



S2S Prediction in GFDL SPEAR: MJO Diversity and Teleconnections

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A S2S prediction system was developed using the GFDL SPEAR model showing its capability in predicting MJO diversity and teleconnections.

Abstract

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A subseasonal-to-seasonal (S2S) prediction system was recently developed using the GFDL SPEAR global coupled model. Based on 20-year hindcast results (2000-2019), the boreal wintertime (November-April) Madden-Julian Oscillation (MJO) prediction skill is revealed to reach 30 days measured before the anomaly correlation coefficient of the real-time multivariate (RMM) index drops to 0.5. However, when the MJO is partitioned into four distinct propagation patterns, the prediction range extends to 38, 31, and 31 days for the fast-propagating, slow-propagating, and jumping MJO patterns, respectively, but falls to 23 days for the standing MJO. A further improvement of MJO prediction requires attention to the standing MJO given its large gap with its potential predictability (15 days). The slow-propagating MJO detours southward when traversing the maritime continent (MC), and confronts the MC prediction barrier in the model, while the fast-propagating MJO moves across the central MC without this prediction barrier. The MJO diversity is modulated by stratospheric quasi-biennial oscillation (QBO): the standing (slow-propagating) MJO coincides with significant westerly (easterly) phases of QBO, partially explaining the contrasting MJO prediction skill between these two QBO phases.

The SPEAR model shows its capability, beyond the propagation, in predicting their initiation for different types of MJO along with discrete precursory convection anomalies. The SPEAR model skillfully predicts the observed distinct teleconnections over the North Pacific and North America related to the standing, jumping, and fast-propagating MJO, but not the slow-propagating MJO. These findings highlight the complexities and challenges of incorporating MJO prediction into the operational prediction of meteorological variables.

78 1. Introduction

79 A pioneering work by Xie et al. (1963) revealed a local oscillatory signal with a prominent 40-
80 50 day period in the western Pacific that has strong modulation on tropical cyclone activities (also
81 see (also see Li et al. 2018). Madden and Julian (1971, 1972) discovered a global-scale 40-50 day
82 oscillatory mode with pronounced eastward propagation across the whole tropics, known as the
83 Madden-Julian Oscillation (MJO), a planetary-scale intraseasonal mode characterized by slow
84 eastward propagation over the tropics. The development and evolution of MJO involve interactions
85 of convection, planetary boundary layer, wave dynamics, moisture, and radiation, and it is also
86 significantly modified by multi-scale interaction and air-sea coupling. Given the complexity of
87 MJO, many theories have been proposed to explain the essential processes responsible for its
88 existence, scale selection, and propagation (e.g., Jiang et al. 2020; Zhang et al. 2020).

89 Compared to synoptic weather variability, the MJO has longer persistence and an oscillatory
90 nature, highlighting the importance of MJO prediction for subseasonal-to-seasonal (S2S)
91 predictions of climate and extreme weather events. For example, the prediction of MJO has been
92 demonstrated to be critical for the medium-range to the subseasonal prediction of tropical cyclones
93 (Jiang et al. 2018; Lee et al. 2018; Lee et al. 2020; Vitart 2009; Xiang et al. 2014). A skillful MJO
94 prediction also benefits the prediction of phenomena including the North Atlantic Oscillation (Lin
95 et al. 2010), atmospheric rivers (DeFlorio et al. 2018; Mundhenk et al. 2018), and the US
96 precipitation (Nardi et al. 2020).

97 Dynamical models have become the primary tool for MJO prediction. Extensive exploration
98 of the predictability of the MJO in dynamical models has achieved substantial advances in recent
99 decades, while a big gap still remains between the prediction skill and the potential predictability
100 (Kim et al. 2018; Kim et al. 2019; Neena et al. 2014; Vitart 2017). A myriad of factors influence

101 MJO prediction, each different among models, such as the convection parameterization (Zhu et al.
102 2020), air-sea coupling (Fu et al. 2013; Harris et al. 2020; Zhu and Kumar 2019), and initialization
103 (Ren et al. 2016; Wu et al. 2020). Additionally, the stratospheric quasi-biennial oscillation (QBO)
104 can rectify the MJO activities (MJO days) and propagation, and influence its prediction skill (Lim
105 et al. 2019; Marshall et al. 2017; Martin et al. 2021; Wang et al. 2019b; Zhang and Zhang 2018).
106 Some systematic biases in model mean states and feedback processes are shown to exert direct
107 effects on the MJO prediction skill (Kim et al. 2019; Lim et al. 2018).

108 It is worth noting that individual MJO events vary markedly from event to event in their
109 amplitude, life cycle, and propagation (Wang and Rui 1990). Kim et al. (2014) revealed that some
110 MJO events propagate across the maritime continent (MC) while some others do not. About 40%
111 of the observed MJO events are blocked by the MC (Kerns and Chen 2020). On the basis of the
112 substantially different propagation features of individual MJO events, Wang et al. (2019a)
113 separated the MJO events into four clusters using a clustering method (standing, jumping, slow-
114 propagating, and fast-propagating events). The standing MJO is referring to the events with a
115 locally oscillatory feature in the Indian Ocean without evident propagation. The jumping MJO
116 represents the cases with a sudden migration of anomalous convection from the eastern Indian
117 Ocean to the western Pacific. They claimed that their existence is controlled by different large-
118 scale background mean states and interaction between tropical wave dynamics and convection. It
119 prompts the question of whether the MJO prediction depends on the MJO propagation
120 characteristic? The objective of this study is twofold: firstly, to introduce a recently developed
121 prediction modeling system targeting S2S prediction; and secondly, to identify the potential skill
122 dependence on MJO diversity using this prediction system.

123 The paper is organized as follows. Section 2 introduces the model, experiments, and
124 methodology. Sections 3 and 4 describe the overall MJO prediction skill and the skill dependence
125 on MJO diversity, respectively. Sections 5, 6, and 7 present the model prediction of MJO
126 propagation, initial development, and teleconnections, respectively, in the context of MJO
127 diversity. We end with a summary and discussion in section 8.

128

129 2. Model, hindcast experiments, and methodology

130 a. Model and hindcast experiments

131 We use the Geophysical Fluid Dynamics Laboratory (GFDL) Seamless System for Prediction
132 and EArth system Research (SPEAR) coupled model. The model was developed as the next
133 generation GFDL modeling system for seasonal to multidecadal prediction and projection (Bushuk
134 et al. 2021; Delworth et al. 2020; Lu et al. 2020; Murakami et al. 2020). To approach the seamless
135 suite of prediction, here, we extend the research focus to the S2S timescale. The SPEAR model
136 shares many components with the GFDL CM4.0 model (Held et al. 2019). In particular, SPEAR
137 uses an atmospheric and land model identical to AM4.0/LM4.0 (Zhao et al. 2018a; Zhao et al.
138 2018b) but with a dynamical vegetation model and a lower resolution MOM6 (Adcroft et al. 2019).
139 There are three configurations of SPEAR that share the same ocean model (horizontal resolution
140 of about 1° and 75 vertical levels) but with three different atmospheric horizontal resolutions,
141 which are referred to as SPEAR_LO (1°), SPEAR_MED (0.5°), and SPEAR_HI (0.25°).
142 SPEAR_MED uses an 0.5 degree AM4.0, which contains 33 vertical levels with the top of the
143 atmosphere at 1 hPa. The 0.5 degree AM4.0 has been documented in Zhao (2020). SPEAR_MED
144 has been demonstrated to produce realistic simulations of extreme weather statistics such as the
145 frequency of tropical cyclones (Murakami et al. 2020), atmospheric rivers (Zhao 2020), and

146 mesoscale convective systems (Dong et al. 2021). SPEAR_MED is used in this study for S2S
147 prediction, and we refer to it as SPEAR hereinafter for simplicity. This model has shown a realistic
148 MJO simulation from its control run (Delworth et al. 2020), offering an excellent opportunity to
149 study the MJO prediction and some related issues. The reader is referred to Delworth et al. (2020)
150 for additional details about this model.

151 Similar to Xiang et al. (2015), initial conditions for the atmosphere and ocean were generated
152 through a simple nudging technique towards observations with several years' integration before
153 prediction. The atmospheric nudging fields include winds, temperature, and specific humidity
154 using the Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-
155 2) analysis data (6-hourly interval) (Gelaro et al. 2017). The sea surface temperature (SST) is
156 nudged to NOAA Optimum Interpolation 1/4 Degree Daily SST Analysis (OISST, v2) (Reynolds
157 et al. 2007). Using the same SPEAR model, the ocean initialization for S2S prediction is much
158 simpler than the seasonal-to-decadal prediction system that adopts a comprehensive ocean data
159 assimilation system (Lu et al. 2020), allowing a later assessment of the potential roles of subsurface
160 ocean initialization on S2S prediction. Hindcasts were carried out every five days from January
161 2000 to April 2019, and ten ensemble members were generated by using perturbed nudging
162 strengths for both the atmosphere and the ocean SST so that they differ from one another in the
163 initial conditions. The nudging of circulation is applied to the whole atmosphere. However, the
164 nudging of moisture field is confined in the free atmosphere with the lowest several model layers
165 (roughly the boundary layer) unperturbed, considering the fact that the moisture field in analysis
166 data is relatively less reliable than other variables and the nudging of moisture within boundary
167 layer may induce large initial shock in a coupled system via strongly altering latent heat flux. Since
168 the MJO is most pronounced in boreal wintertime, we focus on the period from November to the

169 ensuing April. We made 708 hindcast events, and each has ten members. We integrated each
170 hindcast for 45 days.

171 **b. Methodology**

172 The observational anomalies were obtained by removing the time mean and the first three
173 harmonics of the observational climatological annual cycle and subtracting the time-mean
174 anomalies over the previous 120 days. The hindcast anomalies are calculated by removing the
175 model hindcast climatology and also the previous-120 days' time-mean anomalies.

176 The evaluation procedure for MJO prediction is similar to Xiang et al. (2015) and adopts the
177 widely used Real-time Multivariate MJO (RMM) index (Wheeler and Hendon 2004) as a metric
178 to measure the MJO and its prediction. The anomalies of outgoing longwave radiation (OLR) and
179 850 hPa and 200 hPa zonal winds are then projected onto two observed leading multivariate
180 empirical orthogonal function (EOF) modes to obtain the RMM indices (Wheeler and Hendon
181 2004) (Figure S1). The first (second) mode represents the phases with anomalous convection in
182 the Indian Ocean (western Pacific). The observed and predicted two RMM indices (RMM1 and
183 RMM2) are then normalized by the standard deviation of the observed RMM indices. Using the
184 above RMM indices as the predictands, the so-called bivariate anomaly correlation coefficient
185 (ACC) and root mean square error (RMSE) were used here to measure its forecast skill following
186 (Lin et al. 2008). The MJO amplitude is defined as $\sqrt{RMM1^2 + RMM2^2}$.

187 For verification, the data we used comprise the NOAA daily mean interpolated OLR data
188 (Liebmann and Smith 1996) and ERA-5 reanalysis data as observations (C3S, 2017), including
189 winds, two-meter air temperature (t2m), geopotential height, and specific humidity. All data are
190 interpolated to 1°x1° resolution for analysis.

191

192 3. Overall evaluation of the MJO prediction

193 Figure 1a shows the bivariate ACC of MJO prediction in boreal wintertime (November to
194 April) evaluated based on all the hindcasts (708 cases with 10 ensemble members). The mean skill
195 from a single member is about 23 days, as determined by the maximum lead time with the ACC
196 exceeding 0.5. As expected, the ACC for the 10-member ensemble-mean is superior to individual
197 members, with a prediction skill of 30 days. The prediction skill is nearly saturated when using
198 five ensemble members (29 days), and additional ensemble members add little to the MJO
199 prediction skill (Figure S2). The ensemble spread is much smaller than the RMSE (Fig. 1b),
200 indicating an under-dispersive ensemble that may limit the overall prediction skill of this system.
201 The ten-member ensemble mean serves as the basis for all the following analyses, except where
202 otherwise noted.

203 We further investigate the skill dependence on the MJO initial and target amplitude and
204 phases. The skill has a much smaller difference between the initially strong ($|RMM|>1$) and weak
205 ($|RMM|<1$) cases than the target strong and weak cases (Fig. 2a vs. 2c). Here, the target cases are
206 referring to the MJO events during the forecast period. In other words, the skill is more sensitive
207 to the target MJO amplitude during the forecast period than its initial amplitude. Note that some
208 models experience strong sensitivity with initial amplitude, but some do not (Lim et al. 2018). The
209 skill also differs among different MJO phases. A relatively higher skill is found when initiated at
210 phases 3 and 4 with the anomalous wet phase in the eastern Indian Ocean and MC. In comparison,
211 the skill is relatively lower during phases 1 and 2 when the anomalous intense convection occurs
212 in the western and central Indian Ocean (Fig. 2b). The skill is higher for the target phases 3 and 4
213 than the target phases 5 and 6 (Fig. 2d). The above skill dependence on MJO amplitude and phase
214 is generally similar to a previous version of the GFDL model (Xiang et al. 2015).

215 The MJO prediction skill is determined by the error growth in amplitude and propagation
216 speed. Here we examine the MJO amplitude and its phase angle error for initially strong MJO
217 cases (Fig. 3). The phase angle error is estimated between the observed and predicted RMM index
218 following (Rashid et al. 2011). The predicted MJO amplitude agrees well with observation during
219 the first ten days but then decreases very rapidly (Fig. 3a) along with the increase of noise. During
220 the first 25 days, the predicted mean amplitude is comparable but slightly weaker (by 7.7%) than
221 observations. The mean phase angle error in the first 25 days is -4.0° (Fig. 3c), with a magnitude
222 generally smaller than 10.0° for individual phases (Fig. 3d). The individual member has a similar
223 amplitude as observations (Fig. 3a), implying that the amplitude error from ensemble-mean is
224 largely attributed to the rapid increase of noise. Compared with a previous version of the GFDL
225 model (Xiang et al. 2015), the predicted amplitude error (phase angle error) in the first 25 days is
226 reduced by 38% (5%), in agreement with an overall improved MJO prediction skill (30 days vs 27
227 days).

228

229 4. Skill dependence on MJO diversity

230 Given the contrasting propagation behaviors for individual MJO events, it is natural to question
231 whether the MJO prediction is dependent on its propagation patterns. The first step to address this
232 question is to identify individual MJO events. Following Wang et al. (2019a), an MJO event is
233 selected when the area-averaged OLR anomalies in the equatorial Indian Ocean (75°E - 95°E , 10°S -
234 10°N) are negative and have an amplitude greater than one standard deviation for five successive
235 days (roughly during the MJO phases 2 and 3). K-means cluster analysis (Kaufman and Rousseeuw
236 2009) is then applied to classify the MJO events based on their propagation patterns. This analysis
237 identifies four types of MJO events: standing, jumping, slow-propagating, and fast-propagating

238 types (Wang et al. 2019a). Eventually, 55 MJO events were identified during the studied period
239 from January 2000 to April 2019, including 12 standing, 14 jumping, 15 slow-propagating, and 14
240 fast-propagating cases (Table 1). Their contrasting propagation features are apparent from the
241 composite OLR anomalies centered in the midpoint of the selected events (day 0) (Figs. 4c-f).

242 For each MJO cluster, we consider all the hindcasts initiated during the period between 20 days
243 before and 15 days after the midpoint of the selected event (day 0), approximately covering the
244 life cycle of the selected cases. Since the hindcasts are carried out every five days, the total forecast
245 case numbers for these four groups are 88, 104, 116, and 92, respectively. Results show that the
246 fast-propagating MJO possesses the best prediction skill of 38 days (Fig. 4a). The jumping MJO
247 attains a similar prediction skill with the slow-propagating MJO (31 days), albeit the jumping MJO
248 is categorized into the non-propagating group (Wang et al. 2019a). The standing MJO has the
249 lowest skill (23 days). We conclude that the model tends to be more skillful in predicting the
250 propagating and jumping MJO than the standing MJO.

251 The distinct MJO prediction skill among four clusters of MJO is possibly related to their
252 potential predictability. Based on the perfect model assumption, the potential predictability can be
253 estimated by taking one ensemble member as the truth and the ensemble-mean of the other
254 members as predictions. The four clusters of MJO exhibit similar potential predictability (38-39
255 days) (Fig. 4b), which obviously cannot explain the contrasting prediction skill as shown in Fig.
256 4a. We also infer that there is much larger room to improve the prediction of the standing MJO
257 than the other types of MJO, and a further MJO skill enhancement in SPEAR primarily relies on
258 advancing the standing MJO prediction.

259 More insights into the skill dependence on MJO types can be gained by examining the
260 relationship between the MJO prediction and its amplitude (Fig. 5a). For the standing (fast-

261 propagating) MJO, the initially weak cases have relatively lower (higher) skills than the initially
262 strong cases. However, for both the jumping and slow-propagating MJO the model shows a
263 comparable skill between the initially weak and strong cases. The skill spread among different
264 groups of MJO tends to be larger for the initially weak cases than the initially strong cases.
265 Intriguingly, a very similar skill is found for these four types of MJO when initiated at very strong
266 MJO ($|RMM| > 1.5$) (not shown). The MJO prediction is less sensitive to the target amplitude. The
267 skill for target strong (weak) cases is around 35 (10) days for all four clusters of MJO (Figure S3).
268 Therefore, the overall skill diversity (Fig. 4a) is primarily related to the skill difference for initially
269 weak cases.

270 The observed MJO amplitude differs substantially among different types of MJO. Figure 5b
271 displays the observational MJO amplitude for individual groups during the whole forecast period
272 (45 days) by counting all the selected cases. The fast-propagating MJO has the strongest amplitude,
273 followed by the slow-propagating, the jumping MJO, and the standing MJO, which has the
274 smallest mean MJO amplitude. Given this, there are more weak cases for the standing MJO than
275 the other groups, which may account for the overall lower skill for the standing MJO considering
276 the skill-dependence on the amplitude. Compared to the fast-propagating MJO, the relatively lower
277 skill for the slow-propagating MJO may reflect the MC prediction barrier effects (Kim et al. 2018;
278 Weaver et al. 2011), and we will discuss this later.

279 One may wonder whether the relatively lower prediction skill for the standing MJO is related
280 to the intrinsic limitation of the metrics used (bivariate ACC of RMM indices) that may not be
281 appropriate to represent its standing feature in the Indian Ocean (Fig. 4c). To address this, we
282 examine the prediction skill of convection and circulation anomalies in the equatorial Indian Ocean

283 (Figure S4). The skill difference among the four MJO types is broadly consistent with that based
284 on the bivariate ACC (Figure s4 versus Fig. 4a), confirming the robustness of the results.

285

286 5. Prediction of MJO propagation diversity and its interannual modulations

287 5.1 Prediction of the diverse MJO propagations and the underlying mechanisms

288 Figure 6 compares the observed and predicted equatorial (10°S - 10°N) propagation features of
289 MJO initiated five days before the peak phase in the equatorial Indian Ocean (day -5). The broad
290 features of the observed standing, jumping, slow- and fast-propagating MJO events (top two rows)
291 are predicted reasonably well when initiated at day -5 (bottom two rows) despite an underpredicted
292 amplitude. One noticeable deficiency is the underpredicted propagation speed for the slow-
293 propagating MJO initiated at day -5. The predicted convective anomalies gradually fade when
294 reaching the MC without further propagation to the western Pacific (Fig. 6). For the slow-
295 propagating MJO, the issue of underpredicted convection anomalies tends to be more severe when
296 initiated at day -10, together with a too slow propagation (Figure S5). This is partially responsible
297 for the lower prediction skill than the fast-propagating MJO.

298 Extensive studies have been conducted to study the mechanisms for MJO propagations. One
299 group accentuates the role of preconditioning characterized by lower-tropospheric moistening
300 ahead of major convection (Benedict and Randall 2007; Hsu and Li 2012; Kiladis et al. 2005;
301 Wang and Lee 2017). Figure 6 shows that for the standing and jumping MJO, the lower-
302 tropospheric convergence and moistening are in phase with the convective anomalies in the Indian
303 Ocean, cohesive with their rather stationary feature in the Indian Ocean. For the jumping MJO, the
304 anomalous convergence and moistening in the MC even slightly lead the major convection in the
305 Indian Ocean, providing a pathway for the fast transition of convection from the Indian Ocean to

306 the western Pacific. For both the slow and fast-propagating MJO, there is an evident premoistening
307 characterized by lower-tropospheric convergence and moistening located to the east of the major
308 deep convection. The model prediction qualitatively agrees with observations, while the low-
309 tropospheric convergence almost disappears to the east of 150°E for all groups of MJO suggestive
310 of a systematic model bias.

311 The premoistening is predominantly driven by the lower-tropospheric moisture convergence
312 that is related to the Kelvin wave and the resultant equatorial low-pressure at the top of the
313 boundary layer (Haertel 2021; Hsu and Li 2012; Wang 1988; Wang and Lee 2017). Note that the
314 convergence anomalies are mainly ascribable to zonal winds rather than meridional winds. We
315 present, in Figure 7, the spatial patterns of OLR, 850 hPa winds, and 850 hPa geopotential height
316 anomalies. The model prediction initiated at day -5 generally resembles the observed
317 characteristics for these four groups of MJO (Fig. 7).

318 Some indigenous features are identified among these four groups from observations (Fig. 7).
319 The easterly wind anomalies over the MC and western Pacific are much weaker for the standing
320 MJO than the other three groups. Given the strong zonal gradient of climatological moisture in the
321 Indian Ocean, the westerly wind anomalies as a Rossby wave response induce a negative moisture
322 advection and deteriorate the convection anomalies (Adames and Kim 2016), facilitating its phase
323 transition. Meanwhile, the increased atmospheric stability due to convective heating and the
324 resultant decreased SST also contribute to its phase transition. The above physical processes
325 represent a discharge-recharge process responsible for its local oscillatory feature (Bladé and
326 Hartmann 1993). The jumping MJO possesses a weak Rossby wave response but with a far-
327 reaching Kelvin wave component. Unlike the propagating MJO, the jumping MJO's easterly
328 anomalies are confined in the western Pacific without penetrating the MC. The newly formed

329 convection anomalies in the western Pacific are relatively independent of the preceding major
330 convection in the Indian Ocean (Fig. 7). Another notable difference is that the drying anomalies in
331 the MC and western Pacific are significantly weaker for both the standing and jumping MJO than
332 the propagating MJO, which may have some consequences on the MJO propagation (Kim et al.
333 2014). For the fast-propagating MJO, the major convection is coupled to the strong Kelvin waves
334 during the whole period when traversing the MC (Fig. 7). It has a rather meridionally symmetric
335 pattern of anomalous convection during the first week. The major convection even migrates to the
336 Northern Hemisphere together with a northwest-southeast tilted structure at weeks 2 and 3.

337 The observed and predicted features for different kinds of MJO suggest that the tropical wave
338 dynamics and its interaction with the lower-tropospheric moisture may play an important role in
339 MJO propagation, a point emphasized by the so-called convection-dynamics-moisture trio-
340 interaction theory (Wang et al. 2016). However, it is also noticed that for the slow-propagating
341 MJO, the anomalous moisture anomalies tend to decouple from the Kelvin wave during week 3,
342 accompanied by southeastward detouring convection-circulation anomalies to the south of MC.
343 We argue that some other processes may contribute to its further eastward propagation from
344 observations for the slow-propagating MJO, such as the horizontal advection (Kim et al. 2017) or
345 wind-induced surface heat exchange (WISHE) given the mean westerly winds in this region.
346 However, the model presumably has difficulty capturing these possible processes, leading to the
347 rapid termination of MJO in the eastern MC (Figs. 6, 7). It is concluded that the slow-propagating
348 MJO suffers the MC prediction barrier from model predictions, while the fast-propagating MJO
349 seemingly does not have this problem. The fast-propagating MJO has a larger zonal scale than the
350 slow-propagating event, contributing to its faster propagation speed (Adames and Kim 2016; Chen
351 and Wang 2020).

352

353 5.2 Observed and predicted impacts of ENSO and QBO on MJO diversity

354 What are the root causes for the diversified propagation for different types of MJO? Why are
355 the equatorial waves so different for different types of MJO? One possibility is due to the
356 regulation of interannual variability (Fig. 8). Here interannual variability is approximately
357 estimated as the difference between the averaged 30-day unfiltered anomalies and the averaged
358 30-day anomalies with the previous 120-day anomalies removed. Wang et al. (2019a) found that
359 the standing (fast-propagating) MJO is related to a La Nina (central Pacific El Nino) background
360 mean state, while no statistically significant SST anomalies are found in the equatorial Pacific.
361 The results are overall consistent with Wang et al. (2019a) but we also notice there is a significant
362 SST cooling in the far eastern Pacific for the slow-propagating MJO (Fig. 8c), a signature of an
363 increased zonal SST gradient similar to that for the fast-propagating MJO (Fig. 8d). The
364 convection anomalies are dynamically coherent with the lower-boundary SST changes for
365 different clusters of MJO. The modulation of El Nino/Southern Oscillation (ENSO) on MJO is
366 arguably through two processes: the resultant expansion/shrinkage of the warm pool area that may
367 alter the spatial scale of MJO (Lyu et al. 2021; Wang et al. 2019a), and the change of mean
368 moisture and vertical shear over the MC (Jia et al. 2020; Wei and Ren 2019).

369 Besides ENSO, the role of stratospheric QBO on the MJO activities (MJO frequency, duration,
370 amplitude, and propagation) has been articulated recently given the tight QBO-MJO connection in
371 boreal wintertime (Liu et al. 2014; Yoo and Son 2016; Zhang and Zhang 2018). The QBO-MJO
372 coupling becomes even more prominent in recent decades (Klotzbach et al. 2019). Here we found
373 that the occurrence of standing MJO coincides with significant westerly QBO phases (WQBO)
374 (Fig. 8e), in agreement with the conclusion that there is more MC barrier effect during WQBO

375 than EQBO (Zhang and Zhang 2018). The occurrence of slow-propagating MJO is related to
376 significant easterly QBO phases (EQBO) (Fig. 8g). However, there is no significant relationship
377 between the QBO and the other two clusters of MJO (this conclusion is valid even for the
378 December-February when the QBO-MJO connection is most robust) (Fig. 8f and 8h).

379 The model accurately predicts the corresponding interannual variability associated with ENSO
380 and QBO (Figure S6). Similar to the literature (Lim et al. 2019; Marshall et al. 2017), the impacts
381 of QBO on the MJO prediction skill is clearly shown with a higher prediction skill during EQBO
382 than WQBO (31 vs 27 days) (Figure S7). This is also consistent with the finding that the model
383 has better prediction skills for the slow-propagating MJO than the standing MJO (Fig. 4a).
384 Regarding the physical mechanisms to explain the role of QBO on MJO, several possible
385 mechanisms have been proposed including the upper-tropospheric stability, cloud radiative
386 feedbacks, QBO wind anomalies, and the changes to wave propagation (Martin et al. 2021; Yoo
387 and Son 2016; Zhang and Zhang 2018). However, they remain largely untested and there is no
388 consensus on a particular mechanism that can explain all the observed QBO-MJO connections.
389 About how QBO modulates these four types of MJO is an open question. Given the limited sample
390 size of MJO cases (Table 1), the robustness needs to be confirmed by considering more MJO
391 cases.

392

393 6. Predicting the initial development and identifying the precursors

394 This section focuses on understanding the predictability of the initial development in the Indian
395 Ocean and identifying its potential precursors. First, we assessed the model's skill in predicting
396 the target peak phase of MJO (around day 0) with different lead times (Fig. 9). For the standing
397 MJO, the anomalous enhanced convection in the Indian Ocean is highly predictable even with a

398 20-day lead time. For the jumping MJO, the predicted active convection in the eastern Indian
399 Ocean is weak and less robust for a 20-day lead forecast. The prediction of the second convection
400 center in the western Pacific is even more challenging, and both the 15- and 20-day lead forecasts
401 fail to capture it. For both the slow and fast-propagating MJO, the drying anomalies in the western
402 Pacific are less predictable than the wetting anomalies in the Indian Ocean. One issue for the slow-
403 propagating MJO is that the westerly wind anomalies to the west of the convection center are
404 substantially underpredicted. This may contribute to the slowdown of its eastward propagation
405 because of the associated underestimated zonal moisture advection. Note that the selected cases
406 are not completely the same at different lead times given the data availability from model hindcasts.

407 Why does the model have the ability in predicting the initial development of diversified MJO?
408 What are the precursory signals for these four types of MJO? We further examine the time
409 evolution of preceding convection and circulation anomalies from observations (Fig. 10). As a
410 common precursor for all types of MJO, the prevailing easterly wind anomalies in the Indian Ocean
411 drive the coupled system more subtly towards a state in which the anomalous convection is favored
412 in the Indian Ocean (Fig. 10). The convection anomalies exhibit distinctive precursory conditions
413 that may distinguish the occurrence of different types of MJO. For the standing MJO, pronounced
414 drying anomalies cover nearly the whole tropical Indian Ocean between day -20 and day -10 (Fig.
415 10, green boxes in the first column), which decay rapidly from day -15 to day -10 before the onset
416 of the wet phase at around day -10. This indicates that the wet phase is preceded by a local dry
417 phase as an oscillatory mode. For the jumping MJO, relatively small-scale convection anomalies
418 are detected in the southern central equatorial Indian Ocean (Fig. 10, green boxes in the second
419 column), and the resultant easterly winds anomalies are responsible for the onset of the wet phase
420 of MJO in the southwest Indian Ocean.

421 The slow-propagating MJO displays a significant dry phase in the central-to-eastern Indian
422 Ocean during the period between day -20 and day -10 (Fig. 10, green boxes in the third column),
423 which exhibits a clear eastward propagation across the MC to the western Pacific. Note that the
424 dry phase does not show the southward detouring feature near the MC distinguished from its wet
425 phase. For the fast-propagating MJO, the major loading of suppressed convection is anchored in
426 the MC and western Pacific (Fig. 10, green boxes in the fourth column) without an apparent
427 propagation before the initial development of the wet phase in the Indian Ocean. Given the
428 distinctive time evolution of the convection anomalies (Fig. 10), it is inferred that the standing and
429 slow-propagating MJO are mostly “successive MJO”, while the jumping and fast-propagating
430 MJO are mainly “primary MJO”. Here the “successive MJO” is referring to the cases with a
431 preceding event and the “primary MJO” represents the cases originating from the Indian Ocean
432 (Matthews 2008). The model generally predicts a similar time evolution of convection and
433 circulation anomalies as observations for all types of MJO when initiated at day -20 (Fig. 10).

434

435 7. Prediction of teleconnections

436 The impacts of the MJO are not just within the tropics but also in the extratropics as well. The
437 MJO’s extratropical circulation signature has been studied extensively, and many efforts have been
438 made to unravel the physical processes that underlie the establishment of the teleconnections
439 forced by MJO (Ferranti et al. 1990; Stan et al. 2017; Tseng et al. 2019). However, many current
440 climate models still have difficulty in realistically simulating MJO, and the error in the Pacific
441 subtropical jet greatly limits the ability to faithfully produce the MJO teleconnection patterns
442 (Henderson et al. 2017; Wang et al. 2020). A skillful prediction of the relevant tropical convection
443 could allow the prediction of its remote teleconnections to become possible.

444 Chen (2021) has examined the observational circulation anomalies associate with these four
445 types of MJO. Here one example is shown to illustrate the observed and predicted distinctive t2m
446 and 500 hPa geopotential height anomalies (averaged 11-20-day after day 0) associated with these
447 four types of MJO by focusing on the Pacific-North America sector (Fig. 11). For the standing
448 MJO, robust cold t2m anomalies are observed near the Chukchi Sea, northern Canada, and the
449 adjacent seas (Fig. 11a). The jumping MJO excites a zonal wave-train circulation over the
450 northeastern Pacific-North America-North Atlantic sector, with a coherent zonal dipole pattern of
451 t2m anomalies in North America and a significant warming over the Greenland Sea and Norwegian
452 Sea regions (Fig. 11b). The slow- and fast-propagating MJO have a similar teleconnection pathway
453 in the Pacific-North America sector, reminiscent of a typical pattern of the North Pacific
454 Oscillation (NPO) mode with a low-pressure system over Alaska and the Bering Sea and high
455 pressure in northern North America (Rogers 1981). Compared to the slow-propagating MJO, the
456 fast-propagating MJO induces a slightly southward shifted warming in North America (Fig. 11d
457 vs. 11c). For the fast-propagating MJO, the circulation and surface temperature anomalies in the
458 North Atlantic sector project onto the positive phase of North Atlantic Oscillation (NAO) (Fig.
459 11d), as documented in many previous studies (Cassou 2008; Lin et al. 2009). It is of interest to
460 note that the teleconnections associated with the standing and propagating MJO resemble very
461 similar patterns with two leading EOF modes of the wintertime cold extremes in North America
462 (Xiang et al. 2020). This implies that the MJO is one of the major drivers and also a key
463 predictability source for the wintertime extremes in North America but that the occurrence of such
464 extremes may be sensitive to the MJO type.

465 The remarkable teleconnection differences highlight the importance of accurately predicting the
466 propagation characteristic of MJO in the tropics. Inspection of the model hindcasts initiated at

467 around day 0 (strongest convection in the Indian Ocean) reveals a considerable skill in predicting
468 the distinguished circulation and temperature anomalies for the standing, jumping, and fast-
469 propagating MJO (Fig. 11). However, the model struggles to predict the teleconnections associated
470 with the slow-propagating MJO (Fig. 11g). The corresponding pattern correlations between the
471 observed and predicted t2m anomalies are 0.57 (standing), 0.64 (jumping), 0.19 (slow-
472 propagating), and 0.55 (fast-propagating), respectively. We also examined the same time period
473 as in Fig. 11 but initiated at day -5 and found that the model has some skill in predicting the
474 associated teleconnections for the standing and fast-propagating MJO, while the model is limited
475 in its ability to predict the teleconnections for both the jumping and slow-propagating MJO (not
476 shown). The detailed processes leading to the limited skill in predicting its teleconnection remain
477 elusive and require further investigation.

478

479 8. Summary and discussion

480 8.1 Conclusion

481 Improvements in MJO prediction skills are critical for developing prediction products for
482 various weather phenomena. This study introduces a newly developed S2S prediction system using
483 the GFDL SPEAR global coupled model. The wintertime (November-April) MJO prediction is
484 evaluated using 20-year hindcasts (2000-2019). Results show that the model skillfully predicts the
485 MJO for 30 days before the bivariate ACC of the RMM index drops to 0.5 (Fig. 1). The MJO
486 prediction skill is dependent on the MJO propagation features (Fig. 4). The fast-propagating MJO
487 has the best skill of 38 days, followed by the slow-propagating MJO and jumping MJO (31 days),
488 and then the standing MJO (23 days). The diversified skills for different types of MJO are related
489 to their contrasting skills initiated at weak MJO and their amplitude difference (Fig. 5). To further

490 improve the MJO prediction in SPEAR, the key is to advance the prediction of standing MJO given
491 its large gap with its potential predictability (15 days) (Fig 4). The slow-propagating MJO detours
492 southward when traversing the MC and suffers the MC prediction barrier effect, while the fast-
493 propagating MJO propagates across the central MC without the MC prediction barrier issue (Figs.
494 6, 7). The intensity of Kelvin waves and the zonal spatial scales, potentially modulated by the
495 background interannual variability, are essential in determining their different propagations (Figs.
496 7, 8). The MJO diversity is modulated by interannual variabilities from ENSO and QBO. In
497 particular, we found that the occurrence of the standing MJO coincides with significant WQBO
498 phases and the slow-propagating MJO is corresponding to significant EQBO phases. The
499 modulation of QBO on MJO diversity partially explains the contrasting MJO prediction skill
500 between two QBO phases.

501 The SPEAR model exhibits its capability not only in predicting the diversified MJO
502 propagation (Figs. 6, 7) but also in predicting its initial development in the Indian Ocean (Fig. 9)
503 accompanying by contrasting precursory convection signals (Fig. 10). Distinct teleconnections in
504 the northern extratropics are revealed for these four types of MJO, and the SPEAR model
505 realistically predicts its extratropical teleconnection for the standing, jumping, and fast-
506 propagating MJO (averaged 11-20-day after day 0) (Fig. 11). However, the model has little skill
507 in predicting its observed teleconnections for the slow-propagating MJO despite a useful MJO
508 prediction skill of 31 days. It highlights the complexities and challenges of applying a skillful MJO
509 prediction to the operational prediction of MJO impacts, such as the meteorological variables---
510 t2m and precipitation.

511

512 8.2 Discussion

513 Why do the slow-propagating and fast-propagating MJO differ in their propagation pathway
514 when crossing the MC: one through the southern MC and the other through the central MC (Fig.
515 7)? There are two possible reasons for this. First, for the fast-propagating MJO, the suppressed
516 interannual convective variability to the south of MC may prohibit its southward pathway when
517 crossing the MC (Fig. 8d), resulting in a rather equatorially symmetric propagation over the central
518 MC (Fig. 7). Second, the propagation pathway can be modulated by the seasonal variation of the
519 background mean state. Kim et al. (2017) found that the MJO preferentially detours southward
520 near the MC during December-February (DJF), predominantly related to the meridional mean
521 moisture gradient. Here we reveal the seasonal preference about the occurrence frequency of
522 different types of MJO. There are more slow-propagating cases in DJF than March-April (MA) (9
523 vs. 3), but fewer fast-propagating MJO cases in DJF than MA (4 vs. 7) (Table 1), consistent with
524 (Chen 2021). It also implies the MJO propagation speed may have seasonal dependence with fast
525 (slow) propagation speed in DJF (MA). Meanwhile, there are fewer standing MJO cases in MA
526 than DJF (Table 1). The seasonal preference indicates that the background mean state in MA tends
527 to be more favorable for its eastward propagation of MJO than in DJF. Compared to the fast-
528 propagating MJO, the more severe MC prediction barrier problem for the slow-propagating MJO
529 is possibly linked to a more severe mean state bias in DJF than MA. Identifying the potential role
530 and processes of seasonality in regulating the MJO diversity calls for deliberation. There are
531 several other issues that are not addressed here. For example, why does the QBO have pronounced
532 influences on the standing and slow-propagating MJO but not on the other two types of MJO (the
533 seasonal preference of the occurrence of different MJO types may partially explain this as the
534 connection between QBO and MJO is most prominent in DJF)? Why does the model have
535 difficulty in predicting the teleconnections associated with the slow-propagating MJO? Whether

536 and to what extent these findings can be applied to other dynamical models is another issue calling
537 for further studies.

538 Though the SPEAR model produces a comparable or even better MJO prediction skill than the
539 majority of current operational S2S prediction models (Kim et al. 2018; Vitart 2017), there are
540 also some caveats and limitations for the current configuration, developed for high performance
541 computing constraints. For example, the model has a relatively coarse vertical resolution (33 levels)
542 with a low top atmosphere. The initialization is relatively simple, and the land is not explicitly
543 initialized, although it can be constrained by the atmospheric nudging. The system also suffers the
544 under-dispersive issue (the ensemble spread is much smaller than the RMSE) common to many
545 models. These caveats, however, may provide an opportunity to identify the roles of a better
546 representation of the stratosphere and a sophisticated initialization in S2S prediction and should
547 be explored.

548 Understanding and isolating skills with a global model are critical for further model
549 development. We hope that this work provides a framework to identify potential issues for MJO
550 prediction in individual models by examining diversified MJO, which may provide guidance for
551 further model development. Given the different impacts from these four types of MJO, operational
552 forecasters may need to consider more than just the RMM index when monitoring the MJO and
553 forecasting its impacts.

554 The SPEAR seasonal prediction system (Delworth et al. 2020; Lu et al. 2020) is operationally
555 participating in the North American Multi-Model Ensemble (NMME) (Kirtman et al. 2014), but
556 was first developed for research. By developing SPEAR for S2S prediction, we have created a new
557 system for shorter-range prediction that could similarly be used in research to further development
558 in operational modeling. Importantly, the SPEAR model shares two key model components with

559 the Unified Forecast System (UFS) model: the Finite-Volume Cubed-Sphere (FV3) dynamical
560 core (Lin 2004) and MOM6 ocean model (Adcroft et al. 2019). Thus, knowledge derived from the
561 development and use of SPEAR can be used to assist in the development and application of the
562 UFS model.

563

564

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Table and Figure captions

Table 1 The temporal midpoint of the selected four clusters of the observed MJO events. Each MJO case is defined when the area-averaged OLR anomalies in the equatorial Indian Ocean (75°E-95°E, 10°S-10°N) are below one standard deviation for five successive days. The total number of events is shown in the first row in the parentheses.

Figure 1 MJO prediction skill during boreal wintertime (November to April) from 2000 to 2019 made by the GFDL SPEAR model. a) The bivariate anomalous correlation coefficient (ACC) measured by the RMM index from individual members (grey) and ten-member ensemble mean (red). b) the RMM index root mean square error (RMSE) from individual members (grey) and their ensemble mean (red). The blue line denotes the ensemble spread relative to the ten-member ensemble mean.

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Figure 3 Prediction skill for MJO amplitude and phase angle. a) The time evolution of MJO amplitude as a function of forecast lead days for initially strong cases from observations (black) and model prediction from the ensemble mean (solid red) and mean of individual members (dashed

810 red). b) The observed (black bars) and predicted (red bars) MJO amplitude averaged over the first
811 25 days for initially strong cases as a function of eight different MJO phases (x -axis). c) Prediction
812 of MJO phase angle error ($^{\circ}$) as a function of forecast lead time for the initially strong cases. d)
813 The predicted MJO phase error averaged over the first 25 days for initially strong cases as a
814 function of eight different MJO phases (x -axis).

815

816 Figure 4 Four types of MJO events and their prediction skills in the SPEAR model. a) The ACC
817 and b) potential predictability for four clusters of MJO. c) -f) Longitude (x -axis)-time (y -axis)
818 composite of equatorial (10°S - 10°N) OLR anomalies (W/m^2) for four types of MJO centered at
819 day 0 when the domain-averaged OLR anomalies in the equatorial Indian Ocean (10°S - 10°N ,
820 75°E - 95°E) are below one standard deviation for five successive days.

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822 Figure 5 Prediction skill dependence of MJO diversity on the initial amplitude. a) The ACC for
823 four types of MJO initiated at strong ($|\text{RMM}| > 1$; solid) and weak ($|\text{RMM}| < 1$; dash) cases. b) the
824 observed MJO amplitude ($\sqrt{\text{RMM}1^2 + \text{RMM}2^2}$) for four groups of MJO as a function of forecast
825 lead days (x -axis) by counting all the selected cases (initiated between 20 days before and 15 days
826 after day 0). There are 42, 59, 85, 67 initially strong cases and 46, 45, 31, 25 initially weak cases
827 for these four types of MJO.

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829 Figure 6 MJO propagation and proposed mechanisms seen from the equatorial (10°S - 10°N)
830 anomalies as a function of longitude (x -axis) and time lag (y -axis; days) composited for four types
831 of MJO. The first row: observed OLR anomalies (shading; W/m^2) and 850 hPa zonal winds
832 (contours with an interval of 0.6 m/s). The second row: observed lower-tropospheric divergence

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835 rows are similar to the top two but for model predictions initiated at day -5 (5 days before the peak
836 phase in the Indian Ocean). The black stippling denotes the regions at the 10% significance level.

837

838 Figure 7 Comparison of observed and predicted anomalies during the first four weeks initiated at
839 day -5. The observed composite anomalies of OLR (W/m^2), 850 hPa winds (m/s, not shown when
840 wind speed is less than 0.5 m/s), and 850 hPa geopotential height (contours; m^2/s^2) during the first
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846 Figure 8 Regulation of ENSO and stratospheric QBO on MJO diversity. Left panel: The observed
847 interannual SST ($^{\circ}\text{C}$; shading) and OLR anomalies (W/m^2 ; contours) between day -15 and day
848 +15. Right panel: The observed interannual 50 hPa zonal wind anomalies (m/s) between day -15
849 and day +15. The MJO type is indicated at the left of each row. The black stippling denotes the
850 regions at the 10% significance level for SST anomalies (left panel) and 50 hPa zonal wind
851 anomalies (right panel). Note that all cases initialized from November to April are used here.

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853 Figure 9 Model's skill in predicting the target peak phase in the equatorial Indian Ocean (at around
854 day 0) with different lead times for the four types of MJO. First row: the observed composite
855 anomalies of OLR (shading; W/m^2) and 850 hPa winds (m/s, not shown when wind speed is less

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860 Figure 10 Observed precursors for the four types of MJO. First row: the observed composite
861 anomalies of OLR (shading; W/m^2) and 850 hPa winds (m/s, not shown when wind speed is less
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863 second to fourth rows are similar but for 10, 15, and 20 days before the peak phase. The bottom
864 four rows are similar but for the time evolutions of forecast initiated at day -20. The black stippling
865 denotes the regions with significant OLR composite anomalies at the 10% significance level.
866 Green boxes in the lowest panels for both observations and model forecast denote the key regions
867 with precursory OLR signals.

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870 a-d) The composite observational anomalies of 2m temperature (shading; $^{\circ}C$) and 500 hPa
871 geopotential height (contours; m^2/s^2) averaged over 11 to 20 days after the peak phase (between
872 day 11 and 20) for the four types of MJO, e-h) Similar to a-d) but for model predictions initiated
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Table and Figures

Table 1 The temporal midpoint of the selected four clusters of the observed MJO events. Each MJO case is defined when the area-averaged OLR anomalies in the equatorial Indian Ocean (75°E-95°E, 10°S-10°N) are below one standard deviation for five successive days. The total number of events is shown in the first row in the parentheses.

Standing (12)	Jumping (14)	Slow-propagating (15)	Fast-propagating (13)
2003-01-31	2002-01-22	2000-11-18	2002-04-30
2003-11-09	2002-03-21	2001-01-27	2002-11-13
2005-02-18	2004-11-01	2001-11-18	2003-12-09
2008-11-16	2005-01-04	2002-12-23	2005-03-29
2010-11-25	2005-12-12	2006-01-11	2006-12-25
2011-02-03	2006-04-23	2006-03-19	2009-04-09
2011-11-27	2010-03-27	2007-12-13	2012-03-09
2011-12-21	2011-04-30	2008-01-28	2012-11-05
2012-04-21	2012-01-27	2009-11-10	2012-12-27
2017-01-01	2016-02-06	2009-12-30	2018-04-18
2017-02-26	2016-03-15	2010-02-12	2019-01-19
2017-04-12	2017-11-28	2013-02-08	2019-03-03
	2018-01-20	2013-03-31	2019-04-23
	2018-03-05	2015-02-11	
		2015-04-05	

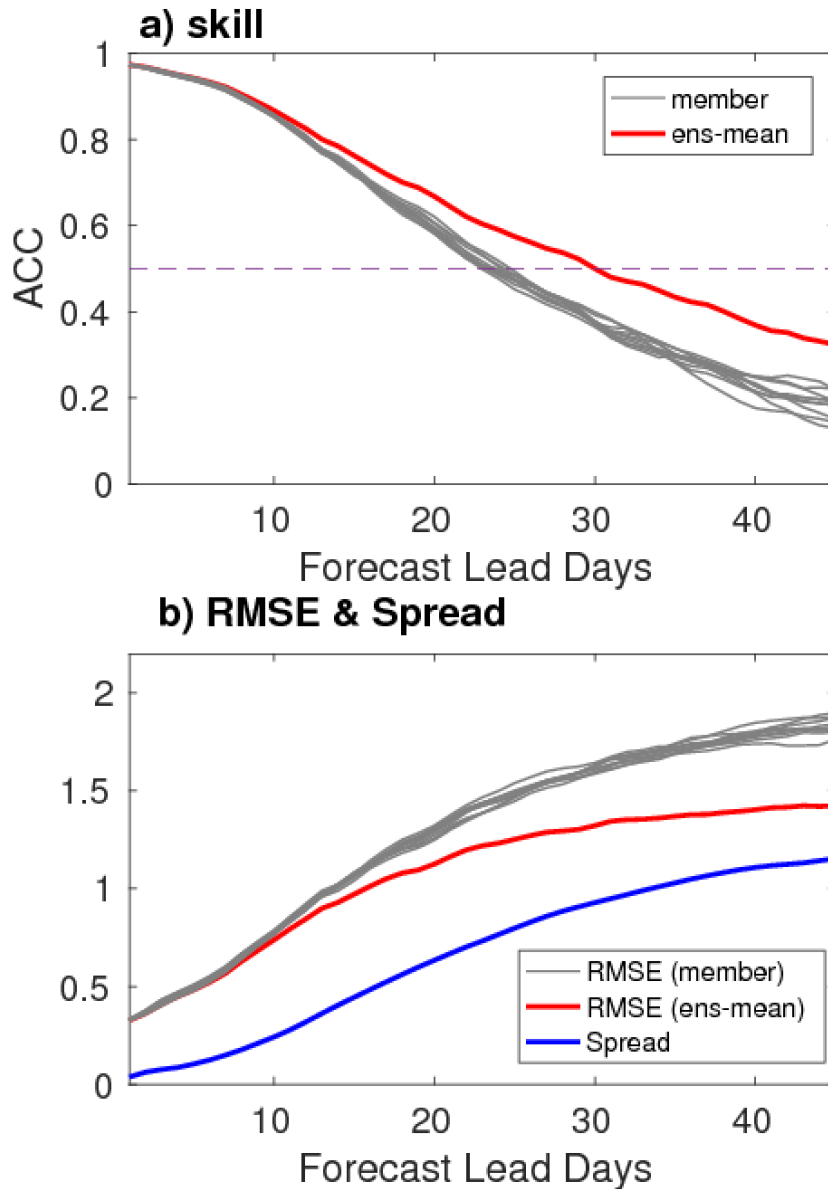


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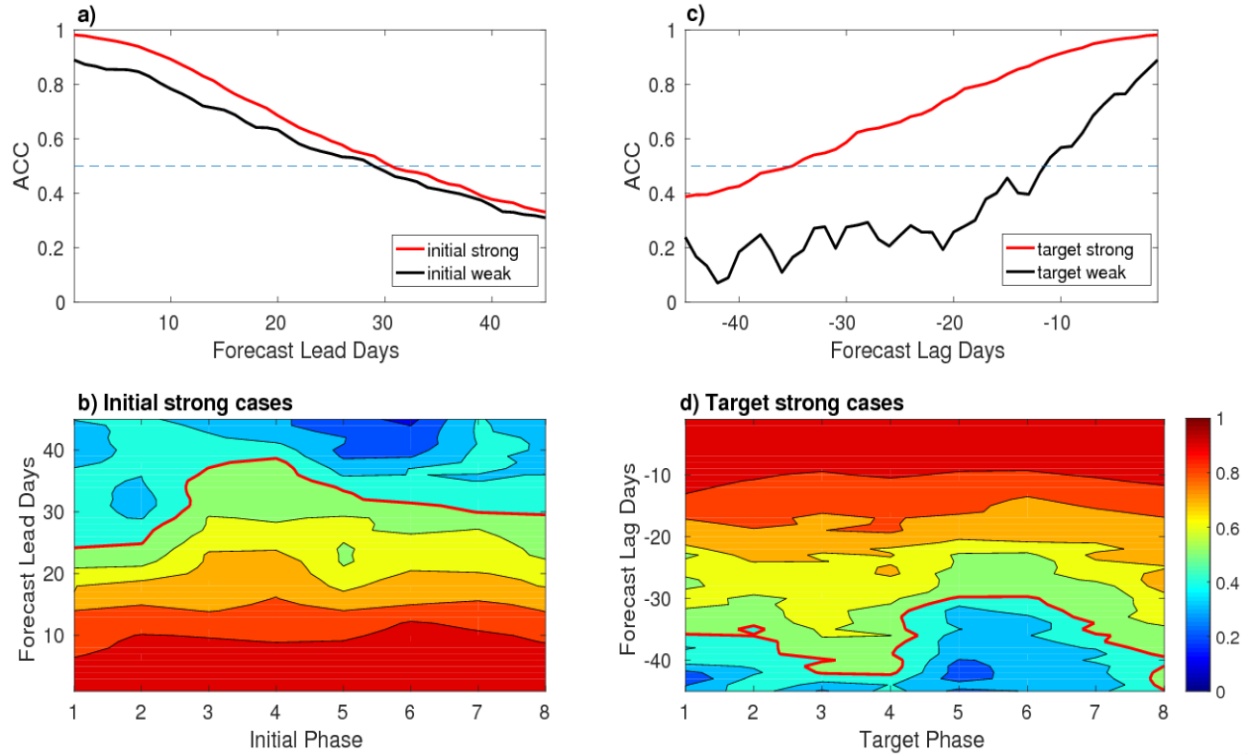


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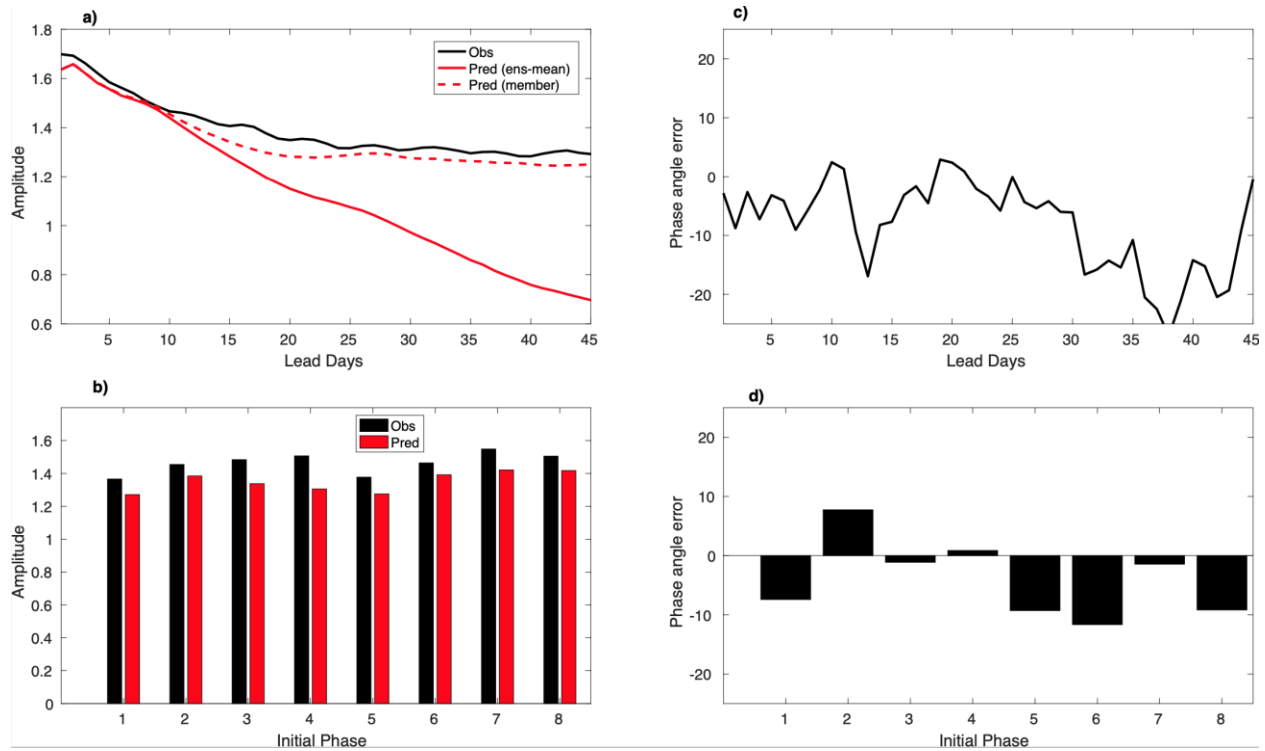


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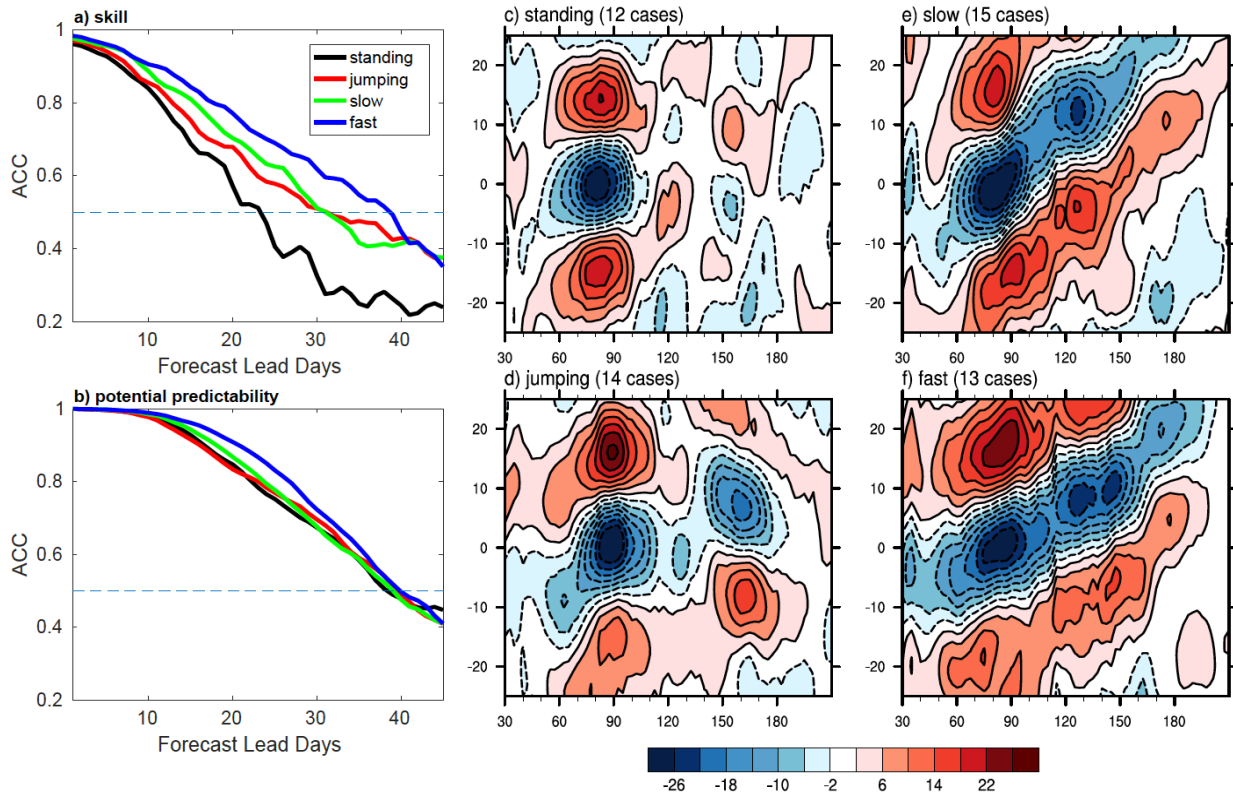


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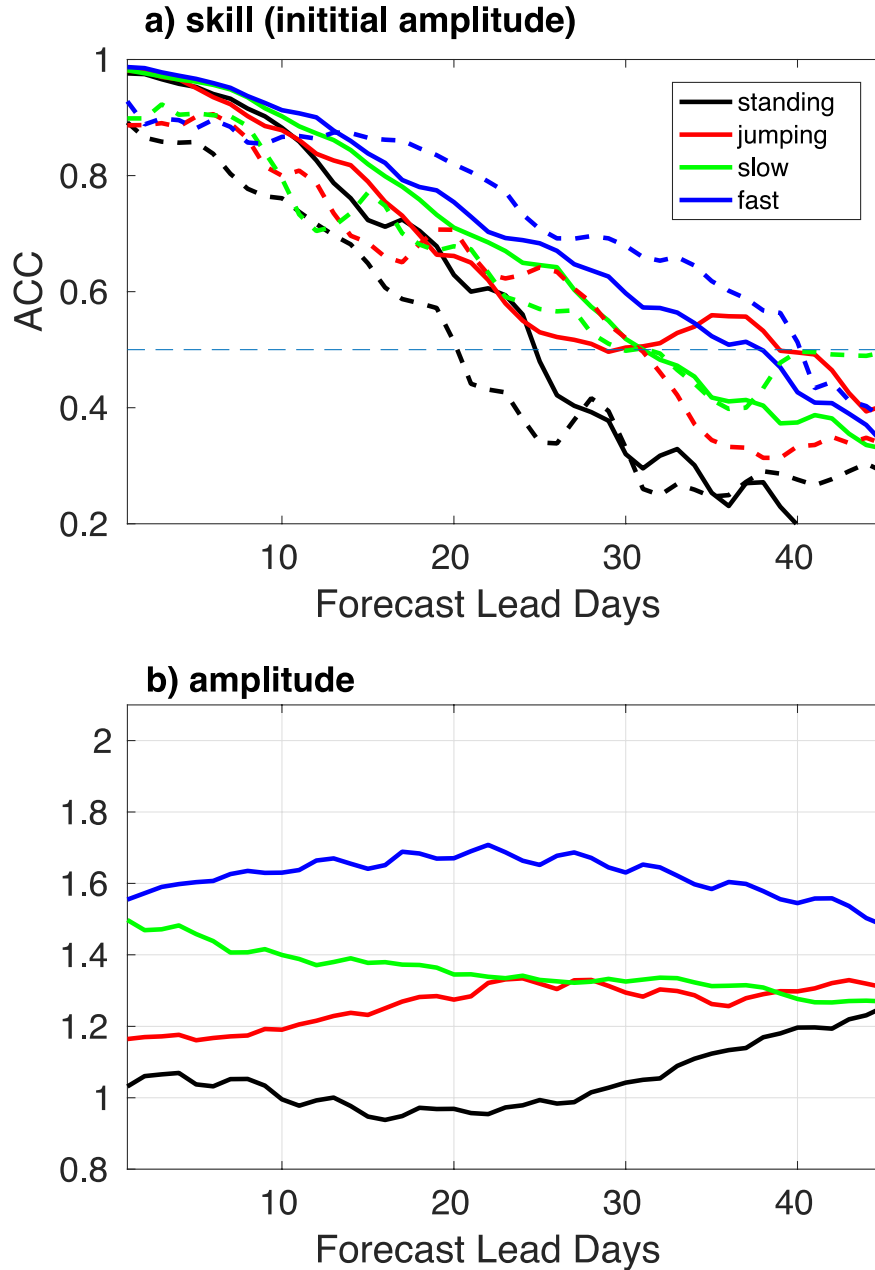


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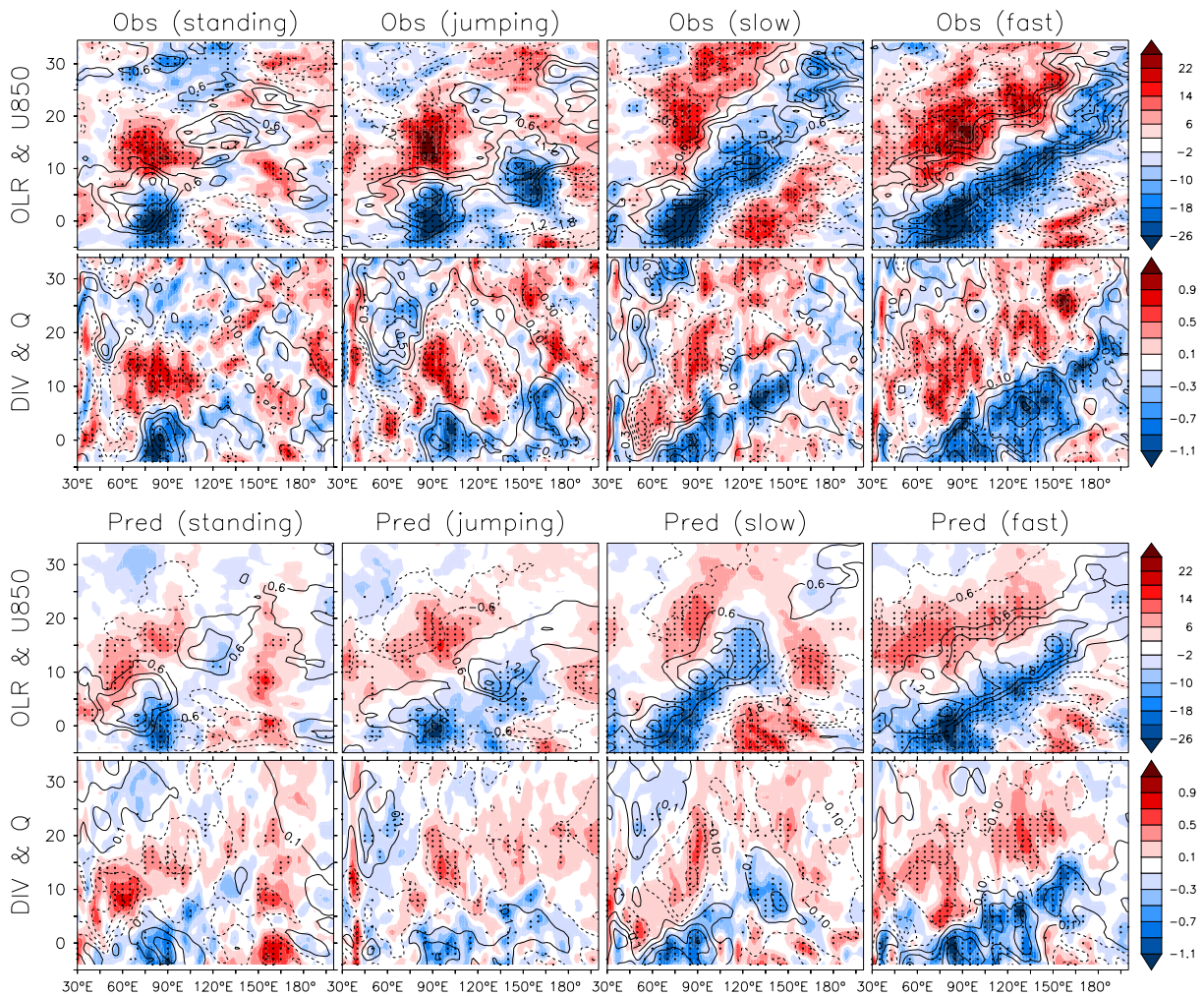


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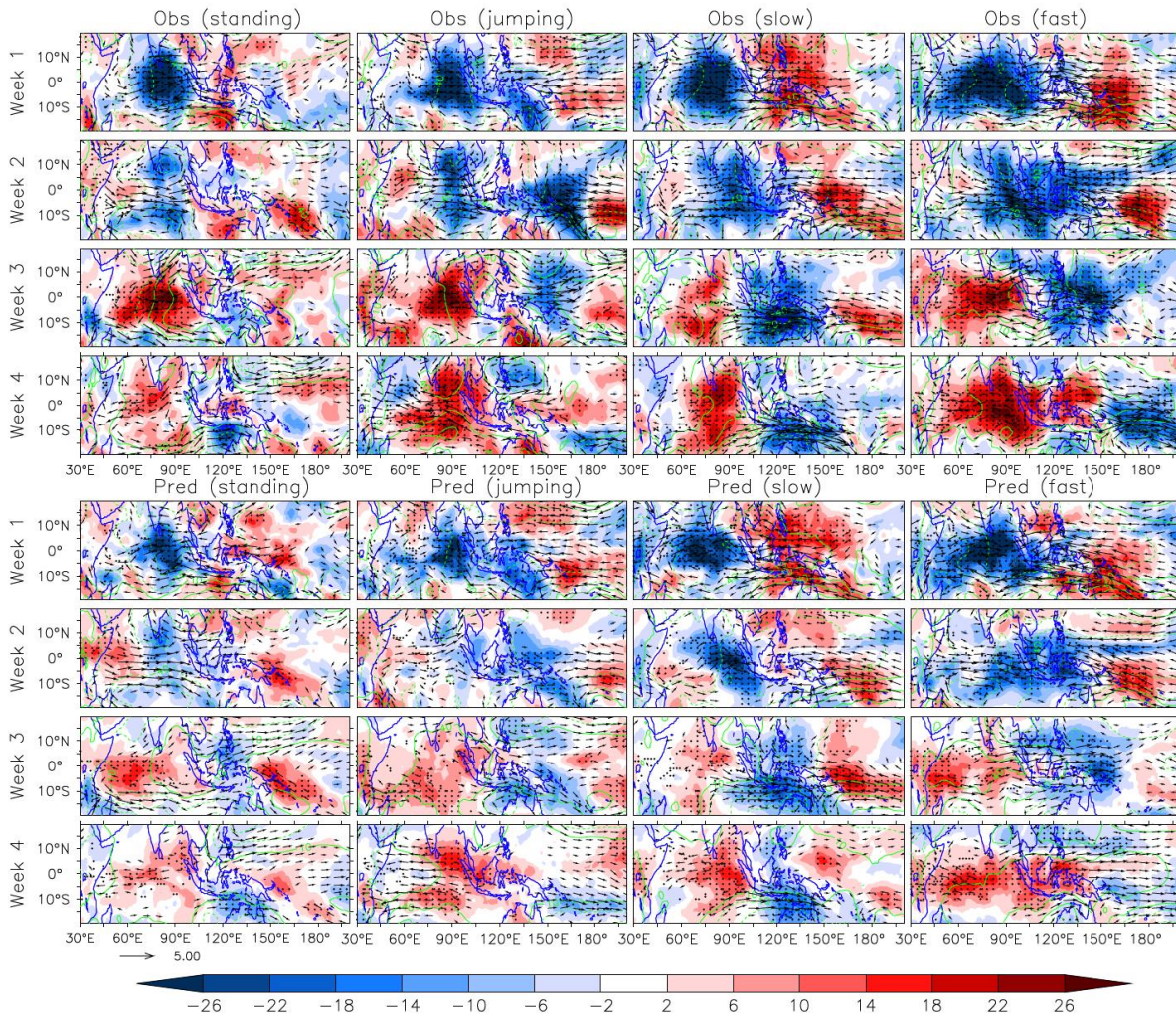


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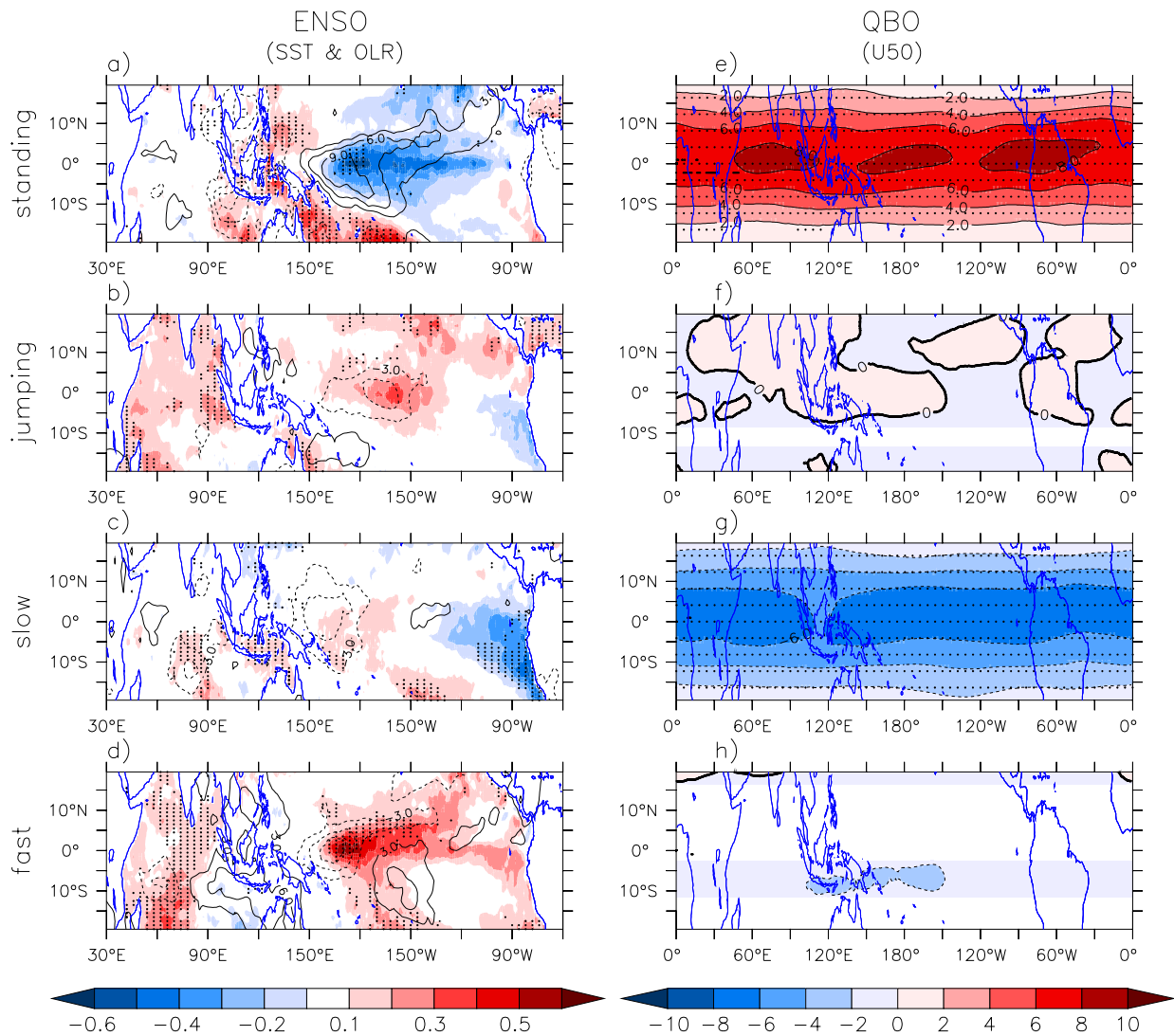


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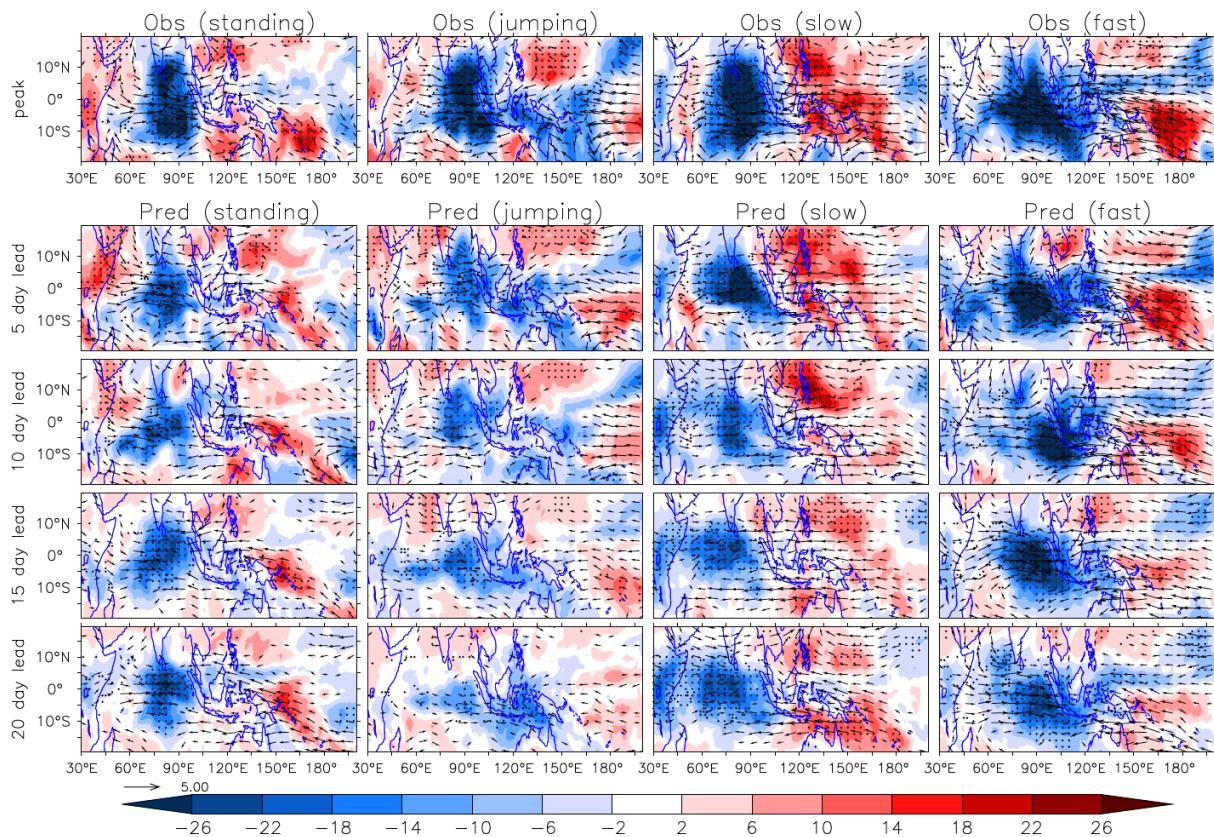


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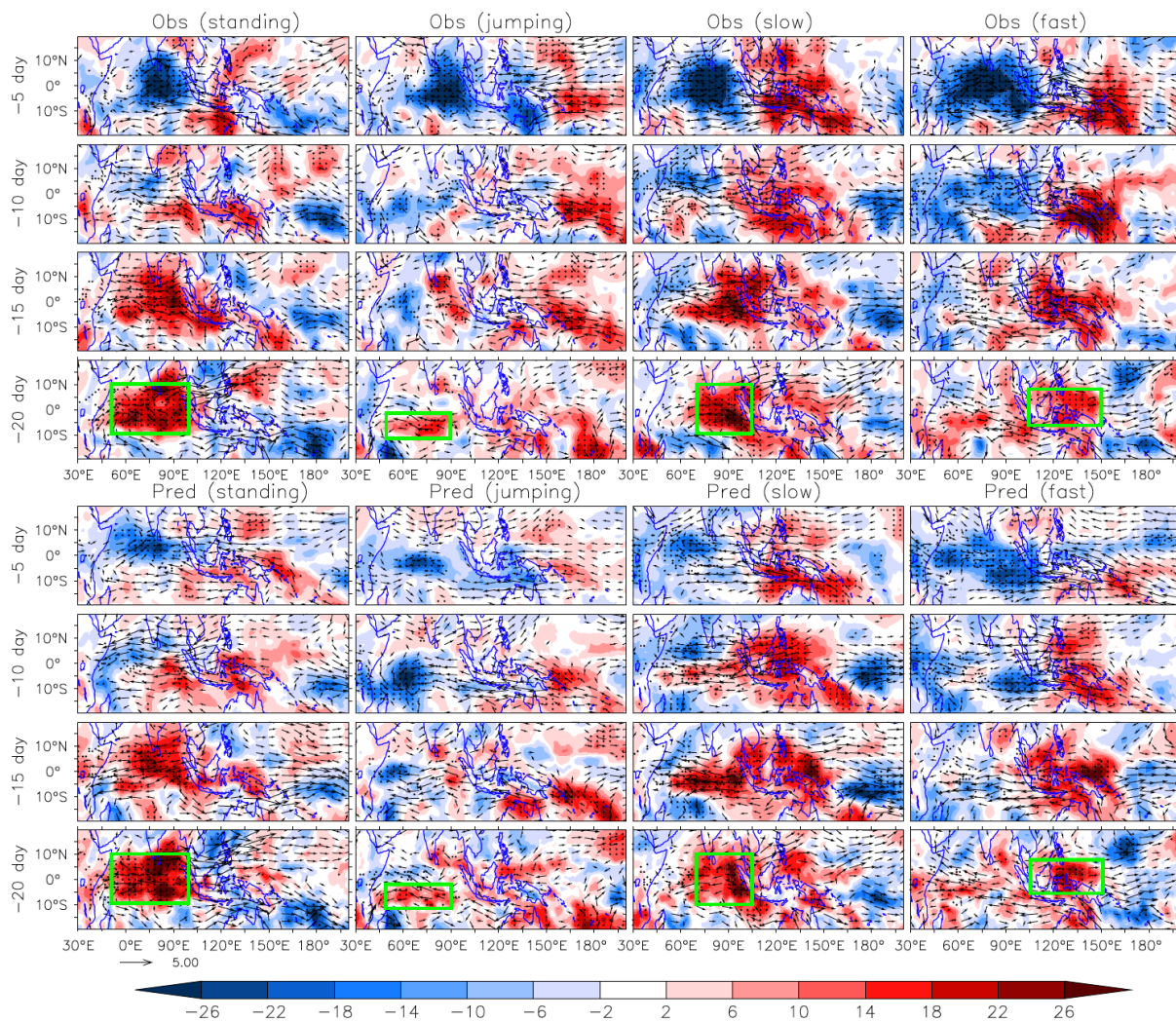


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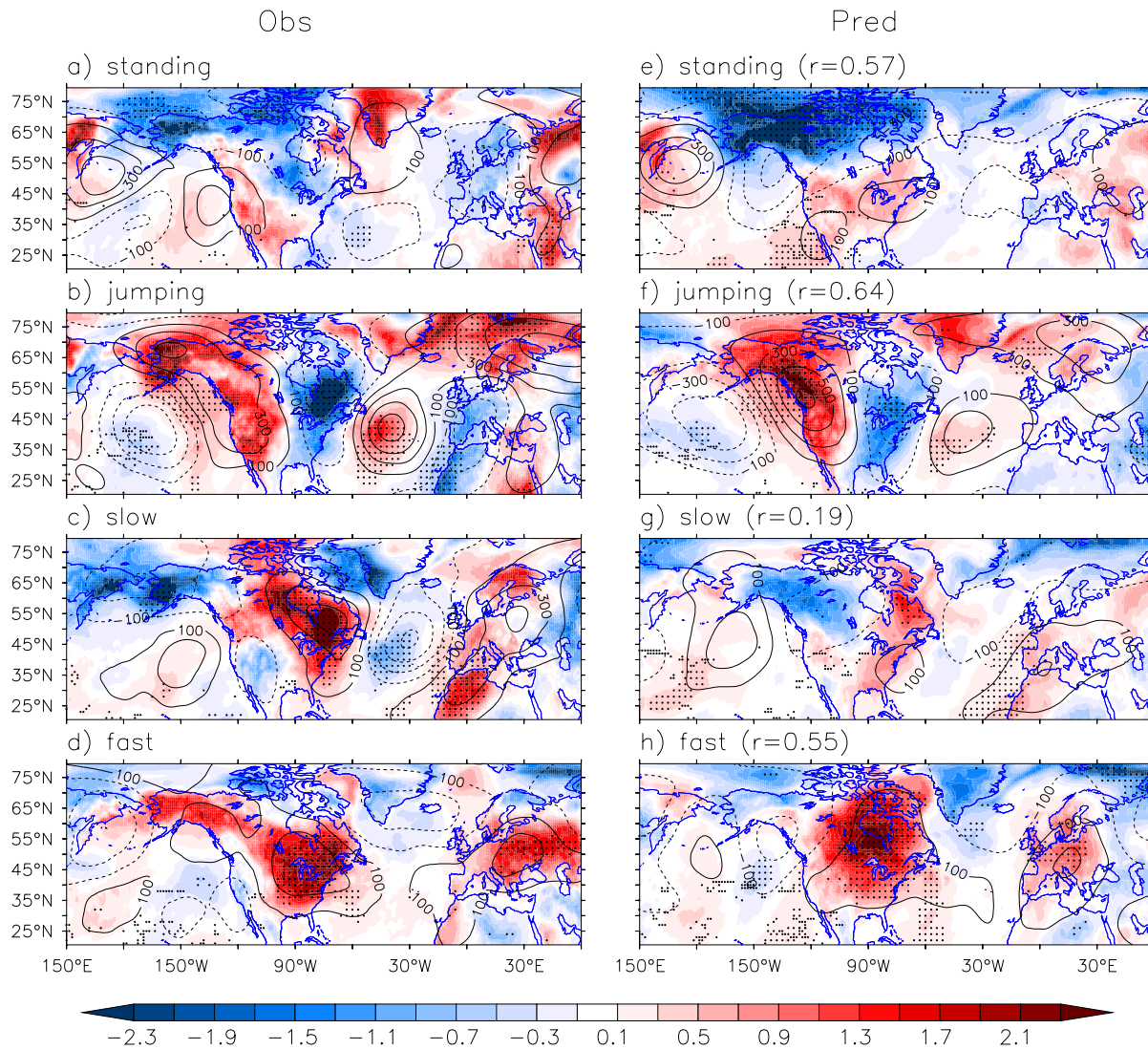


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