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## **Tropical Indian Ocean and ENSO relationships in a changed climate**

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## Abstract

We explore the current (1958-2005 period) and near future (2006-2050 period) teleconnections between El Niño Southern Oscillation (ENSO), Indian Ocean Basin Mode (IOBM), and Indian Ocean Dipole (IOD) as simulated in historical and Representative Concentration Pathway (RCP8.5) simulations of 32 coupled models that participated in the phase five of Coupled Model Intercomparison Project (CMIP5). A set of 16 CMIP5 models out of 32 models, which perform best to simulate tropical climate variability in recent decades, is first selected using a robust method based on the Empirical Orthogonal Function analysis, for detailed analysis.

Most of these models show modest capability in reproducing the seasonal cycle of ENSO types in the current period. Further, amplitude of Indian Ocean (IO) modes is overestimated by the 16 models along with large inter-model spread. Based on these results, a subset of 9 models is formed, which simulate a realistic seasonal phase-locking of ENSO for a robust assessment of future teleconnections.

No significant change in El Niño amplitude is detected in near future. However the IOBM is projected to be weaker during late spring and early summer. The IOD is projected to be stronger during boreal summer in the future relative to the current period. We also investigate if there are any changes from historical to RCP 8.5 simulations in the strength of the IO negative feedback on ENSO with a multiple linear regression approach. The IO negative feedback strengthens significantly in the RCP8.5 scenario due to the increasing role of IOBM in speeding the transition from El Niño to La Niña, despite its reduction of amplitude, In contrast, IOD loses its predictive value in the future projections.

## 20 **1. Introduction**

21 The ability of Coupled Model Intercomparison Project (CMIP5) models (Taylor et al. 2012) to simulate the El Niño  
22 Southern Oscillation (ENSO), Indian Ocean Dipole (IOD) and Indian Ocean Basin Mode (IOBM) phenomena and  
23 inter-relationships among them has been well documented in past studies (Bellenger et al. 2014; Chu et al. 2014; Du  
24 et al. 2013; Jha et al. 2014; Weare et al. 2013; Zhang et al. 2014; Xie et al. 2016; Saji 2018; Cai et al. 2019; Wang  
25 2019). A positive IOD pattern, with warming in the western Indian Ocean (IO) and cooling in the eastern IO  
26 emerges during boreal summer and peak during the boreal fall of the El Niño developing year (Wang 2019). During  
27 the following boreal winter, which corresponds to the peak of El Niño, the cold anomalies in the eastern IO  
28 disappear and a basin-wide warming (e.g. IOBM) emerges during the next boreal spring, and persists in boreal  
29 summer (Xie et al. 2016).

30 Several previous studies have suggested that ENSO may act as a trigger for some IOD events (e.g. Gualdi et al.  
31 2003; Shinoda et al. 2004) and is a significant IOD predictor (Zhao et al. 2019). However, many IOD events have  
32 occurred without a co-occurring El Niño (Saji 2018). Further, several positive IOD events have co-occurred with La  
33 Niñas (e.g. Ashok et al. 2003; Cai et al. 2009). Jourdain et al. (2016), Wang et al. (2019) and Cai et al. (2019) have  
34 further confirmed that the lead-lag relationships between IOD and ENSO are consistent with two-way interactions  
35 between them. Sensitivity coupled experiments have also demonstrated that IOD exists without ENSO in the Pacific,  
36 and is thus an intrinsic mode of Tropical Indian Ocean (TIO) variability (Fischer et al. 2005; Behera et al. 2006; Sun  
37 et al. 2015; Cretat et al. 2017, 2018). Yang et al. (2015) conducted a 10-member coupled simulation and  
38 distinguished the development of IOD by two factors viz., ENSO forcing and internal variability. The “internal”  
39 IOD decays after October, however ENSO-forced IOD further grows into IOBM (Hong et al. 2010), adding  
40 complexity in understanding the relationships between the three climate modes. Interestingly, there is also a decadal  
41 variability in the relationship between IOD and ENSO, and there are multiple decades when the IOD-ENSO  
42 association is significantly weaker (Ashok et al. 2003; Krishnaswamy et al. 2014; Ham et al. 2017).

43 While the IOBM may be considered as the IO response to ENSO through the atmospheric bridge (Klein et al. 1999;  
44 Alexander et al. 2002; Xie et al. 2016), it may feedback on ENSO, and hastens the transitions from El Niño to La  
45 Nina events in the Tropical Pacific (TP; Kug and Kang 2006; Ohba and Ueda 2007; Terray et al. 2016; Xie et al.  
46 2016). Interestingly, this ENSO-induced basin-wide warming in the TIO has more prominent impacts in recent  
47 decades, possibly due to global warming (Zheng et al. 2011; Boschat et al. 2012; Ashok et al. 2014, Hu et al. 2014;  
48 Tao et al. 2015). Dayan et al. (2014) suggest that the influence of IO Sea Surface Temperature Anomaly (SSTA) on  
49 ENSO is due to the IOBM rather than the IOD. However, Hong et al. (2010) have shown that the IOBM is much  
50 stronger when El Niño and IOD co-occur during the preceding year. In addition, Izumo et al. (2010, 2014)  
51 demonstrate that the negative phase of the IOD is an efficient statistical predictor of El Niño 14 months before its  
52 peak According to Jourdain et al. (2016), almost all CMIP5 models establish a significant relationship between IOD  
53 and the following year’s (i.e., 14 months later) ENSO, but the physical mechanisms responsible of this lead  
54 relationship are still elusive.



55 The tropical mean climate will undergo a significant change under global warming (e.g., Liu et al. 2005; Vecchi et  
56 al. 2008; Collins et al. 2010), especially in the western Pacific (Weller et al. 2016), and western IO (Roxy et al.  
57 2014; Cowan et al. 2015), which are key-regions for the tropical IO and ENSO interactions. Cai et al. (2009, 2014),  
58 using CMIPmodels, have shown that, under greenhouse warming, the equatorial IO is evolving towards  
59 climatologically stronger west-minus-east temperature gradients and easterly winds, and is more susceptible to  
60 producing more frequent extreme positive IOD events (Cai et al. 2014). However, this emerging picture is largely  
61 contributed by coupled models, which already simulate excessive IOD variability in the historical period (Li et al.  
62 2016). On the other hand, several other papers (e.g. Chu et al. 2014, Zheng et al. 2013) based on CMIP5 future  
63 projections reported that interannual variance of the IOD mode remains largely unchanged under global warming,  
64 which suggest that this topic needs further analysis. Based on historical simulations and future climate projections of  
65 CMIP5 models, Tao et al. (2015) also suggest that the ENSO-IOBM relationship would enhance in the future.

66 Previous studies have mainly focused on the relationships between IOD, IOBM and ENSO during their respective  
67 developing and peak phases. A notable exception is Jourdain et al. (2016), which showed that the delayed IOD-  
68 ENSO relationship as simulated in CMIP5 models is in good agreement with observations. In contrast, how state-of-  
69 the-art CGCMs simulate the lead-and-lag relationships between these three modes of variability, and how these  
70 significant lead-and-lag relationships, which play a seminal role in seasonal predictability in the tropics (Luo et al.  
71 2010, Zhao et al. 2019), will change in the future, are less known.

72 Given the above background, the present study intends to document the current (e.g. 1958-2005 period) and near  
73 future (e.g. 2006-2050 period) statistics of teleconnections and lead-lag relationships between ENSO, IOBM and  
74 IOD as simulated by 32 CMIP5 coupled models with the help of a robust selection of CMIP5 modelsbased on  
75 Empirical Orthogonal Function (EOF) analysis..

76 This paper is organized as follows. Section 2 provides a description of datasetsand statistical methods we used. In  
77 the section 3, we document how the CMIP5 models simulate the annual mean SST and variance and what are their  
78 projected changes. In section 4, we concentrate on the fidelity of the CMIP5 models in representing the observed  
79 Tropical Indo-Pacific(TIP) variability during recent decades. In sections 5 and 6, we examine the monthly standard  
80 deviations (SD) of Niño3, EMI, IOBM and IOD indices for the current period, and those for the near future. In  
81 sections 7 and 8, we analyse changes in lead-lag correlations between ENSO, IOD and IOBM and in the negative  
82 feedback on ENSO. A summary is presented in the final section.

## 83 **2. Data and Methodology**

### 84 **2.a Simulations, observations and climate indices**

85 Various simulations from the 32 CMIP5 models have been utilized in this study (Taylor et al. 2012):

86 - **Historical (H) simulations (1958-2005):** Theforcings include both natural and anthropogenic forcings.

87 - **Future projections based on Representative Concentration Pathway (RCP8.5) scenario (2006-2050):** The  
88 RCP 8.5 experiments start from the point where the corresponding H runs end (e.g. in 2005), and the radiative  
89 forcing reaches a level of about 8.5 W/m<sup>2</sup> by the end of the twenty-first century.

90 The list of 32 CMIP5 models and their relevant information are provided in Table 1. For each model, the first  
91 ensemble member run has been used and the following variables have been considered in our analysis: SST and  
92 850-hPa zonal wind.

93 For observed SSTs, we used the Hadley Centre SeaIce and SST dataset (HadISST; Rayner et al. 2003) and the  
94 1958-2005 period.

95 We focus on the interannual time scale and mainly on SST. The monthly SSTA are first calculated by removing a  
96 monthly climatology. The climatology is estimated over the period 1958-2005 for observations and the H  
97 simulations, while for RCP 8.5 simulations, the climatology is based on the period 2006-2050. We further  
98 detrended all SST time series with the linear least square method.

99 The canonical ENSO events are determined with the help of the Niño3 index (area-averaged SSTA over 5°N-5°S,  
100 150°W-90°W). We also considered the Modoki ENSO events and we used the El Niño Modoki Index (EMI; Ashok  
101 et al. 2007), to identify them:

$$102 \text{ EMI} = [\text{SSTA}]_A - 0.5 * [\text{SSTA}]_B - 0.5 * [\text{SSTA}]_C \quad (1)$$

103 The square bracket in Equation (1) represents the area-averaged SSTA over each of the regions A (165°E-140°W,  
104 10°S-10°N), B (110°W-70°W, 15°S-5°N), and C (125°E-145°E, 10°S-20°N), respectively.

105 The IOBM is defined as the SSTA averaged over the region 40°E to 110°E and 20°S to 20°N of the Indian ocean  
106 (Yang et al. 2007). Finally, the IOD index is computed as the difference between averaged SSTA over western  
107 box (50°E-70°E, 10°S-10°N) and eastern box (90°E-110°E, 10°S-0) of Indian ocean (Saji et al. 1999).

108 For convenience, we refer to the boreal summer (June-August; henceforth JJA), fall (September-November;  
109 henceforth SON), winter (December through following February; henceforth DJF) and spring (March-May;  
110 henceforth MAM) seasons simply as summer, fall, winter and spring.

## 111 **2.b Selection of CMIP5 models and statistical methods**

112 To assess the performance of the CMIP5 coupled models in simulating the observed tropical SST interannual  
113 variability, a method based on the EOF analysis is used (Bayr and Dommenges 2014; Wang et al. 2015). The  
114 principle of the method is as follows: to compare the spatial structure of SST variability of two different datasets, an  
115 objective way is (i) to define a set of (spatial) vectors as a common basis, (ii) to project the two datasets onto this  
116 common basis, and (iii) to compare the amount of variance described by each vector of the basis for the two  
117 datasets.

118 Note that these computations require that the two datasets share the same spatial grid. Consequently, we have first  
119 interpolated all the CMIP5 outputs onto the HadISST grid, i.e. 1° x 1°, for further analysis. In order to define a  
120 common basis for two datasets,,we generate the leading EOF modes from one dataset. These leading EOF modes  
121 give a synthetic depiction of the main modes of variability in this dataset. In the next step, we simply project the  
122 second dataset onto these (spatial) reference EOF-modes (computed from the first dataset) and estimate the amount  
123 of variance that these reference EOF-modes explain in this projected dataset.

124 In our analysis, we computed the EOF-modes from monthly HadISSTSSTA for the 1958-2005 periodand designate  
125 them as the reference modes. We then projected the time series of the 32 H simulations onto these reference modes.  
126 For each EOF-mode, there exists a difference between the explained variance (in the first dataset) and the projected  
127 explained variance (in the second dataset), subject to the fidelity of the H simulations. This information is then  
128 utilized to generate statistics useful to rank the CMIP5 models, based on their respective performances in replicating  
129 the observed interannual variability during 1958-2005.. The main statistic we useis the normalized Root Mean  
130 Square Error (RMSE). The normalized RMSE is defined as follows:

$$131 \quad \text{RMSE}_{\text{model}} = \sqrt{\sum_{i=1}^n (\lambda_i - \beta_i)^2 / (\sum_{i=1}^n \beta_i)^2} \quad (2)$$

132 Where

133 n is a predefined number of SST reference EOFs (e.g. computed on HadISST dataset), assuming that the  
134 EOFs have been ranked in decreasing order of explained variance.

135  $\lambda_i$  is explained variance from a CMIP5 model onto the reference EOF i;

136  $\beta_i$  is explained variance from the HadISST dataset onto the reference EOF i.

137 The above normalization allows a better comparison of the RMSE values among different models or datasets with  
138 different sampling uncertainties (Wang et al. 2015). A small RMSE value for any model suggests that the model  
139 simulates the observed variability of the climate system well. On the other hand, a RMSE value of 100%  
140 corresponds to errors that are as big as the eigenvalues of the selected EOF modes used to define the RMSE statistic.  
141 As explained by Wang et al. (2015), in most of the cases, this occurs due to a critical mismatch between the leading  
142 EOFs in the two datasets or, alternatively, when modes are mixed or inverted between the two datasets giving an  
143 improper distance between the two datasets.

144 In our analysis, we have used the first 8 reference EOF modes to compute the normalized RMSE. A question that  
145 comes immediately to mind is why we used only 8 degrees of freedom. Following Bretherton et al. (1999) and  
146 Wang et al. (2015), we first used the concept of the effective spatial number of degrees of freedom in order to  
147 determine the number of EOFs to be used to compute the RMSE. However, from our own experience and the work  
148 of Sterl et al. (2007), the number of spatial degrees of freedom is a highly non-robust quantity, which is difficult to  
149 estimate objectively in practice. Here, we have thus simply computed the RMSE from the first 8 modes, as well as  
150 the first 5 modes, from the monthly SSTA for 1958-2005 and different domains and ascertained that the RMSE

151 values don't change much from five to eight modes. Thus, this suggests that the first 8 reference EOFs form a stable  
152 basis for comparing the various datasets and still take into account a large part of the variances in each dataset.  
153 Therefore, for the purpose of grouping the CMIP5 models in different categories according to their performance in  
154 simulating the observed SST variability, RMSE values computed from first 8 modes are a good compromise.

155 Finally, standard regression and correlation analyses have also been performed to document the teleconnection  
156 patterns and their possible changes in a warming climate.

### 157 **3. Model bias and future projections in mean SST and variance**

158 We document first how the CMIP5 models simulate the annual mean SST and mean variance of SSTA and what are  
159 their projected changes. The periods selected for calculating the mean and variance of observation, H and RCP 8.5  
160 simulations are 1958-2005, and 2006-2050, respectively. Fig. 1a represents the annual mean SST from the ensemble  
161 of CMIP5 H simulations. On average, annual mean SST over TP in H simulations is between 26-28°C, but the  
162 equatorial western TP is warmer than eastern TP as expected (Fig. 1 a). Fig. 1b displays statistically significant  
163 mean bias values of CMIP5 ensemble relative to the HadISST for the same period. The simulated SSTs are clearly  
164 too high in the tropical southeastern Pacific and Atlantic and too low in the equatorial Pacific relative to  
165 observations, as also noted by many studies (Richter et al. 2015; Wang et al. 2014). Focusing specifically on the TP,  
166 this implies that the equatorial SST gradient is severely damped in CMIP5 models on average, with significant  
167 implications for ENSO realism in CMIP5 models (Li and Xie 2014). These Pacific SST biases persist from several  
168 generations of CMIP models (Reichler and Kim 2008). Over the TIO, the models show warm SST biases.

169 The difference of ensemble mean SST between RCP 8.5 and H simulations of CMIP5 indicates that the simulated  
170 SST is significantly increasing over all tropical oceans with mean conditions shifting to an El Niño-like pattern in  
171 the TP and a positive IOD like pattern in the TIO (Fig. 1c; Chu et al. 2014). Interestingly, the extent of SST increase  
172 is larger over northern tropical oceans compared to southern part, suggesting that the warming pattern in the Pacific  
173 is not exactly El Niño like. Over the IO, the projected changes suggest that the western IO and South-East IO, off  
174 Australia, will undergo enhanced warming in a global warming scenario (Chu et al. 2014; Zheng et al. 2013).

175 The fidelity of CMIP5 models in simulating the SSTA variance is also assessed (see Fig. 1d-f). Detrended SSTA is  
176 used to compute the variance. The largest SST interannual variability is seen in the eastern Pacific, which is mostly  
177 associated with ENSO variability. The bias in variance is significantly high over the equatorial western and central  
178 Pacific, implying that the ENSO-related SST anomalies are shifted westward in most CMIP5 models (Fig. 1e),  
179 consistent with the cold tongue bias affecting most of the CMIP5 models (see Fig. 1b). IO is also affected by  
180 exaggerated SST variability, consistent with previous studies (Annamalai et al. 2017). In contrast with the changes  
181 in mean SSTs (Fig. 1c), the difference of ensemble variance between H and RCP 8.5 simulations is insignificant  
182 everywhere, even in the TP (Fig. 1f). The implications for ENSO, IOBM or IOD teleconnections will be further  
183 studied in the next sections.

184

185

#### 186 4. SSTA interannual variability in historical CMIP5 simulations

187 In this section, we focus mainly on the fidelity of the CMIP5 models in representing the observed TIP variability  
188 and teleconnections during recent decades (1958-2005) with the help of EOF analysis.

189 These leading EOF modes have been estimated for three different domains, the TIO (40°E-120°E, 30°S-30°N), TP  
190 (110°E-70°W, 30°S-30°N) and TIP (40°E-70°W, 30°S-30°N).

191 The first two leading modes of TP represent the ENSO variability and its different types (Fig. 2 a,b; see Ashok et al.  
192 2007; Marathe et al. 2015, their Fig. 1). The first leading mode of TIO corresponds to IOBM and explains about  
193 40% of variability (Fig. 2d). The second and third modes of TIO SST variability (Fig. 2e and f) are related with IOD  
194 (Saji et al. 1999; Murtugudde et al. 2000) as well as the subtropical IOD (SIOD; Behera and Yamagata 2001), simply  
195 because our domain extends up to 30°S and we consider all the calendar months in the EOF analysis. A positive  
196 SIOD is characterized by cold SST anomalies off Australia and warm SST anomalies in the southwestern IO,  
197 south of Madagascar during boreal winter. The spatial EOF patterns of the first two EOFs over the TIP (Fig. 2 g, h)  
198 and TP (Fig. 2 a, b) are somewhat similar over the TP. This is consistent with the higher SST variability over the TP  
199 compared to the TIO (See Fig. 1d). The dependence of these EOFs to the global warming is also checked by  
200 recomputing these EOF patterns on the detrended SSTs (see Fig. 3). The spatial patterns of most of the leading  
201 EOFs for the three domains remain, in general, unchanged after detrending. This illustrates that the observed climate  
202 change SST signal is projecting on specific modes of SST variability in the TIP. However, for TIP, the 2<sup>nd</sup> and 3<sup>rd</sup>  
203 modes of “raw” are becoming the 3<sup>rd</sup> and 2<sup>nd</sup> modes of detrended SSTs, respectively. The main factor responsible for  
204 this reversed order between the 2<sup>nd</sup> and 3<sup>rd</sup> EOF modes of observed SSTA with or without detrending seems related  
205 the large warming trend over the Indian Ocean warm pool during recent decades (e.g. compare Fig. 2b and Fig. 3c).  
206 The explained variance increases approximately by 2% only for the first leading EOF mode of TP and TIP domain  
207 when the EOFs are computed from the detrended SSTA (see Table 2). But, it decreases significantly, i.e., by 10%  
208 for the leading EOF mode of the TIO, which is reminiscent of the IOBM. This suggests that the TIO is mainly  
209 responsible of the reversed order between the 2<sup>nd</sup> and 3<sup>rd</sup> EOF modes of observed SSTA with or without detrending  
210 in the TIP domain. However, the SST trends do not alter the spatial structures of the leading EOF modes in the  
211 different oceanic basins, only the variance they described. As we are interested in the interannual variability of TIP,  
212 detrended SST data is used throughout our subsequent analysis and, especially, in the computation of the RMSE  
213 statistics, which is discussed in the next paragraph.

214 As mentioned earlier, CMIP5 models have been ranked in the ascending order of their RMSE values for the TIP (see  
215 Table 3). The RMSE values for TIO and TP domains are also listed in Table 3 to assess the robustness of the results  
216 and the dependency to the domain definition. RMSE values for TIP and TP domains are nearly the same, but the  
217 corresponding RMSEs of TIO are different, implying that the models performing best for the TP and TIO are not  
218 necessarily the same. Table 3 shows that for the first twenty-one models, the RMSE for the TIP domain is below  
219 47% and beyond that it reaches suddenly a value of nearly 60%. Thus, these first 21 “best” models are selected for

220 our subsequent analysis. Unfortunately, the RCP 8.5 data was unavailable for five out of these 21 models. Thus, the  
221 number of “best” models available for future projections will become finally 16 for further analysis.

## 222 **5. Seasonal evolution of leading modes in H simulations**

223 The ability of the CMIP5 models to reproduce seasonal cycles of canonical El Niños and that of El Niño Modoki is  
224 measured by the comparing the simulated and observed monthly Standard Deviation (SD) of the Niño3 index and El  
225 Niño Modoki Index (e.g. EMI) (Ham and Kug 2014).

226 ENSO variability has a strong phase locking to the seasonal cycle with the maximum of SSTA in November-January  
227 and minimum in March-May in the eastern Pacific (Ham and Kug 2014; see also Fig. 4a). However, unlike the  
228 observations, many individual models show a different seasonal cycle of evolution, with the peak of the canonical El  
229 Niño occurring at any season (Jourdain et al. 2013; Taschetto et al. 2014) and only a few models have Niño3.4 SST  
230 amplitude similar to or above observations during boreal winter (Taschetto et al. 2014). This can be related to many  
231 factors, especially the spatial shift of simulated SST variability over the equatorial Pacific (Li et al. 2019). It is  
232 important to consider this deficiency if we want to assess the changes of predictability and lead-lag relationships  
233 between the ENSO, IOD and IOBM phenomena in the future projections using CMIP5 models. The observed El  
234 Niño Modoki also peaks in December and January similar to canonical El Niño, but the minimum of EMI occurs in  
235 May and June, slightly later than the minimum of canonical El Niño (see Fig. 4b). It is noticed that very few models  
236 are able to capture the seasonal cycle of the El Niño Modoki. This also has serious implications for simulation of the  
237 seasonal cycle and interannual variability of other major climate processes such as the Indian summer monsoon (e.g.  
238 Jourdain et al., 2013). Note that, in this section, the seasonal evolution of all the “best” 21 models is discussed, as  
239 the H simulations are available for all of them. From the next section onwards, only those models for which both H  
240 and RCP 8.5 simulations are available will be used (e.g. 16 models).

241 Now, the fidelity of the statistics for IOBM and the IOD will be explored. SD of observed IOBM is maximum in  
242 February-March (black curve in Fig. 4c). Many CMIP5 models reproduce this late boreal winter peak in IOBM  
243 variability, but the IOBM amplitude is generally overestimated and the inter-model spread is very large (Fig. 4c; Du  
244 et al. 2013). The observed IOD is also tightly seasonally phase locked to the calendar months and peaks in SON  
245 (black curve in Fig. 4d). In agreement with Jourdain et al. (2016) and Cai et al. (2009), we find that 19 out of 21  
246 CMIP5 models overestimate the IOD peak amplitude, in SON (Fig. 4d). In summary, the CMIP5 models have a  
247 tendency to overestimate the amplitude of the IO modes (Figs 4c,d), especially the IOD despite of the fact that the  
248 TP modes are generally damped in the models (Figs 4a,b).

## 249 **6. Changes in SST variability in near future**

250 We now concentrate on those models, which can at least simulate a reasonable phase-locking of ENSO to the annual  
251 cycle, as this property is key for the realism of the ENSO teleconnections in the coupled models. To quantify the  
252 models’ fidelity in simulating the ENSO phase-locking, the correlations between the monthly SD of Niño3 SST  
253 anomaly for each model and observations are computed (Ham and Kug 2014). Thus, 9 models are selected out of the  
254 16 “best” models, which have a significant positive correlation at the 90% confidence level, (see Table 4). Note that

255 some of the “best” models exhibit even a strong negative correlation (e.g. CSIRO-Mk3-6-0, IPSL-CM5A-LR, IPSL-  
256 CM5A-MR). This demonstrates that the CMIP5 models, which performed best for reproducing the observed ENSO  
257 variability, are not necessarily the models with the best seasonal phase-locking, highlighting the difficulty of  
258 selecting the best CMIP5 models in a universal way. Based on this, we form two groups of models for evaluating the  
259 climate projections, namely, Groups A and B: Group A consists of all 16 models. The Group B consists of the 9  
260 models out of the 16 models, which have a reasonable seasonal phase locking of ENSO.

261 We now focus on the SD changes for the Niño3, EMI, IOBM and IOD indices in the RCP 8.5 simulations. For that  
262 purpose, the percentage change of SD from H to RCP 8.5, for each index is computed as follows:

$$263 \text{ Percent change in SD from H to RCP 8.5} = [(SD_{RCP} - SD_H) / SD_H] * 100\% \quad (3)$$

264 Fig. 5 displays percentage changes in the monthly SD of Niño3 and EMI from H to RCP 8.5 simulations for groups  
265 A and B. Furthermore, the standard-error of simulated percentage change in SDs of indices across the models in  
266 each group is also calculated for each month (Fig. 5). These error bars give an estimate of the robustness of the  
267 change that has occurred across the models. We note that there is a substantial spread in the SD of all indices across  
268 the models (Fig. 5). Group A shows a marked increase in the canonical El Niño amplitude in all months (see Fig.  
269 5a). However the models with a reasonable ENSO phase locking (Group B) demonstrate that this increase is coming  
270 from models in which the ENSO peak is not observed during boreal winter in the historical period (see Fig. 5b). The  
271 Group B of models show strengthening of El Niño in all months except JJA, but the error bars are very large. We  
272 thus conclude that canonical El Niño variability may increase in the future, but this projected increase is insignificant  
273 if we take only into account the models that have realistic ENSO pattern and seasonal cycle in the H simulations.  
274 This result is in agreement with previous studies (Stevenson et al. 2012; Chen et al. 2015; Rashid et al. 2016). The  
275 EMI amplitude, on the other hand, seems to increase significantly in the future during its peak for both Group A and  
276 Group B models (see Figs. 5c and 5d).

277 We shall now discuss the projected changes of the IOBM and IOD (Fig. 6). The percentage changes in the SD of  
278 these indices from H to RCP8.5 simulations suggest that the simulated IOBM amplitude will weaken in future  
279 despite no commensurate robust changes of ENSO (see Figures 6a, b), but the intermodal spread is again relatively  
280 large. However, this decrease in IOBM magnitude is robust during early summer for group B (Fig 6b) and is  
281 consistent with a similar reduction of Niño3.4 amplitude in this group (Fig 5b). To sum up, these results indicate  
282 that, for a high emission scenario, IOBM may not extend till the next boreal summer in future, and hence may  
283 contribute less to the Indian summer monsoon variability (Yang et al. 2007).

284 On the other hand, the SD of IOD is seen to amplify in Group A as well as in Group B models (see Fig. 6c, d) during  
285 boreal summer as the error bars are well above zero. This suggests a strengthening, and an early onset of IOD events.

286

## 287 **7. Changes in the lead-lag correlations between ENSO, IOD and IOBM**

288 We now investigate whether the ENSO, IOD and IOBM relationships will change under anthropogenic global  
289 warming. From this section, we will discuss only the relationship between Niño3, IOD and IOBM indexes because  
290 EMI relationship with IOD and IOBM is not completely known yet in observations.

291 The concurrent relationship among ENSO, IOD and IOBM is assessed with the help of a correlation analysis  
292 between the different pairs of climate indices during their respective peak season in the H and RCP 8.5 simulations  
293 (Table 5). In this context, Table 5 displays the “simultaneous” correlations among IOD (SON), Niño3 (DJF) and  
294 IOBM (MAM) for observations and Groups A and B models. Here, “simultaneous” means that IOD (during SON)  
295 precedes both Niño3 and IOBM (during the following DJF and MAM seasons), and Niño3 (during DJF) precedes  
296 the IOBM by two months. Note first that all the correlations listed in Table 5 are positive and statistically significant  
297 at the 90% confidence level for both observations and CMIP5 models.

298 In the observations, the canonical El Niño peak in boreal winter is preceded by positive IOD peak in the previous  
299 boreal fall, and is followed by the peaking of the IOBM during boreal spring. Due to the tight relationship between  
300 IOD and Niño3 on one hand and between Niño3 and IOBM on the other hand, the correlation between IOD and  
301 IOBM is also positive and significant (Hong et al. 2010). The full multi-model mean (e.g. Group A) realistically  
302 simulates these significant “simultaneous” positive correlations among IOD, ENSO and IOBM during their  
303 respective peak phases in the H simulations, despite weaker amplitude, in agreement with Ha et al. (2016). These  
304 simultaneous correlations in the H simulations are generally further improved if we consider only models in Group  
305 B(e.g. see second row in Table 5). Furthermore, the inter-model spread also decreases from Group A to B models,  
306 which gives even more confidence in the models in Group B for assessing future changes.

307 These simultaneous correlations between IOD, Niño3 and IOBM are, in general, seen to slightly increase in the RCP  
308 8.5 simulations, especially for Group B. There is only one exception to this general rule, the correlation between  
309 IOD and Niño3 in Group A. Notably, the association of IOBM with both Niño3 and IOD becomes stronger in the  
310 future relative to the H period. The inter-model spread is also slightly increasing from H to RCP 8.5 simulations  
311 with one important exception, which concerns again the association between Niño3 and IOBM. However, this inter-  
312 model spread remains quite low, especially for Group B in the RCP 8.5 simulations, suggesting the robustness of  
313 these results.

314 Next, we try to detect if there are any changes from H to RCP 8.5 simulations in the lead relationships between the  
315 IO indexes and the Niño3 index, which will have implications for ENSO predictability (Luo et al. 2010; Izumo et al.  
316 2010; Cai et al. 2019) in the background of increasing anthropogenic warming. A large number of studies have  
317 pointed out the role of IOBM in ENSO transitions (Kug and Kang 2006; Obha and Ueda 2007; Terray et al. 2016).  
318 IOBM is able to trigger low-level easterly wind anomalies over the western equatorial Pacific Ocean, which promote  
319 eastward propagating upwelling Kelvin waves in the equatorial Pacific Ocean during boreal spring (Kug and Kang  
320 2006; Obha and Ueda 2007; Wang 2019). These easterly wind anomalies over the western Pacific are most  
321 significant during and just after the El Niño peak phase and thus hasten the transition from El Niño to La Niña.  
322 However, importantly, the observed correlations for the H period (shown in Table 6), between the MAM(0) IOBM  
323 and D(0)JF(1) Niño3, i.e. when IOBM leads, are quite modest (i.e. -0.17) and statistically not significant for both  
324 observations and Group A. We ascertained the result by employing the Niño3.4 index in place of Niño3 index in the  
325 correlation analysis (not shown). This suggests that not all IOBM events condition the El Niño to La Niña transition  
326 in the TP or, alternatively, that the IOBM feedback on ENSO occurs in another season. This result is strange, but  
327 interesting because while Group A is able to capture this observed relationship with a high fidelity, Group B, which



328 has a more realistic phase-locking to the annual cycle, on the other hand, tends to overestimate the link between  
329 IOBM during MAM and the ENSO state in the next boreal winter in the H simulation (Table 6). However, in the  
330 future projections, the correlation with springtime IOBM leading wintertime Niño3 index is much more negative  
331 and becomes statistically significant at 90% confidence level for both groups A and B. This suggests that the role of  
332 IOBM in speeding the transition from El Niño to La Niña is more significant in the RCP 8.5 projections despite of  
333 the decrease of IOBM amplitude during late boreal spring and early summer highlighted in the preceding section.

334 We now focus on the fidelity of CMIP5 models in simulating the observed tendency of ENSO events to follow the  
335 IOD events in the previous year and the projected changes for this behavior in the RCP 8.5 simulations (see Table 6;  
336 Izumo et al. 2010; Jourdain et al. 2016). The relevant correlations between SON(-1) IOD and D(0)JF(1) Niño3  
337 indexes (e.g. when IOD leads by more than one year the Niño3 index) are shown in Table 6. The lead correlations of  
338 the IOD index with Niño3 index 14 months later are, respectively, -0.39, -0.35 and -0.41 for observations, Group A  
339 and B in the H period. These values are in good agreement with previous results based on observations and H  
340 simulations (Izumo et al. 2014; Jourdain et al. 2016). These correlations are significant at the 90% confidence level  
341 and have stronger amplitude than the corresponding IOBM-Niño3 correlations discussed above, despite of the  
342 longer time lead. However, in the RCP8.5 simulations, these lead correlations of the IOD with Niño3 14 months  
343 later are all decreasing, especially for Group B, despite the “simultaneous” correlations between IOD and Niño3  
344 indexes are almost stable between the H and RCP 8.5 simulations (see Table 5; Chu et al. 2014).

345 The above conclusions are made based on the lead-lag correlation between IOD, IOBM and Niño3 SST time series  
346 in their respective peak seasons. In order to illustrate the associated evolution of SSTA in the TIP domain and how  
347 these SST patterns change from H to RCP8.5 simulations, we selected two typical individual models from Group B,  
348 which perform best according to our two selections rules (based on least normalized RMSE and a realistic seasonal  
349 phase-locking), namely, the GISS-E2-H-CC and ACCESS1-0 models (see Tables 3 and 4). Importantly, the GISS-  
350 E2-H-CC shows the largest absolute amplitude increase (e.g. by 0.32) in IOBM-Niño3 lead correlations and  
351 ACCESS1-0 shows the largest absolute amplitude decrease (e.g. of 0.43) in IOD-Niño3 lead correlation from H to  
352 RCP 8.5 simulations in Group B, making them interesting candidates for illustration of possible physical  
353 mechanisms behind the changes of the lead-lag correlations between the climate indexes in the future projections.

354 First, Figures 7ab confirm that the role of IOBM in the negative feedback of the IO on ENSO has considerably  
355 strengthened in the GISS-E2-H-CC simulations, as both the magnitude and extent of the negative correlations over  
356 TP have increased considerably several months after the occurrence of IOBM events from H to RCP 8.5 simulations  
357 for this model. The results from a complementary regression analysis also show that the amplitude of the associated  
358 SSTA increases considerably from the H to RCP 8.5 simulations (Fig. S1a and b). On the other hand, the IOD-  
359 Niño3 lead correlation and regression SSTA patterns simulated by ACCESS1-0 drastically drop and become  
360 insignificant in future projections (Figs. 7cd and S1cd), also in full agreement with the results from the analysis of  
361 the correlations between the indices (Table 6).

362 We investigated further these different evolutions by computing Hovmöller composite of SST and 850-hPa zonal  
363 wind anomalies for positive and negative IOBM (IOD) events in the GISS-E2-H-CC (ACCESS1-0) simulations  
364 (Figs. 8 and 9).

365 In case of GISS-E2-H-CC, first we calculated standardized index of boreal spring (MAM) IOBM. We selected 11  
366 strong positive IOBM events when the standardized IOBM index is above the 0.7 threshold and 10 negative IOBM  
367 events when it is below -0.7 in the H simulations. Following a similar procedure for future projections, we got 12  
368 positive IOBM events and 11 negative IOBM events in the RCP 8.5 simulations. Comparing the SST and 850-hPa  
369 wind anomalies evolution following the positive IOBM events in the two periods (i.e., Fig. 8a and 8b) for GISS-E2-  
370 H-CC, we find that though a basin-wide IO warming is observed during MAM of year 0 in present period, it's  
371 magnitude is moderate and hence it is not able to trigger significant easterly wind anomalies over the western  
372 Pacific, which may fasten the turnabout of ENSO during year 0, and finally a very weak La Niña event is simulated  
373 in TP at the end of year 0. In contrast, in the future warming scenario, a stronger positive IOBM is seen during  
374 MAM of year 0 accompanied by more significant and stronger easterlies over the western TP at the beginning of  
375 year 0, which trigger a well-defined La Niña event at the end of year 0 (Fig. 8b). Interestingly, the changes from the  
376 H to RCP 8.5 simulations for the GISS-E2-H-CC model concern mainly these positive IOBM events. Negative  
377 IOBM events during MAM of year 0 seem to give rise to moderate El Niño conditions at the end of year 0 in both H  
378 and RCP 8.5 simulations (Fig. 8c and d) despite of the fact that westerlies over the western TP during boreal spring  
379 of year 0 are much better defined in the RCP 8.5 simulation. This suggests that global warming induces a stronger  
380 nonlinearity in the relationship between IOBM and ENSO (Ohba and Watanabe 2012).

381 Following a similar procedure, we selected 11 positive IOD events when standardized IOD index during SON is  
382 above 0.7 and 11 negative IOD events when it is below -0.7 in the H simulation of the ACCESS1-0 model. For  
383 future projection, we got 13 positive IOD events and 13 negative IOD events. The Hovmöllercomposites of SST and  
384 850-hPa zonal wind anomalies in the TIP domain during the H period highlight a very systematic statistical  
385 relationship between both positive and negative IOD events and the evolution of TP SST anomalies in the following  
386 year consistent with previous studies (Fig. 9; Izumo et al. 2010, 2014; Jourdain et al. 2016). However, as noted by  
387 Jourdain et al. (2016), the physical mechanisms responsible for this relationship remain elusive because associated  
388 850-hPa zonal wind anomalies over the western TP at the beginning of year +1 remain weak and are not significant  
389 for both positive and negative IOD events simulated by the ACCESS1-0 model (Fig. 9a and c). Moreover, the main  
390 result is that the role of IOD events in ENSO turnabout is becoming almost negligible in the RCP 8.5 simulation  
391 performed with the ACCESS1-0 model (Fig. 9b and d). Interestingly, this weaker role of IOD in ENSO evolution is  
392 accompanied by a change of the spatial structure of the IOD events during SON, which seem exclusively under the  
393 control of the eastern IOD pole SST anomaly in the future projection by contrast with what is observed in the H  
394 period (Fig. 9b and d)..

395  
396 In summary, the above analysessuggest an increasing role of positive IOBM events in ENSO turnabout and a  
397 stronger asymmetry in the relationship between IOBM and ENSO while the ENSO-IOD link may become weaker in  
398 the future under global warming. Implications for future changes in the “global” negative feedback of the IO on  
399 ENSO and the long lead predictability of Niño3 SST index from IO SST modes are discussed in next section.

400  
401

## 402 8. Changes in IO negative feedback and predictability of ENSO indices from IO SST

403 In this section, we examine the collective and respective influences of IOD, IOBM and also Niño3 persistence on  
404 the “potential” predictability of Niño3 SST anomalies in the following year (e.g. end of year 0 and beginning of year  
405 +1) in the H simulations realm, and corresponding future projections, using a multiple linear regression approach.  
406 Table 7 lists the values of coefficient of determination, i.e.  $R^2$ , for the (multiple) linear prediction of Niño3 at the  
407 start of year +1 (e.g. D of year 0 and JF of year +1) using different predictors such as Niño3 in DJF of year 0, IOD  
408 in SON of year -1 or IOBM in MAM of year 0, and their different combinations using the CMIP5 models. An  $R^2$   
409 between 0 and 1 indicates the extent (e.g. percentage) to which the variance of the dependent variable is explained  
410 by the predictors. As an illustration, an  $R^2$  of 0.10 means that 10% of the variance of the dependent variable is  
411 predictable/described from the selected predictors. Here, we also compare how the predictability of Niño3 in DJF  
412 would change from H to RCP 8.5 for each set of predictors.

413 In the H period, the IOD in SON of year -1 is a better predictor than IOBM for observations, as well as groups A  
414 and B. Niño3 autocorrelation does not seem to play any significant role in the H period (Table 7 first row).  
415 However, in the global warming scenario, results are different: the IOBM ( $R^2 = 0.22$  for Group B) plays a more  
416 important role than IOD ( $R^2 = 0.15$  for Group B) in the Niño3 prediction, consistent with the results in the last  
417 section. The Niño3 SST “potential” predictability is improved and enhanced in the future if we consider IOBM and  
418 IOD together as predictors ( $R^2 = 0.25$  for Group B) as compared to IOBM or IOD alone (see Table 7). Interestingly,  
419 Niño3 and IOBM perform even better ( $R^2 = 0.26$  for Group B) than the pair IOBM and IOD in the RCP 8.5  
420 simulation. This confirms the leading role of IOBM in the RCP 8.5 simulation. We also get improved prediction for  
421 Niño3 from H to RCP 8.5 simulations for both groups A and B if we take Niño3 SST, IOD and IOBM all together  
422 or, alternatively, the pairs IOBM and IOD or IOBM and Niño3. This demonstrates that the “global” negative  
423 feedback of IO on ENSO turnabout increases in the RCP 8.5 simulations, despite IOD is losing its predictive value.  
424 However, the inter-model variability is always increasing in the RCP 8.5 simulations for all the regressions  
425 performed in Table 7.

426 One well-known drawback of  $R^2$  is that it can be driven to any desired value simply by adding predictors. To  
427 overcome this effect, we also used adjusted  $R^2$  statistics (Table 8), which indicate the proportional reduction in the  
428 mean square rather than in the sum of squares (Draper and Smith 1998). The purpose of using adjusted  $R^2$  is to  
429 check whether the predictive value is actually improved when a combination of the Niño3, IOBM and IOD is  
430 considered, and not just because of increasing number of predictors. From Table 8, it is clear again that for Niño3  
431 prediction in the future, considering IOBM and IOD together as predictors would be beneficial ( $R^2 = 0.21$  for Group  
432 B), instead of just taking IOBM (adjusted  $R^2 = 0.2$  for Group B) or IOD (adjusted  $R^2 = 0.13$  for Group B) alone.  
433 However, in the future, the pair IOBM and Niño3 (adjusted  $R^2 = 0.23$  for Group B) performs again better than the  
434 pair IOBM and IOD using adjusted  $R^2$ . We also get again marginally “best” results if we consider all together  
435 Niño3, IOBM with IOD (adjusted  $R^2 = 0.24$  for Group B).

436 Of course, we should also be mindful from the above discussion on the  $R^2$  and adjusted  $R^2$  values, that all these SST  
437 predictors can explain only 20-29% of Niño3 variability at most and, thus, have strong limitations compared to more  
438 traditional ENSO predictors such as the equatorial Pacific WWV or low-level zonal wind anomalies over the  
439 western Pacific (Clarke 2008). But the above discussion gives us a qualitative but useful interpretation of the  
440 changing strength of the negative feedback of the IO on ENSO.

## 441 **9. Summary and discussion**

442 A large set of CMIP5 coupled models are analyzed to assess the present (e.g. 1958-2005) and near future (e.g. 2006-  
443 2050) of ENSO and TIO modes of variability and their teleconnections.

444 First, a method based on EOF analysis is employed for selecting 16 CMIP5 models out of 32, which perform best to  
445 simulate TIP SST variability during recent decades, for further analysis. Despite these 16 CMIP5 models perform  
446 best in simulating the spatial patterns of observed SST variability, many of them have difficulties in simulating the  
447 seasonal phase locking of canonical El Niño events during the H period. Thus, we further selected a subset of 9  
448 models with a realistic ENSO seasonal phase-locking during recent decades (out of the 16) for evaluation of the  
449 robustness of future changes.

450 We then discussed how the leading modes of TP and TIO would change in terms of amplitude and seasonal phase-  
451 locking under global warming. The results infer that canonical El Niño may not change much in the near future. On  
452 the other hand, EMI amplitude seems to increase significantly during its peak season in the near future. In case of  
453 TIO modes, it is found that the IOBM is projected to be weaker during early summer in the RCP8.5 scenario. For  
454 the IOD, while its amplitude may not change significantly during boreal fall, it is projected to strengthen during  
455 boreal summer, pointing to an early onset of IOD events in a future scenario. Interestingly, our results are broadly in  
456 agreement with Chu et al. (2014), despite that these authors used the RCP4.5 scenario at the end of the 21<sup>st</sup> century;  
457 but we focused on a high RCP8.5 emission scenario and a near future period with a different model selection  
458 method.

459 Next, we focus on the changes from H to RCP 8.5 simulations in the lead relationships between the IO and Niño3  
460 indexes. Lead correlation between IOBM MAM(0) and Niño3 D(0)JF(1) is very weak for the present period, which  
461 suggests that not all IOBM events condition the El Niño to La Niña transitions in the TP. However, the role of  
462 IOBM in hastening the El Niño to La Niña transition is much more significant in the RCP 8.5 projections.  
463 Interestingly, the lead correlations of IOD with ENSO follow a reversed evolution and IOD is losing its ENSO  
464 predictive value in the near future. These results are again consistent with the results of Chu et al. (2014). These  
465 changes have been further illustrated by a detailed composite analysis of the evolution of 850-hPa zonal wind and  
466 SST anomalies in two typical models viz., GISS-E2-H-CC and ACCESS1-0. Overall, these composite analyses  
467 suggest an increasing role of positive IOBM events in ENSO turnabout (thus a stronger asymmetry in the  
468 relationship between IOBM and ENSO) and points towards weaker ENSO-IOD correlation under global warming,  
469 especially the lead relationship between IOD events and the SST evolution in the TP during the following  
470 year. Interestingly, this weaker role of IOD in ENSO evolution in the RCP 8.5 simulation of the ACCESS1-0

471 modelis accompanied by a change in the spatial structure of IOD, which shows a predominant contribution of the  
472 eastern IOD pole in the future.

473 Finally, we also examined the collective and respective influences of IOD and IOBM on the “potential”  
474 predictability of Niño3 in the following year in the H simulations realm, and corresponding future projections, using  
475 a multiple linear regression approach. Our results show that the “global” negative feedback of IO on ENSO  
476 turnabout increases significantly in the RCP 8.5 simulations, despite IOD is losing its predictive value in the future  
477 projections.

478 In a nutshell, this study brings out the increasing role of IOBM and negative IO feedback in ENSO transitions in  
479 near future. We admit that inter-model spread in CMIP5 ensemble is a big hurdle, which surely limits the degree of  
480 robustness of our analysis despite our careful selection of the most “realistic” models. In future, we hope to seek for  
481 improved models, which will have a better representation of ENSO, IOD and IOBM. We expect that the new  
482 CMIP6 simulations would serve this purpose better. In parallel, it is particularly important to build more efficient  
483 metrics for model selection in both the CMIP5 and CMIP6 ensembles for a robust assessment of future climates  
484 changes.

485

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490

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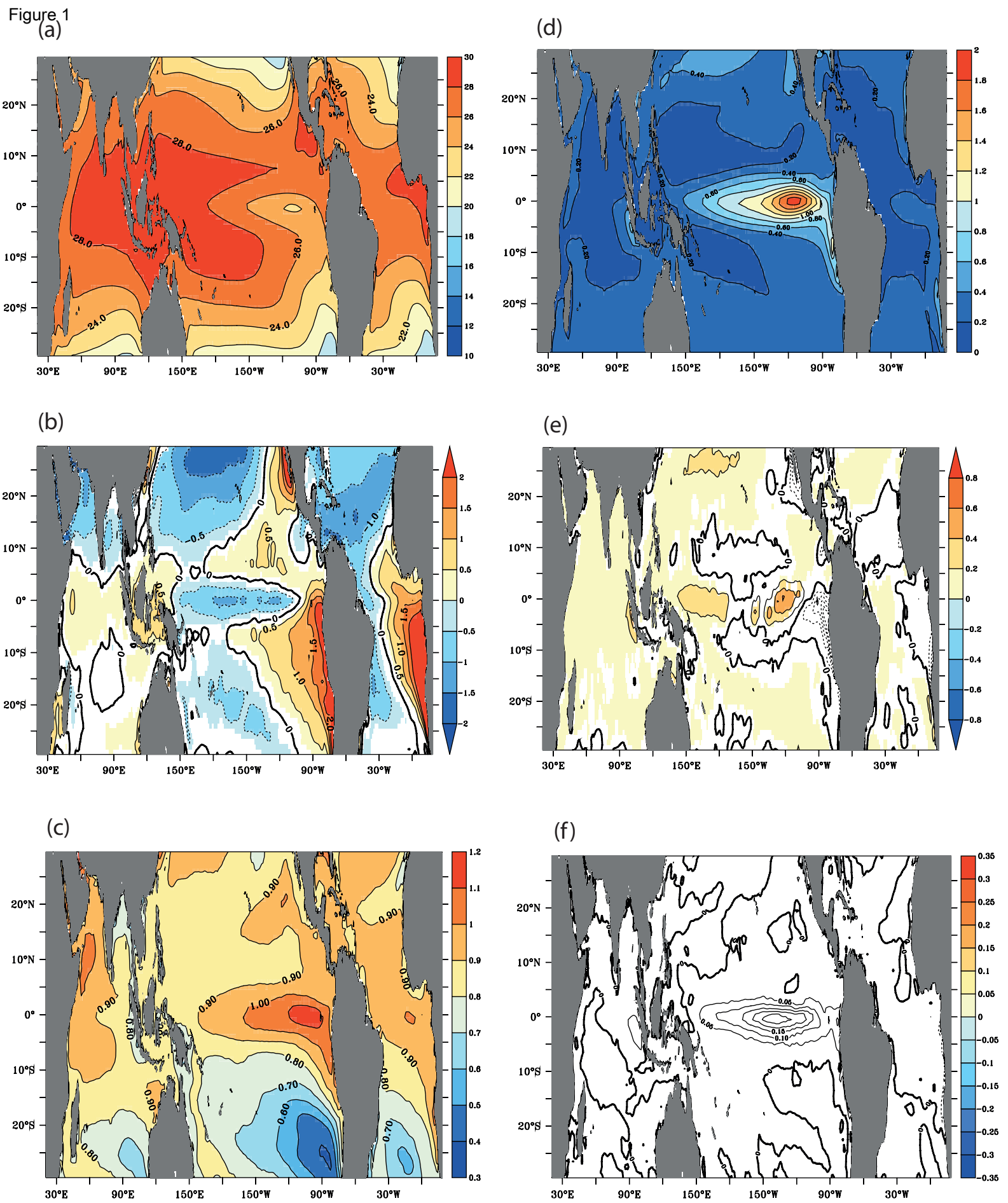


Fig. 1 a) Ensemble annual mean SST ( $^{\circ}\text{C}$ ) from the CMIP5 H simulations, b) annual mean bias ( $^{\circ}\text{C}$ ) of the CMIP5 H ensemble relative to HadISST dataset, c) difference ( $^{\circ}\text{C}$ ) in annual mean SST between H and RCP 8.5 simulations of CMIP5 models, d) Ensemble mean variance ( $^{\circ}\text{C}^2$ ) from the detrended CMIP5 H simulations, e) mean variance bias ( $^{\circ}\text{C}^2$ ) of the detrended CMIP5 H ensemble relative to detrended HadISST dataset, f) difference ( $^{\circ}\text{C}^2$ ) in mean variance between detrended H and RCP 8.5 simulations of CMIP5 models. The RCP 8.5 simulations, changes are given for the period 2006-2050 relative to the period 1958-2005 in the H simulations of the CMIP5 models. The shaded regions in Fig. 1b, c, e, and f are statistically significant at the 90% confidence level according to a Student t or F tests (von Storch and Zwiers 1999)

Figure 2

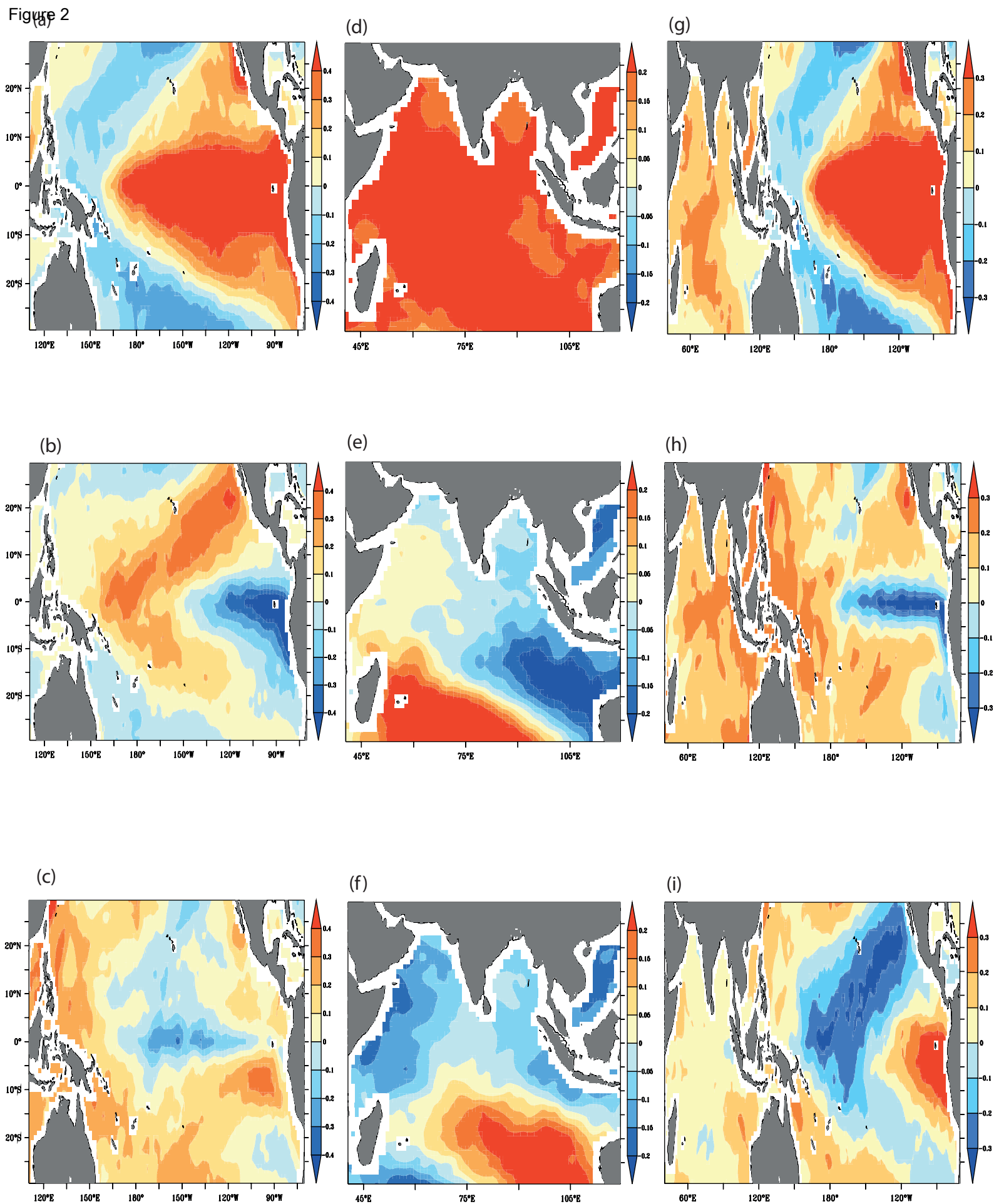


Fig. 2 : The first three leading EOF modes for the TP (a) – (c), TIO (d) – (f) and TIP (g) – (i) estimated from the “raw” monthly SSTA, i.e. before detrending. The percentage of variance explained by the corresponding EOF is listed in Table 2.

Figure 3

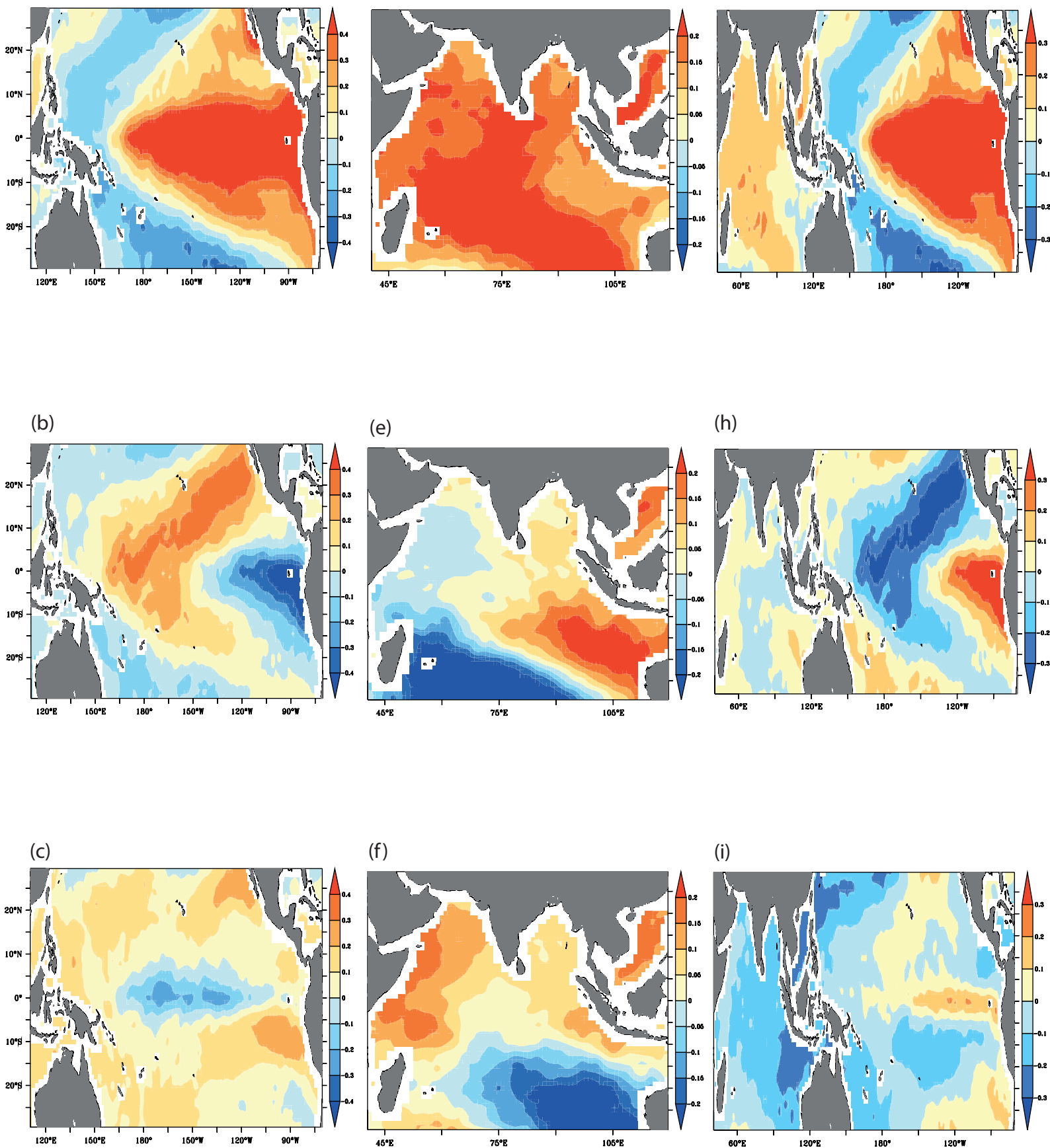


Fig. 3 : As in Fig. 2, but for the first three spatial EOFs of TP (a) – (c), TIO (d) – (f) and TIP (g) – (i) domains after detrending the SSTA. The percentage of variance explained by the corresponding EOF is listed in Table 2.

Figure 4

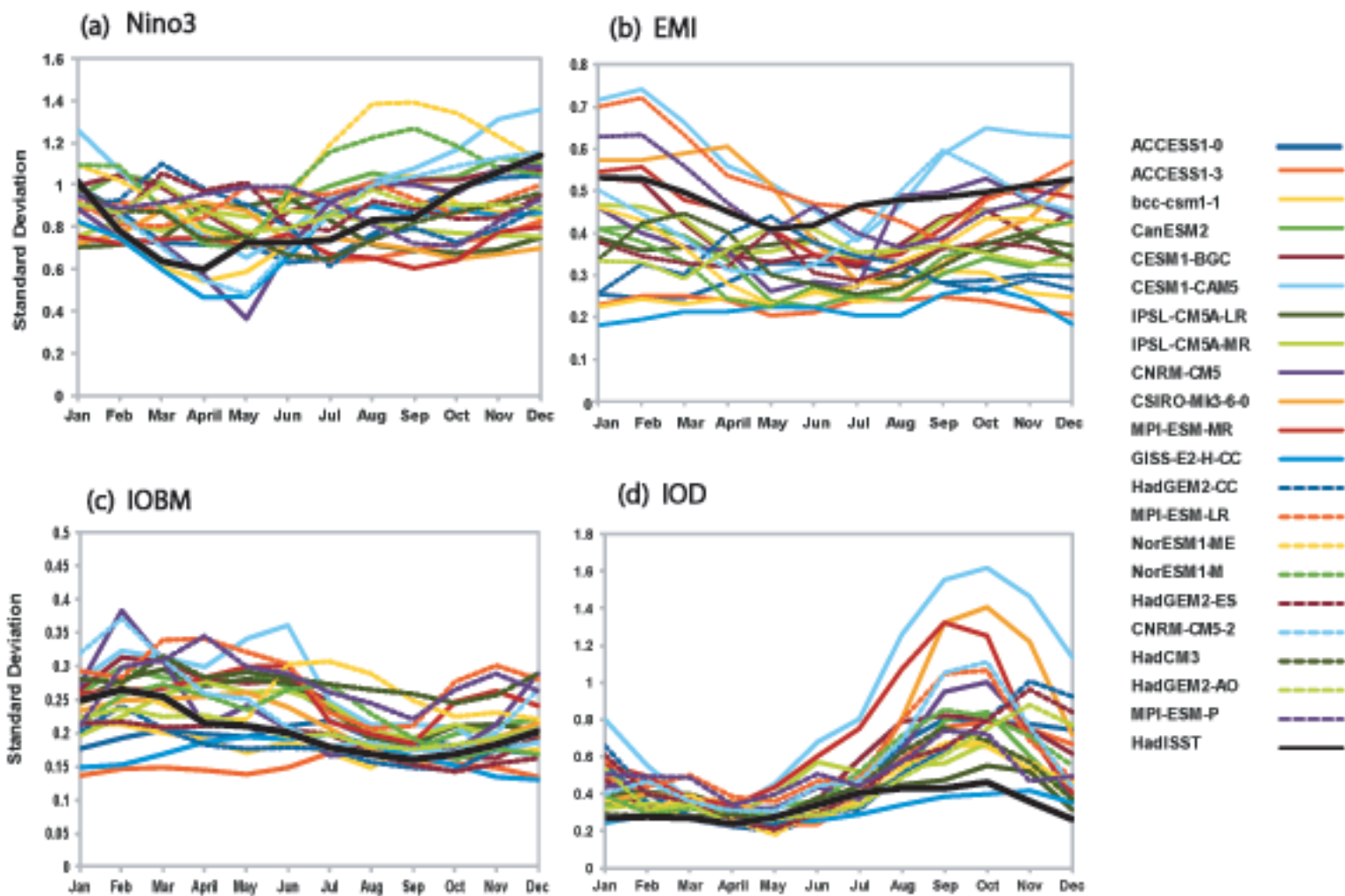
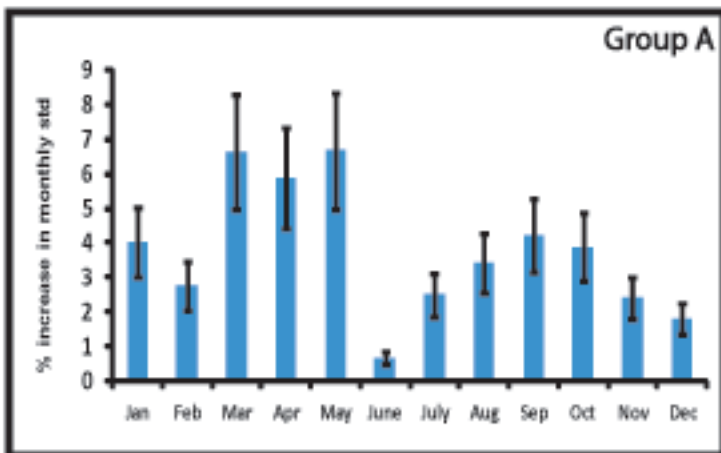


Fig. 4 : Monthly Standard Deviation (SD) of a) Niño3, b) EMI, c) IOBM and d) IOD indices in CMIP5 H simulations. The black curve in each panel denotes the SD from HadISST dataset.

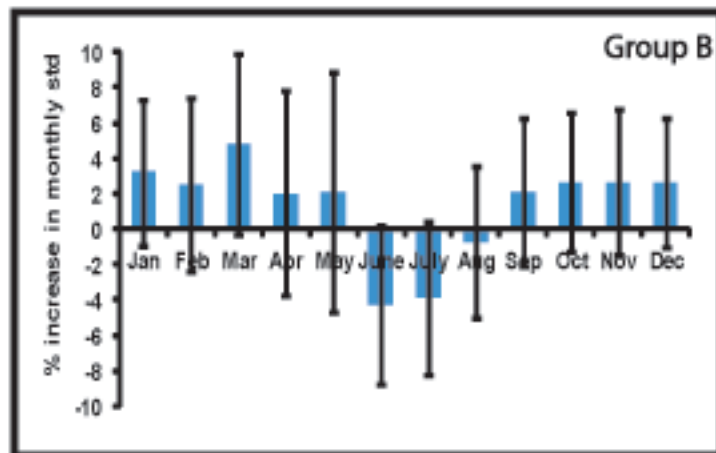


Figure 5

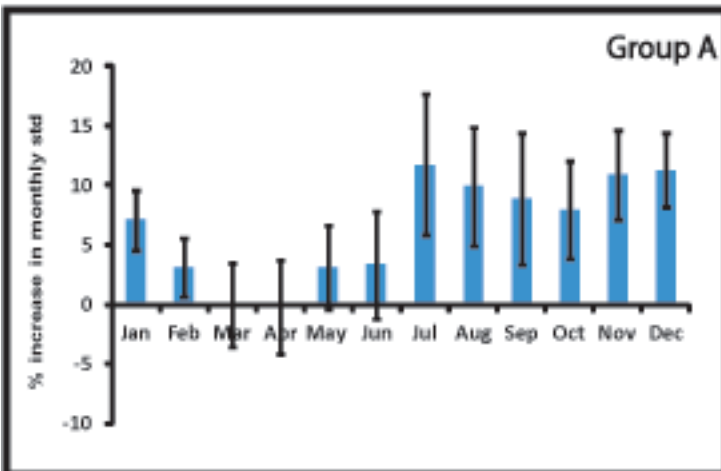
(a) Nino3



(b) Nino3



(c) EMI



(d) EMI

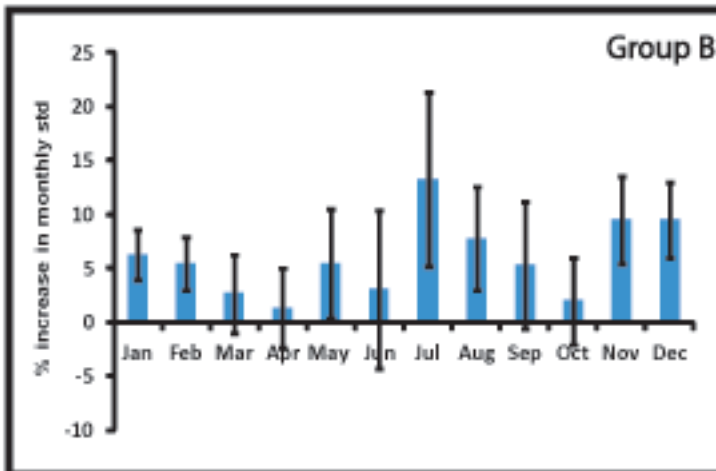
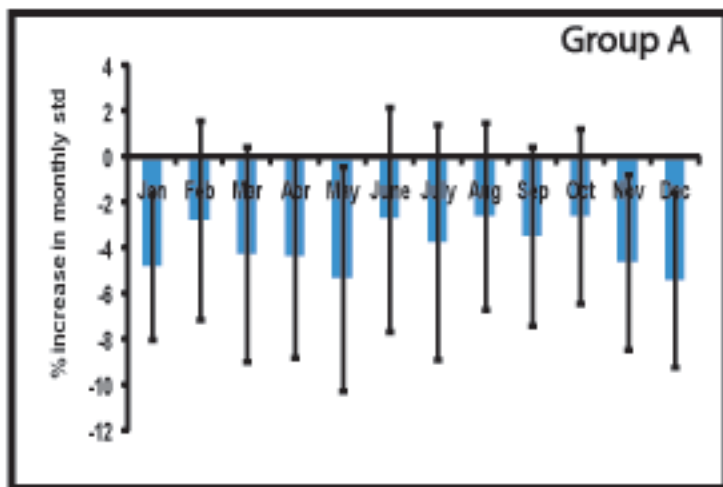


Fig. 5: Percent change in monthly SD of multi-model mean from H to RCP 8.5 of a) Nino3 for Group A, b) Nino3 for Group B, c) EMI for Group A, d) EMI for Group B. The error bars denote the SD of inter-model variability.

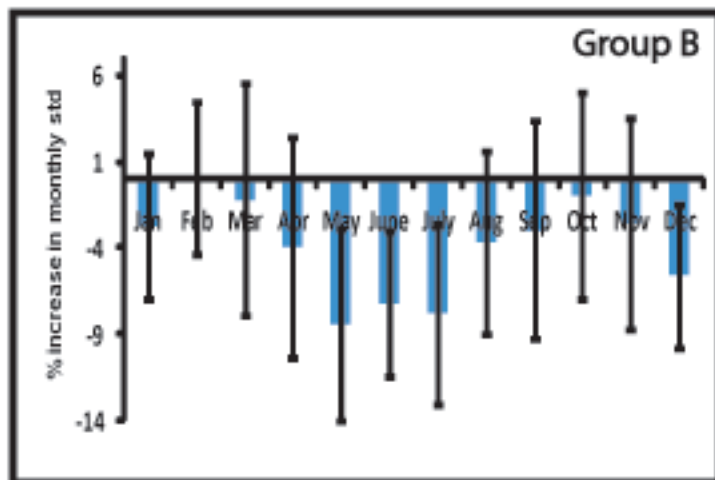


Figure 6

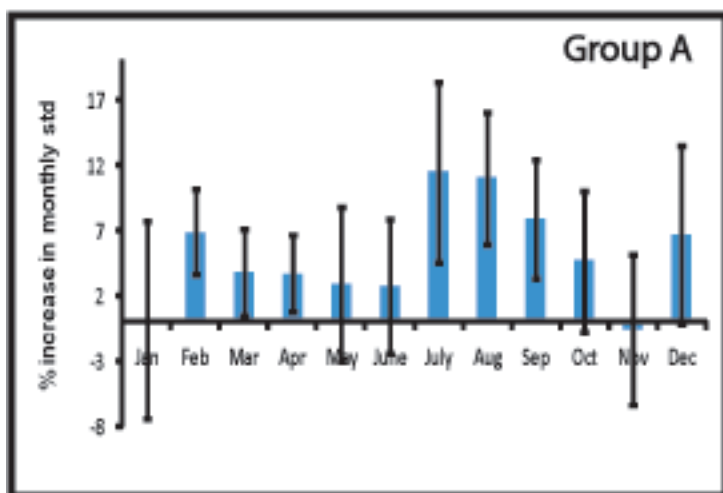
(a) IOBM



(b) IOBM



(c) IOD



(d) IOD

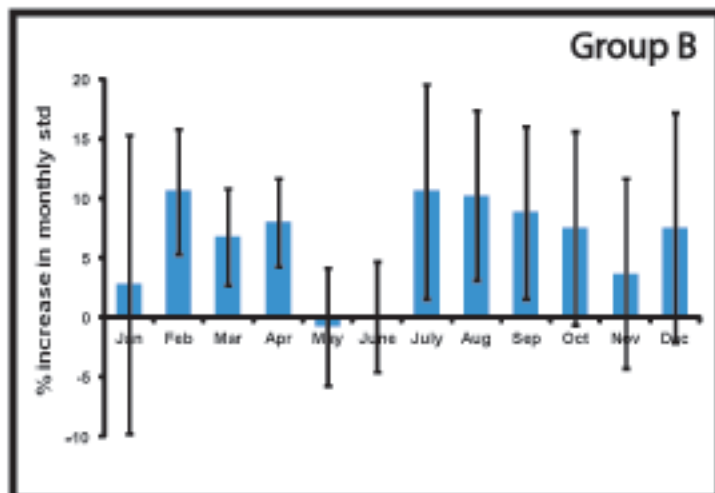


Fig. 6: Percent change in monthly SD of multi-model mean from H to RCP 8.5 of a) IOBM for Group A, b) IOBM for Group B, c) IOD for Group A, d) IOD for Group B. The error bars denote the SD of inter-model variability.

Figure 7

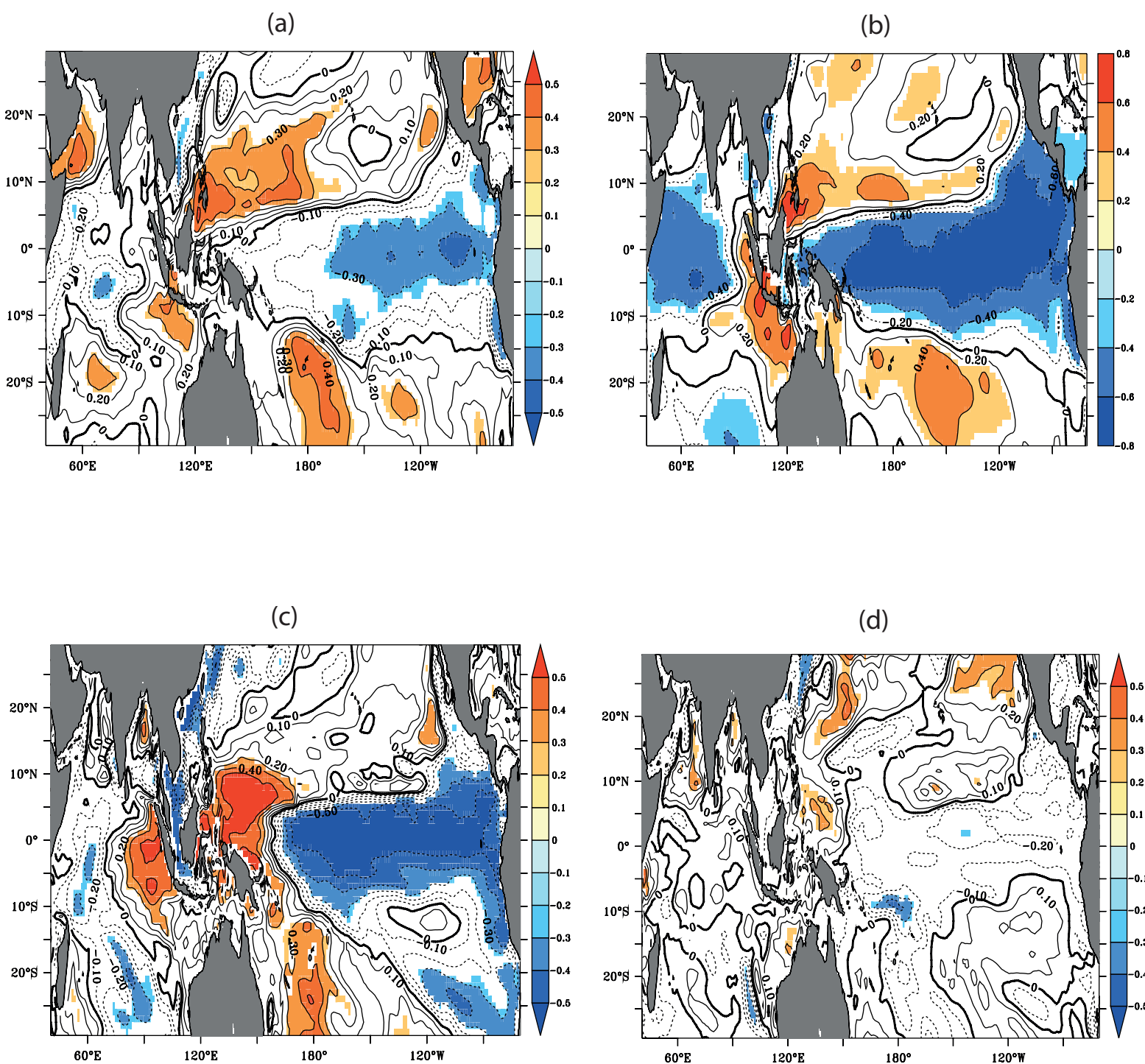


Fig. 7 : Lead correlation patterns between (a) (b) IOBM during MAM of year 0 using GISS-E2-H-CC model and (c) (d) IOD during SON of year -1 using ACCESS1-0 model and SSTA in D(year 0)JF(year+1). The shaded regions are statistically significant at the 90% confidence level according to a 2-tailed Student's t-test. Panels(a) and (c) are plotted using H simulations (1958-2005), and (b) and (d) are plotted using RCP 8.5 simulations (2006-2050).

Figure 8

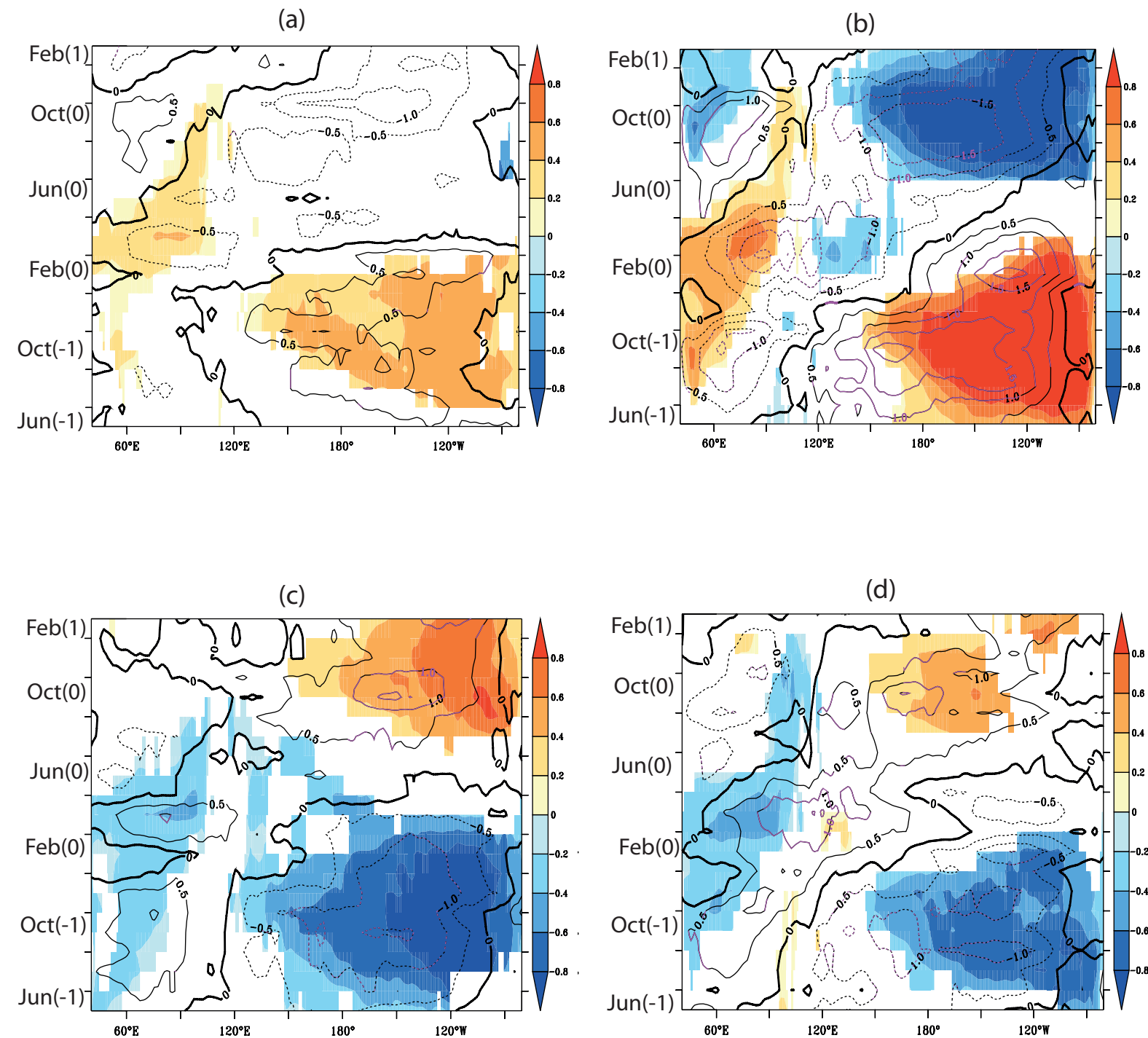


Fig. 8: 5°S–5°N averaged Hovmöller composite of SST (shading, °C) and 850-hPa zonal wind (contour, ms<sup>-1</sup>) anomalies in the TIP domain starting from June of year -1(bottom) to February of year +1(top) as simulated by the GISS-E2-H-CC model. Positive IOBM events in year 0 for (a) H and (b) RCP8.5 simulations. Negative IOBM events in year 0 for (c) H and (d) RCP8.5 simulations. Black bold contours represent zero 850-hPa zonal wind anomalies and dashed contours indicate negative values (e.g. easterly 850-hPa winds). Only significant SSTA above the 90% confidence level are shown (shading). Significant wind anomalies above the 90% confidence level are shown by purple contours. See text for more details.

Figure 9

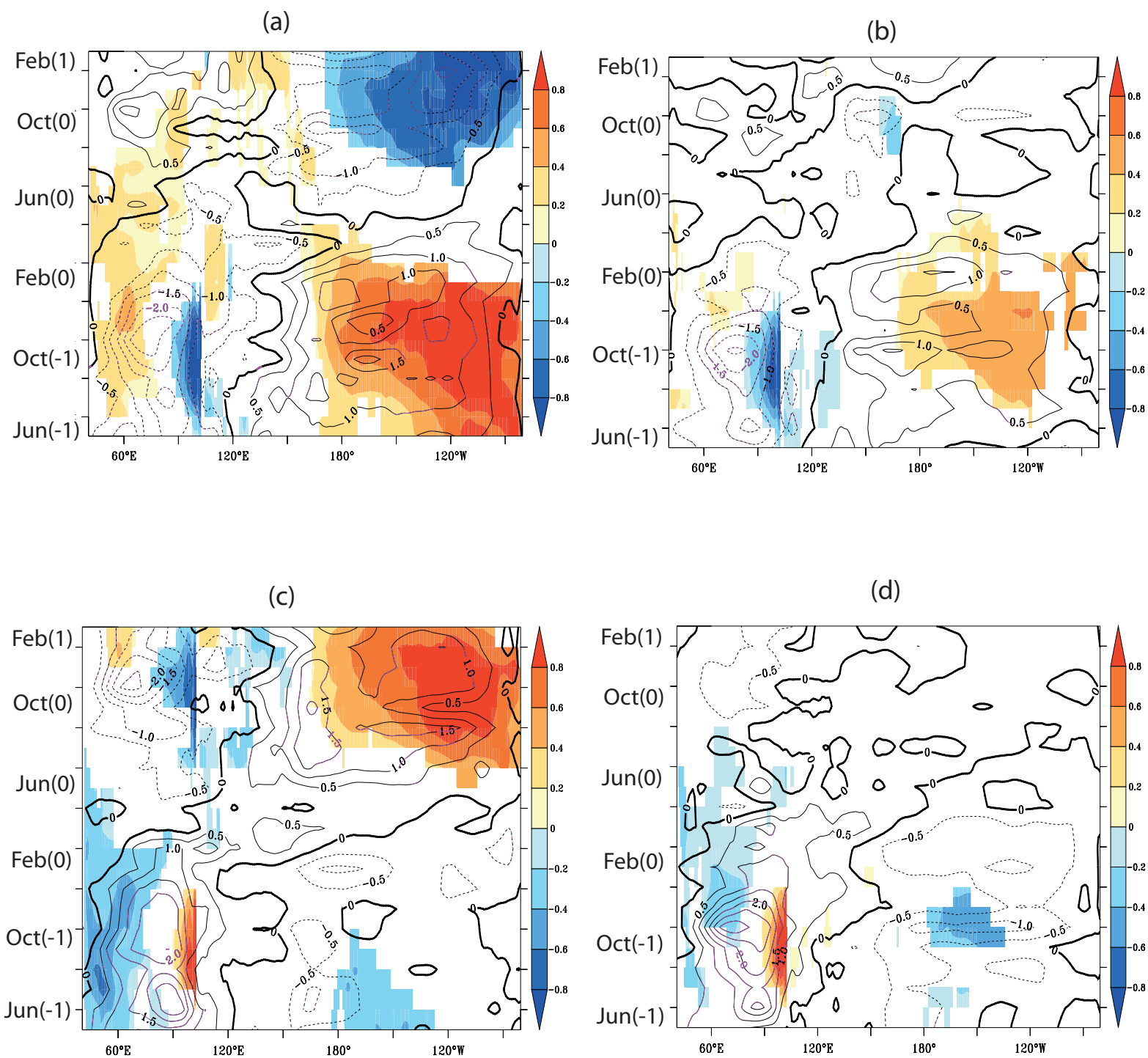


Fig. 9: 5°S–5°N averaged Hovmöller composite of SST (shading, °C) and 850-hPa zonal wind (contour, ms<sup>-1</sup>) anomalies in the TIP domain starting from June of year -1 (bottom) to February of year +1 (top) as simulated by the ACCESS1-0 model. Positive IOD events in year -1 for (a) H and (b) RCP8.5 simulations. Negative IOD events in year -1 for (c) H and (d) RCP8.5 simulations. Black bold contours represent zero 850 hPa zonal wind anomalies and dashed contours indicate negative values (e.g. easterly 850-hPa winds). Only significant SSTA above the 90% confidence level are shown (shading). Significant wind anomalies above the 90% confidence level are shown by purple contours. See text for more details.

**Table 1:**List of CMIP5 models along with their modeling groups and resolution.

<b>Model</b>	<b>Institution</b>	<b>Resolution (latitude× longitude)</b>
ACCESS1.0	Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology, (BOM), Australia	300 × 360
ACCESS1.3	Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology,(BOM), Australia	300 × 360
BCC-CSM1-1	Beijing Climate Center, China Meteorological Administration, China	232 × 360
CCSM4	National Center for Atmospheric Research, USA	384 × 320
CanESM2	Canadian Centre for Climate Modeling and Analysis, Canada	192 × 256
CESM1-BGC	NSF-DOE-NCAR	384 × 320
CESM1-CAM5	NSF-DOE-NCAR	384 × 320
CESM1-WACCM	NSF-DOE-NCAR	384 × 320
CNRM-CM5	Centre National de RecherchesMeteorologiques and Centre Europeen de Recherche et Formation Avancees en CalculScientifique	292 × 362
CNRM-CM5-2	Centre National de RecherchesMeteorologiques and Centre Europeen de Recherche et Formation Avancees en CalculScientifique	292 × 362
CSIRO-Mk3.6.0	Commonwealth Scientific and Industrial Research Organization in collaboration with the Queensland Climate Change Centre of Excellence, Australia	189 × 192
EC-EARTH		292 × 362
GFDL-ESM2M	Geophysical Fluid Dynamics Laboratory, USA	200 × 360
GISS-E2-H	NASA Goddard Institute for Space Studies, NY	90 × 144
GISS-E2-H-CC	NASA Goddard Institute for Space Studies, NY	90 × 144
GISS-E2-R	NASA Goddard Institute for Space Studies, NY	90 × 144
GISS-E2-R-CC	NASA Goddard Institute for Space Studies, NY	90 × 144
HadCM3	Met Office Hadley Centre, UK	144 × 288

HadGEM2-AO	National Institute of Meteorological Research/Korea Meteorological Administration, South Korea	216 × 360
HadGEM2-CC	Met Office Hadley Centre, UK	216 × 360
HadGEM2-ES	Met Office Hadley Centre, UK	216 × 360
INM-CM4	Institute for Numerical Mathematics, Russia	340 × 360
IPSL-CM5A-LR	Institute Pierre-Simon Laplace, France	149 × 182
IPSL-CM5A-MR	Institute Pierre-Simon Laplace, France	149 × 182
MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan	224 × 256
MPI-ESM-LR	Max Planck Institute for Meteorology (MPI-M), Germany	220 × 256
MPI-ESM-MR	Max Planck Institute for Meteorology (MPI-M), Germany	404 × 802
MPI-ESM-P	Max Planck Institute for Meteorology (MPI-M), Germany	220 × 256
MRI-CGCM3	Meteorological Research Institute, Japan	368 × 360
MRI-ESM1	Meteorological Research Institute, Japan	368 × 360
NorESM1-M	Norwegian Climate Centre, Norway	384 × 320
NorESM1-ME	Norwegian Climate Centre, Norway	384 × 320

**Table 2:** Explained variances of the first three leading EOF modes using “raw” and detrended SSTA over three domains viz., TP, TIO and TIP for the 1958-2005 period.

	Explained variance (%)			Explained variance (%)		
	Raw data			Detrended data		
	EOF1	EOF2	EOF3	EOF1	EOF2	EOF3
TP	41.8	10.3	8.0	43.5	10.8	4.7
TIO	39.9	13.2	8.6	29.2	15.9	10.1
TIP	37.9	9.7	8.8	39.4	9.6	2



**Table 3:** List of CMIP5 models, ranked according to normalized RMSE values computed from the first 8 reference EOF modes estimated from detrended TIP SSTA in the HadISST dataset for the 1958-2005 period. The normalized RMSE statistics for TP and TIO domains are also shown to assess the robustness of the ranking of the CMIP5 models with respect to the domain definition.

<b>Rank</b>	<b>TIP</b>	<b>TP</b>	<b>TIO</b>	<b>Model</b>
1.	0.06	0.07	0.62	MPI-ESM-P
2.	0.12	0.11	0.21	HadGEM2-ES
3.	0.12	0.13	0.2	NorESM1-M
4.	0.16	0.17	0.68	CSIRO-Mk3-6-0
5.	0.16	0.16	0.24	HadGEM2-AO
6.	0.17	0.18	0.46	CNRM-CM5-2
7.	0.18	0.18	0.41	CanESM2
8.	0.18	0.18	0.92	HadCM3
9.	0.19	0.19	0.33	IPSL-CM5A-MR
10.	0.20	0.16	0.64	MPI-ESM-LR
11.	0.22	0.24	0.32	CESM1-BGC
12.	0.25	0.26	0.32	IPSL-CM5A-LR
13.	0.25	0.27	0.49	MPI-ESM-MR
14.	0.25	0.26	0.39	CNRM-CM5
15.	0.26	0.25	0.2	ACCESS1-0
16.	0.29	0.29	0.19	HadGEM2-CC
17.	0.30	0.31	0.39	NorESM1-ME
18.	0.32	0.31	0.34	ACCESS1-3
19.	0.40	0.4	0.93	CESM1-CAM5
20.	0.46	0.45	0.36	GISS-E2-H-CC
21.	0.47	0.45	0.21	BCC-CSM1-1
22.	0.59	0.58	0.3	GISS-E2-H
23.	0.59	0.59	0.72	CESM1-WACCM
24.	0.60	0.64	0.5	CCSM4
25.	0.60	0.61	0.24	EC-EARTH
26.	0.63	0.63	0.27	GISS-E2-R
27.	0.66	0.66	0.39	MRI-CGCM3
28.	0.66	0.67	0.33	MRI-ESM-1
29.	0.69	0.71	0.2	GISS-E2-R-CC
30.	0.71	0.69	0.63	INMCM4
31.	1.448	1.43	1.61	GFDL-ESM-2M
32.	1.579	1.51	1.7	MIROC5



**Table 4:** Classification of the CMIP5 models according to their ability to simulate the phase-locking of canonical ENSO events to the seasonal cycle, see text for details. Group A consists of all sixteen models, which have both H and RCP 8.5 simulations. The correlation coefficients between the monthly SD of Niño3 SST for each model and observations are computed and shown in the last column. The models with a positive correlation coefficient significant at 90% confidence level are shown in bold and are classified as Group B.

<b>Sr. No.</b>	<b>Group A</b>	<b>Correlation between Niño3 index of models and observation</b>
1.	NorESM1-M	<b>0.51</b>
2.	CSIRO-Mk3-6-0	-0.78
3.	CanESM2	<b>0.62</b>
4.	IPSL-CM5A-MR	-0.8
5.	MPI-ESM-LR	0.36
6.	CESM1-BGC	<b>0.64</b>
7.	IPSL-CM5A-LR	-0.61
8.	MPI-ESM-MR	0.18
9.	CNRM-CM5	<b>0.73</b>
10.	ACCESS1-0	<b>0.89</b>
11.	HadGEM2-CC	-0.3
12.	NorESM1-ME	<b>0.55</b>
13.	ACCESS1-3	0.2
14.	CESM1-CAM5	<b>0.9</b>
15.	GISS-E2-H-CC	<b>0.71</b>
16.	BCC-CSM1-1	<b>0.57</b>

**Table 5:** Multi model “simultaneous” correlations between IOBM, IOD and Nino3 for H and RCP 8.5 simulations for all models in Groups A and B. The values in parenthesis denote the SD of inter-model correlation for the different pairs of climate indexes. Values in bold are statistically significant at the 90% confidence level according to a 2-tailed Student’s t-test. Each index is computed during its peak season and for each couple of indexes, the first index is leading the second one. See text for more details.

	IOD & IOBM		IOD & Nino3		Nino3 & IOBM	
	H	RCP 8.5	H	RCP 8.5	H	RCP 8.5
<b>Observation</b>	<b>0.47</b>		<b>0.67</b>		<b>0.81</b>	
<b>Group A</b>	<b>0.41</b> (0.18)	<b>0.43</b> (0.21)	<b>0.42</b> (0.2)	<b>0.38</b> (0.25)	<b>0.63</b> (0.13)	<b>0.67</b> (0.12)
<b>Group B</b>	<b>0.46</b> (0.16)	<b>0.52</b> (0.18)	<b>0.53</b> (0.16)	<b>0.54</b> (0.19)	<b>0.63</b> (0.14)	<b>0.69</b> (0.12)

**Table 6:** Multi-model mean of lead correlations between IOD (year 0) and IOBM (year +1) during their peak season and Niño3 index in the following year (e.g. year +1) in H and RCP 8.5 simulations for both Groups A and B models. The values in parenthesis denote the SD of inter-model correlation for the different pairs of climate indexes. Values in bold are statistically significant at the 90% confidence level according to a 2-tailed Student's t-test.

	<b>Historical</b>	<b>RCP 8.5</b>	<b>Historical</b>	<b>RCP 8.5</b>
<b>Fix Moving</b>	<b>IOD Niño3</b>	<b>IOD Niño3</b>	<b>IOBM Niño3</b>	<b>IOBM Niño3</b>
	<b>IOD leads</b>	<b>IOD leads</b>	<b>IOBM leads</b>	<b>IOBM leads</b>
<b>Observation</b>	<b>-0.39</b>		-0.17	
<b>Group A</b>	<b>-0.35</b> (0.16)	<b>-0.32</b> (0.2)	-0.17 (0.22)	<b>-0.32</b> (0.22)
<b>Group B</b>	<b>-0.41</b> (0.1)	<b>-0.35</b> (0.17)	<b>-0.32</b> (0.09)	<b>-0.43</b> (0.19)

**Table 7:** Multi-model mean of coefficient of determination for multiple linear prediction of Niño3 SST in DJF of year+1 (e.g. D of year 0 and JF of year +1) using different predictors from observations, H and RCP 8.5 simulations for both groups A and B. The values in parenthesis denote the SD of inter-model coefficient of determination.

<b>Nino3(1)</b>	<b>Group A</b>		<b>Group B</b>		<b>Observation</b>
	<b>Historical</b>	<b>RCP 8.5</b>	<b>Historical</b>	<b>RCP 8.5</b>	
<b>Nino3 (0)</b>	0.06 (0.09)	0.05 (0.1)	0.09 (0.1)	0.09 (0.12)	0.02
<b>IOBM(0)</b>	0.07 (0.07)	0.15 (0.16)	0.1 (0.06)	0.22 (0.18)	0.03
<b>IOD(-1)</b>	0.14 (0.08)	0.14 (0.12)	0.17 (0.08)	0.15 (0.12)	0.14
<b>Nino3(0), IOBM(0)</b>	0.11 (0.09)	0.18 (0.17)	0.16 (0.08)	0.26 (0.18)	0.03
<b>Nino3(0), IOD(-1)</b>	0.18 (0.08)	0.18 (0.13)	0.22 (0.07)	0.19 (0.14)	0.15
<b>IOBM(0), IOD(-1)</b>	0.18 (0.08)	0.20 (0.16)	0.2 (0.07)	0.25 (0.18)	0.14
<b>Nino3(0), IOD(-1), IOBM(0)</b>	0.22 (0.08)	0.25 (0.17)	0.26 (0.06)	0.29 (0.18)	0.17

**Table 8:** Multi-model mean of adjusted coefficient of determination (adjusted  $R^2$ ) for multiple linear prediction of Niño3 SST in DJF of year +1 (e.g. D of year 0 and JF of year +1) using different predictors from observations, H and RCP 8.5 simulations for both groups A and B. The values in parenthesis denote the SD of inter-model adjusted coefficient of determination.

<b>Nino3(1)</b>	<b>Group A</b>		<b>Group B</b>		<b>Observation</b>
	<b>Historical</b>	<b>RCP 8.5</b>	<b>Historical</b>	<b>RCP 8.5</b>	
<b>Nino3 (0)</b>	0.04 (0.09)	0.04 (0.1)	0.07 (0.1)	0.07 (0.12)	0.003
<b>IOBM(0)</b>	0.05 (0.07)	0.13 (0.17)	0.08 (0.07)	0.2 (0.18)	0.01
<b>IOD(-1)</b>	0.12 (0.09)	0.12 (0.12)	0.15 (0.08)	0.13 (0.12)	0.12
<b>Nino3(0), IOBM(0)</b>	0.07 (0.09)	0.14 (0.17)	0.12 (0.09)	0.23 (0.18)	-0.01
<b>Nino3(0), IOD(-1)</b>	0.14 (0.09)	0.14 (0.14)	0.19 (0.07)	0.15 (0.15)	0.11
<b>IOBM(0), IOD(-1)</b>	0.14 (0.08)	0.17 (0.17)	0.17 (0.08)	0.21 (0.19)	0.1
<b>Nino3(0), IOD(-1), IOBM(0)</b>	0.16 (0.08)	0.19 (0.18)	0.21 (0.06)	0.24 (0.2)	0.11



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