



1 **The Madden Julian Oscillation in high-resolution coupled climate** 2 **simulations: mean state evaluation and historical variability in** 3 **IFS-NEMO**

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10 **Abstract.** This work examines the representation of the MJO in two high-resolution versions of the fully coupled General
11 Circulation Model IFS-NEMO, a new-generation climate model developed at the BSC within the European Project EERIE
12 and the Destination Earth initiative. We analyse two historical HighResMIP simulations of IFS-NEMO performed at two
13 different horizontal resolutions: 9 km and 25 km, to investigate the impact of the resolution on MJO performance. The model
14 correctly reproduces the main dynamical features associated with the MJO when defined via multivariate EOF analysis, and
15 exhibits typical model biases. The model correctly reproduces the spatial properties of the two leading observed EOFs, but
16 the mean amplitude of the MJO and the intensity of the convective signal are generally underestimated, with a reduction of
17 spectral power of about 20% at both resolutions with respect to satellite observations. IFS-NEMO also exhibits a reduced
18 eastward propagation of the intraseasonal precipitation and convective signals associated with the MJO. This is explained by
19 the strong dry bias found in the early phases of the MJO (over the Indian Ocean) in both versions of IFS-NEMO with respect
20 to ERA5. Low-atmospheric moistening is crucial during those phases as moisture accumulation drives both vertical and
21 horizontal humidity advection. Overall, the 10 Km configuration seems to improve the structure of the two leading EOFs and
22 their explained variance, without solving the other biases. The simulations do not reproduce the long-term change of MJO
23 activity observed over the full historical period. In particular, the MJO variance increases in observations, while none of the
24 IFS-NEMO simulations shows a significant trend. This is due to cold ocean and background circulation biases. Finally, the
25 implications that such a discrepancy can have on predictability are discussed by analysing the changes in weighted
26 permutation entropy of the MJO amplitude time series. Contrary to ERA5, the predictability does not increase in IFS-NEMO
27 at both resolutions, as the model fails to reproduce the externally forced predictive component of the MJO, thus questioning
28 their suitability to investigate the projected future evolution.



29 1 Introduction

30 The Madden Julian Oscillation (MJO) is one of the main modes of intraseasonal climate variability in the Tropics. First
31 identified by Madden and Julian (1971), the MJO is a phenomenon characterised by organised convective systems coupled
32 to the atmospheric circulation. It involves an eastward-propagating convective center, which develops over the warm pool of
33 the Indian Ocean and dissipates as it reaches the Central-Eastern Tropical Pacific, preceded by an analogous region of
34 suppressed convection at its eastward end, establishing an oscillation that recurs on timescales from 30 to 80 days. This
35 system can modulate the El Niño–Southern Oscillation (ENSO), triggering some positive ENSO events (Kessler and
36 Kleeman, 2000), and has also been shown to influence the Indian and Australian monsoons (M. C. Wheeler et al., 2009;
37 Taraphdar et al., 2018), tropical cyclone activity (Fowler and Pritchard, 2020) and many other climate phenomena worldwide
38 through atmospheric circulation perturbations (Vitart, 2017; Stan et al., 2022; Yadav et al., 2024). Tightly coupled to the
39 large-scale atmospheric circulation, the MJO constitutes the largest single source of predictability for the climate both in the
40 Tropics and in the extra-tropics on the subseasonal to seasonal (S2S) timescale (Stan et al., 2017).

41 A good representation of the MJO is therefore crucial for forecast models to enhance their prediction skill. Considerable
42 efforts have been devoted by multiple groups around the world (Vitart et al., 2017) to identify and correct common
43 deficiencies of both weather forecast models and General Circulation Models (GCMs) in representing the MJO, with the
44 focus often put on unifying diagnostic procedures to evaluate the model’s behaviour (Waliser et al., 2009). Applications to
45 fully coupled GCMs have shown improvement in the course of the years through increases in horizontal resolution and better
46 convection parametrization, allowing models from the Coupled Model Intercomparison Project phase 6 (CMIP6) to
47 generally outperform their CMIP5 predecessors (Waliser et al., 2009; Ahn et al., 2020). Ocean–atmosphere coupling has
48 emerged as an important factor in this progress: interactive SSTs improve the coherence and propagation speed of the
49 simulated MJO compared to atmosphere-only configurations, particularly through the rectifying effect of air-sea heat fluxes
50 ahead of the convective envelope (Klingaman and Woolnough, 2014; DeMott et al., 2015). Despite these improvements,
51 GCMs still struggle to reproduce key aspects of the observed MJO variability, presenting systematic biases in its amplitude,
52 propagation speed and coherence, with the Maritime Continent barrier – a tendency of models to suppress MJO convection
53 as it crosses the Indonesian archipelago – remaining one of the most documented deficiencies across model generations (Ahn
54 et al., 2020; Jiang et al., 2020; Merryfield et al., 2020).

55 Wheeler and Hendon (2004) established a standard procedure to monitor MJO activity, providing a seasonally independent
56 characterization of its state through the Realtime Multivariate MJO (RMM) indices, which are commonly applied in the S2S
57 prediction community. However, recent studies have illustrated the sensitivity of MJO activity diagnostics and model
58 prediction skill metrics to the index of choice (H. Kim et al., 2018; Liu et al., 2016; Lyu et al., 2019; Stachnik and Chrisler,
59 2020), comparing the RMM approach against single-variable alternatives, such as the Outgoing longwave radiation-based
60 MJO Index (OMI; Kiladis et al., 2014), or the velocity potential index (Ventrice et al., 2013), each carrying distinct
61 advantages and limitations in terms of noise sensitivity, physical interpretability and seasonal dependence.



62 The index choice is also important for exploring the long term variability of the MJO and its response to climate change, as
63 shown by Lyu et al. (2019), who compared the RMM, OMI and relative variations. Differences in the long-term changes in
64 the MJO have also been reported between different reanalysis datasets (Dias et al., 2025). Such a heterogeneity of methods
65 and perspectives, in spite of numerous efforts of standardization, still leads to heterogeneous conclusions (Lyu et al., 2019;
66 Maloney et al., 2019; Weidman et al., 2022).

67

68 These methodological challenges become especially relevant as climate modelling enters the era of storm-resolving global
69 models. Much of the literature on MJO simulation and long-term variability has relied on conventional-resolution GCMs.
70 Some studies have previously highlighted the impacts of explicit convection and storm-resolving resolutions on the MJO
71 representation in models, but limited by reduced spatial or temporal domains (Miura et al., 2007; Holloway et al., 2013). The
72 advent of eddy-permitting and eddy-resolving coupled models opens new opportunities to address some persistent
73 deficiencies. Higher atmospheric resolution can improve the representation of mesoscale convective organisation, sharpen
74 topographic forcing over the Maritime Continent (Jiang et al., 2019), and resolve finer oceanic structures (Roberts et al.,
75 2026) that feed back onto the atmospheric boundary layer — all processes known to influence MJO propagation.

76 The scope of this paper is to investigate the impact of horizontal resolution on the representation of the MJO in two different
77 configurations of the global coupled GCM IFS-NEMO at eddy-permitting (~25 km) and eddy-resolving (~9 km) resolution,
78 evaluating their performance against observational and reanalysis benchmark. The paper additionally examines long-term
79 MJO variability, as captured by the RMM index, and its sensitivity to the choice of the reference period, extending the recent
80 work of Dias et al. (2025). This evaluation allows us to identify the strengths and the shortcomings of its eddy-resolving
81 configuration, which is currently being used at the Earth Sciences Department of the Barcelona Supercomputing Center
82 (BSC) to implement a new generation seasonal-to-decadal (S2D) climate prediction system.

83 The paper is organised as follows. Section 2 describes the GCM, the simulations performed and the validation data, as well
84 as the methodologies employed to characterize and evaluate the MJO. Most metrics used here are well known and have been
85 widely used in recent years of research on the MJO. Section 3 presents the results of the model evaluation with a particular
86 focus on the impact of horizontal resolution on the different metrics. Section 3 also explores the sensitivity of the commonly
87 used RMM index to the choice of the reference period as well as its length. Finally, section 4 summarizes our findings and
88 sets the foundations for the upcoming application of IFS-NEMO to investigate the potential predictability of the MJO,
89 building on the strengths, shortcomings and caveats discussed in the other sections.

90 **2 Data and methods**

91 **2.1 Model and experiment description**

92 The current work is based on the analysis of two historical simulations performed with IFS-NEMO at two different
93 horizontal resolutions. IFS-NEMO is a new generation fully coupled GCM specifically developed within the Destination



94 Earth initiative (Doblas-Reyes et al., 2026) and the European project EERIE for km-scale climate modeling. The model
95 combines version 4.0.7 of the ocean model NEMO (Gurvan et al., 2019) with an EERIE-revised build of cycle 48r1 of the
96 atmospheric model IFS (DE_CY48R1.0_EERIE_20240726). The sea-ice model SI3 (Vancoppenolle et al., 2023) is
97 integrated within NEMO and runs on the same ocean grid, ensuring consistent representation of ice–ocean thermodynamic
98 and dynamical interactions. We use an eddy-rich configuration (IFS-NEMO-ER) with an atmospheric resolution of ~ 9 km
99 (based on a Tco1279 Gaussian octahedral grid) and an ocean at $1/12^\circ$ resolution (based on an eORCA12 tripolar global
100 curvilinear grid), and a lower-resolution configuration (IFS-NEMO-HR) with a ~ 25 km atmosphere (Tco399) and a $1/4^\circ$
101 ocean (eORCA025). In both configurations, the atmosphere is discretized with 137 vertical levels, while the ocean uses 75
102 vertical levels. The three components are coupled through a single executable approach (Mogensen et al. 2012), allowing
103 them to run together using a common time step loop. This tightly integrated setup enables highly efficient, low-latency data
104 exchange, which is critical for high-resolution, fully coupled simulations. The coupling operates at a 1-hour frequency,
105 exchanging essential fields – such as sea surface temperature (SST), surface fluxes, ice cover, and ocean currents – between
106 IFS and NEMO to capture dynamic interactions among the atmosphere, ocean, and sea ice.
107 The simulations performed with IFS-NEMO-HR and IFS-NEMO-ER extend from 1950 to 2014, and correspond to hist-1950
108 experiments from the High Resolution Model Intercomparison Project (Haarsma et al., 2016). Both are initialized from
109 60-year long spin-up experiments with fixed 1950 forcing. For the sake of this analysis, and following common practice,
110 when it comes to MJO diagnostics both model and validation data have been previously regridded onto a common 2.5° by
111 2.5° horizontal grid.

112 2.2 Validation datasets

113 The reanalysis product ERA5 from ECMWF (Hersbach et al., 2020) was used as our primary reference to evaluate the model
114 performance. ERA5 provides observationally constrained, physically consistent meteorological fields and shares IFS as its
115 underlying atmospheric component with the two model versions of IFS-NEMO evaluated — albeit at a different version —
116 making it a particularly coherent benchmark for assessing the model performance. For outgoing longwave radiation (OLR),
117 however, we used a daily satellite-based product provided by NOAA (Liebmann and Smith, 1996), as OLR in ERA5 is
118 diagnosed by the model and not directly assimilated from observations. This product comes on a 2.5° by 2.5° horizontal
119 regular grid and is available continuously from 1979 to present. Our main validation is focused on 1979–2014, the
120 overlapping period between ERA5, the observations and the IFS-NEMO historical simulations. We hereinafter refer to the
121 validation dataset as ERA5-NOAA for the 1979–2014 period. The RMM index, a season-independent metric defined by
122 Wheeler and Hendon (2004) to track the activity of the MJO, was also used for validation and are provided by the Australian
123 Meteorological Bureau at <http://www.bom.gov.au/climate/mjo/graphics/rmm.74toRealtime.txt>. ERA5 has been used as
124 reference also for the validation of the long term variability analysis over the period 1950–2014.

125

126



127 2.3 MJO diagnostics

128 Focusing on different levels of diagnostics such as those introduced by (M. Wheeler and Kiladis 1999; M. C. Wheeler and
129 Hendon, 2004; Waliser, 2009) the main variables used for our analysis are the zonal wind speed at 850 hPa (ua850) and 200
130 hPa (ua200), outgoing longwave radiation at the top of the atmosphere (OLR), precipitation (pr), specific humidity (hus) and
131 sea surface temperature (SST).

132

133 2.3.1 EOF characterization

134 To monitor the MJO, this study leverages the methodology introduced by Wheeler and Hendon (2004), hereinafter WH04.
135 WH04 introduced a procedure that applies an empirical orthogonal function (EOF) analysis to a combined (multivariate)
136 dataset of tropically (15° S–15° N) averaged zonal wind speed at 850 hPa and 200 hPa (ua850, ua200), and outgoing
137 longwave radiation (OLR) fields. The first two principal components of the analysis are used as RMMs. Since it does not
138 require filtering, the WH04 approach is the most suitable for realtime applications (Gottschalck et al., 2010; Rashid et al.,
139 2011; Vitart, 2017). It is also predominantly used to investigate long-term MJO variability (Cui and Li, 2022; Dias et al.,
140 2025; H.-R. Kim et al., 2025). For this reason, we adopted the methodology of WH04, neglecting the ENSO-related
141 variability removal step, as described by Gottschalck et al. (2010).

142

143 For the main validation period the EOF analysis is performed with ERA5 wind fields and OLR from NOAA satellite dataset.
144 To assess the sensitivity of the MJO to the OLR source, we carried out an additional computation that uses both radiation and
145 wind fields from ERA5 (i.e., referred to hereinafter as ERA5). This ERA5-based computation was also applied to earlier
146 periods using sliding 35-year temporal windows with one-year increments until the beginning of the simulated period (i.e.
147 1950), which has allowed us to investigate the multi-decadal variability of the MJO amplitude and phase, similarly to the
148 analysis of Dias et al. (2025). We note that while Dias et al. (2025) state that the length of the window has no qualitative
149 impact on the MJO evolution over time, our longer 35-year window has been found to reduce uncertainty in the computed
150 EOFs, which are more consistent over time. The following different approaches have been considered in the computation of
151 the RMMs to investigate the long-term variability in the MJO:

- 152 • Computing the EOFs as in WH04 separately for each dataset (simulations and ERA5) and sliding window. The
153 main benefit of this method is that the real features of the intraseasonal variability contained in each multivariate
154 subset can be extracted, together with the corresponding variance associated with the first two eigenvectors.
155 However, the RMM-like indices obtained through this procedure cannot be compared across different windows and
156 datasets as the normalization happens independently and the principal components effectively differ, implying that
157 they do not represent the same modes over time.
- 158 • Projecting the simulated intraseasonal ua850, ua200 and OLR anomalies onto present-day (i.e. 1979-2014) EOFs
159 derived from ERA5-NOAA to evaluate how the models represent this fixed representation of the reanalysed MJO
160 over time. This approach yields two new time series that correspond to the RMMs defined by WH04. We



161 additionally “reconstruct” the simulated ua850, ua200 and OLR anomalies by projecting the RMMs thus derived for
162 each dataset onto the same set of EOFs. Such datasets contain the MJO variability as described by the present-day
163 observed EOF. The fraction of variance in the reconstructed dataset can be compared with the one retrieved by the
164 EOF analysis (sum of the first two eigenvalues). This methodology ensures that the long term analysis is consistent
165 for each dataset individually. However, the first two EOFs differ between ERA5 and IFS-NEMO.

166 • Finally, we performed a complementary analysis by reconstructing each multivariate dataset using the present-day
167 EOFs derived from that same dataset (i.e., ERA5-derived EOFs for the ERA5 data and IFS-NEMO-derived EOFs
168 for the IFS-NEMO data).

169 Finally, lag correlations between the first two principal components computed from the EOF analysis on each dataset
170 respectively are used to evaluate their mutual coupling and its influence on the dominant temporal scale of the MJO. Since
171 these components form a pair in quadrature with an approximate phase difference of 90° , the lag at which the maximum
172 correlation occurs provides an estimate of the periodicity of the MJO.

173

174 2.3.2 MJO propagation in space and time

175 For this diagnostic, we first applied a 30-80 day bandpass filter, following previous studies (Waliser, 2009; H.-R. Kim et al.,
176 2025). To investigate how MJO-driven OLR anomalies propagate in time and space, we then computed lag-longitude
177 diagrams showing the correlation of boreal winter (i.e., December to February or DJF) for OLR and ua850 with the
178 corresponding average in a reference region over the Indian Ocean (15° S- 10° N, 75° E- 100° E). While using averages over a
179 large box rather than a single point induces smaller correlation values, this box-average was found to be more suitable to
180 track the actual propagating signal. Additionally, we computed the propagation speed by identifying consecutive correlation
181 maxima at each longitudinal grid point, considering only correlations exceeding a significance threshold of 0.3, using a
182 similar approach to Kim et al. (2025). We then computed the propagation speed as the slope of a linear fit using a
183 least-square method. We observed that extracting the propagation speed with this procedure is sensitive to the arbitrary
184 choice of the significance correlation threshold. Different choices have been found to yield different propagation speeds and
185 could lead to different conclusions. We therefore include an uncertainty estimate obtained from bootstrapping 1000 times the
186 lag-lon pairs — the ones used for the linear fit — allowing for repetition. To improve comparison with reanalysis data, the
187 minimal common longitudinal interval across the three datasets with significant correlations was selected. The significance
188 of the correlation was computed using a Student’s t-test and correcting the number of degrees of freedom for autocorrelation
189 in the time series (Zwiers and Von Storch, 1995; Afyouni et al., 2019).

190 A complementary method to investigate the spatio-temporal aspects of MJO propagation is to compute composite maps of
191 MJO-relevant anomalies for each MJO phase. These phases are defined from the joint evolution of the two leading principal
192 components, whose normalized amplitudes span a two-dimensional phase space. The instantaneous MJO phase is
193 determined by the angle in this phase space, while its amplitude is given by the radial distance from the origin, thereby
194 defining the canonical eight-phase MJO life cycle. To evaluate the propagation of convective signals associated with the



195 MJO, we produced composite maps of precipitation and specific humidity subseasonally filtered anomalies for each phase
196 of the MJO (Wheeler and Hendon, 2004; Cao et al., 2025). The composites of the different phases were then built by
197 averaging all the active days (i.e. the amplitude $A = \sqrt{PC_1^2 + PC_2^2} > 1$) belonging to each respective phase. The composite
198 selection is sensitive to the methodology used to retrieve the RMMs. We computed the composites by deriving the RMMs
199 from projections of the multivariate anomalies onto either a fixed set of EOFs derived from ERA5–NOAA or EOFs
200 computed separately for each dataset (as described in Section 2.3.1). The statistical significance of the composites is
201 computed by selecting the 99 % level from a bootstrapped distribution of a randomly extracted subsample of all the available
202 days, with the same size of the one used for the composite and allowing for repetitions.

203

204 2.3.3 MJO spectral properties

205 The symmetric wavenumber-frequency power spectrum of OLR was computed, following the steps first introduced by M.
206 Wheeler and Kiladis (1999). The methodology involves filtering the spectra by removing a red-noise background obtained
207 for each dataset independently by smoothing the raw spectra an arbitrary amount of times both in the wavenumber and in the
208 frequency domain. Raw spectra are computed on consecutive 96-day segments that overlap for 60 days and averaged.
209 Finally, power is summed for all latitudes between 15° S and 15° N. The significant peaks are identified at a 95 % confidence
210 level of an F-distribution. The total number of degrees of freedom (dof), which can be derived by counting the number of
211 independent 96 over the entire period (1979–2014), is about 1600 ($35 \times 365 \times 12 / 96$). Considering that all segments are not
212 truly independent due to the 60-day overlap, a more conservative estimate yields approximately 1,000 dof. To quantify the
213 differences between IFS-NEMO and observations in terms of MJO spectral power, we computed the averaged ratio between
214 the simulated and the observed power spectra in the intervals from 1/30 to 1/80 days⁻¹ for frequency and from 1 to 4 for
215 wavenumbers (Chang et al., 2020).

216

217 2.3.4 Walker Circulation and Indo-Pacific Warm Pool

218 We characterised the mechanisms responsible for the long term evolution of the MJO activity by investigating the
219 multidecadal changes in the Walker Circulation (WC) and the Indo-Pacific Warm Pool (IPWP). We employed a WC index
220 based on the sea level pressure difference between an Eastern Box (5° S–5° N, 160°–80° W) and Western Box (5° S–5° N,
221 80°–160° E) of the Pacific ocean as defined by Kociuba and Power (2015). Additionally, the long term changes in the IPWP
222 have been evaluated in terms of both its total spatial extension and intensity. The IPWP area is defined as the tropical region
223 with sea surface temperatures above the 28 °C isotherm between the Indian Ocean and the Western Pacific, considered here
224 as the 25° S to 25° N and 40° E to 130° W box. The intensity is the area weighted average within this region (Weller et al.,
225 2016). All data used for this analysis have been previously interpolated to a 1° by 1° horizontal grid.

226

227



228 2.3.6 Weighted Permutation Entropy

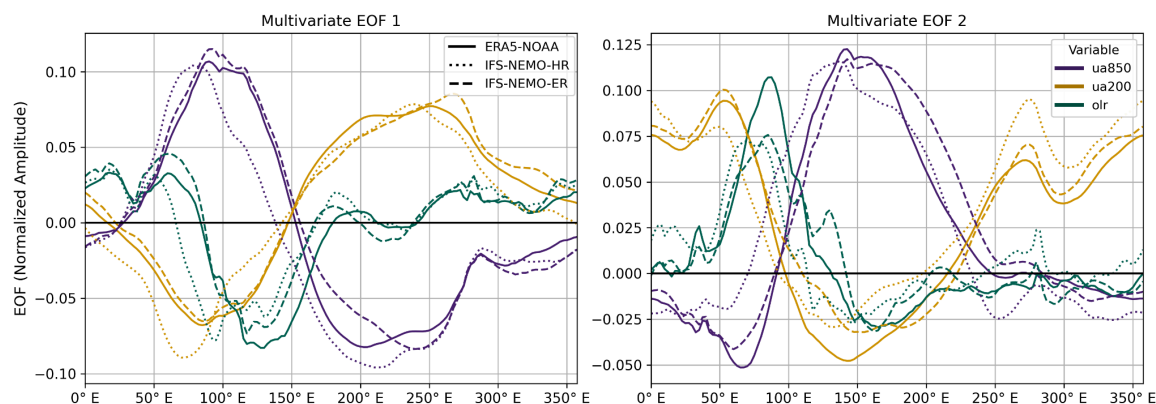
229 Weighted Permutation Entropy (WPE) is a measure that quantifies the complexity of a time series. Specifically, WPE
 230 leverages on the concept of entropy introduced by Shannon (1948) in the context of information theory. Bandt and Pompe
 231 (2002) extended the idea by defining permutation entropy as a tool to classify time series on the basis of the frequency with
 232 which certain patterns (ordinal patterns) recur throughout the timeseries (Leyva et al., 2022). WPE replaces the traditional
 233 permutation entropy definition by using occurrence frequencies that are weighted according to the variance of the selected
 234 ordinal patterns. A time series dominated by a small number of recurring ordinal patterns has low entropy and low
 235 complexity, meaning that its future evolution is more constrained and therefore more predictable; conversely, a high-entropy
 236 series is more random and less predictable. We therefore use WPE as a proxy for MJO predictability, with decreasing
 237 entropy over time indicating that the MJO is becoming a more regular and predictable mode of variability. For mathematical
 238 details, we refer to Du et al. (2024) who were the first ones to apply WPE to study the MJO predictability. We employ the
 239 same technique here to investigate the long term changes in the predictability of MJO associated with the RMMs amplitude.
 240

241 3. Results

242 3.1 MJO evaluation over the most recent period

243 This first part of the results section focuses on the 1979-2014 period, for which the direct OLR observations from NOAA are
 244 available and ERA5 assimilates higher quality and more widespread observations.

245 Figure 1 shows the first two combined EOFs for ERA5-NOAA, and the IFS-NEMO simulations for the 1979-2014 period.
 246 The first two principal components of ERA5-NOAA compare very well with the ones obtained in real-time by the Australian
 247 Bureau of Meteorology with a different set of observations for the 1979-2014 period, as supported by correlation of 0.93 and
 248 0.97, respectively. Similar levels of agreement have been reported in previous analyses between different observation-based
 249 datasets (Rashid et al., 2011).



250 **Figure 1: First two EOFs of the multivariate MJO dataset with ua850 (purple), ua200 (yellow) and OLR (green). Daily anomalies**
 251 **have been retrieved by removing the first three harmonics of the climatology and the previous 120 days mean. The continuous**



252 lines show the EOFs of the ERA5-NOAA while dashed and dotted lines refer to IFS-NEMO-ER and -HR respectively. The EOFs
 253 have been swapped and their sign changed accordingly to match the WH04 order and structure.

254

255 The EOFs of the model have been switched and flipped when required to match the ERA5-NOAA structure for comparison
 256 purposes. While IFS-NEMO underestimates the relative and total amount of variance captured by the first two EOFs at both
 257 resolutions with respect to ERA5-NOAA (Table 1), with HR giving slightly better results, both show good agreement in
 258 terms of spatial distribution, as supported by the correlations in Table 2. IFS-NEMO-ER shows systematically better
 259 correlation values than IFS-NEMO-HR, in particular for OLR, which again supports a more realistic representation of the
 260 MJO spatial structure .

261 However, the lower correlation values for IFS-NEMO-HR may simply be a mathematical artifact arising from the strong
 262 degeneracy of the first two EOFs in that simulation (i.e., their explained variance is very similar), rather than an indication of
 263 deficiencies in the physical characterisation of the MJO. Indeed, previous works have highlighted how the physical
 264 interpretation of EOFs should be done carefully as not all the variance related to the MJO is captured by the first two EOFs
 265 (Roundy, 2015). We also see in Table 2 also that the relative contribution of each variable to the variance explained by the
 266 first 2 PCs as described by Ventrice et al. (2013), is very similar between both IFS-NEMO versions and also with
 267 ERA5-NOAA, with the models slightly overestimating the variance explained by the wind, and underestimating the variance
 268 explained by the OLR.

Dataset	Explained Variance EOF1+2 (%)	X_{ua850} (%)	X_{ua200} (%)	X_{OLR} (%)
ERA5-NOAA	13.4+13.1	46.0	38.5	15.5
IFS-NEMO-HR	10.2+9.3	48.5	39.7	11.8
IFS-NEMO-ER	10.7 +10.0	49.5	38.1	12.4

269

270 **Table 1: (first column) variance explained by the first two EOFs in observations and IFS-NEMO. (columns 2-4) fractional**
 271 **contribution of each variable to the first two PCs with the methodology defined by Ventrice et al. (2013).**

272

Model EOF	ua850	ua200	OLR
IFS-NEMO-HR EOF 1	0.95	0.95	0.82
IFS-NEMO-ER EOF 1	0.99	0.99	0.96
IFS-NEMO-HR EOF 2	0.91	0.94	0.82
IFS-NEMO-ER EOF 2	0.97	0.98	0.94

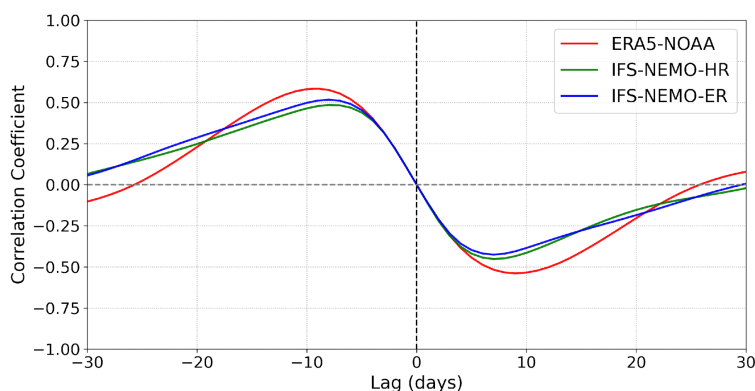
273

274 **Table 2: spatial pattern correlation values of the first two EOFs of ERA5-NOAA and the corresponding EOFs of IFS-NEMO,**
 275 **computed over the 1979-2014 period.**

276

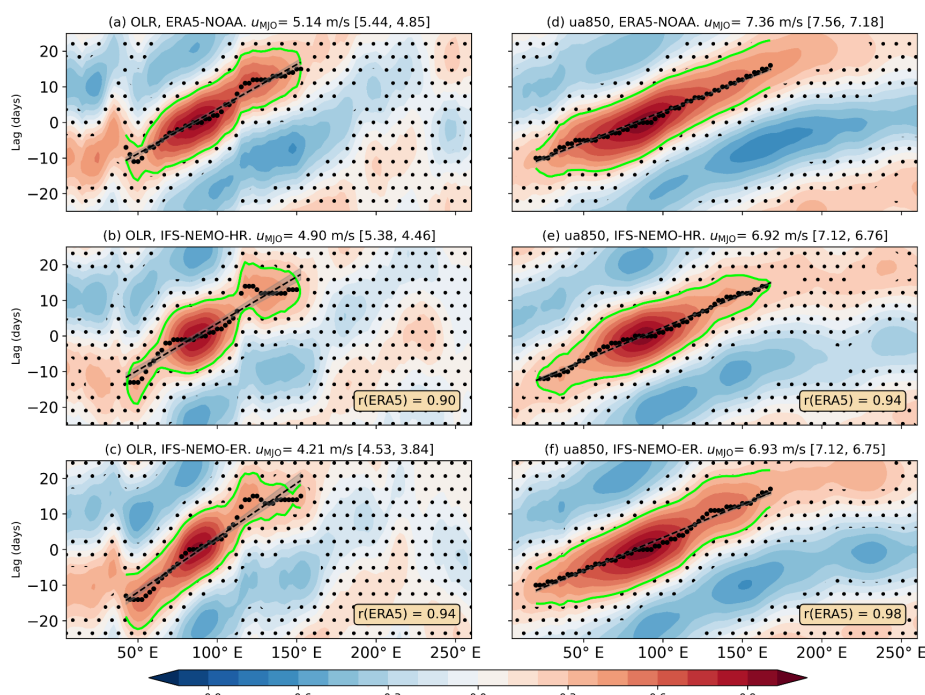


277 We have also inspected the lag-correlation between the first two PCs of each dataset, which informs about the MJO
278 propagation timescales as extracted by the EOF analysis. Figure 2 shows that the maximum correlation between the PCs
279 takes place around day 9-10 for ERA5-NOAA and 1 day earlier in IFS-NEMO, at both resolutions. This may suggest a
280 slightly faster phase progression in the model, which implies a faster eastward propagation, but the difference is small and
281 falls within the uncertainty of the EOF-based lag-correlation approach, which is sensitive to sampling variability and the
282 near-degeneracy of the leading MJO EOFs. The broader lag-correlation tail in IFS-NEMO may reflect weaker phase locking
283 between the leading MJO modes, resulting in a wider and less regular range of effective propagation times.



284 **Figure 2: Lead-lag correlation between the first 2 PCs associated with the two leading EOFs of each dataset (i.e. ERA5-NOAA,**
285 **IFS-NEMO-HR and ER). The sign and order of the PCs have been adjusted so that they are comparable across datasets.**
286

287 An alternative approach to study MJO propagation, applied here following the methodology used in Kim et al. (2025),
288 involves correlating meridionally averaged intraseasonal OLR and ua850 anomalies over a reference region over the Indian
289 Ocean (defined as 75° E–100° E, 15° S–10° N) with the respective meridionally averaged anomalies at different longitudes
290 and time lags, as illustrated in Fig. 3 for the 15° S–10° N band. This latitudinal range captures the core equatorial region
291 where the MJO is most active, ensuring the analysis focuses on the dominant convective signal associated with its
292 propagation.



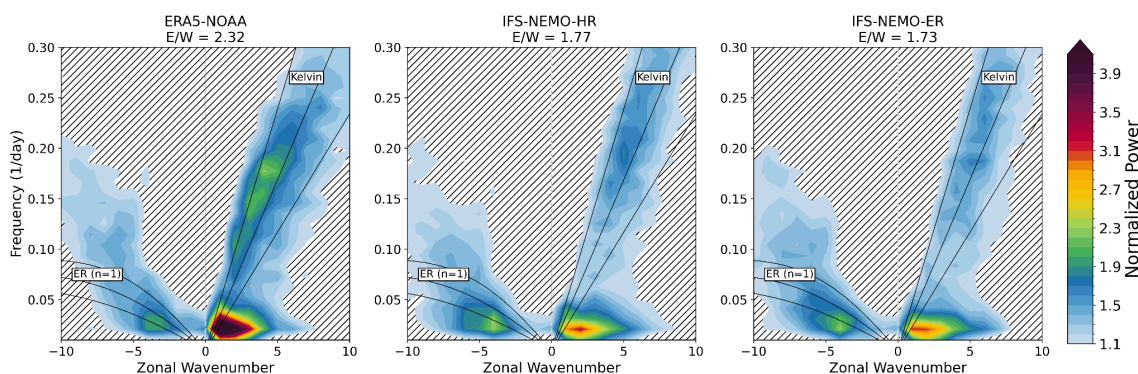
293 Figure 3: Lag - longitude maps of 15° S-10° N meridionally averaged OLR (a, b and c) and ua850 (d, e and f) anomalies
 294 correlation against the Indian Ocean region 75° E-100° E. The propagation speed has been computed following the approach of
 295 Kim et al. (2025). To ensure comparison between datasets the minimal common longitudinal range with significant correlation has
 296 been taken into account ([142.5° E-152° E] for OLR and [20° E-168° E] for ua850). The dashed line shows the linear fit, which has
 297 been computed only on 95% significance peaks. Significance has been adjusted accounting for autocorrelation with corrections
 298 following Zwiers and Von Storch (1995). The shaded grey band indicates the 95 % confidence level obtained from bootstrapping.
 299 Pattern correlations over the entire domain (5–260° E) between IFS-NEMO and ERA5 are shown in the yellow box.

300

301 Such correlation maps are computed for the 1979-2014 period for ERA5-NOAA for the boreal winter season (DJF). The
 302 propagation speed is obtained from the slope of a least-square linear regression and converted to m/s (see Data and methods).
 303 The best estimate of the propagation speed in the observational reference is 5.14 m s⁻¹, for IFS-NEMO-HR is 4.90 m s⁻¹, and
 304 for IFS-NEMO-ER is 4.21 m s⁻¹. Interestingly, the speed in IFS-NEMO-HR is consistent with ERA5 when considering the
 305 uncertainty described by the 95 % percentile range of a bootstrap, and also consistent with the speed in IFS-NEMO-ER. This
 306 analysis underscores the large uncertainties associated with estimating and comparing MJO propagation speeds. The pattern
 307 correlation score indicates that IFS-NEMO-ER better reproduces the correct signal propagation features. Both model
 308 versions struggle to reproduce the right eastward limit of the propagation and its extension beyond the Maritime Continent
 309 (i.e. beyond 150-160° E). This feature is commonly found in models when evaluating the eastward propagation of fields such
 310 as OLR. By contrast, this reduced eastward propagation is not present in the correlation map of ua850, especially for



311 IFS-NEMO-ER, which indicates that the underlying issue might be related to the timing of convection and not necessarily to
 312 the circulation dynamics. In fact, after deep convection is suppressed over the Western Pacific, the convective dynamics tend
 313 to decouple from the horizontal circulation and the propagation continues with a speed similar to that of Kelvin waves
 314 (Zhang, 2005). We finally note that the slope of the linear regression is sensitive to the choice of the correlation contour and
 315 the longitude range over which the regression is computed. However, this does not qualitatively affect the results.
 316 Power spectra of the OLR anomalies have been also calculated to extract the variance of the simulated MJO from its
 317 temporal properties. Only the symmetric spectra is used in this analysis as it has been shown that the antisymmetric
 318 component does not retain significant power associated with the MJO (Wheeler and Kiladis, 1999; Dias et al., 2025). Figure
 319 4 shows the significant power spectra and includes the well-known theoretical dispersion curves (in black) associated with
 320 equatorial Kelvin waves and Rossby waves (Ghil and Childress, 1987). For positive (negative) wavenumbers, significant
 321 peaks are associated with eastward (westward) propagating signals. The dashed lines between $1/30 \text{ days}^{-1}$ and $1/80 \text{ days}^{-1}$
 322 for frequency and between 1 and 4 for wavenumber define the region in the wavenumber-frequency domain commonly
 323 linked to the MJO. Areas with significant peaks in both versions of IFS-NEMO generally coincide with the areas with
 324 significant peaks in observations. However, both model versions underestimate the spectral power of tropical waves and the
 325 MJO. Specifically, within the MJO domain (dashed box) the average power in IFS-NEMO is about 80 % of the observed one
 326 in both resolutions.



327 **Figure 4: Wavenumber-frequency power spectrum of OLR as defined by Wheeler and Kiladis (1999). Significant power in the**
 328 **positive (negative) wavenumber domain refers to eastward (westward) propagating signals. Continuous black lines indicate**
 329 **theoretical dispersion curves for equatorial Rossby (negative wave numbers) and Kelvin (positive wave number) waves. The part**
 330 **of the domain associated with the MJO spans frequencies between $1/80$ and $1/30 \text{ days}^{-1}$ and wavenumbers between 1 and 4. The**
 331 **spectra have been normalised dividing by a red noise background spectrum. Hatched areas indicate regions with significance**
 332 **lower than 95 %.**

333

334 This result is consistent with previous work by Chang et al. (2020) that did not detect any impact of horizontal resolution on
 335 this diagnostic, observing similar MJO power underestimation for two versions of CESM1.3 with nominal resolutions of
 336 0.1° in the ocean (with 0.25° atmospheric resolution) and 1° in the ocean (with 1° atmospheric resolution). We note that both



337 IFS-NEMO versions overestimate the power of equatorial Rossby waves, and underestimate the power of Kelvin waves in
338 the selected region. Figure 4 also shows the Eastward/Westward (E/W) ratios of power-weighted frequency between
339 wavenumbers 1-4 and frequencies from 1/80 to 1/30 days⁻¹. The comparison of the E/W ratios indicates that IFS-NEMO
340 underestimates the eastward propagation of organised convection.

341 We evaluate additional spatial aspects of the MJO looking at the composites of precipitation anomalies (Fig. 5) for each
342 phase of the MJO. We first project the multivariate anomalies of each dataset onto the EOFs of ERA5-NOAA to ensure that
343 phases are consistent for the three datasets. Latitudinally weighted pattern correlation has been computed to compare the
344 composites in IFS-NEMO-HR and -ER with the observation-based dataset over the combined significant areas. Overall,
345 IFS-NEMO-ER better captures the different patterns of ERA5, in particular for phases 4 and 5, while IFS-NEMO-HR only
346 shows a higher correlation in phase 2. The model shows a more limited eastward propagation during the late phases, with
347 much lower and locally confined positive anomalies in phases 7 and 8. This is the phase when the convective cluster has
348 passed the Maritime Continent and is thus more exposed to the influence of sea surface temperatures over the equatorial
349 Pacific. The deficient eastward propagation in later phases is therefore likely due to a combination of the Maritime Continent
350 barrier known issue and a premature suppression of convection by the SST-convection feedback over the equatorial Pacific.
351 Convection is sustained and driven eastward by warm SSTs developing ahead (east) of the MJO active center. The model's
352 SST-convection feedback suppresses convection prematurely over the central/eastern Pacific, most likely due to the cold bias
353 (see Section 3.2) in the Tropical Pacific Ocean, and prevents the correct eastward propagation of the MJO (H.-M. Kim et al.,
354 2016).

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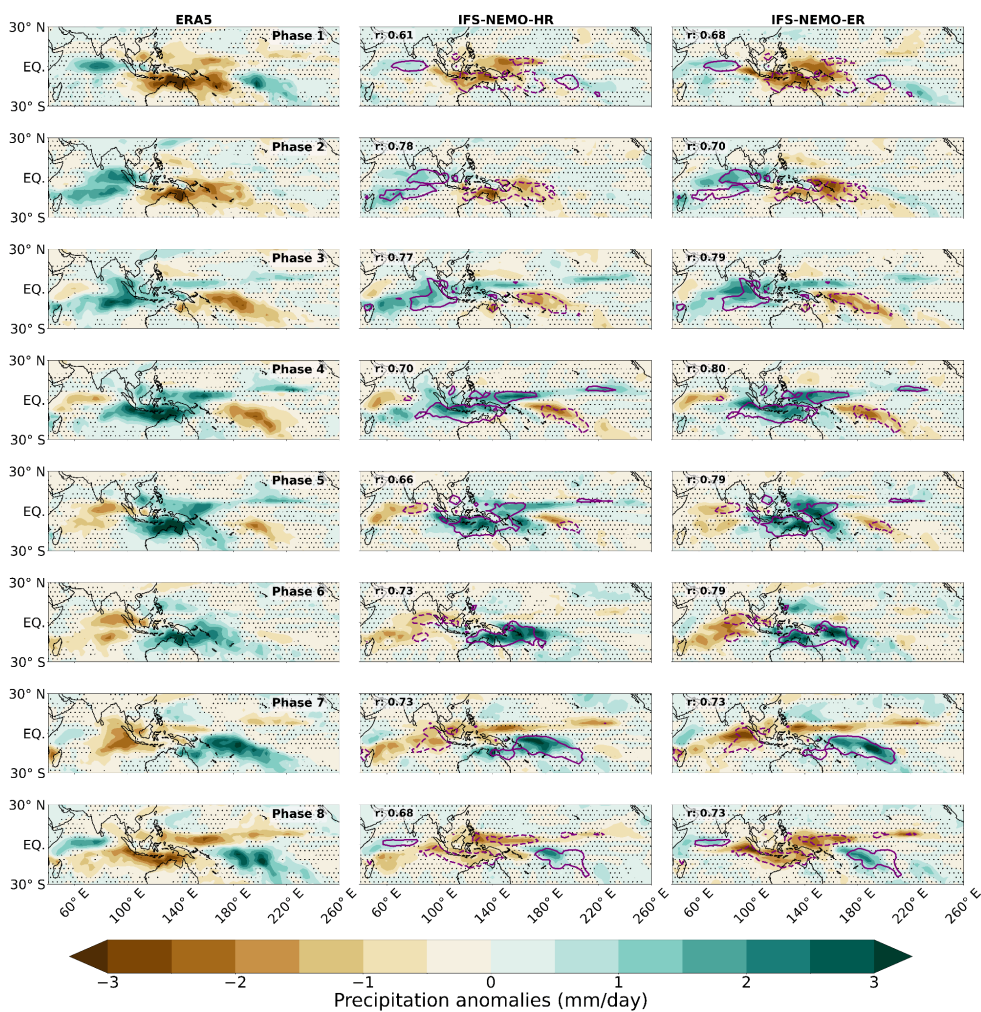
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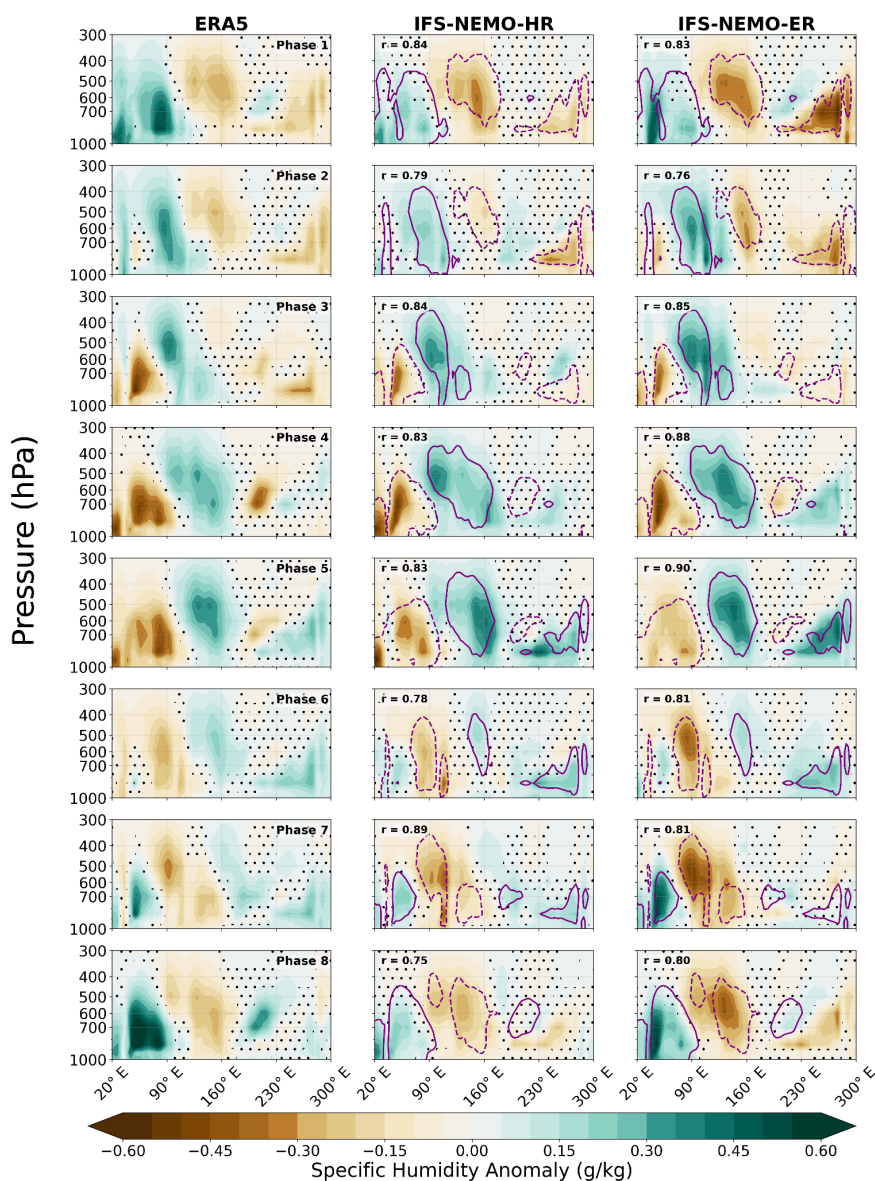
364 **Figure 5: Anomaly composites of intraseasonal precipitation for (a) ERA5, (b) IFS-NEMO-HR and (c) IFS-NEMO-ER. The MJO**
 365 **phases are defined by the RMMs obtained projecting the multivariate anomalies of each dataset onto the EOFs of ERA5-OLR.**
 366 **Dotted areas mark statistically non-significant regions. Significance levels correspond to the 95 % confidence level from a**
 367 **bootstrapping distribution of $n=1000$ samples using all available DJF days. Weighted pattern correlation values shown in the**
 368 **top-left corner of each panel have been computed for the over the union of the significance masks between the two IFS-NEMO**
 369 **versions and ERA5. Purple contours are the reference $\pm 2 \text{ mm day}^{-1}$ contours from ERA5.**

370

371 In order to explain the previous result, we additionally analysed composites of intraseasonal tropical specific humidity
 372 anomalies. The MJO can be framed within the moisture mode theory framework (Chang, 2020). In such theory the vertical
 373 and horizontal moisture gradients and advection drive the development of deep convection as well as the horizontal eastward
 374 propagation. Therefore, it is crucial for the model to correctly reproduce the humidity spatial distribution. The model
 375 correctly represents the main features seen in ERA5, with relatively high pattern correlation during all phases (Figure 6).



376



377 Figure 6: Anomalies composites of intraseasonal tropical (5° S- 5° N) specific humidity vertical cross section for (a) ERA5, (b)
 378 IFS-NEMO-HR and (c) IFS-NEMO-ER. The MJO phases are defined by the RMMs obtained projecting the multivariate
 379 anomalies of each dataset onto the EOFs of the OBS. Dotted areas mark statistically non-significant regions. Significance levels
 380 have been computed at the 95 % level from a bootstrapping distribution of $n=1000$ samples from all available DJF days. Weighted
 381 pattern correlation values have been computed over the union of the significance masks between IFS-NEMO and ERA5. Purple
 382 contours are the reference $\pm 0.15 \text{ g kg}^{-1}$ contours from ERA5.
 383



384 Increasing horizontal resolution in IFS-NEMO does not seem to improve the comparison with ERA5. Low-level moistening
385 over the Indian Ocean warm pool is known to precede deep convection in the atmosphere at the beginning of an MJO cycle
386 (D. Kim et al., 2009; Zhao et al., 2015). While such preconditioning is correctly located in both IFS-NEMO versions, its
387 magnitude is underestimated (especially in phases 1 and 2) with a stronger dry bias in IFS-NEMO-HR. An early wet bias is
388 found in proximity to the Maritime Continent in IFS-NEMO (phase 4). This condition does not favour the propagation of the
389 MJO, as it could lead to anomalous descending atmospheric motion, preventing deep convection from happening (H.-R. Kim
390 et al., 2016). Early strong positive anomalies are also found in IFS-NEMO over the Eastern-Pacific during phase 5. This
391 indicates that moisture is not transported vertically efficiently enough in the model, and it is, on the other hand, propagated
392 eastward relatively quickly, which explains the difficulties in sustaining convection past the Maritime Continent in
393 IFS-NEMO. At the same time IFS-NEMO-ER tends to display drier conditions over the last phases of the MJO life cycle.
394 The low level dry bias in both IFS-NEMO versions during the final phases of the MJO life cycle could be linked to the
395 suppression of precipitation in the same phases over the Central Pacific (Fig. 5). Studies have suggested that increasing
396 vertical resolution could actually improve the mid-troposphere clouds moistening and the vertical transport of water vapor
397 and thus generate a more realistic deep convection generation (Zhang, 2005; Jiang et al., 2020). However, both IFS-NEMO
398 versions use 137 levels in the vertical, which is considerably higher than the models surveyed in those studies, suggesting
399 that vertical resolution alone is not the limiting factor and that the persistent deficiencies in deep convection generation are
400 more likely rooted in the convective parameterization scheme itself.

401

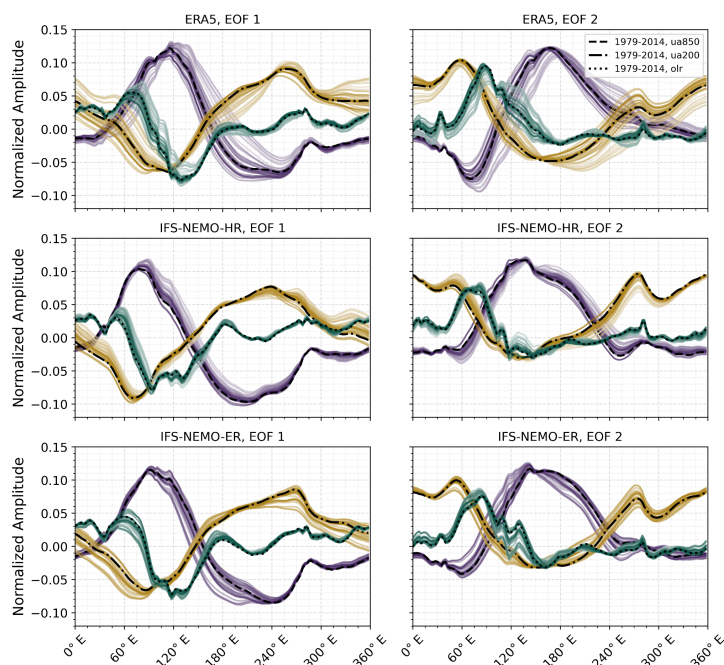
402 3.2 Long term variability of the MJO

403 Understanding the multidecadal variability of the MJO is crucial for better anticipating its future changes. Several works
404 have studied this long-term variability with reanalysis datasets to extend the analyses beyond the satellite era, combining
405 different datasets (Oliver and Thompson, 2011; Cui and Li, 2022; Du et al., 2024; Dias et al., 2025; H.-R. Kim et al., 2025)
406 and techniques (Dasgupta et al., 2020) to address both the MJO changes in activity and predictability. Although uncertainties
407 remain, most of these studies have shown an increase of activity of the MJO over the historical period and have also
408 investigated how the MJO is shaped by climate change and the physical mechanisms behind its response (Bui and Maloney,
409 2018, 2019; Lyu et al., 2019; Maloney et al., 2019; Bui et al., 2023). Understanding and evaluating the behaviour of the MJO
410 over the past warming period is thus crucial to build trust on future projections of MJO activity.

411 This section focuses on the long term changes of MJO activity over the period 1950-2014 in ERA5 and the IFS-NEMO
412 simulations. We first study how the MJO structure evolves along the study period by computing the MJO EOFs in 35 year
413 rolling windows, replicating the methodology of Dias et al. (2025) but with longer time windows. We choose the 35-year
414 window to match the same length covered by OLR satellite observations and because this comparatively longer window
415 ensures smoother transitions when tracking the long-term variations in MJO activity, the frequency of the events and their
416 spatial structure, by reducing the noise associated with other tropical waves and storms.



417 Figure 7 shows the two leading EOFs for ERA5, IFS-NEMO-HR and IFS-NEMO-ER for all the 35-year windows, allowing
 418 temporal overlap with a sliding step of one year. By looking at the spread of the EOFs we conclude that ERA5 has higher
 419 year to year variability in terms of MJO structure than both IFS-NEMO simulations. These year-to-year differences might be
 420 partly due to the sensitivity of the EOF results to the noise induced by Rossby and Equatorial Kelvin waves (Roundy et al.
 421 2009).



422 **Figure 7: First two EOFs of the multivariate MJO dataset with ua850 (red), ua200 (green) and OLR (blue).** for ERA5 and the
 423 **IFS-NEMO simulations in each different 35 year rolling window. For each window, daily anomalies have been retrieved by**
 424 **removing the corresponding 35-year climatology and the previous 120 days mean. The EOFs have been swapped and their sign**
 425 **changed whenever needed to match WH04 order. Lighter shades correspond to earlier windows, while darker shades indicate later**
 426 **ones. The black line for each variable refers to the last 35 years.**

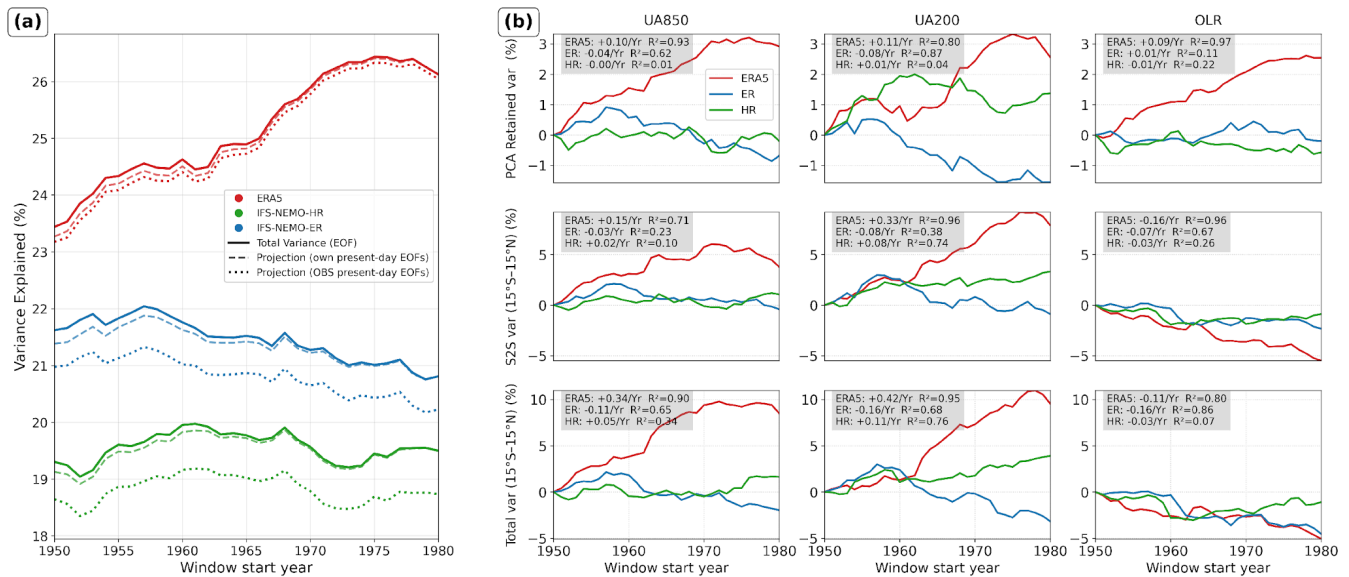
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428 Since the variability associated with the MJO is captured by the combination of two EOFs (Roundy, 2015), and given that
 429 their similar levels of explained variance make them prone to degeneracy (North et al., 1982), we use the total explained
 430 variance as a measure of the long term variability in MJO activity. The continuous lines in Figure 8a represent the variance
 431 as the sum of the eigenvalues associated with the first two modes of the EOF analysis per each window. The dashed lines
 432 represent the variance in the datasets reconstructed with the respective present-day EOFs. The dotted lines represent the
 433 variance in the dataset reconstructed by projecting onto the present-day ERA5-NOAA EOFs. As expected, the dashed lines
 434 converge towards the solid lines as for the last window the two methodologies are mathematically identical. Two
 435 shortcomings are exhibited by IFS-NEMO at both resolutions, which are evident for all the three different ways to project
 436 the variance explained backwards in time: the model underestimates the combined variance associated with the MJO and



437 fails to capture the long term upward trend found in ERA5. Such an increasing trend in MJO activity with rising ocean
 438 temperatures is consistent also with previous works based on both reanalysis datasets and simulations (Pohl and Matthews,
 439 2007; Arnold et al., 2015; Dias et al., 2025). Indeed, regional SSTs are crucial to generate and sustain an active phase of the
 440 MJO (Jones and Carvalho, 2011; DeMott et al., 2014; H.-M. Kim et al., 2016).

441



442 **Figure 8: (a) MJO-related variance in each 35 year moving window as accounted for by the combined variance of the first two**
 443 **EOFs computed directly for each window (solid lines), reconstructed with the first two EOFs of the last window of the respective**
 444 **dataset (dashed lines) or reconstructed with the first two EOFs of the last window in ERA5-OLR (dotted lines). (b) Long-term**
 445 **changes in the variance of the three variables used in the multivariate EOF analysis of the MJO (i.e. UA850, UA200, OLR),**
 446 **computed in successive 35-year windows. Each row shows a different metric: (top) variance retained for each variable with the**
 447 **first two EOFs, (middle) variance of the intraseasonal tropical anomalies (15° S-15° N) used as input to the EOF analysis (filtered**
 448 **by removing the mean of the previous 120 days), and (bottom) total variance in the tropics. Red, green, and blue lines correspond**
 449 **to ERA5, IFS-NEMO-HR, and IFS-NEMO-ER, respectively. Linear trends and their R² values are indicated in the legend boxes.**

450

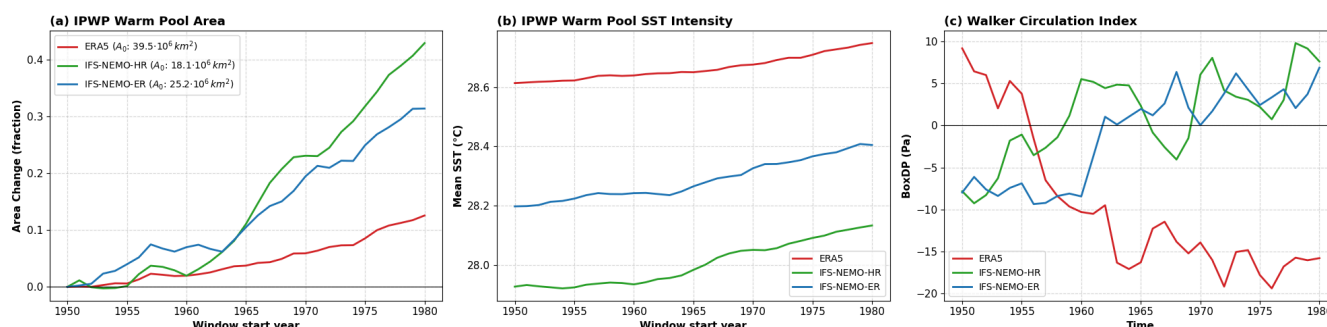
451 To assess if the increase in MJO variance over the second half of the 20th century in reanalyses could be partly driven by the
 452 concomitant warming and expansion of the Indo-Pacific warm pool (IPWP) and the steady increase in atmospheric moisture
 453 with global warming, the MJO variance is compared to the long-term changes in IPWP. If the models underestimate SST
 454 trends in that region, or if the mean SST bias does not translate SST anomalies into enhanced deep convection efficiently
 455 enough, the MJO would not strengthen as observed. Also if the model convection scheme is not sensitive enough to column
 456 moisture, the simulations would fail to translate the moistening trend into stronger MJO variance. However, by inspecting
 457 the long term changes of the IPWP (Fig. 9a-b), we found a higher increase in total area in IFS-NEMO than in ERA5 while
 458 the changes in intensity are comparable. This indicates that the model IPWP temperatures correctly respond to the external



459 forcing and cannot therefore explain the misrepresentation of the evolution of the MJO variance. On the other hand, the
 460 reduced extent of the IPWP area compared to observations (an expression of a cold bias), shown in Fig. S3, could explain
 461 why the MJO variance is systematically underestimated in the model.

462 To further investigate why IFS-NEMO fails to simulate the increase in MJO activity over time, Fig. 8b assesses the
 463 long-term evolution of variance in each of the three variables entering the multivariate EOF analysis (i.e. UA850, UA200,
 464 and OLR) across successive 35-year windows according to three different levels of aggregation: the variance retained by the
 465 two leading EOFs, the variance of the intraseasonal anomalies directly used for the EOF analysis and the total variance of
 466 each variable in the Tropics (15° S-15° N).

467



468 **Figure 9: Time series of: 35-year averages of Indo-Pacific Warm Pool extension anomaly with respect to the period 1950-1984 (a)**
 469 **and intensity (b). The IPWP area is defined as the region where the climatological sea surface temperatures exceed the 28 °C**
 470 **threshold. The intensity anomaly is computed for each window as the area-weighted average over the warm pool region of ERA5.**
 471 **Time series of the WC strength (c) averaged over 35-year windows for ERA5, IFS-NEMO-HR and IFS-NEMO-ER. The recent**
 472 **observed strengthening of the WC is not visible because of the length of the smoothing window.**

473

474 The most remarkable feature in ERA5 is a strong increasing trend in the variance of the low and high troposphere zonal
 475 winds, already reported in Maloney et al. (2019), which is consistent for all temporal aggregations. By contrast, IFS-NEMO
 476 simulations show near-zero or slightly negative trends for all variables and metrics. Interestingly for OLR, while ERA5
 477 shows a robust decrease in its total and intraseasonal variance, also exhibited by the models, its MJO-related variance
 478 substantially increases over time, with the models showing a largely stable evolution. The decrease in total and intraseasonal
 479 OLR variance alongside the increase in MJO-related OLR variance in ERA5 suggests that the MJO is becoming an
 480 increasingly efficient organizer of tropical convection over time, concentrating a growing fraction of convective activity into
 481 coherent intraseasonal events; the failure of the models to reproduce this shift, despite capturing the overall decrease in OLR
 482 variance, points to a specific deficiency in the representation of MJO convective organization rather than in the simulation of
 483 the background convective environment. We highlight that, as indicated by the results of Table 1, the horizontal atmospheric
 484 circulation plays a major role in characterising the EOFs as defined by WH04, with OLR only contributing around 15 % in
 485 observations and less than 12 % in IFS-NEMO, a proportion that stays constant throughout the full period (not shown here).

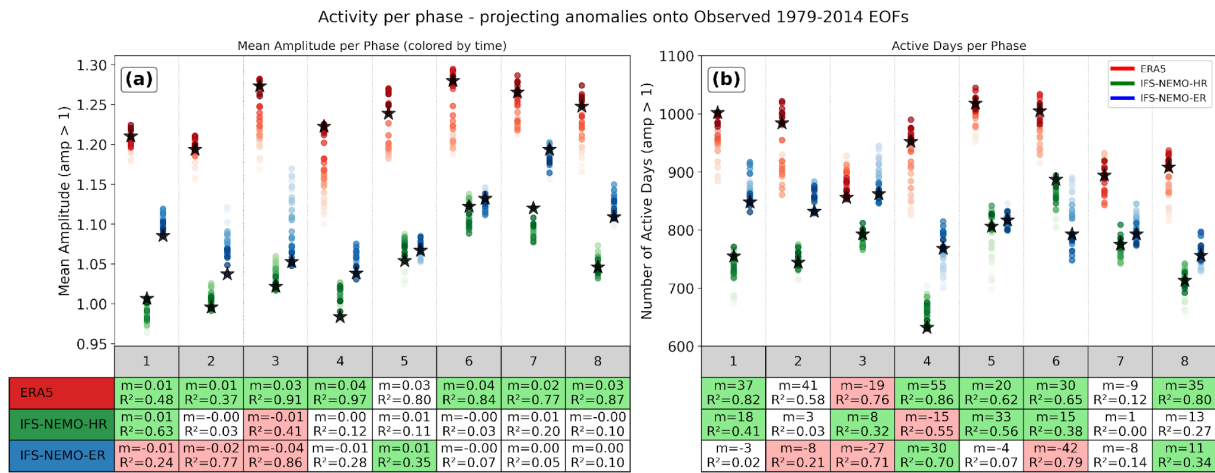


486 Figure 8b suggests that the long term changes in the background atmospheric circulation are misrepresented in IFS-NEMO.
487 Specifically, the MJO is directly intertwined with the WC as the main center of convective dynamics of the MJO moves
488 across the Maritime Continent and develops right to the west of the upward branch of the Walker cell (Chen and Wang,
489 2018). Previous works have studied the impact of the WC strength on the MJO propagation speed (Suematsu and Miura,
490 2022) and have highlighted the impacts of WC bias on the correct evolution of the MJO (H.-M. Kim et al., 2016, Suematsu
491 et al., 2022).

492 We compared the time series of the WC intensity over time between ERA5 and IFS-NEMO (Fig. 9c). We found that ERA5
493 reproduces the well known weakening of the WC observed over the second half of the 20th Century. The recent observed
494 strengthening of WC intensity (Power et al., 2021) appears as merely a slow-down of the weakening trend in the plot for
495 ERA5, since the positive trend is smoothed out by the 35-year running mean. On the other hand, IFS-NEMO shows quite the
496 opposite trends and with weaker amplitude. We note that there is no consensus on whether the recent changes in the WC are
497 due to internal tropical decadal variability or the result of human-induced external forcing (Chung et al., 2019; Power et al.,
498 2021). By inspecting all possible 35-year long windows in IFS-NEMO (following the methods of Kociuba and Power, 2015)
499 we did not detect any significant trend (in either direction), indicating that the model memory is much shorter with respect to
500 ERA5, which prevents it from developing the right kind of internal variability either.

501 These WC shortcomings in IFS-NEMO-HR and IFS-NEMO-ER explain why the models fail to capture the long term trend
502 of the variance retained for each variable and for the total variance associated with the MJO. Specifically, an increase in the
503 WC strength manifests as a positive easterly anomaly over the Maritime Continent, where the ascending branch of the WC is
504 located. This would result in dry air advection into the western Pacific (H.-M. Kim et al., 2016), hindering the correct
505 development of the MJO.

506 We also investigated the changes in activity observed for each of the eight different MJO phases, as the long term response to
507 the global warming forcing does not take place homogeneously over the entire tropical basin explored during a full MJO
508 cycle. Figure 10 shows the number of active days per phase and the mean MJO amplitude during those days when the MJO
509 is computed by projecting the anomalies of each 35-year window onto ERA5-NOAA present-day EOFs.



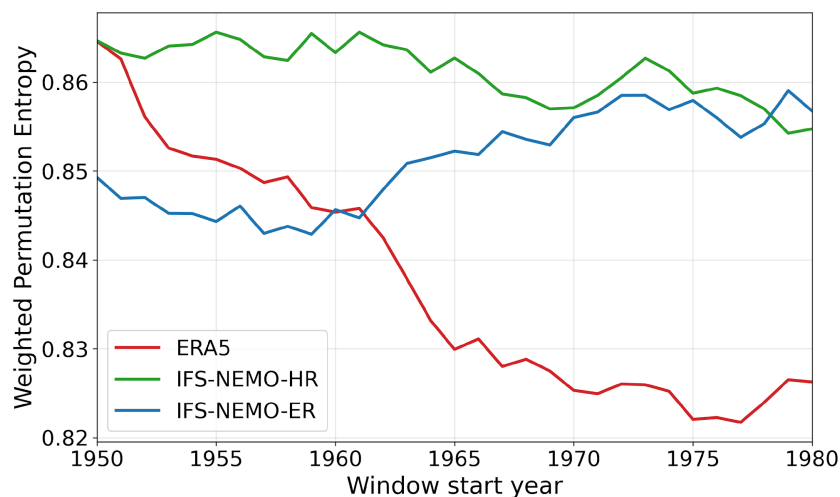
510 **Figure: 10: Evolution of the mean amplitude (left) and number of active days (right) per MJO phase in ERA5 and the IFS-NEMO**
 511 **simulations for each 35-year year window (going from light to darker shades as time progresses). Only the active days for each**
 512 **phase are considered. In all datasets, the phases have been defined projecting the multivariate anomalies on the EOFs for the last**
 513 **35-year window of ERA5. Black stars mark the value for the last 35-year window. The table shows the slope per decade of the**
 514 **trend of the MJO mean amplitude and number of active days, together with the R² value of the linear fit. In the table, green (red)**
 515 **cells indicate a significantly positive (negative) trend in the respective metric, while non-significant trends are not highlighted.**
 516

517 In ERA5 all phases display an increase in the mean amplitude, with strongest changes found over phases 4 to 6, which
 518 correspond to the passing of the main convective center of the MJO over the regions of the IPWP (Yoo et al., 2011). A
 519 significant but weaker increase is also found in phases 7 and 8, with less clear trends for the first two phases.

520 None of the IFS-NEMO simulations consistently captures the observed increase in MJO amplitude in most phases. We also
 521 note that both model versions, and especially IFS-NEMO-HR, systematically underestimate the activity of the MJO when
 522 phases are defined using the present-day ERA5-OLR EOFs; however, this is likely an artifact of the projection, as activity
 523 becomes comparable for all phases between ERA5 and IFS-NEMO when each dataset is projected onto its own present-day
 524 EOFs (Fig. S4). This suggests that the MJO, on average, is as active in IFS-NEMO as it is in ERA5, but with a spatially and
 525 temporally different structure. In terms of active days per phase, ERA5 shows an increase over time for all phases but the
 526 third one, which shows a clear decrease. This suggests that the MJO is spending more time in all basins except on the
 527 western side of the Maritime Continent, possibly reflecting a change in propagation characteristics through all regions. None
 528 of the simulations reproduce these phase-dependent changes in activity.

529 The previous results highlight a different modulation by global warming of the MJO and its spatiotemporal characteristics in
 530 ERA5 and both IFS-NEMO configurations. Such a discrepancy is relevant due to its implications for MJO predictability.

531 Figure 11 shows the changes in weighted permutation entropy for the RMM amplitude, as defined in Du et al. (2024).



532 **Figure 11: Time series of the WPE for the MJO amplitude over 35-year moving windows computed following the methodology**
533 **described by Du et al. (2024) with the embedding parameter $m=5$ and the time delay $\tau=3$. Similar results can be obtained using**
534 **different parameters, which do not affect the conclusions. The WPE can be interpreted as a measure of the predictability of the**
535 **time series, where a negative (positive) trend indicates an increase (decrease) in predictability.**

536

537 For clarity and in the light of the results of Fig. 7b, we show the changes in WPE only for the case that RMMs are computed
538 by projecting the multivariate anomalies of each dataset onto the respective present-day EOFs. The weakening trend in WPE
539 for ERA5, indicative of an increase in predictability, is consistent with the results of Du et al. (2024), with the difference that
540 interannual variability is smoothed out in our analysis because of the larger window length. Interestingly, the trend of WPE
541 in both IFS-NEMO runs does not follow the expected behaviour and remains roughly flat, which suggests that the model is
542 unable to represent — and leverage — the externally forced predictive component of the MJO.

543

544 **4. Conclusions and final remarks**

545 This study evaluates the MJO representation and long-term variability in two historical HighResMIP simulations with
546 IFS-NEMO, a coupled atmosphere-ocean GCM. One of the simulations was run at standard ocean resolution (HR, ~25 km)
547 and another with an eddy-resolving ocean (ER, ~9 km), with atmospheres that match the ocean resolution in both
548 configurations. The eddy-resolving version has the potential of improving the representation of the MJO by better resolving
549 the ocean-atmospheric coupling as well as the Maritime Continent topography. The evaluation reveals a nuanced picture of
550 the impact of the resolution: the ER configuration brings some improvements in the representation of the fundamental
551 spatio-temporal characteristics of the present-day MJO, which are very well captured by IFS-NEMO-HR and
552 IFS-NEMO-ER. Specifically, increasing the model's horizontal resolution improves the spatial structure of the two leading
553 EOFs of the multivariate intraseasonal anomalies dataset, as well as the EOFs variance explained suggesting the overall MJO
554 activity is better constrained at higher resolution. Furthermore, IFS-NEMO-ER correctly reproduces the spatial features of



555 the leading EOFs, with higher OLR pattern correlations than IFS-NEMO-HR, suggesting improved coupling between deep
556 convection and horizontal circulation.

557 However, both versions show lower explained variance than the observed MJO, which is also reflected in an underestimation
558 of the wavenumber–frequency spectral peaks associated with the MJO. The horizontal resolution does not consistently
559 improve the signal propagation of the MJO-related intraseasonal ua850 and OLR anomalies either. Indeed, the propagation
560 speed is better in IFS-NEMO-HR than IFS-NEMO-ER when compared to observations or ERA5. However, IFS-NEMO-ER
561 extends the eastward reach of the MJO’s zonal wind signal compared to IFS-NEMO-HR, with the ua850 correlation map
562 showing a more realistic propagation further into the western Pacific, although similar improvements are not seen for
563 convective fields such as OLR or precipitation. Furthermore, IFS-NEMO does not correctly propagate the convective signal
564 across the Maritime Continent at both resolutions, pointing to deficiencies that are not limited by grid spacing alone. In fact,
565 if we interpret it as a moisture mode, the MJO depends on a strong low-level humidity gradient to sustain and propagate its
566 convective envelope eastward. The dry bias present in IFS-NEMO during phase 1, when the main convective centre is
567 located over the Indian Ocean, weakens this gradient in the Indo-Pacific region, reducing the moisture advection that would
568 otherwise support propagation into and beyond the Maritime Continent. An excessive moisture injection in IFS-NEMO takes
569 place during phases 3, 4 and 5. Such a late moisture accumulation results in a stronger positive anomaly over the Eastern
570 Pacific rather than in the observed deep convection and cloud formation areas, which further suppresses the signal in later
571 phases. Importantly, this bias is not alleviated by increasing horizontal resolution, and vertical resolution is unlikely to be the
572 limiting factor either, as both IFS-NEMO configurations already use 137 levels, considerably more than models in which
573 vertical resolution has been identified as a constraint. The evidence therefore points to the convective parameterization
574 scheme itself as the primary source of this persistent bias.

575 Beyond present-day biases, the failure to reproduce the long-term increase in MJO activity raises more fundamental concerns
576 for climate projections and initialized predictions. Neither IFS-NEMO configuration reproduces the observed positive trend
577 in MJO-related variance seen in ERA5, a key limitation likely linked to a misrepresentation of the atmospheric circulation
578 response to the external forcing. ERA5 captures the well-known weakening of the Walker Circulation over the second half of
579 the 20th century, as well as its more recent strengthening, both of which are closely tied to the modulation of MJO activity
580 through changes in the background tropical circulation. IFS-NEMO, by contrast, exhibits the opposite Walker Circulation
581 trend with much weaker amplitude, and no significant trend is detected across any of the 35-year windows explored,
582 suggesting that the model’s memory is too short to develop the right kind of internal variability, failing also to capture the
583 externally forced changes in tropical circulation. By contrast, the background ocean conditions in IFS-NEMO correctly
584 respond to the external forcing, although the model’s IPWP relatively increases in size and intensity more than in ERA5.
585 Such a positive trend is not leading the trend in MJO variance in the case of IFS-NEMO. The model exhibits a cold ocean
586 bias that is less prominent in the ER configuration, which could explain why IFS-NEMO-ER lowers the bias in total variance
587 of the leading EOFs. However, we note that the cold tropical SST bias in IFS-NEMO complicates the interpretation of the
588 long-term trend results, as this mean state error may dominate over, and partially mask, the model response to the external



589 forcing. Addressing these uncertainties through multi-model comparisons and better constraints on tropical mean state biases
590 will be essential for building confidence in model-based projections of future MJO behaviour.

591 The misrepresentation of the background atmospheric state affects directly the MJO in IFS-NEMO, as the model fails to
592 capture the positive trend in MJO-related variance seen in ERA5. The weighted permutation entropy of the RMMs remains
593 flat in both configurations, indicating that IFS-NEMO cannot leverage the growing predictable component of the MJO that
594 observations suggest is emerging under climate change.

595

596 **Code and data availability**

597 ERA5: Fifth generation of ECMWF atmospheric reanalyses of the global climate. Copernicus Climate Change Service
598 Climate Data Store (CDS). <https://cds.climate.copernicus.eu/#!/search?text=ERA5&type=dataset> .

599 NOAA Interpolated Outgoing Longwave Radiation (OLR) data are provided by the NOAA PSL, Boulder, Colorado, USA,
600 from their website at <https://psl.noaa.gov> .

601 IFS-NEMO simulations: *in the process of being published in the ESGF portal.*

602 The code used to produce the figures will be available in the final version. It is already available upon request to the
603 corresponding author. We used the implementation of the algorithm of Wheeler and Kiladis (1999) from the library
604 https://github.com/brianpm/wavenumber_frequency

605 **Supplement link**

606 The link to the supplement will be included by Copernicus, if applicable.

607 **Author contributions**

608 BM, PO and FD contributed to conceptualization; BM contributed to formal analysis; PO and FD contributed to project
609 administration; NR, MA and DK contributed to data curation; BM and PO contributed to writing – original draft; BM, PO
610 and FD contributed to writing – review & editing. All authors read and approved the final manuscript.

611 **Competing interests**

612 The authors declare that they have no conflict of interest.



613 Disclaimer

614 Views and opinions expressed are those of the author(s) only and do not necessarily reflect those of the European Union or
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