Skilful seasonal prediction of Korean winter temperature

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Korean winter temperature exhibits significant year-to-year variability, an extreme example of which was the severe cold winter of 2012/2013. Such events can have significant societal and financial impacts. We investigate the seasonal forecast skill for Korean winter temperature using Met Office initialised climate prediction systems. We find significant skill using two independent hindcasts covering the last decades. Observed Korean winter temperature variability appears to be driven by large-scale dynamical circulation anomalies with centers over the northwest Pacific High (PH) and the Siberian High (SH). While the model has a good simulation of these observed teleconnections, we find that skilfully predicted PH variability dominates the model skill. This is due to the relatively strong PH teleconnection to highly predictable tropical Pacific and Indian Ocean variability. Whereas, observed SH variability is currently much less predictable in seasonal forecast systems. Furthermore, we find that the modelled SH exhibits lower predictability than the observed SH, suggesting a model “signal-to-noise” problem over extratropical East Asia which is similar to that reported over northern Europe. We explore one possible pathway, the representation of stratosphere–troposphere coupling, by examining the model simulation of stratospheric sudden warming (SSWs) events. While the SSW frequency and the spatial pattern of surface circulation response appears well simulated, the amplitude of the model response over SH appears anomalously weak. Nevertheless, we conclude that current seasonal forecasts of Korean winter temperature are skilful and have the potential to provide useful climate services.

KEYWORDS
Korea, seasonal prediction, sudden stratospheric warming

1 INTRODUCTION

The winter climate of the Korean Peninsula exhibits substantial year-to-year variability. In particular, cold surges and heavy snow cause socioeconomic impacts on transportation, agriculture and energy supply and demand. For example, the heavy snow damage in the 2012/2013 winter ranked second out of the total causes of damage during 2013 (2013 Disaster annual report, National Emergency Management Agency). The climate impacts of this cold winter even extended to offshore aquaculture where the cool sea temperatures resulted in a large reduction in marine productivity. Skilful seasonal forecasts would therefore allow decision-makers to prepare in advance for such extreme impacts.

The Korean peninsular is located on the edge of East Asia and influenced by both Pacific Ocean and continental climate variability. Previous studies have shown that winter temperature and precipitation in East Asia are influenced by variations of large-scale pressure gradients between the Siberia High, Aleutian Low and the polar tropospheric jet near Japan (Jhun and Lee, 2004; Chen et al., 2005). Similarly, previous studies show that cold Korean winters are influenced by a cold surge from the continent (especially Siberia) northwest of Korea (Ding and Krishnamurti, 1987; Wu and Wang, 2002; Park et al., 2011).

Some evidence of seasonal Korean winter temperature predictability has been reported before. An empirical statistical model showed skill (anomaly correlation coefficient:
$r \sim 0.5$) for Korean winter temperature over 1954–2003, using a number of lagged predictors (Kim et al., 2007). Kim et al. (2017) showed weak positive skill for Korean winter temperature of $r = 0.35$ over 1983–2006 by defining a new sea level pressure (SLP)-based East Asia winter monsoon (EAWM) index and $r = 0.19$ based on multi-model ensemble (MME) from APEC Climate Center (see also Jeong et al., 2017).

Here we examine the skill of seasonal forecasts of Korean winter temperature using an example from the latest generation of dynamical seasonal prediction systems. We describe these systems in section 2 and present the direct model skill for Korean winter temperature. In section 3 we examine the large-scale circulation that drives Korean winter temperature variability in both the observations and the model. We then examine the driving role of both the El Niño–Southern Oscillation (ENSO) and sudden stratospheric warming events (SSWs) on these large-scale circulation patterns in sections 4 and 5, respectively. Finally, we discuss our results and present conclusions in section 6.

2 | SKILFUL SEASONAL PREDICTIONS

We investigate the seasonal predictability and drivers of Korean winter temperature using retrospective forecasts from the Met Office Global Seasonal forecast system (GloSea5, MacLachlan et al., 2015) and decadal prediction system (DePreSys3, Dunstone et al., 2016). Both systems use the Hadley Centre Global Environmental Model version 3 at the Global Coupled model 2 configuration (HadGEM3-GC2, Williams et al., 2015). The model is run at relatively high resolution of N216 (~60 km) with 85 quasi-horizontal levels providing a well resolved stratosphere and an upper boundary near the mesopause. The ocean has a grid spacing of 0.25° globally, with 75 vertical levels. To compare with the observed variability and assess the seasonal skill of the hindcasts, we use the ERA-Interim reanalysis data set. In this paper we focus primarily on the GloSea5 operational seasonal prediction system that provides a 23-year hindcast over the period 1993/1994–2015/2016, with 23 ensemble members each year (7 members initialised on each of 25th October and the 1st and 2th November). We also examine the first months of the Met Office research decadal prediction system, DePreSys3, with 36 years covering the period 1980/1981 to 2015/2016 and comprising 40 ensemble members, initialised on 1st November each year.

To analyse winter temperature over Korea, we define a box located at 33°–39°N, 125°–130°E (green box in Figure 1b,d). Figure 1a shows time series of Korean winter (DJF) temperature using the ERA-Interim reanalysis data set and the ensemble mean hindcasts. Both GloSea5 and DePreSys3 systems show skill, assessed by calculating the centred Pearson correlation coefficient ($r \sim 0.5$) which is significant at the 1% confidence level using a one-sided Student’s $t$ test ($p \sim .01$), over their respective hindcast periods. In particular, both systems are able to predict the colder sequence of winters experienced from winter 2009/2010 that culminated in the exceptionally cold winter of 2012/2013 which caused significant climate impacts over Korea. The longer DePreSys3 hindcast period also allows us to examine the skill of the model in predicting the previous period of cold Korean winters in the early 1980s. The model also successfully predicts colder winters during this period, although the transition to milder winters at the end of the 1980s is not as abrupt as that observed. This significant seasonal prediction skill is very encouraging for the development of useful climate services.

3 | PREDICTABLE DYNAMICS

We now examine the dynamical drivers of Korean winter temperature and how well these are both simulated and predicted. For simplicity, and due to the availability of daily data required in section 5, for the rest of the paper we only show results from the operational GloSea5 seasonal system (hereafter the “model”) but we note that results are qualitatively similar for the DePreSys3 system. We first use observed mean sea level pressure (MSLP from ERA-Interim) to investigate the large-scale circulation associated with variability in Korean winter temperatures.

We calculate the correlation between the observed Korean temperature time series (Figure 1a) and the winter MSLP fields to produce the observed correlation map (Figure 1b) which highlights two areas of strong significant correlation (black boxes). One is located over central East Asia and is negatively correlated with Korean temperatures, while the other is located over the northwest Pacific and is positively correlated. These patterns are consistent with previous literature and we define these two boxes as the “Siberian High” (SH, 50°–65°N, 90°–120°E) and the “Pacific High” (PH, 25°–45°N, 145°–170°E). The position and sign of both of these SH and PH MSLP anomalies give a consistent circulation pattern, resulting in southerly advection over the Korean peninsula giving mild winters, or northerly advection giving cold winters. It is tempting to interpret SH and PH as a dipole pressure anomaly, for example similar to the North Atlantic Oscillation (NAO), where the two regions vary in concert to drive geostrophic circulation anomalies. However, this is not the case as, unlike the NAO, there is no significant correlation between SH and PH ($r = -0.05$, $p > .1$). This suggests that these two regions are independent and may combine either constructively or destructively in any given winter.

We now examine how well the model is able to reproduce the observed circulation patterns associated with Korean winter temperature variability. To do this we calculate equivalent correlation maps between model MSLP and
model Korean winter temperature for each model ensemble member and then plot the average correlation map in Figure 1c. We find a very similar circulation pattern, with both the SH and PH regions implicated as before with similar position and slightly stronger strength, although the deep tropics are much more weakly correlated than in the observations. In order to explain the source of model skill for predicting observed Korean temperature, we correlate it against the winter ensemble mean MSLP (Figure 1d). Here we again see a similar MSLP correlation pattern, however the SH region is now much weaker relative to PH. This suggests that the model ensemble mean PH signal is the dominant predictable influence. The ensemble mean SH and PH indices are plotted as time series in Figure 2a and the correlations are quoted in Table 1. The predictable (ensemble mean) SH correlation with Korean temperature is indeed weaker than PH ($r = -0.40$ vs. $r = 0.55$ respectively). In contrast, the correlations in individual members (and observations, Table 1) show a much greater role for the SH ($r = -0.73$ and $r = 0.62$ respectively).

The use of large-scale circulation indices such as SH and PH may provide more skilful forecasts of Korean temperatures than are provided directly by the direct model temperature output. This is similar to the case for the NAO and UK winter temperatures (Scaife et al., 2014). We test this idea, using the predicted SH and PH indices, via multiple linear regression, to predict observed Korean temperatures. In this case the resulting skill (Figure 2a, red line) was almost identical to the direct model temperatures ($r = 0.55$ vs. $r = 0.54$). Furthermore, the inclusion of SH in the regression does not improve the skill over using PH alone (Table 1). Hence we only examine SH and PH indices to explain the model skill, rather than as part of a potential alternative forecast methodology.

Given the apparently weak influence of the model ensemble mean SH signal on Korean temperature variability, we now examine the skill of predicting MSLP and the SH and PH indices themselves in Figure 2b,e. As expected, we find weaker skill for predicting SH ($r = 0.30$, $p = .16$) than we do PH ($r = 0.48$, $p = .02$), explaining the dominance of PH in driving model ensemble mean Korean temperature. So, despite the high fidelity of the model SH teleconnections in each individual member (as shown in Figure 1c) and its importance in observed Korean temperatures, the ensemble mean SH is poorly predicted and hence is not the dominant driver of model Korean temperature predictions.
We further probe the skill of SH to try to establish whether this region has inherently low predictability, or whether there is evidence that current seasonal forecast systems are not yet sufficiently skilful. By plotting the SH and PH skill as a function of ensemble size (Figure 2b) we find that the SH skill increases and asymptotes more slowly than PH. This is consistent with other recent work on the skill of northern extratropical winter circulation, where modes such as the NAO or Arctic Oscillation (AO) have been shown to only be skilfully predicted using large ensembles (e.g., Scaife et al., 2014; Eade et al., 2014; Stockdale et al., 2015; Dunstone et al., 2016). This is due to a “signal-to-noise paradox” (Eade et al., 2014; Dunstone et al., 2016), whereby the model has higher skill for predicting the observed variability (Figure 2c) than it does itself (Figure 2d plots the model-model skill). The ratio of these two skill indices has been defined as the “ratio of predictable components” (RPC; Eade et al., 2014) and is shown in Figure 2e. For a perfect forecast system, RPC = 1. Where RPC > 1 (red colours), predominantly in the north of Figure 2e (including most of the SH region), this indicates forecast underconfidence where the model is more skilful at predicting the observations than predicting its own ensemble members. Whilst regions where RPC < 1 (blue colours), present predominantly in the south (including parts of the PH region), show forecast overconfidence which is a classic feature of seasonal forecast models in the Tropics. In the next sections we use this information to explore a tropical driver for PH variability and a stratospheric driver for SH variability.

### Table 1: Correlations between the observed Korean winter temperature and MSLP in SH/PH using observations and model ensemble mean hindcasts

|                | Observations | Model          |
|----------------|--------------|----------------|
|                | SH | PH | MLR | SH | PH | MLR |
| Observed winter Korea temperature | -0.67 | 0.53 | 0.84 | -0.40 (-0.73) | 0.55 (0.62) | 0.55 (0.81) |

Note. Significant values beyond 90% significance are in bold. The values in brackets are the average correlations between individual members.

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4 | **ENSO AS A KEY DRIVER OF KOREAN WINTER TEMPERATURE PREDICTIONS**

Previous studies have shown how PH variability in the northwest Pacific is related to sea surface temperature (SST) variability in the tropical Pacific and Indian Oceans (Son et al., 2014; Kim et al., 2015). This is illustrated in Figure 3a, where we correlate the observed PH index with...
fields of SST. We find significant correlations between the observed PH and SST in the tropical Pacific Niño3.4 ENSO region \((r = 0.46)\) and the Indian Ocean \((r = 0.66)\). However, previous studies have shown that ENSO drives significant variability in the tropical Indian Ocean (Baquero-Bernal et al., 2002; Dommenget and Latif, 2002; Yu and Lau, 2004; Yeh et al., 2009; Wang and Wang, 2014) and we find a cross-correlation of \(r = 0.8\) between the two indices. We also find a strong positive relationship between PH and SSTs along the Kuroshio current region, located to the southwest of PH. The relationship between PH and these Pacific and Indian Ocean regions is weaker in the model members (Figure 3b), consistent with our previous finding in Figure 1c, but shows a very similar pattern. Finally, we examine the relationship in the model ensemble mean (Figure 3c) and find that the predictable part of PH is very strongly related to ENSO variability and to a lesser extent the Indian Ocean and the Kuroshio current region. Given that ENSO is highly predictable on seasonal timescales it is not surprising that ENSO is the dominant driver of the ensemble mean PH variability.

5 | **THE ROLE OF THE STRATOSPHERE**

Earlier we identified a strong role for the SH variability in driving observed (and individual model members) Korean winter temperature variations but a relatively modest role for ensemble mean SH in driving the model Korean winter temperature forecast skill due to the lack of predictability of SH itself. We also showed that the predictable component of the model may be too weak compared to the predictable component of the observations in the SH region (Figure 2e). We now further explore how that may arise by examining one pathway by which the stratosphere can influence winter MSLP in the SH region. Sudden stratospheric warming (SSW) events describe a rapid break-down of the polar vortex, resulting in anomalous easterly winds that descend to the troposphere and affect surface weather with a typical timescale of weeks (Kidston et al., 2015). For example, northern European winters are colder than normal when SSW events occur (Boville, 1984; Scaife and Knight, 2008; Kolstad et al., 2010; Mitchell et al., 2013; Sigmoid et al., 2013; Scaife et al., 2016). Song et al. (2015) have examined the impact of SSW on winter temperature over East Asia (including Korea) and showed a weak cooling after SSW but the results were not statistically significant. Here we attempt to use the much larger data set available from all the model ensemble members to find the robust signature of SSW on Korean winter temperatures and compare this to that observed.

We define SSW events when daily mean zonal winds at 10 hPa and 60°N become negative (easterly). We use the additional constraint that SSW start dates must be separated by at least 20 days (Charlton and Polvani, 2007) in order to identify unique events. We search over days in December to February, and then analyse the evolution over the 60 days following the SSW onset.

We first analysed the ERA-Interim reanalysis and find 13 SSWs from the observed 23 winters (with both 1998/1999 and 2001/2002 having two SSWs). We then investigated SSW events using daily data from the GloSea5 hindcast over 483 simulated winters (21 member ensemble, 23 winters). We find 303 SSW events (with 24 events occurring in the same year). This gives an SSW incidence of 63% in the model which compares very well with the observed 57% over the same period and the results found in independent ensembles by Scaife et al. (2016). Although comparison with the observed time series is difficult (as it is a near binary occurrence), we find that winters with observed SSWs in general have above average numbers of model SSWs, with the exception of winter 2005/2006 (Scaife and Knight, 2008). This confirms long-range predictability for the seasonal occurrence of SSWs (Scaife et al., 2016). The largest number of model SSW events occurred in winter 2002/2003, which was the only winter where the total SSW number (25) exceeds the number of ensemble members (21), suggesting that an SSW in 2002/2003 was highly likely (Kuroda, 2008) as was observed.

We now examine the impact of SSW events on East Asian surface climate by creating composite anomalies of temperature and MSLP for the 60 days following the onset of a SSW event (Figure 4). As expected, the observed temperature composite (Figure 4a) shows cold anomalies over high latitudes of Asia and warm anomalies to the south. The corresponding model temperature anomaly maps (Figure 4b) have a very similar spatial pattern but a weaker amplitude. In both observations and model composites Korea is located quite near to the division between these two regions but in both cases shows a warm signal. We explore this further by plotting the area average temperature over Korea in Figure 4c, where we find a robust warming in the observed composite. In the model composite, we find a much weaker warm signal that is not quite significant, despite the fact that the much larger number of model events provides us with much tighter confidence intervals.

We find a similar story for corresponding MSLP anomalies (Figure 4d,f), whereby the model simulates well the observed spatial circulation pattern associated with an SSW but with lower amplitude. The common MSLP pattern is for high pressure over the Arctic and low pressure over most of mid-latitude Asia, which would project on the negative phase of the AO. The SH region of interest is located in the low-pressure anomaly region, consistent with driving southerly advection of warmer air over Korea. We examine the area average of the SH box in Figure 4f and find a similar situation to that for temperature, whereby the model has smaller confidence intervals but a weaker mean signal.
The smaller amplitude surface climate response to an SSW event in the model relative to the observations has different potential explanations. First, the small sample of observed events may have resulted in a biased estimate of the true strength of the observed response. Second, the model response could be genuinely anomalously small. We investigate the first explanation by randomly sampling 13 model SSW events from the 303 total events and compare the resulting distribution of mean Korean temperature and SH values with that observed. We find that there is a 19% (Korean temperature) and 9% (SH MSLP) chance that the observed composite could have been picked at random from the model events. Hence, we cannot exclude the possibility that the observed signals could have occurred by chance. However, the smaller ensemble mean MSLP response to SSWs is consistent our previous finding that the SH model-model predictability is too small (RPC < 1). So the strength of the stratosphere-troposphere teleconnection, as represented via SSW events, is one possible example of a process that may be too weak in the model.

6 | DISCUSSION AND CONCLUSIONS

Due to the location of the Korean Peninsula, there are multiple influences on its winter temperature variability. These include drivers to the east, over the Pacific Ocean, and those from the west, over continental East Asia. We investigated the connection between Korean winter temperature variability and large-scale dynamical circulation in observations, model ensemble members and the predictable (ensemble mean) model signal (Figure 1). While individual model members are able to well simulate the observed influence of SH and PH regions on Korean temperature variability, it is the PH component that dominates the predictable forecast signal. This is likely due to the strong connection between the ensemble mean PH and the variability in tropical Pacific SSTs (particularly over the ENSO region, Son et al., 2014, Kim et al., 2015) which are highly predictable on seasonal timescales. In contrast, observed SH variability is poorly predicted by the model and SH skill increases more slowly as a function of the number of ensemble members than the PH. Furthermore, the SH skill of the model in predicting itself appears to be lower than for predicting the observations, suggesting a spuriously weak model predictable signal (RPC > 1, Figure 2e). This points to the presence of a “signal-to-noise paradox” for extratropical circulation over the SH region, which is similar that found for the NAO (Eade et al., 2014; Scaife et al., 2014; Dunstone et al., 2016) and the AO mode (Riddle et al., 2013; Kang et al., 2014; Stockdale et al., 2015), that coincides with the SH.
Although a satisfactory explanation for the signal-to-noise paradox has yet to be discovered a solution could potentially lead to higher skill in the SH region and hence greater skill for Korean winter temperature. There are many possible model deficiencies which could be responsible for a spuriously small model predictable signal in extratropical circulation (see Scaife and Smith, 2018 for a review). Here we focus on one of these, the fidelity of the model stratosphere–troposphere teleconnection and in particular, the downward influence of SSW events. We find agreement between the model and observations that, on average, SSW events lead to warmer Korean temperatures over the 2 months following an SSW. The benefit of using very large ensembles of model hindcast data is that more robust relationships can be established. Interestingly, we find that the strength of both the circulation response over East Asia (SH) and the model Korean temperature response are too small. We conclude that further examination of the model processes that control the downward propagation of the SSW signal is required and may lead to improved predictability of East Asian surface climate from stratosphere–troposphere teleconnections.

In summary, we have shown significant skill ($r \sim 0.5$, $p \sim .01$) for seasonal predictions of winter temperatures over the Korean Peninsula. Hence, current dynamical model predictions are capable of predicting an increased risk of extremes, such as the anomalously cold winters at the start of the 1980s and around 2010–2013. The potential therefore exists for the development of a Korean climate service based on seasonal temperature forecasts for winter which could provide valuable advanced warning to government and industry contingency planners.

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NOTE
1http://www.korea.kr/archive/expDocMainList.do.

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REFERENCES
Baquero-Bernal, A., Latif, M. and Legutke, S. (2002) On dipolelike variability of sea surface temperature in the tropical Indian Ocean. Journal of Climate, 15(11), 1358–1368.
Boville, B.A. (1984) The influence of the polar night jet on the tropospheric circulation in a GCM. Journal of the Atmospheric Sciences, 41, 1132–1142.
Charlton, A.J. and Polvani, L.M. (2007) A new look at stratospheric sudden warmings. Part I: climatology and modelling benchmarks. Journal of Climate, 20, 449–469.

Chen, W., Yang, S. and Huang, R.H. (2005) Relationship between stationary planetary wave activity and the East Asian winter monsoon. Journal of Geophysical Research, 110, D14110. https://doi.org/10.1029/2004JD005669.

Ding, Y.H. and Krishnamurti, T.N. (1987) Heat budget of the Siberian high and the winter monsoon. Monthly Weather Review, 115, 2428–2449.

Dommegnet, D. and Latif, M. (2002) A cautionary note on the interpretation of EOFs. Journal of Climate, 15(2), 216–225.

Dunstone, N., Smith, D., Scaife, A., Hermanson, L., Eade, R., Robinson, N., Andrews, M. and Knight, J. (2016) Skillful predictions of the winter North Atlantic Oscillation one year ahead. Nature Geoscience, 9, 809–814.

Eade, R., Smith, D., Scaife, A., Wallace, E., Dunstone, N., Hermanson, L. and Robinson, N. (2014) Do seasonal-to-decadal climate predictions underestimate the predictability of the real world? Geophysical Research Letters, 41, 5620–5628. https://doi.org/10.1002/2014GL061146.

Jeong, J.-H., Lee, H., Yoo, J.H., Kwon, M.H., Yeh, S.-W., Kug, J.-S., Lee, J.-Y., Kim, B.-M., Son, S.-W., Min, S.-K., Lee, H., Lee, W.-S., Yoon, J.-H. and Kim, H.-K. (2017) The status and prospects of seasonal climate prediction of climate over Korea and East Asia: a review. Asia-Pacific Journal of Atmospheric Sciences, 53(1), 149–173. https://doi.org/10.1007/s13143-017-0008-5.

Jhun, J.G. and Lee, E.J. (2004) A new East Asian winter monsoon index and associated characteristics of the winter monsoon. Journal of Climate, 17(4), 711–726.

Kang, D., Lee, M.-I., Im, J., Kim, D., Kim, H.-M., Kang, H.-S., Schubert, S.D., Arribas, A. and MacLachlan, C. (2014) Prediction of the Arctic Oscillation in boreal winter by dynamical seasonal forecasting systems. Geophysical Research Letters, 41, 3577–3585.

Kadison, I., Scaife, A.A., Hardiman, S.C., Mitchell, D.M., Butchart, N., Baldwin, M.P. and Gray, L.J. (2015) Stratospheric influence on tropospheric jet streams, storm tracks and surface weather. Nature Geoscience, 8(6), 433–440.

Kim, M.-K., Kim, Y.-H. and Lee, W.-S. (2007) Seasonal prediction of Korean regional climate from preceding large-scale climate indices. International Journal of Climatology, 27, 925–934. https://doi.org/10.1002/joc.1448.

Kim, S., Kim, H.-S., Min, S.-K., Son, H.-Y., Won, D.-J., Jung, H.-S. and Kug, J.-S. (2015) Intra-winter atmospheric circulation changes over East Asia and North Pacific associated with ENSO in a seasonal prediction model. Asia-Pacific Journal of Atmospheric Sciences, 51(1), 49–60.

Kim, S.-T., Sohn, S.-J. and Kug, J.-S. (2017) Winter temperatures over the Korean Peninsula and East Asia: development of a new index and its application to seasonal forecast. Climate Dynamics, 49, 1567–1581. https://doi.org/10.1007/s00382-016-3402-2.

Kolstad, E.W., Breiteig, T. and Scaife, A.A. (2010) The association between stratospheric weak polar vortex events and cold air outbreaks. Quarterly Journal of the Royal Meteorological Society, 136, 886–893.

Kuroda, Y. (2008) Role of the stratosphere on the predictability of medium-range weather forecast: a case study of winter 2003–2004. Geophysical Research Letters, 35, L19701. https://doi.org/10.1029/2008GL034902.

MacLachlan, C., Arribas, A., Peterson, K.A., Maidens, A., Fereday, D., Scaife, A. A., Gordon, M., Vellinga, M., Williams, A., Comer, R.E., Camp, J., Xavier, P. and Madec, G. (2015) Global seasonal forecast system version 5 (GloSea5): a high-resolution seasonal forecast system. Quarterly Journal of the Royal Meteorological Society, 141, 1072–1084. https://doi.org/10.1002/qj.2396.

Mitchell, D.M., Gray, L.J., Anstey, J., Baldwin, M.P. and Charlton-Perez, A.J. (2013) The influence of stratospheric vortex displacements and splits on surface climate. Journal of Climate, 26, 2688–2682. https://doi.org/10.1175/JCLI-D-12-00030.1.

Park, T.W., Ho, C.H. and Yang, S. (2011) Relationship between Arctic Oscillation and cold surges over East Asia. Journal of Climate, 24, 68–83. https://doi.org/10.1175/2010JCLI3529.1.

Riddle, E.E., Butler, A.H., Furtado, J.C., Cohen, J.L. and Kumar, A. (2013) CFSv2 ensemble prediction of the wintertime Arctic Oscillation. Climate Dynamics, 41, 1099–1116. https://doi.org/10.1007/s00382-013-1850-5.

Scaife, A.A. and Smith, D. (2018) A signal-to-noise paradox in climate science. npj Climate and Atmospheric Science, 1, 28. https://www.nature.com/articles/s41612-018-0038-4.

Scaife, A.A. and Knight, J.R. (2008) Ensemble simulations of the cold European winter of 2005/6. Quarterly Journal of the Royal Meteorological Society, 134, 1647–1659. https://doi.org/10.1002/qj.312.

Scaife, A.A., Arribas, A., Blockley, E., Brookshaw, A., Clark, R.T., Dunstone, N., Eade, R., Fereday, D., Folland, C.K., Gordon, M., Hermanson, L., Knight, J.R., Lea, D.J., MacLachlan, C., Maidens, A., Martin, M., Peterson, A.K., Smith, D., Vellinga, M., Wallace, E., Waters, J. and Williams, A. (2014) Skillful long-range prediction of European and North American winters. Geophysical Research Letters, 41, 2514–2519. https://doi.org/10.1002/2014GL059637.

Scaife, A.A., Karpechko, A.Y., Baldwin, M.P., Brookshaw, A., Butler, A.H. Eade, R., Gordon, M., MacLachlan, C., Martin, N., Dunstone, N. and Smith, D. (2016) Seasonal winter forecasts and the stratosphere. Atmospheric Science Letters, 17, 51–56.

Sigmund, M., Scinocca, J.F., Kharin, V.V. and Shepherd, T.G. (2013) Enhanced seasonal forecast skill following stratospheric sudden warmings. Nature Geoscience, 6, 98–102. https://doi.org/10.1038/ngeo1698.

Son, H.-Y., Park, J.-Y., Kug, J.-S., Yoo, J. and Kim, C.-H. (2014) Winter precipitation variation over Korean Peninsula associated with ENSO. Climate Dynamics, 42, 3171–3186.

Song, K.H., Son, S.-W. and Woo, S.-H. (2015) Impact of sudden stratospheric warming on the surface air temperature in East Asia. Atmosphere, 25(3), 461–472.

Stockdale, T.N., Molenti, F. and Ferranti, L. (2015) Atmospheric initial conditions and the predictability of the Arctic Oscillation. Geophysical Research Letters, 42, 1173–1179.

Wang, X. and Wang, C. (2014) Different impacts of various El Niño events on the Indian Ocean Dipole. Climate Dynamics, 42, 991–1005.

Williams, K.D., Harris, C.M., Bodas-Salcedo, A., Camp, J., Comer, R.E., Copsey, D., Fereday, D., Graham, T., Hill, R., Hinton, T., Hyder, P., Ineson, S., Masato, G., Milton, S.F., Roberts, M.J., Rowell, D.P., Sanchez, C., Shelly, A., Sinha, B., Walters, D.N., West, A., Woolings, T. and Xavier, P.K. (2015) The Met Office global coupled model 2.0 (GC2) configuration. Geoscientific Model Development, 88, 1509–1524.

Wu, B. and Wang, J. (2002) Winter Arctic Oscillation, Siberian High and East Asian winter monsoon. Geophysical Research Letters, 29, 1897. https://doi.org/10.1029/2002GL015373.

Yeh, S.-W., Kug, J.-S., Dewitte, B., Kwon, M.-H., Kirtman, B.P. and Jin, F.-F. (2009) El Niño in a changing climate. Nature, 461, 511–514. https://doi.org/10.1038/nature08316.

Yu, J.Y. and Lau, K.M. (2004) Contrasting Indian Ocean SST variability with and without ENSO influence: a coupled atmosphere–ocean GCM study. Meteorology and Atmospheric Physics, 90, 179–191. https://doi.org/10.1007/s00703-004-0094-7.

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