



A Process-Based Evaluation Metric for the Pacific–Japan Pattern (PJEM) and its Influence on Asian Summer Extreme

El Noh¹, Sang-Yoon Jun², Sang-Wook Yeh³, Yu Kosaka⁴, Joowan Kim^{1,5,*}

¹Earth Environment Research Center, Kongju National University, Gongju, 32588, South Korea

5 ²Korea Polar Research Institute, Incheon, 21990, South Korea

³Department of Marine Sciences and Convergent Technology, Hanyang University, Ansan, 15588, South Korea

⁴Research Center for Advanced Science and Technology, University of Tokyo, Tokyo, 153-8904, Japan

⁵Department of Atmospheric Sciences, Kongju National University, Gongju, 32588, South Korea

10 *Correspondence to:* Joowan Kim (joowan.k@gmail.com)

Abstract. The Pacific–Japan (PJ) pattern is the dominant teleconnection over the western North Pacific in boreal summer and exerts substantial control on East Asian temperature, precipitation, and marine heat extremes. Despite its importance, the PJ pattern is simulated with large inter-model spread in current climate models, and a systematic, process-based framework for its evaluation has been lacking. Here, we propose the PJ pattern as a process-based evaluation metric for East Asian
15 summer weather and climate simulations. The framework decomposes the PJ into four physically meaningful components — horizontal circulation structure, physical source, wave properties, and weather impacts — that together form a coherent chain of causality from tropical forcing to regional climate response. We apply the framework to 23 CMIP6 historical simulations using a common basis function method that enables consistent inter-model comparison against ERA5. The CMIP6 models generally reproduce the spatial structure of the PJ with high pattern correlations (> 0.8), but exhibit a remarkably wide
20 spread in amplitude (25–170 % of observations). This spread is explained by a coherent physical chain: convective and moisture variability over the subtropical western Pacific drives the wave source, which is transmitted to mid-latitudes via the meridional wave activity flux, and ultimately translates into downstream temperature, precipitation, and SST responses over East Asia. The proposed framework, summarized in a single hexagonal diagram, is reproducible and modular, and offers an efficient, physically interpretable diagnostic for assessing East Asian climate simulation capability in current and future
25 model generations.

1 Introduction

Observations have revealed increasing frequency and intensity of climate extremes in many regions with global warming (IPCC, 2023). In particular, East Asia, where summer extremes are active, is becoming increasingly vulnerable to heatwaves and heavy precipitation events (e.g., Perkins et al., 2012). Recent studies indicate that these extreme events are multi-scale
30 phenomena, and interactions between synoptic and predominating regional low-frequency systems play an important role in developing summer extremes (Lee and Lee, 2016). Thus, detailed characterizations of the regional low-frequency systems



and their roles in weather extremes are essential for understanding and projecting future regional extremes (Song et al., 2018).

East Asia is located on the western boundary of the North Pacific Subtropical High (NPSH), which is a predominant summertime background circulation in this region (e.g., Guan et al., 2019; Song et al., 2018). The NPSH plays a crucial role in shaping the prevailing southwesterly over East Asia, facilitating subtropical–midlatitude interaction in this region. It also significantly affects climate extremes over East Asia, particularly in boreal summer (e.g., Wang et al., 2009; Zhou et al., 2022). Numerous studies have highlighted distinct regional impacts on weather and climate extremes associated with the westward expansion of the NPSH (Wang et al., 2009; Choi and Kim, 2019; Noh et al., 2021; Tseng et al., 2023). Furthermore, many studies have examined the influences of organized convection around the NPSH on East Asian weather and climate (Kosaka and Nakamura, 2006; Nitta, 1987; Noh et al., 2021, 2023; Yeo et al., 2019), because organized convection generates Rossby waves (Hoskins and Karoly, 1981; Sardeshmukh and Hoskins, 1988) that influence weather patterns over East Asia along the western boundary of the NPSH (Sohn et al., 2001; Yihui and Chan, 2005).

The overall features are summarized in Fig. 1. The NPSH is a persistent planetary-scale system over the western North Pacific (Fig. 1a). Organized convection is well identified over the western Pacific and Bay of Bengal (Fig. 1b; blue shading) through the averaged minimum outgoing longwave radiation (OLR), while its day-to-day variability is largest over the subtropical western North Pacific (red contour). This implies that the subtropical western North Pacific is a significant atmospheric Rossby wave source, as demonstrated by the wave activity flux in Fig. 1c. These Rossby waves often propagate to the midlatitudes along the western boundary of the NPSH (Fig. 1c; Nitta, 1987; Yeo et al., 2019) and play a crucial role in East Asian weather and climate extremes (Kosaka et al., 2012; Kosaka and Nakamura, 2010; Noh et al., 2021, 2023).

Originally, Nitta (1987) proposed this as the Pacific–Japan (PJ) pattern in order to highlight its meridional propagation and regional impact on Japan. In fact, the PJ pattern has broader influences over East Asia, significantly modulating the summer monsoon and weather conditions on intraseasonal and interannual timescales (Gao et al., 2016; Huang et al., 2024; Kim et al., 2012; Kosaka et al., 2013; Kubota et al., 2016; Kwon et al., 2024). Previous studies have primarily focused on the effect of the PJ pattern on extreme heat waves in East Asia (Lee and Lee, 2016; Noh et al., 2021). Additionally, other studies reported that the opposite phase of the PJ can also enhance frontal-type (baiu/mei-yu frontal) rainfall in East Asia (Gao et al., 2016; He et al., 2018). The state of the PJ pattern likely provides essential information for understanding the weather and climate extremes in East Asia on both intraseasonal and interannual scales.

However, predicting the PJ pattern remains a significant challenge because it is affected by several coupled atmosphere–ocean processes. Kosaka et al. (2013) discussed the complexities involved in the prediction, emphasizing the role of coupled Pacific–Japan and Indian Ocean basin modes. Xie et al. (2009, 2016) suggested that predictability of the PJ is also affected by the coupling process with the previous winter El Niño–Southern Oscillation (ENSO). For interannual prediction, several studies have evaluated the performance of PJ simulations using various climate models and reported that the PJ pattern could be roughly captured by several climate models, but with significantly large inter-model spread (e.g., Kosaka and Nakamura, 2011; Gong et al., 2018). Intraseasonal prediction of the PJ is also being tested by operational weather prediction agencies



due to its importance in weather forecasts, while its prediction skill is still limited at intraseasonal timescales, partly due to uncertainties in western Pacific convection. Because the PJ drives summer extremes over East Asia on intraseasonal timescales, a poor simulation of the PJ limits the prediction of these extremes.

Previous studies have focused on understanding the physical structures and potential impact of the PJ pattern. The forecast skill of the PJ in numerical models has been insufficiently reported despite its necessity. Particularly, the simulated physical processes involved in the PJ pattern (convection, wave propagation, and regional impacts) require systematic analysis. In this context, we propose a process-based evaluation framework for the simulated PJ in numerical models (both weather and climate models). This framework encompasses four key metrics that are essential for adequate PJ representation: (1) spatial structures of the atmospheric circulation, (2) convection as a physical source, (3) wave properties including both source and propagation, and (4) weather impacts over East Asia. In addition, we evaluate the PJ in climate models participating in the Coupled Model Intercomparison Project Phase 6 (CMIP6) as an example.

This study is organized as follows. Sect. 2 describes the data, PJ definition, and the common basis function (CBF) methodology used for model evaluation. Sect. 3 presents the process-based evaluation metrics and assesses how well the physical aspects of the PJ are simulated across models. Sect. 4 provides a summary and discussion on the implications.

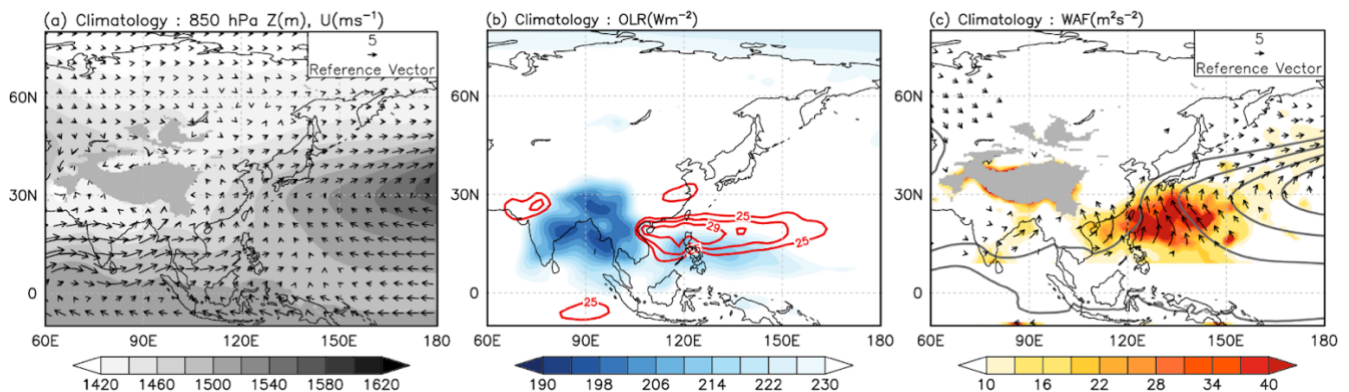


Figure 1. Climatology (1959–2014) of the July–August mean: (a) 850 hPa geopotential height (shading, m) and horizontal wind patterns (vector, m s⁻¹); (b) outgoing longwave radiation (shading, W m⁻²), with the OLR standard deviation (red contour above 25 W m⁻² with +2 interval); and (c) 850 hPa TN wave activity flux (vector, m² s⁻²) and its standard deviation (shading, m² s⁻²), with geopotential height (contour, m).

2 Data and methods

2.1 Data

The primary dataset used for the metrics is the 6-hourly European Centre for Medium-Range Weather Forecasts Reanalysis version 5 (ERA5; Hersbach et al., 2020). We use data for the 1959–2014 period, which matches the majority of



the CMIP6 historical runs. ERA5 was regridded to a $1.5^\circ \times 1.5^\circ$ resolution. We selected all available models from the CMIP6 historical simulations (Supplementary Table S1), and only one initial ensemble member (r1i1p1f1) is used for the evaluation. Historical simulations of CMIP6 were forced by natural solar and volcanic variations as well as anthropogenic radiative forcing (Taylor et al., 2012). The model output data were also regridded to $1.5^\circ \times 1.5^\circ$ (as in ERA5) to compare the model simulations with observations. The variables used in this study are summarized in Supplementary Table S1.

2.2 Analysis method

The reference PJ pattern was defined in ERA5 using empirical orthogonal function (EOF) analysis of the 850 hPa relative vorticity field (Kosaka et al., 2012; Kosaka and Nakamura, 2010). The region for the EOF analysis was confined to East Asia (0° – 60° N, 110° – 160° E; box in Fig. 2a) to avoid discontinuities in model data near the Tibetan Plateau. The PJ pattern was identified by the first principal component (PC) of the EOF analysis, and the PJ index is computed by projecting the vorticity data onto the PC.

The PJ pattern is calculated separately for intraseasonal and interannual timescales using daily and monthly data, respectively, to better capture the observed variability. The derived patterns are highly similar. For the PJ pattern on the intraseasonal timescale, a 10-day running average was used to remove high-frequency variability. All anomaly fields were computed by removing the daily climatology defined for the period 1959–2014.

We used the common basis function (CBF) method (Lee et al., 2019) to evaluate model performance across CMIP6 simulations. Since individual models often exhibit different EOF patterns compared to observations, direct comparison of climate patterns can be unrealistic (Gong et al., 2018; Kosaka and Nakamura, 2011; Lee et al., 2019). The CBF method addresses this issue by projecting model variability onto the observed (reference) EOF patterns, enabling consistent inter-model comparisons (Lee et al., 2019). This approach has been successfully applied in studies examining both intraseasonal (Sperber and Annamalai, 2008; Sperber et al., 2005) and interannual variability (Bonfils et al., 2015; Lee et al., 2019). Detailed steps of the CBF method are summarized in the Appendix A, and the analysis code is made available on GitHub (https://github.com/noel-dyn/PJEM_v1.0).

2.3 Wave activity flux

To diagnose the northward propagation of Rossby wave energy associated with the PJ pattern, we use the meridional component of the wave activity flux (F_y) based on Takaya and Nakamura (2001). F_y is derived from the perturbation stream function (ψ') and the horizontal background wind (U, V), and is expressed as

$$F_y = \frac{p}{2|U|} \left[U \left(\frac{\partial \psi'}{\partial x} \frac{\partial \psi'}{\partial y} - \psi' \frac{\partial^2 \psi'}{\partial x \partial y} \right) + V \left(\left(\frac{\partial \psi'}{\partial y} \right)^2 - \psi' \frac{\partial^2 \psi'}{\partial y^2} \right) \right]$$



where p is the pressure normalized by 1000 hPa, and $|U|$ is the magnitude of the background wind. F_y quantifies how strongly the wave energy is transported northward, and is used in this study to evaluate the wave propagation component of the framework (Sect. 3.2.3).

3 Results

3.1 The key components of the PJ

To establish a process-based evaluation framework, we first summarize the key physical components and downstream impacts of the PJ in observation data. Figure 2 illustrates the primary atmospheric features associated with the negative phase of the PJ pattern, derived from regression against the $-PJ$ index. We choose the negative phase as its physical understanding is more straightforward, while the signals are exactly opposite for the positive phase except for the wave activity flux. The horizontal structure of the PJ is manifested in the 850 hPa geopotential and relative vorticity fields (Fig. 2a), which show a distinct meridional tripole structure extending from the tropical western Pacific to the mid-latitudes. This pattern represents the characteristic structure of meridionally propagating Rossby waves in East Asia, with alternating cyclonic and anticyclonic circulations along the East Asian coast (Nitta, 1987; Kosaka and Nakamura, 2006).

The wave properties of the PJ are illustrated through the Rossby wave source (Sardeshmukh and Hoskins, 1988) and wave activity flux (Takaya and Nakamura, 2001; Fig. 2b). The Rossby wave source shows strong positive anomalies over the subtropical western Pacific region (black box in Fig. 2b), with the wave activity flux vectors demonstrating meridional energy propagation toward the mid-latitudes along the western boundary of the North Pacific Subtropical High (Sardeshmukh and Hoskins, 1988; Kosaka and Nakamura, 2010). The decomposition of the Rossby wave source (Fig. S1) reveals that wave generation is predominantly driven by the stretching component rather than advection, indicating that the PJ pattern is primarily forced by convergent/divergent flow associated with deep convection, which enhances vorticity anomalies through stretching effect (Sardeshmukh and Hoskins, 1988; Hoskins and Karoly, 1981).

The physical source of the PJ pattern is closely linked to convective variability over the subtropical western Pacific. The outgoing longwave radiation (OLR) anomalies (Fig. 2c) reveal enhanced convection over the key source region (15° – 25° N, 110° – 160° E), reconfirming that enhanced deep convection serves as the source of the PJ pattern. This enhanced convection is accompanied by increased moisture content in the lower troposphere, as shown by strong specific humidity anomalies at 850 hPa (Fig. 2d). The co-location and horizontal structure of OLR and moisture anomalies imply the fundamental role of organized subtropical convection (such as BSISO; Lee et al., 2013) in driving the PJ pattern (Nitta, 1987; Kosaka and Nakamura, 2006; Kosaka et al., 2013).

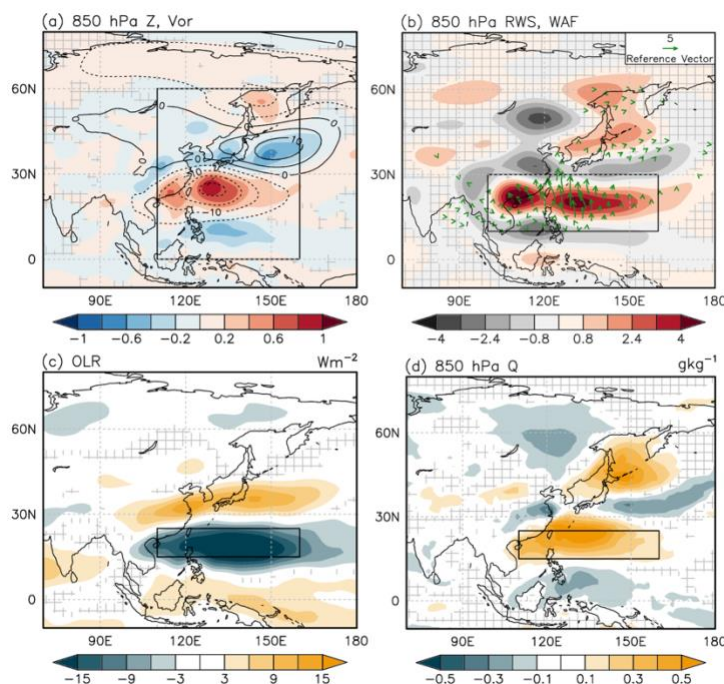


Figure 2. Atmospheric fields regressed onto the negative phase of the Pacific–Japan index (–PJ): (a) 850 hPa relative vorticity ($10^{-5} s^{-1}$) and geopotential height (m), (b) 850 hPa Rossby wave source (shading, $10^{-11} s^{-2}$) and wave activity flux (green vector, $m^2 s^{-2}$), (c) outgoing longwave radiation ($W m^{-2}$), and (d) 850 hPa specific humidity ($10^{-2} g kg^{-1}$). The wave activity flux was computed from the regressed stream function, rather than directly regressed onto the –PJ index. Gray hatching represents statistically non-significant areas at the 95 % confidence level.

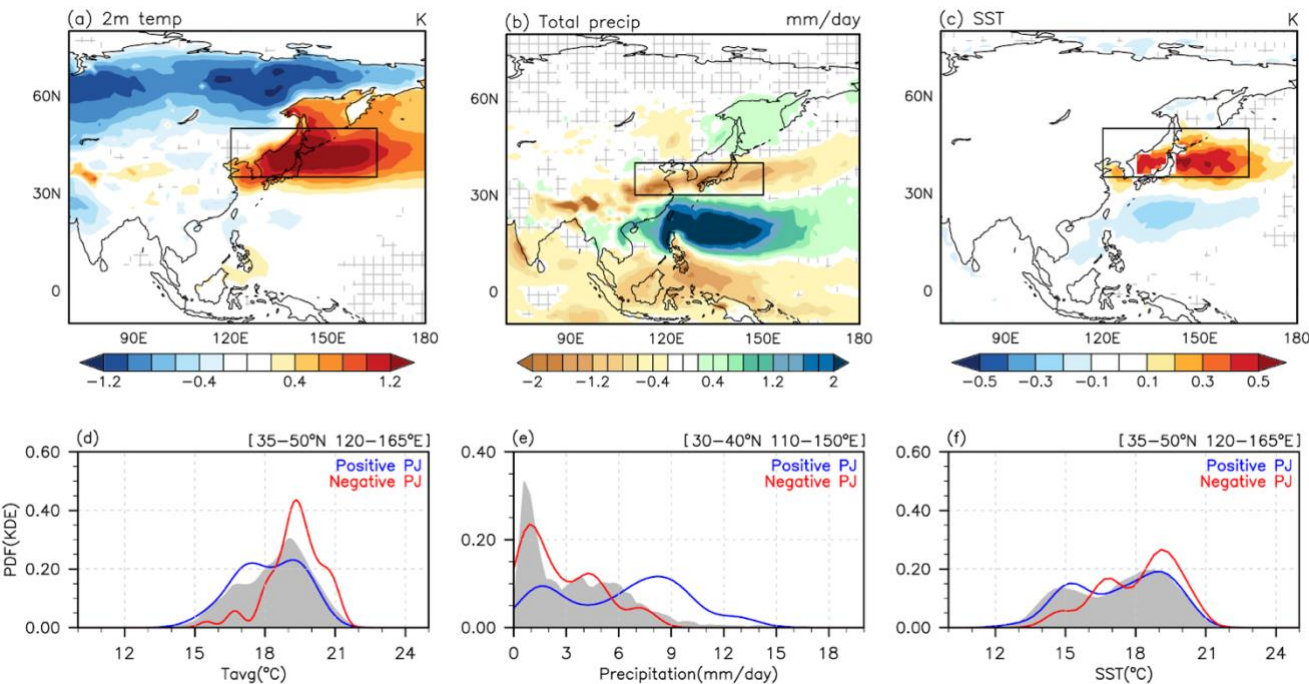
The downstream impacts of the PJ on East Asian weather and climate are demonstrated in Fig. 3. The pattern significantly modulates near-surface climate features across East Asia, with distinct impacts on temperature, precipitation, and ocean temperature. For example, during negative PJ phases, pronounced surface warming occurs over Japan and Korea (Fig. 3a), with surface air temperature (SAT) anomalies exceeding $1^{\circ}C$, accompanied by similar warming patterns in sea surface temperatures (SST; Fig. 3c). This warming is driven by the anticyclonic circulation of PJ (Fig. 2a) over Japan that promotes advection of warm and moist air along with enhanced insolation, which contribute to both atmospheric and marine heatwaves (Noh et al., 2021, 2023). The precipitation pattern (Fig. 3b) shows that the negative PJ significantly weakens the East Asian monsoon front, while the positive PJ does the opposite (Kosaka et al., 2011).

The probability density functions (PDFs) for different PJ phases (Fig. 3d–f) quantitatively demonstrate the impact on extreme weather. During the negative PJ (red curves), both SAT and SST distributions shift significantly toward higher values compared to those in the positive phase (Fig. 3d, f). The similar but much more pronounced feature is also found in station observations, and a coupled atmosphere–ocean process associated with the midlatitude anticyclonic circulation of negative PJ was identified as a primary cause of this warming on intraseasonal timescales (Noh et al., 2021, 2023). For



precipitation (Fig. 3e), the frequency of high-intensity events ($6\text{--}12\text{ mm day}^{-1}$) increases during the positive PJ (blue curve), implying the intensification of the monsoon front and associated heavy rain events.

175 These features could serve as benchmarks for evaluating how weather and climate models simulate the PJ and associated extremes over East Asia. The key features are summarized in Table 1 according to their physical processes. The corresponding variables and target regions are also documented in detail to facilitate model evaluations.



180 **Figure 3. Relationship between the Pacific–Japan pattern and surface variables during 1959–2014:** (a) ERA5 2-meter temperature ($^{\circ}\text{C}$), (b) daily precipitation (mm day^{-1}), and (c) sea surface temperature (SST, $^{\circ}\text{C}$). Non-significant regions at the 95 % confidence level are hatched in gray. Probability density functions (PDFs) for (d) temperature, (e) daily precipitation, and (f) SST of the black box regions specified in (a, b, c) for negative (red), positive (blue), and neutral (gray) PJ conditions. The PDFs are calculated using kernel density estimation (KDE).

185

Table 1. Evaluation metric table of the Pacific–Japan (PJ) pattern.

No.	PJ process	Evaluation variables	Domain
1	Horizontal structure	850 hPa vorticity; 850 hPa geopotential height	$0^{\circ}\text{--}60^{\circ}\text{ N}$, $110^{\circ}\text{--}160^{\circ}\text{ E}$
2	Physical source	Outgoing longwave radiation (OLR); 850 hPa specific humidity	$15^{\circ}\text{--}25^{\circ}\text{ N}$, $110^{\circ}\text{--}160^{\circ}\text{ E}$
3	Wave properties	Propagation (meridional wave activity)	$10^{\circ}\text{--}25^{\circ}\text{ N}$, $110^{\circ}\text{--}160^{\circ}\text{ E}$



		flux); Source (horizontal divergence)	
4	Impact on extremes	TAS (2-m temperature); SST (sea surface temperature); total precipitation	30°–45° N, 120°–160° E (TAS, SST); 30°–40° N, 110°–150° E (Prcp)

3.2 Evaluation of the PJ processes in CMIP6 models

Based on the physical components summarized in Sect. 3.1, we evaluate the PJ patterns simulated in CMIP6 models using the proposed process-based metrics (Table 1): 1) horizontal circulation structure, 2) physical sources (convection and lower-tropospheric moisture), 3) wave properties (source and propagation), and 4) downstream weather impacts. We apply this framework to 23 daily CMIP6 historical simulations.

3.2.1 Horizontal circulation structure

Following the metric, the PJ patterns in 850-hPa relative vorticity from reanalysis (ERA5; Fig. 4a, b) and simulations (multi-model ensemble mean, MME; Fig. 4c, d) are compared on interannual and intraseasonal timescales. Overall, the PJ patterns of ERA5 and MME show good agreement, though the simulated pattern is more zonally elongated and stronger than observed one, particularly for the intraseasonal variability (Figs. S2 and S3). The explained variances are 12.1 and 8.5% on interannual and intraseasonal timescales, respectively. The MME values are comparable to those in ERA5, while individual models show a large spread (Fig. 5). The percentage variance of the simulated PJ ranges from 5.7 to 22.8 % on the interannual timescale and from 5.4 to 15.1 % on the intraseasonal timescale, and the values are linearly correlated. This linearity suggests that interannual PJ variability may largely reflect the accumulation of intraseasonal PJ fluctuations governed by similar physical processes.

The identified 850-hPa vorticity patterns are further compared in a Taylor diagram (Fig. S4). All models reproduce the PJ spatial pattern reasonably well (spatial correlations > 0.8 on both timescales), but amplitudes vary widely from 25 to 170 % of observations. This spread is notably larger than for other major Northern Hemisphere atmospheric modes (Lee et al., 2019). Such large amplitude diversity, despite the consistently high pattern correlations, indicates that models capture where the PJ acts but disagree on how strongly it acts. The result points to the strength of underlying tropical-midlatitude coupling, rather than its spatial geometry, as the primary source of inter-model (or prediction) uncertainty.

This amplitude diversity becomes clearer when the models are grouped by their intraseasonal PJ variability (Fig. 6). The high-variability group (Fig. 6a; five models with the highest variability) shows more organized and intense pattern than that of the low-variability group (Fig. 6b; five models with the lowest variability). This diversity is not confined to the horizontal structure but also extends into the vertical. Models reasonably capture the northward-tilted baroclinic structure (Figs. S5–S8), which governs the energy conversion that maintains the PJ (Kosaka and Nakamura, 2006). However, its intensity is overestimated in the high-variability models and underestimated in the low-variability ones. This co-variation between horizontal and vertical structure is consistent with previous results showing that models better simulating the PJ exhibit

higher baroclinic energy conversion efficiency (Gong et al., 2018). Overall, this diversity in the PJ variability indicates that current models still do not adequately capture the PJ, highlighting the need to compare inter-model differences in the wave sources and propagation that drive this variability.

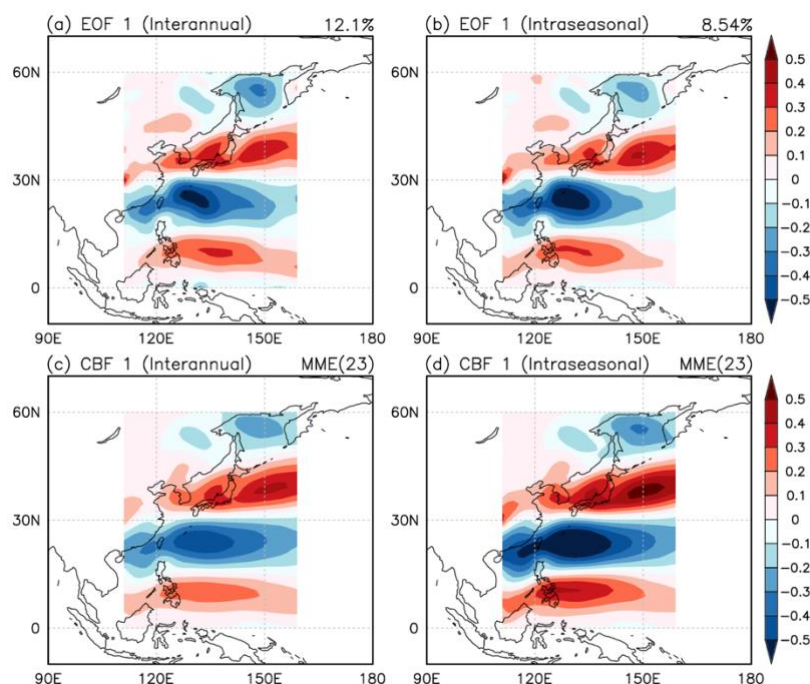


Figure 4. Spatial distribution of the first Empirical Orthogonal Function (EOF) mode of the 850 hPa relative vorticity anomalies over the period 1959–2014. Panels (a) and (b) display the spatial patterns for the first leading mode at the interannual and intraseasonal timescales with ERA5, accounting for 12.1 % and 8.5 % of the variance, respectively. Panels (c) and (d) show the spatial pattern of the common basis function (CBF) for the multi-model ensemble mean (MME).

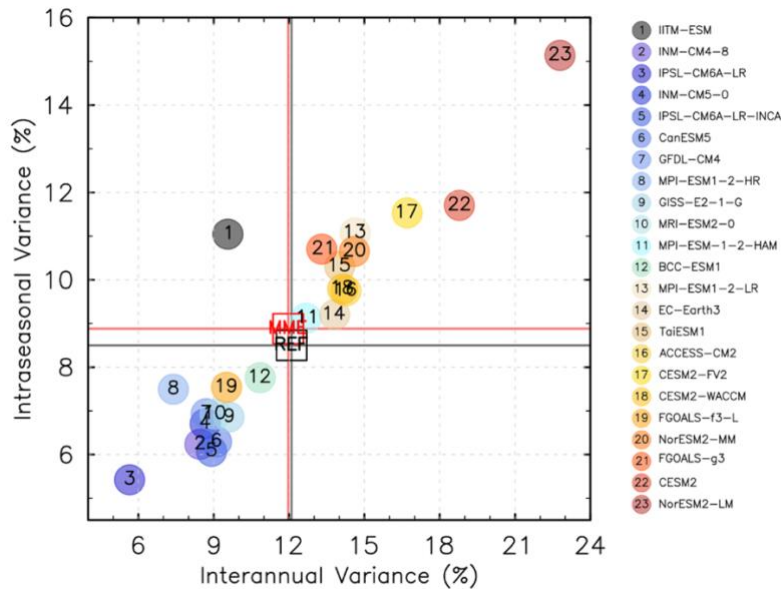


Figure 5. Percentage variances of the CBFs relative to total interannual (abscissa) and intraseasonal (ordinate) variances for each CMIP6 model. The variances of ERA5 EOFs are marked by the black open square (REF), serving as a reference point. The average variances of CMIP6 models are marked by the red open square (MME). Each number corresponds to an individual model.

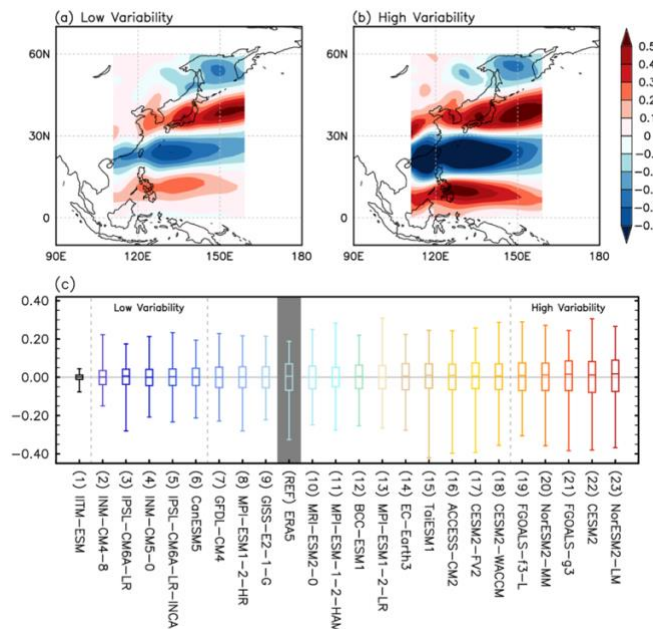


Figure 6. Intraseasonal CBF patterns ($\times 10^{-5} \text{ s}^{-1}$) of multi-model ensembles with (a) low and (b) high variability. (c) The intraseasonal PJ variability range of 23 CMIP6 models; the model with negligible variability (black box plot) is excluded from subsequent analyses for failing to capture the PJ pattern. The gray shaded box indicates ERA5 (REF). The five CMIP6 models on



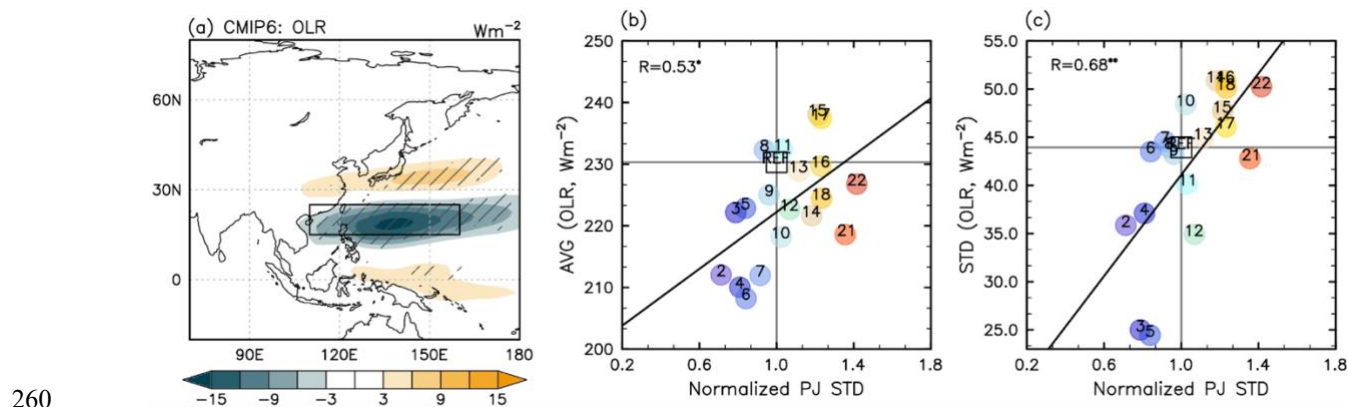
the left (right) side represent the low (high) variability models. The box and whisker represent the 25th–75th and 10th–90th percentile ranges of the CBF projection coefficient ($\times 10^{-5} \text{ s}^{-1}$), respectively, with the line inside the box showing the median.

240

3.2.2 Physical sources

Within the proposed framework, the physical source of the PJ is evaluated through the convective activity over the subtropical western Pacific, which drives the PJ pattern through Rossby wave generation. We use OLR as a direct measure of deep convective activity in the key source region (15° – 25° N, 110° – 160° E; black box in Fig. 7a). The MME OLR regression onto the negative PJ index (Fig. 7a) reproduces the observed enhanced convection, confirming that models broadly capture the convective signature of the PJ. The mean convection is underestimated in most models but is linearly related to the simulated PJ variability (Fig. 7b, $R = 0.53^*$), and its intraseasonal variability shows an even stronger linear relationship (Fig. 7c, $R = 0.68^{**}$). Lower-tropospheric moisture, which sustains deep convection through moisture convergence in boreal summer, shows a coherent enhancement with the OLR signal (15° – 25° N, 110° – 160° E; black box in Fig. 8a). The moisture–convection relationship, however, is asymmetric across models (Fig. 8b). The mean moisture is barely related to the mean convection (Fig. 8b, $R = 0.055$), whereas their day-to-day variations are closely linked (Fig. 8c, $R = 0.67^{**}$).

This decoupling implies that the simulated PJ source is governed by intraseasonal moisture–convection coupling rather than by the mean climate state, so that even models with biased mean states can reproduce a realistic PJ source as long as this variability is well captured. This distinction is important because conventional model evaluation focuses mainly on the mean state, while the variability-driven coupling that sustains the PJ source is not directly assessed. Therefore, by focusing on this variability-driven coupling, the proposed source metric, can directly evaluate whether a model captures the physical process that generates the PJ.



260



Figure 7. (a) Multi-model average of the outgoing longwave radiation (OLR, W m^{-2}) regressed onto the intraseasonal negative PJ index ($-PJ$). The gray hatch represents statistically significant areas at the 95 % confidence level. (b, c) Scatter plots between the normalized standard deviation of the Pacific–Japan pattern and (b) the climatological mean OLR, (c) the OLR variability (standard deviation) over the Philippine Sea (black box region in a) for intraseasonal timescales. Each numbered dot denotes an individual CMIP6 model, and the "REF" point shows ERA5. The correlation coefficient (R) is indicated in the top-left of each panel. A single asterisk (*) denotes statistical significance at the 95 % confidence level, and a double asterisk (**) denotes significance at the 99 % level.

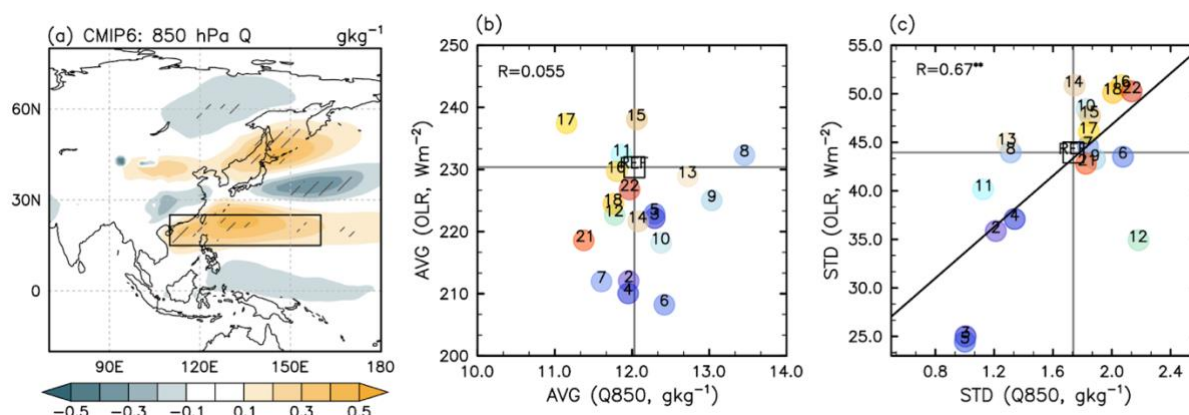


Figure 8. (a) Multi-model average of 850 hPa specific humidity (Q_{850} , g kg^{-1}) regressed onto the intraseasonal negative PJ index ($-PJ$). The gray hatch represents statistically significant areas at the 95 % confidence level. (b, c) Scatter plots between (b) the climatological mean of OLR and Q_{850} , and (c) the variability (standard deviation) of OLR and Q_{850} over the Philippine Sea (black box region in a) for intraseasonal timescales. Each numbered dot denotes an individual CMIP6 model, and the "REF" point shows ERA5. The correlation coefficient (R) is indicated in the top-left of each panel.

3.2.3 Wave properties

As the next part of the metric, we evaluate how well models reproduce the wave properties of the PJ, that is, how the wave energy propagates northward toward the mid-latitudes and shapes the PJ pattern. The 850 hPa horizontal divergence quantifies wave generation in the source region (10° – 25° N, 110° – 160° E; black box in Fig. 9c, d), since the wave source over this region is dominated by the stretching component driven by convective convergence (Sect. 3.1, Fig. S1). and the meridional component of the wave activity flux (F_y ; see Analysis Method in Data and methods) quantifies how strongly the wave energy moves northward (10° – 25° N, 110° – 160° E; black box in Fig. 10c, d), based on its established role as a diagnostic of meridional energy propagation (Takaya and Nakamura, 2001).

Most CMIP6 models simulate stronger and larger convergence variability than observations (Fig. 9a, b), suggesting that part of the inter-model spread in PJ amplitude is originated in an overly strong convective forcing. The variability of convergence is more closely related to the simulated PJ variability ($R = 0.81^{**}$) than the mean state is ($R = 0.62^{**}$), and the high-variability models produce clearer and stronger convergence patterns than the low-variability models (Fig. 9c, d). For

wave propagation, F_y shows strong correlations with the simulated PJ variability in both its mean state ($R = 0.93^{**}$) and its
 290 variability ($R = 0.94^{**}$). The high-variability models generate well-organized northward flux vectors, while the low-
 variability models show weaker and less coherent ones (Fig. 10c, d). Wave propagation is also more efficient during
 negative PJ phases, when convection over the subtropical western Pacific is stronger (Fig. S9).

Notably, even though most models simulate larger wave source variability than observations, wave propagation does not
 become uniformly strong across models. In particular, the weaker wave propagation in the low-variability models appears to
 295 result not from a weaker convective source but from a less favorable background flow for wave propagation. This implies
 that the simulated PJ variability depends not only on the wave source variability but also on the background flow along
 which the wave propagates. Because F_y integrates both effects into a single quantity that directly reflects the strength of
 wave energy reaching the mid-latitudes, it serves as a suitable variable for evaluating wave propagation in the framework.

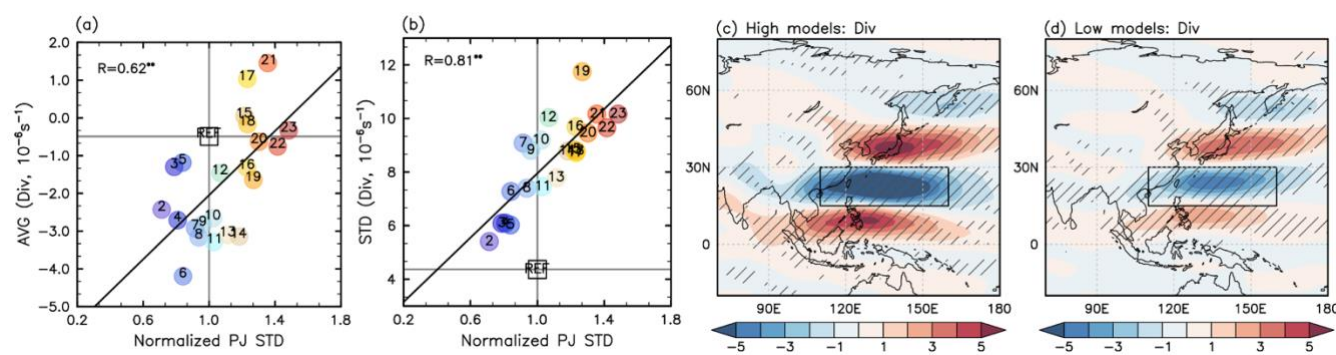


Figure 9. (a, b) Scatter plot of the standardized deviations of the Pacific–Japan pattern with the averaged and variability of 850 hPa horizontal divergence ($10^{-6} s^{-1}$) over the Philippine Sea (black box region in c, d), respectively. Each numbered point corresponds to an individual CMIP6 model, and the "REF" point marks the normalization reference for deviations. (c, d) The 850 hPa horizontal divergence (shading, $10^{-6} s^{-1}$) regressed onto the negative PJ index for (c) high-variability and (d) low-variability
 305 models. The gray hatch in (c, d) represents statistically significant areas at the 95 % confidence level.

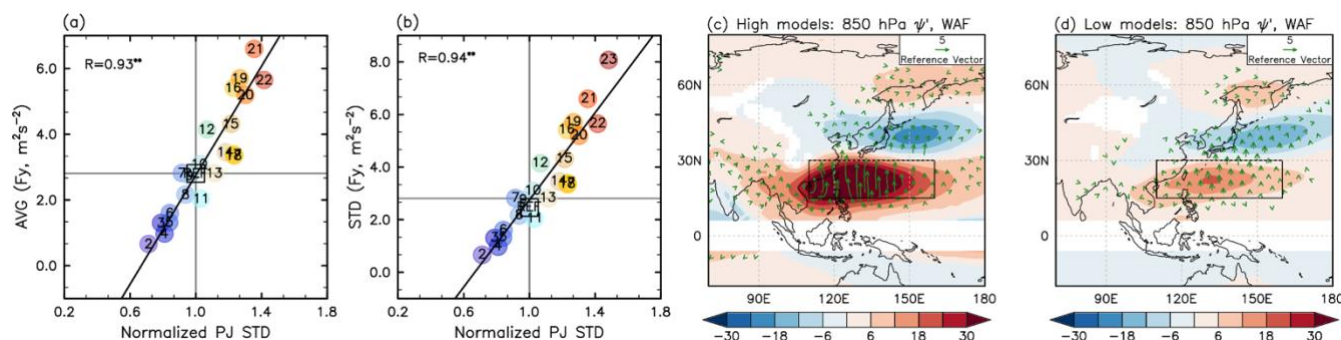


Figure 10. (a, b) Scatter plot of the standardized deviations of the Pacific–Japan pattern with the averaged and variability of the meridional component of the wave activity flux (F_y , $m^2 s^{-2}$) over the Philippine Sea (black box region in c, d), respectively. Each
 310 numbered point corresponds to an individual CMIP6 model, and the "REF" point marks the normalization reference for



deviations. (c, d) The 850 hPa stream function (shading, 10^{-5} s^{-1}) and wave activity flux (vector, $\text{m}^2 \text{ s}^{-2}$) for (c) high-variability and (d) low-variability models.

315 3.2.4 Weather impacts

As the final part of the metric, we evaluate how well models reproduce the downstream weather impacts of the PJ on East Asian climate. We use three surface variables that represent the distinct regional response (Sect. 3.1): 2-m temperature, precipitation, and sea surface temperature (SST) over East Asia (black box in Fig. 11a–c). Consistent with observations (Fig. 3a–c), the simulated PJ reproduces the main surface responses, including pronounced warming and reduced precipitation
 320 over Korea and Japan, along with co-located SST warming extending into the Kuroshio Extension region (Fig. 11a–c). The amplitude of these regional responses scales with the strength of the simulated PJ, as models with stronger PJ variability show larger fluctuations in temperature (Fig. 11d, $R = 0.48^*$), precipitation (Fig. 11e, $R = 0.51^*$), and SST (Fig. 11f, $R = 0.54^*$).

The phase-dependent character of the PJ impact is also well reproduced. As in observations (Fig. 3d–f), the simulated
 325 PDFs show that negative PJ phases shift temperature and SST toward warmer values while reducing precipitation, whereas positive phases produce the opposite response with enhanced heavy rainfall and cooling (Fig. 12, Fig. S10, and S11). Under SSP5-8.5, these phase-dependent responses are preserved but intensified, with both temperature and heavy rainfall extremes becoming more pronounced. This suggests that the PJ may amplify extreme weather events over East Asia under future warming.

330 The consistent correlations between PJ strength and regional climate response ($R \approx 0.5$) indicate that the PJ exerts substantial control on East Asian summer climate, although other local and large-scale processes also contribute to the region's summer variability. Models that preserve realistic PJ behavior therefore provide more reliable regional projections, supporting the use of PJ evaluation as a practical diagnostic for East Asian climate simulation.

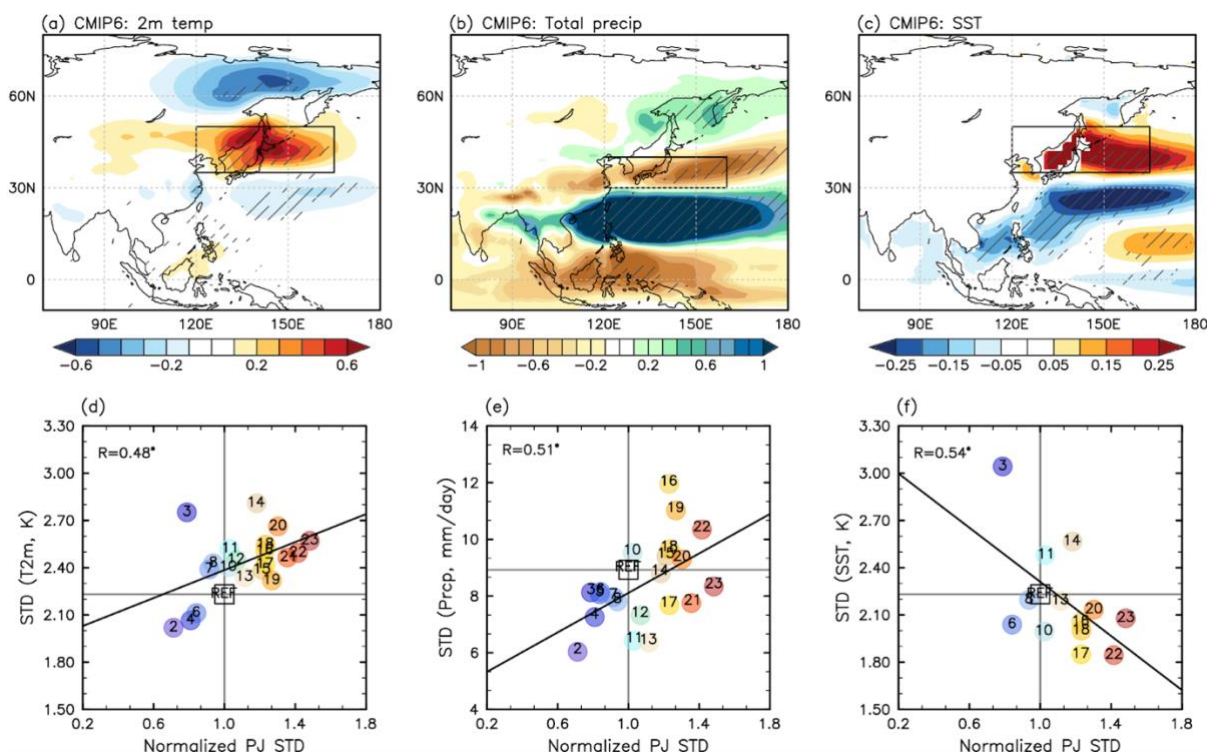


Figure 11. Surface climate anomalies associated with the Pacific–Japan pattern during 1959–2014: (a) 2-meter air temperature (SAT, K), (b) precipitation (mm day⁻¹), and (c) sea surface temperature (SST, K) regressed onto the negative PJ index. Scatter plot of the standardized deviations of the Pacific–Japan pattern with the variability of (d) SAT, (e) precipitation, and (f) SST over the box region in (a–c), respectively.

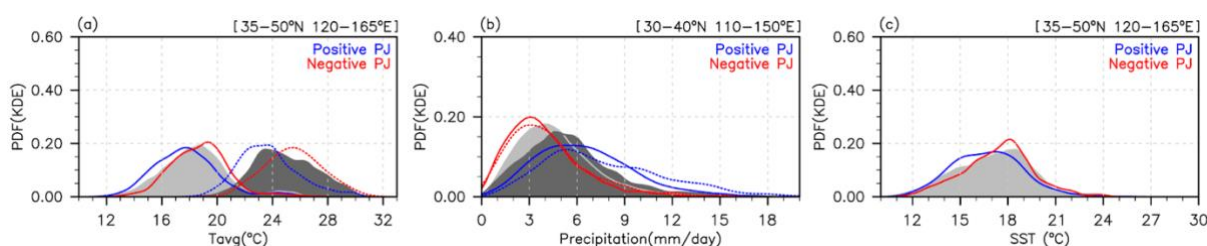


Figure 12. Probability density functions (PDFs) for (a) daily 2-meter temperature, (b) daily precipitation, and (c) daily sea surface temperature of the black box regions specified in Fig. 11a–c for negative (red), positive (blue), and neutral (gray) PJ conditions. PDFs for the future climate (2081–2100) are also presented based on SSP5-8.5 (dotted lines and dark gray shading). The PDFs are calculated using kernel density estimation (KDE).



4 Summary and discussion

This study proposes the Pacific–Japan (PJ) pattern as a process-based evaluation metric for East Asian summer weather and climate simulations. The framework decomposes the PJ into four physically meaningful components: (1) horizontal circulation structure, (2) physical source, (3) wave properties, and (4) weather impacts, which together form a coherent chain of causality from tropical forcing to regional climate response. To test the framework, we apply it to 23 CMIP6 historical simulations using the common basis function (CBF) method, which enables consistent inter-model comparison against ERA5.

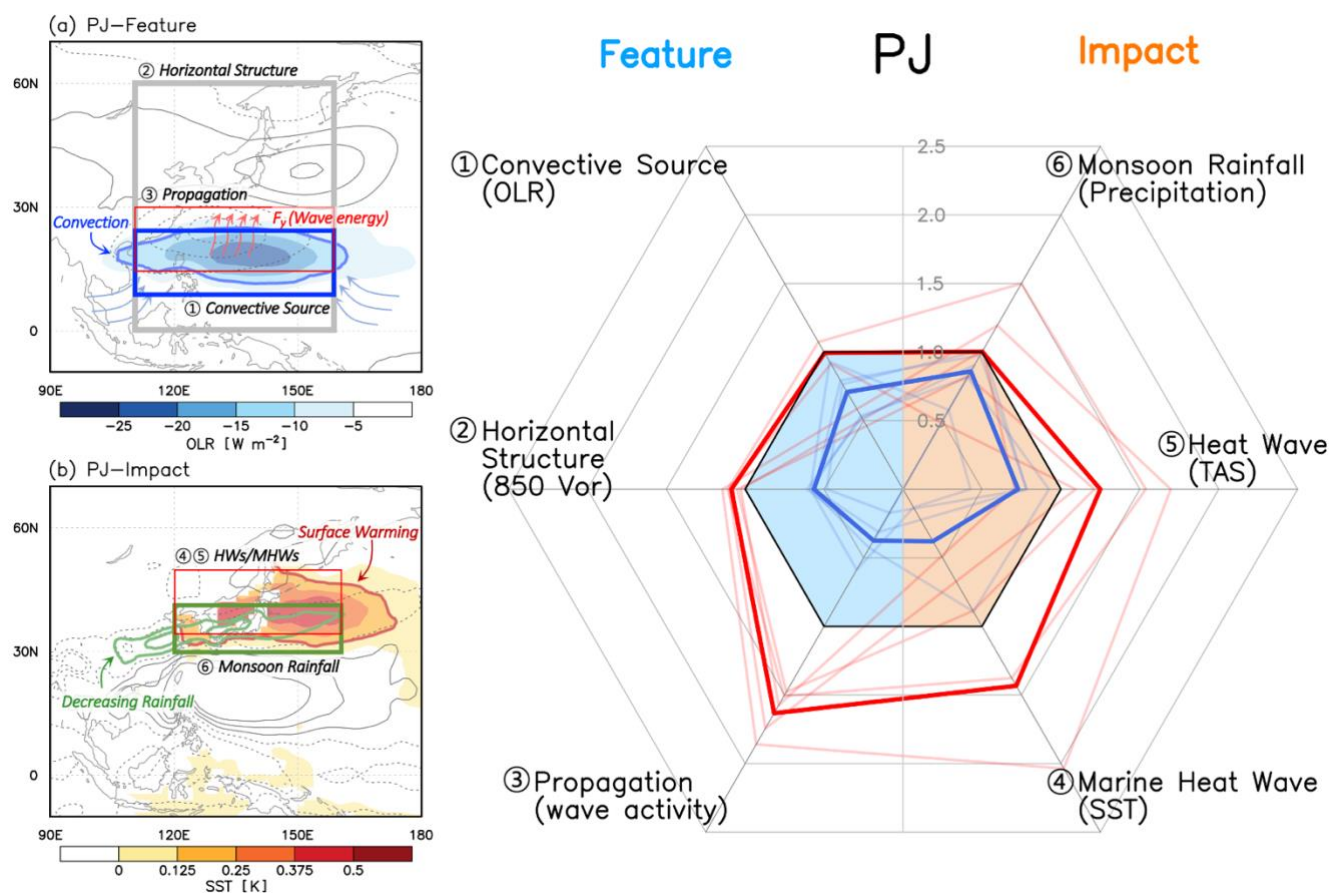
The application to CMIP6 reveals clear differences across models. 1) The models generally reproduce the PJ spatial pattern but show a wide spread in amplitude (25–170 % of observations) across simulations. 2) For the physical source, the mean convection is underestimated in most models but is linearly related to the simulated PJ variability, with the intraseasonal variability rather than the mean climate state governs the simulated PJ source. 3) For the wave properties, most models simulate stronger convergence and larger convergence variability than observations, and the meridional wave activity flux indicates as the most effective discriminator of inter-model diversity. 4) The simulated PJ clearly modulates downstream temperature, precipitation, and SST responses over East Asia, and the phase-dependent impacts are well reproduced and preserved under future climate projections.

The proposed framework is summarized in Fig. 13, which condenses the six metrics into a single hexagonal diagram that allows direct visual comparison of model performance against observations. The six axes are arranged with the three PJ-Variability metrics (Source, Propagation, Pattern) on the left and the three PJ-Impact metrics (Prcp, TAS, SST) on the right, and the distance from the center represents how closely a model agrees with ERA5 (REF = 1.0). This visualization makes it straightforward to identify in which component a given model overestimates or underestimates the observed PJ, and to compare contrasting groups of models. For instance, the high-variability models (red) overestimate most metrics relative to ERA5, while the low-variability models (blue) underestimate them, illustrating that the framework clearly distinguishes the two groups across all six components. It is worth noting that the convective source (OLR) is not particularly stronger in the high-variability models than in observations, even though the propagation (WAF), the resulting pattern (CBF), and the downstream impacts (TAS, SST, Prcp) are clearly overestimated. This suggests that the inter-model spread in PJ amplitude might be related not only to the convective source itself but also to the background flow along which the wave propagates. It is also worth considering whether OLR alone fully reflects the aspect of convective intensity most relevant to the PJ. Such differences across components are easy to see in this representation, even though they are often missed by single-score evaluations.

This process-based diagnostic offers practical value for model development. Instead of giving a single skill score, the framework points to specific physical processes and target regions (Table 1) where each model needs improvement, helping developers focus on the relevant component. Because each metric is based on a clearly defined variable and region, the framework is reproducible and modular, and can be readily applied to other models and forecast systems. Given that the PJ



governs a large part of East Asian summer variability and its associated extremes, this framework offers a physically clear way to improve PJ simulations and, in turn, the prediction of regional weather and climate.



385 **Figure 13. Process-based evaluation framework of the Pacific-Japan (PJ) pattern. (a, b) Schematic of the six evaluation components and their target regions: (a) PJ-Feature — ① Convective Source (OLR), ② Horizontal Structure (850 hPa vorticity), and ③ Propagation (wave activity flux); (b) PJ-Impact — ④ Marine Heat Wave (SST), ⑤ Heat Wave (TAS), and ⑥ Monsoon Rainfall (Precipitation). Black rectangles indicate the analysis domains (Table 1), and shaded contours depict the characteristic negative-PJ anomalies. The blue and red arrows in (a) denote the moisture flux convergence and the northward Rossby wave energy propagation (F_y), respectively. The red and green contours in (b) indicate surface warming over Korea and Japan and decreasing monsoon rainfall over the East Asian frontal region, respectively. (Right) Hexagonal diagram showing the normalized standard deviation of each metric for the five high-variability (red) and five low-variability (blue) CMIP6 models, with bold lines indicating the group means and thin lines showing individual models. The PJ-Feature metrics (①–③) are arranged on the left and the PJ-Impact metrics (④–⑥) on the right. The black hexagon denotes the ERA5 reference (REF = 1.0).**

395

Appendix A: Common basis function (CBF) method

In this Appendix, we detail the common basis function (CBF) methodology to consistently compare the PJ pattern simulated in multiple CMIP6 models. The CBF method is fundamentally designed to facilitate the comparison of the statistical characteristics of EOFs that appear differently in various models and observational data. This method projects model anomalies onto the observed EOF patterns, thereby providing a framework for consistently comparing the variability simulated by various models with observations. The flowchart of the CBF method is shown in Fig. A1, and the sequential steps are as follows:

- Step 1: Calculate the observed EOFs, which have unit variance.
- Step 2: Compute the dot product of spatial patterns of the simulated anomalies onto the observed EOF patterns for each time step. This projection generates the unnormalized CBF PC time series for each model simulation, which is then normalized to unit variance.
- Step 3: Calculate linear regression coefficients (slopes) between the CBF PC time series and the simulated anomalies at each grid point.
- Step 4: Multiply the CBF PC time series by the slopes (from Step 3) to reconstruct the spatio-temporal variability of the model mode. This maximizes the simulated variance related to the observed pattern. By comparing the area-weighted means of the temporal variance from the reconstructed mode and the original anomaly, we calculate the percent of total variance explained by a given mode.
- Step 5: Multiply the slopes (from Step 3) by the standard deviation of the CBF PC time series. This constructed CBF pattern of anomalies is used for the calculation of skill metrics.

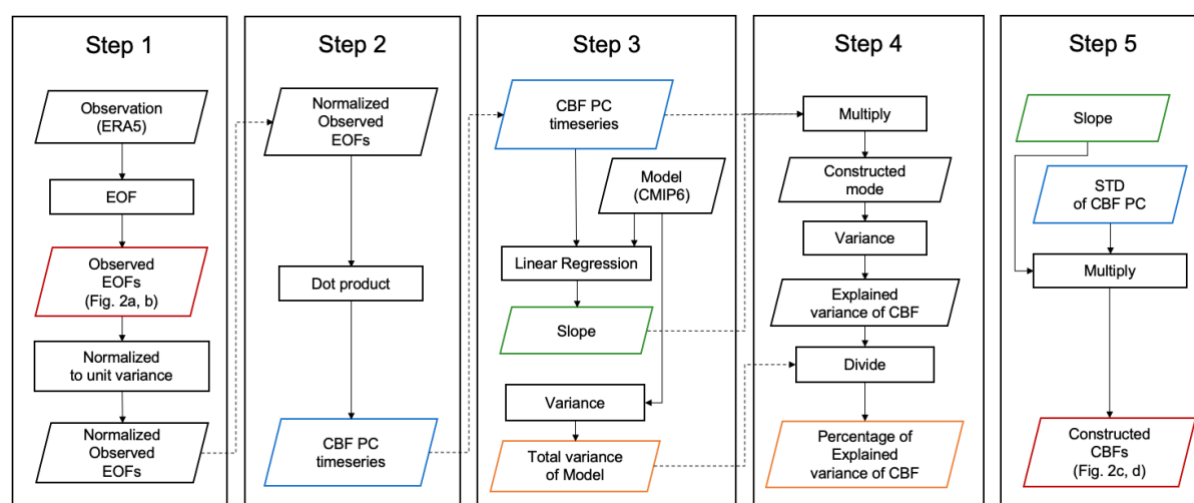


Figure A1. Flowchart of the common basis function (CBF) procedure. Black rectangles and parallelograms indicate the process and result of calculations, respectively. The colored parallelograms indicate the main input or output data for each step. The red parallelograms in Step 5 indicate the final results of the CBF calculation.



420 **Code and data availability**

The ERA5 reanalysis data are available from the Copernicus Climate Change Service (C3S) Climate Data Store (<https://doi.org/10.24381/cds.bd0915c6>, Hersbach et al., 2020). The CMIP6 historical and SSP5-8.5 model output are available from the Earth System Grid Federation (<https://esgf-node.llnl.gov/projects/cmip6/>). The analysis code implementing the PJEM framework is publicly available on GitHub (https://github.com/noel-dyn/PJEM_v1.0) and archived
425 on Zenodo (<https://doi.org/10.5281/zenodo.21767275>).

Author contributions

EN and JK designed the study and developed the process-based evaluation framework. EN performed the data analysis and prepared the figures. JK supervised the project. SYJ, SWY, and YK contributed to the interpretation of the results and refinement of the framework. EN and JK prepared the manuscript with contributions from all co-authors.

430 **Competing interests**

The authors declare that they have no conflict of interest.

Acknowledgements

We acknowledge the World Climate Research Programme's Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modelling groups (listed in Supplementary Table S1) for producing and making available
435 their model output.

Financial support

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korean government (MSIT) (grant no. 2023R1A2C1007401) and Korea Institute of Marine Science & Technology Promotion (KIMST) funded by the Ministry of Oceans and Fisheries (RS-2026-25543619).

440 **References**

Bonfils, C. J. W., Santer, B. D., Phillips, T. J., Marvel, K., Leung, L. R., Doutriaux, C., and Capotondi, A.: Relative contributions of mean-state shifts and ENSO-driven variability to precipitation changes in a warming climate, *J. Climate*, 28, 9997–10013, <https://doi.org/10.1175/JCLI-D-15-0341.1>, 2015.



- Choi, W. and Kim, K.-Y.: Summertime variability of the western North Pacific subtropical high and its synoptic influences
 445 on the East Asian weather, *Sci. Rep.*, 9, 7865, <https://doi.org/10.1038/s41598-019-44414-w>, 2019.
- Gao, Q., Sun, Y., and You, Q.: The northward shift of Meiyu rain belt and its possible association with rainfall intensity
 changes and the Pacific–Japan pattern, *Dyn. Atmos. Oceans*, 76, 52–62, <https://doi.org/10.1016/j.dynatmoce.2016.08.005>,
 2016.
- Gong, H., Wang, L., Chen, W., Wu, R., Huang, G., and Nath, D.: Diversity of the Pacific–Japan pattern among CMIP5
 450 models: role of SST anomalies and atmospheric mean flow, *J. Climate*, 31, 6857–6877, <https://doi.org/10.1175/JCLI-D-17-0541.1>, 2018.
- Guan, W., Hu, H., Ren, X., and Yang, X.-Q.: Subseasonal zonal variability of the western Pacific subtropical high in
 summer: climate impacts and underlying mechanisms, *Clim. Dynam.*, 53, 3325–3344, <https://doi.org/10.1007/s00382-019-04705-4>, 2019.
- 455 He, S., Gao, Y., Furevik, T., Wang, H., and Li, F.: Teleconnection between sea ice in the Barents Sea in June and the Silk
 Road, Pacific–Japan and East Asian rainfall patterns in August, *Adv. Atmos. Sci.*, 35, 52–64,
<https://doi.org/10.1007/s00376-017-7029-y>, 2018.
- Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., et al.: The ERA5 global reanalysis, *Q. J.
 Roy. Meteor. Soc.*, 146, 1999–2049, <https://doi.org/10.1002/qj.3803>, 2020.
- 460 Hoskins, B. J. and Karoly, D. J.: The steady linear response of a spherical atmosphere to thermal and orographic forcing, *J.
 Atmos. Sci.*, 38, 1179–1196, [https://doi.org/10.1175/1520-0469\(1981\)038<1179:TSLROA>2.0.CO;2](https://doi.org/10.1175/1520-0469(1981)038<1179:TSLROA>2.0.CO;2), 1981.
- Huang, W., Hua, L., Zhong, L., Yang, Y., and Gong, Z.: Recent opposite trends of atmospheric rivers over East Asia and
 western North Pacific driven by the Pacific Decadal Oscillation, *J. Geophys. Res.-Atmos.*, 129, e2023JD039147,
<https://doi.org/10.1029/2023JD039147>, 2024.
- 465 IPCC: Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of
 the Intergovernmental Panel on Climate Change, Cambridge University Press, <https://doi.org/10.1017/9781009157896>,
 2023.
- Kim, J., Li, R. C., and Zhou, W.: Effects of the Pacific–Japan teleconnection pattern on tropical cyclone activity and extreme
 precipitation events over the Korean peninsula, *J. Geophys. Res.-Atmos.*, 117, D18109,
 470 <https://doi.org/10.1029/2012JD017677>, 2012.
- Kosaka, Y. and Nakamura, H.: Structure and dynamics of the summertime Pacific–Japan teleconnection pattern, *Q. J. Roy.
 Meteor. Soc.*, 132, 2009–2030, <https://doi.org/10.1256/qj.05.204>, 2006.
- Kosaka, Y. and Nakamura, H.: Mechanisms of meridional teleconnection observed between a summer monsoon system and
 a subtropical anticyclone. Part I: The Pacific–Japan pattern, *J. Climate*, 23, 5085–5108,
 475 <https://doi.org/10.1175/2010JCLI3413.1>, 2010.



- Kosaka, Y. and Nakamura, H.: Dominant mode of climate variability, intermodel diversity, and projected future changes over the summertime western North Pacific simulated in the CMIP3 models, *J. Climate*, 24, 3935–3955, <https://doi.org/10.1175/2011JCLI3907.1>, 2011.
- 480 Kosaka, Y., Chowdary, J. S., Xie, S.-P., Min, Y.-M., and Lee, J.-Y.: Limitations of seasonal predictability for summer climate over East Asia and the northwestern Pacific, *J. Climate*, 25, 7574–7589, <https://doi.org/10.1175/JCLI-D-12-00009.1>, 2012.
- Kosaka, Y., Xie, S.-P., Lau, N.-C., and Vecchi, G. A.: Origin of seasonal predictability for summer climate over the northwestern Pacific, *P. Natl. Acad. Sci. USA*, 110, 7574–7579, <https://doi.org/10.1073/pnas.1215582110>, 2013.
- 485 Kubota, H., Kosaka, Y., and Xie, S.: A 117-year long index of the Pacific–Japan pattern with application to interdecadal variability, *Int. J. Climatol.*, 36, 1575–1589, <https://doi.org/10.1002/joc.4441>, 2016.
- Kwon, Y., Park, C., Son, S.-W., and Kim, J.: Modulation of East Asian atmospheric rivers by the Pacific–Japan teleconnection pattern, *Environ. Res. Lett.*, 19, 064055, <https://doi.org/10.1088/1748-9326/ad4fa6>, 2024.
- Lee, J.-Y., Wang, B., Wheeler, M. C., Fu, X., Waliser, D. E., and Kang, I.-S.: Real-time multivariate indices for the boreal summer intraseasonal oscillation over the Asian summer monsoon region, *Clim. Dynam.*, 40, 493–509, <https://doi.org/10.1007/s00382-012-1544-4>, 2013.
- 490 Lee, J., Sperber, K. R., Gleckler, P. J., Bonfils, C. J. W., and Taylor, K. E.: Quantifying the agreement between observed and simulated extratropical modes of interannual variability, *Clim. Dynam.*, 52, 4057–4089, <https://doi.org/10.1007/s00382-018-4355-4>, 2019.
- Lee, W. and Lee, M.: Interannual variability of heat waves in South Korea and their connection with large-scale atmospheric circulation patterns, *Int. J. Climatol.*, 36, 4815–4830, <https://doi.org/10.1002/joc.4671>, 2016.
- 495 Nitta, T.: Convective activities in the tropical western Pacific and their impact on the Northern Hemisphere summer circulation, *J. Meteorol. Soc. Jpn.*, 65, 373–390, https://doi.org/10.2151/jmsj1965.65.3_373, 1987.
- Noh, E., Kim, J., Jun, S.-Y., Cha, D., Park, M., Kim, J.-H., and Kim, H.: The role of the Pacific–Japan pattern in extreme heatwaves over Korea and Japan, *Geophys. Res. Lett.*, 48, e2021GL093990, <https://doi.org/10.1029/2021GL093990>, 2021.
- 500 Noh, E., Kim, J., Jun, S.-Y., Pak, G., Kim, J.-H., and Kim, H.-G.: Atmospheric pathway of marine heatwaves over the northwestern Pacific, *Sci. Rep.*, 13, 22821, <https://doi.org/10.1038/s41598-023-49833-4>, 2023.
- Perkins, S. E., Alexander, L. V., and Nairn, J. R.: Increasing frequency, intensity and duration of observed global heatwaves and warm spells, *Geophys. Res. Lett.*, 39, L20714, <https://doi.org/10.1029/2012GL053361>, 2012.
- Sardeshmukh, P. D. and Hoskins, B. J.: The generation of global rotational flow by steady idealized tropical divergence, *J. Atmos. Sci.*, 45, 1228–1251, [https://doi.org/10.1175/1520-0469\(1988\)045<1228:TGOGRF>2.0.CO;2](https://doi.org/10.1175/1520-0469(1988)045<1228:TGOGRF>2.0.CO;2), 1988.
- 505 Sohn, B.-J., Chung, H.-S., Kim, D.-H., Perkey, D., Robertson, F. R., and Smith, E. A.: Use of satellite-derived water vapor data to investigate northwestward expansion of North Pacific subtropical high during 1995 summer, *J. Meteorol. Soc. Jpn.*, 79, 1059–1075, <https://doi.org/10.2151/jmsj.79.1059>, 2001.



- Song, F., Leung, L. R., Lu, J., and Dong, L.: Future changes in seasonality of the North Pacific and North Atlantic
 510 subtropical highs, *Geophys. Res. Lett.*, 45, 11959–11968, <https://doi.org/10.1029/2018GL079940>, 2018.
- Sperber, K. R. and Annamalai, H.: Coupled model simulations of boreal summer intraseasonal (30–50 day) variability, Part
 1: systematic errors and caution on use of metrics, *Clim. Dynam.*, 31, 345–372, <https://doi.org/10.1007/s00382-008-0367-9>,
 2008.
- Sperber, K. R., Gualdi, S., Legutke, S., and Gayler, V.: The Madden–Julian oscillation in ECHAM4 coupled and uncoupled
 515 general circulation models, *Clim. Dynam.*, 25, 117–140, <https://doi.org/10.1007/s00382-005-0026-3>, 2005.
- Takaya, K. and Nakamura, H.: 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, [https://doi.org/10.1175/1520-0469\(2001\)058<0608:AFOAPI>2.0.CO;2](https://doi.org/10.1175/1520-0469(2001)058<0608:AFOAPI>2.0.CO;2), 2001.
- Taylor, K. E., Stouffer, R. J., and Meehl, G. A.: An overview of CMIP5 and the experiment design, *B. Am. Meteorol. Soc.*,
 520 93, 485–498, <https://doi.org/10.1175/BAMS-D-11-00094.1>, 2012.
- Tseng, W., Lin, S., Wang, Y., Lo, S., Lo, M., Lee, S., et al.: Impact of Pacific–Japan pattern on temperature and heatwave
 events in summer over Taiwan, *Int. J. Climatol.*, 43, 7067–7081, <https://doi.org/10.1002/joc.8252>, 2023.
- Wang, B., Liu, J., Yang, J., Zhou, T., and Wu, Z.: Distinct principal modes of early and late summer rainfall anomalies in
 East Asia, *J. Climate*, 22, 3864–3875, <https://doi.org/10.1175/2009JCLI2850.1>, 2009.
- 525 Xie, S.-P., Hu, K., Hafner, J., Tokinaga, H., Du, Y., Huang, G., and Sampe, T.: Indian Ocean capacitor effect on Indo–
 western Pacific climate during the summer following El Niño, *J. Climate*, 22, 730–747,
<https://doi.org/10.1175/2008JCLI2544.1>, 2009.
- Xie, S.-P., Kosaka, Y., Du, Y., Hu, K., Chowdary, J. S., and Huang, G.: Indo-western Pacific ocean capacitor and coherent
 climate anomalies in post-ENSO summer: A review, *Adv. Atmos. Sci.*, 33, 411–432, <https://doi.org/10.1007/s00376-015-5192-6>,
 530 2016.
- Yeo, S., Yeh, S., and Lee, W.: Two types of heat wave in Korea associated with atmospheric circulation pattern, *J. Geophys.*
Res.-Atmos., 124, 7498–7511, <https://doi.org/10.1029/2018JD030170>, 2019.
- Yihui, D. and Chan, J. C. L.: The East Asian summer monsoon: an overview, *Meteorol. Atmos. Phys.*, 89, 117–142,
<https://doi.org/10.1007/s00703-005-0125-z>, 2005.
- 535 Zhou, T., Zhang, W., Zhang, L., Clark, R., Qian, C., Zhang, Q., et al.: 2021: A year of unprecedented climate extremes in
 eastern Asia, North America, and Europe, *Adv. Atmos. Sci.*, 39, 1598–1607, <https://doi.org/10.1007/s00376-022-2063-9>,
 2022.