Predictable Mode of Tropical Intraseasonal Variability in Boreal Summer

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ABSTRACT: This work uses a 19-yr ensemble hindcast of the European Centre for Medium-Range Weather Forecasts (ECMWF) and the average predictable time (APT) method to detect the most predictable tropical intraseasonal variability (ISV) mode. The first and most predictable mode (APT1) of tropical ISV is similar to a joint merger of the two Madden-Julian oscillation (MJO) modes with more weight on the second mode and is characterized by a tripole pattern with two positive centers in the equatorial western Indian Ocean and central Pacific Ocean and a negative center over the Maritime Continent. The APT1 doubles the skillful prediction period made by the MJO defined by a correlation skill of 0.5 (approximately 25 days in the ECMWF model), demonstrating its potential to become a skillful prediction target and to offer powerful subseasonal prediction sources. The underlying physical process and predictability source of the APT1 are further analyzed. The APT1 is very similar to the pattern triggered by the most predictable tropical intraseasonal sea surface temperature (SST) anomalies mode, suggesting its oceanic origin. Tropical ocean-atmosphere interaction plays a critical role in the APT1 by enhancing the evolution of tropical convection cells under WES (wind-evaporation-SST) and Bjerknes feedbacks. The internal atmospheric processes also have an important impact on the formation and maintenance of the APT1.

KEYWORDS: Atmosphere-ocean interaction; Madden-Julian oscillation; Climate prediction; Forecast verification/skill; Intraseasonal variability

1. Introduction

Intraseasonal (subseasonal) prediction has an enormous economic and societal value and significantly impacts climate-sensitive areas in terms of water resources, agriculture, forestry, ecosystems, human health, and so on (e.g., Kim et al. 2018). Intraseasonal prediction has recently attracted widespread attention and been intensively studied. However, seasonal to subseasonal (S2S) prediction is still a very challenging issue due to its complex transient nature between low-frequency seasonal climate prediction and relatively high-frequency weather forecasts, which result from different physical processes. Generally, the former is more related to large-scale, barotropic structures, whereas the latter is often associated with synoptic baroclinic processes.

The source of predictability on an intraseasonal time scale stems from tropical intraseasonal variability (ISV), which is dominantly represented by the Madden-Julian oscillation (MJO) (e.g., Waliser 2011; Zhang et al. 2013). Thus, MJO prediction must be improved to enhance S2S prediction. Several international projects on the MJO, such as the Intraseasonal Variability Hindcast Experiment (ISVHE), the WWRP/WCRP Subseasonal to Seasonal Prediction Project (hereafter S2S Project), and the international field campaign

CINDY/DYNAMO, have significantly improved MJO prediction (e.g., Kim et al. 2018). Now, many operational weather forecasting centers routinely monitor MJO forecasts using the real-time multivariate MJO (RMM) index (e.g., Neena et al. 2014; Wu et al. 2016; Wang et al. 2014; Rashid et al. 2011; Lim et al. 2018). Nonetheless, MJO prediction is far from meeting the actual demands of S2S prediction. Recently, Peng et al. (2020) systematically evaluated MJO prediction skill using a comprehensive ensemble of the S2S project product and showed that the MJO prediction skill for most models is approximately 16–30 days, which is consistent with the literature (e.g., Liu et al. 2017; Rashid et al. 2011; Kim et al. 2014, 2018).

While the MJO is still a critical target toward the improvement in S2S prediction, a more predictable mode for tropical ISV may enable us to extract more predictable signals for better S2S prediction. The more predictable mode also allows us to identify the specific predictable target that has the best actual prediction skill compared to any other modes. This idea is behind the fact that the MJO mode is obtained only by maximizing the intraseasonal variability (variance) rather than predictability. A mode could be identified to maximize ISV predictability and to be used to explore the benefits for improving S2S prediction. We apply the average predictability time (APT), a recently developed predictability analysis method, to the ECMWF ensemble hindcast product to identify the most predictable ISV mode. For simplicity, we only use outgoing longwave radiation (OLR), a good indicator of large-scale deep convection, to represent tropical ISV. Emphasis is placed on the boreal summer season because of the critical importance of summer precipitation

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for Asian countries (e.g., [Hu et al. 2005](#)) and the relatively low MJO prediction skill in this season (e.g., [Wang et al. 2014](#); [Liu et al. 2017](#); [Peng et al. 2020](#)).

This paper is organized as follows. The data, APT method, and predictability assessment metrics are briefly introduced in [section 2](#). [Section 3](#) assesses the actual prediction skill of the tropical intraseasonal OLR. [Section 4](#) presents the most predictable tropical ISV mode and a discussion on its underlying mechanism. A summary and discussion are finalized in [section 5](#).

2. Data and methods

a. Data

In this study, we use the ECMWF OLR and sea surface temperature (SST) ensemble hindcasts from the S2S project database ([Vitart et al. 2017](#)). All data are interpolated with a 2.5° by 2.5° resolution. The ensemble hindcast begins on the first day of every week from January 2000 to December 2018 with an ensemble size of 10. Each hindcast lasts 46 days. Only hindcast data with target months in June, July, and August (JJA), that is, initial conditions in May, June, and July, are analyzed.

The atmospheric observation dataset, using ERA-Interim reanalysis data ([Dee et al. 2011](#)) between September 1999 and December 2018, includes daily OLR, zonal wind at 850 hPa (U850) and 200 hPa (U200), surface latent heat, and surface shortwave radiation. The daily SST from Optimum Interpolation SST version 2 ([Reynolds et al. 2002](#)) is used as the observed SST.

All the data, including the hindcast and reanalysis data, are from 0° – 360° longitude and 15°S – 15°N latitude.

b. Extraction of intraseasonal variability

All analyses are conducted on an intraseasonal scale, and intraseasonal variability extraction is performed based on the methodology described in [Wheeler and Hendon \(2004\)](#), except that instead of using the averaged field between 15°S and 15°N , we use the two-dimension spatial field. The following steps were used to process the variable $\mathbf{V}$:

- 1) Calculate the $\mathbf{V}$ anomalies by removing the daily climatology and first three harmonics of the annual cycle based on the 2000–18 period to remove the seasonal cycle influence.
- 2) Subtract the mean from the most recent 120 days to remove low-frequency variability. For reanalysis data, the most recent 120-day mean ahead of (and including) each day is easily subtracted owing to the integrality and sufficient length of the data time. However, for the hindcast at each initial time, only 46-day forecasts are available. Thus, reanalysis data on the corresponding days substitute the required data. For instance, for the hindcast initialized on 3 January 2000 at lead time 0, the data from the most recent 120 days include reanalysis data from 4 September 1999 to 2 January 2000 and the hindcast on 3 January 2000. For the hindcast at lead time 10, the data used to calculate the 120-day mean include reanalysis data from 14 September 1999 to 2 January 2000 and the hindcast from 3 to 13 January 2000.

After data preprocessing, the time period used in the below analysis is from January 2000 to December 2018. The RMM index is

calculated for validation, which is obtained by applying the multivariate empirical orthogonal function (MEOF) analysis onto combined intraseasonal OLR, U850, and U200 data. Conventionally, the principal components (PCs) of the first two leading MEOF modes (RMM1 and RMM2) are used to measure the MJO signal. The hindcasted RMM indices are obtained by projecting the OLR hindcasts on the OLR component of the MEOF mode derived from the observed OLR, U850, and U200 data as mentioned above. We also use the single variable EOF of observed OLR for this projection, and get lower prediction skill than the former. We choose the RMM indices that result in higher predication skill because we wish to put a higher comparison standard for the APT1, ensuring its comparison against MJO to be fairer.

For convenience, all variables used below refer to the extracted intraseasonal variability unless otherwise specified.

c. APT method

The average predictability time (APT), proposed by [Delsole and Tippett \(2009\)](#), is the method used to extract the most predictable mode. The signal-to-total variance ratio is widely used to measure potential predictability (e.g., [Tang et al. 2008a,b](#); [Kumar and Hu 2014](#)) and is related to APT ([Jia et al. 2015](#)). For an ensemble prediction, the variance of the ensemble mean denotes the signal, and the ensemble spread over all predictions measures the noise uncertainty. The total variance, the sum of the signal and noise variance, is often referred to as the climatology variance. APT is defined as follows:

$$\text{APT} = 2 \sum_{t=1}^{\infty} \frac{\sigma_{\text{sig}}^2(t)}{\sigma_{\text{total}}^2}, \quad (1)$$

where $\sigma_{\text{sig}}^2(t)$ is the variance of the signal at lead time t , and σ_{total}^2 is the total variance.

This method looks for a projected vector $\mathbf{q}$ that optimizes APT. In the projected space, Eq. (1) is

$$\text{APT} = 2 \sum_{t=1}^{\infty} \frac{\mathbf{q}^T \mathbf{\Sigma}_{\text{sig}}(t) \mathbf{q}}{\mathbf{q}^T \mathbf{\Sigma}_{\text{total}} \mathbf{q}}, \quad (2)$$

where $\mathbf{\Sigma}_{\text{sig}}(t)$ is the covariance matrix of the signal variance at lead time t , and $\mathbf{\Sigma}_{\text{total}}$ is the covariance matrix of the total variance.

According to the Rayleigh quotient theorem, the vectors that optimize Eq. (2) are given by the eigenvectors of the generalized eigenvalue problem:

$$2 \sum_{t=1}^{\infty} \mathbf{\Sigma}_{\text{sig}}(t) \mathbf{q} = \lambda \mathbf{\Sigma}_{\text{total}} \mathbf{q}. \quad (3)$$

The eigenvalue λ measures the APT predictability associated with the corresponding eigenvector. Eigenvectors are conventionally ordered by descending eigenvalues, so that the first eigenvector maximizes APT, and the second maximizes the APT besides the first one, and so on. The eigenvectors are uncorrelated. This decomposition of APT is analogous to the empirical orthogonal function (EOF) analysis but decomposes predictability instead of variance.

The above calculation gives the projected vector $\mathbf{q}$. The corresponding predictable components can be obtained by

FIG. 1. Anomaly correlation coefficients (ACCs) between the observations and predictions of tropical intra-seasonal OLR in the ECMWF ensemble prediction model using all initial conditions for targeted JJA months between January 2000 and December 2018. The dotted ACCs refer to those at the 95% significance level. The 0.5 contour is highlighted with thick black lines.

$\mathbf{q}^T \mathbf{x}$, where $\mathbf{x}$ is the original data. And the spatial pattern associated with each component can be obtained by projecting the time series $\mathbf{q}^T \mathbf{x}$ onto the original data $\mathbf{x}$.

In practice, we perform the APT in a PC-reduced space to avoid the computation of a singular matrix produced by spatial points much larger than the sample numbers. The first 90 PCs are used, but the results are not very sensitive to the number of PCs. We choose all hindcasts with lead time up to 40 days for the APT calculation. The sensitivity experiment shows that the results remain robust after the lead time beyond 40 days.

d. Predictability assessment metrics

1) ACTUAL PREDICTION SKILL

The actual prediction skill of APT1, RMM1, and RMM2 is measured by the anomaly correlation coefficient (ACC) and root mean square error (RMSE) and defined as follows:

$$\text{ACC}(\tau) = \frac{\sum_{t=1}^N [O(t)M(t, \tau)]}{\sqrt{\sum_{t=1}^N O^2(t)} \sqrt{\sum_{t=1}^N M^2(t, \tau)}}, \quad (4)$$

$$\text{RMSE}(\tau) = \sqrt{\frac{1}{N} \sum_{t=1}^N [O^2(t) + M^2(t, \tau)]}, \quad (5)$$

where N is the total number of initial conditions, $O(t)$ is the observed value at initial time t , and $M(t, \tau)$ is the prediction at initial time t and lead time τ .

We use the bivariate anomaly correlation coefficient (BACC) and bivariate anomaly root-mean-square error (BRMSE) to examine the actual prediction skill of the MJO, which is widely

adopted for MJO prediction skill evaluation (e.g., Lin et al. 2008; Rashid et al. 2011; Kim et al. 2014):

$$\begin{aligned} \text{BACC}(\tau) &= \frac{\sum_{t=1}^N [O1(t)M1(t, \tau) + O2(t)M2(t, \tau)]}{\sqrt{\sum_{t=1}^N [O1^2(t) + O2^2(t)]} \sqrt{\sum_{t=1}^N [M1^2(t, \tau) + M2^2(t, \tau)]}}, \end{aligned} \quad (6)$$

BRMSE(τ)

$$= \sqrt{\frac{1}{N} \sum_{t=1}^N \{[O1(t) - O2(t)]^2 + [M1(t, \tau) - M2(t, \tau)]^2\}}, \quad (7)$$

where $O1(t)$ and $O2(t)$ are the observed RMM1 and RMM2 at initial time t , and $M1(t, \tau)$ and $M2(t, \tau)$ are the respective prediction at initial time t and lead time τ .

2) POTENTIAL PREDICTABILITY

The signal-to-total variance ratio (STR) is used to obtain the potential predictability of APT1, RMM1, and RMM2 and is a common measure of potential predictability (e.g., Tang et al. 2008a,b; Kumar and Hu 2014):

$$\text{STR} = \frac{\sigma_{\text{sig}}^2}{\sigma_{\text{total}}^2}. \quad (8)$$

The square root of STR is equivalent to the correlation of the signal component to the targeted prediction and is actually a

FIG. 2. Signal variance at lead times of 10, 20, 30, and 40 days.

perfect correlation skill that assumes that the observation is an arbitrary ensemble member (e.g., [Tang et al. 2014](#)).

3. Actual prediction skill of intraseasonal OLR in the boreal summer

First, we examine the actual prediction skill of tropical intraseasonal OLR in the boreal summer. [Figure 1](#) shows the

spatial distribution of ACCs at lead times of 10, 20, 30, and 40 days. High prediction skill is distributed in the western Indian Ocean (IO), the Maritime Continent (MC), the central and northeastern Pacific Ocean (PO), and the equatorial Atlantic Ocean (AO).

We present the signal variance, noise variance, and the signal-to-total variance ratio (STR) for different lead times in [Figs. 2, 3, and 4](#), respectively, to shed light on actual

FIG. 3. Ratio of noise to total variance at lead times of 10, 20, 30, and 40 days.

FIG. 4. Ratio of signal to total variance at lead times of 10, 20, 30, and 40 days.

prediction skill distribution. Figure 2 shows a large signal variance in the eastern IO, MC, central PO, and south of the equatorial eastern PO; however, STR is small in these regions except in the MC and central PO (Fig. 4), which is consistent with the large noise there (Fig. 3). The low potential predictability (i.e., STR) is also consistent with the low actual prediction skill over these regions presented in Fig. 1. Relatively high STR in low-signal areas such as the western IO, northeastern PO, and equatorial AO (Fig. 4) is due to low noise in these areas (Fig. 3). These results indicate that noise strength is more important than signal in determining the tropical intraseasonal OLR predictability for most regions except over the MC and the equatorial central PO where the signal plays an equivalent role.

4. Most predictable mode of tropical intraseasonal convection in the boreal summer

a. Leading APT mode

Figure 5a shows the leading APT mode (APT1) of tropical OLR. Apparently, the predictability is not spatially uniform in tropical regions, and the three large predictability centers are located in the IO, MC, and equatorial central Pacific Ocean (ECPO); the much stronger centers in the latter two form a dipole pattern.

We investigate the relationship of the MJO (the dominant tropical mode on an intraseasonal scale) and APT1. Figure 5b shows the first two leading MEOF modes. Two poles in the IO and western PO exist in the leading MEOF mode, and the MC regions show broad, large values in the second MEOF mode.

Thus, APT1 is a joint merger of the two MJO modes with much more weight on the second mode.

We conduct a diagnosis analysis to explore the underlying physical process of the APT1 mode. Considering possible factors affecting tropical OLR we select SST, surface latent heat flux, shortwave radiation, and zonal wind at 850 and 200 hPa. Surface sensible heat flux and longwave radiation are ignored, because their magnitude is approximately one order smaller than that of surface latent heat flux and shortwave radiation (Maloney 2009; Li et al. 2020).

Figure 6a is the regression of the APT1 time series onto OLR and closely resembles Fig. 5a; large negative OLR over the MC is associated with active convection, and positive OLR over the western IO and equatorial PO (especially large in the ECPO) are due to suppressed convection. In the SST regression map, three large loading regions are almost consistent with those in APT1 mode but have opposite signs, that is, positive values over the MC and western PO and negative values in the equatorial IO (EIO) and the equatorial central and eastern PO (ECEPO; Fig. 6b). Warming summer SST over the MC and western PO promotes tropical convection and decreases OLR. Surface convergence induces vertical ascending motion and divergence aloft, enhancing the Walker cells associated with convective activity. Consequently, westerly zonal wind anomalies throughout the EIO and the easterly zonal wind anomalies across the equatorial PO are found at lower levels (850 hPa) (Fig. 6c); the opposite is true at upper levels (200 hPa) (Fig. 6f). Two areas (parts of the aforementioned cells) of relatively cooling SST in the EIO and ECEPO are associated with descending motion, clear skies, and depressed convection, as indicated by positive shortwave radiation

FIG. 5. (a) The most predictable mode of intraseasonal OLR. (b) Two leading MEOF modes of intraseasonal OLR in JJA.

(Fig. 6d). Such cells offer positive feedbacks to further strengthen convection activity over the MC. On the one hand, wind anomalies enhance evaporation and cool the SST in the EIO and ECEPO (e.g., McPhaden and Foltz 2013), further decreasing latent heat (Fig. 6c) and forming the wind–evaporation–SST positive feedback. On the other hand, equatorial wind anomalies tilt the thermocline, which deepens along the MC and shallows in the EIO and ECEPO to cause surface warming along the MC and western PO and cooling in the EIO and ECEPO by upwelling. This is a typical Bjerknes

feedback. Thus, the APT1 pattern is a good representation of the physical process responsible for the evolution of tropical convection activity from the eastern IO to the western PO. Active convection over the MC offers strong signals, and depressed convection over the EIO and ECEPO decreases the noise level; both contribute to the highly predictable components in these areas, as shown in APT1.

Thus, the APT1 predictability source has an oceanic origin that is inherent to a specific SST pattern (Fig. 6b). We calculate the most predictable mode for the tropical SST using the

FIG. 6. Regression patterns of the observed (a) OLR (W m^{-2}), (b) SST ($^{\circ}\text{C}$; lead APT1 5 days), (c) surface latent heat flux (W m^{-2}), (d) shortwave radiation (W m^{-2}), (e) zonal wind at 850 hPa (m s^{-1}), and (f) zonal wind at 200 hPa (m s^{-1}) onto the observed APT1 time series. The black dots indicate significance at the 95% confidence level.

FIG. 7. (a) APT1 mode of tropical intraseasonal SST and (b) the regression pattern of the observed OLR (W m^{-2}) on the APT1 mode of SST.

ensemble dataset (Fig. 7a). The most predictable SST mode almost resembles the oceanic regression pattern of the APT1 of OLR characterized by a tripole structure with strong cooling in the ECEPO and a weak dipole between the MC and EIO as shown in Fig. 6b. Figure 7b is the regression map of the APT1 of SST onto observed OLR and shows a pattern almost identical to that of the APT1 of OLR (Fig. 5a) with a spatial correlation coefficient 0.81. This further confirms that the most predictable SST and the most predictable component of tropical convection activity are related closely by the air–sea interaction.

b. APT1 predictability

Figure 8 presents the observed APT1 time series, observed RMM1 and RMM2 indices, and predicted APT1 time series at a lead time of 1 day. The observed APT1 time series are obtained by projecting observed OLR onto the APT1 mode (Fig. 5a). A significant correlation of 0.64 between observed APT1 and RMM2 is found; there is no significant correlation between observed APT1 and RMM1.

A practical application of APT analysis is to extract the potential predictable target (i.e., APT1) to produce the best actual prediction skill. For validation, we evaluated the actual prediction skill measured by predicted APT1 and the observed counterpart (Fig. 9a). For comparison, the MJO prediction skills, measured by RMM1, RMM2, and the bivariate index, are also presented. If ACC of 0.5 is defined as a threshold of

skillful prediction, the prediction skill of APT1 mode is more than 46 lead days, significantly higher than all MJO indices, which range from 22 to 25 days. Additionally, RMSE is correspondingly reduced (Fig. 9b).

Figure 9c shows the potential predictability of the APT1 mode and the MJO. Here, the potential predictability is measured using perfect correlation, which is equivalent to the square root of the ratio of signal variance to total variance. Compared to the RMM1 and RMM2 results, APT1 improves significantly for lead times after 6 days. The APT1 potential predictability is approximately 0.2 higher than that of MJO at lead times greater than 15 days. All these results indicate that APT1 is better than MJO RMM indices not only for actual prediction skill but also for potential predictability.

To shed some light on the result that the APT1 is much more predictable than MJO RMM indices, we conducted the spectrum analysis (Zangvil 1977) for both the OLR APT1 and RMM on the observational space, which is presented in Fig. 10. The magnitude of RMM indices (i.e., the square root of the sum of RMM1 squared and RMM2 squared) is used as the RMM, which is a general forecast index used by many operational weather forecast centers (e.g., Neena et al. 2014; Wu et al. 2016; Lim et al. 2018). The results show that the OLR APT1 has strong spectra on the intraseasonal and interannual scales whereas the RMM only has statistically significant spectra on the intraseasonal scale. These significant variabilities are highly incorporated with their oceanic counterparts at the same time scales as shown in the following discussions. In

FIG. 8. Time series of the observed APT1 mode (blue), RMM1 (green), and RMM2 (black), and the predicted APT1 mode at a lead time of 1 day (red).

FIG. 9. (a) ACCs and (b) RMSEs of APT1 and RMM indices in JJA. (c) Potential predictability of APT1 and RMM indices in JJA.

particular, the RMM spectra are much divergent on the intra-seasonal scale, peaking in various frequencies from 4 days to 3 weeks. In contrast, the OLR APT1 converges the energy on narrower scales, with significant peaks at 1 week, 2 weeks, and 3 years. A more convergent signal should be more predictable, suggesting that the APT1 is more predictable probably due to not only spatial pattern as discussed in the context, but also some intrinsic properties in its temporal variation. These spatial-temporal features of APT1, which are in fact an integral of predictable component of tropical convection extracted by the APT method, render the APT1 more predictable than the RMM.

FIG. 10. Spectra of the observed OLR (a) APT1 and (b) RMM. The x axis is the frequency, and the y axis is the power multiplied by the corresponding frequency. The area under the power curve in any frequency band is equal to variance.

c. Relationship between the APT1 mode and the MJO

To explore the relationship between the APT1 mode and MJO modes, we conduct a regression analysis similar to Fig. 6 but use both MEOF1 and MEOF2 modes instead of the APT1 mode. The MEOF2 regression is shown in Fig. 11, which is similar to Fig. 6 in structure, with certain differences in the loading magnitude of some variables. As in Fig. 6b, the SST in Fig. 11b is closely connected with the MEOF2 mode but has a

FIG. 11. As in Fig. 6, but with the MEOF2 mode regression.

FIG. 12. As in Fig. 6, but with the MEOF1 mode regression.

relatively smaller magnitude than the APT1 regression in Fig. 6b. The loading magnitudes of atmospheric variables, especially zonal winds, are relatively larger, probably because the MEOF analysis contains winds. The ECEPO positive shortwave radiation is much smaller than that in the APT1 regression (Fig. 6d), suggesting relatively poor capability of MEOF2 in capturing internal atmospheric process in ECEPO.

Figure 12 shows the regression results of all variables related to the MEOF1 mode. The OLR has large loadings in the IO and western PO (Fig. 12a). The large latent heat flux value in the western PO provides energy for strong, active convection (Fig. 12c), probably caused by evaporation from strong zonal winds (Figs. 12e,f). However, unlike APT1 and MEOF2, SST plays a minimal role in the MEOF1 regression—as indicated by tiny regression coefficients—suggesting that the MEOF1 mode might be affected by the large-scale structure of the internal atmospheric dynamics rather than ocean–atmosphere interaction. This may explain why MEOF1 is less predictable than MEOF2 (Fig. 9). The different roles of SST in the two MJO modes may also explain the paradoxical conclusions obtained

from previous studies concerning how the ocean affects MJO (e.g., Fu et al. 2015; Shelly et al. 2014; Kim and Kang 2008), namely that the importance of the ocean may change with different phases of the MJO.

Figure 13 shows the lead–lag correlation of the APT1 of tropical SST against the APT1 of OLR, RMM1, and RMM2, respectively. It displays that the OLR APT1 has much higher correlation with SST APT1 than MJO indices, suggesting the better capability of OLR APT1 in describing the large-scale air–sea coupled relationship than MJO indices. To explore the role of SST, we perform spectrum analysis. Figure 14a shows the spectra of SST APT1, displaying two significant peaks on intraseasonal and interannual scales, both of which probably contribute predictable signals to OLR APT1. For a further understanding of their relationship, we conduct cross-spectrum analysis. Shown in Fig. 14b is the magnitude squared coherence of SST APT1 against OLR APT1 and RMM, respectively, clearly showing the strong coherent interaction between SST and OLR at the two frequency bands. One significant feature in Fig. 14b is that the coherence of SST APT1 and OLR APT1

FIG. 13. Lag correlations between the time series of the APT1 of SST against the APT1 of OLR (blue), RMM1 (red), and RMM2 (green). Negative values mean that the APT1 of SST leads the other variable.

FIG. 14. (a) As in Fig. 10, but for the SST APT1. (b) Magnitude squared coherence of SST APT1 against the RMM (blue) and OLR APT1 (orange), respectively. The black dashed line is the 95% significant value.

is much larger than that of SST APT1 and RMM on both frequency bands. This may explain why the OLR APT1 is more predictable than MJO indices.

We also conduct similar analysis for the SST in the IO and PO separately and obtain similar results except that the Pacific SST APT1 has the maximum correlation at zero lag but the Indian SST APT1 has the maximum correlation at lead time of 5–7 days or so (not shown). This suggests a possible interaction process between Indian SST, Pacific SST, and the OLR, namely that, a strong coupling between SST anomaly and the deep convection occurs in the warming pool of PO as shown in the APT1 spatial pattern (Fig. 5a), resulting in their good simultaneous correlation and also strengthening the Walker cell there. The strengthened Walker cell results in strong vertical motion over MC and IO and causes the surface wind anomalies

over the tropical eastern Indian Ocean, which in turn changes the SST there by horizontal advection and vertical mixing.

5. Summary and discussion

In this study, we apply the APT method to the summer OLR ensemble hindcast of the ECMWF model in the S2S project database to investigate the predictability of tropical intraseasonal variability and to extract the most predictable mode. The results show that the most predictable mode has a tripole pattern that is centered on the IO, MC, and ECPO, with a much stronger dipole structure forming in the latter two areas. Figure 15 (a sketch diagram of the physical process) demonstrates that the most predictable mode stems from the tropical interaction between the ocean and atmosphere during the evolution of tropical convection cells. The greatest summer SST warming is in the MC, where warm water and land surface cause lower-level convergence and upper-level divergence that favor deep convection development. Divergence aloft spreads outward air parcels, causing descending motion and suppression of convection by cooling in the central and eastern PO and the western IO. Convection cell evolution is further enhanced by wind–evaporation–SST and Bjerknes positive feedbacks. Consequently, strong convection signals over the MC and stable depressed convection (relatively small noise) in the central PO and western IO offer relatively high predictability in these areas.

A potential practical application of APT1 is to be used as a skillful prediction target. A comparison of actual and potential prediction skill among APT1 and MJO indices reveals the advantages of the former, as APT1 doubles the skillful prediction period of MJO defined by a correlation skill of 0.5 for approximately 25 days in the ECMWF model. The APT1 better characterizes the dominant physical process responsible for the evolution of tropical convection from the IO to the PO. Although the first MJO mode addresses the role of internal atmospheric dynamics and the second mode emphasizes the importance of air–sea interaction, the APT1 mode combines and describes the mutual contributions in the framework of signal-to-noise analysis and places more weight on the second MJO mode. Further analysis shows excellent coherence between APT1 and the most predictable tropical SST mode, indicating that the source of APT1 predictability is oceanic.

FIG. 15. Sketch of the predictability source processes of the APT1 of OLR.

Additionally, APT1 is more likely related to the second MJO mode, suggesting the critical role of the ocean as a source of MJO predictability.

The filtering technique in this study uses a 120-day running mean, which is a widely used strategy in the subseasonal prediction community, because alternative processing techniques for S2S prediction with a bandpass filter are impractical and intractable. However, caution should be exercised, because the 120-day running mean technique could leak energy and contain interannual variability signals. In this study, we also use a bandpass filter of 20–60 days to extract intraseasonal signals for the regression analysis. The amplitudes apparently decrease (not shown), suggesting that the high contribution of SST to APT1 contains interannual components.

To validate if the reported results are model dependent, we perform a similar analysis using ensemble hindcasts of CNRM (Météo-France/Centre National de Recherche Météorologiques), UKMO (the United Kingdom Met Office), and NCEP (U.S. National Centers for Environmental Prediction) in the S2S database and find that the APT1 modes driven from these hindcasts are very similar to that of Fig. 4a; thus, APT1 is very general and governed by inherent physical and dynamical processes, as discussed in this paper.

The MJO plays a fundamental role in S2S prediction and is the subseasonal predictability source at middle latitudes. This work proposes an MJO-like intraseasonal mode, which is more predictable than MJO. APT1 is expected to offer an improved source for S2S prediction at middle latitudes and to improve subseasonal midlatitude climate prediction.

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Data availability statement. This publication is supported by multiple datasets, which are openly available at locations cited in the reference section.

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