediction time scales of the Subarctic Atlantic ocean climate. I highlight the challenge of predicting temperature variability in the presence of the NAO, and the potential to improve predictions via ocean memory.

While I make progress toward understanding the variability and predictability of the Subarctic Atlantic Ocean, I open more questions to answer. Why the salinity and temperature in the same water parcel show such discrepancy of their predictive skill and how they covary need further investigations. I also notice that both salinity and temperature anomalies propagations have some disconnects (dashed line in **Fig. A. 4**b-e) around Faroe Ridge and the Faroe-Shetland Channel. This discontinuity indicates that the shallow Greenland-Scotland Ridge is a challenge for prediction due to the complex shelf-sea dynamics (Koul et al. 2021). Different observational datasets show uncertainty at the Greenland-Scotland ridge (Borchert et al. 2018). Fully addressing the discontinuity of anomaly propagation is feasible when there are more available and reliable observational data in the future. This dissertation qualitatively disentangles the variability and predictability of upper ocean properties in the Subarctic Atlantic the roles of the SPG and the NAO. The remaining issue is the quantitative contribution of the SPG and the NAO. The contributions of ocean advection and heat flux to the heat content in the Norwegian Sea are still debated (Mork et al. 2014; Asbjørnsen et al. 2019; Carton et al. 2011). Numerical experiments may facilitate to separate effects of atmospheric forcing and ocean dynamics for accurate quantifications and how much predictability we can derive from them. The insights I present here are based on statistics. A more practical and relevant question is how to identify the predictability source for single predicted years. Besides, the asymmetric impact of the NAO on the prediction skill of temperature is also worth noticing. Whether and why NAO + is better predicted than NAO – could be interesting and important to investigate in the future. Last but not least, to bridge the theory with operational prediction, it is essential to explore how to harness predictions with ocean memory presented here via powerful tools like machine learning**.**

Overall, this dissertation establishes the prominent role of ocean circulation in downstream ocean predictability and highlights the challenge of predicting ocean temperature in the Subarctic Atlantic. The poor prediction of ocean temperature in the Subarctic Atlantic goes hand in hand with predicting the NAO. Nevertheless, I emphasize that the lagged impact of the NAO stored in ocean dynamics can constrain Subarctic Atlantic and therefore may provide windows of opportunity for prediction. The ocean memory can be potentially harnessed to improve subdecadal prediction of the Norwegian Sea temperature. This dissertation illuminates the imprint of ocean dynamics in the subarctic climate prediction and opens the door for investigating potentially associated downstream predictability for the earth system, marine ecosystems in particular.

Appendices

A North Atlantic Subpolar Gyre Provides Downstream Ocean Predictability

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NORTH ATLANTIC SUBPOLAR GYRE PROVIDES DOWNSTREAM OCEAN PREDICTABILITY

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Abstract

Slowly varying large-scale ocean circulation can provide climate predictability on decadal time scales. It has been hypothesized that the North Atlantic subpolar gyre (SPG) exerts substantial influence on climate predictability. However, a clear identification of the downstream impact of SPG variations is still lacking. Using the MPI-ESM-LR1.2 decadal prediction system, we show that along the Atlantic water pathway, a dynamical link to the SPG causes salinity to be considerably better predicted than temperature. By modulating the slow northward ocean propagation, the subsurface memory of SPG variations enables salinity to be skillfully predicted up to 8 years ahead. In contrast, the SPG loses influence on temperature before Atlantic water penetrates into the Nordic Seas, and in turn limits temperature to be predicted only 2 years ahead. This study identifies the key role of SPG signals in downstream prediction and highlights how SPG signals determine prediction time scales for different quantities, opening the door for investigating potentially associated predictions in the subarctic for the earth system, marine ecosystems in particular.

A.1 Introduction

The poleward propagation of thermohaline anomalies in the North Atlantic Ocean provides oceanic and continental climate predictability on decadal time scale (Borchert et al. 2018; Langehaug et al. 2022; Yeager and Robson 2017). However, previous studies have not identified whether the variations of the Subpolar Gyre of the North Atlantic (SPG) exert influence on the downstream ocean prediction (Langehaug et al. 2017). In this study, we investigate the role of the SPG in decadal prediction along the Atlantic water pathway with emphasis on subsurface temperature and salinity, demonstrating a robust connection for the latter.

It has been documented that the high predictability of the SPG resides in the initialization and persistence of the Atlantic meridional overturning circulation (AMOC), and ocean dynamics over the subpolar North Atlantic (Borchert et al. 2021; Koul et al. 2021). Understanding the downstream impact of the SPG is crucial for earth system prediction in the subarctic (Langehaug et al. 2022). Several studies showed that the SPG dominates properties of the Atlantic Inflow into the Nordic Seas by modulating the proportion of subpolar and subtropical waters in the Atlantic Inflow on interannual to decadal time scales (Asbjørnsen et al. 2021; Hátún et al. 2005; Koul et al. 2019; Sarafanov et al. 2008). A strong SPG feeds cold and fresh subpolar water to the Atlantic Inflow, while a weak SPG allows northward extension of warm and saline subtropical water. Downstream of the SPG, via the North Atlantic Current, the Norwegian Atlantic Current advects across the Faroe-Iceland Ridge and the Faroe-Shetland Channel and circulates in a counterclockwise direction in the Nordic Seas (Årthun and Eldevik 2016; Chepurin and Carton 2012). It takes 3-7 years for the upper ocean anomalies to progress from the eastern SPG to the Fram Strait and Barents Sea (Holliday et al. 2008; Koul et al. 2022). The well identified high predictability of the SPG (Borchert et al. 2021; Koul et al. 2021) together with its prominent influence on the slow northward propagation of thermohaline anomalies hints at potentially high decadal predictability in the downstream ocean.

Efforts have been taken to explore the impact of the SPG on predictability of downstream sea surface temperature (SST) in dynamical prediction systems (Langehaug et al. 2017), but the manifestation of SPG signals in the downstream upper ocean prediction has not been clearly identified. Significant SST skill along the Atlantic water pathway is limited to 1-2 lead years in dynamical prediction systems (Langehaug et al. 2022), rather than a decade as demonstrated in an observation-based study (Årthun et al. 2017). Research from a forced ocean model indicated that SST along the Atlantic water pathway is more dominated by the overlaying atmospheric interannual variability than subsurface variability (Langehaug et al. 2019), implying that the impact of the SPG may manifest in the prediction of subsurface ocean. Recent studies revealed a close linkage between the SPG and the subsurface salinity in the Barents Sea (Koul et al. 2022), and showed that the SPG signals can lead to skillful statistical prediction of fish stocks in the Barents Sea a decade in advance (Koul et al.

2021). The evident impact of the SPG on the downstream salinity prediction, but unclear impact on the SST prediction, agrees well with notions that salinity anomalies along the Atlantic water pathway mostly remain unchanged, while temperature anomalies are modified by the atmosphere through surface heat fluxes (Koul et al. 2021; Asbjørnsen et al. 2019; Mork et al. 2014).

To disentangle the connection of SPG variations with temperature and salinity prediction along the Atlantic water pathway, we carry out a comparison of prediction between salinity and temperature along the Atlantic water pathway with emphasis on forecast lead years 3-5, for the period 1970-2019. Then we examine the propagation of SPG signals based on lag correlation and composite results, and investigate the impact of SPG signals on prediction skill at individual forecast lead years. Here, the retrospective initialized decadal predictions (hindcasts) are based on the Max-Planck-Institute Earth System Model version 1.2, low-resolution set up (MPI-ESM-LR1.2). The corresponding assimilation experiment (ASSIM) is employed as observational reference. We use anomaly correlation coefficient (ACC) metrics to evaluate the agreement between hindcasts and ASSIM (see Methods).

A.2 Results

Salinity is better predicted than temperature along the Atlantic water pathway

We first assess the prediction skill of sea surface salinity (SSS) and sea surface temperature (SST) at lead years 3-5 in the northern North Atlantic (**Fig. A. 1**a, b). The SSS is skillfully predicted in the eastern SPG region. SST is slightly better predicted than SSS, which agrees with Borchert et al. 2021 that models generally show high SST skill in the SPG region. However, the skill of SSS is higher than the skill of SST along the Atlantic water pathway, especially in the Nordic Seas (**Fig. A. 1**a, b). This difference in skill (**Fig. A. 1**c) is significant over the eastern and western Nordic Seas, where the Atlantic water anomalies move northward and southward, respectively. The ACC difference between salinity and temperature along the Atlantic water pathway is robust with EN4 (Good et al. 2013) and Atlas (Korablev et al. 2014) as observational references (**Fig. A. 6**).

To further understand the ACC difference between salinity and temperature along the Atlantic water pathway, we choose the Nordic Seas (box in **Fig. A. 1**a) as representative and compare the ACC from hindcasts with ACC from persistence at different depth layers in the Nordic Seas (**Fig. A. 1**d). Here, we use a statistical persistence forecast as a reference when evaluating hindcasts prediction skill arising from model dynamics (see Methods). The ACC in both hindcasts and persistence generally increases with depth (**Fig. A. 1**d). This is expected because of the decreasing influence from the atmosphere. One notable exception is that ACC of temperature in hindcasts first decreases with depth until about 100m, and then increases. Dynamical predictions for salinity and temperature perform sharply differently: the ACC of salinity, especially in the subsurface, is significantly higher than that of temperature, and this is also the case for their counterparts in persistence forecast. Moreover, the ACC of salinity from hindcasts is higher than the ACC from persistence in all depth layers above 500 meters (**Fig. A. 1**d). In contrast, the ACC of subsurface temperature from hindcasts is even lower than ACC from persistence. Salinity and temperature both show general high ACC in the SPG region (**Fig. A. 1**a, b), but they have discrepancy along the Atlantic water pathway. We conjecture from these findings that the SPG may play a stronger role in salinity prediction than that in temperature prediction along the Atlantic water pathway. To investigate a possible dynamical mechanism, we use a density based SPG index (**Fig. A. 2**a; see Methods) which captures the connection between SPG variability and water properties in the eastern subpolar North Atlantic (Koul et al. 2020), and we use the depth-averaged anomalies over 150-310 meter as representative of subsurface properties in the remaining part of this study.

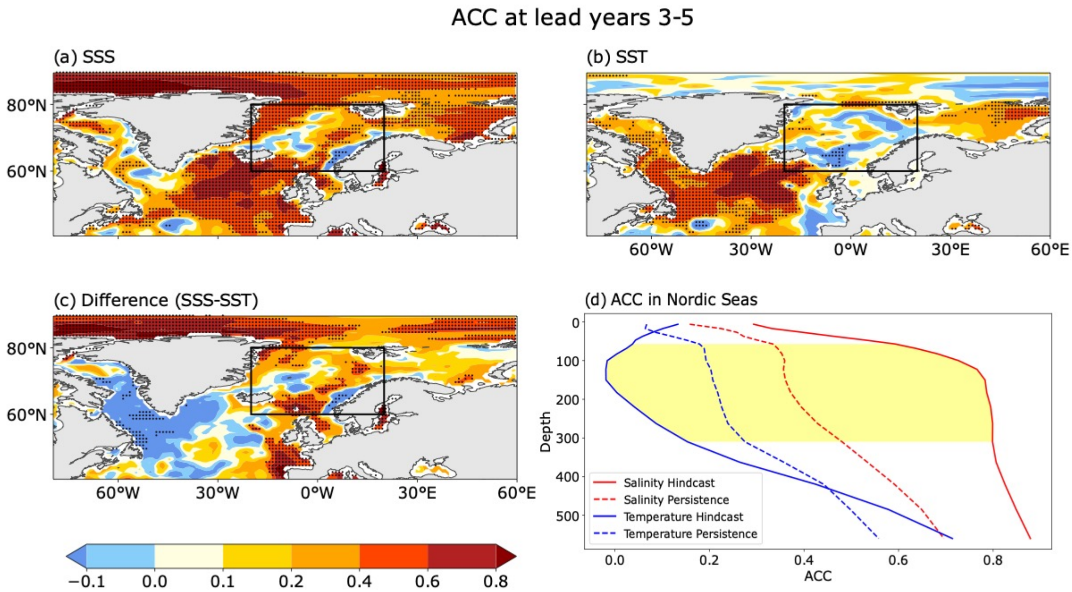

Fig. A. 1 The anomaly correlation coefficient (ACC) and ACC difference for detrended annual mean salinity and temperature at lead years 3-5. ACC between hindcast and ASSIM for (a) sea surface salinity (SSS), (b) sea surface temperature (SST) for the period 1970-2019. (c) ACC difference between SSS and SST in hindcast. (d) ACC in hindcast (solid line) and persistence (dash line) for salinity (red) and temperature (blue) at different depths in the Nordic Seas for the period 1975-2019. Stippling in (a)-(c) denotes the ACC or ACC difference is significant at 95% confidence level based on block bootstrapping. Yellow shading in (d) denotes the ACC difference between salinity and temperature in hindcast is significant at 95% confidence level based on block bootstrapping. The box outlined in black in (a)-(c) shows the area used to calculate the ACC in the Nordic Seas.

Poleward propagation of SPG signal and its impact on prediction skill

We investigate the co-variability of the SPG variations and salinity and temperature changes in the northern North Atlantic using lagged correlation analysis. Subsurface salinity in the Nordic and Barents Seas is significantly correlated with SPG variability (Fig. A. 2b). The prominent salinity anomalies induced by the SPG propagate into the Nordic Seas after 3-5 years. In comparison, downstream temperature is less correlated with SPG variability (Fig. A. 2c), and the lag correlation is only significant in the northwestern Nordic Seas and western Barents Sea (Fig. A. 2c).

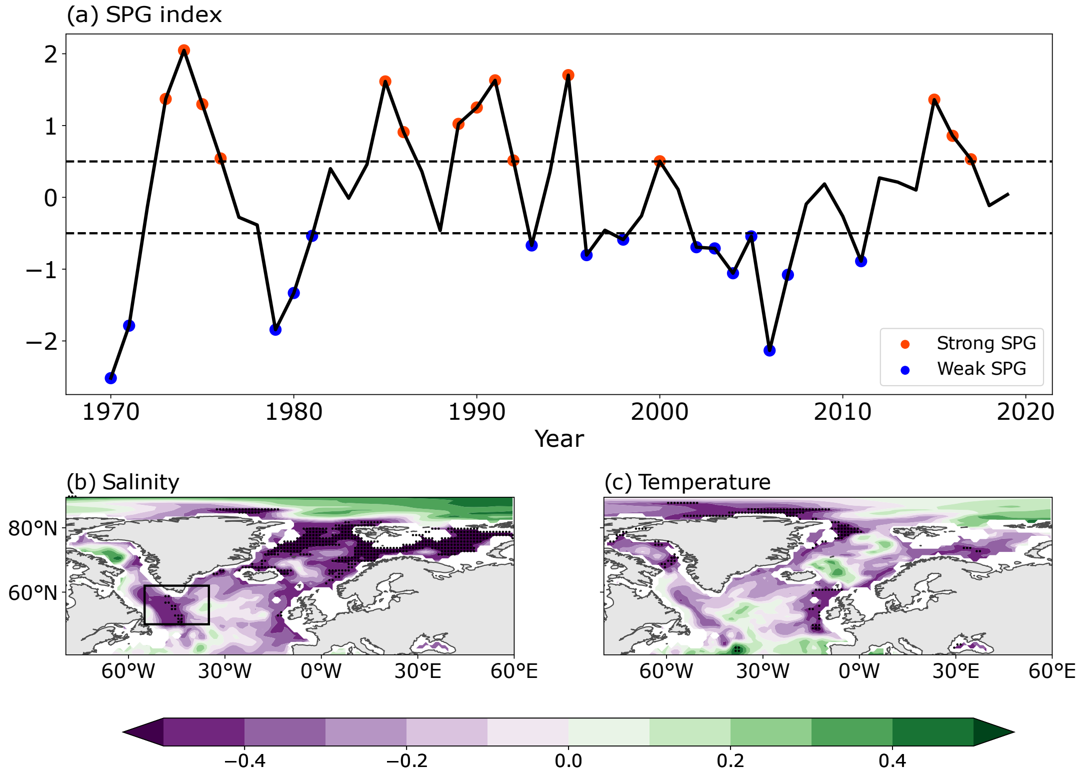

Fig. A. 2 Time series of the SPG index and its lag correlation with subsurface salinity and temperature anomalies for the period 1970-2019. (**a**) Standardized time series of SPG index. Lag correlation between the SPG index and subsurface (**b**) salinity and (**c**) temperature at lag years 3-5 (salinity and temperature lag SPG index) in ASSIM. The SPG index is defined as density anomaly at 310m depth over 55-35°W, 50-62°N [area outlined in black in (**b**)]. The positive (negative) SPG index indicates strong (weak) SPG circulation and strong (red dots) and weak SPG (blue dots) phases are identified with above 0.5 and below -0.5, respectively. Stippling in (**b**) and (**c**) denotes 95% confidence level based on Student's *t* test.

To study the influence of the SPG on salinity and temperature along the Atlantic water pathway, we define strong and weak SPG phases with above and below 0.5 standard deviation, respectively. Composite results (Fig. A. 3a-e) from hindcasts constructed from the difference between weak SPG phases and strong SPG phases further support the pronounced SPG influence on salinity along the Atlantic water pathway, especially in the Nordic Seas. After a weak SPG phase, positive salinity anomalies develop and persist in the SPG region and saline subtropical water dominates the Atlantic Inflow, penetrating into the Nordic and Barents Seas in the following 4 years. The saline water in the eastern SPG region flows across the Faroe-Iceland Ridge and the Faroe-Shetland Channel after 1 year (Fig. A. 3b), and moves along with the Norwegian Atlantic Current (Fig. A. 3c) into the Nordic Seas. The salinity anomalies arrive at the Fram Strait and Barents Sea after 3 years (Fig. A. 3d), reaching the western Nordic Seas along with the East Greenland Current (Fig. A. 3e).

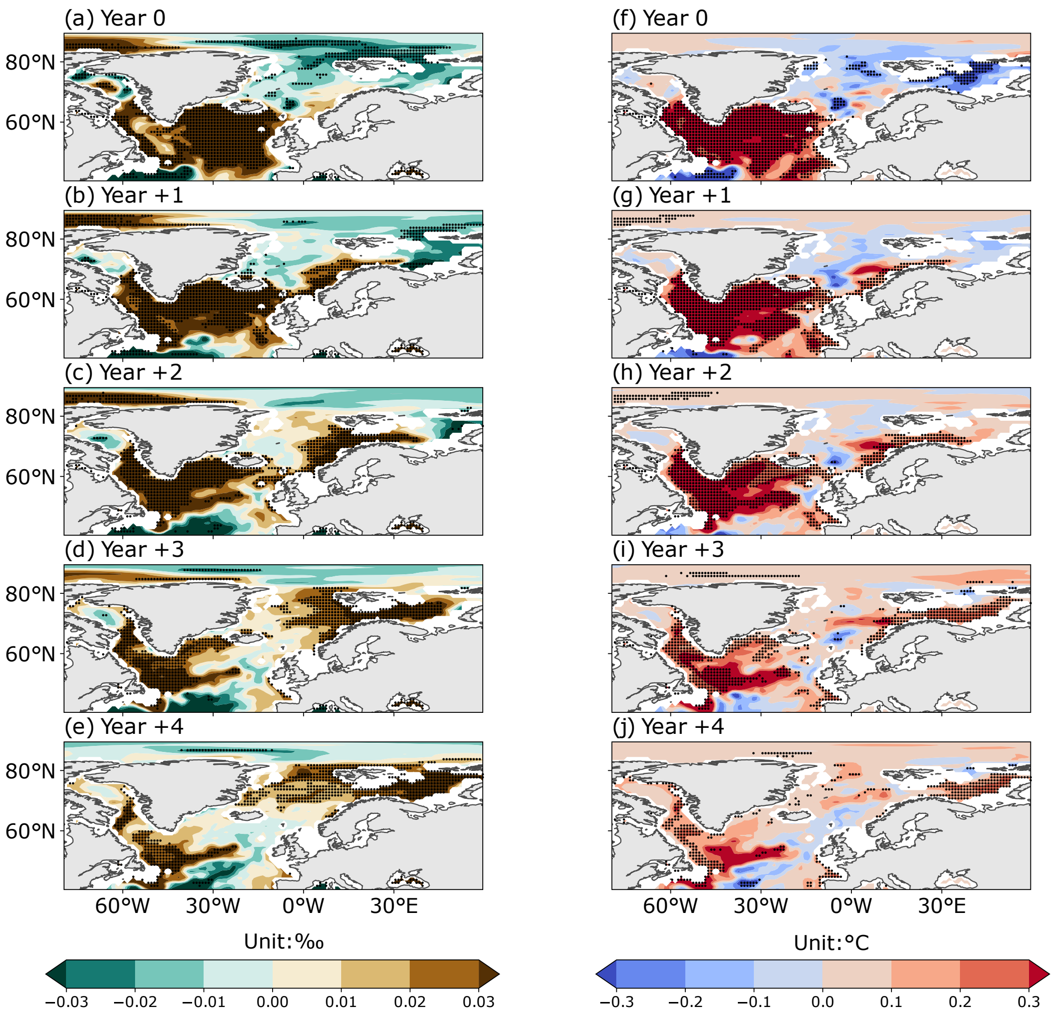

Fig. A. 3 Composite anomalies according to the SPG phases (weak phase minus strong phase). (a)-(e) Composite salinity anomalies from year 0 to year 4 according to the SPG phases in hindcast. (f)-(j) As in (a)-(e), but for temperature. Stippling denotes 95% confidence level based on bootstrap test. Strong and weak SPG phases are identified with above 0.5 and below -0.5 standard deviation of the SPG index, respectively.

Similar to positive salinity anomalies, positive temperature anomalies caused by a weak SPG persist in the SPG region and progress northward into the Nordic Seas. However, the regions in the Nordic Seas that show significant temperature anomalies are smaller, and temperature anomalies persist for a shorter period, when comparing counterparts from salinity anomalies (compare Fig. A. 3a-e and f-j). Positive temperature anomalies are only significant in the eastern Nordic Seas for 1-3 years (Fig. A. 3j-i) and are significant in the Barents Sea after 3 years (Fig. A. 3i-j). After 4 years, there are significant saline anomalies while less prominent warm anomalies in the Nordic Seas (Fig. A. 2e, j). For a strong SPG phase, similar results appear for the propagation of less saline and cold anomalies, respectively. The results suggest that the SPG exerts a weak influence on temperature along the Atlantic water pathway, while poleward ocean currents may play a role in connecting salinity in the Nordic Seas with the SPG strength.

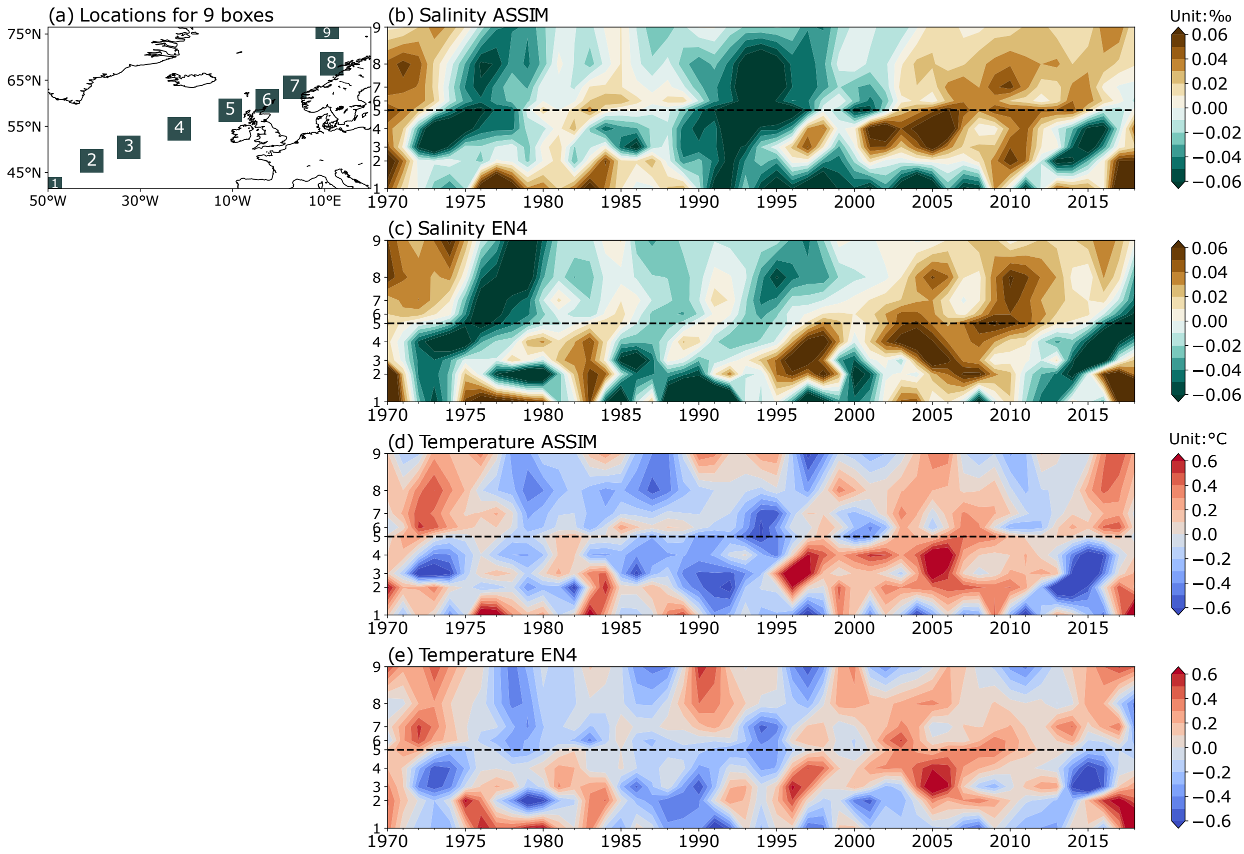

Fig. A. 4 Poleward propagation of subsurface salinity and temperature anomalies along the Atlantic water pathway. (a) 9 green boxes as representative along the Atlantic water pathway (Årthun et al. 2017). Hovmöller diagrams of subsurface salinity anomalies along the Atlantic water pathway from (b) ASSIM and (c) EN4. (d)-(e) As in (b)-(c), but for temperature. The dashed line in (b)-(e) approximates the Greenland-Scotland Ridge. Time series for 9 boxes are 3-30-yr band-pass filtered for illustrative purposes.

We investigate the role of poleward propagation of salinity and temperature signals by following their propagation along the North Atlantic Current, 9 boxes (Fig. A. 4a) with size of 5°× 5° are selected along the North Atlantic Current-Norwegian Atlantic Current pathway, and centers of the boxes are consistent with Årthun et al. 2017. Hovmöller diagrams (Fig. A. 4Figure 4b, d) show a clear tilt of anomalies in ASSIM, especially for salinity. When there are strong anomalies in the SPG (box 3 in Fig. A. 4a), salinity and temperature anomalies progress from the SPG to the Fram Strait (box 9 in Fig. A. 4a). For instance, induced by a weak SPG phase in 1970 and a strong SPG phase in 1990, both salinity and temperature anomalies propagate into the Nordic Seas after around 3-7 years, but less prominent for temperature. For a strong SPG phase in 1974 and a weak SPG phase in 1980, temperature anomalies show no clear propagation of signal into the Nordic Seas and are relatively constrained to the subpolar region or southern Nordic Seas (Fig. A. 4d). In contrast, salinity anomalies propagate all the way through to the Fram Strait and persist for several years (Fig. A. 4b). The propagation of the subsurface salinity and temperature signals is similar with the propagation of the SST signals found in a previous study[15]. Notice that low-pass filtering and a complex principal component analysis make the leading mode of SST propagation smooth (Figure 5a in Årthun et al. 2017), still there are slight discontinuities at the Greenland-Scotland Ridge (compare Figure 5a in Årthun et al. 2017 and Fig. A. 4b-e). Inspection of the Hovmöller diagrams from EN4 data indicates consistent results (compare Fig. A. 4b, d and 4c, e), suggesting that the salinity and temperature signals may be carried by poleward ocean currents modulated by the SPG variations.

To further understand the mechanism driving the poleward transport of signals, we decompose salt and heat transport anomalies at the Faroe-Shetland Channel into changes due to velocity anomalies, changes due to salinity or temperature anomalies, and changes due to eddy activity (Fig. A. 7). Both the salt and heat transport anomalies are dominated by the velocity component, confirming the key role of ocean advection in volume transport anomalies (Langehaug et al. 2022; Arthun et al. 2021). However, the impacts of the salinity component and the temperature component terms, respectively, on the total transport anomalies are different. The amplitude of the salinity component is as small as that of the eddy component, and both are negligibly small compared to total transport anomalies. While the contribution of temperature component to total transport anomalies is comparable with that of velocity component in some years, even with negative contribution. These results indicate that ocean dynamics almost completely govern salt transport anomalies, and dominate heat transport anomalies. Temperature variability plays a subdominant role in heat transport anomalies, which explains why the link of the SPG to downstream salinity is stronger than that to downstream temperature. Downstream temperature exhibits pronounced interannual variability and has low signal-to-noise ratio. In addition, temperature anomalies tend to be modified by the negative feedback of air-sea flux (Frankignoul and Hasselmann 1977), therefore the SPG signals are damped more in temperature than in salinity.

A lead-lag correlation analysis between the salinity anomalies along the Atlantic water pathway (boxes in Fig. A. 4) and the SPG index further supports the different downstream influence of the SPG. The significant negative correlation stays in the subpolar North Atlantic when salinity leads the SPG index (Fig. A. 5a), indicating the origin of the signal is the subpolar North Atlantic rather than further south in the subtropics. The salinity signal propagates from the subpolar region (box 3 in Fig. A. 4a) to the Nordic Seas with increasing time lag in ASSIM. The salinity at the Fram Strait (box 9 in Fig. A. 4a) is significantly correlated with the SPG index from lag year 2 to lag year 6, indicating the persistent downstream influence of the SPG. The hindcasts reproduce the progression of the SPG signal to the Nordic Seas (Fig. A. 5b), with a slight discontinuity where the anomalies pass across the Faroe-Iceland Ridge and the Faroe-Shetland Channel (between box 5 and box 6 in Fig. A. 4a). This discontinuity is consistent with previous studies (Koul et al. 2021; Langehaug et al. 2019). As a result, the prominent correlation between salinity and the SPG is persistent in different hindcast lead years, therefore we conclude that the model skillfully predicts the propagation of salinity signals from the SPG into the Nordic Seas. Benefiting from the poleward propagation and persistence of SPG signals, after lead year 3, the salinity in the eastern Nordic Seas is better predicted (Fig. A. 5c) than upstream for the same forecast lead year. The salinity in the northernmost Nordic Seas (box 9 in Fig. A. 4a) is skillfully predicted at lead year 8 when the ACC in subpolar regions becomes negative.

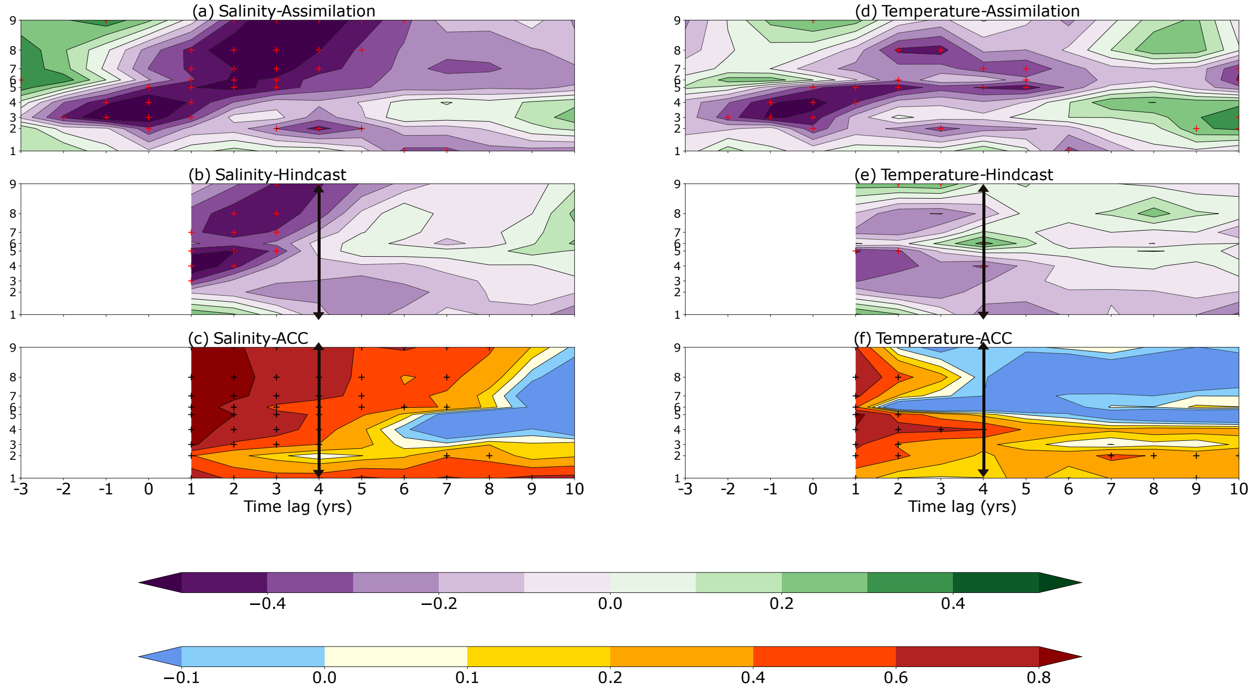

Fig. A. 5 Cross-correlation coefficients and ACC along the Atlantic water pathway. Cross-correlation between the SPG index and subsurface salinity along the Atlantic water pathway (green boxes in Figure 3a) from (a) ASSIM and (b) hindcast. The x-axis in (b) denotes the lag years for cross-correlation (salinity lags the SPG) and the hindcast lead years for salinity. (c) ACC for salinity at different hindcast lead years. (d)-(f) As in (a)-(c), but for temperature. Stippling in (a), (b), (d) and (e) denotes 90% confidence level based on Student's t test. Stippling in (c) and (f) denotes 95% confidence level based on block bootstrapping. The black arrows in (b), (c), (e), (f) highlight the lag (lead) years 4.

Temperature shows a similar pattern for cross-correlation as salinity (compare Fig. A. 5a and d). When temperature leads the SPG index, the significant correlation stays in the subpolar North Atlantic. When the SPG index leads temperature, the correlation is less prominent comparing to salinity. There is no clear poleward propagation of the temperature signal in ASSIM, which is also the case for the hindcasts (Fig. A. 5e). This may be due to that temperature signals are damped due to negative feedback of air-sea flux (Frankignoul and Hasselmann 1977) along the Atlantic water pathway. Consequently, the ACC of temperature along the ocean currents is generally lower than ACC of salinity (compare Fig. A. 5c and f), except in the eastern subpolar North Atlantic (box 4 in Fig. A. 4a). The shallow Greenland-

Scotland ridge (box 6 in **Fig. A. 4**a) has a large negative influence on temperature prediction, where temperature ACC drops to zero after lead year 1. The ACC of temperature in the Nordic Seas becomes negative after 2 or 3 lead years. Unlike salinity, the influence of the SPG on temperature prediction skill is constrained to the subpolar region. The different influence from the SPG manifests itself especially after lead year 4, when high ACC of salinity moves northward to the Nordic Seas while ACC of temperature becomes negative and shows no further poleward propagation. The findings are robust when we use a SPG index based on sea surface height (SSH) anomalies for cross-correlation with salinity and temperature, and when we use EN4 as reference to evaluate the ACC along the North Atlantic pathway (**Fig. A. 8** and **Fig. A. 9**). As discussed earlier, temperature variability also plays a role in heat transport anomalies and is largely influenced by the atmospheric variability (Langehaug et al. 2019). This difference between salinity and temperature lead to the stronger link of the SPG to downstream salinity than that to downstream temperature. These results further manifest that downstream salinity is better predicted than temperature due to this stronger dynamical links to the SPG.

A.3 Discussion

Based on the MPI-ESM-LR1.2 decadal prediction system, we show that the SPG contributes to the high performance of downstream salinity prediction by modulating salt transport anomalies. Our results support that the poleward propagation of thermohaline anomalies is essential for subarctic decadal prediction (Langehaug et al. 2022; Årthun et al. 2017; Langehaug et al. 2019), and the hindcasts capture this physical process for salinity along the Atlantic water pathway properly. We confirm that the SPG plays a key role in modulating water properties in the Atlantic Inflow into the Nordic Seas (Koul et al. 2021; Asbjørnsen et al. 2021). We further demonstrate that SPG signals contribute to salinity prediction, which in turn may benefit earth system prediction in the subarctic, including fishery predictions as well as predictions of habitat of vulnerable species (Burgos et al. 2020). In contrast to salinity, models show low predictive skill for temperature along the Atlantic water pathway (Langehaug et al. 2022, 2017) and temperature anomalies propagate downstream only to a limited degree (Langehaug et al. 2022). In general, decadal prediction systems and their underlying models may differently represent the ocean dynamics behind the propagation of salinity and temperature signals and the air-sea interaction, either due to model bias or due to the initialization procedure. One can expect some impact on the prediction skill. Nevertheless, in terms of the prediction skill of SST in the SPG, for example, MPI-ESM is not significantly different from other models (Giorgetta et al. 2013).

It is interesting to notice the different link of the SPG to downstream salinity and temperature, and the discrepancy of their predictive skill. Velocity anomalies of ocean currents drive both salt and heat transport anomalies as previous studies concluded (Langehaug et al. 2022; Arthun et al. 2021). Nevertheless, downstream temperature shows pronounced interannual variability and has low signal-to-noise ratio, and temperature anomalies are more impacted by air-sea interaction (Årthun and Eldevik 2016; Frankignoul and Hasselmann 1977) than salinity anomalies. This may explain why the dynamical link of the SPG to downstream salinity is stronger than that to downstream temperature. Consequently, the SPG signals benefit salinity but not temperature prediction. Further investigation into the low temperature prediction skill along the Atlantic water pathway (Langehaug et al. 2022, 2017) is beyond the scope of this study. Given that the prediction skill of temperature in the Nordic Seas is even lower than persistence, we speculate that MPI-ESM-LR1.2 may have model issues which may degrade temperature prediction, for example, ocean models may have difficulties in simulating mesoscale activity at narrow channels (Langehaug et al. 2022), which would impact the signal transition through the Faroe-Shetland Channel. How the representation of air-sea interaction (Årthun and Eldevik 2016; Frankignoul and Hasselmann 1977) in models plays a role in low predictability of temperature is also worth further investigation.

On the other hand, temperature anomalies do propagate from the SPG to the downstream in some years. The difference between salinity and temperature anomaly propagation is that temperature signals tend to break at the Greenland-Scotland ridge. We notice that both salinity and temperature anomalies have some disconnects (dashed line in **Fig. A. 4**b-e) around Faroe Ridge and the Faroe-Shetland Channel. This discontinuity of anomaly propagation for both salinity and temperature indicates that the shallow Greenland-Scotland Ridge is a challenge for prediction due to the complex shelf-sea dynamics (Koul et al. 2021). The poor correlation of temperature between south of the Greenland-Scotland Ridge and downstream is common for ocean models (Langehaug et al. 2022), and also can be seen in EN4 in our study. To the north of the Greenland-Scotland Ridge, temperature shows high lead-lag correlation with temperature at the Fram Strait, anomalies propagating from Faroe-Iceland Ridge to the Fram Strait in ASSIM (**Fig. A. 10**a, c). Similar results (**Fig. A. 10**b, d) from the historical runs support that MPI-ESM-LR is capable of simulating mechanism of anomaly propagation. Besides, different observational datasets show uncertainty at the Greenland-Scotland ridge (Borchert et al. 2018). Fully addressing the discontinuity of anomaly propagation with currently available observational data is hardly possible.

We conclude that the SPG provides downstream ocean predictability by modulating volume transport anomalies along the Atlantic water pathway. We further highlight that the SPG signal can manifest itself differently in downstream salinity and temperature, which leads to different prediction skill for temperature and salinity in the same model. The link of the SPG to downstream salinity is stronger than that to downstream temperature, and therefore salinity is better predicted than temperature. The significant SPG-induced temperature anomalies persist up to the eastern Nordic Seas for 2-3 years, and are skillfully predicted up to 2 years ahead. In contrast, SPG-induced salinity anomalies persist into the Nordic Seas significantly for 6 years, and are skillfully predicted up to 8 years ahead. Our results reveal that the manifestation and persistence of SPG signals determine the prediction time scales of downstream ocean climate. This study firmly establishes the prominent role of ocean circulation in downstream ocean predictability, illuminating the imprint of ocean dynamics in the subarctic climate prediction and opening the door for investigating potentially associated downstream predictability for the earth system, marine ecosystems in particular.

A.4 Methods

Decadal prediction system

In this study we use retrospective forecasts (Hindcasts) from our decadal prediction system based on MPI-ESM-LR1.2 (Giorgetta et al. 2013; Mauritsen et al. 2019). The 16-member hindcast ensemble is initialized from a 16-member weakly coupled assimilation experiment (ASSIM) each November 1st from 1960-2019 (Brune and Baehr 2020; Hövel et al. 2022; Polkova et al. 2019) and run for 10 years. We thus analyze the hindcasts for their common time frame 1970-2019. The assimilation covers the time period 1958-2020 and consists of a 16-member oceanic Ensemble Kalman filter (Brune et al. 2015) that assimilates monthly temperature and salinity profiles from EN4 using the Parallel Data Assimilation Framework (PDAF; Nerger and Hiller 2013). There is no assimilation of satellite derived SST. The availability of in-situ observations of North Atlantic temperature is slightly better than that of salinity, therefore the nominal observational coverage of temperature over the whole time period 1958-2020 is larger than that of salinity. However, in practical terms of monthly averaged profiles available to the assimilation, there is no big difference between temperature and salinity, with the largest differences in the 1960s, and almost no difference with the Argo floats (Wong et al. 2020) in place from 2004 onward. In each assimilation member, atmospheric temperature, vorticity, and divergence at all atmospheric levels above 900 hPa, as well as surface pressure are nudged to ERA40/ERA-Interim/ERA5 reanalysis (Dee et al. 2011; Hersbach et al. 2020; Uppala et al. 2005). There is no direct assimilation of atmospheric surface temperature. Both assimilation and hindcasts use external forcing according to CMIP6 (Eyring et al. 2016), with historical forcing until 2014 and SSP245 assumed after 2014. More details on the decadal prediction system can be found in Polkova et al. 2019 and Brune & Baehr 2020.

Observational references

We utilize ASSIM and two other observation-based datasets, EN4 analysis (Good et al. 2013), and Atlas (Korablev et al. 2014) as observational reference to investigate the skill of decadal prediction. Please note that all three references are not independent, because Atlas profiles are contained in EN4 profiles, and ASSIM is ingesting EN4 profiles. However, results from EN4 analysis and Atlas are consistent with results from ASSIM (Supplementary Figure 1 and 4). Atlas data doesn't cover the period of 2013-2019, which we would like to include in our analysis. Both ASSIM and EN4 analysis ingest the same sub-surface temperature and salinity profiles (from EN4), with different algorithms. Therefore, we decide to present our findings with the dynamically consistent ASSIM rather than the statistically interpolating EN4 analysis as a reference in this paper.

Data processing

All hindcasts and ASSIM are linearly detrended and remapped to 1°× 1° horizontal resolution prior to analysis. Monthly model output is averaged into yearly means, and yearly anomalies are formed against its climatology, which is defined as the 50-yr (1970-2019) mean of 16-member ensemble mean in hindcasts and ASSIM. No data filtering is applied in our study, except for Hovmöller diagrams where time series are 3-30-yr band-pass filtered for illustrative purposes. The persistence forecast is predicting future condition statistically based on past data, which is commonly used as a reference when evaluating dynamical prediction skill. In this study, the persistence forecast is constructed from ASSIM with the first order autoregression model. For fair comparison with hindcasts at lead years 3-5, we use a 3-yr average and predict next 3-5 years in autoregression model. The weight in space is considered when we calculate the area average (North et al. 1982). In this study, we use water salinity at 6m depth as SSS, and the depth-averaged anomalies over 150-310m to represent subsurface properties of salinity and temperature.

Significant test

We use the anomaly correlation coefficient (ACC) to evaluate prediction skill. The confidence level of the ACC and the ACC difference is estimated with a block bootstrapping methodology (Hans R. Kunsch 1989). The 95% confidence interval is the 2.5th and 97.5th percentile range of 1000 random resampling with replacement, and we use block bootstrapping to account for the autocorrelation in the time series. The block length is decided based on the e-folding decorrelation scales in the Nordic Seas, which is 2 years for sea surface salinity (SST) and sea surface salinity (SSS), 3 years for subsurface temperature, and 4 years for subsurface salinity. The two-tailed Student's *t* test is used to assess the significance of lag correlation and cross-correlation, and the autocorrelation of time series is taken into consideration by calculating the effective degrees of freedom (Bartlett 1935).

Index definition

The SPG index in this study is defined as the area-averaged (55-35°W, 50-62°N) density anomaly at 310m (Tesdal et al. 2018), which well captures the connection between the SPG variability and water properties in the eastern subpolar North Atlantic (Koul et al. 2020). The SPG strength is positively correlated with the size of the SPG (e.g., Figure 2d and 4d in Koul et al. 2020) in EN4, also in the MPI-ESM-LR preindustrial control simulation, but less prominent. On average, a strong SPG expands to the eastern SPG region in MPI-ESM-LR. Therefore, the density based SPG index is well suited to our study. Our findings are robust when we compare against an SPG index defined as the principal component of the second Empirical Orthogonal Function (EOF) of annual mean SSH anomalies (Koul et al. 2020). The two SPG indices agree well with each other (**Fig. A. 11**) and show similar patterns for cross-correlation (**Fig. A. 8**).

Data availability

The prediction from the MPI-ESM-LR1.2 decadal prediction system can be accessed via
http://hdl.handle.net/hdl:21.14106/098c6104e3d89943248aa61ff69db972adb3baf6
(Brune et al. 2021).

Code availability

The source codes are available from the corresponding author upon reasonable request.

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Author contributions

Conception of the work: Hongdou Fan, Leonard F. Borchert, Johanna Baehr
Acquisition of data: Sebastian Brune
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Writing - original draft: Hongdou Fan
Writing - review & editing: Hongdou Fan, Leonard F. Borchert, Sebastian Brune, Vimal Koul, Johanna Baehrs

Competing interests

The Authors declare no Competing Financial or Non-Financial Interests.

A.5 Supplementary Information

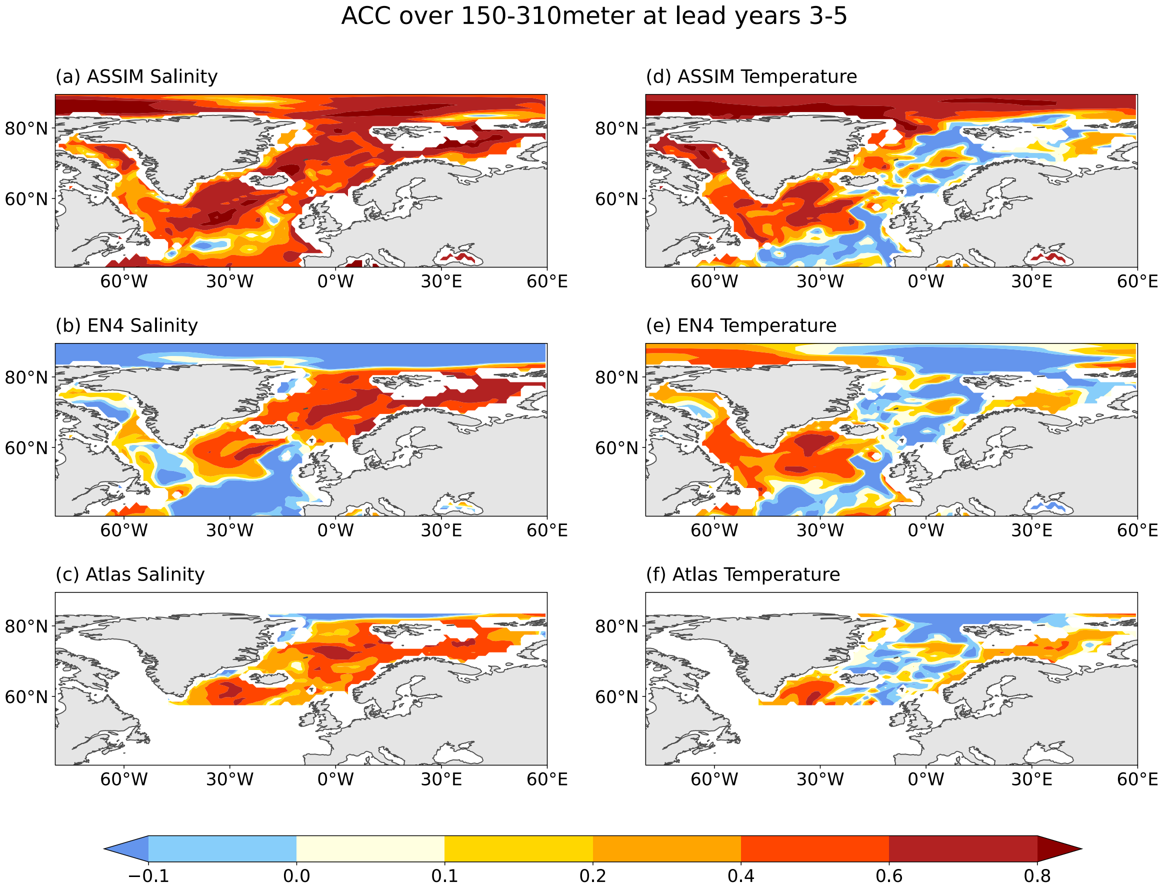

Fig. A. 6 The anomaly correlation coefficient (ACC) over 150-310 meter for detrended annual mean salinity and temperature at lead years 3-5. ACC of salinity between hindcast and (a) ASSIM, (b) EN4, (c) Atlas. (d)-(f) As in (a)-(c), but for temperature. (a), (b), (d) and (e) are results for period 1970-2019, (c) and (f) are results for 1970-2012.

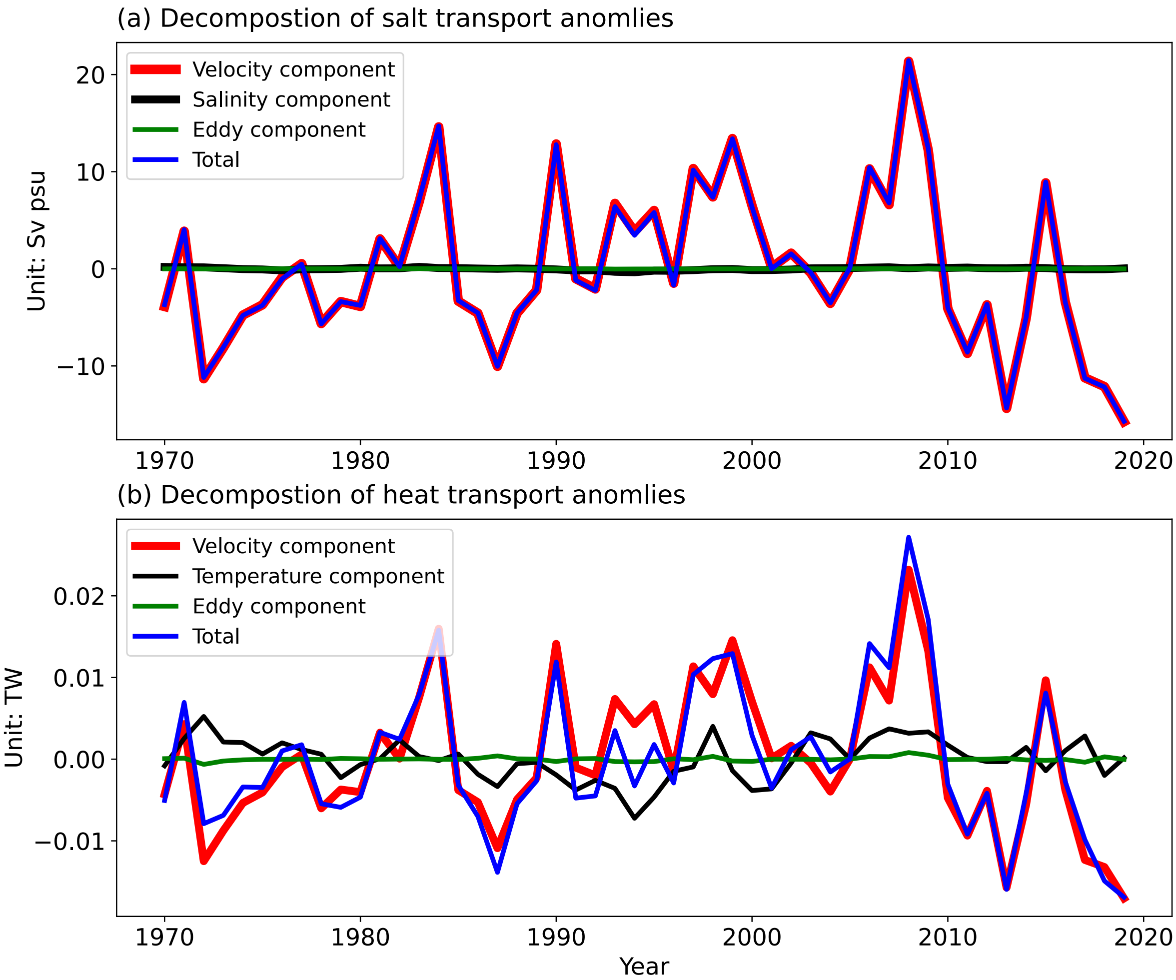

Fig. A. 7 Decomposition of salt and heat transport anomalies at the Faroe-Shetland Channel in ASSIM for the period 1970-2019. (**a**) Salt transport anomalies (blue line) and its velocity component ($\mathbf{V}'\bar{S}$, red line), salinity component ($\overline{\mathbf{V}}S'$, black line), and eddy component ($\mathbf{V}'S'$, green line). (**b**) Heat transport anomalies (blue line) and its velocity component ($\mathbf{V}'\bar{T}$, red line), temperature component ($\overline{\mathbf{V}}T'$, black line), and eddy component ($\mathbf{V}'T'$, green line).

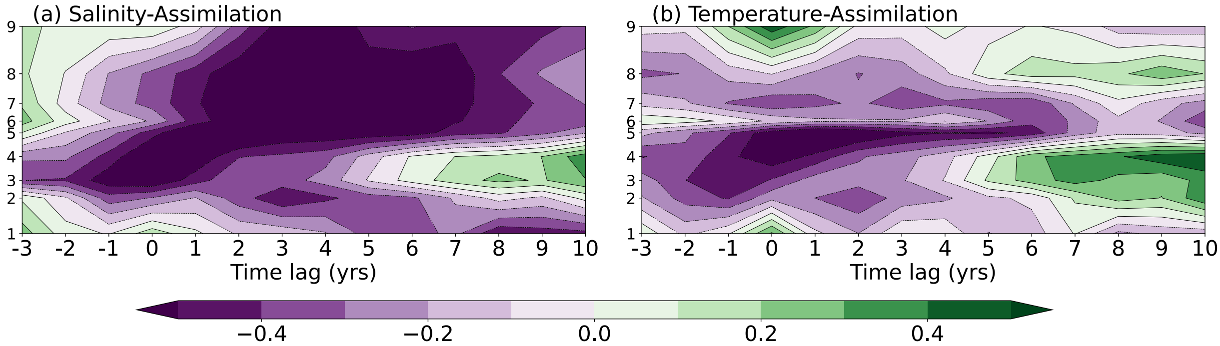

Fig. A. 8 Cross-correlation between PC2 SSH SPG index and subsurface properties along the Atlantic water pathway in ASSIM. Cross-correlation between PC2 SSH SPG index and (a) salinity and (b) temperature. The x-axis denotes the lag years for cross-correlation (salinity or temperature lags SPG).

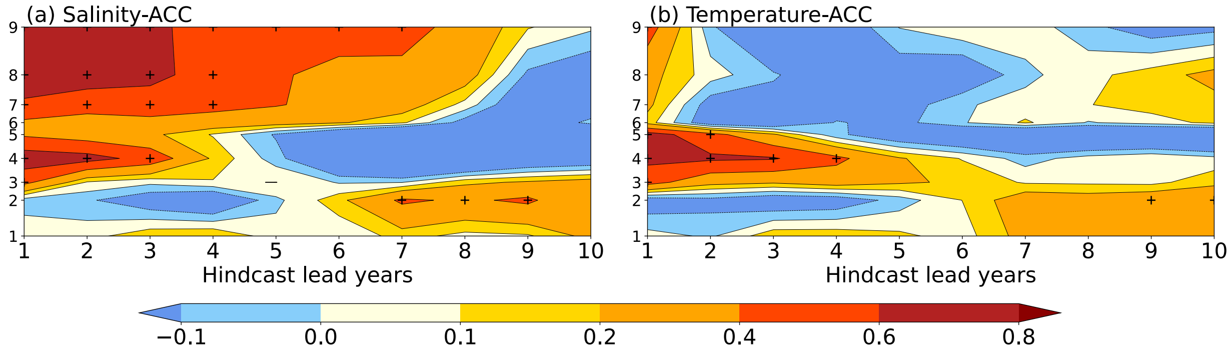

Fig. A. 9 The anomaly correlation coefficient (ACC) between hindcasts and EN4 along the Atlantic water pathway. ACC for (a) salinity and (b) temperature at different hindcast lead years. Stippling denotes 95% confidence level based on block bootstrapping.

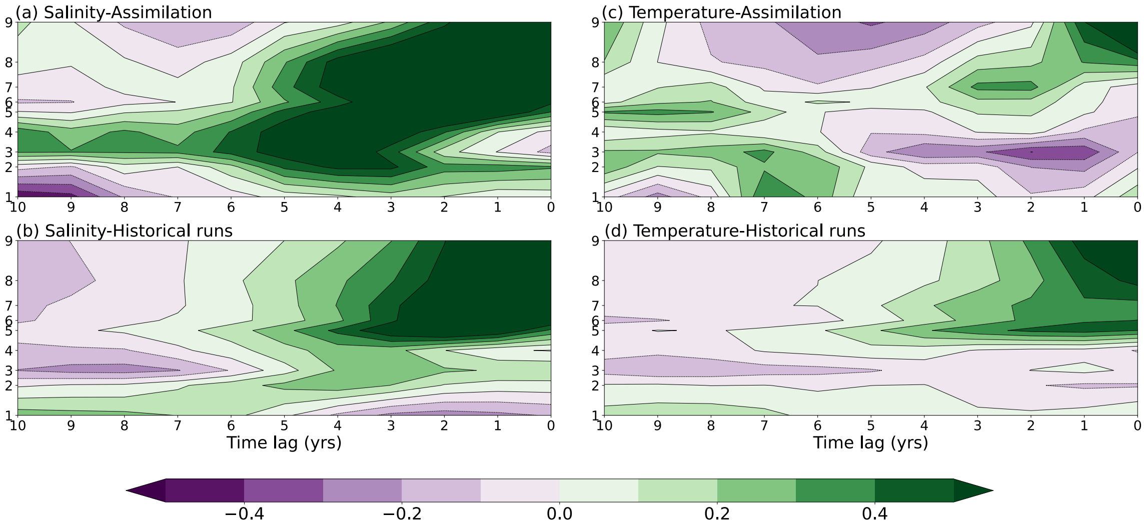

Fig. A. 10 Cross-correlation of subsurface properties between box 9 and boxes along the Atlantic water pathway. Cross-correlation for subsurface salinity in (a) ASSIM and (b) historical runs. (c)-(d) As in (a)-(b), but for temperature. The x-axis denotes the lag years for cross-correlation (box9 lags other boxes).

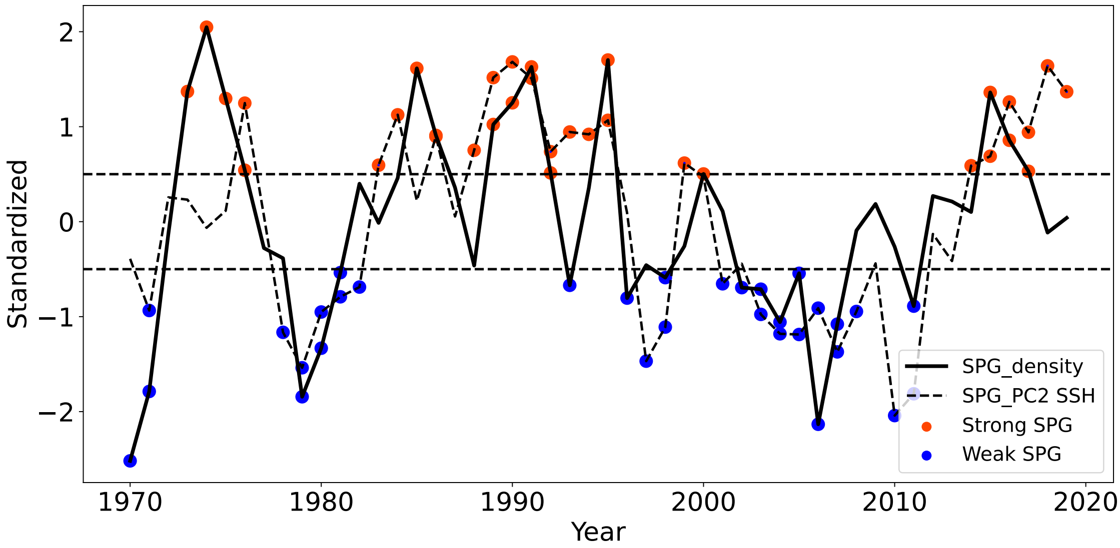

Fig. A. 11 Time series of SPG indices based on density (black line) and PC2 SSH (dashed line) in ASSIM for the period 1970-2019. Density based SPG index is defined as density anomaly at 310m depth over 55-35°W, 50-62°N, PC2 SSH SPG index is defined as the principal component of the second EOF of annual mean SSH anomalies. Time series are standardized, and strong (red dots) and weak SPG (blue dots) events are identified with above 0.5 and below -0.5, respectively.

B Lagged and Transient Impacts of the NAO on Subdecadal Variability of the Norwegian Sea Temperature

The work in this chapter is submitted to a journal as:

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Lagged and Transient Impacts of the NAO on Subdecadal Variability of the Norwegian Sea Temperature

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Abstract

We use the MPI-ESM-LR1.2 model to disentangle the role of the North Atlantic Oscillation (NAO) in the subdecadal variability of the Norwegian Sea upper ocean temperature. With emphasis on the subdecadal time scale, we are able to detect the lagged and transient impacts of the NAO on the Norwegian Sea temperature. By inducing temperature anomalies in the subpolar North Atlantic via buoyancy forcing, the lagged impact of the NAO manifests itself through the oceanic pathway. The resulting temperature anomalies in the subpolar North Atlantic show a clear poleward propagation and spread across the Norwegian Sea in the following 4-5 years. The NAO also exerts a transient impact on the Norwegian Sea temperature by modulating turbulent heat flux and wind-driven transport into the Norwegian Sea. The positive (negative) NAO elevates (lowers) sea surface height along the Norwegian continental shelf and enhances (reduces) temperature transport into the Norwegian Sea simultaneously. The twofold, lagged and transient impact of the NAO, limits the predictability of the Norwegian Sea temperature. Although the lagged impact of the NAO stores as ocean memory and emerges 4-5 years later, the transient impact may damp and counteract the lagged oceanic signal, leading to only 1-year predictability of Norwegian Sea temperature. We find that the initialized positive NAO events largely contribute to this 1-year predictability, and we demonstrate that the lagged impact of the NAO via slow ocean dynamics is potentially predictable. The emergence of ocean memory reveals the possibility to improve subdecadal prediction of the Norwegian Sea temperature.

Significance Statement

We demonstrate that the NAO dominates the subdecadal variability of upper ocean temperature in the Norwegian Sea in a twofold way, lagged and transient impact. By investigating the associated mechanisms, we argue that this twofold impact holds the key to poor prediction of the Norwegian Sea temperature in dynamical models. It is essential to not only predict both transient and lagged impacts of the NAO correctly, but also capture the overlying timing of two impacts correctly. We highlight the challenge in predicting Norwegian Sea temperature, which is inherent to the low predictability of the NAO due to chaotic dynamics. Nevertheless, our study sheds light on higher temperature predictability from the imprint of ocean dynamics.

B.1 Introduction

Connecting the northern North Atlantic Ocean with the Artic Ocean, the Norwegian Sea has been widely studied for its crucial influence on climate and fishery. It has been documented that both large-scale oceanic circulation, such as the North Atlantic subpolar gyre (SPG) and large-scale atmospheric circulation, such as the North Atlantic Oscillation (NAO; Hurrell 1995) contribute to temperature variability in the Norwegian Sea (Asbjørnsen et al. 2019). It remains unknown how the NAO exerts impact on the Norwegians Sea temperature and why the impact of the SPG is limited. In this study, we disentangle the roles of the NAO and the SPG in subdecadal variability of the Norwegian Sea temperature, and reveal insights into its predictability.

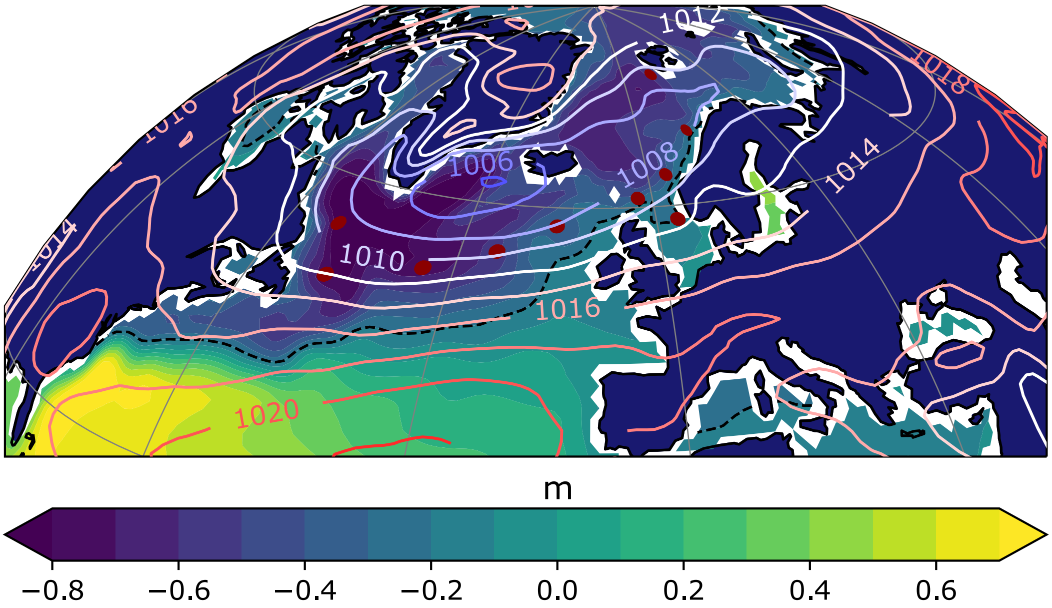

Fig. B. 1 Overview map of the North Atlantic sector in assimilation based on MPI-ESM-LR1.2. Climatological sea surface height (SSH; shading; m) and sea level pressure (SLP; contour; hPa) during 1970-2019. The SSH with values of -0.2m is highlighted by a black dashed contour. Dark red dots show positions along the subpolar gyre, the North Atlantic Current and the Norwegian Atlantic Current.

The prominent feature of interactions between the NAO and the northern North Atlantic Ocean (Fig. B. 1) poses a challenge for investigations into variability and predictability of temperature along the Atlantic water pathway. The counterclockwise ocean circulations in the subpolar gyre (i.e., the SPG) and in the Nordic Seas are both to a large extent driven by the overlaying sea level pressure patterns. The low sea level pressure centered around Iceland is commonly identified as the northern center of the NAO (Hurrell 1995), a representation of dominant atmospheric variability in the Northern Hemisphere. The influence of the NAO on the Norwegians Sea can be traced back to when oceanic temperature anomalies appear in the subpolar region. Superimposed by the atmospheric variability, oceanic temperature anomalies can be modified on their way northward to the Norwegians

Sea (Carton et al. 2011; Fan et al. 2023; Mork et al. 2014). Therefore, the NAO can exert influence on the Norwegians Sea downstream both locally and remotely.

Abundant papers investigated hydrographic anomalies in the Norwegians Sea, reporting on their connection to the NAO forcing (e.g., Lien et al. 2014; Chafik et al. 2015). However, how the temperature variability in the Norwegians Sea is impacted by the NAO has not been fully understood. From monthly to decadal timescales, previous studies have hinted at but not identified the role of the NAO in temperature variability in the Norwegian Sea. On the monthly time scale, Lien et al. 2014 claimed that the NAO can affect instantaneously the depth of the Atlantic Water via wind-induced Ekman transport, but the influence on heat transport is only seen in the Svinøy section, not other sections in southern Norwegian Sea (Richter et al. 2012). On the interannual time scale, the covariability between the NAO and heat transport at Svinøy is insignificant (Fig. 10 in Chafik et al. 2015). On interannual to decadal time scales, closed heat budget diagnostics indicated that ocean heat content anomalies in the Norwegian Sea are largely controlled by ocean heat transport (Årthun and Eldevik 2016; Asbjørnsen et al. 2019), and the roles of the NAO and wind-driven transport were not clearly depicted. On the decadal time scale, the NAO was not a vital contributor to Norwegian Sea temperature changes (Årthun et al. 2017). Whether the impact of the NAO on the Norwegian Sea temperature variability is detectable remains an open question.

The key of addressing this issue may reside in the focused time scales. As mentioned above, different time scales are involved when studying air-sea interaction in the North Atlantic sectors. Both the NAO and hydrographic anomalies in the Norwegian Sea exhibit remarkable subdecadal variability. It was found that temperature transport and volume transport to the Norwegian Sea, and heat content of the Norwegian Sea, show prominent variability on an 8-9-year time scale (Muilwijk et al. 2018; Chepurin and Carton 2012). This time scale coincides with a pronounced 8-year spectral peak of the NAO (Årthun et al. 2017), hinting at their connection in the subdecadal frequency band. In this study, we demonstrate that it is essential to focus on the subdecadal time scale to detect the impact of the NAO on the Norwegian Sea temperature variability. We identify that the impact of the NAO on the Norwegian Sea temperature variability is twofold, with a lagged impact and a transient component. We thus further investigate the limited predictability derived from the initialized NAO.

This paper is laid out as follows. Section 2 describes the datasets and methodology used in this study. Sections 3 identifies the subdecadal variability of temperature in the Norwegian Sea and section 4 investigates the twofold impact of the NAO on the Norwegian Sea temperature. Section 5 explores the predictability derived from the initialized NAO. Finally, section 6 discusses some remaining issues and concludes the key findings.

B.2 Data and Methodology

a. Model simulations

In this study we use model simulations from the 80-member initialized decadal prediction system based on the MPI-ESM-LR1.2 (Krieger et al. 2022; Hövel et al. 2022; Brune and Baehr 2020; Polkova et al. 2019). For consistency reasons, we analyze the time period 1970-2019. The prediction system is based on the MPI-ESM in its low resolution version (MPI-ESM-LR1.2, Mauritsen et al. 2019), with a nominal resolution of approximate 150km and 40 vertical levels in the ocean component MPIOM (Jungclaus et al. 2013), and a resolution of approximate 200km with 47 vertical levels in the atmospheric component ECHAM6 (Stevens et al. 2013).

We use the assimilation simulation (ASSIM) from the decadal prediction system as our reference to investigate mechanism associated with temperature variability. We examine the use of ASSIM against EN4 analysis (Good et al. 2013) as a possible reference, our results are robust against the choice of the reference product (not shown). The assimilation consists of a 16-member oceanic Ensemble Kalman filter (Brune et al. 2015) that assimilates monthly temperature and salinity profiles from EN4 (Good et al. 2013) using the Parallel Data Assimilation Framework (Nerger and Hiller 2013). In each assimilation member, atmospheric temperature, vorticity, and divergence at all atmospheric levels above 900 hPa, as well as surface pressure are nudged to ERA40/ERA-Interim/ERA5 reanalysis (Dee et al. 2011; Hersbach et al. 2020; Uppala et al. 2005). There is no direct assimilation of atmospheric surface temperature. We also use the 80-member retrospective forecasts (hindcasts) from the prediction system to analyze the impact of the NAO on predictions of Norwegian Sea temperature. The hindcast ensemble is initialized from ASSIM each November 1st from 1960-2019 and run for 10 years. All simulations of the decadal prediction system use external forcing according to CMIP6 (Eyring et al. 2016), with historical forcing until 2014 and SSP245 assumed after 2014. Here our analyses only consider the corresponding ensemble mean of the simulations.

b. Data processing and methodology

All ASSIM and hindcasts data are linearly detrended and are remapped to $1^{\circ}\times 1^{\circ}$ horizontal resolution prior to analysis. To best extract the subdecadal variability of area averaged Norwegian Sea temperature, we remove the non-linear trend with the Ensemble Empirical Mode Decomposition method (EEMD, discussed below). Monthly model output is averaged into yearly means, and yearly anomalies are calculated with respect to its climatology, which is defined as the 50-yr (1970-2019) mean of the 16-member ensemble mean in ASSIM and the 80-member ensemble mean in hindcasts. In this study, we focus on the influence of the atmosphere on upper ocean temperature in the Norwegian Sea. We therefore use the depth-averaged anomalies over the upper 310m to represent ocean temperature. The weight in space is considered when we calculate the area average (North et al. 1982). We use a block bootstrapping methodology (Hans R. Kunsch 1989) for the significance test. The 95% confidence interval is the 2.5th and 97.5th percentile range of 1000-times random resampling with replacement, and we use block bootstrapping to account for the autocorrelation in the time series. The block length is chosen based on the e-folding decorrelation scales in the subdecadal component of the Norwegian Sea temperature, which is 2 years.

We define the NAO index as the difference of area-averaged sea level pressure anomalies between the Azores (28°-20°W, 36°-40°N) and Iceland (25°-16°W, 63°-70°N; Dunstone et al. 2016). We examine both winter mean (the mean of December, January, and February) and annual mean NAO. The winter NAO is slightly better correlated with Norwegian Sea temperature than the annual NAO is (**Fig. B. 8**), which is comprehensible as the NAO variability is mostly dominated by winter NAO. We present lead-lag correlation with winter NAO for illustrative purposes. Our findings are robust when we compare against an NAO index defined as the principal component of the first Empirical Orthogonal Function (EOF). The SPG index in this study is defined as the area-averaged (55°-35°W, 50°-62°N) density anomaly at 310m (Tesdal et al. 2018), which well captures the connection between the SPG variability and water properties in the eastern subpolar North Atlantic (Koul et al. 2020). To examine the vertical structure of temperature anomalies along the main core of Atlantic water, 10 locations along the North Atlantic Current and Norwegian Atlantic Current are connected with great circle paths. The locations are consistent with Årthun et al. (2017), except that we add 2 locations in the subpolar region and 1 location in the North Sea to examine possible machinimas causing oceanic temperature anomalies.

We use the Ensemble Empirical Mode Decomposition (EEMD; Wu and Huang 2009) approach to extract the subdecadal variability. The EEMD has been widely used in signal analysis especially in nonlinear and nonstationary time series analysis. Contrast to the conventional Fourier analysis with prior basis functions, the EEMD adaptively derives Intrinsic Mode Functions (IMFs) with variable amplitude and frequency (Huang et al. 1998). The EEMD has been confirmed as an efficient tool to extract physically meaningful components from complicated data series in geophysical fields (e.g., Wu et al. 2009; Yan et al. 2022). For example, the IMFs can correspond to different time-scales variability, from annual cycle to nonlinear trend (Qian et al. 2011; Wu et al. 2007). The core idea of the EEMD algorithm is to seek intrinsic modes of oscillations (i.e., IMFs) based on local extrema. In this study, the EEMD is applied to the Norwegian Sea temperature time series to extract subdecadal variability, which is represented by the second IMF (i.e., c_2) of Norwegian Sea temperature time series (**Fig. B. 9**). Take the temperature time series $x(t)$ as an example, the conceptual procedure is as follows (Wu et al. 2007):

1. Identify and connect all local maxima and minima with a cubic spline, respectively, and get two envelopes.

2. Obtain the average of two envelopes as $m(t)$, and extract the local oscillation $h(t)$:

$$h(t) = x(t) - m(t) \tag{1}$$

3. Apply steps 1 and 2 to the latest $h(t)$, until $m(t)$ is close to zero. The last $h(t)$ is the first IFM $c(t)$, with the highest frequency of local oscillation. Get residue $r(t)$ by subtracting $c(t)$ from $x(t)$:

$$r(t) = x(t) - c(t) \tag{2}$$

Repeat steps 1-3 for the residue $r(t)$ to get the other IMFs until last $r(t)$ is a monotonic function. Hence, $x(t)$ is decomposed into IMFs and the last residual component $r_n(t)$:

$$x(t) = \sum_{i=1}^{n} c_i\,(t) + r_n(t) \tag{3}$$

In practice, white noise is added to $x(t)$ to avoid subjective selection and scale mixing (Wu and Huang 2009). The procedure 1-3 is repeated for thousands of times with slightly different white noise each time. The robust IFMs are obtained by averaging all results. The significant test of IFMs is based on energy density function which is χ^2 distributed (Wu and Huang 2004). We also decompose NAO index, SPG index, tendency of ocean heat content, turbulent heat flux, and temperature transport (**Fig. B. 10**) to remove interannual variability (represented as c_1). Spectral analysis shows that they all show an 8-year period (not shown). For computational reasons, the EEMD is not applied to grid fields.

B.3 Results

B.3.1 Subdecadal variability of upper ocean temperature in the Norwegian Sea

The area-averaged upper ocean temperature in the Norwegian Sea (0°-20°E, 60°-76°N) exhibits prominent subdecadal variability (**Fig. B. 2**), which explains 61% of the total variance. The spectral analysis shows that this subdecadal variability has a period of 8 years, in accordance with a pronounced 8-year spectral peak of the NAO (Årthun et al. 2017). The results suggest a possible connection between subdecadal variability of the Norwegian Sea temperature and the NAO. To reveal insight into this connection, we analyze the lead-lag correlation between the Norwegian Sea temperature and the NAO (**Fig. B. 2**). The Norwegian Sea temperature is significantly negatively correlated with the NAO when the NAO leads by 5-6 years and positively correlated at a lead time of 0-1 years, respectively. These peaks imply a lagged impact and a simultaneous impact of the NAO on the Norwegian Sea temperature. The 5-6 years lagged correlation motivates us to examine whether the NAO stores signals in slow ocean dynamics, which here is represented as SPG variations. It has been demonstrated that the SPG variations can influence hydrographic anomalies in the Nordic Seas about 3 years later, via modulating the poleward propagation of thermohaline anomalies (Fan et al. 2023). There is a small but significant correlation peak when the SPG precedes Norwegian Sea temperature by 3 years (Fig. B. 2b), confirming the impact of ocean dynamics on the Norwegian Sea temperature. Furthermore, the NAO leads the SPG by 1-2 years, suggesting that the NAO may impact the Norwegian Sea temperature by inducing SPG variations. From the results, we deduce that there are two pathways for the NAO to exert influence on the Norwegian Sea temperature: a lagged oceanic pathway via the SPG and transient influence. In the next section, this twofold impact is investigated in detail to reveal the associated processes dominating the Norwegian Sea temperature.

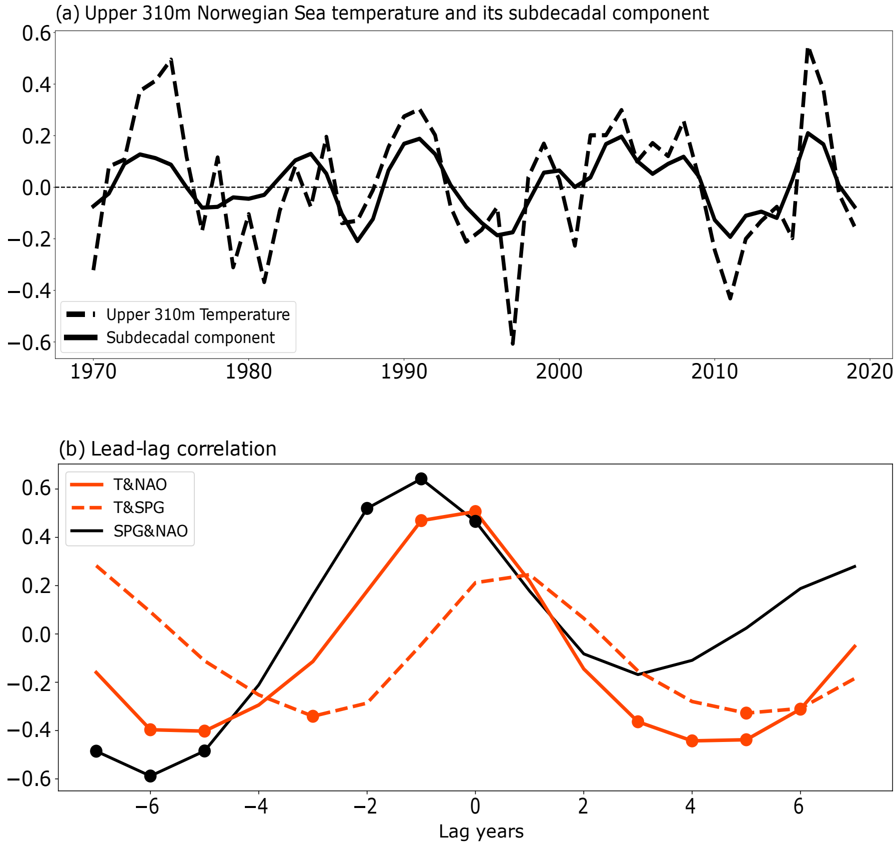

Fig. B. 2 (a) Time series of upper 310m temperature in the Norwegian Sea (black dashed line) and its subdecadal component (black solid line) extracted with EEMD method. The subdecadal component explains 61% of total variability. (b) Lead-lag correlation between subdecadal components of the Norwegian Sea temperature and winter NAO (orange solid line; negative years denote winter NAO leads), the Norwegian Sea temperature and the SPG (orange dashed line; negative years denote the SPG leads), and the SPG and winter NAO (black solid line; negative years denote winter NAO leads). The dots in (b) indicate 95% confidence level based on block bootstrapping.

B.3.2 Twofold impact of the NAO on the Norwegian Sea temperature

a. Lagged impact: oceanic pathway

To provide insight into the responsible mechanisms, we regress the subdecadal component of the Norwegian Sea temperature (solid line in Fig. B. 2a) onto atmospheric and oceanic fields (Fig. B. 3). At lag year 5 (here the Norwegian Sea temperature lags the corresponding fields), the sea level pressure shows prominent positive anomalies to the north of 60°N and negative anomies to the south of 60°N (Fig. B. 3a), resembling the typical negative NAO (NAO –) pattern (Fig. 3 in Smith et al. 2020). The easterly wind anomalies prevail across the subpolar North Atlantic, superimposed on the climatology of westerly wind over the subpolar. As a result, the westerlies are suppressed. There are negative zonal wind stress anomalies in the subpolar North Atlantic, leading to positive turbulent heat flux anomalies (positive heat flux means ocean gains heat). The subpolar North Atlantic gains heat from the atmosphere, resulting in warm ocean anomalies to the north of 45°N. At lag year 4, the warm ocean anomalies develop stronger in the subpolar, extending to the south of Greenland (Fig. B. 3d-f). In addition, the negative zonal wind stress anomalies can enhance northward Ekman transport, contributing to warm ocean anomalies in the SPG. The subpolar ocean responds to the NAO – pattern with warm SPG variations, in agreement with previous studies on sea surface temperature (SST) (Khatri et al. 2022; Krahmann et al. 2001). The results confirm our inference that the NAO forces the SPG variations. We next investigate how these warm SPG variations forced by the NAO – propagate northward to the downstream and modify the Norwegian Sea temperature.

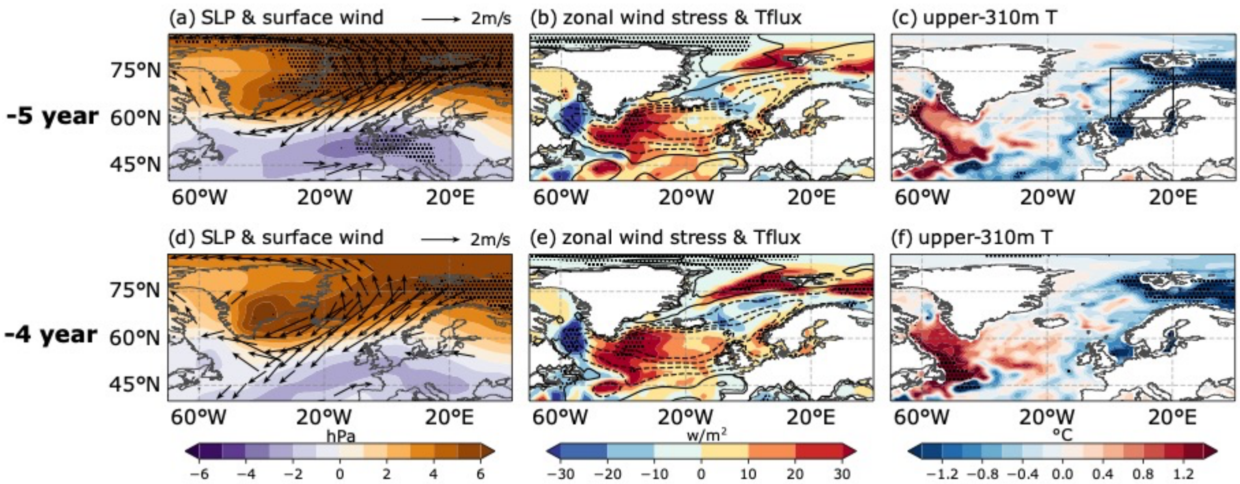

Fig. B. 3 Regression coefficients of annual (a) SLP (shading; hPa) and surface wind (arrow; m/s), (b) turbulent heat flux (shading; w/m^2) and zonal wind stress (contour; N/m^2), and (c) upper 310m temperature (°C) anomalies onto the subdecadal component of the Norwegian Sea temperature (black solid line in Fig. 2a) at lag year 5. The subdecadal component of the Norwegian Sea temperature lags by 5 years. (d)-(f) As in (a)-(c), but when the subdecadal component of the Norwegian Sea temperature lags by 4 years. Stippling in shading fields indicates 95% confidence level based on block bootstrapping. The arrows whose magnitude are smaller than 1m/s are masked out in (a) and (d). The area outlined in black (0°-20°E, 60°-76°N) in (c) is used to calculate the area-averaged temperature in the Norwegian Sea (Fig. B. 2a).

The vertical cross sections along the North Atlantic current and the Norwegian Atlantic current (see Methods) show that warm anomalies in the SPG extend to 100m in the mixed layer at lag year 4-5 (Fig. B. 4). The warm anomalies move poleward

while stretching below the core of the North Atlantic Current at lag year 2-4. This indicates that the response of the SPG variations to the NAO is stored into the subsurface ocean. The warm anomalies appear in the eastern subpolar gyre region at lag year 3, and the previously cold North Sea is warming up (Fig. B. 4c). The warm anomalies move to the North Sea and Norwegian Sea at lag year 2. The poleward warm anomalies are enhanced, and they occupy the Norwegian Sea at lag year 0-1. The entire water column down to 600m in the Norwegian Sea shows significant warm anomalies (Fig. B. 4e-f). The propagation time of 3-5 years for the anomalies propagation is in line with previous studies, indicating that the propagation is operated by ocean advection (Fan et al. 2023; Årthun et al. 2021). We note that the warm anomalies are insignificant at the entrance of the Norwegian Sea (between station 5 and 6) during the propagation. This may have to do with the transient influence of the NAO and will be discussed in the following section.
The results indicate that as a response to NAO –, warm anomalies are originated in the subpolar region. The identified warm SPG variations move northward along ocean currents to the Norwegian Sea in the following 4-5 years. The prominent enhancement of warm anomalies in the Norwegian Sea at lag year 0-1 implies that other factors, acting more instantaneously, may transiently modulate temperature in the Norwegian Sea besides the oceanic pathway. This transient impact is investigated in the next section.

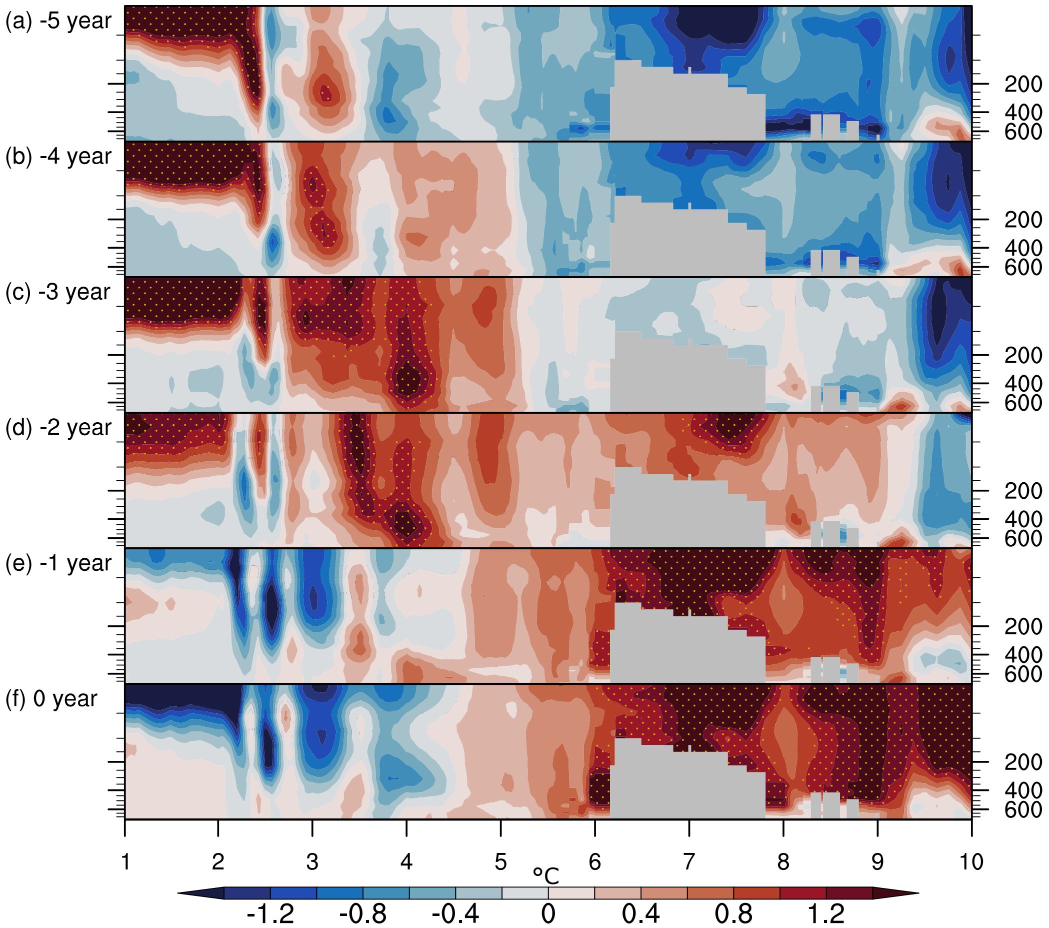

Fig. B. 4 Regression coefficients of annual temperature anomalies (°C) along ocean currents (depicted as dark red dots in Fig. 1) onto the subdecadal component of the Norwegian Sea temperature (black solid line in Fig. 2a) at lag year 5-0 in (a)-(f), respectively. The subdecadal component of the Norwegian Sea temperature lags. Stippling indicates 95% confidence level based on block bootstrapping. The positions of cross-sections along ocean currents are shown as red dots in **Fig. B. 1**. The cross-sections are interpolated onto great circle paths.

b. Transient impact: temperature transport and turbulent heat flux

The sea level pressure field switches from the previously NAO – pattern (**Fig. B. 3**a, d) to the NAO + pattern (**Fig. B. 5**a) at lag year 1. With the presence of a cyclone centered around Iceland, northeastward wind anomalies prevail in the southern Norwegian Sea. The sea surface height is elevated along the Norwegian continental shelf, and the associated temperature transport is enhanced (**Fig. B. 5**b). This result suggests that the increased temperature transport may be induced by the stronger along-shelf wind. The correlation between NAO index and temperature transport is 0.41, supporting previous studies which proposed that the NAO + spins up the North Atlantic circulation and causes high volume transport to the Norwegian Sea (Sundby and Drinkwater 2007; Muilwijk et al. 2018; Chafik et al. 2015). Moreover, inspection of the associated turbulent heat flux indicates that the Norwegian Sea, and in particular its southern part gains heat from the atmosphere (**Fig. B. 5**c). These positive heat flux anomalies can be caused by warm air mass transport due to the NAO + pattern. The wind-driven temperature transport and positive turbulent heat flux into the Norwegian Sea are both in favor of warm anomalies in the Norwegian Sea at lag year 1 (**Fig. B. 4, Fig. B. 5**). At lag year 0, the positive sea level height and along-shelf temperature transport are stronger developed (**Fig. B. 5**f). Besides the atmospheric forcing, the increased temperature transport along shelf can be caused by the larger temperature gradient toward the Norwegian Sea (Chafik et al. 2015). Therefore, the warm anomalies in the Norwegian Sea become larger although the influence from heat flux becomes insignificant (**Fig. B. 5**g, h), indicating the leading role of temperature transport. As a result, the superimposed NAO + pattern leads to the prominent enhancement of warm anomalies along ocean currents at lead year 1 and 0 (**Fig. B. 4** e, f and **Fig. B. 5**d, h).

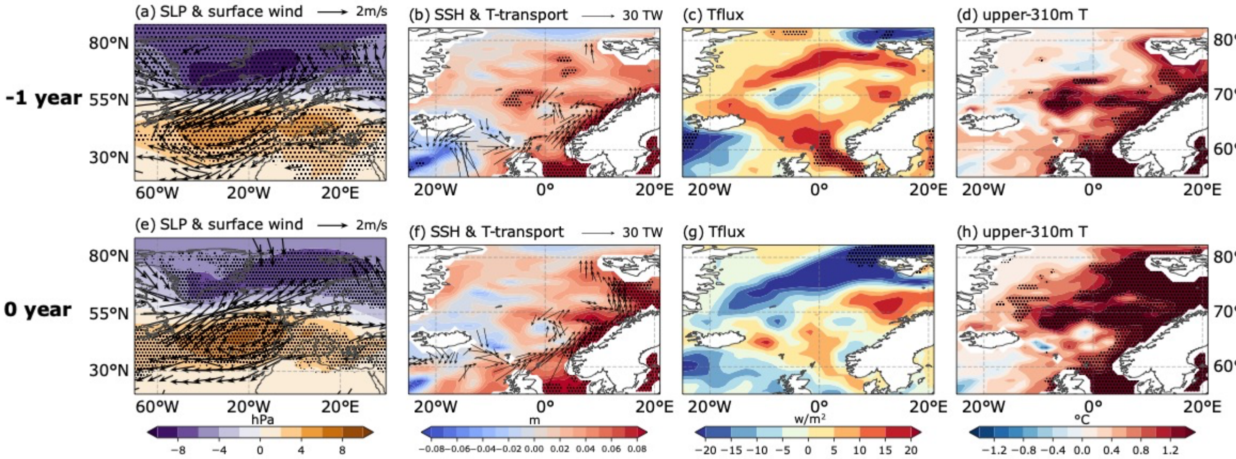

Fig. B. 5 As in Fig. 3 but onto (a) SLP (shading; hPa) and surface wind (arrow; m/s), (b) SSH (shading; m) and temperature transport (arrow; W), (c) turbulent heat flux (w/m^2), and upper 310m temperature (°C) at (a)-(d) lag year 1 and (e)-(h) lag year 0, respectively. The arrows whose magnitude are smaller than 10TW are masked out in (b), (f).

The dominance of transient factors in Norwegian Sea temperature motivates us to analyze the corresponding subdecadal components of the heat budget in the Norwegian Sea (Fig. B. 6a). The temperature transport across the Iceland-Faroe channel and the Faroe-Scotland channel largely drives the variability of the tendency of ocean heat content in the Norwegian Sea, especially before 2000. After 2000, the temperature transport and tendency of ocean heat content become almost anticorrelated. The contribution of turbulent heat flux to the tendency of ocean heat content is also ineligible, especially after 2007. The temperature transport and turbulent heat flux are in phase in some years for example in the 1980s, while they are out of phase in some years for example in the 2000s. The result indicates that both transient advective effects and heat flux are responsible for variability of Norwegian Sea temperature, and they are evolving in time. Furthermore, the associated turbulent heat flux shows spatial variability in the Norwegian Sea (Fig. B. 5c-f). At lag year 1, the heat flux is significantly related to temperature to the northeast of Faroe-Scotland Channel, indicating that the entrance is the key region where ocean currents gain or lose heat prominently. The local modifications of temperature around the Faroe-Scotland Channel are in line with previous finding of the discontinuity of poleward thermohaline propagation across the Faroe-Scotland Chanel (Fan et al. 2023; Langehaug et al. 2019). The results suggests that the overlaying atmosphere may rapidly modify temperature anomalies along the Atlantic water pathway. Inspection of the correlation between the NAO index and temperature suggests the increasing influence of the overlying atmosphere along ocean currents after crossing the Faroe-Scotland Channel (Fig. B. 6b). The insignificant correlation in the transition zone highlights the uncertainty in the eastern North Atlantic and around the Faroe-Scotland Channel.

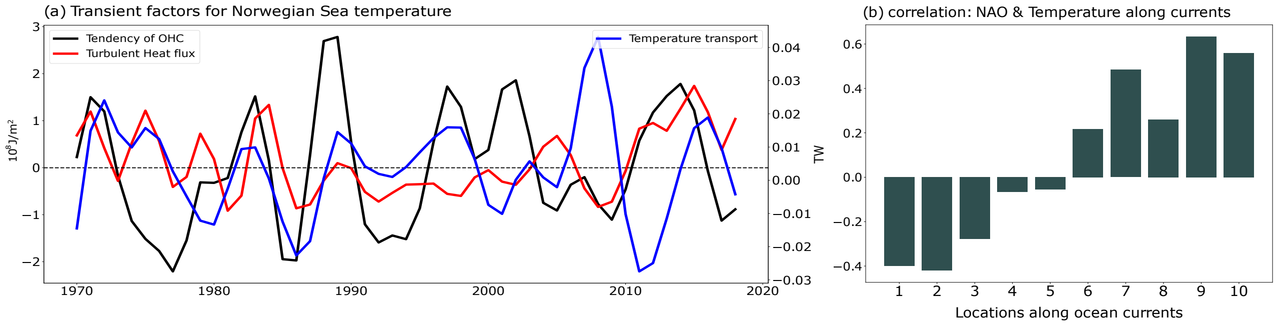

Fig. B. 6 (a) Time series for tendency of upper 310m ocean heat content (black), surface turbulent heat flux (red) in the Norwegian Sea (0°-20°E, 60°-76°N), and horizontal temperature transport between Iceland and Scotland in the upper 310m (blue). The tendency of ocean heat content is calculated as year-to-year difference and the turbulent heat flux is integrated over 1 year. The temperature transport is the sum of transport at Iceland-Faroe channel at the Faroe-Scotland channel. Subdecadal components for time series are extracted with EEMD method. (b) Correlation coefficients between NAO index and ocean temperature along ocean currents. The ocean temperature along currents is calculated with a box of 5°× 5° with centers at dark red dots in Fig. B. 1.

Overall, the NAO exerts a twofold, lagged and transient, impact on temperature variability in the Norwegian Sea. The lagged impact originates in the SPG and modulates Norwegian Sea temperature via the oceanic pathway. The transient impact of the NAO dominates Norwegian Sea temperature via wind-driven transport and turbulent heat flux. Given the short-term memory of the atmosphere (Fan et al. 2020), we conjecture that this twofold impact of the NAO may lead to the low prediction skill of temperature in the Norwegian Sea (Langehaug et al. 2017; Fan et al. 2023). To shed light on the limited predictability of temperature in the Norwegian Sea, we explore the impacts of the NAO on prediction in the next section.

B.3.3 Predictability derived from the initialized NAO

To investigate the impacts of the NAO on subdecadal predictability of temperature in the Norwegian Sea, we analyze the 80-ensemble member hindcast set based on the MPI-ESM-LR1.2 (see Methods). We examine to what extent the lagged impact of the NAO via the oceanic pathway is manifested in predictability of Norwegian Sea temperature. As discussed in section 4a, warm (cold) anomalies induced by NAO – (NAO +) in the subpolar region circulate poleward to the Norwegian Sea in the following 4-5 years (Fig. B. 4). If the predictive signals are stored in the ocean currents, it will lead to consequent warm (cold) anomalies in the Norwegian Sea 5 years after NAO – (NAO +) events. The inspection of temperature anomalies in the Norwegian Sea 5 years later after NAO events confirms this conjecture (Fig. B. 7a). In ASSIM, the majority of traced NAO – (NAO +) events end up with warm (cold) anomalies in the Norwegian Sea 5 years later. This means oceanic signals due to the NAO emerge and constrain Norwegian Sea temperature 5 years later, thus can potentially provide predictability 5 years later after NAO events. However, this predictability 5 years after NAO events is not manifested in hindcasts. The

Norwegian Sea temperature is poorly predicted at forecast lead year 6 regardless of the initialized phases of the NAO (Fig. B. 7a). The initialized NAO + events barely exert influence on prediction 5 years later, noticing that warm and cold anomalies are predicted with similar likelihood. The initialized NAO – events slightly change the likelihood of prediction, by nudging it toward warm anomalies 5 years later. About two thirds of the traced NAO – events end up with moderate warm anomalies. Although the lagged impact of the NAO is stored by ocean memory is not reproduced in hindcasts, the results reveal that the Norwegian Sea temperature might be more predictable than model results expect. The manifestation of the lagged impact of the NAO in ASSIM indicates that there is ample space to improve the prediction of Norwegian Sea temperature via slow ocean dynamics.

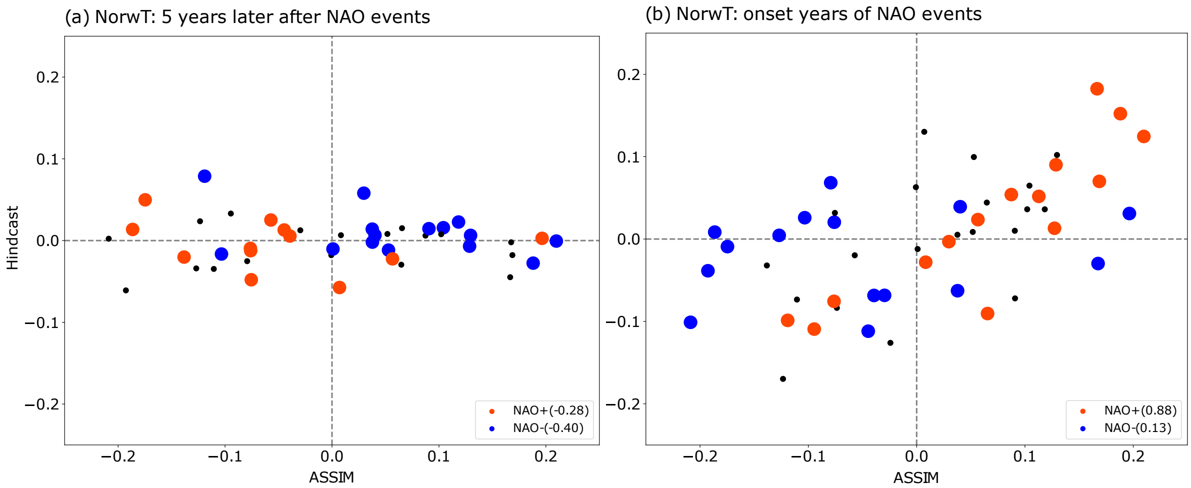

Fig. B. 7 Norwegian Sea temperature anomalies (a) 5 years after NAO events and (b) at onset years of NAO events in ASSIM and in Hindcast. The temperature anomalies from Hindcast are at forecast lead year 6 in (a) and forecast lead year 1 in (b), respectively. Red (blue) dots denote NAO + (–) events at onset years. Brackets give the prediction skill for Norwegian Sea temperature anomalies according to NAO + (–) events at onset years.

In comparison, the simultaneous impact of the NAO on temperature prediction is more prominent. The Norwegian Sea temperature is skillfully predicted at forecast lead year 1. The prediction skill measured with linear correlation between hindcasts and ASSIM Norwegian Sea temperature is 0.58 at forecast lead year 1. The scatter plot (Fig. B. 7b) further shows that warm anomalies are better predicted than cold anomalies at forecast lead year 1, especially during NAO + events. It indicates that warm anomaly and its predictability can be largely attributed to the initialized NAO + events. A plausible explanation for this asymmetry is that NAO + enhances the climatology of atmospheric circulation and ocean currents (Fig. B. 5), while NAO – damps previously induced water anomalies from the SPG. Consequently, the temperature prediction skill at forecast lead year 1 is sensitive to the phase of the NAO. The Norwegian Sea temperature is well predicted with the skill of 0.88 when the NAO is initialized as NAO +, while there is no skill for temperature when the NAO is initialized as NAO –. Additionally, it is noticed that NAO + events are better predicted with the skill of 0.42 than NAO – events with skill of -0.44 at forecast lead year 1, but the predictability of the NAO is not the focus of this paper. The prediction of Norwegian Sea temperature at forecast lead year 1 confirms the dominance of the transient impact of the NAO (**Fig. B. 6**b), and further supports previous analysis that the signal of warm anomalies can be enhanced by the NAO + (**Fig. B. 5**).

The prediction skill of Norwegian Sea temperature is to a large extent derived from the initialized NAO via the transient impact. This transient impact is manifested as skillful prediction at forecast lead year 1 especially during NAO + events, which are in favor of transporting warm air and enhancing oceanic signals. While for NAO – events, the magnitude of the propagated anomalies can be damped, therefore they are worse predicted. The initialized NAO constrains Norwegian Sea temperature for 2 years (Fan et al. 2023), but Norwegian Sea temperature is only skillfully predicted 1 year in advance (**Fig. B. 15**). The lagged impact of the NAO via the ocean dynamics constrains Norwegian Sea temperature 4-5 years later after NAO events. However, this lagged impact is limited and not reproduced in hindcasts, thus providing limited predictability for the Norwegian Sea temperature. For skillful prediction of Norwegian Sea temperature, it is essential to not only predict both transient and lagged impacts of the NAO correctly, but also predict the timing of two impacts correctly. This twofold impact may hold the key to poor prediction of the Norwegian Sea temperature in models. Nevertheless, the lagged impact of the NAO via slow ocean dynamics reveals the potential to harness ocean memory to improve prediction of Norwegian Sea temperature.

B.4 Discussion and Conclusion

a. Discussion

In this study, we show that the lagged and transient impacts of the NAO substantially contribute to subdecadal variability of Norwegian Sea temperature, and we further manifest the limited predictability of the Norwegian Sea temperature derived from the initialized NAO conditions. Our results corroborate previous findings (Muilwijk et al. 2018; Årthun et al. 2017) that it is essential to focus on the subdecadal time scale to disentangle the impacts of the NAO on variability of the Norwegian Sea temperature. The lagged impact originated in the subpolar ocean is along the line with previous studies that the ocean is driven by the atmosphere on the subdecadal timescale in the mid-latitude North Atlantic (e.g., Gulev et al. 2013). We confirm that the NAO plays a crucial role in triggering SPG variations via buoyancy forcing and wind stress (Khatri et al. 2022), and that the forced SPG variations are carried downstream by poleward ocean propagation and modulate water variability in the Norwegian Sea (e.g., Fan et al. 2023; Langehaug et al. 2019). Different from the Norwegian Sea temperature, the SPG variations are well predicted, benefiting from initialization and persistence of Atlantic meridional overturning circulation (Borchert et al. 2021; Koul et al. 2021). Our findings support the predominant role of the transient impact of the NAO in the Norwegian Sea temperature variability via wind-driven transport and turbulent heat flux (e.g., Lien et al. 2014; Mork et al. 2014). We further demonstrate the 1-year predictability provided by initialized NAO + conditions and highlight the emergence of the lagged impact via ocean advection, which can be harnessed to improve the subdecadal prediction of temperature in the Norwegian Sea.

The lagged and transient impacts of the NAO may be responsible to different propagation speeds of water anomalies in the Nordic Seas reported in several studies (e.g., Chafik et al. 2015; Yang and Pratt 2013). It was documented that there are slow and fast propagation speeds of water anomalies caused by different mechanisms (Lien et al. 2014; Sundby and Drinkwater 2007; Broomé and Nilsson 2018). The slow one propagates along ocean currents with eddy mixing, resulting in advection speed of 2-3 cm s^{-1}(Sundby and Drinkwater 2007; Langehaug et al. 2022). The fast one is wind-generated and appears almost instantaneously long the Norwegian continental shelf with Kelvin waves. The contributions of ocean advection and heat flux to the heat content in the Norwegian Sea are still debated (Mork et al. 2014; Asbjørnsen et al. 2019; Carton et al. 2011). Numerical experiments are required to separate the effect of atmospheric forcing and ocean dynamics for accurate quantifications.

Our results of lagged and transient impacts of the NAO suggest that the poor prediction of temperature in the Norwegian Sea (Fan et al. 2023) can be partially attributed to this twofold impact. Skillful predictions demand reproducing both lagged impact and simultaneous atmospheric condition, and the twofold impacts shall overlay each other with the right timing. Furthermore, the lagged impact via ocean advection and transient impact via heat flux and oceanic heat transport may cancel each other (Krahmann et al. 2001), increasing the difficulty of prediction. This may explain why models show different prediction skills for temperature and salinity, and they have different propagation speeds although in the same water parcel (Fan et al. 2023; Yashayaev and Seidov 2015). Temperature tends to be modified by the NAO-like wind forcing along the poleward propagation, while salinity as a passive tracer is governed by horizontal oceanic advection. Consequently, the prediction skill of temperature is lower than prediction skill of salinity in the Norwegian Sea.

It is further noticed that the impact of the NAO on temperature prediction asymmetrically depends on the phases of the NAO. The Norwegian Sea temperature is skillfully predicted 1 year in advance when NAO is initialized as NAO +, while there is barely skill when NAO is initialized as NAO –. The asymmetric impact of the NAO is likely caused by the asymmetric persistence of the NAO itself. It was demonstrated that NAO – persists longer due to the stronger positive eddy feedback in the mid-latitude North Atlantic (Barnes and Hartmann 2010). This was supported by a study indicating that warm SST anomalies triggered by NAO – in the subpolar persist for a few years while cold SST anomalies triggered by NAO + persist only for 1 year (Khatri et al. 2022). Consider the typical 8-year spectral peak of the NAO, the NAO – most likely switches to NAO + when the previously induced warm temperature anomalies arrive in the Norwegian Sea along ocean currents. The NAO + amplifies the existing propagating warm anomalies by enhancing ocean heat transport and warm air transport to the Norwegian Sea (Carton et al. 2011; Muilwijk et al. 2018). The NAO – may damp the magnitude of the propagating anomalies. Therefore, this phase sensitivity is inherent to the periodicity and dynamics of the NAO, and the predictability of the Norwegian Sea temperature resides in the NAO +. Our results further show that NAO + is better predicted than NAO –, which could be interesting to explore in the future.

b. conclusion

We conclude that the NAO dominates subdecadal variability of the Norwegian Sea temperature in a twofold way. The lagged impact of the NAO originated in the subpolar region via buoyancy forcing, is carried by poleward ocean currents and leads to consequent changes in the Norwegian Sea temperature 4-5 years later, while the transient NAO exerts influence on the Norwegian Sea temperature by modulating heat flux and wind-driven transport into the Norwegian Sea. With the oceanic pathway and direct influence, the twofold impact of the NAO reveals insights into the low predictability of the Norwegian Sea temperature. The transient impact may counteract the lagged oceanic signal and rapidly modify ocean temperature, thus limit subdecadal predictability. We further reveal the asymmetric impact of the NAO phase on temperature predictability and this asymmetry is inherent to the periodicity and dynamics of the NAO. We demonstrate that the initialized NAO + provides 1-year predictability to the Norwegian Sea temperature. Our study highlights that the challenge of predicting the Norwegian Sea temperature goes hand in hand with predicting the NAO. Nevertheless, here we emphasize that the lagged impact stored in ocean dynamics can constrain the Norwegian Sea temperature a few years later and therefore may provide windows of opportunity for prediction. The ocean memory can be potentially harnessed to improve subdecadal prediction of the Norwegian Sea temperature.

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Data Availability Statement

The prediction from the MPI-ESM-LR1.2 decadal prediction system can be accessed via https://hdl.handle.net/21.14106/098c6104e3d89943248aa61ff69db972adb3baf6 (Brune et al. 2021). The python implementation of EEMD can be accessed via: https://pyemd.readthedocs.io/en/latest/eemd.html.

B.5 Supplementary Information

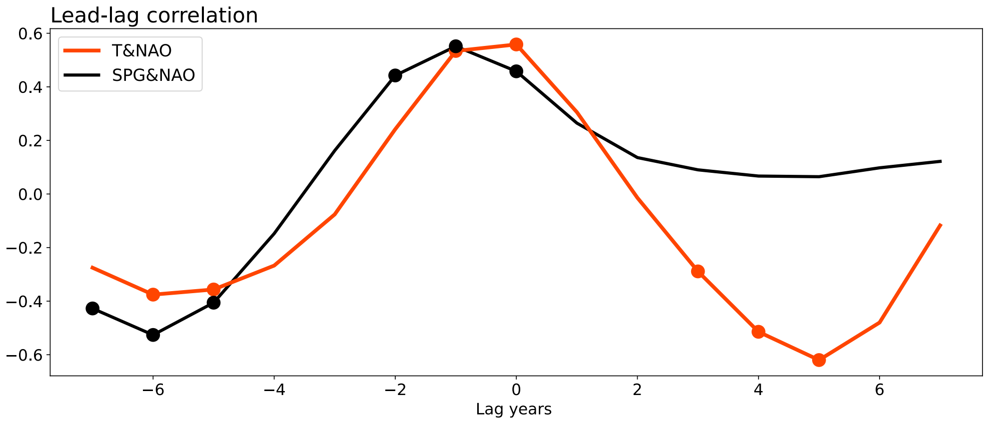

Fig. B. 8 Lead-lag correlation between subdecadal components of the Norwegian Sea temperature and annual NAO (orange solid line; negative years denote winter NAO leads) and the SPG and annual NAO (black solid line; negative years denote winter NAO leads). The dots indicate 95% confidence level based on block bootstrapping.

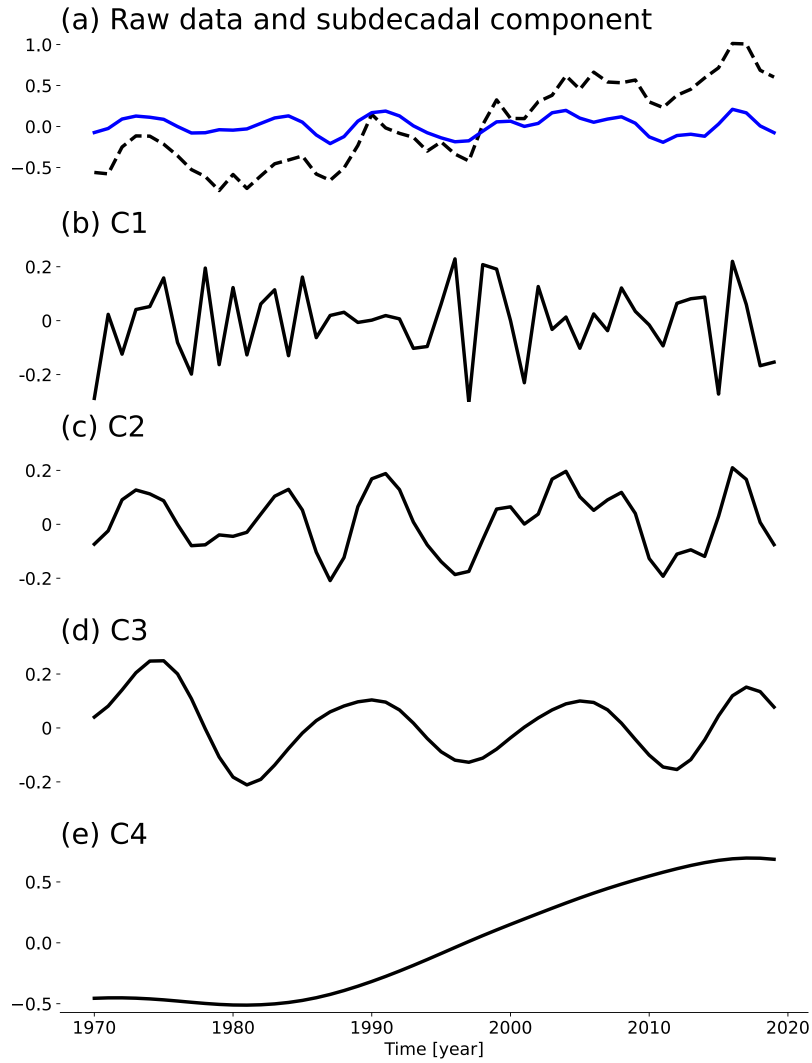

Fig. B. 9 (a) Time series of upper 310m temperature (°C) in the Norwegian Sea (black dashed line) and its subdecadal component (blue solid line; i.e., c_2) extracted with EEMD method. (b)-(e) Intrinsic Mode Functions (IMFs) derived by EEMD.

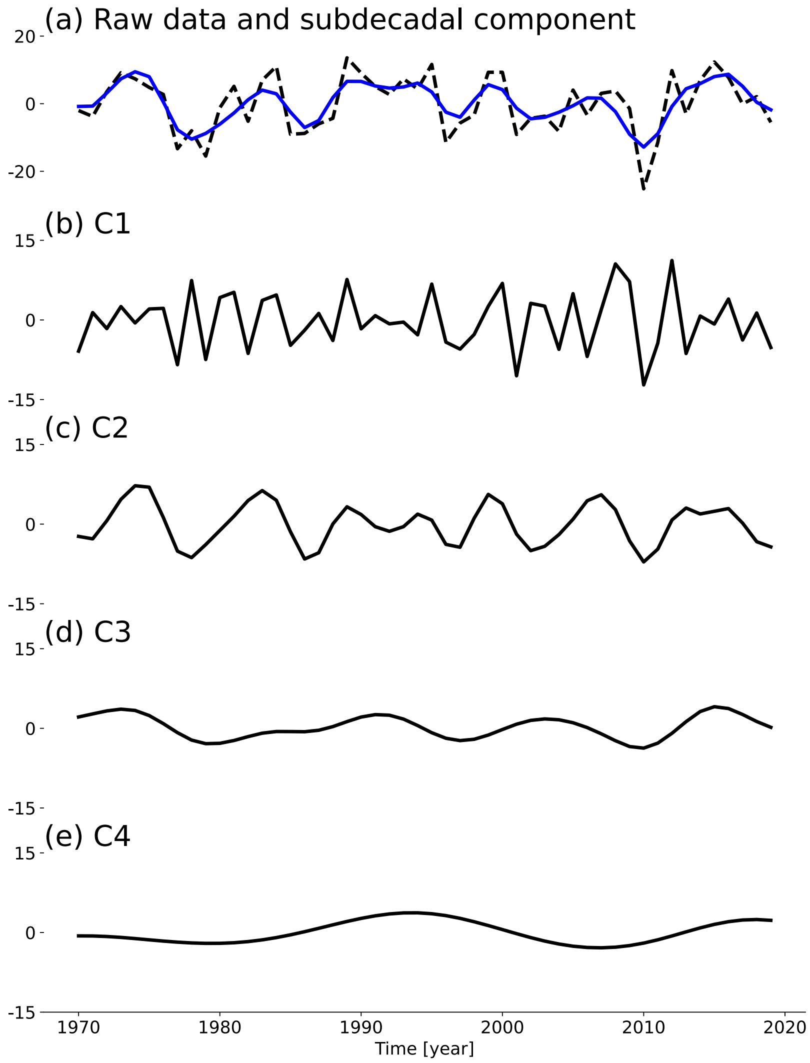

Fig. B. 10 (a) Time series of winter NAO (black dashed line; hPa) and its subdecadal component (blue solid line; i.e., $\sum_{i=2}^{4} c_i$) extracted with EEMD method. (b)-(e) Intrinsic Mode Functions (IMFs) derived by EEMD.

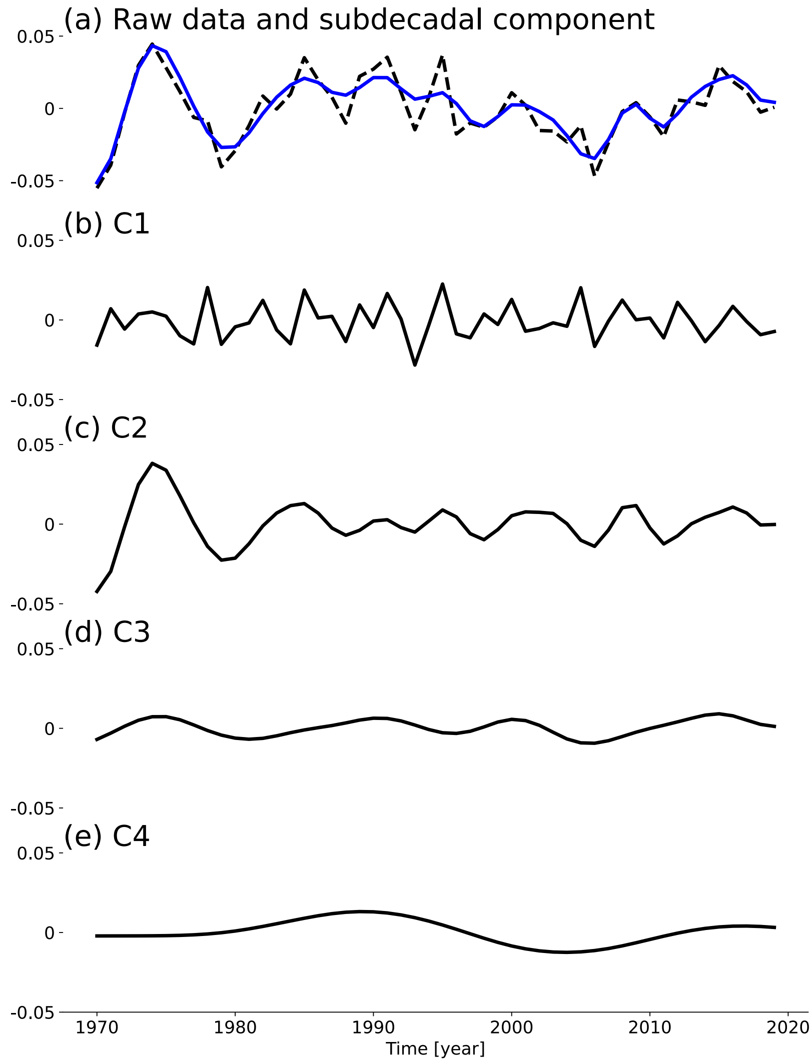

Fig. B. 11 As in Fig. B.10 but for SPG index (kg/m^3).

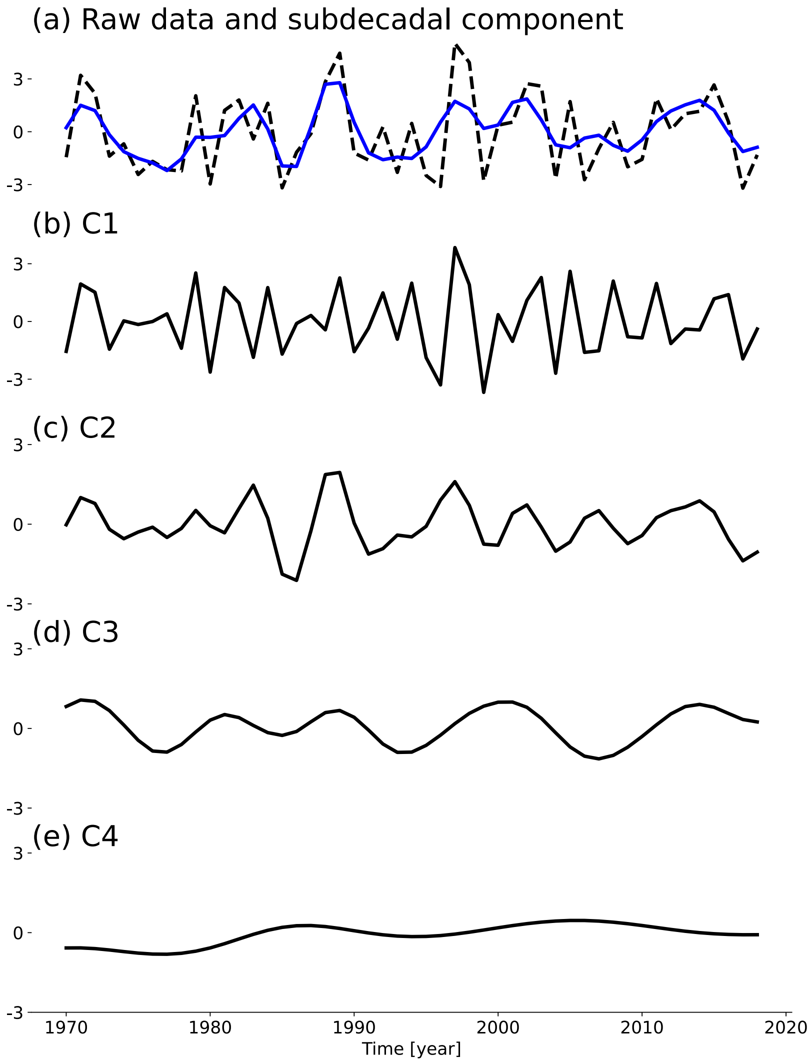

Fig. B. 12 As in Fig. B.10 but for tendency of upper 310m ocean heat content (10^8 J/m^2) in the Norwegian Sea.

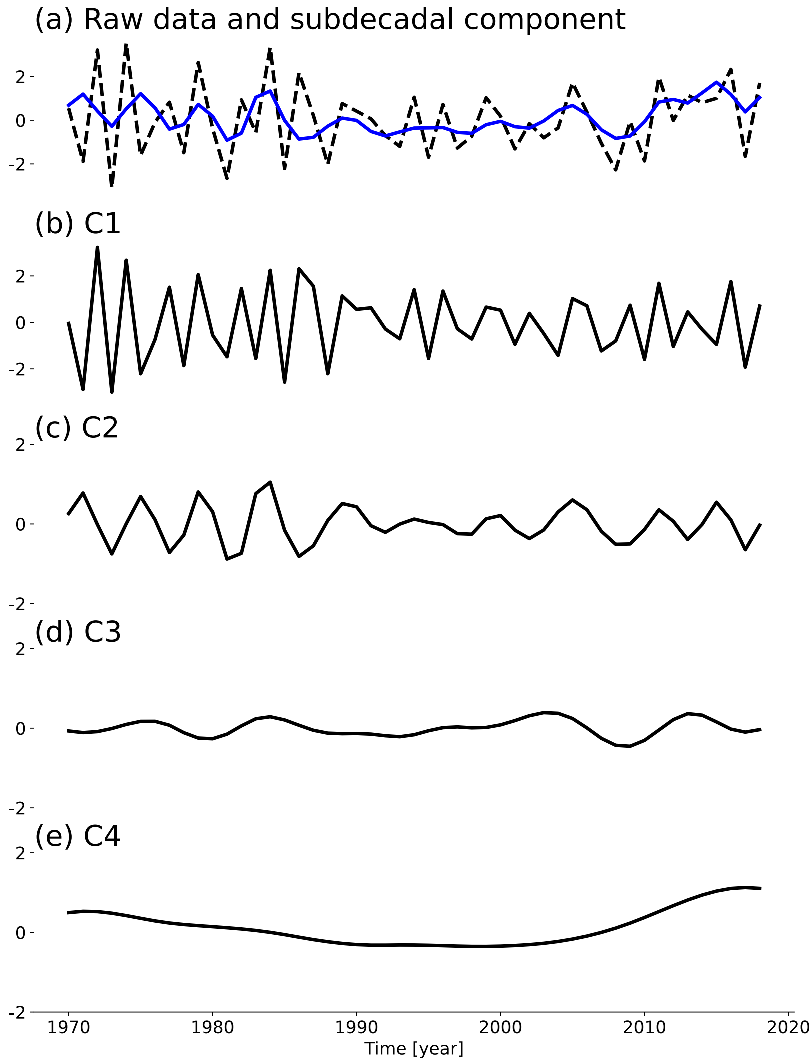

Fig. B. 13 As in Fig. B.10 but for surface turbulent heat flux (10^8 J/m^2) in the Norwegian Sea.

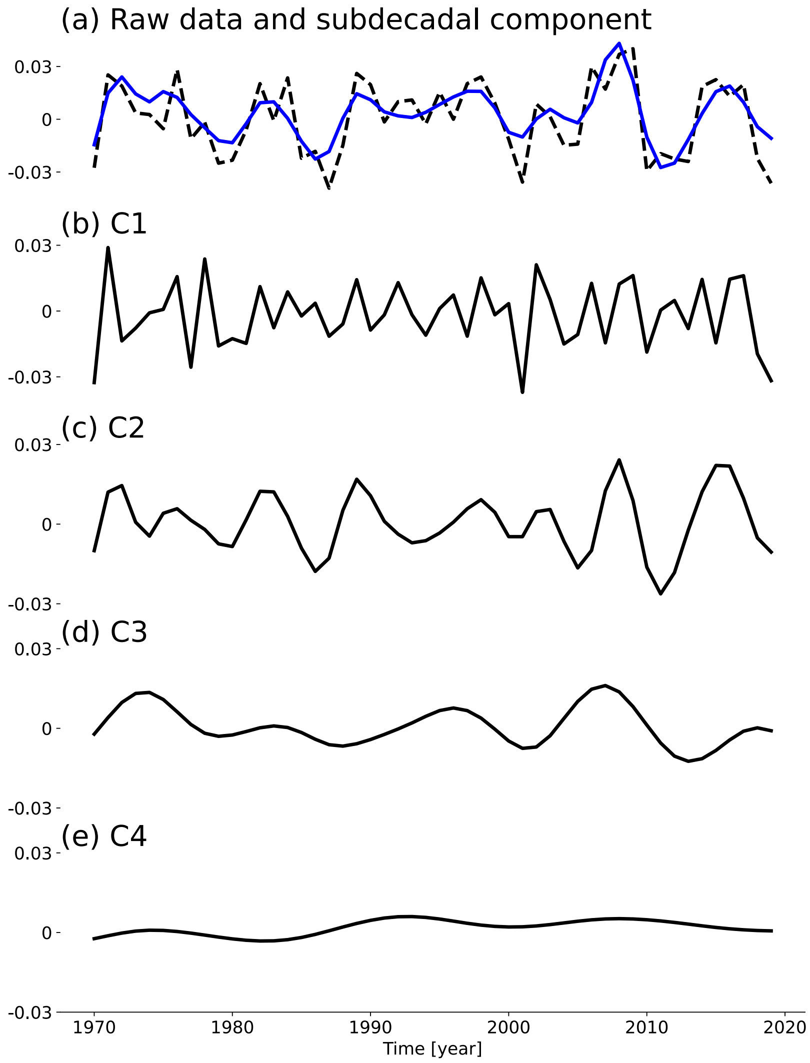

Fig. B. 14 As in Fig. B.10 but for horizontal temperature transport (TW) between Iceland and Shetland in the upper 310m ocean.

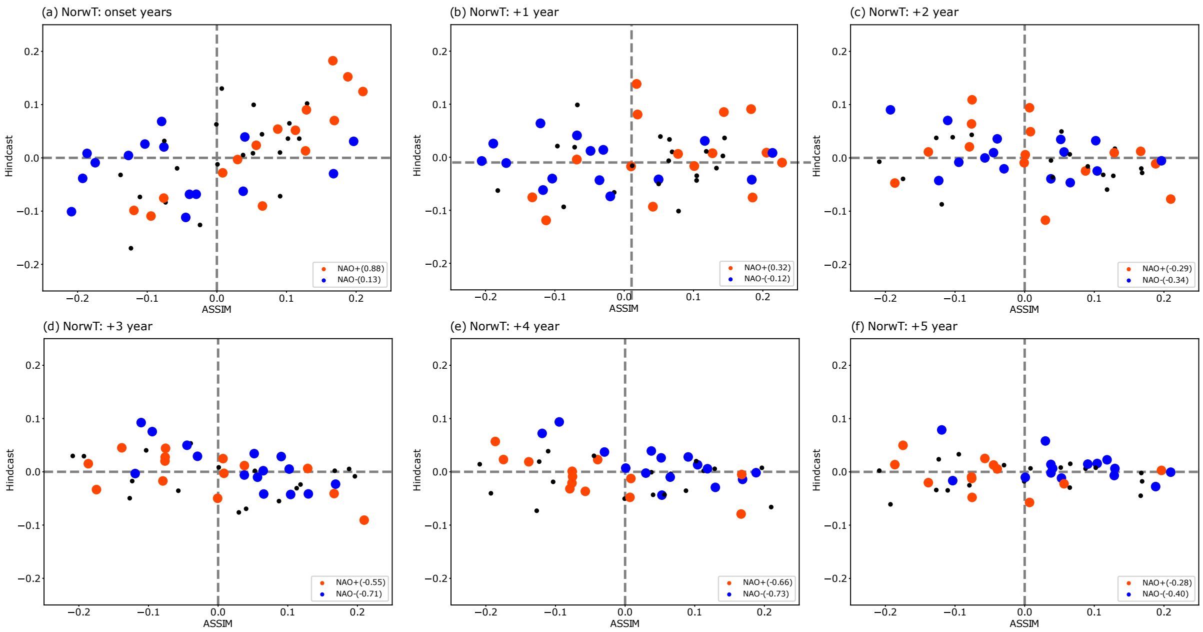

Fig. B. 15 Norwegian Sea temperature anomalies (a) 0, (b) 1, (c), 2, (d) 3, (e) 4, (f) 5 years later after NAO events in ASSIM and in Hindcast. The temperature anomalies from Hindcast are at forecast lead year 1-6 in (a)-(f), respectively. Red (blue) dots denote NAO + (–) events at onset years. Brackets give the prediction skill for Norwegian Sea temperature anomalies according to NAO + (–) events at onset years.

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Hiermit erkläre ich an Eides statt, dass ich die vorliegende Dissertationsschrift selbst verfasst und keine anderen als die angegebenen Quellen und Hilfsmittel benutzt habe.

I hereby declare upon oath that I have written the present dissertation independently and have not used further resources and aids than those stated.

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