Representation and Predictability of the East Asia–Pacific Teleconnection in the Beijing Climate Center and UK Met Office Subseasonal Prediction Systems

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ABSTRACT

Based on the empirical orthogonal function (EOF) analysis, the East Asia–Pacific (EAP) teleconnection is extracted as the leading mode of the subseasonal variability over East Asia in summer, with a meridional tripole structure and significant periods of 10–30 and 50–70 days. A two-dimensional phase–space diagram is established for the EAP index and its time tendency so as to monitor the real-time state of EAP events. Based on the phase composite analysis, the general circulation anomalies first occur over the high-latitude area of Europe centered near Novaya Zemlya at the beginning of EAP events. These general circulation anomalies then influence rainfall over Northeast China, North China, and the region south of the Yangtze River valley (YRV) as the phases of EAP event progress. The representation, predictability, and prediction skill of the EAP teleconnection are examined in the two fully coupled subseasonal prediction systems of the Beijing Climate Center (BCC) and UK Met Office (UKMO GloSea5). Both models are able to simulate the EAP meridional tripole over East Asia as the leading mode and its characteristics of evolution as well, except for the weaker precursors over Novaya Zemlya and an inconspicuous influence on precipitation over Northeast China. The actual prediction skill of the EAP teleconnection during May–September (MJJS) is about 10 days in the BCC model and 15 days in the UKMO model based on correlation measures, but is higher when initialized from the EAP peak phases or when targeted on strong EAP scenarios. However, both of the ensemble prediction systems are under-dispersive and the predictable signals extend to 18 and 30 days in BCC and UKMO models based on signal-to-error metrics, indicating that there may be further scope for enhancing the capability of these models for the EAP teleconnection prediction and the associated impacts studies.

Key words: East Asia–Pacific (EAP) teleconnection, subseasonal, phase–space diagram, prediction skill, predictability

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1. Introduction

The East Asia–Pacific (EAP) or Pacific–Japan teleconnection is recognized as one of the dominant modes of the interannual variability of the East Asian summer monsoon (EASM). It was first proposed by Huang and Li (1987, 1988) and Nitta (1987) and shows a clear meridional wave train over East Asia. During the boreal sum-

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mer, the anomalous convective activity around the Philippines may trigger the northward-propagating Rossby wave energy to form this poleward tripole teleconnection. The typical EAP teleconnection is characterized by positive geopotential height (anticyclonic) anomalies over the Sea of Okhotsk and western Pacific subtropical areas, together with negative geopotential height (cyclonic) anomalies over East Asia (Huang, 1992, 1994; Huang and Sun, 1992, 1994; Nitta and Hu, 1996; Kosaka and Nakamura, 2006, 2010; Lu and Lin, 2009). Both the convective anomalies around the Philippines and the zonal wave dispersion at middle and high latitudes along the westerly waveguide are important for the formation of meridional tripole structure of the EAP teleconnection (Bueh et al., 2008; Wang et al., 2018). Hence the main components of the EASM (e.g., the monsoon trough, western Pacific subtropical high, Meiyu front, subtropical westerly jet, and Okhotsk block) are tightly connected by the EAP teleconnection (Lu, 2004; Weng et al., 2004; Hirota and Takahashi, 2012). Accordingly, the persistent positive (negative) EAP-type circulation anomalies may lead to cool (hot) summers in Japan and floods (droughts) in the Yangtze River valley (YRV) and Songhua River basin in China (Lau and Weng, 2002; Huang, 2004; Wakabayashi and Kawamura, 2004; Min et al., 2005; Kosaka et al., 2011), in addition to the southward (northward) migration of the position of genesis of tropical cyclones and their tracks (Huang and Wang, 2010; Li et al., 2014; Ko and Liu, 2016). Therefore, the EAP teleconnection is an important target of concern for the subseasonal to seasonal (S2S) prediction in East Asia.

Although the EAP teleconnection pattern was first extracted and investigated on seasonal to interannual timescales (Huang and Li, 1987; Nitta, 1987), its variability on intraseasonal timescales has attracted increasing attention in recent decades (Bueh et al., 2008; Shi et al., 2008; Wu et al., 2013). The impact of typical EAP teleconnection pattern on persistent heavy precipitation in YRV has been investigated (Chen and Zhai, 2015; Li L. et al., 2016, 2018). Hsu et al. (2020) showed the crucial role that the EAP pattern had in the formation of a record-breaking heatwave over Northeast Asia, which further confirmed that the EAP teleconnection is an important predictability source of the subseasonal variability in boreal summer. However, most of these studies have focused on the biweekly or synoptic timescales, while limited attention has been paid to the relatively longer subseasonal scale (Wu et al., 2013, 2016b; Wang et al., 2016). One of the main objectives of this study is therefore to confirm the existence of EAP teleconnection on the subseasonal timescale and to detect its oscillation period, as well as its characteristics during different stages of evolution. Although the simultaneous modulation of the teleconnection on precipitation over YRV has been documented, the impact of the EAP teleconnection throughout its life cycle is still an open question, especially its influence over North and Northeast China.

Dynamic models are now the most powerful tool for the S2S prediction. The prediction skill for dominant subseasonal variability, such as the Madden–Julian oscillation (MJO), is a key indicator of the capability of dynamic prediction systems (Robertson et al., 2015; Vitart, 2017). Remarkable progress has been achieved in the last decade in the simulation (Ahn et al., 2017) and prediction (Kim et al., 2018) of MJO as a result of improvements in model parameterization, horizontal and vertical resolution, initialization scheme, and inclusion of ocean coupling (Fu and Wang 2004; Woolnough et al., 2007; Pegion and Kirtman, 2008; Hirons et al., 2013; Liu et al., 2019; Wu et al., 2020). Specifically, MJO can be skillfully predicted three to four weeks in advance according to the evaluation of the S2S prediction project participant models (Vitart, 2017; Lim et al., 2018), and the predictability of MJO can reach as high as 40 days for ensemble prediction (Kim et al., 2014; Neena et al., 2014). However, as a primary variability in EASM, the representation and prediction skill of the EAP teleconnection has not previously been investigated on the subseasonal timescale. Therefore, a thorough assessment of the predictability and prediction skill of the EAP teleconnection and a further understanding of potential sources of errors in current operational forecast systems are crucial to guide further improvements and to provide a foundation for the S2S prediction of EASM.

This study aims to evaluate the predictability and prediction skill of EAP in two state-of-the-art dynamic model systems underpinning operational forecasts: the Beijing Climate Center Climate System Model (BCC_CSM1.2; Wu et al., 2014) and the UK Met Office global coupled model (UKMO GloSea5; MacLachlan et al., 2015), which are two of the participants in the S2S prediction project (Vitart et al., 2017). The bivariate anomaly correlation of the real-time multivariate MJO (RMM) index suggests that BCC and UKMO models can predict MJO events up to about 16 and 25 days in advance (Liu et al., 2017; Vitart, 2017; Lim et al., 2018), and perhaps even longer when initiated with the improved moisture conditions or for strong MJO events (Wu et al., 2020). The prediction skill of the boreal summer intraseasonal oscillation (BSISO) index can reach up to 11 and 16 days for BSISO1 events and 8 and 12 days for BSISO2 events in BCC and UKMO models (Jie et al., 2017), respect-
ively, indicating that both models have considerable prediction capability for dominant modes of the subseasonal variability. The prediction performance of the two models for the Asian summer monsoon on the seasonal timescale have been documented by Li C. F., et al. (2016) and Liu et al. (2018). In this study, we will systematically compare the predictability, prediction skill, and ensemble dispersion of the two dynamic model systems for the subseasonal prediction of EAP by using large sets of hindcasts, which is expected to lead to a better understanding of the common representation and model problems of the prediction of the EAP teleconnection on the subseasonal timescale.

The remainder of this paper is organized as follows. Section 2 introduces the observational and hindcast data as well as the verification methods. Section 3 gives the definition and spectrum of the EAP index as well as the evolution characteristics of EAP events based on phase composites. Section 4 investigates representations of the EAP teleconnection and its evolution characteristics in BCC and UKMO models. Section 5 examines the predictability and prediction skill of the EAP teleconnection. The summary and discussion are presented in Section 6.

2. Data and methods

2.1 Observations

The daily NCEP/NCAR Reanalysis-1 geopotential height and wind field data (Kalnay et al., 1996) and the NOAA outgoing longwave radiation (OLR) data (Liebmann and Smith, 1996) are used for the analysis and model verification with a horizontal resolution of 2.5° × 2.5°. The vertical integrated moisture flux is calculated by using the ECMWF reanalysis (ERA)-Interim data (Dee et al., 2011) with a horizontal resolution of 1.5° × 1.5°. A daily high-resolution (0.25° × 0.25°) gridded rainfall dataset (CN05.1; Wu and Gao, 2013) is used to avoid the uneven spatial distribution of station data. All the observational data cover the time period of 1981–2018 and the climatology is defined as the 30-yr average during 1981–2010.

2.2 Model hindcasts

Two dynamic prediction systems—namely, the BCC Climate Prediction System for S2S version 1 (BCC-CPS-S2Sv1) based on BCC_CSM1.2 and the Global Seasonal Forecasting System (GloSea5) from the UKMO—are used to analyze the representation and predictability of the EAP teleconnection on the subseasonal timescale.

BCC_CSM1.2 is a fully coupled global climate–carbon model (Wu et al., 2014). It consists of the atmospheric component of the BCC Atmospheric General Circulation Model version 2.3 (BCC_AGCM2.3) with a triangular 106 horizontal resolution and 40 hybrid sigma/pressure vertical levels (T106L40), ocean component of the Modular Ocean Model version 4 (MOM4-L40), land component of the BCC Atmosphere and Vegetation Interaction Model version 1.0 (BCC_AVIM1.0), and sea ice component of the sea ice simulator. The initial conditions are generated by applying a nudging technique toward the NCEP1 dataset for the atmospheric analysis and three-dimensional variational data assimilation method for the oceanic analysis (Jie et al., 2014; Liu et al., 2017). BCC_CSM1.2 is run every day to make a 60-day integration for the hindcast period of 1994–2014. Each forecast consists of 4 lagged-average forecast ensemble members, which are initialized at 0000 UTC on the first forecast day and at 1800, 1200, and 0600 UTC on the previous day.

The GloSea5 model (MacLachlan et al., 2015) consists of the atmospheric component of the Global Atmosphere 6.0 (GA6.0) at T216 and 85 vertical levels with the top at 85 km, ocean component of the Global Ocean 5.0 (GO5.0; Megann et al., 2014) of the Nucleus for European Modelling of the Ocean (NEMO), sea ice component of the Global Sea Ice 6.0 (GSI6.0; Rae et al., 2015), and land component of the Global Land 6.0 (GL6.0; Walters et al., 2017) of the Joint UK Land Environment Simulator (JULES). The hindcasts are initialized on the 1st, 9th, 17th, and 25th of each month for 1993–2015, with the 60-day integration and 7 ensemble members based on the lagged-average forecast method.

This study mainly focuses on the hindcasts initialized during May–September (MJJAS) for the time periods of 1995–2014 in BCC and 1993–2015 in the UKMO subseasonal prediction models. All the hindcast data are horizontally interpolated onto 2.5° × 2.5° grids.

2.3 Methodology

A non-traditional filtering method suitable for real-time prediction similar to that used by Wheeler andendon (2004) and Hsu et al. (2015) is applied to observational and model hindcast data to extract the subseasonal signal of the EAP teleconnection. First, the climatological annual cycle is removed by subtracting the 0–3 harmonics of the climatological daily data; second, the interannual variability is removed by subtracting the previous 120-day running mean field; and third, the synoptic-scale variability is removed by applying a 5-day running average. Note that the model’s climatology is calculated for each lead day (LD) and the previous 120-day mean as the forecast on Day j consists of the preceding 120 − (j + 1)
Similar to MJO, the EAP prediction skill is measured by using the correlation coefficient (COR) and root-mean-square error (RMSE; Kim et al., 2018), which are defined as below:

\[
\text{COR}(\tau) = \frac{\sum_{i=1}^{N} [a(t)b(t, \tau)]}{\sqrt{\sum_{i=1}^{N} [a^2(t)]} \sqrt{\sum_{i=1}^{N} [b^2(t, \tau)]}},
\]

(1)

\[
\text{RMSE}(\tau) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} [a(t) - b(t, \tau)]^2},
\]

(2)

where \(a(t)\) is the observed EAP index \((I_{EAP})\) on time \(t\), \(b(t, \tau)\) is the corresponding forecast for time \(t\) with a lead time of \(\tau\) days, and \(N\) is the number of forecasts. \(\text{COR}(\tau) = 0.5\) is usually chosen as a threshold for skillful prediction because the large sets of hindcasts will dramatically decrease the significant correlation coefficient criterion (Rashid et al., 2011). Because the EAP index is normalized, RMSE for a climatological forecast \((I_{EAP} = 0)\) is 1.0, which will be taken as the threshold for skillful prediction of RMSE (Lin et al., 2008).

This study uses two different approaches to evaluate the EAP predictability. The first approach is based on anomaly correlation metrics (Kim et al., 2014). The predictability of a single member is calculated by the COR(\(\tau\)) between one ensemble member and each of the other ensemble members, and then averaged over subsamples. The ensemble predictability is measured in the same way, but between one ensemble member and the mean of the remaining ensemble members. In general, the predictability of a single member is lower than that of the ensemble mean.

The second predictability evaluation method is defined by the signal-to-noise metrics (Neena et al., 2014). The EAP signal \((S_j)\) on LD\(j\) is calculated as below:

\[
\langle S_j^2 \rangle = \frac{1}{N \times nk} \sum_{i=1}^{N} \sum_{k=1}^{nk} [(EAP_{ijk})^2],
\]

(3)

where \(N\) is the total number of forecasts, \(nk\) is the ensemble size, and \(EAP_{ijk}\) represents the forecast EAP index of a particular case \(i\) on LD\(j\) by a single ensemble member \(k\). The mean-square error \((E_j)\) for each LD\(j\) is given by:

\[
\langle E_j^2 \rangle = \frac{1}{N \times m_1} \sum_{i=1}^{N} \sum_{\text{pair}=1}^{m_1} [(EAP_{ij1} - EAP_{ij2})^2],
\]

(4)

Here, \(k_1\) and \(k_2\) represent the control and perturbed forecasts and \(m_1\) represents the number of possible control–perturbed pairs. Although a single ensemble member is taken as the control forecast, the perturbed forecast is different for the single member or the ensemble-mean predictability estimate. In the former, every other ensemble member is regarded as the perturbed forecast; in the latter, it takes the average of all the other ensemble members. Therefore the predictability is defined as the LD at which the mean-square error becomes as large as the mean signal.

Note that, in some studies (e.g., Scaife et al., 2014), the actual skill that was evaluated by validating predictions against the corresponding observations is referred to as “predictability” and the potential skill based on treating one of the ensemble members as a proxy for the observations is referred as “the perfect predictability”. These concepts are identical in meaning to the “prediction skill” and “predictability” in this paper.

3. Characteristics of the EAP teleconnection on the subseasonal timescale

In order to extract the spatial pattern of the EAP teleconnection, an empirical orthogonal function (EOF) analysis was applied to the normalized 5-day running mean 500-hPa geopotential height (H500) anomalies in summer (June–August; JJA) during the time period of 1981–2018 over the region \((10^\circ–75^\circ\text{N}, 110^\circ–150^\circ\text{E})\). Following the method described by Hart and Grumm (2001), the standard deviation used for standardization was calculated via a 21-day smooth window (from 1981 to 2010) centered on the day being investigated. We took the seasonal variation of the variability of geopotential height into consideration. Figure 1a shows that the leading EOF mode with the explained variance of 18.6% is characterized by a clearly meridional tripole structure with two positive anomaly centers located in the tropical western Pacific (WP) and northern Sea of Okhotsk (OK), and a negative center located in the midlatitudes of East Asia (EA), which is considered to be the canonical positive phase of the EAP teleconnection (Huang and Li, 1987; Wang et al., 2016). This suggests that the EAP teleconnection is also the dominant teleconnection mode over East Asia on the subseasonal timescale during boreal summer.

A daily EAP index \((I_{EAP})\) is defined according to these three atmospheric activity centers over WP \((12.5^\circ– 22.5^\circ\text{N}, 115^\circ–135^\circ\text{E})\), EA \((35^\circ–45^\circ\text{N}, 120^\circ–140^\circ\text{E})\), and OK \((60^\circ–70^\circ\text{N}, 120^\circ–140^\circ\text{E})\).

\[
I_{EAP} = (H_{WP} - H_{EA} + H_{OK})/3,
\]

(5)

where \(H_{WP}\), \(H_{EA}\), and \(H_{OK}\) represent the geopotential
height anomalies averaged over WP, EA, and OK, respectively. Note that $H_{WP}$, $H_{EA}$, and $H_{OK}$ were normalized by the standard deviation calculated via a 21-day smooth running window. The $I_{EAP}$ can be calculated for all seasons, but should be normalized by the standard deviation of JJA during the time period of 1981–2010. The
time series of $I_{EAP}$ is highly consistent with that of the first principal component (PC1) during JJA from 1981 to 2018 (Fig. 1b), with a correlation coefficient of 0.93. It confirms that the EAP index defined here is capable of capturing the variability of leading EOF mode. Figure 1c shows the seasonal cycle of the amplitude of $I_{EAP}$ obtained by calculating the standard deviation of $I_{EAP}$ via a 21-day smooth running window. The results show that the amplitude of $I_{EAP}$ is generally small during boreal winter and increases around late April, reaching a maximum from late June to August. This unique seasonal cycle implies that the EAP relationship among WP, EA, and OK characterizes JJA in boreal summer. Although the standard deviation of $I_{EAP}$ is also relatively high in late October, this month is usually considered as the transition season, with a climatology distinct from that of boreal summer. Therefore, consistent with previous studies (such as Wang et al., 2016), boreal summer is defined here as extending from May to September (MJJAS).

The EAP indices from 1981 to 2018 are analyzed year-by-year by wavelet transform and then averaged for 38 yr (Fig. 2a), and the MJJAS daily average spectrum is shown in Fig. 2b. The shading and red dotted line (values > 0) represent the denoised energy spectrum value at the 95% confidence level, corresponding to the significant oscillation period. The largest wavelet power spectrum is in mid-August and has a period of about 65 days. Two significant bands are seen in the oscillation period of the EAP index with a period of 50–70 days throughout MJJAS and a period of 10–30 days from mid-May to July and from mid-August to September, peaking at around 60 and 25 days, respectively.

Figure 3 shows the lead–lag relations between the EAP teleconnection and some well-recognized sub-seasonal dominant modes (such as MJO and BSISO). There is only a weak relationship between the EAP teleconnection and MJO in terms of RMM indices, suggesting a limited influence of MJO on EASM (Lee et al., 2013). By contrast, the EAP teleconnection can, to some extent, be reflected by BSISO, with a maximum simultaneous correlation of 0.38 with BSISO1-1 (PC1 in Lee et al., 2013) and a maximum correlation of −0.34 when the EAP teleconnection leads BSISO2-1 (PC3) by 1 day. This result is reasonable because BSISO1-1 and BSISO2-1 can also capture the cyclone or anticyclone over the western Pacific. However, compared with the BSISO indices defined by Lee et al (2013), which mainly cover the areas of Indian summer monsoon and western north Pacific summer monsoon, the EAP index focuses on East Asia and reflects the anomalies over middle and high latitudes. In addition, the relatively higher correlations were obtained among the EAP index, East Asia–western North Pacific ISO index (Lin, 2013), and the western Pacific ISO index (Lee and Wang, 2016; Yang et al., 2020), showing that these indices also can reflect the anomalies over mid and high-latitude East Asia (figures omitted).

As suggested by Plaut and Vautard (1994), the time tendency of $I_{EAP}$ (denote as $I_{EAP}'$) has a high lead–lag correlation with $I_{EAP}$, which can be calculated by the central finite difference method:

$$ I_{EAP}'(t) = \frac{[I_{EAP}(t+\Delta t) - I_{EAP}(t-\Delta t)]}{2\Delta t}, \quad (6) $$

where $\Delta t$ represents the length of time and is equal to one day in this study. The analysis of lead–lag correlations between the EAP index and its tendency (Fig. 3c) shows
that $I_{EAP}'$ tends to lead $I_{EAP}$ by about 4 days for variability in the range of 10–30 days with a correlation of 0.89 and at a lag of 10 days for variability in the 30–90-day range with a correlation of 0.91.

Given the strong lead–lag behavior of $I_{EAP}$ and $I_{EAP}'$ (Figs. 4a, b), it is reasonable to establish a two-dimensional phase–space diagram of $[-I_{EAP}', -I_{EAP}]$ to monitor the evolution of EAP events visually, with the state of EAP teleconnection as a point in the diagram. Similar to Wheeler and Hendon (2004), we divide the two-dimen-

![Figure 3](image)

Fig. 3. Lead–lag correlation coefficients between (a) the EAP index with RMM1, RMM2, and itself; (b) the EAP index with BSISO1-1, BSISO1-2, BSISO2-1, and BSISO2-2; and (c) the EAP index and its time tendency, during MJJAS of 1981–2018. The dashed line is the 95% confidence level for the correlations in (a) and (b).

![Figure 4](image)

Fig. 4. Time series of the normalized 5-day running mean EAP index and its time tendency in MJJAS of (a) 2016 and (b) 2018. (c) The phase–space diagram of $[-I_{EAP}', -I_{EAP}]$ in MJJAS 2016, with different months in different colors.
sional phase–space diagram into eight phases (Fig. 4c) and the implication of each phase can be inferred by following the definition and combined position of $I_{EAP}$ and $I_{EAP}'$. To be specific, Phases 2–3 (6–7), in which amplitudes of the normalized EAP index are larger than their corresponding normalized time tendency ($|I_{EAP}| > |I_{EAP}'|$), indicate the positive (negative) peak phases of EAP events with a “+−+” (“−−−”) meridional wave train with the anomalous center of precipitation located over EA (WP and OK). The difference between Phases 2 and 3 (or Phases 6 and 7) lies in the sign of $I_{EAP}'$, which represents the EAP events in the developing (Phases 2 and 6) or decaying (Phases 3 and 7) state. By contrast, amplitudes of the normalized time tendency are larger than their corresponding normalized EAP index ($|I_{EAP}| < |I_{EAP}'|$) in Phases 8–1 and 4–5, which can be viewed as transition phases from positive to negative events (Phases 4–5) or negative to positive events (Phases 8–1). Figure 4c shows the evolution of EAP activities during MJJAS 2016 in terms of a phase–space diagram. Many of the sequential days trace anticlockwise circles around the origin as a result of the lead–lag relationship between $I_{EAP}$ and $I_{EAP}'$, with two strong positive and three strong negative EAP events signified by large amplitudes.

Considering the dual significant spectra of the EAP index (Fig. 2) rather than the lead–lag composite, phase composites for anomalies in H500 and OLR are shown in Fig. 5 to depict characteristics of the evolution of EAP events. The composites are performed only on those cases where the amplitude of $[−I_{EAP}', −I_{EAP}]$ is $> 1.0$—that is, $(I_{EAP}^2 + I_{EAP}'^2)^{1/2} > 1.0$. The wave activity flux (WAF) defined by Takaya and Nakamura (2001) is used to diagnose the energy dispersion of Rossby wave-like perturbations, which is independent of the wave.

![Fig. 5](image-url)
phase and parallel to the local group velocity. In the transition phase to positive EAP events (Phase 1), a significant negative anomaly center exists over the high-latitude area of Europe centered near Novaya Zemlya, from which strong Rossby wave activity propagates east and southeast to the OK and EA. The poleward energy dispersion from the subtropical WP is discernible, corresponding to the suppression of convective activity to the east of the Philippines. During the peak phases (Phases 2–3), anomalies over the OK are enhanced by obtaining the upstream energy from Novaya Zemlya, which is weakened itself.

The depressed convection in WP propagates westward, and the convergence between the poleward wave fluxes from WP and southward wave fluxes from the OK markedly strengthen the negative center over EA. Therefore, the canonical EAP-type meridional tripole formed with a zonally extended structure. In Phase 4, the subtropical depressed convection continues to move westward, and the Rossby energy disperses east and southeast from the OK and EA center, enhancing the anomalies over North Pacific and the Aleutian Islands. New negative anomalies and active convection emerge over Novaya Zemlya and WP, which could be the precursor of the next negative EAP event. The spatial evolution of negative EAP events during Phases 5–8 is nearly the same as the opposite signs of positive events, except for the stronger amplitude of subtropical convection anomalies as well as the slightly weaker OK anomaly center, indicating the greater contribution of subtropical activities to the formation of negative EAP events. In addition, according to the numbers of days falling within each phase shown in Fig. 5, the observed EAP states are basically even distributed, with the maximum discrepancy of 25 days between Phases 1 and 7.

Figure 6 shows the phase composites of the vertically integrated moisture flux and precipitation anomalies in China. In general, the spatial pattern of the moisture flux is strongly modulated in EA, as are the rainfall anomalies over North China and south of the YRV basin during different stages of the life cycle of the EAP teleconnection. In Phase 1 (the transition phase of positive EAP events), an anomalous moisture flux cyclone lies in the Sea of Japan, steering moisture to Northeast China on its northern flank and enhancing local precipitation. In Phases 2–3 (the peak phase of positive EAP events), the anomalous anticyclone over the subtropical western Pacific migrates westward, forming an anticyclone–cyclone pair at low to midlatitudes of EA. The confluence between the northerly winds driven by the anomalous cyclone as well as the southwesterly winds to the northern flank of the anticyclone significantly strengthen precipitation over the YRV basin, consistent with previous studies on synoptic scales (Chen and Zhai, 2015; Wang et al., 2018). The anomalous northerlies over North China weaken the transport of moisture and local precipitation. The low-latitude cyclone moves westward and strengthens the southwesterly winds over the south of YRV in Phase 4. At the same time, the transport of moisture originating from the Bay of Bengal is reinforced, leading to anomalous rainfall over the eastern Tibetan Plateau and southern YRV. The configurations of negative EAP events during Phases 5–8 also nearly mirror the positive events, except for the stronger amplitude of the anomalous low-latitude cyclone, which is consistent with the results shown in Fig. 5.

4. Representation of the EAP teleconnection in BCC and UKMO models

To determine the existence and spatial pattern of the EAP teleconnection in BCC and UKMO models, the EOF analysis was first applied to the forecast at different LDs. The results of this section are based on the ensemble-mean for both the BCC and UKMO models. Figure 7 shows that a similar meridional tripole structure (“+ − +”) is clearly identified by the leading EOF mode of the 5-day running mean 500-hPa normalized geopotential height anomalies for a lead time of 10 (LD10), 20 (LD20), and 30 (LD30) days, respectively. Although the explained variances are slightly larger in the model and the subtropical positive center is located to the south of center in the observational data (e.g., LD10), both the BCC and UKMO models generally capture the EAP teleconnection pattern well, confirmed by the fact that the COR values are > 0.7 for all the LDs and are up to 0.9 in the BCC model. In addition, positive anomalies over WP are stronger than observations in the UKMO model, possibly indicating the overestimate of air–sea interactions in tropical areas.

Characteristics of the evolution of EAP teleconnection in BCC and UKMO models and their impacts on precipitation in China are evaluated. Although a composite can be determined for each LD, the results of the lead 10 days in the BCC model and 11–15 days in the UKMO model are chosen because of their respective prediction skills and hindcast intervals (every day for the BCC model and four times each month for the UKMO model). Figures 8 and 9 show the composite of OLR, H500 anomalies, and WAF plotted against their respective predicted EAP index in BCC and UKMO models. Compared with the observations (Fig. 5), there are some defi-
cits, such as the weak precursors over Novaya Zemlya in the UKMO model as well as estimate of the zonal elongation of each anomalous center in the BCC model, although both models still capture the realistic meridional tripole structure of the EAP teleconnection as well as the energy dispersion characteristics of the Rossby wave, such as the eastward and southeastward dispersions of energy at high latitudes and the confluence of energy in the southward and poleward dispersions over EA. Features of the other LDs are similar (figures omitted), indicating that the models are in general capable to capture the realistic characteristics of the evolution of EAP dur-

Fig. 6. As in Fig. 5, but for the anomalous precipitation rate in China (color shading; mm day$^{-1}$) and vertically integrated water vapor flux (vector; $10^4$ g m$^{-1}$ s$^{-1}$). Stipples for precipitation and thick black vectors for water vapor flux mark the results that are significant at the 95% confidence level.
Figures 10 and 11 show composites of the vertically integrated moisture flux and precipitation anomalies in BCC and UKMO models at LDs of 10 and 11–15 days, respectively. Anomaly patterns in the model are consistent with the observations (Fig. 6), but there are still some biases, especially for precipitation. For instance, in the early developing stage of the EAP teleconnection (Phases 1–2 and 5–6), its modulation on precipitation over Northeast China is clear in the observations, but is much weaker in the BCC model and almost absent in the UKMO model. In addition, during the peak and decaying stages of EAP events (Phases 3–4 and 7–8), the significance and coverage of precipitation anomalies over North China and south of YRV are much smaller than those in the observations, especially for the BCC model. Therefore, although representations of the structure of EAP teleconnection and its related circulation are generally well captured in BCC and UKMO models, there are still difficulties in the realistic simulation of the modulation of precipitation anomalies by the EAP teleconnection. In general, the precipitation anomaly is proportional to the divergence of column-integrated moisture flux ($\nabla \cdot qV$), which is largely dominated by the moisture convergence
Further analysis shows that both the unrealistic convergence of the low-level circulation and distribution of the moisture (He et al., 2019) contribute to the bias in precipitation in the model (figures omitted). Because the anomalies are composited against the predicted EAP index, these differences mainly come from model errors rather than a lack of predictability. These deficits may contribute to the lower prediction skill for precipitation over East Asia in the S2S models (de Andrade et al., 2019), which may be improved by dynamic–statistical downscaling methods (Wu et al., 2018).

5. Predictability and prediction skill of EAP teleconnection on subseasonal timescales

The prediction skill of the EAP teleconnection in BCC and UKMO models is calculated to show the actual skill in the current subseasonal prediction systems, while the predictability shows the theoretically achievable skill with a perfect model and initial conditions. Both the observational and hindcast EAP indices used a 5-day running mean with subtraction of the previous 120-day mean to remove the synoptic and interannual variability, as described in Section 2.3. First, the predictability and prediction skill of the ensemble-mean and individual ensemble members in BCC and UKMO models are examined by using the COR metric. As shown by the blue lines in Figs. 12a, b, the single-member skill is about 8 days for the BCC model and 12 days for the UKMO model with the criterion of COR decreasing to 0.5. As expected, the ensemble-mean prediction skill (red lines) is clearly superior to that of individual members, in particular for the lead time beyond 7 days, with the skill reaching out to 10 and 15 days in BCC and UKMO models, respectively. Enhancement in the skill of ensemble
prediction is slightly larger in the UKMO model (3 days) than that in the BCC model (2 days), which may result from more ensemble members (7 members in the UKMO model and 4 members in the BCC model) and a more effective ensemble system as shown by the ensemble spread (Figs. 13a, b). If 0.3 is taken as the criterion for a useful COR skill, the EAP teleconnection can be predicted out to a lead time of 17 and 22 days for BCC and UKMO models, respectively.

Compared with the other dominant intraseasonal variabilities, the prediction skill of the EAP teleconnection is lower than that of MJO (Kim et al., 2018), but comparable with that of BSISO (Jie et al., 2017). In addition, for the two significant timescales of the EAP teleconnection (Fig. 2b), prediction skills for the variability of 30–80 days reach up to 21 and 23 days for BCC and UKMO models, respectively, much higher than those for the variability of 10–30 days (13 and 16 days for BCC and UKMO models, respectively), indicating that the relatively low prediction skill of the EAP index may mainly be attributed to the difficulty in reliable prediction of the 10–30 day timescale (Zhu and Li, 2017; figures omitted). The predictability is much higher than the prediction skill. It is 12 and 14 days for individual members in BCC and UKMO models, and remains > 0.5 at the 30-day lead time for the ensemble-mean prediction, showing a considerable scope for improvement.

The individual predictability and prediction skills of the three activity centers of the EAP teleconnection (WP, EA, and OK) were examined (Figs. 12c, d). Although the predictability decreases from low to high latitudes, the prediction skill of EA is slightly higher than that of WP during the first 15 days in both the BCC and UKMO models, which is in contrast with the traditional concept that the prediction skill of geopotential height is mostly confined to tropical regions (Wang et al., 2009; Ding,
The skill gap between WP/EA and OK is larger in the UKMO model than that in the BCC model, showing that the superiority of UKMO model is mainly from low and midlatitudes where air–sea interactions provide more predictable contributions. The prediction skills measured by RMSE metrics are presented in Figs. 13a, b. The error increases more slowly in the UKMO model than that in the BCC model, with RMSE reaching the climatological forecast value (1.0) at 12 and 8 days for the single-ensemble member, and 19 and 14 days for the ensemble-mean in UKMO and BCC models, respectively. These results are exactly the same with COR metrics for the single member, but slightly longer for prediction of the ensemble-mean. The
ensemble spread, defined as the standard deviation of members to the ensemble mean, was also examined to estimate uncertainties in the prediction system. In a perfect system, the ensemble spread would be equal to RMSE for a large sample of forecasts. Figures 13a and b show that RMSE exceeds the ensemble spread from the beginning in both the BCC and UKMO models, indicating that the ensemble prediction systems are either under-dispersive or contain large systematic errors such as drifts, consistent with previous studies on the prediction of MJO (Kim et al., 2014; Neena et al., 2014; Wu et al., 2016a). However, the UKMO model shows better characteristics, with more closeness of the spread and RMSE curves, which is consistent with its higher ensemble-
Fig. 12. The predictability (correlation coefficient; dashed) and prediction skill (correlation coefficient; solid) of the EAP index as a function of the forecast LD for MJJAS in (a, c) BCC and (b, d) UKMO models. In (a, b), the solid and dashed lines represent the prediction skill and predictability of individual members (blue) and ensemble mean (red), respectively. In (c, d), the solid and dashed lines represent the prediction skill and predictability of the EAP teleconnection (red), WP (blue), EA (green), and OK (brown), respectively.

Fig. 13. As in Fig. 12, but for (a, b) RMSE (solid lines) and ensemble spread (dashed line) as well as (c, d) predictability (signal-to-error metric). In (a, b), the blue and red solid lines represent RMSE of individual members and ensemble mean respectively, and the red dashed line represents the ensemble spread. In (c, d), the saturation of blue solid error growth curve (single-member estimate) with respect to the signal (red line) marks the EAP predictability for individual forecasts (denoted by the left black vertical line) and the saturation of green solid error growth curve (ensemble-mean estimate) with respect to the signal marks the potential predictability of the EAP teleconnection for the ensemble-mean forecasts (right black vertical line).
mean skill improvement (Neena et al., 2014).

Figures 13c and d show the predictability estimates of the EAP teleconnection using the signal-to-error metrics. The average errors (blue, single-member method; green, ensemble method) and average signal (red) estimates are shown as a function of the LD for BCC and UKMO models. Following Neena et al. (2014), the single-member and ensemble-mean estimates of the EAP predictability were obtained from LD when the single-error (blue) and the ensemble-error (green) curves became as large as the signal (red). The exponential growth in the error is evident for both the single-member and ensemble estimates, with a slower error growth stage for the first five days of the hindcast and followed by a phase of the faster error growth; the error was saturated after about 25 days.

As a result of the faster error growth, the predictability of the BCC model is shorter than that of the UKMO model, with about 12 and 14 days for single-member estimates as well as 18 and 30 days for ensemble estimates in BCC and UKMO models, respectively. Compared with the current prediction skill, these results are encouraging because they indicate that both the BCC and UKMO models still have a scope for improvement in their EAP prediction skills, especially for the ensemble prediction, by up to one to two weeks before reaching their estimates of predictability.

Figure 14 assesses the dependence of EAP predictability and prediction skill on the initial phase and calendar year. In general, the prediction skill is relatively higher for forecasts initialized with the EAP peak phases (e.g., Phases 2–3 and 6–7) than that with the transition phases (Phases 4–5 and 8–1) in both models; so is the predictability. Specifically, there is a higher prediction skill for positive EAP events in the BCC model and for negative EAP events in the UKMO model. In addition, there is a large interannual variability for the prediction skill of the EAP teleconnection, with the relatively higher skill in MJJAS of 1994, 1998, 2006, and 2014 in both models. The interannual variation of the predictability limits that indicated by the ratio of the signal-to-error, in good agreement with the prediction skills, but neither shows a clear dependence on the dominant interannual variability, such as the El Niño–Southern Oscillation or Indian Ocean dipole; further investigation is therefore required to determine associated driving factors.

Further investigation clearly shows that the EAP prediction skill and predictability depend on the initial and target amplitudes of the EAP index (Fig. 15). The weak or strong EAP scenarios can be distinguished by judging whether the observed standard deviation of $I_{EAP}$ is less than or greater than one. Figures 15a and b show that the initially strong scenarios show a systematically higher COR skill than the initially weak scenarios for the first 14 days of the forecast, especially in the BCC model, with the prediction skill extended from 9 to 12 days with the criterion of COR decreasing to 0.5. However, increase in the prediction skill is limited in the UKMO model after the 15-day forecast. By contrast, Figs. 15c, d show that the EAP prediction skill is dramatically improved from target weak scenarios to strong ones, with the skill increasing from 6 to 15 days in the BCC model and from 10 to 20 days in the UKMO model, implying that predictions are more reliable for the upcoming strong EAP events. The predictability is also slightly higher for the initial and target strong EAP scenarios, but the discrepancy in predictability between the initially strong and weak scenarios is smaller than that of the prediction skill, indicating that the relatively lower prediction skill is partly attributed to deficiencies in the model initialization for the initially weak scenarios.

To further compare the evolution characteristics of EAP between the observation and hindcasts, Fig. 16 shows composite phase–space diagrams with respect to different initial phases of the EAP teleconnection, which are calculated with the initially combined strong EAP scenarios [$I_{EAP}^2 + I_{EAP}^2 > 1.0$]. The phase diagram is plotted for a 21-day target forecast period with an interval of 1 day. It is clear that the composited sequential days trace anticlockwise circles around the origin. Characteristics of the evolution of EAP in the model are generally consistent with the observations, except for the slightly faster decay speeds, such as the composites initiated from Phases 1, 2, 5, and 6 in the BCC model as well as Phases 1, 4, and 7 in the UKMO model. In addition, the damping time of the EAP teleconnection is shorter than that of MJO (Wheeler and Hendon, 2004), which may contribute to its relatively low predictability (Fig. 12).

6. Summary and discussion

The evolution characteristics of the EAP teleconnection on the subseasonal timescale and its potential impact on summer rainfall in China were investigated by using a phase composite analysis in this paper. The representation of the EAP teleconnection and its associated influence on circulation and precipitation anomalies in the current BCC and UKMO subseasonal prediction systems were also examined, together with its predictability and prediction skill. The main findings are summarized as follows.

The meridional tripole EAP teleconnection pattern can
be extracted as the leading mode during boreal summer over East Asia on subseasonal timescales, similar to previous studies on interannual or synoptic timescales (Huang and Li, 1987; Chen and Zhai, 2015; Wang et al., 2018). The daily EAP index is defined according to the variation of three anomalous activity centers (WP, EA, and OK), which has significant oscillation periods of 10–30 and 50–70 days. Given the intrinsic lead–lag relationship between the EAP index and its time tendency, a two-dimensional phase–space diagram is proposed to monitor the real-time state of the EAP teleconnection. Geopotential height precursors are found over the high-latitude area of Europe centered near Novaya Zemlya in the developing stage of EAP events, with the Rossby wave energy dispersing to the east and southeast toward the OK and EA. The convergence of poleward WAFs from WP and southward WAFs from the OK over EA jointly stimulates the advance and maintenance of the EAP pattern during the peak stage. The continual westward propagation of the WP anomaly, as well as the

Fig. 14. The ensemble prediction skill (shading) and predictability (contour) of the EAP index as a function of the forecast LD and the (a, b) initial phase and (c, d) calendar year for (a, c) BCC and (b, d) UKMO models. The prediction skill is computed via correlation coefficient for the period of MJJAS, while the predictability is represented by the ratio of signal to the ensemble-mean estimate error. The red line indicates that the ratio of signal-to-error equals one.
The southeastward dispersion of energy from EA and the OK anomaly, eventually erodes the EAP teleconnection. The influence on precipitation exerted by the EAP teleconnection first appears in Northeast China and then mainly resides over North China and south of the YRV basin in its peak and decaying stages, with the strengthening anticyclone–cyclone moisture flux pair prevailing at low to midlatitudes of EA.

Both the BCC and UKMO models are capable of maintaining the EAP-type meridional tripole over East Asia as their leading EOF modes for various lead times. Characteristics of the evolution of EAP are also gener-

Fig. 15. The predictability (COR; dashed lines) and prediction skill (COR; solid lines) of the EAP index for the (a, b) initial and (c, d) target weak scenarios (observed standard deviation of $I_{EAP} < 1$; blue lines) and strong scenarios (observed standard deviation of $I_{EAP} > 1$; red lines) as a function of the forecast LD in (a, c) BCC and (b, d) UKMO models.

Fig. 16. Composite phase–space diagrams of the EAP teleconnection for observations (solid lines) and forecasts (dashed lines) of (a) BCC and (b) UKMO models. The dots denote the states of each day from the start date of forecast. Only the EAP scenarios with an initial combined amplitude > 1 in the observational dataset are used in the composite diagrams.
ally well simulated in the models, except for the weaker precursors over Novaya Zemlya in the UKMO model as well as overestimate of the zonal elongation of WP and EA anomalies in the BCC model. However, the modulation of rainfall in China by the EAP teleconnection is much weaker than the observations in both models, especially for the anomaly over Northeast China in the developing stages of the EAP teleconnection (in the UKMO model) and over south of YRV in its decaying stages (in the BCC model), which may undermine the direct prediction skill for precipitation over East Asia in these models.

The prediction limit of the EAP teleconnection during MJJAS is about 10–8 days for the ensemble-mean (single member) in the BCC model and 15 (12) days in the UKMO model using correlation coefficient metrics, and can reach up to 14 (8) days and 19 (12) days using RMSE metrics. The prediction error exceeds the ensemble spread from the beginning of forecast, indicating that both ensemble prediction systems are under-dispersive and less effective. This may be related to some large systematic errors in the models, such as drifts, especially for the BCC ensemble prediction. The predictability limit of the EAP teleconnection reaches 12 and 14 days for the single-member prediction, and 18 and 30 days for ensemble-mean prediction using the signal-to-error metrics in BCC and UKMO models, respectively.

The dependence of the EAP teleconnection prediction skill and predictability on the initial phase and calendar year was also investigated. The prediction skill is higher when initialized from the EAP peak phases than that from the transition phases, especially for positive peak phases in the BCC model and negative peak phases in the UKMO model. The interannual variability of the prediction skill is in agreement with that of the predictability. The results also show that the model displays moderate improvements starting from an existing EAP teleconnection in the first 15 days of forecast, and the target strong EAP scenarios achieve much higher skills than the target weak scenarios, which imply more skillful prediction of the upcoming strong EAP events. In addition, characteristics of the evolution of EAP index in the models are generally consistent with the observations, except for a slightly faster decaying speed.

The concept of a “signal-to-noise paradox” has been proposed previously in climate science. This paradox depicts the discrepancy between the prediction skill and potential predictability of a climate model, with evidence showing that the model is able to predict the observed climate variability better than the estimation from its low signal-to-noise ratio (Scase and Smith, 2018). The paradox is usually attributed to the weak amplitude of predictable signals, especially in the Atlantic sector. However, it is hard to identify any evidence of the paradox in this study because the predictability of EAP index is higher than the actual prediction skill in both the BCC and UKMO models (Figs. 13, 14). Nonetheless, interpretation of the gap between the potential and actual skill as room for improvement should be treated with caution. There is an essential assumption that the statistical characteristics of the observed time series should be identical to those of the model predicted time series (Kumar et al., 2014), otherwise the larger (smaller) signal-to-noise ratio would lead to the overestimate (underestimate) of true predictability (Scase and Smith, 2018).

This study defined the EAP index based on EOF analysis of H500. We also compared it with the index based on other variables, such as the 850-hPa zonal wind (Wu et al., 2013; Li et al., 2020). The results are similar, except for the slightly stronger signals at low latitudes. However, the definition of EAP index based on H500 is more consistent with the well-recognized canonical structure of the EAP teleconnection (Nitta, 1987; Huang, 1992, 2004) and it is more convenient for operational departments to monitor the individual variability of each active center in the atmosphere (WP, EA, and OK). In addition, the stronger mid and high-latitude anomalies can be reasonably captured by this index, such as the precipitation over Northeast China (Fig. 6).

Section 3 established a two-dimensional phase–space diagram of $[-I_{EAP}', -I_{EAP}]$ to analyze the evolution of EAP teleconnection. Theoretically, for an index with a sinusoidal time series, $I = \sin(\omega t)$, the time tendency can be obtained as $I' = \omega \cos(\omega t)$, which has the same oscillation period but with a phase shift (Fig. 17). Therefore, for a propagation mode, it is convenient to capture its propagation characteristics by a combination of $I$ and $I'$. However, for a standing mode (i.e., $f(x,y,t) = A(x,y) \sin(\omega t)$), the combination of $I$ and $I'$ only represents its phase transition, but does not result in artificial propagation. In addition, the opposite signs of the EAP index and EAP tendency index ($[-I_{EAP}', -I_{EAP}]$) were used to establish a two-dimensional phase–space diagram for two reasons: (1) the trace of EAP teleconnection will rotate in anticlockwise circles around the origin given $I_{EAP}$ lags $I_{EAP}'$, similar to the widely used RMM (Wheeler and Hendon, 2004) and BSISO (Lee et al., 2013) indices; and (2) the transition from Phase 1 to 8 will be analogous to the evolution of sine function (Fig. 17), which is much easier to understand.

Figure 2 reveals two significant oscillation periods of 10–30 and 50–70 days. Possible distinctions in the evolution between these two timescales and fundamental driv-
Fig. 17. The sketch of time evolution of a sinusoidal index [$I = \sin(\omega t)$] and its time tendency [$I' = \omega \cos(\omega t)$]. The phase division corresponds to that of Fig. 4c. Here, $\omega = 2\pi/T$, $T = 40$, and $I'$ is multiplied by $1/\omega$.

...ing factors require further investigation. The lower direct prediction skill of precipitation over East Asia (de Andrade et al., 2019) may partly be attributed to the poor representation of the modulation of precipitation by the EAP teleconnection. Considering the relatively higher prediction skills of the EAP teleconnection, which can reach up to two weeks, a dynamic–statistical downscaling model (Wu et al., 2018) may help to improve the precipitation prediction skill. In addition, the predictability and prediction skill of the EAP teleconnection show large interannual variations, which should also be investigated in the future.

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REFERENCES

Ahn, M.-S., D. Kim, K. R. Sperber, et al., 2017: MJO simulation in CMIP5 climate models: MJO skill metrics and process-oriented diagnosis. *Climate Dyn.*, 49, 4023–4045, doi: 10.1007/s00382-017-3558-4.

Bueh, C., N. Shi, L. R. Ji, et al., 2008: Features of the EAP events on the medium-range evolution process and the mid- and high-latitude Rossby wave activities during the Meiyu period. *Chinese Sci. Bull.*, 53, 610–623, doi: 10.1007/s11434-008-0005-2.

Chen, Y., and P. M. Zhai, 2015: Synoptic-scale precursors of the East Asia/Pacific teleconnection pattern responsible for persistent extreme precipitation in the Yangtze River Valley. *Quart. J. Roy. Meteor. Soc.*, 141, 1389–1403, doi: 10.1002/qj.2448.

de Andrade, F. M., C. A. S. Coelho, and I. F. A. Cavalcanti, 2019: Global precipitation hindcast quality assessment of the Subseasonal to Seasonal (S2S) prediction project models. *Climate Dyn.*, 52, 5451–5475, doi: 10.1007/s00382-018-4457-z.

Dee, D. P., S. M. Uppala, A. J. Simmons, et al., 2011: The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Quart. J. Roy. Meteor. Soc.*, 137, 553–597, doi: 10.1002/qj.828.

Ding, Y. H., 2011: Progress and prospects of seasonal climate prediction. *Adv. Meteor. Sci. Technol.*, 1, 14–27. (in Chinese)

Fu, X. H., and B. Wang, 2004: The boreal-summer intraseasonal oscillations simulated in a hybrid coupled atmosphere–ocean model. *Mon. Wea. Rev.*, 132, 2628–2649, doi: 10.1175/MWR2811.1.

Hart, R. E., and R. H. Grumm, 2001: Using normalized climatological anomalies to rank synoptic-scale events objectively. *Mon. Wea. Rev.*, 129, 2426–2442, doi: 10.1175/1520-0493(2001)129<2426:Uncatr>2.0.co;2.

He, Z., P. C. Hsu, X. W. Liu, et al., 2019: Factors limiting the forecast skill of the boreal summer intraseasonal oscillation in a subseasonal-to-seasonal model. *Adv. Atmos. Sci.*, 36, 104–118, doi: 10.1007/s00376-018-7242-3.

Hirons, L. C., P. Inness, F. Vitart, et al., 2013: Understanding advances in the simulation of intraseasonal variability in the ECMWF model. Part I: The representation of the MJO. *Quart. J. Roy. Meteor. Soc.*, 139, 1417–1426, doi: 10.1002/qj.2060.

Hirota, N., and M. Takahashi, 2012: A tripolar pattern as an internal mode of the East Asian summer monsoon. *Climate Dyn.*, 39, 2219–2238, doi: 10.1007/s00382-012-1416-y.

Hsu, P.-C., T. Li, L. J. You, et al., 2015: A spatial–temporal projection model for 10–30 day rainfall forecast in South China. *Climate Dyn.*, 44, 1227–1244, doi: 10.1007/s00382-014-2215-4.

Hsu, P.-C., J.-Y. Lee, and K.-J. Ha, 2016: Influence of boreal summer intraseasonal oscillation on rainfall extremes in southern China. *Int. J. Climatol.*, 36, 1403–1412, doi: 10.1002/joc.4433.
Rae, J. G. L., H. T. Hewitt, A. B. Keen, et al., 2015: Development of the global sea ice 6.0 CICE configuration for the Met Office global coupled model. Geosci. Model Dev., 8, 2221–2230, doi: 10.5194/gmd-8-2221-2015.

Rashid, H. A., H. H. Hendon, M. C. Wheeler, et al., 2011: Prediction of the Madden–Julian oscillation with the POAMA dynamical prediction system. Climate Dyn., 36, 649–661, doi: 10.1007/s00382-010-0754-x.

Ren, P. F., H.-L. Ren, J.-X. Fu, et al., 2018: Impact of boreal summer intraseasonal oscillation on rainfall extremes in southeastern China and its predictability in CFSv2. J. Geophys. Res. Atmos., 123, 4423–4442, doi: 10.1029/2017JD028043.

Robertson, A. W., A. Kumar, M. Peña, et al., 2015: Improving and promoting subseasonal to seasonal prediction. Bull. Amer. Meteor. Soc., 96, ES49–ES53, doi: 10.1175/BAMS-D-14-00139.1.

Scaife, A. A., and D. Smith, 2018: A signal-to-noise paradox in climate science. npj Climate Atmos. Sci., 1, 28, doi: 10.1038/s41612-018-0038-4.

Scaife, A. A., M. Athanassiou, M. Andrews, et al., 2014: Predictability of the quasi-biennial oscillation and its northern winter teleconnection on seasonal to decadal timescales. Geophys. Res. Lett., 41, 1752–1758, doi: 10.1002/2013GL059160.

Shi, N., C. Bueh, L. J. Li, et al., 2008: The impact of mid- and high-latitude Rossby wave activities on the medium-range evolution of EAP events in the pre-rainy period of South China. Acta Meteor. Sinica, 66, 1020–1031, doi: 10.11676/qxxb2008.091. (in Chinese)

Takaya, K., and H. Nakamura, 2001: A formulation of a phase-independent wave-activity flux for stationary and migratory quasigeostrophic eddies on a zonally varying basic flow. J. Atmos. Sci., 58, 608–627, doi: 10.1175/1520-0469(2001)058<0608:AFMAF>2.0.CO;2.

Vitart, F., 2017: Madden–Julian Oscillation prediction and teleconnections in the S2S database. Quart. J. Roy. Meteor. Soc., 143, 2210–2220, doi: 10.1002/qj.3079.

Vitart, F., C. Ardidouze, A. Bonet, et al., 2017: The subseasonal to seasonal (S2S) prediction project database. Bull. Amer. Meteor. Soc., 98, 163–175, doi: 10.1175/BAMS-D-16-0017.1.

Wakabayashi, S., and R. Kawamura, 2004: Extraction of major connections in the S2S database. J. Climate, 17, 4531–4543, doi: 10.1175/JCLI-D-13-00624.1.

Nitta, T., and Z.-D. Lin, 2009: Role of subtropical precipitation anomalies in maintaining the summertime meridional teleconnection over the western North Pacific and East Asia. J. Climate, 22, 2058–2072, doi: 10.1175/2008JCLI4444.1.

MacLachlan, C., A. Arribas, K. A. Peterson, et al., 2015: Global Seasonal forecast system version 5 (GloSea5): A high-resolution seasonal forecast system. Quart. J. Roy. Meteor. Soc., 141, 1072–1084, doi: 10.1002/qj.2396.

Wang, L. J., C. Wang, and D. Guo, 2018: Evolution mechanism of EAP high-latitude Rossby wave activities on the medium-range timescales. J. Geophys. Res. Atmos., 123, 1069–1092, doi: 10.1002/2013GL059160.

Wang, B., Y.-Y. Lee, I.-S. Kang, et al., 2009: Advance and prospect of seasonal prediction: Assessment of the APCC/CliPAS 14-model ensemble retrospective seasonal prediction (1980–2004). Climate Dyn., 33, 93–117, doi: 10.1007/s00382-008-0460-0.

Wang, J. B., Z. P. Wen, R. G. Wu, et al., 2016: The mechanism of growth of the low-frequency East Asia–Pacific teleconnection and the triggering role of tropical intraseasonal oscillation. Climate Dyn., 46, 3965–3977, doi: 10.1007/s00382-015-2815-7.

Wang, L. J., C. Wang, and D. Guo, 2018: Evolution mechanism of synoptic-scale EAP teleconnection pattern and its relationship to summer precipitation in China. Atmos. Res., 214, 150–162, doi: 10.1016/j.atmosres.2018.07.023.

Weng, H. Y., A. Sumi, Y. N. Takayabu, et al., 2004: Interannual-
interdecadal variation in large-scale atmospheric circulation and extremely wet and dry summers in China/Japan during 1951–2000. Part I: Spatial patterns. J. Meteor. Soc. Japan Ser. II, 82, 775–788, doi: 10.2151/jmsj.2004.775.

Wheeler, M. C., and H. H. Hendon, 2004: An all-season real-time multivariate MJO index: Development of an index for monitoring and prediction. Mon. Wea. Rev., 132, 1917–1932, doi: 10.1175/1520-0493(2004)132<1917:AARMMI>2.0.CO;2.

Woolnough, S. J., F. Vitart, and M. A. Balmaseda, 2007: The role of the ocean in the Madden–Julian Oscillation: Implications for MJO prediction. Quart. J. Roy. Meteor. Soc., 133, 117–128, doi: 10.1002/qj.4.

Wu, J., and X.-J. Gao, 2013: A gridded daily observation dataset over China region and comparison with the other datasets. Chinese J. Geophys., 56, 1102–1111. (in Chinese)

Wu, J., X. F. Xu, F. F. Jin, et al., 2013: Research of the intraseasonal evolution of the East Asia–Pacific pattern and its maintenance mechanism. Acta Meteor. Sinica, 71, 476–491, doi: 10.11676/qxxb2013.038. (in Chinese)

Wu, J., H.-L. Ren, J. Q. Zuo, et al., 2016a: MJO prediction skill, predictability, and teleconnection impacts in the Beijing Climate Center Atmospheric General Circulation Model. Dyn. Atmos. Oceans, 75, 78–90, doi: 10.1016/j.dynatmoce.2016.06.001.

Wu, J., X.-F. Xu, F.-F. Jin, et al., 2016b: Numerical simulation of the influence of baroclinic basic flow on cyclone perturbation low-frequency development in East Asia summer monsoon areas. Chinese J. Geophys., 59, 1222–1234, doi: 10.6038/cjg20160405. (in Chinese)

Wu, J., H.-L. Ren, X. F. Xu, et al., 2018: Seasonal modulation of MJO’s impact on precipitation in China and its dynamical-statistical downscaling prediction. Meteor. Mon., 44, 737–751. (in Chinese)

Wu, J., H.-L. Ren, B. Lu, et al., 2020: Effects of moisture initialization on MJO and its teleconnection prediction in BCC sub-seasonal coupled model. J. Geophys. Res. Atmos., 125, e2019JD031537, doi: 10.1029/2019JD031537.

Wu, T. W., L. C. Song, W. P. Li, et al., 2014: An overview of BCC climate system model development and application for climate change studies. J. Meteor. Res., 28, 34–56, doi: 10.1007/s13351-014-3070-2.

Yang, Y., Z. W. Zhu, T. Li, et al., 2020: Effects of western Pacific intraseasonal convection on surface air temperature anomalies over North America. Int. J. Climatol., 40, 2913–2923, doi: 10.1002/joc.6373.

Zhu, Z. W., and T. Li, 2017: The statistical extended-range (10–30-day) forecast of summer rainfall anomalies over the entire China. Climate Dyn., 48, 209–224, doi: 10.1007/s00382-016-3070-2.