Forecast Skill of the NAO in the Subseasonal-to-Seasonal Prediction Models

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ABSTRACT: The prediction skill of the North Atlantic Oscillation (NAO) in boreal winter is assessed in the operational models of the WCRP/WWRP Subseasonal-to-Seasonal (S2S) prediction project. Model performance in representing the contribution of different processes to the NAO forecast skill is evaluated. The S2S models with relatively higher stratospheric vertical resolutions (high-top models) are in general more skillful in predicting the NAO than those models with relatively lower stratospheric resolutions (low-top models). Comparison of skill is made between different groups of forecasts based on initial condition characteristics: phase and amplitude of the NAO, easterly and westerly phases of the quasi-biennial oscillation (QBO), warm and cold phases of ENSO, and phase and amplitude of the Madden-Julian oscillation (MJO). The forecasts with a strong NAO in the initial condition are more skillful than with a weak NAO. Those with negative NAO tend to have more skillful predictions than positive NAO. Comparisons of NAO skill between forecasts during easterly and westerly QBO and between warm and cold ENSO show no consistent difference for the S2S models. Forecasts with strong initial MJO tend to be more skillful in the NAO prediction than weak MJO. Among the eight phases of MJO in the initial condition, phases 3–4 and phase 7 have better NAO forecast skills compared with the other phases. The results of this study have implications for improving our understanding of sources of predictability of the NAO. The situation dependence of the NAO prediction skill is likely useful in identifying “windows of opportunity” for subseasonal to seasonal predictions.

KEYWORDS: North Atlantic Oscillation; Subseasonal variability; Numerical weather prediction/forecasting; Model evaluation/performance; Teleconnections

1. Introduction

The North Atlantic Oscillation (NAO) is a dominant mode of the extratropical atmospheric variability, with a profound influence on the weather and climate of the Northern Hemisphere, especially over Europe and eastern North America (e.g., Hurrell 1995, Hurrell et al. 2003). The NAO is closely related to the northern annular mode (NAM) or the Arctic Oscillation (AO; Thompson and Wallace 1998). It has a time scale ranging from days to decades (e.g., Hurrell 1995), and usually reaches its maximum amplitude in boreal winter (e.g., Wallace and Gutzler 1981; Barnston and Livezey 1987).

Given the important role of the NAO for extratropical weather, it is of substantial importance to predict the NAO activity. The NAO forecast skill on the seasonal time scale was found to be in general low or moderate in early studies (e.g., Doblas-Reyes et al. 2003; Derome et al. 2005; Johansson 2007; Kim et al. 2012). Recently, a significantly improved prediction skill of the winter NAO was reported in Scaife et al. (2014) for the U.K. Met Office seasonal forecast system, with a correlation of 0.62 between the ensemble mean and the observed NAO index of December–February based on 20 years of reforecasts started from November. On the subseasonal time scale from two weeks to two months, a limited number of previous studies have assessed the NAO prediction skill. With forecasts of five winters from a high-resolution

version of the NCEP coupled Climate Forecast System (CFS), Johansson (2007) reported that the NAO skill is quite low, with a correlation of only 0.30 at day 15 between the forecast and observed NAO index. Pegion et al. (2019) analyzed the NAO forecast skill based on the reforecast dataset of seven subseasonal forecast models participating in the Subseasonal Experiment (SubX), a North American research-to-operations project for subseasonal predictions. All individual models exhibit a correlation skill for the NAO index above 0.5 through week 2 (average of days 8–14) for forecasts initialized in Northern Hemisphere winter.

The objective of this study is to document the skill of predicting the NAO on the subseasonal time scale by the state-of-the-art global dynamical models that participate in the World Climate Research Programme (WCRP)/World Weather Research Programme (WWRP) Subseasonal-to-Seasonal (S2S) prediction project. The S2S project aims to improve forecast skill and understanding on the subseasonal to seasonal time scale with special emphasis on high-impact weather events (Vitart et al. 2012; Vitart and Robertson 2018). An increasing number of studies have been conducted using the S2S dataset on different aspects of subseasonal predictions (e.g., de Andrade et al. 2019; Lim et al. 2018, 2019; Schwartz and Garfinkel 2020). However, there has not been a systematic assessment and comparison of performance for these S2S models on the NAO prediction. In addition to looking at the general performance of the S2S models in predicting the NAO, we attempt to link the NAO forecast to different processes that may contribute the NAO forecast skill. The results would possibly be helpful in future model development and in improving understanding of the NAO variability and prediction on the subseasonal time scale.

It is generally accepted that the NAO/AO is largely generated by processes internal to the atmosphere (e.g., Limpasuvan

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and Hartmann 1999; Greatbatch 2000; Hurrell et al. 2003; Franzke et al. 2004). Because of this, the predictability of the NAO is considered to be limited beyond the synoptic time scale. However, the success of the U.K. Met Office seasonal prediction system in predicting the winter mean NAO suggests that some slowly varying processes are contributing to the NAO variability, possibly including the El Niño–Southern Oscillation (ENSO), Arctic sea ice anomalies, and stratospheric processes (Scaife et al. 2014). On the subseasonal time scale, the NAO is observed to have a lagged connection with the Madden–Julian oscillation (MJO), the prominent mode of tropical variability on the intraseasonal time scale characterized by large-scale convection propagating eastward along the equator (e.g., Madden and Julian 1971, 1994; Zhang 2005). The MJO influences the global atmosphere through diabatic heating-induced Rossby wave propagation and teleconnections (e.g., Stan et al. 2017). The positive (negative) NAO tends to occur 10–15 days following the MJO phase 3 (phase 7) (Cassou 2008; Lin et al. 2009). As defined in Wheeler and Hendon (2004), the MJO phase 3 (phase 7) corresponds to enhanced (reduced) convection in the tropical Indian Ocean and suppressed (enhanced) convection in the western Pacific, with a dipole structure of tropical diabatic heating anomaly. Most of the S2S models are able to capture such an MJO–NAO connection (e.g., Vitart 2017). Through analysis of a reforecast experiment with an early version of the operational atmospheric model of Environment and Climate Change Canada, Lin et al. (2010) reported that a strong initial MJO leads to a better NAO forecast skill than a weak MJO. Forecasts starting from an MJO of the dipole convection anomaly (phases 2, 3, 6, and 7) are found to be more skillful in predicting the NAO than other phases. It is, therefore, interesting to evaluate how the MJO–NAO connection contributes to the NAO forecast in the S2S models.

The NAO variability is likely influenced by several stratospheric processes. An important feature of the AO/NAO is its coupling with the stratospheric polar vortex in the boreal winter season. The stratospheric polar vortex anomaly can propagate downward to influence the tropospheric AO/NAO (e.g., Baldwin and Dunkerton 1999, 2001; Kidston et al. 2015). In addition to the tropospheric Rossby wave propagation, the MJO influence on the NAO can possibly go through a stratospheric pathway, through vertically propagating Rossby waves induced by the MJO thermal forcing (e.g., Garfinkel et al. 2012; Jiang et al. 2017; Barnes et al. 2019). Another stratospheric process that can influence the NAO is the quasi-biennial oscillation (QBO), which is a tropical lower stratospheric downward propagating zonal wind variation with a period of about 28 months. The QBO is observed to influence the MJO and its associated influence in the North Pacific (e.g., Son et al. 2017), and it is also observed to modulate the MJO–NAO teleconnection by changing the wintertime seasonal mean background flow in the Northern Hemisphere middle and high latitudes (Feng and Lin 2019). Considering the role of stratosphere in the NAO variability as discussed above, it is likely important for prediction models to reasonably well capture major stratospheric processes. It is thus useful to know how the NAO prediction skill is sensitive to the model vertical resolution

in the stratosphere. Whether or not the NAO skill is dependent on the QBO phase is also of great interest.

Several recent studies have investigated the influence of positive and negative NAO on the predictability on the S2S time scale. For example, Ferranti et al. (2015) observed that the subseasonal forecasts in the North Atlantic–European sector are more skillful for the negative NAO weather regime than for the positive NAO. Lin (2020) reported that subseasonal forecasts in the Arctic region initialized with a negative AO are more skillful than those starting from a positive AO, which may result from the influence of the stratospheric polar vortex. The NAO forecast skill is expected to be dependent on its amplitude. A stronger NAO would be more predictable than a weak NAO, likely due to difference in signal-to-noise ratio (e.g., Compo and Sardeshmukh 2004; Johansson 2007). How the NAO forecast skill depends on the phase and amplitude of the NAO itself in the S2S models is unclear.

Another process that may influence the subseasonal NAO forecast is ENSO. The NAO/AO variability was found to be associated with ENSO (e.g., L’Heureux et al. 2017). There is a possible stratospheric pathway linking the tropical forcing of ENSO to the NAO (e.g., Toniazzo and Scaife 2006). On the other hand, ENSO can influence the MJO–NAO teleconnection by changing the background flow for the MJO induced Rossby wave propagating into the high latitudes. Roundy et al. (2010) observed that the MJO influence on the NAO is greatest during La Niña conditions. Whether or not the S2S models can represent such ENSO influence and how the NAO forecast skill is dependent on the ENSO state are, therefore, useful questions to explore.

In this study, we look at factors that may influence the NAO skill. Following the discussion above, we compare the forecast skill of the NAO on the subseasonal time scale between different groups of forecasts based on initial condition characteristics. These include comparisons between positive and negative NAO, strong and weak NAO, easterly and westerly QBO, warm and cold phases of ENSO, strong and weak MJO, and among different phases of the MJO.

This paper is organized as follows. The data from the models and observations and the methods are introduced in section 2. The ensemble mean NAO skill over all the available forecasts in the hindcast period of the S2S models is presented in section 3. The sensitivity of NAO skill to the models’ stratospheric vertical resolution is briefly discussed. Section 4 discusses contribution of different processes to the NAO forecast skill by grouping forecasts under different initial conditions. A summary is given in section 5.

2. Data and method

The S2S project, which aims to improve the forecast skill and understanding on the subseasonal to seasonal time scale (Vitart and Robertson 2018), was launched by WWRP and WCRP. The accessible data provided by the S2S project dataset include the real-time forecast and reforecast data from 11 operational centers. In this study, we use the reforecast data from these 11 centers: the Australian Bureau of Meteorology (BoM), the China Meteorological Administration (CMA), the

TABLE 1. Description of the S2S models and their reforecasts used in this study.

Model name	Reforecast period	Reforecast frequency	Model resolution (model top)	Ensemble size
BoM	1981–2013	6 times per month	T47 L17 (10 hPa)	33
CMA	1994–2014	Twice per week	T106 L40 (0.5 hPa)	4
CNRM	1993–2014	4 times per month	TL255 L91 (0.01 hPa)	15
ECCC	1995–2014	Weekly	$0.45^\circ \times 0.45^\circ$ L40 (2 hPa)	4
ECMWF	1997–2017	Twice per week	Tco639/Tco319 L91 (0.01 hPa)	11
HMCR	1985–2010	Weekly	$1.1^\circ \times 1.4^\circ$ L28 (5 hPa)	10
ISAC	1981–2010	Every 5 days	$0.8^\circ \times 0.56^\circ$ L54 (roughly 6.8 hPa)	5
JMA	1981–2012	3 times per month	TL479/TL319 L100 (0.01 hPa)	5
KMA	1991–2010	4 times per month	$0.83^\circ \times 0.56^\circ$ L85 (85 km)	3
NCEP	1999–2010	Daily	T126 L64 (0.02 hPa)	4
UKMO	1993–2015	4 times per month	$0.83^\circ \times 0.56^\circ$ L85 (85 km)	7

Institute of Atmospheric Science and Climate of the National Research Council (ISAC), Météo-France/Centre National de Recherches Météorologiques (CNRM), Environment and Climate Change Canada (ECCC), the European Centre for Medium-Range Weather Forecasts (ECMWF), the Hydrometeorological Centre of Russia (HMCR), the Japan Meteorological Agency (JMA), Korea Meteorological Administration (KMA), the National Centers for Environmental Prediction (NCEP), and the U.K. Met Office (UKMO).

Some information on the reforecasts from the S2S models used in the present study is provided in Table 1, including the period covered by the reforecasts and the ensemble size. The analysis is performed on the boreal winter season when the NAO has a stronger amplitude than in the other seasons. The reforecasts analyzed are initialized within the period from the beginning of November to the end of February, so that the forecast target dates fall mainly into the extended winter season of November–March (NDJFM). The reforecasts were performed at individual centers with their model versions that were in operation during the period from the beginning of November 2017 to the end of February 2018. The length of the reforecasts varies from model to model. Although the frequency of the initialization of NCEP is daily, the reforecasts are selected twice a week to have a comparable sample size as other centers. More details on the models can be found in Vitart et al. (2017) and Lim et al. (2019). To assess the potential influence of the stratosphere, one useful way to categorize the models is to divide them into two groups, those with a high vertical stratospheric resolution and those with a low stratospheric resolution. Following Domeisen et al. (2020), the models with high stratospheric resolution are defined as “high-top models”: CNRM, ECMWF, JMA, KMA, NCEP, and UKMO. The KMA model shares the same model resolutions as the UKMO model (Vitart et al. 2017). Therefore, according to the definition of Domeisen et al. (2020), the KMA model belongs to the group of the high-top models. The low stratospheric resolution models or “low-top models” are those from BoM, CMA, ISAC, ECCC, and HMCR.

To calculate the forecast anomaly for a given year, the daily climatology is subtracted which is calculated as the mean of all the reforecasts initialized on the same date of

all the other years (e.g., in a cross-validation framework). For instance, there are 20 reforecasts started on each 1 January from 1998 to 2017, with a length of 46 days in the ECMWF model. To calculate the forecast anomaly for the reforecast of 1 January 2017, the daily climatology removed is the average of the 19 reforecasts initialized on 1 January from 1998 to 2016. It should be noted that due to limited samples the model climatology calculated this way likely has a day-to-day variability with a higher frequency than a climatological annual cycle. The climatology is lead time dependent, so the forecast anomaly for each lead time is obtained by subtracting the respective climatology. As the model climatology estimated from the reforecast is subtracted, the forecast anomaly does not include the model mean biases.

The reforecasts are compared to the reanalysis data from the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) Reanalysis 1 (Kalnay et al. 1996). The data have a daily temporal resolution covering the period 1948 to present and a global spatial resolution of 2.5° latitude $\times$ 2.5° longitude. The observed anomalies corresponding to the reforecast dates of each individual model are calculated in the same way as for that model. It should be noted that there exist more modern reanalysis datasets than the NCEP–NCAR. As this study deals with the NAO variability, which has a planetary scale, the results presented here are not expected to be notably different if a different reanalysis dataset is used.

The daily real-time multivariate MJO (RMM) index as the description of the MJO of Wheeler and Hendon (2004) is downloaded from <http://www.bom.gov.au/climate/mjo/graphics/rmm.74toRealtime.txt>. The RMM index is based on an empirical orthogonal function (EOF) analysis of the meridionally averaged zonal wind at 850 and 200 hPa, and the outgoing longwave radiation (OLR) anomalies between 15°S and 15°N . RMM1 and RMM2 are the first two principal components. The amplitude of the MJO is defined as $\sqrt{(\text{RMM1})^2 + (\text{RMM2})^2}$. In the following comparison of NAO skill, the strong MJO forecast group refers to those with MJO amplitude in the initial condition greater than 1, whereas the weak MJO group has amplitude smaller than 1. The eight phases of the MJO are defined as in Wheeler and Hendon (2004).

TABLE 2. The sample size of the selected initial conditions. The positive (negative) NAO is selected when the NAO index is greater (smaller) than 0.5 (-0.5). The strong (weak) NAO is defined with the absolute value of the NAO index greater (smaller) than 1. See the text for definition of other categories.

	Total	Positive NAO	Negative NAO	Strong NAO	Weak NAO	EQBO	WQBO	El Niño	La Niña	Strong MJO	Weak MJO
BoM	825	312	260	349	476	200	175	200	150	530	295
CMA	420	158	126	173	247	100	100	80	100	264	156
CNRM	374	136	111	152	222	85	85	68	85	244	130
ECCC	360	140	113	142	218	90	90	54	90	234	126
ECMWF	700	254	210	280	420	175	210	140	140	458	242
HMCR	468	185	149	207	261	90	126	126	72	311	157
ISAC	720	270	219	303	417	168	168	192	96	467	253
JMA	384	145	128	173	211	84	84	96	72	261	123
KMA	340	129	109	149	191	68	68	85	51	223	117
NCEP	432	157	126	178	254	108	144	72	36	277	155
UKMO	391	144	119	170	221	102	85	68	85	257	134

The NAO index is calculated by projecting the Z500 anomaly onto the NAO spatial pattern defined as the second rotated EOF mode of monthly mean NCEP–NCAR reanalysis Z500 anomalies over the Northern Hemisphere (Fig. 1 of Lin et al. 2009). To compare the forecast skill between strong and weak NAO, two groups of forecasts are selected when the initial condition has an amplitude of NAO index greater and smaller than 1.0, respectively. The forecasts with an initial NAO index larger than 0.5 are categorized as positive NAO, while those with the NAO index smaller than -0.5 as negative NAO.

The easterly and westerly phases of the QBO (EQBO and WQBO, respectively) were classified based on the winter average [December to February (DJF)] of the zonal wind between 10°S and 10°N at 50 hPa of the reanalysis data. Following Son et al. (2017), a winter average that is greater (less) than 0.5 (-0.5) the temporal standard deviation is defined as a WQBO (EQBO) year.

The ENSO events are defined by the monthly Niño-3.4 index downloaded from the National Oceanic and Atmospheric Administration (NOAA; <https://psl.noaa.gov/data/correlation/nina34.anom.data>). El Niño (La Niña) years are defined when the DJF mean Niño-3.4 index is greater (less) than 1 (-1) standard deviation.

The NAO forecast skill is evaluated as the correlation coefficient between the predicted and observed NAO indices for each lead time. The correlation is computed over the available forecasts for a given model. The root-mean-square error (RMSE) for the NAO index is also calculated for each model. For both the correlation and the RMSE, the model ensemble mean is used as the forecast.

The correlation skill is also calculated for each group of forecasts based on the initial condition groups as described above. Table 2 lists the sample size of all the groups.

The analysis is based on all the reforecast data available for individual models so that the reforecast periods are different for the different models. To see if the results are sensitive to the reforecast period, we have repeated the analysis for the reforecast period from 1999 to 2010 that is common to all the S2S models. The results are very similar to those using the full

reforecast period of individual models. A disadvantage of using only the 11 common years is that there are small numbers of El Niño/La Niña, and EQBO/WQBO winters. Therefore, the results presented below are from all available reforecast data for each model.

3. The NAO forecast skill

Figure 1 shows the NAO correlation skill (Fig. 1a) and the RMSE (Fig. 1b) as a function of lead time obtained using all the available start dates as described in Table 1 for the forecasts of extended boreal winter. All the models are seen to have a correlation score above 0.5 for more than 12 days (Fig. 1a). This result is in general consistent with Pegion et al. (2019), indicating that the S2S models have a similar level of NAO forecast skill as the SubX models. Note that the ECCC and NCEP models are in both the S2S and SubX datasets. The high-top models (shown in solid lines) appear to have a better NAO forecast skill than the low-top models (dashed lines). The correlation of most high-top models remains above 0.5 for about 15 days or more, whereas that of the low-top models drops below 0.5 around day 12–14. After day 5, the correlation of most low-top models starts to decrease more quickly than that of the high-top models. After day 20, the correlation of all the models is lower than 0.4, and the differences between the high-top and low-top models are not apparent anymore.

The results for the RMSE are shown in Fig. 1b. Not too surprisingly, the results are consistent with those of Fig. 1a. In general, the high-top models have a lower RMSE than the low-top models. The RMSE of the low-top models increases more quickly in the first few days, and for most models the errors approach saturation around days 16–20 when the curve becomes flat.

Figure 2a shows the correlation skill of the averaged NAO index of day 11–day 15 as the center of the boxes for all the S2S models and the multimodel ensemble average of low- and high-top models. The box-and-whisker plots provide an estimate of the confidence level in the correlations. A bootstrap resampling procedure is applied here with 10 000 subsamples of the

FIG. 1. (a) Correlation skill and (b) RMSE of ensemble mean NAO index as a function of lead time during boreal winter for the 11 S2S models. Low-top models are presented as dashed lines, and the high-top models are presented as solid lines.

ensemble mean in order to estimate the uncertainty of the ensemble prediction skill. The top and bottom of the boxes represent the 25th and 75th percentiles of the test samples, and the whiskers are the 5th and 95th percentiles. The models are seen to roughly fall into two groups: the low-top models (in blue color) with lower correlations and the high-top models (in green) with higher correlations and better forecast skill. The skills for the multimodel ensemble mean of these two groups are seen to be well separated. A maximum lead time of skillful forecast is defined as the lead time when the correlation skill drops to 0.5, which is similar to the predictability limit in days as discussed in Domeisen et al. (2020). Shown in Fig. 2b is the maximum lead time in days of skillful NAO forecast for all the S2S models and the multimodel ensemble mean of low-top and high-top models. The result is consistent with Fig. 2a. It appears that, as far as predicting the NAO is concerned, there is added value in having a higher stratospheric resolution. The NAO variability is influenced by several stratospheric processes as discussed in the introduction. It would thus seem to be important for an S2S model to resolve the stratosphere. Although the multimodel ensemble means for the high-top and low-top model groups are separated, individual models are not, as indicated by the error bars. For example, the ECCS model

has about the same skill as the KMA, indicating that factors other than the vertical resolution are also contributing.

4. Skill dependence on initial condition related to different processes

a. The skill dependence on the NAO phase and amplitude

It was found in previous studies that the distribution of the wintertime daily NAO index is negatively skewed (e.g., Woollings et al. 2010), suggesting that a negative NAO may behave differently from a positive NAO. The process of an MJO influence on the negative NAO was found to be different from that on the positive NAO (e.g., Cassou 2008). It is thus of interest to see how the forecast skill of the negative NAO differs from that of the positive NAO. Here we compare the NAO forecast skill when the forecasts are initialized with the two different phases of the NAO (i.e., with the NAO index greater than 0.5 and smaller than -0.5). The sample size for each case available for each model is shown in Table 2. Figure 3a shows the NAO correlation skill from the reforecasts initialized with the negative and positive NAO events. In general, the negative NAO events tend to be more predictable—as

FIG. 2. (a) Correlation between the 10th–15th day averaged ensemble mean NAO index and observations as the median of the box-and-whisker plot. The two sides of the box represent the 25th and 75th percentiles of the distribution computed from a 10 000 bootstrap resampling procedure. The whiskers are the 5th and 95th percentiles. (b) Maximum lead time in days of skillful forecast when the NAO correlation skill drops to 0.5. The error bars indicate the 95% confidence interval estimated from a Student's t test. Shown in green and blue are high-top and low-top models and their respective multimodel averages.

measured by the anomaly correlation score—than their positive counterparts.

Figure 3b summarizes the maximum lead time in days of skillful forecast for positive and negative NAO for all the S2S models. As can be seen, the negative NAO generally tends to have a longer lead time of skillful forecast than the positive NAO, which is the case for seven of the 11 models, and three models (CMA, CNRM, and JMA) have statistically significant differences. This result is in agreement with previous studies (e.g., Ferranti et al. 2015). Lin (2020) found that the negative NAOs tend to be more persistent in time than the positive ones, which could explain at least in part the difference in the skill scores seen above. Autocorrelation of the NAO index indicates that negative NAOs are more persistent than positive NAOs in all the S2S models except for the JMA model, which that does not show a clear difference (not shown). It can also be seen from Fig. 3b that the high-top models tend to have a better forecast skill than the low-top models, especially for the negative NAO.

Next, we look at the NAO forecast skill dependence on the initial NAO amplitude regardless of its phase. Compared in Fig. 4 is the maximum lead time of skillful forecast in days

for forecasts of strong and weak NAO for the S2S models, where the strong (weak) NAO cases are those with an NAO index amplitude greater (smaller) than one standard deviation. In all 11 models, it is evident that the forecasts initialized with strong NAO have better forecast skill than those with weak NAO, and the difference is statistically significant for most models. It confirms that a strong NAO, which represents a significant departure of atmospheric state with a structure of the dominant mode of variability from climatology, is more predictable than a weak NAO. This is consistent with previous studies (e.g., Johansson 2007). Interestingly, the difference of skill between strong and weak NAO appears more apparent in low-top models than high-top models. This implies that the high-top models have more impact when the NAO index is not active, and a well-resolved stratosphere may help to improve the forecast skill for the weak NAO.

b. Skill dependence on the QBO phase

It was found in previous studies that the QBO is coherent with the NAM (Coughlin and Tung 2001) and that the EQBO tends to coexist with negative NAOs in the troposphere during

FIG. 3. (a) Correlation between the model ensemble mean and observed NAO index as a function of lead time for the 11 S2S models with initial positive and negative NAO. (b) Maximum lead time in days of skillful forecast of the NAO index when correlation skill drops below 0.5 for forecasts initialized with positive and negative NAO. The error bars indicate the 95% confidence interval estimated from a Student's t test. The positive and negative NAO cases are defined as those with the NAO index greater than 0.5 and smaller than -0.5 , respectively.

DJF more than is the case for the WQBO (Boer and Hamilton 2008). We assess here how the NAO forecast skill is modulated by the QBO and whether the high-top models do better than the low-top models in capturing the QBO influence.

The maximum lead time in days when the correlation skill drops to 0.5 is compared in Fig. 5 between forecasts initialized in EQBO and WQBO winters. We do not see a consistent

difference in the quality of the forecasts for the EQBO and WQBO periods, even in the high-top models.

There are several possible influences of the QBO on the NAO variability. The QBO was observed to influence the wintertime stratospheric polar vortex (e.g., Holton and Tan 1982). The changes in the stratospheric polar vortex and the associated AO can propagate downward to influence the

FIG. 4. Maximum lead time in days of skillful forecast of the NAO index when correlation skill drops below 0.5 for forecasts initialized with strong and weak NAO. A strong (weak) NAO refers to that with the amplitude greater (smaller) than one standard deviation. The error bars indicate the 95% confidence interval estimated from a Student's t test.

FIG. 5. As in Fig. 4, but for forecasts with EQBO and WQBO initial condition.

tropospheric NAO (e.g., Baldwin and Dunkerton 1999). In addition, the QBO is observed to influence the MJO, with stronger MJO during easterly QBO than westerly QBO (e.g., Son et al. 2017). This implies a stronger influence in the northern extratropics as a direct response to the MJO during easterly QBO. On the other hand, the QBO can modulate the MJO–NAO teleconnection through modifications to the seasonal mean background flow, leading to a stronger NAO response in westerly QBO winters (Feng and Lin 2019). The relative importance of the different processes related to the QBO–NAO connection, some with competing effects, is unclear. This may partly explain why there is no consistent sensitivity of NAO skill to the phase of QBO among the S2S models, with different models capturing, or not, some of these processes.

Lim et al. (2019) evaluated the QBO prediction skill of the S2S models and found that although most models were able to reproduce the alternation of the zonal wind at 50 hPa, the amplitude of the zonal wind in the low-top models was reduced significantly. Figure 5 shows that whatever the skill of the models at predicting the QBO itself, for all of them there is no significant difference in the prediction skill of the NAO under EQBO versus WQBO conditions.

c. Influence of ENSO

Numerous studies have been performed on the extratropical atmospheric response to ENSO. The most studied response patterns include the Pacific–North American pattern (PNA; e.g., Wallace and Gutzler 1981) and the tropical–Northern Hemisphere pattern (TNH; e.g., Barnston et al. 1991). The influence of ENSO on the North Atlantic sector is relatively

weak and less consistent compared to that in the North Pacific and North American region. There are some studies showing strong impact of ENSO on the NAO (e.g., L’Heureux et al. 2017). ENSO is found to modulate the seasonal-mean mid-latitude flow and thus influence the MJO–NAO teleconnection on the subseasonal time scale. As reported in Roundy et al. (2010), the MJO–NAO teleconnection is stronger during the La Niña winters than during El Niño winters. This suggests that the NAO forecast skill may be higher during La Niña versus El Niño conditions.

Figure 6 presents the maximum lead time of skillful forecast in days for the forecasts made in El Niño and La Niña winters for all the S2S models. It is interesting to note that the general skill of the NAO during extreme phases of ENSO (both El Niño and La Niña) is somewhat higher than the overall skill for other groups of forecasts, as is evident from a comparison of Fig. 6 with Figs. 2b, 3b, 4, and 5. However, the difference between El Niño and La Niña is not consistent among the models. Four models do show a better NAO skill during La Niña than El Niño, but the other models show either the opposite result or little difference. This indicates that although the extreme phases of ENSO likely helps the NAO prediction skill, the difference of influence between El Niño and La Niña is difficult to capture in the S2S models.

d. Influence of the MJO

A number of studies have evaluated the MJO prediction skill in the S2S models (e.g., Vitart 2017; Lim et al. 2018, 2019; Kim et al. 2019; Pegion et al. 2019). The prediction skill of the MJO, in terms of lead time when the correlation between the forecast and observed MJO indices drops to 0.5, ranges from

FIG. 6. As in Fig. 4, but for forecasts with El Niño and La Niña initial condition.

FIG. 7. As in Fig. 4, but for forecasts with strong and weak MJO initial condition. A strong (weak) MJO refers to that with the amplitude greater (smaller) than 1.

about 15 to 30 days in the winter seasons in the S2S models. This opens the possibility that these S2S models may be able to draw on the predictability of the MJO and the known connection of the MJO to NAO (e.g., Cassou 2008; Lin et al. 2009; Vitart 2017) to have some improved NAO forecast skill when MJO is active. In this subsection, the NAO forecast skill is compared between forecasts with strong and weak MJO in the initial conditions. In addition, the NAO skill is analyzed for forecasts grouped according to the eight different phases of the MJO.

Figure 7 compares the NAO forecast skill (maximum lead time of skillful forecast in days) when the initial conditions contain weak and strong MJO events, regardless of the phase of the MJO (the possible influence of the phase of the MJO will be discussed later). As can be seen, the forecasts initialized with a strong MJO tend to be somewhat more skillful than those starting from a weak MJO. This is true for 8 of the 11 S2S models. The result is consistent with Lin et al. (2010) and indicates that the MJO–NAO teleconnection is likely beneficial for the subseasonal prediction of the NAO. The difference in NAO prediction skill between strong and weak MJO, however, is not statistically significant for the individual S2S models.

We now examine the dependence of NAO skill in the S2S models on the location of the MJO convection (i.e., the phase of the MJO). To that end, the active MJO events (with amplitude larger than 1) were classified according to the eight phases defined by Wheeler and Hendon (2004). The NAO correlation forecast skill is presented in Fig. 8 as a function of initial MJO phase and lead time.

For almost all models, the NAO skill is higher when initialized with MJO phase 7. Six models show correlation skill above 0.5 at day 20 for the forecasts initialized with MJO phase 7. MJO phases 3–4 also tend to lead to a relatively high NAO skill for some models. The forecasts initialized in MJO phases 5–6 seem to have the lowest NAO forecast skill.

MJO phases 3 and 7 correspond to tropical convection and diabatic heating anomalies of a dipole structure in the Indian Ocean and western Pacific, respectively (Wheeler and Hendon 2004). Previous studies have demonstrated that the MJO–NAO teleconnection is the strongest following these two phases of the MJO (e.g., Cassou 2008; Lin et al. 2009; Vitart 2017). The above result indicates that most of the S2S models benefit from the MJO–NAO teleconnection with respect to

MJO phases 3 and 7, which contributes to improved NAO forecast skill.

Several previous studies have acknowledged that the RMM index is dominated by the circulation and perhaps does not represent the convection of the MJO very well (e.g., Straub 2013; Ventrone et al. 2013). We have repeated our calculation based on the OLR-based MJO index (OMI; Kiladis et al. 2014, obtained from the website of <https://psl.noaa.gov/mjo/mjoindex/omi.1x.txt>). The general features of the above-discussed dependence of NAO skill on the amplitude and phase of the MJO do not change with this alternative MJO index (not shown).

5. Summary and conclusions

In this study, the prediction skill of the NAO is investigated using the operational forecast models that participated in the WWRP/WCRP S2S project. The analysis was conducted to see if there is a link between the NAO forecast skill and different factors and processes that may influence the NAO in these models.

The overall NAO correlation skill in Northern Hemisphere winter from all the available reforecasts indicates that the current S2S models are able to predict the NAO with a correlation skill higher than 0.5 for about 12–16 days. Most of the models with a relatively higher stratospheric resolution, tend to maintain a correlation forecast skill above 0.5 a few days longer than the so-called low-top models. Consistent with the correlation skill, the RMSE of the high-top models is seen to grow more slowly than that of the low-top models.

The NAO skill is found to be dependent on the phase and amplitude of the initial NAO. The negative NAO appears to have a better forecast skill than the positive NAO. Previous studies have shown that the daily NAO distribution is negatively skewed and negative NAO occasionally has extremely large amplitude (e.g., Woollings et al. 2010). Some of the negative NAO cases are possibly associated with signals from the stratospheric polar vortex anomalies related to sudden stratospheric warming events, providing a possible explanation for more persistent and more predictable negative NAO than positive NAO (e.g., Lin 2020). Most of the S2S models seem to be able to represent the phase dependent forecast skill of the NAO to some degree. On the other hand, the negative NAO is often associated with atmospheric blocking events in the North

FIG. 8. NAO correlation skill as function of initial MJO phase as the y axis and lead time as the x axis. The gray contour line is the correlation of 0.5.

Atlantic. The life span of blocking episodes is longer during the negative NAO than the positive NAO (e.g., [Shabbar et al. 2001](#)). It is possible that the blocking activity also contributes to the phase dependence of the NAO forecast skill. Further studies are needed to better understand why a negative NAO is more predictable than a positive NAO and to quantify the contribution from different processes.

As for the dependence of NAO skill on the initial NAO amplitude, it is quite clear that most S2S models are able to produce a more skillful NAO prediction for strong NAO than weak NAO. This suggests that as the dominant mode of variability in the Northern Hemisphere the NAO is more predictable than typical weather.

When the potential influence of the phase of the QBO on the model performance of the NAO forecasts is examined, no convincing evidence is found, both phases yielding similar skill scores. Even the high-top models showed no appreciable difference in skill scores between the two QBO phases. Thus, the QBO influence on the NAO seen in observations (e.g., [Coughlin and Tung 2001](#)) was not captured by the S2S models in the present analysis.

Extreme events of ENSO appear to contribute to the NAO forecast skill. The phase of ENSO, however, does not make a

clear and consistent difference for the NAO skill in the S2S models.

A comparison of forecasts performed with respect to the MJO amplitude in the initial conditions, regardless of its position, reveals ([Fig. 7](#)) that in general the forecasts initialized with strong MJO tend to have a better NAO forecast skill than those starting from weak MJO. The difference is seen in most S2S models, although it may not always be statistically significant. On the other hand, the relationship between the NAO skill and the MJO phase is clearer. An examination of the correlation skill scores as a function of the phase of the MJO ([Fig. 8](#)) shows that a more skillful NAO prediction is achieved when the forecast starts from MJO phases 7 and 3–4 than from other phases. This indicates that the S2S models are able to take advantage of the observed link between the NAO and the MJO as observed in previous studies (e.g., [Cassou 2008](#); [Lin et al. 2009](#)). The NAO skill appears to be more dependent on the location of the tropical convection anomaly of the MJO (i.e., the phase) than its amplitude. This is consistent with previous studies showing that the MJO–NAO teleconnection is the strongest when the tropical MJO convection has a dipole distribution (e.g., [Ferranti et al. 1990](#); [Lin et al. 2009](#)), that is, in phases 3 and 7.

Through analyzing the NAO prediction skill under different conditions, this study has implications for improving our understanding of sources of predictability of the NAO and subseasonal to seasonal predictions. The overall NAO forecast skill limit of 12–16 days reflects that the NAO variability is dominated by the synoptic-scale weather-related processes that have a predictability limit of about two weeks. Beyond that, there are some slowly varying processes that can contribute to the NAO prediction skill occasionally. Extreme phases of ENSO are found to lead to increased NAO prediction skill. The occurrence of MJO convection in the Indian Ocean and western Pacific also has positive contribution to the NAO prediction. The prediction for strong NAO is more skillful than for weak NAO. A negative NAO appears more predictable than a positive NAO. Such situation dependence of the NAO prediction skill provides possibility for better NAO prediction under specific conditions. An important strategy for subseasonal to seasonal prediction is to identify those “windows of opportunity” (e.g., National Academies of Sciences, Engineering, and Medicine 2016).

In general, the “high-top” models tend to produce a better overall NAO prediction skill than the “low-top” models. This suggests that a better representation of the stratosphere with a higher vertical resolution may be important for the NAO prediction. We note that there are differences in addition to the stratospheric resolution among the high-top and low-top models. As the NAO prediction skill is influenced by the MJO phase, a better representation of the MJO and its associated teleconnections can likely lead to improved NAO predictions. For example, previous studies found that the model performance in MJO simulation is sensitive to the convection parameterization scheme (e.g., Bechtold et al. 2008). Therefore, the NAO prediction will likely benefit from improved convection parameterization scheme as well.

The relationship between the NAO forecast skill and the horizontal resolution of the model as listed in Table 1 is not obvious. For example, the ISAC, KMA, and UKMO models have similar horizontal resolution, but the NAO prediction skill is different. Regarding the ensemble size, there is also no clear relationship with the ensemble mean NAO prediction skill. Most of the S2S reforecasts used in this study have a small ensemble size and here only the ensemble mean skill is analyzed, information related to ensemble spread and probability skill score is unknown. Further analysis of the impact of other aspects of model formulation on NAO forecast skill, and its sensitivity to the initial atmospheric state, is warranted.

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