

# Geophysical Research Letters



## RESEARCH LETTER

10.1029/2019GL083059

### Key Points:

- The observed correlation between autumn Barents-Kara sea ice and the winter NAO has not been stationary over time
- An ice-NAO correlation as high as in recent decades is rare since 1865 but within the possible range due to internal climate variability
- According to a large ensemble of climate models, external climate drivers do not give rise to variations in the ice-NAO correlation

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### Citation:

Kolstad, E. W., & Screen, J. A. (2019). Nonstationary relationship between autumn Arctic sea ice and the winter North Atlantic oscillation. *Geophysical Research Letters*, 46. <https://doi.org/10.1029/2019GL083059>

Received 28 MAR 2019

Accepted 9 JUN 2019

Accepted article online 24 JUN 2019

## Nonstationary Relationship Between Autumn Arctic Sea Ice and the Winter North Atlantic Oscillation

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**Abstract** The North Atlantic Oscillation (NAO) has a dominating influence on wintertime weather in the North Atlantic region, and therefore, it is of great interest to predict the NAO several months ahead. While state-of-the-art dynamical forecast models appear to be increasingly skillful in predicting the NAO, statistical methods with comparable or higher predictive skill are still often used. An inherent problem with statistical methods is that any empirical relationship between predictors and the NAO may be valid for some periods but subject to change over time. Here we use a set of new centennial reanalyses and large-ensemble simulations with multiple climate models to discover clear evidence of nonstationarity in the lagged correlation between autumn Barents-Kara sea ice and the winter NAO. This nonstationarity leads us to question the causality and/or robustness of the ice-NAO link. We caution against indiscriminately using Barents-Kara sea ice to predict the NAO.

**Plain Language Summary** European winter weather is heavily influenced by the North Atlantic Oscillation (NAO). The so-called positive NAO brings mild and wet conditions to northern Europe in winter, and the negative NAO tends to be cold and dry. Scientists attempt to forecast the NAO in advance by one of two ways: using complex weather forecast models or using relatively simple statistical equations. Although statistical methods can outperform more complicated forecast models, they assume that predictor relationships do not change over time. This assumption is not always valid. In this study we examined the relationship over time between autumn sea ice in the Barents-Kara Seas and the winter NAO. In recent decades, a strong relationship has been observed whereby especially reduced autumn sea ice often precedes negative NAO in the following winter. When we looked further back in time, however, we found that the ice-NAO relationship has been highly changeable and sometimes, the complete opposite to that seen recently. An analysis of hundreds of simulations from multiple climate models confirms that the ice-NAO relationship varies a lot, just due to natural climate variability. Our results suggest it is unwise to make predictions of the winter NAO based on autumn sea ice.

## 1. Introduction

Skillful forecasting of wintertime weather anomalies several months in advance appears attainable. As the North Atlantic Oscillation (NAO) is the dominant mode of variations in atmospheric circulation anomalies in the extratropical North Atlantic (Hurrell, 1995), it is often the benchmark target for seasonal prediction studies in that region. Recently, dynamical seasonal forecasting models have shown skill in predicting NAO anomalies a season to a year ahead (Baker et al., 2018; Dunstone et al., 2016). The source of this skill is still not fully understood, but one potential factor of many is the autumn sea ice in the Kara Sea (Scaife et al., 2014). By combining empirical predictors and dynamical models, Dobrynin et al. (2018) used a sub-sampling approach to obtain very high NAO prediction skill. Statistical models often show even higher skill than state-of-the-art dynamical systems for forecasting the NAO. In a recent study by Wang et al. (2017), anomalies of sea ice concentration, sea surface temperature (SST), and snow cover were used to predict the NAO (and surface variables) several months ahead. In their empirical model, autumn Barents-Kara (BK) sea ice was the strongest predictor of the winter NAO. Hall et al. (2017) also identified autumn sea ice as a key statistical predictor of the winter NAO over the period 1980–2016. It is worth noting that in the analyses of Wang et al. (2017) and Hall et al. (2017), the skill of NAO predictions was highly sensitive to the inclusion, or not, of the large downward trend in sea ice, with higher skill when using detrended time series. This sensitivity raises potential concerns about the robustness of the ice-NAO link.

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An argument against relying on predictions based on past training data is that empirical relationships may change over time. Kolstad and Árrthun (2018) recently showed that seasonal anomalies of the NAO and Central England Temperature were strongly linked to Northeast Atlantic SST anomalies several months before during the satellite era (i.e., after 1979), but according to a twentieth century reanalysis, these relationships did not hold before that. Another example of nonstationarity of teleconnections is that the lagged correlation between Eurasian snow cover and midlatitude weather (Cohen & Entekhabi, 1999) did not emerge until the 1970s (Douville et al., 2017; Peings et al., 2013).

The aim of this study is to investigate the stationarity of NAO predictability based on Arctic sea ice in the BK Seas. Many studies have explored the influence of sea ice variations on the atmospheric circulation (e.g., Alexander et al., 2004; Herman & Johnson, 1978; Murray & Simmonds, 1995; Petoukhov & Semenov, 2010). More specifically, the link between autumn sea ice anomalies and subsequent winter weather has been widely studied (e.g., Caian et al., 2018; Francis et al., 2009; García-Serrano et al., 2015; Honda et al., 2009; Hopsch et al., 2012; Jaiser et al., 2012; Koenigk et al., 2016; Kretschmer et al., 2016). One physical mechanism that has been proposed is a stratospheric pathway linking low sea ice to negative NAO (Dethloff et al., 2019; Nakamura et al., 2015; Sun et al., 2015). While many of the aforementioned studies have observed a positive correlation between interannual variability in autumn BK sea ice and the winter NAO over recent decades, this link is not robust in model simulations. Model experiments with specified reductions in sea ice have yielded a full spectrum of NAO responses, from a significant positive shift (Cassano et al., 2014; Screen et al., 2014), to no significant effect (Singarayer et al., 2006; Strey et al., 2010), to a significant negative shift (Magnusdottir et al., 2004; Seierstad & Bader, 2009).

It is not clear why models diverge in this regard (Screen et al., 2018; Smith et al., 2019), but one possible explanation could be that the relationship between autumn sea ice and winter NAO is nonstationary, perhaps due to the response being dependent on the background climate state (Smith et al., 2017), or the response could be nonlinear with respect to the magnitude or spatial pattern of sea ice loss (Chen et al., 2016; McKenna et al., 2018; Overland et al., 2016; Peings & Magnusdottir, 2014; Petoukhov & Semenov, 2010; Semenov & Latif, 2015; Sun et al., 2015). Furthermore, causality of the observed relationship is still questionable. Even in those model experiments that reproduce the observed relationship between reduced sea ice and the negative NAO phase, it is often unclear what is the specific contribution from autumn sea ice loss. Recently, Blackport and Screen (2019) performed model experiments to isolate the role of autumn sea ice loss from that in other seasons. These authors found that although year-round sea ice loss enhanced the negative phase of the winter NAO, solely autumn sea ice loss had no discernable effect on the winter NAO.

In summary, there are many open questions regarding the apparent link between autumn sea ice and the winter NAO. Here we seek to address some of those questions, specifically: Has the observed correlation between autumn sea ice and the winter NAO been stationary over time? Is the observed ice-NAO correlation in recent decades unprecedented or usual in a longer-term context? According to large climate model ensembles, how much variation in the ice-NAO correlation arises due to external climate drivers versus internal climate variability?

## 2. Data and Methods

For the period after 1979 we used the ERA-Interim reanalysis (Dee et al., 2011). We also used longer reanalyses: version 2c of NCEP's Twentieth Century Reanalysis (Compo et al., 2011; 20CR henceforth), which covers 1850–2014, but as recommended, we only used the period after 1865 due to a bias in marine observations between 1851 and 1865 (NOAA ESRL PSD, n.d.), and the ECMWF's CERA-20C (Laloyaux et al., 2018) and ERA-20C (Poli et al., 2016), which end in 2010 and go back to 1901 and 1900, respectively. CERA-20C is a coupled reanalysis with 10 ensemble members, and we used each member individually. 20CR consists of 56 ensemble members, but we used ensemble means of each variable.

We also used all simulations from the following ensembles: the 40-member Community Earth System Model Large Ensemble Project (Kay et al., 2014), which covers 1920–2100 and is referred to henceforth as CESM (we only used data up to 2080); the 100-member Max Planck Institute Grand Ensemble (MPI hereafter), which covers 1850–2100 (Bittner et al., 2016); the 50-member Canadian Earth System Model Large Ensemble (CanESM2 hereafter; Kirchmeier-Young et al., 2017), covering 1950–2080; and a 30-member

ensemble based on the GFDL ESM2M model (GFDL hereafter; Rodgers et al., 2015), which starts in 1950 and ends in 2100. Up until 2005 the models used observed external forcing, and after that they followed the RCP8.5 emissions scenario (Meinshausen et al., 2011).

Following Hall et al. (2017), we computed time series for BK sea ice based on area averages from 70°N to 85°N and between 30°E and 90°E. Our results were not sensitive to the choice of boundaries. Sea ice data were taken from all the reanalyses and models, and in addition, we used sea ice from the data set compiled by Walsh et al. (2017) based on satellite data and historical sources. The sea ice data series are not consistent across the observational-based data sets. In 20CR version 2c, the sea ice is based on the COBE-SST2 data set (Hirahara et al., 2014), and the sea ice in ERA-20C is taken from the Hadley Centre Sea Ice and Sea Surface Temperature data set version 2.1 (HadISST2; Titchner & Rayner, 2014). As CERA-20C is a coupled ocean-atmosphere reanalysis, its sea ice is simulated, but it is constrained by observations as both the ocean and atmosphere were nudged toward observations.

The NAO index based on pressure data from Stykkisholmur, Iceland, and Lisbon, Portugal, was downloaded from NCAR's Climate Data Guide (Hurrell & National Center for Atmospheric Research Staff, 2018) and standardized. For the climate models and reanalyses, the NAO index was computed in several steps. First, time series of sea level pressure (SLP) data for the nearest grid points to the two stations were compiled. Second, these were standardized individually. Third, a new time series consisting of the difference between the standardized SLP data from Lisbon and Stykkisholmur was created. Fourth, that time series was standardized.

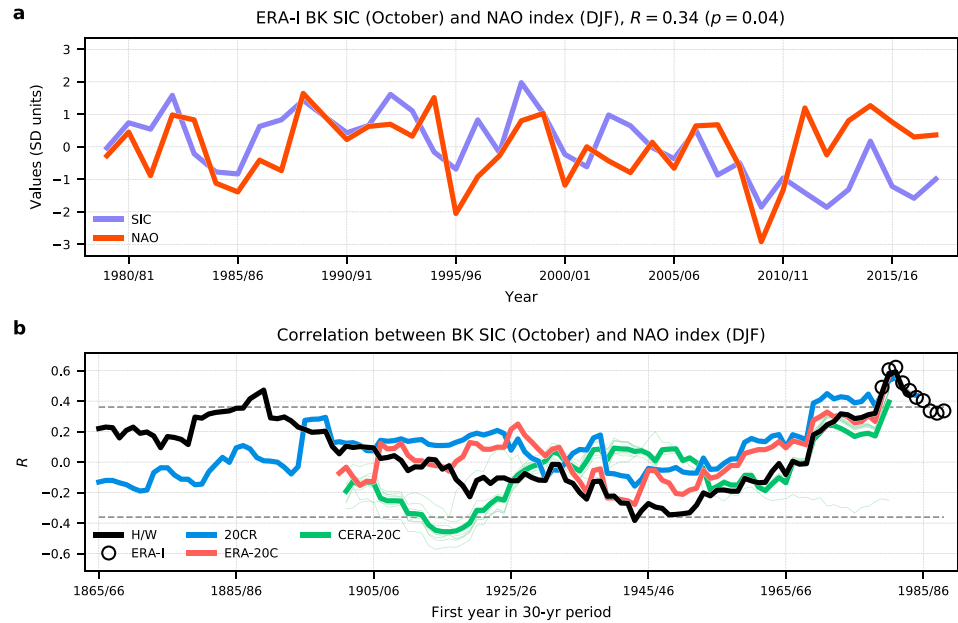
We define  $R$  as the interannual Pearson's correlation between area-averaged BK sea ice in October and the NAO index in the subsequent winter from December to February. When  $R$  refers to the correlation between sea ice based on Walsh et al. (2017) and Hurrell's NAO index, we label it "H/W."

Most of the analysis is based on 30-year time series, none of which were detrended (see discussion in section 4). To assess the statistical significance of  $R$  and other correlations, we created 10,000 pairs of time series consisting of 30 random numbers drawn from the normal distribution and computed the correlations between each pair. We then defined the 2.5th and 97.5th percentiles of the 10,000 correlation coefficients as the thresholds for significance at the 5% level.

### 3. Results

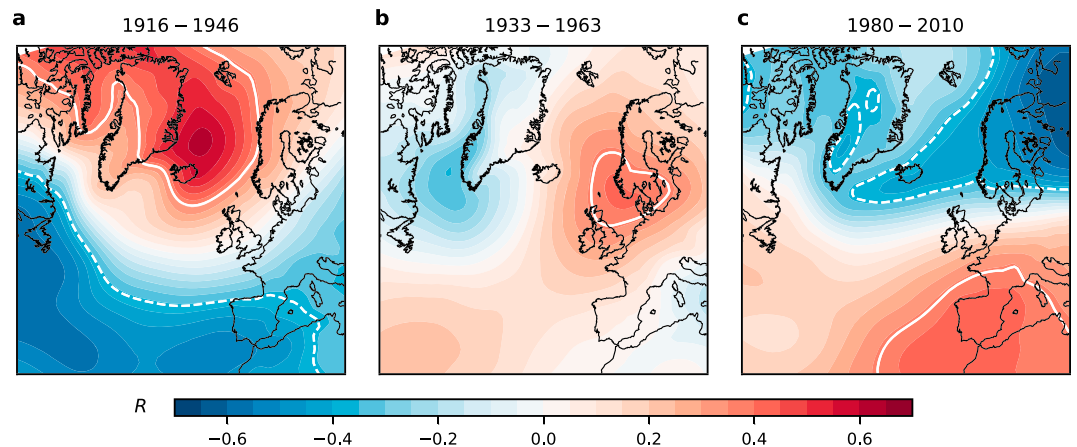
Figure 1a shows standardized BK sea ice in October in blue and the station-based NAO index in red. The sea ice time series is based on ERA-Interim and covers the 39 October months from 1979 to 2017, and the NAO index is for the period from 1979/1980 to 2017/2018. The correlation is 0.34, and it is significant at the 5% level ( $p = 0.04$ ). The magnitude of the correlation is somewhat sensitive to the time period analyzed. In Figure 1b, the black circles show  $R$  calculated from ERA-Interim sea ice and Hurrell's NAO index for each possible 30-year period. The first of these 30-year periods starts in 1979, and the last starts in 1988. The first seven 30-year periods yield significant correlations, with a maximum correlation of 0.62 in the period 1981–2010. During the last three 30-year periods, the correlations are not significant. Such significant positive correlation has been reported numerous times before, but past studies have not considered the time period before 1979.

To examine the evolution of  $R$  further back in time, we use Hurrell's NAO index and Walsh et al. (2017) BK sea ice. The black line in Figure 1b shows  $R$  for each possible 30-year period, now starting in 1865. We find that  $R$  is significantly positive in the most recent period and in agreement with the values of  $R$  derived using ERA-Interim sea ice. Looking at the period before 1979,  $R$  is only significantly positive for 30-year periods starting in the late 1800s and is significantly negative or nearly so for some 30-year periods starting in the 1940s. This suggests that  $R$  is highly nonstationary and can even assume negative values. This nonstationarity is supported by all three reanalyses, although there are clear differences between the data sets. In particular, the coupled reanalysis CERA-20C diverges from the other data sources, as it is the only one with significantly negative  $R$  for periods starting in the 1910s. There is a marked shift in 20CR and ERA-20C from low sea ice variability before about 1960 to much higher variability after that, and this could be a reason for the weak correlations in those data sets in the pre-satellite era.



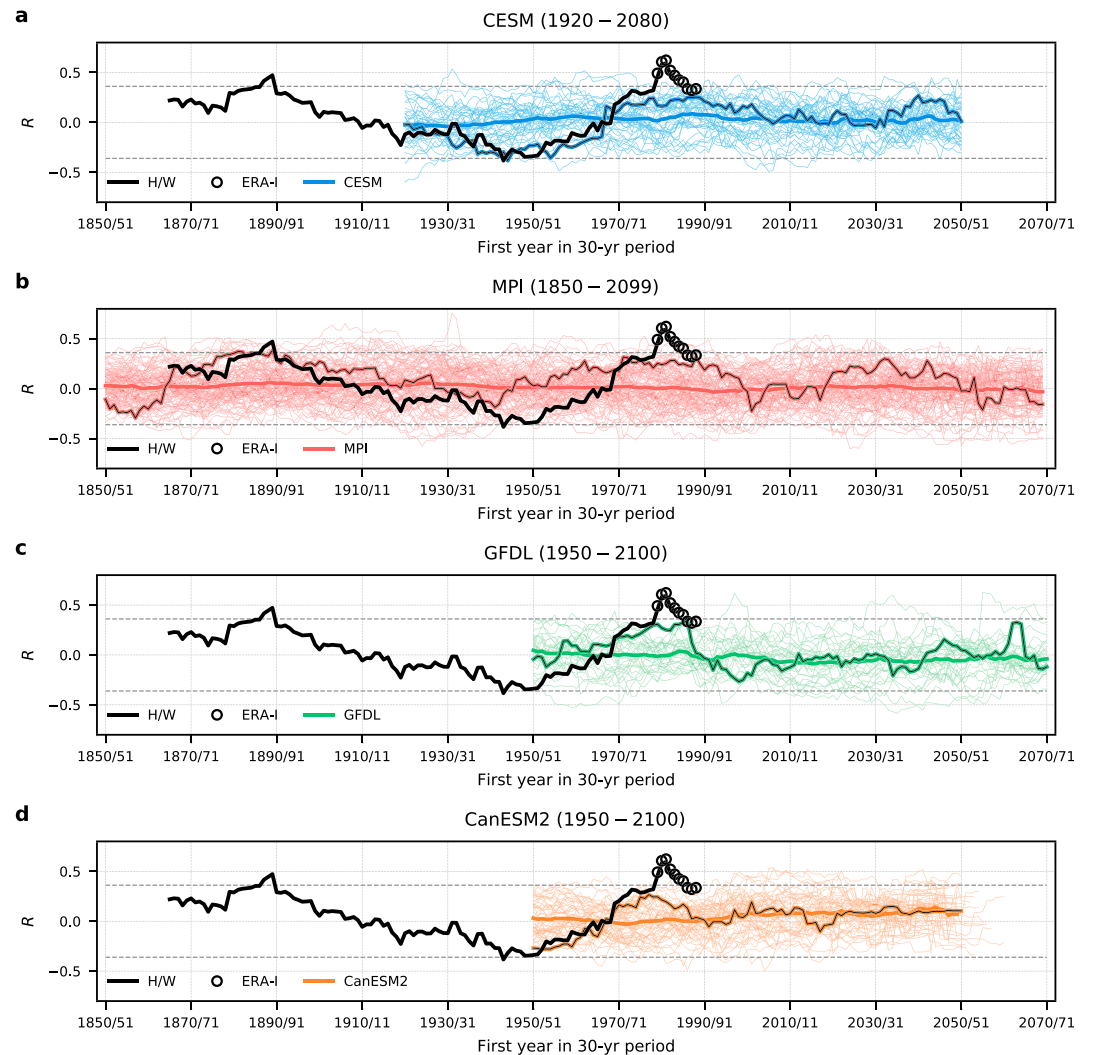
**Figure 1.** Correlation between Barents-Kara (BK) sea ice concentration (SIC) in October and the North Atlantic oscillation (NAO) index in winter (December-January-February, DJF), based on ERA-Interim (a) and longer time series (b). The dashed lines in (b) indicate the thresholds for statistical significance at the 5% level for 30-year periods.

To illustrate how the correlation between autumn BK ice and North Atlantic winter SLP has varied in time and space, Figure 2 shows maps of grid point correlations for the three 30-year periods for which  $R$  was most negative, closest to zero, and most positive (according to CERA-20C). For the 30-year period with the most negative  $R$  (starting in 1916), the pattern resembles the negative phase of the NAO (Figure 2a). The correlations for the 30-year period of neutral  $R$  (starting in 1933) bear little resemblance to the NAO. For the 30-year period with the most positive  $R$  (starting in 1980), the spatial pattern is consistent with a positive NAO index, even if the northern center of action is far from Iceland (Figure 2c). These results demonstrate that the temporal variability of  $R$  is associated with radical differences in the circulation patterns linked to sea ice variability and is not just due to subtle changes in the NAO centers of action (Pedersen et al., 2016).



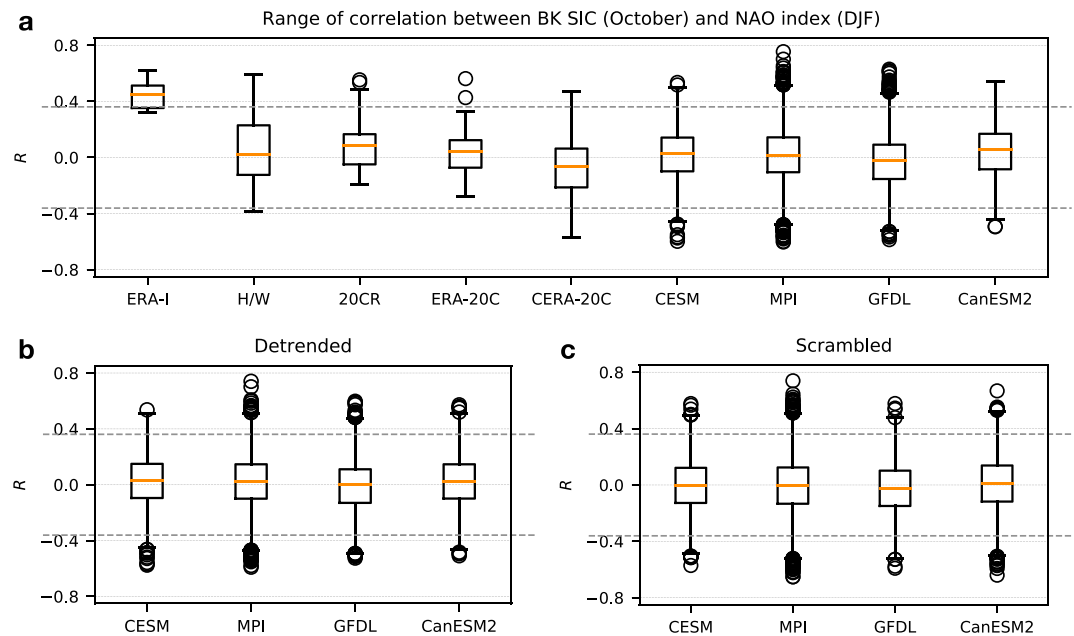
**Figure 2.** Maps of correlation between area-averaged Barents-Kara sea ice in October and winter (December-January-February) mean sea level pressure at each grid point, based on CERA-20C data, for the 30-year period when the ice-North Atlantic Oscillation correlation was most negative (a), closest to zero (b), and most positive (c). The white contours show the thresholds for statistical significance at the 5% level.





**Figure 3.** Correlation between Barents-Kara sea ice in October and the North Atlantic oscillation index in winter (December-January-February), based on data from CESM (a), MPI (b), GFDL (c), and CanESM2 (d). The thick black lines are the same as the one in Figure 1b. The mixed black and colored lines show the ensemble member that has the highest correlation with H/W during their overlapping periods. The bold colored lines show the ensemble median up to the point where more than half of the ensemble members have invalid correlations (due to sea ice loss), and the dashed lines indicate the positive and negative thresholds for statistical significance at the 5% level for 30-year periods.

We now turn to the question of how much  $R$  varies due to internal climate variability, as depicted by large ensembles of climate model simulations. Figure 3a shows the time evolution of  $R$  between 1920 and 2080 in 40 realizations of the Community Earth System Model, which differ from each other only in their temporal depiction of internal climate variability. The ensemble-mean  $R$  is close to zero in all 30-year periods and shows no trend. Individual ensemble members, however, show significant (multi) decadal variability, with  $R$  fluctuating between positive and negative values. This shows two things: first, this model confirms the nonstationarity of  $R$ , and second, this nonstationarity appears to arise due to internal climate variability and is not a forced response to external climate drivers. We note that because the temporal variability of  $R$  is internally driven, we do not expect the simulated variability of  $R$  to be in phase with the observed variability of  $R$ . However, if we preferentially select the ensemble member that best matches the observations, we find that this individual ensemble member fairly well captures the observed time evolution of  $R$ , suggesting the model is adequately capturing the magnitude and time scales of variability in  $R$ . Other single-member evolutions of  $R$  supported this finding (not shown).



**Figure 4.** Box plots illustrating the range of correlations between Barents-Kara (BK) sea ice concentration (SIC) in October and the winter (December-January-February) North Atlantic Oscillation index for each data source. Each box extends from the lower ( $Q_1$ ) to the upper quartile ( $Q_3$ ) of  $R$ , and the horizontal lines show the median. The upper “whiskers” extend to the highest data points lower than  $Q_3 + 1.5$  IQR, where IQR is the interquartile range defined as  $IQR = Q_3 - Q_1$  and the lower whiskers extend to the lowest data points greater than  $Q_1 - 1.5$  IQR. The circles show outliers, and the dashed lines indicate the positive and negative thresholds for statistical significance at the 5% level for 30-year periods.

Results based on simulations from three other large ensembles are shown in Figures 3b–3d. In each case we observe (1) that there is no discernible forced trend in  $R$ ; (2) that  $R$  fluctuates between positive and negative values due to internal variability but is rarely significantly positive or negative for long time periods; and (3) that individual ensemble members show internally driven variability of  $R$  on (multi)decadal time scales, consistent with observations.

Last, Figure 4a summarizes the range of  $R$ -values found in observations, reanalyses, and models. Given that we find no forced variability (i.e., trends) in  $R$ , we combine all possible 30-year periods, and for each model, all ensemble members, into a single distribution. It is clear that the recent period, as depicted by ERA-Interim, is unusual in having a median value of  $R$  that is significant. The data sources covering longer time periods all have median values of  $R$  that are far from significant. However, the positive values in ERA-Interim are not without precedent. All the reanalyses and models display occurrences of positive correlation as high or higher than seen in ERA-Interim. We note that the MPI model suggests  $R$  can reach as high as almost 0.8, which is appreciably higher than observed in recent decades. With the exception of ERA-Interim, all the data sources suggest that  $R$  can assume significantly negative values.

#### 4. Discussion

Our results indicate that  $R$  does not have consistent magnitude or even a preferred sign. Long-term observations, reanalyses, and climate models all suggest that  $R$  is most often small and statistically insignificant; however, large decadal variability can give rise to rare 30-year periods of significantly positive or significantly negative  $R$  values. While we found some minor differences in the frequency distributions of  $R$  between data sets, this result is robust in each of the climate models and reanalyses. It appears that recent decades, particularly the 1980s, 1990s, and 2000s, are one such example of a rare 30-year period with highly positive  $R$ . Since around 2010,  $R$  has decreased.

Even though the climate models display no multidecadal trends in the mean value of  $R$ , the projected sea ice decline through the 21st century may have an impact on the decadal variability of  $R$ . To investigate this possibility, we repeated the analysis after first removing the forced sea ice decline (by subtracting the ensemble

mean). As shown in Figure 4b, the ranges of  $R$  were indistinguishable from those shown in Figure 4a. The implication is that—insofar as the climate models are realistic—the loss of sea ice does not lead to a forced change of the mean or variability of the ice-NAO correlation.

There are several possible interpretations of the nonstationarity in  $R$ , which we briefly discuss here. First, the nonstationarity could imply that the ice-NAO relationship is noncausal and that  $R$  fluctuates simply due to internal climate variability. To test this interpretation, we created another set of  $R$  for the climate models where instead of using matching 30-year periods for sea ice and NAO, we correlated random 30-year periods of sea ice data with other random 30-year periods of NAO data. Figure 4c shows that the resulting ranges for  $R$  were indistinguishable from those shown in Figure 4a. This suggests that the spread of  $R$  seen in Figure 4a could arise purely from random sampling of two unrelated physical variables. Second, if there is a causal relationship, it could be very weak and masked by internal variability. An alternative third perspective is that the ice-NAO relationship is an example of necessary but insufficient causation, leading to intermittency in  $R$  (Overland et al., 2016). A specific case of necessary causation that could explain the nonstationarity of  $R$  is dependence on the background climate state. For example, the magnitude and even sign of the NAO response to sea ice may depend on the background climatological flow via the refraction of planetary waves (Smith et al., 2017). In such a way it is plausible that decadal variability in the North Atlantic climate could control the magnitude and sign of  $R$ . Further work is required to ascertain which of these valid interpretations is/are correct.

The nonstationarity in  $R$  serves as a warning about the potential pitfalls of statistical predictions. Empirical prediction models and machine learning based on a certain training period may fail when applied to a different prediction period. Such nonstationarity is an argument for using and improving dynamical models, which might be able to simulate the processes that give rise to nonstationarity. Indeed, past studies have found that the skill of dynamical NAO forecasts varies over time (Kumar & Chen, 2018; O'Reilly et al., 2017; Weisheimer et al., 2019), which might indicate nonstationarity in the drivers of NAO variability. Anecdotally, skill in predicting the NAO (Weisheimer et al., 2017) shows broadly consistent multidecadal variability to that shown here for  $R$ . It is unclear whether the strength of  $R$  is important for the skill of NAO predictions or whether both NAO prediction skill and  $R$  vary due a common influence, such as the mean background state.

#### Acknowledgments

E. W. K. was supported by the Research Council of Norway through the Seasonal Forecasting Engine project (Grant 270733) and by the Blue-Action project under the European Union's Horizon 2020 research and innovation program (Grant 727852). J. A. S. was supported by the Natural Environment Research Council (NE/N018486/1) and The Leverhulme Trust (PLP-2015-215). The authors would like to thank the editor and two reviewers for their help in improving the paper. We also thank Keith Rodgers, John Fyfe, and Holger Pohlmann for providing access to model output from the GFDL, CanESM2, and MPI large ensembles, respectively, ahead of their public release and Marius Årthun for taking part in the initial phase of our study. The complete CESM and MPI large ensembles have been publicly released and are obtainable at <http://www.cesm.ucar.edu/projects/community-projects/LENS/> and <https://www.mpimet.mpg.de/en/grand-ensemble/>, respectively. Selected variables (including those used here) from the CanESM2 and GFDL large ensembles have been collated by the U.S. CLIVAR Large Ensembles Working Group and made publicly available online ([https://www.earth-systemgrid.org/dataset/ucar.cgd.cesm4.CLIVAR\\_LE.html](https://www.earth-systemgrid.org/dataset/ucar.cgd.cesm4.CLIVAR_LE.html)).

## 5. Conclusions

We have shown that the interannual correlation between autumn BK sea ice and the winter NAO is nonstationary and displays considerable (multi)decadal variability. The strong positive correlation observed in recent decades is a rare occurrence in the historical record, but it is within the range of internal variability as simulated by climate models. Large climate model ensembles suggest that internal climate variability can give rise to infrequent periods of significant positive or significant negative correlation but that the correlation is most often weak. We find no evidence for variability in the ice-NAO correlation due to external climate drivers, such as anthropogenic greenhouse gases. Although the recent observed high correlation can be explained purely by internal variability, we cannot fully rule out a contribution from external forcing superimposed on the internal variability, in part because it remains unclear whether or not climate models can adequately represent physical links between sea ice and the NAO. Also, some modeling studies do suggest a forced response of the NAO to sea ice loss, albeit weak compared to internal variability. Our results reveal that the ice-NAO correlation is nonrobust and raise further questions about the causality of this proposed connection, or at least, the strength of any causal relationship. Given the clear nonstationarity of the ice-NAO relationship, we caution against the use of autumn sea ice as a statistical predictor of the NAO.

## References

- Alexander, M. A., Bhatt, U. S., Walsh, J. E., Timlin, M. S., Miller, J. S., & Scott, J. D. (2004). The atmospheric response to realistic Arctic sea ice anomalies in an AGCM during winter. *Journal of Climate*, 17(5), 890–905. [https://doi.org/10.1175/1520-0442\(2004\)017<0890:TARTRA>2.0.CO;2](https://doi.org/10.1175/1520-0442(2004)017<0890:TARTRA>2.0.CO;2)
- Baker, L. H., Shaffrey, L. C., Sutton, R. T., Weisheimer, A., & Scaife, A. A. (2018). An intercomparison of skill and overconfidence/underconfidence of the wintertime North Atlantic oscillation in multimodel seasonal forecasts. *Geophysical Research Letters*, 45, 7808–7817. <https://doi.org/10.1029/2018GL078838>

- Bittner, M., Schmidt, H., Timmreck, C., & Sienz, F. (2016). Using a large ensemble of simulations to assess the Northern Hemisphere stratospheric dynamical response to tropical volcanic eruptions and its uncertainty. *Geophysical Research Letters*, *43*, 9324–9332. <https://doi.org/10.1002/2016GL070587>
- Blackport, R., & Screen, J. A. (2019). Influence of Arctic sea ice loss in autumn compared to that in winter on the atmospheric circulation. *Geophysical Research Letters*, *46*, 2213–2221. <https://doi.org/10.1029/2018GL081469>
- Caian, M., Koenigk, T., Döschner, R., & Devasthale, A. (2018). An interannual link between Arctic sea-ice cover and the North Atlantic oscillation. *Climate Dynamics*, *50*(1-2), 423–441. <https://doi.org/10.1007/s00382-017-3618-9>
- Cassano, E. N., Cassano, J. J., Higgins, M. E., & Serreze, M. C. (2014). Atmospheric impacts of an Arctic sea ice minimum as seen in the Community Atmosphere Model. *International Journal of Climatology*, *34*(3), 766–779. <https://doi.org/10.1002/joc.3723>
- Chen, H. W., Zhang, F., & Alley, R. B. (2016). The robustness of midlatitude weather pattern changes due to Arctic sea ice loss. *Journal of Climate*, *29*(21), 7831–7849. <https://doi.org/10.1175/JCLI-D-16-0167.1>
- Cohen, J., & Entekhabi, D. (1999). Eurasian snow cover variability and Northern Hemisphere climate predictability. *Geophysical Research Letters*, *26*(3), 345–348. <https://doi.org/10.1029/1998gl900321>
- Compo, G. P., Whitaker, J. S., Sardeshmukh, P. D., Matsui, N., Allan, R. J., Yin, X., et al. (2011). The twentieth century reanalysis project. *Quarterly Journal of the Royal Meteorological Society*, *137*(654), 1–28. <https://doi.org/10.1002/qj.776>
- Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., et al. (2011). The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Quarterly Journal of the Royal Meteorological Society*, *137*(656), 553–597. <https://doi.org/10.1002/qj.828>
- Dethloff, K., Handorf, D., Jaiser, R., Rinke, A., & Klinghammer, P. (2019). Dynamical mechanisms of. *Arctic Amplification*, *1436*(1), 184–194. <https://doi.org/10.1111/nyas.13698>
- Dobrynin, M., Domeisen, D. I. V., Müller, W. A., Bell, L., Brune, S., Bunzel, F., et al. (2018). Improved teleconnection-based dynamical seasonal predictions of boreal winter. *Geophysical Research Letters*, *45*, 3605–3614. <https://doi.org/10.1002/2018GL077209>
- Douville, H., Peings, Y., & Saint-Martin, D. (2017). Snow-(N)AO relationship revisited over the whole twentieth century. *Geophysical Research Letters*, *44*, 569–577. <https://doi.org/10.1002/2016GL071584>
- Dunstone, N., Smith, D., Scaife, A., Hermanson, L., Eade, R., Robinson, N., et al. (2016). Skilful predictions of the winter North Atlantic oscillation one year ahead. *Nature Geoscience*, *9*(11), 809–814. <https://doi.org/10.1038/ngeo2824>
- Francis, J. A., Chan, W., Leathers, D. J., Miller, J. R., & Veron, D. E. (2009). Winter Northern Hemisphere weather patterns remember summer Arctic sea-ice extent. *Geophysical Research Letters*, *36*, L07503. <https://doi.org/10.1029/2009gl037274>
- García-Serrano, J., Frankignoul, C., Gastineau, G., & de la Cámara, A. (2015). On the Predictability of the winter Euro-Atlantic climate: Lagged influence of autumn Arctic sea ice. *Journal of Climate*, *28*(13), 5195–5216. <https://doi.org/10.1175/JCLI-D-14-00472.1>
- Hall, R. J., Scaife, A. A., Hanna, E., Jones, J. M., & Erdélyi, R. (2017). Simple statistical probabilistic forecasts of the winter NAO. *Weather and Forecasting*, *32*(4), 1585–1601. <https://doi.org/10.1175/WAF-D-16-0124.1>
- Herman, G. F., & Johnson, W. T. (1978). The sensitivity of the general circulation to Arctic sea ice boundaries: A numerical experiment. *Monthly Weather Review*, *106*(12), 1649–1664. [https://doi.org/10.1175/1520-0493\(1978\)106<1649:TSOTGC>2.0.CO;2](https://doi.org/10.1175/1520-0493(1978)106<1649:TSOTGC>2.0.CO;2)
- Hirahara, S., Ishii, M., & Fukuda, Y. (2014). Centennial-scale sea surface temperature analysis and its uncertainty. *Journal of Climate*, *27*(1), 57–75. <https://doi.org/10.1175/JCLI-D-12-00837.1>
- Honda, M., Inoue, J., & Yamane, S. (2009). Influence of low Arctic sea-ice minima on anomalously cold Eurasian winters. *Geophysical Research Letters*, *36*, L08707. <https://doi.org/10.1029/2008gl037079>
- Hopsch, S., Cohen, J., & Dethloff, K. (2012). Analysis of a link between fall Arctic sea ice concentration and atmospheric patterns in the following winter. *Tellus A: Dynamic Meteorology and Oceanography*, *64*(1), 18,624. <https://doi.org/10.3402/tellusa.v64i0.18624>
- Hurrell, J., & National Center for Atmospheric Research Staff. (2018). The climate data guide: Hurrell North Atlantic oscillation (NAO) index (station-based). Retrieved from <https://climatedataguide.ucar.edu/climate-data/hurrell-north-atlantic-oscillation-nao-index-station-based>
- Hurrell, J. W. (1995). Decadal trends in the North-Atlantic oscillation: Regional temperatures and precipitation. *Science*, *269*(5224), 676–679. <https://doi.org/10.1126/science.269.5224.676>
- Jaiser, R., Dethloff, K., Handorf, D., Rinke, A., & Cohen, J. (2012). Impact of sea ice cover changes on the Northern Hemisphere atmospheric winter circulation. *Tellus*, *64*(1), 11,595. <https://doi.org/10.3402/tellusa.v64i0.11595>
- Kay, J. E., Deser, C., Phillips, A., Mai, A., Hannay, C., Strand, G., et al. (2014). The Community Earth System Model (CESM) large ensemble project: A community resource for studying climate change in the presence of internal climate variability. *Bulletin of the American Meteorological Society*, *96*(8), 1333–1349. <https://doi.org/10.1175/BAMS-D-13-00255.1>
- Kirchmeier-Young, M. C., Zwiers, F. W., & Gillett, N. P. (2017). Attribution of extreme events in Arctic sea ice extent. *Journal of Climate*, *30*(2), 553–571. <https://doi.org/10.1175/JCLI-D-16-0412.1>
- Koenigk, T., Caian, M., Nikulin, G., & Schimanke, S. J. C. D. (2016). Regional Arctic sea ice variations as predictor for winter climate conditions. *Climate Dynamics*, *46*(1-2), 317–337. <https://doi.org/10.1007/s00382-015-2586-1>
- Kolstad, E. W., & Årthun, M. (2018). Seasonal prediction from Arctic sea surface temperatures: Opportunities and pitfalls. *Journal of Climate*, *31*(20), 8197–8210. <https://doi.org/10.1175/JCLI-D-18-0016.1>
- Kretschmer, M., Coumou, D., Donges, J. F., & Runge, J. (2016). Using causal effect networks to analyze different Arctic drivers of midlatitude winter circulation. *Journal of Climate*, *29*(11), 4069–4081. <https://doi.org/10.1175/JCLI-D-15-0654.1>
- Kumar, A., & Chen, M. J. C. D. (2018). Causes of skill in seasonal predictions of the. *Arctic Oscillation*, *51*(5-6), 2397–2411. <https://doi.org/10.1007/s00382-017-4019-9>
- Lalouaux, P., de Boissesson, E., Balmaseda, M., Bidlot, J.-R., Broennimann, S., Buizza, R., et al. (2018). CERA-20C: A coupled reanalysis of the twentieth century. *Journal of Advances in Modeling Earth Systems*, *10*, 1172–1195. <https://doi.org/10.1029/2018MS001273>
- Magnusdottir, G., Deser, C., & Saravanan, R. (2004). The effects of North Atlantic SST and sea ice anomalies on the winter circulation in CCM3. Part I: Main features and storm track characteristics of the response. *Journal of Climate*, *17*(5), 857–876. [https://doi.org/10.1175/1520-0442\(2004\)017<0857:TEONAS>2.0.CO;2](https://doi.org/10.1175/1520-0442(2004)017<0857:TEONAS>2.0.CO;2)
- McKenna, C. M., Bracegirdle, T. J., Shuckburgh, E. F., Haynes, P. H., & Joshi, M. M. (2018). Arctic sea ice loss in different regions leads to contrasting Northern Hemisphere impacts. *Geophysical Research Letters*, *45*, 945–954. <https://doi.org/10.1002/2017GL076433>
- Meinshausen, M., Smith, S. J., Calvin, K., Daniel, J. S., Kainuma, M. L. T., Lamarque, J. F., et al. (2011). The RCP greenhouse gas concentrations and their extensions from 1765 to 2300. *Climatic Change*, *109*(1-2), 213–241. <https://doi.org/10.1007/s10584-011-0156-z>
- Murray, R. J., & Simmonds, I. (1995). Responses of climate and cyclones to reductions in Arctic winter sea ice. *Journal of Geophysical Research*, *100*(C3), 4791–4806. <https://doi.org/10.1029/94jc02206>



- Nakamura, T., Yamazaki, K., Iwamoto, K., Honda, M., Miyoshi, Y., Ogawa, Y., & Ukita, J. (2015). A negative phase shift of the winter AO/NAO due to the recent Arctic sea-ice reduction in late autumn. *Journal of Geophysical Research: Atmospheres*, *120*, 3209–3227. <https://doi.org/10.1002/2014JD022848>
- NOAA ESRL PSD. (n.d.) Twentieth century reanalysis (V2c): Opportunities for improvement. Retrieved from [https://www.esrl.noaa.gov/psd/data/gridded/20thC\\_ReanV2c/opportunities.html](https://www.esrl.noaa.gov/psd/data/gridded/20thC_ReanV2c/opportunities.html)
- O'Reilly, C. H., Heatley, J., MacLeod, D., Weisheimer, A., Palmer, T. N., Schaller, N., & Woollings, T. (2017). Variability in seasonal forecast skill of Northern Hemisphere winters over the twentieth century. *Geophysical Research Letters*, *44*, 5729–5738. <https://doi.org/10.1002/2017GL073736>
- Overland, J. E., Dethloff, K., Francis, J. A., Hall, R. J., Hanna, E., Kim, S.-J., et al. (2016). Nonlinear response of mid-latitude weather to the changing Arctic. *Nature Climate Change*, *6*(11), 992–999. <https://doi.org/10.1038/nclimate3121>
- Pedersen, R. A., Cvijanovic, I., Langen, P. L., & Vinther, B. M. (2016). The impact of regional Arctic sea ice loss on atmospheric circulation and the NAO. *Journal of Climate*, *29*(2), 889–902. <https://doi.org/10.1175/JCLI-D-15-0315.1>
- Peings, Y., Brun, E., Mauvais, V., & Douville, H. (2013). How stationary is the relationship between Siberian snow and Arctic Oscillation over the 20th century? *Geophysical Research Letters*, *40*, 183–188. <https://doi.org/10.1029/2012GL054083>
- Peings, Y., & Magnusdottir, G. (2014). Response of the wintertime Northern Hemisphere atmospheric circulation to current and projected Arctic sea ice decline: A numerical study with CAM5. *Journal of Climate*, *27*(1), 244–264. <https://doi.org/10.1175/JCLI-D-13-00272.1>
- Petoukhov, V., & Semenov, V. A. (2010). A link between reduced Barents-Kara sea ice and cold winter extremes over northern continents. *Journal of Geophysical Research*, *115*, D21111. <https://doi.org/10.1029/2009JD013568>
- Poli, P., Hersbach, H., Dee, D. P., Berrisford, P., Simmons, A. J., Vitart, F., et al. (2016). ERA-20C: An atmospheric reanalysis of the twentieth century. *Journal of Climate*, *29*(11), 4083–4097. <https://doi.org/10.1175/JCLI-D-15-0556.1>
- Rodgers, K., Lin, J., & Frölicher, T. (2015). Emergence of multiple ocean ecosystem drivers in a large ensemble suite with an Earth system model. *Biogeosciences*, *12*(11), 3301–3320. <https://doi.org/10.5194/bg-12-3301-2015>
- Scaife, A. A., Arribas, A., Blockley, E., Brookshaw, A., Clark, R. T., Dunstone, N., et al. (2014). Skillful long-range prediction of European and North American winters. *Geophysical Research Letters*, *41*, 2514–2519. <https://doi.org/10.1002/2014GL059637>
- Screen, J. A., Deser, C., Simmonds, I., & Tomas, R. (2014). Atmospheric impacts of Arctic sea-ice loss, 1979–2009: Separating forced change from atmospheric internal variability. *Climate Dynamics*, *43*(1–2), 333–344. <https://doi.org/10.1007/s00382-013-1830-9>
- Screen, J. A., Deser, C., Smith, D. M., Zhang, X., Blackport, R., Kushner, P. J., et al. (2018). Consistency and discrepancy in the atmospheric response to Arctic sea-ice loss across climate models. *Nature Geoscience*, *11*(3), 155–163. <https://doi.org/10.1038/s41561-018-0059-y>
- Seierstad, I., & Bader, J. (2009). Impact of a projected future Arctic Sea Ice reduction on extratropical storminess and the NAO. *Climate Dynamics*, *33*(7–8), 937–943. <https://doi.org/10.1007/s00382-008-0463-x>
- Semenov, V. A., & Latif, M. (2015). Nonlinear winter atmospheric circulation response to Arctic sea ice concentration anomalies for different periods during 1966–2012. *Environmental Research Letters*, *10*(5), 054020. <https://doi.org/10.1088/1748-9326/10/5/054020>
- Singarayer, J. S., Bamber, J. L., & Valdes, P. J. (2006). Twenty-first-century climate impacts from a declining Arctic sea ice cover. *Journal of Climate*, *19*(7), 1109–1125. <https://doi.org/10.1175/JCLI3649.1>
- Smith, D. M., Dunstone, N. J., Scaife, A. A., Fiedler, E. K., Copsey, D., & Hardiman, S. C. (2017). Atmospheric response to Arctic and Antarctic sea ice: The importance of ocean–atmosphere coupling and the background state. *Journal of Climate*, *30*(12), 4547–4565. <https://doi.org/10.1175/JCLI-D-16-0564.1>
- Smith, D. M., Screen, J. A., Deser, C., Cohen, J., Fyfe, J. C., García-Serrano, J., et al. (2019). The Polar Amplification Model Intercomparison Project (PAMIP) contribution to CMIP6: Investigating the causes and consequences of polar amplification. *Geoscientific Model Development*, *12*(3), 1139–1164. <https://doi.org/10.5194/gmd-12-1139-2019>
- Strey, S. T., Chapman, W. L., & Walsh, J. E. (2010). The 2007 sea ice minimum: Impacts on the Northern Hemisphere atmosphere in late autumn and early winter. *Journal of Geophysical Research*, *115*, D23103. <https://doi.org/10.1029/2009JD013294>
- Sun, L., Deser, C., & Tomas, R. A. (2015). Mechanisms of stratospheric and tropospheric circulation response to projected Arctic sea ice loss. *Journal of Climate*, *28*(19), 7824–7845. <https://doi.org/10.1175/JCLI-D-15-0169.1>
- Titchner, H. A., & Rayner, N. A. (2014). The Met Office Hadley Centre sea ice and sea surface temperature data set, version 2: 1. Sea ice concentrations. *Journal of Geophysical Research: Atmospheres*, *119*, 2864–2889. <https://doi.org/10.1002/2013JD020316>
- Walsh, J. E., Fetterer, F., Scott Stewart, J., & Chapman, W. L. (2017). A database for depicting Arctic sea ice variations back to 1850. *Geographical Review*, *107*(1), 89–107. <https://doi.org/10.1111/j.1931-0846.2016.12195.x>
- Wang, L., Ting, M., & Kushner, P. J. (2017). A robust empirical seasonal prediction of winter NAO and surface climate. *Scientific Reports*, *7*(1), 279. <https://doi.org/10.1038/s41598-017-00353-y>
- Weisheimer, A., Decremier, D., MacLeod, D., O'Reilly, C., Stockdale, T. N., Johnson, S., & Palmer, T. N. (2019). How confident are predictability estimates of the winter North Atlantic Oscillation? *Quarterly Journal of the Royal Meteorological Society*. <https://doi.org/10.1002/qj.3446>
- Weisheimer, A., Schaller, N., O'Reilly, C., MacLeod, D. A., & Palmer, T. (2017). Atmospheric seasonal forecasts of the twentieth century: Multi-decadal variability in predictive skill of the winter North Atlantic Oscillation (NAO) and their potential value for extreme event attribution. *Quarterly Journal of the Royal Meteorological Society*, *143*(703), 917–926. <https://doi.org/10.1002/qj.2976>