The Role of Air-Sea Coupling on November-April Intraseasonal Rainfall Variability Over the South Pacific

Sunil Kumar Pariyar (✉ sunil.pariyar@uib.no)

University of Bergen <https://orcid.org/0000-0002-6477-3358>

Noel Keenlyside

University of Bergen

Wan-Ling Tseng

Research Center for Environmental Changes Academia Sinica

Huang Hsiung Hsu

Research Center for Environmental Changes Academia Sinica

Ben-jei Tsuang

National Chung Hsing University College of Engineering

Research Article

Keywords: Tropical intraseasonal variability, Madden-Julian Oscillation, air-sea interaction, South Pacific

Posted Date: September 28th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-809904/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

---

1   **The role of air-sea coupling on November-April intraseasonal rainfall variability over the South Pacific**

2   Sunil Kumar Pariyar, Noel Keenlyside, Wan-Ling Tseng, Huang-Hsiung Hsu, and Ben-jei Tsuang

3   **Acknowledgements**

4   The authors would like to thank Thomas Spengler and Bhuwan Chandra Bhatt for their valuable insights during the early
5   discussion of this study. This work is supported by European Research Council-Synchronization to Enhance Reliability of
6   Climate Prediction (ERC-STERCP) Project (Grant Agreement 648982) funded by the European Union's H2020
7   programme, European Research Council Executive Agency. We are grateful to the National Center for High-performance
8   Computing, Taiwan, for computer time and facilities.

9   Sunil Kumar Pariyar
10   Geophysical Institute and Bjerknes Centre for Climate Research, University of Bergen, Norway
11   Email: sunil.pariyar@uib.no

12   Noel Keenlyside
13   Geophysical Institute and Bjerknes Centre for Climate Research, University of Bergen, Norway

14   Wan-Ling Tseng
15   Research Center for Environmental Changes, Academia Sinica, Taiwan

16   Huang Hsiung Hsu
17   Research Center for Environmental Changes, Academia Sinica, Taiwan

18   Ben-jei Tsuang
19   Department of Environmental Engineering, National Chung-Hsing University, Taichung, Taiwan

We investigate the impact of resolving air-sea interaction on the simulation of the intraseasonal rainfall variability over the South Pacific using the ECHAM5 atmospheric general circulation model coupled with the Snow-Ice-Thermocline (SIT) ocean model. We compare the fully coupled simulation with two uncoupled ECHAM5 simulations, one forced with sea surface temperature (SST) climatology and one forced with daily SST from the coupled model. The intraseasonal rainfall variability over the South Pacific is reduced by 17% in the uncoupled model forced with SST climatology and increased by 8% in the uncoupled simulation forced with daily SST, suggesting the role of air-sea coupling and SST variability. The coupled model best simulates the key characteristics of two intraseasonal rainfall modes over the South Pacific with reasonable propagation and correct periodicity. The spatial structure of the two rainfall modes in all three simulations is very similar, suggesting these modes are primarily generated by the dynamics of the atmosphere. The southeastward propagation of rainfall anomalies associated with two leading rainfall modes in the South Pacific depends upon the eastward propagating MJO signals over the Indian Ocean and western Pacific. Air-sea interaction seems crucial for such propagation as both eastward and southeastward propagations are substantially reduced in the uncoupled model forced with SST climatology. The simulation of both eastward and southeastward propagations improved considerably in the uncoupled model forced with daily SST; however, the periodicity differs from the coupled model. Such discrepancy in the periodicity is attributed to the changes in the SST-rainfall relationship with weaker correlations and the nearly in-phase relationship.

Keywords: Tropical intraseasonal variability, Madden-Julian Oscillation, air-sea interaction, South Pacific

1 Introduction

The rainfall variability in the South Pacific shows a wide range of timescales: synoptic variability associated with extratropical wave trains (Matthews 2012), Madden-Julian Oscillation (MJO) related intraseasonal variability (Matthews and Li 2005, Matthews 2012, Pariyar et al. 2019), and interannual and interdecadal variability influenced by El Niño–Southern Oscillation (ENSO) and Interdecadal Pacific Oscillation (IPO) (Folland et al. 2002, Griffiths et al. 2003). Among these, the intraseasonal timescale dominates the rainfall variability, explaining 50-60% (40-50%) of total daily rainfall variance along the South Pacific Convergence Zone (SPCZ) in November-April (May-October) (Pariyar et al. 2019). In particular, two large-scale rainfall modes primarily dominate the intraseasonal rainfall variability in the South Pacific in both seasons (Matthews 2012; Pariyar et al. 2019). However, these leading modes are more pronounced in November-April, contributing up to 60% of daily intraseasonal rainfall variability over the large areas of SPCZ (Pariyar et al. 2019).

Observations indicate that the two leading modes of intraseasonal rainfall variability in November-April over the South Pacific are linked to the Madden-Julian Oscillation (MJO) (Pariyar et al. 2019). In particular, the enhanced/suppressed and shifted SPCZ modes with dry and wet episodes of rainfall in this region with a typical timescale of

30-80-day are associated with the enhanced and suppressed phases of the MJO. Based on observations, we proposed two mechanisms for these modes; wind-evaporation-SST and low-level frictional moisture convergence for the southeastward propagation tendency of these modes that could explain their different connections to the MJO (Pariyar et al. 2019). In both cases, the SSTs seem relevant, with positive SST anomalies typically leading the convection patterns; however, to what extent do the intraseasonal SST anomalies interact with the atmosphere and contribute to the propagation of rainfall anomalies in the South Pacific is not clear.

One way to address these issues is to use general circulation models (GCMs). Many previous studies have discussed the role of air-sea interaction for the eastward propagation of intraseasonally varying rainfall anomalies with a particular focus on the MJO over the Indian Ocean and western Pacific (Flatau et al. 1997; Hendon 2000; Woolnough et al. 2000; Kemball-Cook et al. 2002; Fu et al. 2003; Fu and Wang 2004; Sperber et al. 2005; Lin et al. 2006; Zhang et al. 2006; Pegion and Kirtman 2008; Wu et al. 2008; Bollasina and Nigam 2009; Wang and Seo 2009; DeMott et al. 2011; Roxy et al. 2013). In particular, many modelling studies have shown that the MJO induced SST variability over the tropical Pacific tends to enhance the low-level convergence, which increases the development of shallow convection and preconditions eastward propagation (Fu et al. 2003; Roxy et al. 2013; Tseng et al. 2015). In contrast, other studies argued that the local wind-evaporation-SST feedback increases surface evaporation, eventually increasing low-level moisture convergence (e.g., Marshall et al. 2008). However, studies on the role of air-sea interaction in intraseasonal rainfall variability over the South Pacific are scarce. Further, we are not aware of any modelling studies on the southeastward propagation of intraseasonal rainfall variability over this region and their connection to the MJO. Therefore, we investigate these issues in detail using a state-of-art model.

Here we use the ECHAM5-SIT model, as it can realistically simulate the key characteristics of the MJO, which is strongly linked to the modes of intraseasonal rainfall variability in the South Pacific (Pariyar et al. 2019). Despite substantial improvements in GCMs, most are considered poor in their MJO simulation skill, and very few are capable of simulating the MJO well (Kim et al. 2008; Hung et al. 2003; Ahn et al. 2017; Jiang et al. 2015). ECHAM5 coupled with the snow-ice thermocline (SIT) one-column ocean model (ECHAM5-SIT) is one of the few models that reasonably simulates the MJO in terms of amplitude, periodicity, propagation speed, and vertical structure (Tseng et al. 2015; Jiang et al. 2015). In particular, we use the outputs primarily from three model experiments performed by Tseng et al. (2015). These coupled and uncoupled experiments were used to demonstrate the key role of ocean-atmosphere interaction involving the upper few meters of the ocean in simulating the MJO. Here we use them to investigate how the representation of air-sea interaction and the simulation of the MJO impact the intraseasonal variability over the South Pacific. We focus on November-April as the intraseasonal variability in the South Pacific is more pronounced, and the influence of the MJO is greatest (Pariyar et al. 2019).

2 Model, data, and methods

We use the simulations from ECHAM5-SIT model as described in Tseng et al. (2015). The atmospheric component, ECHAM5, is an atmospheric general circulation model developed at the Max Planck Institute for Meteorology

(MPI) (Roeckner 2003). The model has a horizontal resolution of T63 (~1.8 degrees) and 31 vertical layers from surface to 10hPa. The Nordeng convection scheme was used in the model (Nordeng 1994). The ocean component is the one column snow-ice-thermocline (SIT) ocean model (Tu and Tsuang 2005; Tsuang et al. 2009). SIT is based on the turbulent kinetic energy approach suggested by Gaspar et al. (1990) and determines the ocean temperature, salinity and zonal and meridional currents in each depth according to the salinity, momentum, and energy budget in a one-column model. The ocean model used in this study has already been validated over the tropical ocean (Tu and Tsuang 2005), the South China Sea (Lan et al. 2010), and the Caspian Sea (Tsuang et al. 2001; Arpe et al. 2018). SIT has 42 vertical layers with 12 in the upper 10 meters of the ocean in its standard configuration. The fine upper ocean resolution enables air-sea interaction on diurnal to intraseasonal time scales to be well represented. To account for neglected horizontal processes, the ocean is weakly nudged (with a 30-day time scale) to the observed climatological ocean temperature only below 10-meter depth.

We mainly use three experiments from Tseng et al. (2015) to investigate the role of SST and the impact of air-sea coupling on the simulation of intraseasonal variability in the South Pacific (Table 1). The first experiment (C-CTL) includes a fully coupled control simulation for 25 years. Note that coupling was done only over the tropical domain (30°S–30°N), and outside of this region, observed SST climatology is prescribed to ECHAM5. The second experiment (A-CLIM) comprises an atmosphere-only simulation forced with monthly SST climatology from the coupled simulation. Note the comparison of A-CLIM with C-CTL provides an assessment of the impact of air-sea coupling on intraseasonal variability. The third experiment (A-DAY) is an uncoupled simulation forced with daily SST from the coupled simulation. Here, the ocean is forcing the atmosphere, but the atmospheric influence on the ocean is absent. Even though the atmospheric feedback to the ocean is suppressed, the SST still varies on intraseasonal time scales, and therefore allows us to understand the impact of SST variability on the simulation of the intraseasonal variability. For more details on different experiments, readers are referred to Tseng et al. (2015).

Apart from the three main experiments, we use five additional simulations. To assess the role of ocean vertical resolution, we use two experiments in which the fine resolution of the upper ocean was replaced with the first layer of either 16.8 m (C-17m) or 59.3 m (C-59m) thickness. To assess the role of air-sea interaction in different regions, we use three experiments with regional coupling over the Indian Ocean (C-IO; 30°N–30°S, 50°E–100°E), the western Pacific (C-PO; 30°N–30°S, 110°E–180°E), and the Indian-western Pacific region (C-IPO; 30°N–30°S, 40°E–180°E).

We use the daily TRMM 3B42 version 7 rainfall estimates (Huffman et al. 2007) for comparing the mean state and the spatio-temporal variability of dominant large-scale rainfall patterns with the control simulation. We obtain the TRMM data with a horizontal resolution of 0.25 degrees from 1998 to 2018. For comparing the propagation mechanism, we use daily ERA-Interim data sets from 1998 to 2018 (Dee et al. 2011) with a horizontal resolution of 0.75 degrees. We interpolate both TRMM and ERA-Interim data sets to a regular 1.8 degrees grid to be consistent with the model.

The dominant intraseasonal rainfall modes are characterized by an Empirical Orthogonal Function (EOF) analysis based on 10-90-day bandpass filtered data for November to April, similar to our previous study (Pariyar et al. 2019). Our entire analysis uses November to April as this is the rainy season in the South Pacific. Before EOF analysis, we

120 compute the daily rainfall anomalies by subtracting the annual rainfall climatology. We detrend the anomalies and apply a
121 10-90-day Butterworth bandpass filter to remove the long-term trend and retain intraseasonal variability. We perform the
122 EOF analysis over the western Pacific (120°E-150°W; 20°N-25°S) to be consistent with our previous study ([Pariyar et al.](#)
123 [2019](#)). Note that all the analysis presented for observations is similar to our previous study unless stated otherwise. Readers
124 are referred to [Pariyar et al. \(2019\)](#) for more details. We repeat a similar analysis for the model data. To compare the
125 observed EOF modes with the model simulations, we project the model simulations onto the observed EOF modes. The
126 main reason for doing this is to ensure that the EOF modes in both model and observations represent the same mode of
127 variability.

128 We test the significance of the leading EOF modes against a stochastic null hypothesis based on first-order
129 autoregressive (AR1) and spatial isotropic diffusive processes ([Dommenges 2007](#)). This test compares the observed EOF
130 modes with the EOF modes of the null hypothesis fitted to the observations. The observed EOF modes statistically different
131 from the fitted EOF modes are then considered the distinct EOF modes. We also apply the North's rule to distinguish the
132 leading modes from the higher modes ([North et al. 1982](#)).

133 We compute the power spectra for two principal components (PCs) for November-April and then average
134 over 25 years. We test for statistical significance of the power spectra from a red-noise spectrum at the 99.9% confidence
135 level ([Torrence and Compo 1998](#)). We compute the 99.9% confidence level by multiplying the red noise spectrum by the
136 99.9th percentile value of the chi-squared distribution ([Gilman et al. 1963](#)). To understand the phase relationship between
137 leading EOFs, we compute the lag-correlation between two PCs. We apply the two-tailed Student's t-statistic at the 95%
138 confidence level for the statistical significance of the correlation.

139 We compute lagged composites to represent the lifecycle and propagation characteristics of the leading
140 intraseasonal rainfall modes. The composites are based on intraseasonal rainfall events identified by standardized PCs with
141 values higher than 0.5 standard deviations. We average the data for days before and after the event to illustrate the evolution
142 of rainfall events. We compute the lag- composites for other variables in the same manner. For the statistical significance of
143 the lag- composites, we implement the two-tailed Student's t-statistic at the 95% confidence level ([Harrison and Larkin](#)
144 [1998](#)). To represent the eastward propagation over the Indian Ocean and the western Pacific, we average the rainfall
145 composites from 5°N to 10°S; these composites represent the eastward propagation from the Indian Ocean to the western
146 Pacific. We compute the southeastward propagation for the South Pacific by averaging rainfall anomalies along the diagonal
147 axis corresponding to the SPCZ in each EOF mode. We construct the diagonal axis by identifying the maximum rainfall
148 anomaly for each latitude along the SPCZ in each EOF mode. Later, we fit a linear diagonal line based on these maximum
149 rainfall values. We average the data from 10 degrees to the east to 10 degrees to the west of the diagonal axis for each
150 latitude.

151 We compute the lag-correlation coefficients between two PC time series to understand the phase relationship
152 between leading EOF modes. Likewise, we perform a lag-correlation analysis to establish the phase relationship between
153 SST and other atmospheric variables, namely latent heat flux (LHF, positive upwards), sensible heat flux (SHF, positive

upwards), rainfall (PCP), 10-meter wind speed (WS). We perform this analysis for both coupled and uncoupled simulations. To establish a relationship between MJO and the leading EOF modes, we compute the lag-correlation coefficients between the real-time multivariate MJO (RMM) index suggested by [Wheeler and Hendon \(2004\)](#) and the PC time series. We obtain the daily RMM indices (RMM1 and RMM2) from the Australian Bureau of Meteorology website (<http://www.bom.gov.au/climate/mjo/>). For the model, we compute the RMM indices as described by [Wheeler and Hendon \(2004\)](#). We apply the two-tailed Student's t-statistic at the 95% confidence level for the statistical significance of lag correlation coefficients. We use MATLAB R2017b to create all the figures and Adobe Illustrator CC to create the schematic.

3 Comparison of the coupled control simulation with observations

3.1 Mean and intraseasonal variability of the rainfall

The mean climate from coupled and uncoupled simulations with an identical model experiment has been evaluated previously by [Tseng et al. \(2015\)](#) over the Indo-Pacific region; therefore, we will only briefly summarize the comparison of the mean state and intraseasonal (10-90-day) variability of rainfall from the coupled simulation with observations over the South Pacific. [Figure 1](#) shows the 25 years climatology of daily rainfall and daily intraseasonal (10-90-day) standard deviations in November-April for observations and three main model simulations.

ECHAM5-SIT simulates quite similar spatial distribution of the mean rainfall over the South Pacific in the coupled experiment and uncoupled experiments forced with coupled model daily climatology and daily varying SST ([Fig. 1b-d](#)). In general, the coupled model overestimates the rainfall climatology with a slightly more zonal orientation of the SPCZ (black diagonal dashed lines, [Fig 1b](#)). Also, the component of the ITCZ to the north of the equator is largely absent. These features are more exaggerated in the two uncoupled simulations. The more zonal orientation of the SPCZ is a common problem in most global climate models ([Brown et al. 2011](#)) and linked to SST biases. For example, a group of climate models with flux adjustment or dynamical corrections to correct the SST bias realistically simulate the SPCZ position ([Brown et al. 2011](#); [Shen et al. 2016](#)). The coupled model used in our study also has a warm SST bias over the South Pacific ([Tseng et al. 2015](#)), and such warm SST bias can explain these rainfall biases.

Past studies have shown a poor simulation of the tropical intraseasonal variability is linked to the simulation of the basic-state surface westerlies in the Indian Ocean and western Pacific ([Hendon 2000](#); [Innes and Slingo 2003](#); [Inness et al. 2003](#)). The climatology of the 10-meter zonal winds over the western Pacific in the coupled and uncoupled model simulations is similar to observations ([Supplementary Fig. 1](#)). In particular, the westerly winds over the western Pacific are reasonably well simulated by the model. However, a key difference is the westerly flow in the coupled model, slightly weaker and extends to the far east than observations. Despite this, the coupled model reasonably captures the overall spatial distribution of the intraseasonal variability (10-90-day) ([Fig. 1f](#)).

3.2 Dominant intraseasonal (10-90-day) rainfall modes

185 We now show that ECHAM5-SIT can capture the observed spatio-temporal structure of intraseasonal rainfall
186 variability in the South Pacific. We perform an EOF analysis of the daily 10-90-day filtered rainfall anomalies over the
187 western Pacific (25°S–20°N to 120°E–150°W) for observations and coupled model.

188 The first two EOF modes explain about 11% of the 10-90-day rainfall variability in observations, whereas, in
189 the coupled model, this value is about 15%. The coupled model captures the large-scale spatial structures of the leading
190 EOF modes pretty well (Fig. 2d-e). The EOF1 mode in observations has maximum rainfall loadings along the mean SPCZ
191 position (Fig. 2a), whereas the EOF2 mode has maximum rainfall anomalies southwest of the climatological SPCZ position
192 (Fig. 2b). We term the EOF1 (EOF2) mode as enhanced (shifted) SPCZ mode (Pariyar et al. 2019), and these features are
193 well represented in the model. Despite these similarities, there is one main difference. In C-CTL, the major axis of rainfall
194 anomalies in the SPCZ in both EOF modes is more zonal than observations (diagonal black lines, Fig. 2d-e), consistent with
195 the more zonal orientation of the mean SPCZ (Fig. 1b).

196 The comparison of power spectra for two EOF modes between C-CTL and observations shows comparable
197 results with maximum variance concentrated in the 30-80-day period. The observed power spectra of two EOF modes peak
198 around 40-50 days (Fig. 2c). Consistent with observations, the power spectra for both PCs in the coupled model peak
199 around 40-50 days (Fig. 2f). However, the variance associated with the PCs is lower in the coupled model, consistent with
200 the weaker intraseasonal variability simulated by the model.

201 To assess the temporal relationship between two EOF modes, we compute the lag-correlation between two
202 PCs for raw and 30-80-day filtered PC time series. We chose the 30-80-day period because of the pronounced peaks of
203 power spectra on this time scale. The lag-correlation analysis reveals that two EOF modes in C-CTL are related with a
204 correlation coefficient of 0.42 at ten days. In observations, this lag-correlation is relatively weak ($r \sim 0.21$; at eight days)
205 (Supplementary Fig. 2). The stronger lag relationship in the model suggests that the two EOF modes may partly represent
206 the same mode of variability, unlike in observations.

207 As the power spectra in both C-CTL and observations show pronounced peaks on the typical MJO timescale
208 (i.e., 30-80-day), we compute the lag-correlation coefficients between two MJO indices (RMM1 and RMM2). In
209 observations, RMM1 leads PC1 by two days ($r \sim 0.56$) and negative of PC1 leads RMM2 by eight days ($r \sim 0.58$)
210 (Supplementary Fig. 3); and RMM1 leads PC2 by 12 days ($r \sim 0.41$), and PC2 leads RMM2 by one day ($r \sim 0.46$). Consistent
211 with observations, in C-CTL, RMM1 leads PC1 by four days ($r \sim 0.66$) and negative of PC1 leads RMM2 by six days
212 ($r \sim 0.49$); and for EOF2, PC2 leads RMM1 by five days ($r \sim 0.54$), and RMM2 leads PC2 by three days ($r \sim 0.39$).

213 3.3. Rainfall propagation characteristics

214 We summarize the propagation features in the form of time-longitude and time-latitude plots based on the lag-
215 composites described in Section 2 (Fig. 3). The time-longitude plots represent the eastward propagation from the Indian
216 Ocean to the western Pacific. Similarly, the time-latitude plots represent the southeastward propagation in the South Pacific.

217 We consider the eastward propagation over the Indo-Pacific region because the southeastward propagation of the rainfall
218 variance on the intraseasonal time scale over the South Pacific is associated with the eastward propagating MJO signal
219 (Pariyar et al. 2019).

220 The eastward propagation of the rainfall anomalies from the Indian Ocean to the western Pacific in both EOF
221 modes simulated in C-CTL is comparable to observations (Fig. 3e-f); however, the amplitudes of the rainfall anomalies are
222 slightly weaker in the model, particularly over the Indian Ocean and western Pacific. The southeastward propagation over
223 the South Pacific is also well simulated in C-CTL. In particular, the southeastward propagation between 10°N and 10°S in
224 observations is quite pronounced with relatively stationary signals between 10°S and 20°S (Fig. 3c-d). This feature is nicely
225 simulated in C-CTL with comparable amplitudes of rainfall anomalies (Fig. 3g-h).

226 **4 Role of air-sea interaction**

227 To understand the role of air-sea coupling, we compare both uncoupled simulations (A-CLIM and A-DAY)
228 with C-CTL. In A-CLIM, the atmosphere is forced with the daily SST climatology, and therefore the intraseasonal SST
229 variability is largely suppressed. In A-DAY, the SST forcing the atmosphere has the same intraseasonal SST variability as in
230 C-CTL, but the atmosphere does not influence the SST. In both uncoupled experiments, we use the SST from the coupled
231 experiment to ensure that any differences between coupled and uncoupled simulations are not because of the difference in
232 the SST mean state but solely because of the impact of SST variability and air-sea coupling.

233 *4.1. Mean state and intraseasonal variability of the rainfall*

234 The spatial structures of the daily rainfall climatology for both uncoupled simulations closely resemble the
235 coupled simulation with comparable magnitudes (Fig. 1c-d). However, there is one noticeable difference. The orientation of
236 the SPCZ in both uncoupled models is more zonal (diagonal dashed lines, Fig. 1). Consequently, the location of the
237 maximum rainfall is shifted more to the equator. These differences in the mean SPCZ positions in both uncoupled models
238 can be attributed to air-sea coupling, as they have identical SST climatology to C-CTL.

239 The overall intraseasonal rainfall variability over the South Pacific in A-CLIM is reduced compared to C-
240 CTL (Fig. 1g). In contrast, the intraseasonal variability is increased in A-DAY (Fig. 1h). In particular, the changes in
241 intraseasonal variability are more evident over the SPCZ. To quantify such changes, we compute weighted area average
242 standard deviations over the SPCZ (160°E-170°W, 5°S-15°S) for all three simulations (black rectangular box, Fig. 1h). We
243 chose this region because the maximum standard deviations are mainly concentrated along the SPCZ in all three
244 simulations. There is a 17% reduction of the intraseasonal variability in A-CLIM compared to C-CTL. Such a reduction in
245 the intraseasonal variability can be attributed to the impact of suppressed SST variability and the absence of air-sea coupling
246 (Tseng et al. 2015).

247 We observe about 8% increase in the intraseasonal rainfall variability in A-DAY compared to C-CTL,
248 suggesting the ocean-atmosphere interaction in the coupled model dampens the intraseasonal rainfall variability over the
249 South Pacific. [Pegion and Kirtman \(2008\)](#) observed a similar increase in rainfall variability in the uncoupled model forced
250 with daily SST from a coupled model. They further argue that, in the uncoupled model, the prescribed SST can cause local
251 rainfall anomalies as long as the wind circulation is favourable for convection. In contrast, in reality and in the coupled
252 model, the SST anomalies are damped by the atmospheric response. Thus, relatively larger rainfall anomalies are expected
253 in the uncoupled simulation, so the rainfall variability increases.

254 4.2 Simulation of leading EOF modes

255 The first two EOF modes in both uncoupled models explain roughly 14 and 15% of the total 10-90-day
256 rainfall variability, comparable to that of the coupled model (15%). The spatial structures of the two leading EOF modes in
257 both uncoupled simulations are similar to coupled simulation ([Fig. 2g-h, j-k](#)). However, the maximum rainfall anomalies are
258 shifted southwestward of the SPCZ in uncoupled simulations.

259 Although the overall large-scale rainfall structures for both EOF modes in both uncoupled models are
260 comparable to the coupled model, the power spectra differ. The power spectra of two PCs for A-CLIM show no evidence of
261 pronounced peaks in the 30-80-day period ([Fig. 2i](#)). The overall spectra for both PCs are relatively flat, and the variance is
262 distributed over the entire 10-90-day frequency band. This shows that the intraseasonal variability represented by two EOF
263 modes does not have any preferred oscillatory period. In contrast, the power spectra of two PCs in A-DAY show
264 pronounced peaks in the 30-80-day period with comparable amplitudes to C-CTL ([Fig. 2l](#)); however, the peaks with
265 maximum power are shifted to the left from about 40 days in C-CTL to 60 days.

266 To further quantify the impact of air-sea coupling on the variance associated with two PCs, we compute the
267 mean power associated with two PCs by averaging the power spectrum in the 30-80-day band (Pow_{SP}). Note that the mean
268 power is computed for each PC separately and averaged to obtain a single value. In the absence of air-sea coupling and SST
269 variability, the variance associated with two PCs in the 30-80-day band is significantly reduced in A-CLIM ($Pow_{SP} \sim 0.19$)
270 than C-CTL ($Pow_{SP} \sim 0.34$). Interestingly, the variance in A-DAY ($Pow_{SP} \sim 0.33$) is quite comparable to C-CTL, suggesting
271 the role of SST variability on enhancing the intraseasonal rainfall variability by exciting the atmosphere. Note that the mean
272 power in the 30-80-day band for all three simulations is different than the mean read noise spectra; however, the peaks with
273 maximum power are pronounced and statistically significant at 99.9% level only for C-CTL and A-DAY ([Fig. 2](#)).

274 Besides, air-sea interaction also seems to affect the phase relationship between two leading PCs. The two PCs
275 in C-CTL show a lag-correlation coefficient of 0.42 at ten days lag in the 30-80-day period. The relationship between PCs is
276 largely reduced in A-CLIM ($r \sim 0.19$). In contrast, the lag-correlation between two PCs in A-DAY is quite comparable
277 ($r \sim 0.41$) to C-CTL; however, the lag is increased by roughly three days (lag ~ 13 days) ([Supplementary Fig. 2](#)). Such a longer
278 lag reflects the longer periodicity in A-DAY.

Our previous study shows that the eastward propagating MJO signal is crucial for the southeastward propagation associated with the leading patterns of intraseasonal rainfall variability in the South Pacific (Pariyar et al. 2019). We, therefore, investigate the MJO-South Pacific teleconnection in the coupled and uncoupled model simulations. Prescribing climatological SST from the coupled model degrades the MJO simulation: the dominant intraseasonal timescale becomes longer, and the eastward propagation speed becomes slower (Tseng et al. 2015); the MJO simulation is better when prescribing intraseasonal varying (A-DAY) rather than climatological fixed SST (A-CLIM). However, the MJO-South Pacific teleconnection differs markedly between the uncoupled simulations, as indicated by lag-correlation between our PCs and the RMM indices (Supplementary Fig. 3). The maximum MJO-PCs lag-correlation coefficients in the 30-80-day period in C-CTL ranges from -0.39 to +0.66. These values are reduced to -0.26 to +0.3 in A-CLIM and somewhat comparable in A-DAY ($r \sim -0.46$ to +0.7); this is consistent with the better simulation of the MJO in A-DAY compared to A-CLIM.

290 4.4 Propagation characteristics and mechanism

The 30-80-day rainfall propagation characteristics for the uncoupled simulations are summarized in the form of time-longitude and time-latitude plots, as before (Fig. 3i-p). The eastward propagation from the Indian Ocean to the western Pacific is significantly reduced in A-CLIM (Fig. 3i-j). Consistent with this, the southeastward propagation over the South Pacific is also considerably weakened (Fig. 3k-l), attributed to the degraded simulation of the MJO in the absence of air-sea coupling and SST variability (Tseng et al. 2015) and its teleconnection to the South Pacific, as discussed in Section 4.3.

In A-DAY, both eastward and southeastward propagations are improved (Fig. 3m-p). In particular, the eastward propagations from 110°E to 150°W and southeastward propagations from 10°N to 20°S are pretty comparable to C-CTL for both EOF modes (Fig. 3e-f). Such improvements in both eastward and southeastward propagations suggest that intraseasonally varying SST anomalies are crucial for rainfall propagation over the Maritime Continent and the South Pacific, partly attributed to relatively better representation of the MJO in A-DAY compared to A-CLIM (Tseng et al. 2015).

It is evident that C-CTL can simulate the key propagation characteristics of rainfall anomalies over the South Pacific. Also, SST variability appears to play a role in such propagation. Therefore, we compare the propagation mechanisms between C-CTL and A-DAY. We do not show a similar comparison for A-CLIM because of the considerably weak southeastward propagation. We construct the time-longitude plots for anomalies of rainfall and other atmospheric variables as before. We do not show propagation for EOF2, as it is similar to that of EOF1.

The propagation mechanisms associated with the two EOF modes in observations are briefly summarized (Supplementary Fig. 4; see Pariyar et al. 2019 for more details). The key observed mechanisms for the southeastward propagation are wind-evaporation-SST feedback and low-level frictional moisture convergence for EOF1 and EOF2 mode, respectively. Even though the mechanisms differ, warm SST anomalies lead the active convection by 12-14 days in both

311 cases. Likewise, cold SST anomalies lag the convection by the same number of days. The warm SST anomalies are
312 generally followed by low pressure and low-level moisture convergence anomalies. In the EOF1 mode, warm SST and low
313 SLP anomalies are primarily in phase with each other, between the equator and 15°S, followed by increased latent heat flux
314 (evaporation), low-level wind speed, and low-level moisture convergence anomalies that are mostly in phase with rainfall.
315 Opposite anomalies occur for decreased rainfall phase. These variations are broadly consistent with the wind-evaporation-
316 SST feedback. In contrast, for the EOF2 mode, SLP anomalies are much weaker, and increased evaporation and wind speed
317 follow increased rainfall between the equator and 15°S. Instead, the low-level moisture convergence anomalies lead the
318 convection. The more detailed analysis provides evidence that low-level frictional moisture convergence is a relevant
319 mechanism for the EOF2 mode (Pariyar et al. 2019).

320   The coupled model simulates a similar southeastward propagation mechanism for both EOF modes that
321 resemble EOF2 in observations (Fig. 4). In particular, warm SST anomalies lead maximum rainfall by 12-14 days (Fig. 4a),
322 and low pressure and low-level moisture flux convergence anomalies slightly lead the rainfall (Fig. 4b-c). The evaporation
323 is enhanced as represented by positive latent heat flux anomalies (Fig. 4d), and surface wind speeds are increased 2-3 days
324 after the maximum rainfall (Fig. 4f). In observations, the rainfall relationship with SST and key atmospheric variables
325 simulated in C-CTL is comparable with EOF2 mode. Therefore, the low-level frictional moisture convergence mechanism
326 seems relevant for the southeastward propagation in C-CTL for both EOF modes. Unlike in observations, the wind-
327 evaporation-feedback does not appear essential for the southeastward propagation of rainfall anomalies associated with the
328 EOF1 mode.

329   The relationships between rainfall and other atmospheric variables in A-DAY are similar to C-CTL (Fig. 4g-
330 l); however, the SST relationship differs. In A-DAY, the warm SST anomalies are more or less in phase with rainfall
331 anomalies (Fig. 4g), while in C-CTL, SST anomalies lead rainfall anomalies by 12-14 days (Fig. 4a). Interestingly, the
332 phase lagging among low-level moisture convergence, wind speeds, latent heat flux, and rainfall in C-CTL and A-DAY are
333 similar. The low-level frictional moisture convergence seems to be a relevant mechanism for both EOF modes in A-DAY
334 and C-CTL.

335   The shorter lag between SST and rainfall on the intraseasonal timescale is a key characteristic of uncoupled
336 models. Many previous studies have observed a similar change in the SST-rainfall relationship (Fu et al. 2003; Fu and Wang
337 2004; Zheng et al. 2004; Pegion and Kirtman, 2008). The change in the SST-rainfall relationship in the uncoupled
338 simulation suggests that the coupling is necessary to simulate the correct phase relationship. The atmosphere modulates the
339 SST anomalies produced by turbulent fluxes as atmospheric convection adjusts to SST anomalies in the coupled simulation.
340 In such interaction, both rainfall and SST anomalies propagate together, maintaining a quadrature relationship.

341   In contrast, in the uncoupled model, the surface fluxes modulated by the atmosphere have no impact on the
342 SST. Thus, the atmospheric adjustment is almost in phase with the prescribed SST anomalies. The correct SST-rainfall
343 phase relationship is essential because the warm SST ahead of the convection acts to lower the surface pressure, promoting
344 the moisture convergence and helping to destabilize the atmosphere (Waliser et al. 1999; Kemball-Cook et al. 2002;

345 [Maloney and Kiehl 2002](#)). Therefore, changes in the SST-rainfall relationship have a noticeable influence on the
346 organization and propagation of the surface convergence, which is also evident in our results.

347 The phase relationship between rainfall and SST is essential for propagating tropical intraseasonal variability
348 ([Fu et al. 2003](#); [Zheng et al. 2004](#); [Pegion and Kirtman 2008](#)). As the intraseasonal SST variability is primarily controlled by
349 surface heat fluxes ([Flatau et al. 1997](#); [Hendon and Glick 1997](#); [Jones et al. 1998](#); [Zhang and Anderson 2003](#)), the
350 relationship between SST and surface fluxes largely determines the strength and phase of the SST-rainfall relationship. That
351 is why most of the uncoupled models fail to reproduce the observed SST-rainfall relationship, as the prescribed SSTs do not
352 interact with atmospheric surface fluxes in the model. Therefore, it is interesting to investigate how the SST-rainfall
353 relationship changes between coupled and uncoupled simulations and how such changes are attributed to changes in the
354 SST relationship with the surface fluxes and wind speed.

355 We perform a lag-correlation between SST and other atmospheric variables (PCP, LHF, SHF, WS) ([Fig. 5](#)).
356 We estimate the lag correlation coefficients for both C-CTL and A-DAY by taking a weighted area average over 160°E-
357 170°W and 5°S-15°S (black rectangular box, [Fig. 1h](#)). We choose this region for two reasons. First, it corresponds to the
358 region of maximum intraseasonal variance, and second, it covers the region of maximum variance correspond to two EOF
359 modes in both coupled and uncoupled simulations ([Fig. 2d,j](#)). We compute the weighted area average over the selected
360 region for desired variables, and from the derived time series, we obtain the lag-correlation for November-April. Note that
361 we compute the lag correlation coefficients for November-April and later averaged over 25 years.

362 The phase relationship between SST and rainfall has changed substantially, both in magnitudes and phasing in
363 A-DAY than C-CTL ([Fig. 5a](#)). In particular, the relationship between SST and other variables is weaker in A-DAY. The
364 correlation coefficients between SST and rainfall are 0.66 and 0.44 for C-CTL and A-DAY, respectively, with positive lags
365 of 13 and three days. The nearly in-phase relationship in A-DAY suggests that the atmospheric quickly respond to the SST
366 anomalies and associated circulation change to produce rainfall anomalies. Also, the lag-correlation is asymmetric in A-
367 DAY. For the negative rainfall events, the SST-rainfall correlation is reduced. For example, a maximum negative correlation
368 of -0.72 is observed at -8 days in C-CTL. A negative correlation of -0.23 is observed at -21 days in A-DAY. Such an
369 asymmetry and weaker SST-PCP relationship reflect the lack of atmospheric response to SST anomalies and partly explain
370 increased intraseasonal rainfall variability and longer periodicity in A-DAY. In the absence of atmospheric feedback to local
371 SST, the rainfall anomalies would grow as long as the large-scale wind anomalies are favourable, leading to larger rainfall
372 variability. In contrast, the atmospheric feedback dampens the SST anomalies in the coupled case, eventually reducing
373 rainfall variability ([Pegion and Kirtman, 2008](#)).

374 The weaker SST-rainfall relationship in A-DAY is attributed to the weaker association between SST and other
375 variables (SHF, LHF, WS) with significant changes in lead-lag relationships. We observe the highest reduction in the
376 maximum positive correlation coefficients between SST and wind speed with a value of 0.54 at 17 days in C-CTL to 0.23 at
377 five days in A-DAY ([Fig. 5d](#)). Such a weakening of the SST-wind speed relationship indicates a lack of atmospheric

influence on the ocean. This is because, on the intraseasonal timescale, the perturbation of SST anomalies over the tropical Pacific is attributed to wind-driven surface latent heat flux anomalies (Wu and Chen 2015), consistent with the weaker SST-LHF/SHF relationship. The maximum positive lag correlation coefficients between SST and LHF (SHF) for C-CTL and A-DAY are 0.45 at 14 days (0.65 at 12 days) and 0.34 at four days (0.49 at three days), respectively (Fig. 5b-c). Such a weaker relationship between SST and surface fluxes and reduced lags in A-DAY suggest that the contribution of the local SST variations to the variability of the surface fluxes are reduced; hence the fluctuations in surface fluxes are dominated by the remotely forced wind speed anomalies. Consistent with the SST-rainfall relationship, the correlation between SST and surface fluxes are asymmetric, with significantly weaker correlation coefficients and delayed SST-flux adjustment during negative rainfall events.

4.5 Role of ocean vertical resolution and regional coupling

The analysis above shows the importance of air-sea interaction for the propagation and timescale of the intraseasonal variability in the South Pacific. To further assess the role of local air-sea interaction versus remote air-sea interaction and the role of the upper ocean, we use five additional experiments: two experiments with coarser ocean vertical resolution (C-17m and C-59m) and three regional coupling simulations (C-IO, C-IPO, and C-PO).

We repeat a similar analysis as before for all five experiments. The spatial structures of the two leading EOF modes simulated in all five experiments are pretty identical to C-CTL (figure not shown). Note that the two leading EOF modes are identified as statistically different from red-noise with isotropic diffusion. Although the power spectra associated with two EOF modes in all five simulations are less pronounced than C-CTL, the power spectra for C-17m, C-59m, and C-IPO show well-defined and statistically significant peaks in the 30-80-day period (Supplementary Fig. 5). In contrast, the power spectra for C-IO and C-PO are relatively flat, with no evidence of pronounced peaks in the 30-80-day period. Consistent with this, the lag-correlation between two PCs in the 30-80-day period for C-17m, C-59m, and C-IPO are somewhat comparable to C-CTL. In contrast, for the remaining two experiments (C-IO and C-PO), the relationships are weaker (Supplementary Fig. 6).

To investigate the rainfall propagation characteristics in the 30-80-day period over the South Pacific and associated eastward propagation in the Indian Ocean and the western Pacific, we compute the 30-80-day time-longitude and time-latitude composites of rainfall anomalies as before (Fig. 6). Both experiments with coarser ocean vertical resolution, in general, capture both eastward and southeastward propagations of rainfall anomalies and are somewhat comparable to C-CTL (Fig. 6a-b, e-f). Interestingly, the eastward propagation in C-59m is slightly slower than C-17m, and the southeastward propagation over the South Pacific is relatively weak. For regional coupling experiments, both eastward and southeastward propagation of rainfall anomalies is degraded in all three experiments (Fig. 6i-t). Among three simulations, C-IPO best simulates both eastward and southeastward propagations (Fig. 6m-p). For C-PO, the eastward propagating rainfall signal is simulated over the coupled part of the domain but not over the Indian Ocean. In contrast, the southeastward propagation is comparable to C-IPO (Fig. 6q-t). On the other hand, C-IO does not reproduce the eastward and southeastward propagation

411 (Fig. 6i-l). These results suggest the air-sea interaction over the western Pacific is essential for the propagating
412 intraseasonal rainfall variability associated with the two EOF modes.

413 To quantitatively compare the performance of all eight simulations, we use ten metrics; five for the MJO, four for
414 the intraseasonal variability over the South Pacific, and one for MJO-South Pacific teleconnection. The first MJO metric is
415 the percentage variance explained by the two leading modes (Prct_{MJO}) based on the combined EOF (CEOF) analysis of daily
416 OLR, U850, and U200 (Wheeler and Hendon 2004). The second metric is the eastward/westward power ratio (E/W ratio),
417 obtained by dividing the sum of spectral power over the 30-80-day band by its westward propagating counterpart. This
418 metric provides an estimate of the eastward propagating feature of the MJO (Kim et al. 2009). The third metric represents
419 the coherency in the MJO propagation, computed by averaging the absolute values of maximum and minimum lead-lag
420 correlation coefficients between RMM1 and RMM2 (Rmax_{MJO}) (Sperber and Kim 2012). Note that the lead-lag correlation
421 coefficients are computed for the 30-80-day filtered RMM indices. The fourth metric, a measure of the MJO (PMJO)
422 periodicity, is formulated by computing twice the time interval between maximum and minimum lag-correlation between
423 30-80-day filtered RMM indices. The fifth metric represents the mean power in the 30-80-day frequency band as
424 represented by the power spectra of two RMM indices (Pow_{MJO}). The power spectrum is averaged over the 30-80-day band
425 for each RMM index and later averaged for both RMM indices to define a single index. We compute the mean power for
426 the red-noise spectra similarly for comparison.

427 The first metric of four metrics representing the intraseasonal variability over the South Pacific is the percentage
428 variance explained by the two leading EOF modes based on daily rainfall data in the 10-90-day period (Prct_{SP}). The second,
429 third, and fourth metrics measure the relationship between two PCs, the periodicity of the variability in the 30-80-day
430 period, and the average variance in the 30-80-day frequency band as represented in the power spectra of two PCs. The
431 computation of the maximum correlation coefficient (Rmax_{SP}), the periodicity (P_{SP}) for two leading PCs, and mean power in
432 30-80-day band (Pow_{SP}) is similar to that for MJO indices, as described before. To define a metric that measures the strength
433 of teleconnection between the MJO and the leading EOF modes in the 30-80-day period, we average the absolute values of
434 maximum and minimum lead-lag correlation coefficients between PCs and two RMM indices ($\text{Rmax}_{\text{MJO-SP}}$). The correlation
435 coefficients between each PC and two RMM indices are averaged to produce a single metric for convenience. The summary
436 of metrics for observation and model experiments is presented in Table 2.

437 Among the eight simulations, C-CTL best simulates the key characteristics of the MJO and its eastward
438 propagation. Although the variance explained by two RMM indices in C-CTL is slightly lower than observations, it is still
439 better than the remaining seven simulations. The MJO simulation skill degrades in models with coarser ocean vertical
440 resolution and regional coupling as indicated by lower Prct_{MJO} and E/W ratio. However, in most of these simulations, the
441 phase relationship between two RMM indices and their periodicity in a 30-80-day period is comparable to C-CTL. The
442 MJO propagation is worst in A-CLIM and C-IO, as indicated by lower values of E/W ratio, Prct_{MJO} , and Rmax_{MJO} . In
443 general, all coupled simulations perform better than the two uncoupled (A-DAY and A-CLIM) and two regionally coupled
444 (C-IO and C-PO) simulations. The mean power in the 30-80-day band based on the power spectra of two RMM indices is
445 higher than observations in all eight simulations; however, the power differs among models. For example, the mean power

446 is largely reduced in A-CLIM and C-IO compared to C-CTL. For the remaining seven experiments, the mean power is quite
447 comparable to C-CTL. Even though the MJO periodicity and the mean power in 30-80-day band in the majority of the
448 models are similar, the peaks with maximum power for both RMM indices are more pronounced in C-CTL, C-17m, C-59m,
449 C-IPO, and A-DAY than A-CLIM, C-IO and C-PO ([Supplementary Fig. 7](#)).

450 For the intraseasonal variability over the South Pacific, all model simulations overestimate the variance
451 explained by the two EOF modes. The values of explained variance ranged from 14.2 to 15.5% in the models, compared to
452 10.8% in observations. The phase relationship between two PCs ($R_{\max_{SP}}$) is comparable among experiments except for A-
453 CLIM and C-IO. These two simulations show lower values of maximum correlation coefficients between two PCs that are
454 interestingly quite comparable to observations. The periodicity of the EOF modes in the 30-80-day period (P_{SP}) is pretty
455 similar among all simulations except A-DAY. In A-DAY, the periodicity is a little longer ($P_{SP} \sim 50$ days) than other
456 simulations, consistent with the longer periodicity for the MJO in this simulation ([Tseng et al. 2015](#)). The mean power in the
457 30-80-day band is underestimated in the coupled model ($Pow_{SP} \sim 0.34$). The mean power is largely reduced in all other
458 simulations except A-DAY. Although the mean power in the 30-80-day band is quite similar among simulations, the peaks
459 associated with the power spectra of two PCs are more pronounced and statistically significant in some simulations. For
460 example, the maximum peak associated with two PCs in C-CTL, A-DAY, C-17m, C-59m, and C-IPO are statistically
461 significant at the 99.9% level. These peaks are less pronounced and not statistically significant in the remaining simulations
462 (A-CLIM, C-IO, and C-PO).

463 It is noteworthy that the MJO related variability in the 30-80-day period not necessarily dictates the
464 corresponding variance associated with two EOF modes in the South Pacific but rather enhances the oscillation of these
465 modes. It is evident from [Table 2](#) that the mean power in the 30-80-day band for the MJO is quite similar in all simulations
466 except A-CLIM and C-IO; however, in the case of two EOF modes in the South Pacific, the mean power is comparable
467 among models except C-CTL and A-DAY. Interestingly, the power spectra for two PCs in C-CTL, A-DAY, C-17m, C-59m,
468 and C-IPO show pronounced and statistically significant peaks, consistent with pronounced peaks for two RMM indices in
469 these simulations.

470 Even though the characteristics of EOF modes, the phase relationship between PCs, and periodicity are
471 comparable among different simulations, their relationship with the MJO differ. For example, C-CTL best simulates the
472 MJO-South Pacific teleconnection as indicated by comparable values of $R_{\max_{MJO-SP}}$ to observations. The coupled models in
473 general (C-17m, C-59m, C-IPO) better represent the MJO-South Pacific teleconnection than the uncoupled model (A-
474 CLIM). In particular, A-CLIM and C-IO perform worst in representing MJO-South Pacific teleconnection. The considerably
475 weaker MJO-South Pacific teleconnection in the uncoupled model (A-CLIM) and regionally coupled models (C-IO and C-
476 PO) are consistent with the degraded simulation of the MJO in these models. However, the MJO simulation and MJO-South
477 Pacific teleconnection are better in C-PO than C-IO.

478 5 Summary and discussion

479 We investigate the role of air-sea coupling and SST variability in the simulation of dominant intraseasonal
480 (10-90-day) rainfall modes over the South Pacific using the ECHAM5-SIT model. The fully coupled ECHAM5-SIT model
481 is capable of capturing the key characteristics of the intraseasonal rainfall variability over the South Pacific and its
482 relationship with the MJO. It is, therefore, a useful tool to study the mechanisms for the intraseasonal rainfall variability
483 over this region.

484 Air-sea interaction is essential for the intraseasonal variability over the South Pacific. The overall
485 intraseasonal rainfall variability along the SPCZ is reduced when the air-sea interaction is suppressed. The intraseasonal
486 variability in the 30-80-day period is also reduced in the leading EOF modes over the South Pacific without air-sea
487 interaction. However, a considerable fraction of intraseasonal variability is observed without air-sea interaction, attributed to
488 the internal dynamics of the atmosphere.

489 The spatial structure of the dominant patterns of intra-seasonal rainfall variability appears independent of
490 active air-sea interaction. The rainfall patterns associated with the two EOF modes are present in both coupled and
491 uncoupled simulations and are comparable to observations. The spatial structure of the dominant modes remains nearly
492 identical in coupled and uncoupled models, while their amplitudes differ. This strongly suggests that the internal dynamics
493 of the atmosphere primarily generate these intraseasonal modes.

494 Prescribing intraseasonal SST variability improves both eastward and southeastward propagations associated
495 with two EOF modes. In particular, intraseasonally varying SST tends to produce rainfall variability associated with two
496 EOF modes that are pretty comparable to the coupled model, but the periods are longer. Such a longer periodicity in the
497 absence of air-sea interaction is consistent with a longer periodicity of the MJO ([Tseng et al. 2015](#)). The SST-rainfall
498 relationship dramatically changes when the atmosphere does not interact with the ocean, leading to asymmetry in the SST-
499 rainfall lead-lag relationship and longer oscillation of rainfall events.

500 Air-sea interaction and intraseasonal SST variability are responsible for differences in the simulation of the
501 MJO related eastward propagating rainfall variability, the southeastward propagation of rainfall anomalies over the South
502 Pacific, and their teleconnection. In the absence of air-sea interaction (A-CLIM), ECHAM5 fails to simulate the
503 southeastward propagation over the South Pacific, consistent with significantly weaker eastward propagation over the
504 Indian Ocean and western Pacific and degraded simulation of the MJO. On the other hand, SST variability plays an essential
505 role in initiating and organizing both eastward and southeastward propagations (A-DAY). Both eastward and southeastward
506 propagations are well simulated in two models with coarser vertical ocean resolution and one with coupling over the Indian
507 Ocean and western Pacific (C-17m, C-59m, C-IPO), consistent with a better simulation of the MJO ([Tseng et al. 2015](#))
508 compared to uncoupled and two other regionally coupled experiments in the Indian Ocean (C-IO) and western Pacific (C-
509 PO).

510   The differences in southeastward propagation of rainfall anomalies over the South Pacific between coupled
511 and uncoupled simulations are partly attributed to the eastward propagating signals in the Indian Ocean and western Pacific.
512 These eastward propagating rainfall signals are primarily associated with the MJO and play an important role in enhancing
513 the southeastward propagations in the South Pacific. Models with better MJO and associated eastward propagations (C-
514 CTL, A-DAY, C-17m, C-59m, C-IPO) tend to have more realistic southeastward propagations in the South Pacific,
515 consistent with better MJO-South Pacific teleconnection in these models than one with degraded MJO simulation (A-CLIM,
516 C-IO, C-PO).

517   The primary mechanism for the southeastward propagation associated with two EOF modes in the model is
518 the low-level moisture convergence leading rainfall patterns, i.e., frictional moisture convergence. However, in
519 observations, the two EOF modes show different mechanisms, i.e., wind-SST-evaporation for EOF1 mode and low-level
520 frictional moisture convergence mechanism for EOF2 mode (Pariyar et al. 2019). Thus, the observed wind-SST-evaporation
521 mechanism is not simulated in the model. The simulation of propagation mechanisms for the tropical intraseasonal
522 variability, particularly the MJO, is challenging, and the propagation mechanism differs among models (DeMott et al.
523 2015). Tseng et al. (2015), in their analysis with identical model experiments, argued that the improved MJO propagation in
524 the coupled models is mainly due to enhanced frictional convergence ahead of the convection. Therefore, for the given
525 ECHAM-SIT model configuration, the low-level moisture convergence seems to be the primary mechanism for the
526 propagation of intraseasonal variability in both the Indian Ocean-western Pacific and the South Pacific. Thus, similar
527 experiments with other models are necessary to investigate why the wind-evaporation-feedback mechanism is missing in
528 this model.

529   Our previous study hypothesized that the connection between the South Pacific and South China Sea for
530 EOF2 mode might explain the differences in the mechanisms for two EOF modes. Precisely, we observe statistically
531 significant low-level wind circulation anomalies along the South China Sea for EOF2 mode in observations, which is absent
532 in EOF1 mode. Therefore, we proposed that the large-scale forcing from the South China Sea could contribute to the low-
533 level frictional convergence over the South Pacific. However, we do not find this connection in the coupled model as the
534 circulation anomalies over the South China Sea are missing in both EOF modes (Supplementary Fig. 8). This suggests that
535 the difference in propagation mechanisms in observations is not primarily linked to the large-scale forcing from the South
536 China Sea, but rather the absence of such a feature in our model could partly explain why the two modes are better related
537 to each other and the MJO.

538   Our results suggest that air-sea coupling is vital for enhancing intraseasonal rainfall variability in the South
539 Pacific and initiating and organizing rainfall propagation associated with dominant intraseasonal modes in the South Pacific.
540 However, the spatial structures of such modes are primarily generated by the internal dynamics of the atmosphere, and the
541 amplitude of the variability is partly linked to the MJO. The key findings of this study should motivate future work on
542 intraseasonal variability in the South Pacific, and in particular, it is important to investigate model dependency.

543   **6 Declarations**

544   *6.1 Funding*

545   This work is supported by European Research Council-Synchronization to Enhance Reliability of Climate Prediction (ERC-
546   STERCP) Project (Grant Agreement 648982) funded by the European Union’s H2020 programme, European Research
547   Council Executive Agency.

548   *6.2 Conflicts of interest/Competing interests*

549   The authors declare that they have no competing interests.

550   *6.3 Availability of data and material*

551   The model data is available upon request.

552   *6.4 Code availability*

553   The MATLAB code for all the analysis and graphics is available upon request.

554   *6.5 Author’s contributions*

555   Sunil Kumar Pariyar: Conceptualization, methodology, data analysis, writing the original draft
556   Noel Keenlyside: Supervision, conceptualization, methodology, review and editing, funding acquisition
557   Wan-Ling Tseng: Model experimental design, model simulations, review
558   Huang Hsiung Hsu: Review
559   Ben-jei Tsuang: Model experimental design, review

560   *6.6 Ethics approval*

561   Not applicable

562   *6.7 Consent to participate*

563   Not applicable

564   *6.8 Consent for publication*

565   Not applicable

566   **References**

- 567   Ahn MS, Kim D, Sperber KR, Kang IS, Maloney E, Waliser D, Hendon H (2017) MJO simulation in CMIP5 climate
568   models: MJO skill metrics and process-oriented diagnosis. *Climate dynamics* 49(11-12):4023-4045
- 569   Arpe K, Tsuang BJ, Tseng YH, Liu XY, Leroy SAG (2018) Quantification of climatic feedbacks on the Caspian Sea level
570   variability and impacts from the Caspian Sea on the large-scale atmospheric circulation.. *Theoretical and Applied*
571   *Climatology* 1–14
- 572   Bollasina M, Nigam S (2009) Indian Ocean SST, evaporation, and precipitation during the South Asian summer monsoon in
573   IPCC-AR4 coupled simulations. *Climate Dynamics* 33(7-8):1017
- 574   Brown JR, Power SB, Delage FP, Colman RA, Moise AF, Murphy BF (2011) Evaluation of the South Pacific Convergence
575   Zone in IPCC AR4 climate model simulations of the twentieth century. *Journal of Climate* 24(6):1565-1582.
- 576   Dee DP, Uppala SM, Simmons AJ, Berrisford P, Poli P, Kobayashi S, et al (2011) The ERA-Interim reanalysis:
577   Configuration and performance of the data assimilation system. *Quarterly Journal of the royal meteorological society*
578   137(656):553-597
- 579   DeMott CA, Klingaman NP, Woolnough SJ (2015) Atmosphere-ocean coupled processes in the Madden-Julian oscillation.
580   *Reviews of Geophysics* 53(4):1099-1154
- 581   DeMott CA, Stan C, Randall DA, Kinter III JL, Khairoutdinov M (2011) The Asian monsoon in the superparameterized
582   CCSM and its relationship to tropical wave activity. *Journal of Climate* 24(19):5134-5156
- 583   Dommenget D (2007) Evaluating EOF modes against a stochastic null hypothesis. *Climate dynamics* 28(5): 517-531
- 584   Flatau M, Flatau PJ, Phoebus P, Niiler PP (1997) The feedback between equatorial convection and local radiative and
585   evaporative processes: The implications for intraseasonal oscillations. *Journal of the Atmospheric Sciences* 54(19):2373-
586   2386
- 587   Fu X, Wang B (2004) Differences of boreal summer intraseasonal oscillations simulated in an atmosphere–ocean coupled
588   model and an atmosphere-only model. *Journal of Climate* 17(6):1263-1271
- 589   Fu X, Wang B, Li T, McCreary JP (2003) Coupling between northward-propagating, intraseasonal oscillations and sea
590   surface temperature in the Indian Ocean. *Journal of the Atmospheric Sciences* 60(15):1733-1753

591 Gaspar P, Grégoris Y, Lefevre JM (1990) A simple eddy kinetic energy model for simulations of the oceanic vertical mixing:
 592 Tests at station Papa and Long-Term Upper Ocean Study site. *Journal of Geophysical Research: Oceans* 95(C9):16179-
 593 16193

594 Gilman DL, Fuglister FJ, Mitchell Jr JM (1963) On the power spectrum of “red noise”. *Journal of the Atmospheric Sciences*
 595 20(2):182-184

596 Harrison DE, Larkin NK (1998) El Niño-Southern Oscillation sea surface temperature and wind anomalies, 1946–1993.
 597 *Reviews of Geophysics* 36(3):353-399

598 Hendon HH (2000) Impact of air–sea coupling on the Madden–Julian oscillation in a general circulation model. *Journal of*
 599 *the Atmospheric Sciences* 57(24):3939-3952

600 Hendon HH, Glick J (1997) Intraseasonal air–sea interaction in the tropical Indian and Pacific Oceans. *Journal of Climate*
 601 10(4):647-661

602 Hendon, H. H, & Salby, M. L. (1994) The life cycle of the Madden–Julian oscillation. *Journal of the Atmospheric Sciences*
 603 51(15):2225-2237

604 Huffman GJ, Bolvin DT, Nelkin EJ, Wolff DB, Adler RF, Gu G, et al (2007) The TRMM multisatellite precipitation analysis
 605 (TMPA): Quasi-global, multiyear, combined-sensor precipitation estimates at fine scales. *Journal of hydrometeorology*
 606 8(1):38-55

607 Hung MP, Lin JL, Wang W, Kim D, Shinoda T, Weaver SJ (2013) MJO and convectively coupled equatorial waves
 608 simulated by CMIP5 climate models. *Journal of Climate* 26(17):6185-6214

609 Inness PM, Slingo JM (2003) Simulation of the Madden–Julian oscillation in a coupled general circulation model. Part I:
 610 Comparison with observations and an atmosphere-only GCM. *Journal of Climate* 16(3):345-364

611 Inness PM, Slingo JM, Guilyardi E, Cole J (2003) Simulation of the Madden–Julian oscillation in a coupled general
 612 circulation model. Part II: The role of the basic state. *Journal of Climate* 16(3):365-382

613 Jiang X, Waliser DE, Xavier PK, Petch J, Klingaman NP, Woolnough SJ et al (2015) Vertical structure and physical
 614 processes of the Madden-Julian oscillation: Exploring key model physics in climate simulations. *Journal of Geophysical*
 615 *Research: Atmospheres* 120(10):4718-4748

616 Jones C, Waliser DE, Gautier C (1998) The influence of the Madden–Julian oscillation on ocean surface heat fluxes and sea
 617 surface temperature. *Journal of Climate* 11(5):1057-1072

618   Kemball-Cook S, Wang B, Fu X (2002) Simulation of the intraseasonal oscillation in the ECHAM-4 model: The impact of
619   coupling with an ocean model. *Journal of the atmospheric Sciences* 59(9):433-1453

620   Kim D, Sperber K, Stern W, Waliser D, Kang IS, Maloney E et al (2009) Application of MJO simulation diagnostics to
621   climate models. *Journal of Climate* 22(23):6413-6436

622   Kim HM, Hoyos CD, Webster PJ, Kang IS (2008) Sensitivity of MJO simulation and predictability to sea surface
623   temperature variability. *Journal of Climate* 21(20):5304-5317

624   Kim HM, Hoyos CD, Webster PJ, Kang IS (2010) Ocean–atmosphere coupling and the boreal winter MJO. *Climate*
625   *dynamics* 35(5):771-784

626   Kim HM, Kim D, Vitart F, Toma VE, Kug JS, Webster PJ (2016) MJO propagation across the Maritime Continent in the
627   ECMWF ensemble prediction system. *Journal of Climate* 29(11):3973-3988

628   Klingaman NP, Woolnough SJ (2014) The role of air–sea coupling in the simulation of the Madden–Julian oscillation in the
629   Hadley Centre model. *Quarterly Journal of the Royal Meteorological Society* 140(684):2272-2286

630   Lan YY, Tsuang BJ, Tu CY, Wu TY, Chen YL, Hsieh CI (2010) Observation and Simulation of Meteorology and Surface
631   Energy Components over the South China Sea in Summers of 2004 and 2006. *Terrestrial, Atmospheric & Oceanic Sciences*
632   21(2)

633   Lin JL, Kiladis GN, Mapes BE, Weickmann KM, Sperber KR, Lin W et al (2006) Tropical intraseasonal variability in 14
634   IPCC AR4 climate models. Part I: Convective signals. *Journal of climate* 19(12):2665-2690

635   Locarnini RA, Mishonov AV, Antonov JI, Boyer TP, Garcia HE (2006) *World Ocean Atlas 2005, Volume 1: Temperature*. S.
636   Levitus, Ed. NOAA Atlas NESDIS 61, U.S. Government Printing Office, Washington, D.C

637   Madden RA, Julian PR (1972) Description of global-scale circulation cells in the tropics with a 40–50 day period. *Journal of*
638   *the atmospheric sciences* 29(6):1109-1123

639   Maloney ED, Kiehl JT. (2002) MJO-related SST variations over the tropical eastern Pacific during Northern Hemisphere
640   summer. *Journal of climate* 15(6):675-689

641   Marshall G, Alves O, Hendon HH (2008) An enhanced moisture convergence–evaporation feedback mechanism for MJO
642   air–sea interaction. *Journal of the Atmospheric Sciences*, 65(3):970-986.

643 Matthews AJ (2012) A multiscale framework for the origin and variability of the South Pacific Convergence Zone.
644 Quarterly Journal of the Royal Meteorological Society 138(666):1165-1178

645 Matthews AJ, Li HYY (2005) Modulation of station rainfall over the western Pacific by the Madden-Julian oscillation.
646 Geophysical Research Letters 32(14)

647 Nordeng TE (1994) Extended versions of the convective parametrization scheme at ECMWF and their impact on the mean
648 and transient activity of the model in the tropics. Research Department Technical Memorandum 206(1-41)

649 North GR, Bell TL, Cahalan RF, Moeng FJ (1982) Sampling errors in the estimation of empirical orthogonal functions.
650 Monthly weather review 110(7):699-706

651 Pariyar SK, Keenlyside N, Bhatt BC, Omrani NE (2019) The dominant patterns of intra-seasonal rainfall variability in May-
652 October and November-April over the Tropical Western Pacific. Monthly Weather Review 147(8):2941-2960

653 Pegion K, Kirtman BP (2008) The impact of air–sea interactions on the predictability of the tropical intraseasonal
654 oscillation. Journal of Climate 21(22):5870-5886

655 Roeckner E, Bäuml G, Bonaventura L, Brokopf R, Esch M, Giorgetta M et al (2003) The atmospheric general circulation
656 model ECHAM 5. PART I: Model description

657 Roxy M, Tanimoto Y, Preethi B, Terray P, Krishnan R (2013) Intraseasonal SST-precipitation relationship and its spatial
658 variability over the tropical summer monsoon region. Climate Dynamics 41(1):45-61

659 Serra YL, Jiang X, Tian B, Amador-Astua J, Maloney ED, Kiladis GN (2014) Tropical intraseasonal modes of the
660 atmosphere. Annual Review of Environment and Resources 39:189-215

661 Shen ML, Keenlyside N, Selten F, Wiegner W, Duane GS (2016) Dynamically combining climate models to
662 “supermodel” the tropical Pacific. Geophysical Research Letters 43(1):359-366

663 Sperber KR, Gualdi S, Legutke S, Gayler V (2005) The Madden–Julian oscillation in ECHAM4 coupled and uncoupled
664 general circulation models. Climate Dynamics 25(2-3):117-140

665 Sperber KR, & Kim D (2012) Simplified metrics for the identification of the Madden–Julian oscillation in models.
666 Atmospheric Science Letters 13(3):187-193

667 Torrence C, Compo GP (1998) A practical guide to wavelet analysis. Bulletin of the American Meteorological society
668 79(1):61-78

669 Tseng WL, Hsu HH, Keenlyside N, June Chang CW, Tsuang BJ, Tu CY, Jiang LC (2017) Effects of surface orography and
 670 land–sea contrast on the Madden–Julian oscillation in the Maritime Continent: A numerical study using ECHAM5-SIT.
 671 *Journal of Climate* 30(23):9725-9741

672 Tseng WL, Tsuang BJ, Keenlyside NS, Hsu HH, Tu CY (2015) Resolving the upper-ocean warm layer improves the
 673 simulation of the Madden–Julian oscillation. *Climate Dynamics* 44(5-6):1487-1503

674 Tsuang BJ, Tu CY, Arpe K (2001) Lake parameterization for climate models

675 Tsuang BJ, Tu CY, Tsai JL, Dracup JA, Arpe K, Meyers T (2009) A more accurate scheme for calculating Earth’s skin
 676 temperature. *Climate dynamics* 32(2-3):251-272

677 Tu CY, Tsuang BJ (2005) Cool-skin simulation by a one-column ocean model. *Geophysical research letters* 32(22)

678 Waliser DE, Lau KM, Kim JH (1999) The influence of coupled sea surface temperatures on the Madden–Julian oscillation:
 679 A model perturbation experiment. *Journal of the Atmospheric Sciences* 56(3):333-358

680 Wang W, Seo KH (2009) The Madden-Julian oscillation in NCEP coupled model simulation. *TAO: Terrestrial, Atmospheric
 681 and Oceanic Sciences* 20(5):7

682 Wheeler MC, Hendon HH (2004) An all-season real-time multivariate MJO index: Development of an index for monitoring
 683 and prediction. *Monthly Weather Review* 132(8):1917-1932

684 Woolnough SJ, Slingo JM, Hoskins BJ (2000) The relationship between convection and sea surface temperature on
 685 intraseasonal timescales. *Journal of Climate* 13(12):2086-2104

686 Wu R, Chen Z (2015) Intraseasonal SST variations in the South China Sea during boreal winter and impacts of the East
 687 Asian winter monsoon. *Journal of Geophysical Research: Atmospheres*, 120(12):5863-5878

688 Wu R, Kirtman BP, Pegion K (2008) Local rainfall-SST relationship on subseasonal time scales in satellite observations and
 689 CFS. *Geophysical Research Letters* 35(22)

690 Zhang C (2013) Madden–Julian oscillation: Bridging weather and climate. *Bulletin of the American Meteorological Society*
 691 94(12):1849-1870

692 Zhang C, Anderson SP (2003) Sensitivity of intraseasonal perturbations in SST to the structure of the MJO. *Journal of the
 693 atmospheric sciences* 60(17):2196-2207

- 694 Zhang C, Dong M, Gualdi S, Hendon HH, Maloney E.D, Marshall A et al (2006) Simulations of the Madden–Julian
695 oscillation in four pairs of coupled and uncoupled global models. *Climate Dynamics* 27(6):573-592
- 696 Zheng Y, Waliser DE, Stern WF, Jones C (2004) The role of coupled sea surface temperatures in the simulation of the
697 tropical intraseasonal oscillation. *Journal of Climate* 17(21):4109-4134

698 List of Figures

699	Fig. 1 November-April daily rainfall (mm day^{-1}) climatology (top panel) and intraseasonal (10-90-day) standard deviations	
700	(bottom panel) for (a,e) observations (b,f) coupled model (c,g) uncoupled simulation forced with SST climatology, and (d,h)	
701	uncoupled simulation forced with daily SST. For both observations and the models, the mean and standard deviations are	
702	computed for 25 years. The black dashed diagonal lines are the climatological position of the mean rainfall axis of the SPCZ	
703	computed by fitting a linear line based on the maximum rainfall values along the SPCZ. The black rectangular box	
704	represents the area chosen to compute the weighted area average of different variables in sections 4.1 and 4.2	27
705	Fig. 2 Spatial structures of leading EOF modes based on daily 10-90-day filtered rainfall anomalies (mm day^{-1}) and power	
706	spectra of each PC of two EOF modes for (a-c) observations (d-f) coupled model, (g-i) uncoupled model forced with SST	
707	climatology, and (j-l) uncoupled model forced with daily SST. The power spectrum is calculated for November-April and	
708	then averaged over 25 years. The solid red (blue) line is for PC1 (PC2). The solid and dashed horizontal black lines	
709	represent the red noise spectrum (PC1-solid; PC2-dashed) computed from the lag-one autocorrelation. The horizontal grey	
710	lines are the 99.9% confidence level needed to reject a null hypothesis of red noise (PC1-solid; PC2-dashed). The black	
711	solid diagonal lines are the climatological position of the mean rainfall axis of the SPCZ. The black dashed lines are the	
712	diagonal axis of SPCZ in each EOF mode. All diagonal lines are computed by fitting a linear line based on the maximum	
713	rainfall values along the SPCZ	28
714	Fig. 3 Time-longitude and time-latitude composites of 30-80-day rainfall anomalies (mm day^{-1}) for (a-d) observations, (e-h)	
715	coupled model, (i-l) uncoupled model forced with SST climatology, and (m-p) uncoupled model forced with daily SST. The	
716	first two columns represent the eastward propagation from the Indian Ocean to the western Pacific, and the last two columns	
717	represent the southeastward propagation in the South Pacific. For the eastward propagation, we compute the average	
718	between 5°N - 10°S . We average along the diagonal axis over the South Pacific (black diagonal dashed lines, Fig. 2) for the	
719	southeastward propagation. The diagonal axis is constructed by following the maximum rainfall anomalies along the rainfall	
720	bands over the South Pacific associated with the EOF modes in observations. For each latitude, the region from 10 degrees	
721	to the east to 10 degrees to the west of the diagonal axis is chosen for averaging, and the respective longitudes are also	
722	provided. The rainfall lag composites are computed from standardized PCs for selected strong events with values greater	
723	than 0.5 standard deviations. Only significant values at the 95% confidence level are shown	29
724	Fig. 4 Time-longitude and time-latitude composites of 30-80-day rainfall anomalies (shaded, mm day^{-1}) and other	
725	atmospheric fields [contours, sea surface temperature ($^{\circ}\text{C}$, contour interval 0.05, beginning at ± 0.05); sea level pressure	
726	(hPa, contour interval 0.2, beginning at ± 0.2); 1000-hPa moisture flux divergence ($10^{-6} \text{ g kg}^{-1} \text{ s}^{-1}$, contour interval 6,	
727	beginning at ± 5); latent heat flux (W m^{-2} , contour interval 4, beginning at ± 4 , positive upwards); sensible heat flux (W m^{-2} ,	
728	contour interval 0.5, beginning at ± 0.5 , positive upwards); 10-meter wind speed (m s^{-1} , contour interval 0.3, beginning at	
729	± 0.3] for (a-f) coupled model, and (g-l) uncoupled model forced with daily SST. We average along the diagonal axis over	
730	the South Pacific (black diagonal dashed lines, Fig. 2). The diagonal axis is constructed by following the maximum rainfall	
731	variance along the rainfall bands over the South Pacific associated with each EOF mode in observation. For each latitude,	
732	the region from 10°E and 10°W of the diagonal axis is chosen for averaging, and the respective longitudes are also provided.	
733	The lag composites are computed from standardized PCs by selecting strong events with values greater than 0.5 standard	
734	deviations. Only significant values at the 95% confidence level are shown. Solid contours represent positive anomalies, and	
735	dashed contours are for negative anomalies	31
736	Fig. 5 Lag-correlation of 30-80-day filtered SST with the (a) rainfall, (b) LHF (positive upwards), (c) SHF (positive	
737	upwards) and (d) 10-meter wind speed, averaged over the South Pacific (160°E - 170°W ; 5°S - 15°S) for coupled C-CTL	
738	(solid) and uncoupled A-DAY (dashed) simulations. For positive lags, SST leads other fields	33
739	Fig. 6 Time-longitude and time-latitude composites of 30-80-day rainfall anomalies (mm day^{-1}) for (a-d) C-17m, (e-h) C-	
740	59m, (i-l) C-IO, (m-p) C-IPO, and (q-t) C-PO. For the eastward propagation, we compute the average between 5°N - 10°S .	
741	We average along the diagonal axis over the South Pacific (black diagonal dashed lines, Fig. 2) for the southeastward	
742	propagation. The diagonal axis is constructed by following the maximum rainfall anomalies along the rainfall bands over	
743	the South Pacific associated with each EOF mode in observations. For each latitude, the region from 10°E and 10°W of the	
744	diagonal axis is chosen for averaging, and the respective longitudes are also provided. The rainfall lag composites are	
745	computed from standardized PCs by selecting strong events with values greater than 0.5 standard deviations. Only	
746	significant values at the 95% confidence level are shown	34

747   **List of Tables**

748   **Table 1** Description of experiments 36

749   **Table 2** Metrics used to measure ECHAM5-SIT skill in representing the key characteristics of the MJO, intraseasonal

750   rainfall variability in the South Pacific and their teleconnection.....37

751 **Fig. 1** November-April daily rainfall (mm day^{-1}) climatology (top panel) and intraseasonal (10-90-day) standard deviations
 752 (bottom panel) for (a,e) observations (b,f) coupled model (c,g) uncoupled simulation forced with SST climatology, and (d,h)
 753 uncoupled simulation forced with daily SST. For both observations and the models, the mean and standard deviations are
 754 computed for 25 years. The black dashed diagonal lines are the climatological position of the mean rainfall axis of the SPCZ
 755 computed by fitting a linear line based on the maximum rainfall values along the SPCZ. The black rectangular box
 756 represents the area chosen to compute the weighted area average of different variables in sections 4.1 and 4.2

Fig. 2 Spatial structures of leading EOF modes based on daily 10-90-day filtered rainfall anomalies (mm day^{-1}) and power spectra of each PC of two EOF modes for (a-c) observations (d-f) coupled model, (g-i) uncoupled model forced with SST climatology, and (j-l) uncoupled model forced with daily SST. The power spectrum is calculated for November-April and then averaged over 25 years. The solid red (blue) line is for PC1 (PC2). The solid and dashed horizontal black lines represent the red noise spectrum (PC1-solid; PC2-dashed) computed from the lag-one autocorrelation. The horizontal grey lines are the 99.9% confidence level needed to reject a null hypothesis of red noise (PC1-solid; PC2-dashed). The black solid diagonal lines are the climatological position of the mean rainfall axis of the SPCZ. The black dashed lines are the diagonal axis of SPCZ in each EOF mode. All diagonal lines are computed by fitting a linear line based on the maximum rainfall values along the SPCZ

769 represent the southeastward propagation in the South Pacific. For the eastward propagation, we compute the average
770 between 5°N-10°S. We average along the diagonal axis over the South Pacific (black diagonal dashed lines, [Fig. 2](#)) for the
771 southeastward propagation. The diagonal axis is constructed by following the maximum rainfall anomalies along the rainfall
772 bands over the South Pacific associated with the EOF modes in observations. For each latitude, the region from 10 degrees
773 to the east to 10 degrees to the west of the diagonal axis is chosen for averaging, and the respective longitudes are also
774 provided. The rainfall lag composites are computed from standardized PCs for selected strong events with values greater
775 than 0.5 standard deviations. Only significant values at the 95% confidence level are shown

C-CTL: EOF1

A-DAY: EOF1

776 **Fig. 4** Time-longitude and time-latitude composites of 30-80-day rainfall anomalies (shaded, mm day^{-1}) and other
 777 atmospheric fields [contours, sea surface temperature ($^{\circ}\text{C}$, contour interval 0.05, beginning at ± 0.05); sea level pressure
 778 (hPa, contour interval 0.2, beginning at ± 0.2); 1000-hPa moisture flux divergence ($10^{-6} \text{ g kg}^{-1} \text{ s}^{-1}$, contour interval 6,
 779 beginning at ± 5); latent heat flux (w m^{-2} , contour interval 4, beginning at ± 4 , positive upwards); sensible heat flux (w m^{-2} ,

780 contour interval 0.5, beginning at ± 0.5 , positive upwards); 10-meter wind speed (m s^{-1} , contour interval 0.3, beginning at
781 ± 0.3] for (a-f) coupled model, and (g-l) uncoupled model forced with daily SST. We average along the diagonal axis over
782 the South Pacific (black diagonal dashed lines, [Fig. 2](#)). The diagonal axis is constructed by following the maximum rainfall
783 variance along the rainfall bands over the South Pacific associated with each EOF mode in observation. For each latitude,
784 the region from 10°E and 10°W of the diagonal axis is chosen for averaging, and the respective longitudes are also provided.
785 The lag composites are computed from standardized PCs by selecting strong events with values greater than 0.5 standard
786 deviations. Only significant values at the 95% confidence level are shown. Solid contours represent positive anomalies, and
787 dashed contours are for negative anomalies

788 **Fig. 5** Lag-correlation of 30-80-day filtered SST with the (a) rainfall, (b) LHF (positive upwards), (c) SHF (positive
789 upwards) and (d) 10-meter wind speed, averaged over the South Pacific (160°E-170°W; 5°S-15°S) for coupled C-CTL
790 (solid) and uncoupled A-DAY (dashed) simulations. For positive lags, SST leads other fields

791 **Fig. 6** Time-longitude and time-latitude composites of 30-80-day rainfall anomalies (mm day^{-1}) for (a-d) C-17m, (e-h) C-
792 59m, (i-l) C-IO, (m-p) C-IPO, and (q-t) C-PO. For the eastward propagation, we compute the average between 5°N - 10°S .
793 We average along the diagonal axis over the South Pacific (black diagonal dashed lines, [Fig. 2](#)) for the southeastward
794 propagation. The diagonal axis is constructed by following the maximum rainfall anomalies along the rainfall bands over
795 the South Pacific associated with each EOF mode in observations. For each latitude, the region from 10°E and 10°W of the
796 diagonal axis is chosen for averaging, and the respective longitudes are also provided. The rainfall lag composites are
797 computed from standardized PCs by selecting strong events with values greater than 0.5 standard deviations. Only
798 significant values at the 95% confidence level are shown

799 **Table 1** Description of experiments

Experiments	SST	Description
1. C-CTL	Coupled	Model coupled over the tropical domain (30°N-30°S), with the finest vertical resolution (1 meter in the upper 10 meters)
2. A-CLIM	Uncoupled	Atmosphere-only forced by monthly SST climatology from C-CTL
3. A-DAY	Uncoupled	Atmosphere-only forced by daily SST from C-CTL
4. C-17m	Coupled	The first ocean vertical level starts at 16.8 m
5. C-59m	Coupled	The first ocean vertical level starts at 59.3 m
6. C-IO	Coupled	Coupled over the Indian Ocean only (30°S–30°N, 50°E–100°E)
7. C-IPO	Coupled	Coupled over the Indian Ocean and western Pacific only (30°S–30°N, 40°E–180°E)
8. C-PO	Coupled	Coupled over the western Pacific only (30°S–30°N, 110°E–180°E)

800 **Table 2** Metrics used to measure ECHAM5-SIT skill in representing the key characteristics of the MJO, intraseasonal
801 rainfall variability in the South Pacific and their teleconnection

Experiments	MJO-related metrics					Key characteristics of intraseasonal rainfall modes in the South Pacific				MJO-South Pacific teleconnection
	Percentage variance explained by EOF1 and EOF2 based on combined EOF analysis of daily OLR, U850, and U200 over the Indo-Pacific [Pct _{mjo} (%)]	East-west power ratio [ewp _{mjo}]	Maximum lag-correlation between 30-80-day filtered RMM indices [Rmax _{mjo}]	MJO periodicity based on 30-80-day filtered RMM indices [P _{mjo} (days)]	Mean power in the 30-80-day band based on the power spectra for two RMM indices [Pow _{MJO}]	Percentage variance explained by EOF1 and EOF2 based on daily 10-90-day filtered rainfall data over the South Pacific [Pct _{sp} (%)]	Maximum lag-correlation coefficient between 30-80-day filtered PCs [Rmax _{sp}]	Periodicity of EOF modes [P _{sp} (days)]	Mean power in the 30-80-day band based on the power spectra for two PCs [Pow _{sp}]	Maximum lag-correlation coefficient between 30-80-day filtered PCs and RMM indices [Rmax _{mjo-sp}]
Observations	40.1	4.4	0.80	42	0.72	10.8	0.20	40	0.45	0.47
C-CTL	32.2	4.0	0.73	40	0.96	15.0	0.36	38	0.34	0.48
A-CLIM	25.6	3.0	0.55	40	0.81	14.2	0.21	38	0.19	0.28
A-DAY	27.4	3.4	0.70	46	1.02	14.9	0.30	50	0.33	0.40
C-17m	30.2	3.6	0.72	42	0.93	15.2	0.32	44	0.21	0.44
C-59m	28.5	3.6	0.70	42	0.99	15.5	0.26	40	0.20	0.43
C-IPO	31.0	3.6	0.71	42	1.01	15.3	0.32	40	0.19	0.43
C-IO	27.4	2.6	0.61	40	0.87	14.2	0.20	36	0.18	0.28
C-PO	28.3	3.3	0.71	42	0.94	14.3	0.27	40	0.17	0.35

803   **Fig. 1** November-April 10-meter zonal wind (m s^{-1}) climatology for (a) observations, (b) coupled model, (c) uncoupled
804   model forced with SST climatology, and (d) uncoupled model forced with daily SST. For both observations and the models,
805   the climatology is computed for 25 years

806 **Fig. 2** Lag correlation between daily time series of PC1 and PC2 for (a) observations (b) coupled model (c) uncoupled
 807 model forced with SST climatology (d) uncoupled model forced with daily SST. The correlation coefficients are computed
 808 for November–April and then averaged over 25 years. The solid line is for raw PCs (10–90-day), and the dashed lines are for
 809 30–80-day bandpass filtered PCs. Positive (negative) values indicate lead (lag). Positive lags are PC1 leading PC2. The
 810 horizontal red dashed line represents the 95% confidence level based on the two-tailed Student's t statistic

Fig. 3 Lag correlation of each PC with RMM1 (solid lines) and RMM2 (dashed lines) index for (a-b) observations, (c-d) coupled model, (e-f) uncoupled model forced with SST climatology, and (g-h) uncoupled model forced with daily SST. The

813 correlation is computed for November-April and then averaged over 25 years. The horizontal red dashed line represents the
814 95% confidence level based on the two-tailed Student's t-test. For positive lag, the RMM indices lead the PCs

815 **Fig. 4** Schematic of the southeastward propagation mechanism identified from observations. For EOF1, we propose the
 816 wind-evaporation-SST feedback mechanism: The southeasterly wind anomalies to the southeast of the active convection
 817 produce warm SST and low SLP anomalies, because they oppose the background winds and cause weaker wind speed, less
 818 evaporation, and reduced turbulent fluxes. In contrast, the evaporation is enhanced as indicated by positive latent heat flux
 819 anomalies just ahead of the active convection because of the stronger background wind (i.e., northwesterly wind anomalies).
 820 In combination with increased evaporation, the low-pressure anomalies associated with warm SSTs initiate moisture
 821 convergence ahead of the convection. On the other hand, the increased evaporation within and back of the active convection
 822 associated with northwesterly wind anomalies combined with reduced shortwave radiation (increased cloudiness) cool the
 823 ocean back of the convection to initiate the negative phase. Here, the relationship between wind, SST, and evaporation is
 824 important for the propagation, with warm SST and low SLP anomalies leading the active convection. The moisture
 825 convergence is in phase with the rainfall and does not contribute to the propagation. In EOF2 mode, we propose a low-level
 826 frictional moisture convergence mechanism: the warm SST anomalies to the southeast of active convection due to the
 827 increased shortwave radiation (clear sky conditions) and reduced evaporation (southeasterly wind anomalies, i.e., weaker
 828 background winds) promote low SLP anomalies and initiate low-level frictional moisture convergence. Due to northeasterly
 829 wind anomalies within and back of the convection, the stronger background winds enhance evaporation, cooling the ocean.
 830 Here, the relationship between wind, low-level moisture convergence, and rainfall is crucial for propagation, with low-level
 831 convergence leading the rainfall. The evaporation anomalies do not necessarily contribute to the rainfall anomalies but
 832 rather play an important role in modifying the SST anomalies during the transition from warm to cold phases and vice versa

Fig. 5 Power spectra associated with leading EOF modes based on daily 10-90-day filtered rainfall anomalies for (a) C-IO, (b) C-IPO, (c) C-PO, (d) C-17m, (e) C-59m. The power spectrum is calculated for November-April and then averaged over 25 years. The solid red (blue) line is for PC1 (PC2). The solid and dashed horizontal black lines represent the red noise spectrum (PC1-solid; PC2-dashed) computed from the lag-one autocorrelation. The grey horizontal lines are the 99.9% confidence level needed to reject a null hypothesis of red noise (PC1-solid; PC2-dashed)

838 **Fig. 6** Lag correlation between daily time series of PC1 and PC2 for (a) C-IO (b) C-IPO (c) C-PO (d) C-17m, and (d) C-
 839 59m. The correlation coefficients are computed for November–April and then averaged over 25 years. The solid line is for
 840 raw PCs (10–90-day), and the dashed lines are for 30–80-day bandpass filtered PCs. Positive (negative) values indicate lead
 841 (lag). Positive lags are PC1 leading PC2. The horizontal red dashed line represents the 95% confidence level based on the
 842 two-tailed Student's *t* statistic

Fig. 7 Power spectra associated with RMM indices for (a) C-CTL, (b) A-CLIM, (c) A-DAY, (d) C-IO, (e) C-IPO, (f) C-PO, (g) C-17m, and (h) C-59m. The power spectrum is calculated for November-April and then averaged over 25 years. The solid red (blue) line is for RMM1 (RMM2). The solid and dashed horizontal black lines represent the red noise spectrum (RMM1-solid; RMM2-dashed) computed from the lag-one autocorrelation. The grey horizontal lines are the 99.9% confidence level needed to reject a null hypothesis of red noise (RMM1-solid; RMM2-dashed)

848 **Fig. 8** Anomaly composites of rainfall (shaded, mm day^{-1}), sea level pressure (contours, mb), and 10-meter wind (vectors, m s^{-1}) associated with two EOF modes in November-April for (a-b) observations and (c-d) C-CTL. The solid (dashed) contours
849 represent positive (negative) values. The composites are computed from standardized PCs for selected strong events with
850 values greater than 0.5 standard deviations. Only significant values at the 95% confidence level are shown
851