

# *Evaluation of easterly wave disturbances over the tropical South Atlantic in CMIP6 models*

Article

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47    **1      Introduction**

48    Northeast Brazil (NEB), encompassing the states of Alagoas (AL), Sergipe (SE), and the eastern Bahia (BA),  
 49    Pernambuco (PE), Paraíba (PB), and Rio Grande do Norte (RN), comprises ~18% of Brazil's territory and is home  
 50    to ~60 million inhabitants. In recent years, the region has witnessed significant investments in the industrial and  
 51    agro-industrial sectors, establishing it as the third-largest economy in Brazil, following the Southeast and South  
 52    regions. Due to its vast expanse and diverse physical characteristics, NEB can be divided into sub-regions with  
 53    distinct climates and precipitation regimes. Oliveira et al. (2017) identified five such sub-regions based on rainfall  
 54    characteristics: north coast, south coast, north semiarid, south semiarid, and northwest. The lowest total annual  
 55    precipitation occurs in the north (654.09 mm year<sup>-1</sup>) and south (810.42 mm year<sup>-1</sup>) semiarid regions, while the  
 56    north coast and northwest NEB regions experience the highest annual precipitation (1450 mm year<sup>-1</sup>). Rodrigues et  
 57    al. (2020) observed distinct rainy seasons across NEB, with precipitation occurring between February and May in  
 58    the north, April and July on the north coast, and December and March in the south and semiarid coast.

59    The spatial and temporal variability of rainfall regimes in NEB is influenced by a myriad of global,  
 60    synoptic and regional-scale processes. At the synoptic scale, various processes influence the NEB's precipitation  
 61    regime. These include the penetration of cold fronts or their remnants between latitudes 5°S and 18°S (Kousky  
 62    1979; Molion and Bernardo 2002), the Intertropical Convergence Zone (ITCZ) (Hastenrath and Heller 1977;  
 63    Nobre 1993; Nobre and Shukla 1996; Melo 2009), Upper-Tropospheric Cyclonic Vortices (UTCV) (Kousky and  
 64    Gan 1981; Gan and Kousky 1986; Alves 2001; Oliveira et al. 2017; Dos Reis et al. 2021), Mid-Tropospheric  
 65    Cyclonic Vortices (Fedorova et al. 2016), and Easterly Wave Disturbances (EWD) (Neiva 1975; Yamazaki and  
 66    Rao 1977; Ferreira et al. 1990; Pontes da Silva 2011; Gomes et al. 2015; Gomes et al. 2019). For example,  
 67    Oliveira et al. (2017) emphasize the importance of UTCV and the South Atlantic Convergence Zone (SACZ) in  
 68    shaping NEB's precipitation regime, highlighting mechanisms that lead to dry periods in the south coasts and  
 69    rainy periods in the north coasts.

70    EWDs are transient synoptic-scale disturbances, propagating from east to west in the trade wind region,  
 71    that significantly contribute to NEB's precipitation, with over half of the total annual precipitation in the eastern  
 72    NEB is associated with these systems (Gomes et al. 2019). These disturbances as evidenced by those two recent  
 73    extreme precipitation events in east coast of NEB during 2022 and 2023 (Lyra et al. 2024; Freitas 2022; Portela  
 74    2022). EWD activity can be observed in all tropical ocean basins with peaked between latitudes of 10-15° in both  
 75    hemispheres during warmer months (Hollis et al. 2023). Its frequency also varies across regions and atmospheric  
 76    levels, notably at 700 hPa (South Atlantic Ocean, South Pacific Ocean) or 850 hPa (central North Pacific Ocean,  
 77    South Indian Ocean), with 700 hPa showing higher activity (Hollis et al. 2023). While studies on EWDs in the  
 78    Southern Hemisphere (SH) are limited compared to the NH, recent efforts have been made to characterize these  
 79    systems, particularly in the Tropical South Atlantic (TSA) basin close to the Brazilian coast. However, challenges  
 80    arise from the variability in EWD structure and characteristics, influenced by their propagation within zonal  
 81    currents and seasonal variations (Asnani 1993). Different identification methods and study periods used in  
 82    previous research have resulted in discrepancies in the observed characteristics of EWDs, albeit with some notable  
 83    similarities (Table 1).

84    **Table 1** Characteristics of EWDs over the Tropical South Atlantic Basin according to referenced studies.

85    For identifying and tracking EWDs in this region, Gomes et al. (2015) used an automated method, called TRACK,  
 86    based on Hodges (1995, 1999), who developed it for tracking EWDs on the East African coast (Hopsch et al.

2007; Serra et al. 2010; Thorncroft and Hodges 2001). Applying this tracking method on 21 years (1989-2009) of European Centers for Medium-Range Weather Forecasting interim reanalysis (ERA1) data, Gomes et al. (2019) successfully tracked 342 EWDs out of 518 manually detected EWDs in the TSA, a success rate of 66%. The majority of the untracked EWDs formed very close to the coast of the continent and were filtered out due to the selection criteria. Gomes et al. (2019) observed that 97% of the EWDs reached the NEB coast during their evolution, 64% showed significant convective characteristics and 14% reached the Amazon region. The highest frequency of EWDs was found between April and August (rainy season), with 429 cases identified, which accounted for 60% of the total precipitation from the coast of Alagoas to the east of Paraíba. The other months presented less than half of the cases, where the periods with the lowest frequency are between October and December, and are more frequent in La Niña years, especially in years with stronger or longer-lasting ENSO episodes. Regarding the genesis of EWDs, the authors identified five associated systems. The main contributor is frontal remnants that propagate at low latitudes, accountig for 72.20% of cases. Convective clusters of the west coast of Africa contribute to 10.04% cases, followed by the ITCZ at 6.37%, and UTCV at 1.54%.

To explore these complex characteristics of the EWDs, numerical models have become indispensable. In particular, the Coupled Model Intercomparison Project (CMIP) models (Eyring et al. 2016) have been instrumental across different regions of the globe (e.g., Dong and Dong 2021; Ngoma et al. 2021; Shiru and Chung 2021; Babaousmail et al. 2021). Studies evaluating CMIP6 model performance over South America reveal mixed results, with challenges in accurately reproducing precipitation characteristics (e.g., Rivera and Arnould 2020; Ortega et al. 2021), particularly during monsoon seasons (Dias et al. 2021). While some models excel the results of Firpo et al. (2022) showed better model performance in reproducing spatial patterns of winter (JJA) precipitation, others struggle, especially in regions like NEB (Firpo et al. 2022). Model limitations in simulating cloud physics and the Low-Level Jet Stream contribute to discrepancies in summer precipitation estimates, with underestimations in the Amazon region and overestimations in NEB (Reboita et al. 2010; Firpo et al. 2022). Despite these challenges, models generally captured the annual cycle of precipitation over NEB, albeit with some overestimations during wet months.

Further evaluations across various CMIP model generations (CMIP3, CMIP5, and CMIP6) underscores deficiencies in representing precipitation and climate extremes in tropical SA (Medeiros et al. 2022). Model performance varied depending on the specific index investigated and the macro-region of Brazil under consideration, with pronounced uncertainties in the north and northeast, and lower uncertainties in the south and southeast. Although no single model emerged as superior, CMIP6 models exhibited better performance over north, southeast, and south regions compared to earlier versions. However, challenges persists in accurately simulating key meteorological features that characterize the climate in various regions of South America, such as the ITCZ, Subtropical and polar jet streams, Bolivian High, and the NEB trough (Bazzanella et al. 2023), particularly in summer months. Common characteristics observed across all models include superior performance in winter, a double trend of the ITCZ in both summer and winter, underestimation of precipitation in northern Brazil, and overestimation on the west coast of South America and NEB during summer.

Understanding how climate models simulate observed historical climate provides useful information about their reliability in projecting future climate change. Hence, this study aims to evaluate the CMIP6 models' ability to capture the characteristics of EWDs over the TSA during peak activity period (April to August) in the current climate. Through comprehensive evaluation and comparison with observational data, this study seeks to contribute to better understanding of model performance and its implications for future climate projections. The rest of the

128 paper is organized as follows: Section 2 describes data and methods, Section 3 discusses results, followed by  
129 conclusions in Section 4.

130 **2 Material and methods**

131  
132 The choice of the study area (Fig. 1; 5°N-20°S and 0°-60°W) was driven by our objective to capture the nuanced  
133 variations in precipitation patterns within the NEB and the adjacent TSA. The study area encompasses most of the  
134 Brazilian territory, including the entire NEB and parts of the Brazilian north and southeast regions, and the TSA  
135 covering the entire coastline of the NEB extending toward the West African coast. To better represent the different  
136 precipitation regimes within the NEB and the variety of meteorological systems that influence this region, the total  
137 area was divided into 8 subareas: area 1 (5-15°S and 45-40°W) represents the semiarid region; area 2 (5-15°S and  
138 40-35°W) represents the NEB coast; areas 3 (5-15°S and 35-30°W) and 4 (5-15°S and 30-25°W) represent the  
139 path of EWDs until they reach the NEB; and areas 5.1 (5°N-0° and 35-20°W), 5.2 (0-5°S and 35-20°W), 6.1 (5°N-  
140 0° and 20-5°W), and 6.2 (0-5°S and 20-5°W) represent the ITCZ region, divided to better represent its seasonal  
141 displacement.

142 **Fig. 1** The study area (5°N-20°S and 0°-60°W) and its 8 subareas: 1 (5-15°S and 45-40°W) represents the semiarid  
143 region; area 2 (5-15°S and 40-35°W) represents the NEB coast; 3 (5-15°S and 35-30°W) 4 (5-15°S and 30-25°W)  
144 represent the path of EWDs until they reach the NEB; and 5.1 (5°N-0° and 35-20°W), 5.2 (0-5°S and 35-20°W),  
145 6.1 (5°N-0° and 20-5°W), and 6.2 (0-5°S and 20-5°W) represent the ITCZ region.

146 In CMIP phase 6, substantial updates were introduced compared to the prior phase (Eyring et al. 2016).  
147 Notably, this phase includes the CMIP's historical simulations and the Diagnostic, Assessment, and  
148 Characterization of Klima (DECK) framework, which contains the Atmospheric Model Intercomparison Project  
149 (AMIP) historical simulations. This aims to ensure model continuity and preserve fundamental characteristics  
150 across CMIP phases. An innovative addition in this phase is the endorsed Model Intercomparison Projects (MIP),  
151 specifically designed to address targeted questions and bridge scientific gaps from earlier CMIP phases.

152 Outputs from AMIP models and CMIP's historical simulations were utilized at the highest available spatial  
153 resolution (Table 2). Model selection was contingent upon the presence of the first ensemble member (r1i1p1f1)  
154 within the specified analysis scope. Given the relatively small scale of EWDs compared to other synoptic-scale  
155 systems, the High-Resolution Model Intercomparison Project (HighResMIP) was employed with increased  
156 horizontal resolutions of approximately 50 km or 25 km in both the atmosphere and ocean (Haarsma et al., 2016).  
157 Specifically, outputs from coupled models (hist-1950) and atmospheric models (highresSST-present) from the first  
158 level of HighResMIP were considered for this study.

159 **Table 2** Description of the CMIP6 models used in this study.

160 Precipitation estimates from the Global Precipitation Climatology Project Version 3.1 (GPCP; 0.5° x 0.5°;  
161 Huffman et al. 2020; Bazzanella et al. 2023) were used to evaluate model performance. Developed under the  
162 auspices of the World Climate Research Program (WRCP), GPCP provides global monthly precipitation estimates  
163 by combining rain gauge stations, satellite data, and sounding observations. The GPCP dataset is available from  
164 1983. The assessment of model performance was conducted over the common period of 1983-2014, during which  
165 both GPCP and model outputs are available. For consistent comparisons, all data were interpolated to a uniform 1°  
166 x 1° grid resolution.

167 **2.1 Statistical analysis**

168 The robustness of precipitation from each CMIP6 model and their ensembles at both annual and seasonal (April to  
 169 August) time scales are assessed by comparing them to GPCP. The ensembles comprise the mean of all models  
 170 within each model set (CMIP, AMIP, hist-1950, and highresSST-present). Climatological annual and seasonal  
 171 averages were computed from monthly data.

172 For evaluating the coherence of CMIP6 model ensembles against GPCP over the entire study area (Fig. 1),  
 173 we use various statistical measures, such as Arithmetic Mean (Eq. 1), Mean Bias (Eq. 2), and Spread (Eq. 3).  
 174 These parameters represent precipitation values from individual models ( $P_p$ ), ensembles ( $E_p$ ), and GPCP ( $O_p$ ) at  
 175 each grid point ( $n$ ) within the total domain presented in Figure 1.

$$176 \quad MEAN = \frac{1}{n} \sum_{t=1}^n (E_p) \quad (1)$$

$$177 \quad BIAS = \frac{\sum_{p=1}^n E_p}{n} - \frac{\sum_{p=1}^n O_p}{n} \quad (2)$$

$$178 \quad SPREAD = \sqrt{\frac{1}{n} \sum_{p=1}^n (P_p - E_p)^2} \quad (3)$$

179 For evaluating model performance over subareas for annual precipitation variability, Box Plots (Tukey  
 180 1977) were constructed. The calculations utilized outputs from CMIP, AMIP, hist-1950 and highresSST-present  
 181 models across all eight subareas.

182 For evaluating performance of individual models, we use Taylor diagrams (Taylor 2001), whose  
 183 parameters include Pearson correlation ( $R^2$ ; Eq. 4) between simulated ( $P_i$ ) and observed ( $O_i$ ) precipitation and the  
 184 model's normalized standard deviation (Eq. 5). Annual mean precipitation values in each of the eight subareas  
 185 were employed for this analysis. Additionally, to create a ranking based on the model's performance, other  
 186 parameters such as Root Mean Square Error (RMSE; Eq. 6) and Taylor Skill Score (TSS; Eq. 7) were utilized.  
 187 Here,  $R^2$  (Eq. 4) denotes the correlation coefficient of the spatial pattern between model outputs and observations,  
 188  $R^2_L$  is the highest achievable value (set to 1), and  $\sigma_P$  and  $\sigma_O$  are the simulated and observed standard deviations,  
 189 respectively

$$190 \quad R^2 = \frac{\sum_{i=1}^n (P_i - \bar{P}_i)(O_i - \bar{O}_i)}{\sqrt{\sum_{i=1}^n (P_i - \bar{P}_i)^2} \sqrt{\sum_{i=1}^n (O_i - \bar{O}_i)^2}} \quad (4)$$

$$191 \quad \sigma_N = \frac{\sigma_P}{\sigma_O} \quad (5)$$

$$192 \quad RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_i - O_i)^2} \quad (6)$$

$$193 \quad TSS = \frac{4(1+R^2)^2}{(\frac{\sigma_P}{\sigma_O} + \frac{\sigma_O}{\sigma_P})^2 (1+R^2_L)^2} \quad (7)$$

195 **2.2 Automatic tracking algorithm**

196 An automatic tracking algorithm was applied to models that exhibited superior performance in the previous stage.  
 197 Data were obtained for zonal and meridional winds at 6-hour intervals from 1989 to 2009 - the period  
 198 corresponding to the climatology proposed by Gomes et al. (2019). The number of vertical levels varied among  
 199 models, with the majority providing data for levels at 850, 500, and 250 hPa, while some models also included  
 200 levels at 925, 700, 600, and 50 hPa. In addition to the Gomes et al. (2019) study, a TRACK run using the  
 201 European Centers for Medium-Range Weather Forecasting reanalysis version 5 (ERA5) was also used to evaluate

202 model performance.

203 For identifying the EWDs in the CMIP6 models, we used the automatic identification and tracking method  
204 TRACK (Hodges 1995, 1999). This method identifies and tracks EWDs based on the minimum of relative  
205 vorticity in the southern hemisphere, which signifies cyclonic systems, adhering to specific criteria concerning  
206 their lifetime and distance traveled. Given the distinct characteristics of EWDs in the TSA and TNA, including  
207 their intensity and distance traveled (Asnani 1993), adjustments were made to the tracking algorithm to enable the  
208 identification of systems along the TSA that reach the NEB coast. Thus, the identification and tracking criteria  
209 used here are the same as those in Gomes et al. (2015, 2019). The main changes include applying the tracking  
210 algorithm at a higher resolution, from T42 ( $\sim 310$  km) to T63 ( $\sim 210$  km), reducing the minimum distance traveled  
211 by EWDs to 500 km ( $\sim 5^\circ$ ), requiring a persistence of at least 1.5 days, and setting the minimum threshold of  
212 relative vorticity to  $-0.5 \times 10^{-5} \text{ s}^{-1}$  or lower. The algorithm was applied at the 850 hPa level, where the centers of  
213 relative vorticity are more intense and better identified.

214 **3 Results and discussions**

215 **3.1 Climatology of ensembles and their spread**

216 The climatological characteristics and variability of precipitation among different ensemble simulations are  
217 examined in this section. Figure 2 shows the annual (left column) and seasonal climatology (right column) of  
218 precipitation for the CMIP (Fig. 2b, g), AMIP (Fig. 2c, h), hist-1950 (Fig. 2d, i), and highresSST-present (Fig. 2e,  
219 j) ensembles, as well as for GPCP observations (Fig. 7a, f). GPCP data show regions of low precipitation over the  
220 TSA that are associated with the Subtropical High, and areas with heavy precipitation exceeding  $4 \text{ mm day}^{-1}$  that  
221 are associated with the ITCZ and northern Brazil. For April to August (AMJJA), minimal precipitation is observed  
222 over the São Francisco basin (Fig. 2f) across all ensembles, with highresSST-present best representing their spatial  
223 extent (Fig. 2e). Moreover, regions along the NEB coasts exhibit precipitation exceeding  $3 \text{ mm day}^{-1}$ , indicative of  
224 the EDWs activity, consistent with previous studies (Gomes et al., 2019). The GPCP annual climatology  
225 (Fig. 2a) exhibits two precipitation nuclei, one in the northern coast and the other in the southern coast, while the  
226 seasonal climatology (Fig. 2f) reveals a broader area of precipitation exceeding  $4 \text{ mm day}^{-1}$  covering the entire  
227 eastern NEB. The AMIP ensemble best represented both areas of high precipitation (Fig. 2c, h), while ensembles  
228 with higher resolution (HighResMIP) faced difficulties in reproducing these features, especially hist-1950 (Fig. 2d,  
229 i). Although large-scale spatial patterns were captured in all ensembles, limitations are observed in precipitation  
230 intensity, especially along the NEB coast and the ITCZ. Among the ensembles, CMIP showed the greatest  
231 differences in both intensity and positioning of observed precipitation patterns.

232 **Fig. 2** Annual (left column) and seasonal (right column, April to August or AMJJA) average precipitation ( $\text{mm}$   
233  $\text{day}^{-1}$ ) from the GPCP (a, f), CMIP (b, g), AMIP (c, h), hist-1950 (d, i), and highresSST-present (e, j) model  
234 ensembles during the period of 1983–2014.

235 Figure 3 illustrates the annual (left column) and seasonal bias (right column) in precipitation among the  
236 ensembles for CMIP (Fig. 3a, e), AMIP (Fig. 3b, f), hist-1950 (Fig. 3c, g), and highresSST-present (Fig. 3d, h).  
237 All ensembles overestimated precipitation in the northern NEB and the adjacent latitudinal band of the TSA, with  
238 the CMIP ensemble displaying the most pronounced bias of  $+2.5 \text{ mm day}^{-1}$  for the annual mean (Fig. 3a) and  $+3$   
239  $\text{mm day}^{-1}$  for the seasonal mean (Fig. 3e) over the adjacent TSA. On the other hand, low bias is evident in the  
240 HighResMIP (Fig. 3c, d, g, h) in this same region. In all cases, precipitation was underestimated over the NEB

241 coast, especially during the peak activity of the EWDs. The highest bias in this region was found in the high-  
242 resolution models (Fig. 3g, h). This bias is also evident, albeit to a lesser extent, in the HighResMIP (Fig. 3c, d),  
243 CMIP (Fig. 3a) and AMIP (Fig. 3b), particularly in the coastal areas of Bahia. The HighResMIP ensemble showed  
244 biases close to 0 mm day<sup>-1</sup> over the semi-arid region of the NEB (Fig. 3c, d), corroborating with their better  
245 representation of the subsidence region over the São Francisco basin (Fig. 2f). Additionally, part of the northern  
246 Brazil showed lower precipitation in all ensembles. Overall, deviations were more pronounced in the seasonal  
247 climatology and in the CMIP ensembles (Fig. 3a, e).

248 **Fig. 3** Bias for annual (left column) and seasonal (right column) mean precipitation (mm day<sup>-1</sup>) for the CMIP (a,e),  
249 AMIP (b,f), hist-1950 (c,g), and highresSST-present (d,h) model ensembles during the period of 1983-2014. The  
250 dashed line corresponds to the Bias values.

251 The spatial distribution of the spread between the ensemble members (Fig. 4) shows greater uncertainty at  
252 latitudes farther north and decreasing toward southern latitudes, particularly close to the ITCZ. Using a spread line  
253 equal to 1 mm day<sup>-1</sup> as a threshold, it becomes apparent that for CMIP, this line is near 15°S over the continent  
254 and 10°S over the TSA for the annual mean (Fig. 4a), while for the seasonal mean (Fig. 4e), this line is close to  
255 8°S on the continent and 12°S on the TSA. This feature is observed in all ensembles and is more pronounced in  
256 hist-1950, where the line is located near 20°S over the continent and 5°S on the TSA for the annual mean (Fig. 4c).  
257 Thus, the decrease is more pronounced over land compared to the TSA, especially in the annual mean. The spread  
258 in the seasonal mean of the HighResMIP shows the lowest uncertainty over the continent, especially in hist-1950,  
259 where a region with values less than or equal to 0.25 mm day<sup>-1</sup> is observed over the São Francisco basin (Fig. 4g).  
260 In the seasonal maps (Fig. 4; right column), the NEB coast stands out as a region with higher uncertainty  
261 compared to the surrounding areas, especially in the CMIP (Fig. 4e) and AMIP (Fig. 4f) ensembles.

262 **Fig. 4** The annual (left column) and seasonal (right column) precipitation spread (mm day<sup>-1</sup>) for the CMIP (a, e),  
263 AMIP (b, f), hist-1950 (c, g), and highresSST-present (d, h) during the period of 1983-2014. The dashed line  
264 corresponds to the annual and seasonal climatological average of precipitation.

### 265 3.2 Annual Cycle

266 Figure 5 shows the annual cycle of precipitation in each subarea (Fig. 1) for CMIP models (green box), AMIP (red  
267 box), hist-1950 (gray box), and highresSST-present (blue box), along with GPCP data as a reference (dotted black  
268 line). All model sets successfully capture the annual precipitation cycle in all subareas. The model ensembles  
269 exhibit greater spread in the first half of the year (January to June). During this period, the largest discrepancies  
270 compared to GPCP data were observed, with overestimation of precipitation in all areas except for subareas 5.1  
271 and 6.1, where underestimation occurred.

272 The uncertainty and discrepancy against GPCP data were more pronounced in subareas corresponding to  
273 the ITCZ (5.1, 5.2, 6.1, and 6.2), especially in the northern part (5.1 and 6.1), and in the CMIP models. In other  
274 subareas, the models showed greater proximity to the GPCP, especially between July and October, extending into  
275 December in subareas 2, 3, and 4, and from May to October in subarea 1. The AMIP and HighResMIP models  
276 exhibited similar patterns, which significantly differed from the CMIP models. Nonetheless, the hist-1950 models  
277 significantly deviated from these patterns from April to June in areas 1, 2, 3, and 5.2 (Fig. 5a, b, c, f).

278 **Fig. 5** Annual cycle of model and observation for the 8 subareas as depicted in Fig. 1. The green (CMIP), red  
279 (AMIP), gray (hist-1950), and blue (highresSST-present) box plots represent the distribution of monthly

280 precipitation for all members in areas: 1(a), 2(b), 3(c), 4(d) , 5.1(e), 5.2(f), 6.1(g) and 6.2(h). The black line  
281 overlaid on the diagram represents the annual precipitation variability of GPCP and the open circles are the  
282 outliers.

283 **3.3 Individual Model Analysis**

284 **Fig. 6** Taylor diagram for the annual mean precipitation in the 8 subareas (as shown in figure 1). The normalized  
285 standard deviation is shown on the x-axis and y-axis, and the correlation coefficient is shown on the curved side.

286 The performance of individual models for annual mean precipitation across 8 subareas is shown in Taylor  
287 diagrams for CMIP (Fig. 11a), AMIP (Fig. 11b), hist-1950 (Fig. 11c), and highresSST-present (Fig. 11d) models.  
288 CMIP, AMIP, hist-1950, and highresSST-present models exhibit normalized standard deviation (correlation)  
289 values between 0.57-6.99 mm day<sup>-1</sup> (0.001-0.987), 0.37-3.35 mm day<sup>-1</sup> (0.28-0.990), 0.14-4.52 mm day<sup>-1</sup> (0.018-  
290 0.96), and 0.73-2.26 mm day<sup>-1</sup> (0.398-0.993), respectively. Same coupled models within CMIP, exhibited  
291 correlation values close to 0, such as MPI-ESM1-2-HR (0.001) and EC-Earth3-Veg (0.009), as well as BCC-  
292 CSM2-MR (0.018) from hist-1950. HighresSST-present models showed the highest correlations, with HadGEM3-  
293 GC31-HH from hist-1950 being the only model with a correlation exceeding 0.90 in area 5.1. Among CMIP,  
294 AMIP, and highresSST-present models, area 6.2 exhibited the highest correlations, followed by 5.2 and 1, while  
295 area 5.1 showed the lowest values in AMIP and highresSST-present models. Thus, better model performance is  
296 observed in the south of the ITCZ, the semi-arid region, and the NEB coast compared to the north of the ITCZ and  
297 adjacent ATS. For hist-1950 models, the highest correlations are found in area 1, followed by areas 6.1 and 5.2,  
298 with the lowest correlation observed in area 3, indicating better performance in the semi-arid and ITCZ than the  
299 adjacent ATS. Regarding the normalized standard deviation, highresSST-present models show values closest to  
300 the reference (1), while CMIP models are the farthest away. In CMIP, AMIP, and highresSST-present models,  
301 values in areas 5.1 and 6.1 (north of the ITCZ) are closest to 1 mm day<sup>-1</sup>, while the farthest are in areas 4 and 2  
302 (NEB's coast and ATS). This suggests that although models may exhibit high correlation in certain areas, they also  
303 show greater dispersion of annual means compared to GPCP in those same areas.

304 Despite some models performing well in certain regions and poorly in others, consistency across all areas  
305 was considered in selecting the best models. Noteworthy models include ECMWF-IFS-HR and MRI-AGCM3-2-H  
306 from highresSST-present, along with ECMWF-IFS-LR and CMCC-CM2-VHR4. ECMWF-IFS-HR exhibited  
307 correlation exceeding 0.92 in all areas except for area 3 (0.88), outperforming its lower-resolution counterpart.  
308 ECMWF-IFS-LR, which showed values over 0.90 except for areas 3 (0.83) and 5.1 (0.86), with both models  
309 having similar average standard deviations: 1.100 mm day<sup>-1</sup> (ECMWF-IFS-HR) and 1.108 mm day<sup>-1</sup> (ECMWF-  
310 IFS-LR). CMCC-CM2-VHR4 achieved values exceeding 0.90, except for area 5.1 (0.71). MRI-AGCM3-2-H  
311 exhibited correlations exceeding 0.92, except for areas 2 (0.80), 3 (0.71), and 4 (0.85), with standard deviations  
312 between 1.103 and 1.270 mm day<sup>-1</sup>. Among the AMIP models, CMCC-CM2-SR5 stood out with a correlation  
313 exceeding 0.92, except for area 5.1 (0.67), with standard deviations between 0.76 and 1.62. INM-CMS-0 and  
314 CAS-FGOALS-I3-L exhibited correlations exceeding 0.90 in areas 5.2 and 6.2, respectively. BCC-CSM2 from  
315 CMIP demonstrated a correlation exceeding 0.90 in area 6.2, outperforming its higher-resolution counterpart,  
316 which exhibited the lowest correlation. Despite inferior results compared to highresSST-present, ECMWF-IFS-HR  
317 and CMCC-CM2-VHR4 also performed well among hist-1950 models.

318 **Fig. 7** Annual and seasonal values of RMSE (mm day<sup>-1</sup>) (a), and annual values of R<sup>2</sup> and TSS (b), corresponding  
319 to the average of the 8 subareas for each model.

320 To select the best performing models, we examine the RMSE (Fig. 7a), TSS and Pearson correlation (Fig.  
321 7b) for both annual and seasonal means of the eight subareas for each model, see supplementary material Table 1S  
322 for CMIP models, Table 2S for highresSST-present models, Table 3S for hist-950 models and Table 4S for AMIP  
323 models. The results indicate that the RMSE is generally lower for the annual period compared to seasonal period,  
324 with CMIP models exhibiting the highest values: 1.6-3.4 mm day<sup>-1</sup> (annual) and 1.6-4.0 mm day<sup>-1</sup> (seasonal).  
325 AMIP models showed closely clustered values, between 1 and 1.8 mm day<sup>-1</sup>, with CAS.FGOALS-f3-L and AS-  
326 RCEC.TaiESM1 standing out from the rest. Among the HighResMIP models, 4 highresSST models had RMSE  
327 below 1 mm day<sup>-1</sup>: ECMWF-IFS-HR, ECMWF-IFS-LR, CMCC-CM2-VHR4, and MRI-AGCM3-2-H, along with  
328 the ensemble. In contrast, only the HadGEM3-GC31-HH model from the hist-1950 had RMSE below 1 mm day<sup>-1</sup>.  
329 The TSS index and Pearson correlation varies from 0 to 1, with values closer to 1 indicating better model  
330 performance. In CMIP models, only the NCC.NorESM2-MM model exhibits a TSS exceeding 0.6 (0.619). The  
331 four aforementioned highresSST models had TSS above 0.8 and average correlation above 0.9. The HadGEM3-  
332 GC31-HH model from hist-1950 exhibited both correlation and TSS above 0.8. Standout AMIP models were  
333 CMCC-CM2-SR5 with TSS of 0.837, and average correlation of 0.910, and AS-RCEC.TaiESM1 with 0.859 and  
334 0.894, respectively.

335 Table 3 lists the top three performing models from each ensemble. CAS.FGOALS-f3-L and AS-  
336 RCEC.TaiESM1 models excelled in both CMIP and AMIP ensembles, with AMIP showing the better results  
337 overall. CMCC-CM2-SR5 was the best-performing model among AMIP models, although its CMIP version did  
338 not yield satisfactory results, having one of the lowest TSS (0.401). ECMWF-IFS-LR from highresSST showed  
339 excellent performance, ranking second best overall, but was not included in the set as its values were slightly  
340 lower than ECMWF-IFS-HR, a higher-resolution model, emphasizes the role of resolution in model performance.

341 **Table 3** TSS (annual), RMSE (annual and seasonal), bias (annual and seasonal), R<sup>2</sup> (annual), and normalized  
342 standard deviation of the models with the best performance from each set, corresponding to the average of the 8  
343 subareas for each model.

### 344 3.4 TRACK

345 Due to missing U and V wind components within the study period for some selected models, the analysis of  
346 EWDs was conducted on 9 out of the 12 selected models, comprising two from each model set. Only the 850 hPa  
347 level was evaluated in contrast to previous studies (GOMES et al., 2015 and 2019; HOLLIS et al., 2023) due to  
348 data limitations. For the same reason, the ensembles were not included in this analysis stage despite achieving  
349 good results.

350 The EWD's identified in the models showed similar characteristics to those reported by Gomes et al.  
351 (2019), with mean lifetimes ranging from 5.84 to 6.51 days and phase speeds between 6.37 and 7.07 m s<sup>-1</sup>, closely  
352 aligning with ERA5 (5.78 days and 7.29 m s<sup>-1</sup>). Both datasets indicated EWD lifetimes approaching the  
353 climatological value of 4 to 6 days, albeit slightly slower at 9.5 m s<sup>-1</sup>. The frequency of EWDs during 1989 to  
354 2019 showed similarities between ERA5 (27 EWD year<sup>-1</sup>) and climatology (25 EWD year<sup>-1</sup>). However, overall,  
355 the models overestimated the number of EWD's per year, between 41.1 and 49.5 EWDs year<sup>-1</sup> in CMIP and AMIP  
356 models, with the NCC.NorESM2-MM from CMIP closest to climatology (31.1 EWDs year<sup>-1</sup>). This difference is  
357 accentuated in the HighResMIP coupled and atmospheric models, which showed ~3 times more EWDs (74.7 and  
358 78.6 EWD year<sup>-1</sup>) compared to the climatological average and ERA5 (Table 4). As noted by Hollis et al. (2023),  
359 the most prominent level of EWD occurrence in the TSA is at 700 hPa. Hence, the choice to evaluate only at the

360 850 hPa might have resulted in increased noise, particularly in high-resolution models, with some cyclonic  
361 vorticity centers potentially not being accurately characterized as EWDs.

362 **Table 4** EWD characteristics identified by TRACK method and the correlation between models and ERA5 and  
363 Gomes et al. (2019) of EWD interannual variability ( $R^2$ ) from 1989 to 2019.

364 Although the differences between ERA5 (this work) and ERA-Interim (GOMES et al., 2019), we observe  
365 the same variability pattern over the years (Fig. 8). Figure 8 presents the EWD frequency from 1989 to 2009 for  
366 each model. Evaluating the interannual variations of EWD between the models and from ERA5 and the  
367 climatology of Gomes et al. (2019), a low correlation is observed in both cases, with the ECMWF-IFS-HR  
368 (highresSST-present) and AS-RCEC.TaiESM1 (highresSST-present) (AMIP) presenting the highest values  
369 (~0.35). Because of that, the CMIP6 models were unable to reproduce the interannual variation of EWDs as  
370 observed in both climatology and ERA5, making it impossible to observe variations during El Niño and La Niña  
371 years.

372 **Fig. 8** EWD's frequency from 1989 to 2019 identified in coupled models (red bars) and atmospheric models (blue  
373 bars) for CMIP and AMIP models (a), and for hist-1950 and highresSST-present (b). The solid black dashed line  
374 represents the EWD's frequency identified by ERA5 reanalysis data, and the solid line represents the EWD's  
375 climatological frequency from Gomes et al. (2019).

376 Assessing the EWD's genesis locations using ERA5 (Fig. 9a), a concentration was observed between 25-  
377 15°W, with a northwest-southeast inclination and another cluster near the African coast between 5-10°E. These  
378 core positions align closely with the two main systems associated with EWD formation (Gomes et al., 2019),  
379 namely the frontal remnants propagating at low latitudes and the convective clusters off the west coast of Africa.  
380 While these cores were observed in all models, except for the HighResMIP models, additional cores were detected  
381 in other models: one positioned farther north between the aforementioned cores and another near the NEB coast  
382 (Fig. 9b-e).

383 Analysis of the EWD density map based on ERA5 reveals two centers of higher EWD frequency, one near  
384 the NEB coast and the other near the west coast of Africa, coinciding with the genesis regions of these systems.  
385 The CMCC-CM2-VHR4 models from hist-1950 and highresSST-present (Fig. 9m) were the only ones unable to  
386 capture both of these core clusters, although their magnitude was closer to CMIP and AMIP models. Overall, the  
387 HighResMIP models better represented the magnitude of both EWD's genesis and density, with the ECMWF  
388 models standing out (Fig. 9g, i, p, r).

389 **Fig. 9** Tracking statistics at 850 hPa to the rainy season (AMJJA) of 1989-2009. Genesis density (left column) per  
390 unit area ( $\sim 10^6 \text{ km}^2$ ) per season and Track density (right column) per unit area ( $\sim 10^6 \text{ km}^2$ ) per season, of EWDs  
391 based on ERA5 (a, j) and CMIP models: NorESM2 (b, i), TaiESM1 (c, j); AMIP model: CMCC-CM2 (d, k),  
392 TaiESM1 (e, l); hist-1950 models: CMCC-CM2-VHR4 (f, m) and ECMWF-IFS-HR (g, n); highresSST models:  
393 CMCC-CM2-VHR4 (f, m) and ECMWF-IFS-HR (g, n). The continuous line corresponds to the values.

394 **4 Conclusion**

395 A comprehensive evaluation was conducted using 17 CMIP (historical), 16 AMIP, 7 hist-1950, and 10  
396 highresSST-present models, focusing on their ability in replicating the annual and seasonal evolution of  
397 precipitation associated with EWDs over the southern tropical Atlantic. While the model ensembles exhibited

398 consistent representations of precipitation, they struggled to accurately capture the precipitation intensity over the  
399 NEB coast, often underestimating it, while exhibiting overestimation in the northern NEB and TSA regions. A  
400 larger discrepancy between models and observations was found from January to June, with prevalent  
401 overestimation across most subareas. The highest uncertainty among the models was observed at the northern  
402 latitudes, whereas it was lower at the southern latitudes.

403 Analysis of normalized standard deviation and correlation revealed that better model performance was  
404 generally observed in regions south of the ITCZ, including the semi-arid and NEB coast, compared to those north  
405 of the ITCZ and adjacent TSA. On the other hand, standard deviations were better captured north of the ITCZ,  
406 indicating that despite higher correlation over some areas, certain models exhibited greater dispersion in the same  
407 areas.

408 CMIP models showed the poorest correlation and standard deviation, while highresSST-present models  
409 performed the best, a trend echoed across multiple statistical measures such as the RMSE and TSS. Top-  
410 performing models from each ensemble were identified, with atmospheric models, particularly those with higher  
411 resolutions, demonstrating superior performance compared to coupled models. Better performing models include  
412 CAS.FGOALS-f3-L and AS-RCEC.TaiESM1 in the CMIP and AMIP, with the AMIP version showcasing better  
413 results than its CMIP counterpart. CMCC.CMCC-CM2-SR5 emerged as the best-performing model among the  
414 AMIP models; however, in CMIP, it presented the lowest TSS values. In the hist-1950 and highresSST ensembles,  
415 CMCC-CM2-VHR4 and ECMWF.ECMWF-IFS-HR models emerged as top performers, particularly in their  
416 atmospheric versions. Overall, in our analysis, atmospheric models outperformed coupled models, especially those  
417 with higher resolutions (highresSST-present).

418 The three best-performing models in each set were selected: CMIP (AS-RCEC.TaiESM1, CAS.FGOALS-  
419 f3-L, and NCC.NorESM2-MM), AMIP (CAS.FGOALS-f3-L, AS-RCEC.TaiESM1, and CMCC.CMCC-CM2-  
420 SR5), hist-1950 (HadGEM3-GC31-HH, CMCC-CM2-VHR4, and ECMWF.ECMWF-IFS-HR), and highresSST  
421 (MRI.MRI-AGCM3-2-H, CMCC-CM2-VHR4, and ECMWF.ECMWF-IFS-HR).

422 Despite data limitations, the TRACK analysis was performed on a subset of models (9 out of 12), revealing  
423 mean lifetime ( $\sim$ 6 days) and phase speed ( $\sim$ 7 m s $^{-1}$ ) values of EWDs closely resembling ERA5 (5.78 days and 7.29  
424 m s $^{-1}$ ), albeit with discrepancies in frequency. While ERA5 and climatological EWD frequencies showed opposite  
425 phases between 1989 and 1993, consistent variability patterns were still observed over time. However, most  
426 models overestimated EWD frequency ( $\sim$ 45 EWDs year $^{-1}$ ) compared to ERA5 ( $\sim$ 26 EWDs year $^{-1}$ ), except for a  
427 few models (e.g., NorESM2-MM,  $\sim$ 31 EWDs year $^{-1}$ ). The majority of models failed to reproduce the interannual  
428 variation in EWDs, except CMCC-CM2-SR5 (AMIP), NCC.NorESM2-MM (CMIP) and CMCC-CM2-VHR4  
429 (hist-1950).

430 Two major genesis areas of EWDs were found from observations: one over the TSA and the other near the  
431 African coast. Models generally captured the key features observed in ERA5, aligning with known EWD  
432 formation systems. Most models successfully reproduced core positions near the NEB coast and the African west  
433 coast, with HighResMIP models, particularly those from ECMWF, demonstrating superior performance in  
434 capturing both core positions and magnitudes.

435 In conclusion, while improvements are still necessary, CMIP6 models exhibited promising capabilities in  
436 simulating spatial and temporal patterns in precipitation, as well as EWD characteristics over the NEB and  
437 adjacent TSA regions. Atmospheric models, especially those with higher spatial resolution, performed better,  
438 emphasizing the importance of higher resolution in model outcomes.

439

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442       **Data availability:** Data available in a publicly accessible repository that does not issue DOIs Publicly  
443       available datasets were analyzed in this study. This data can be found here: [<https://esgf-data.dkrz.de/search/cmip6-dkrz/>], [<https://measures.gesdisc.eosdis.nasa.gov/data/GPCP/GPCPMON.3.1/>] and  
444       [<https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-pressure-levels?tab=overview#!%2Fdataset%2Freanalysis-era5-single-levels%3Ftab=overview>]

445       **Conflicts of Interest:** The authors declare no conflicts of interest.

446

447       **References**

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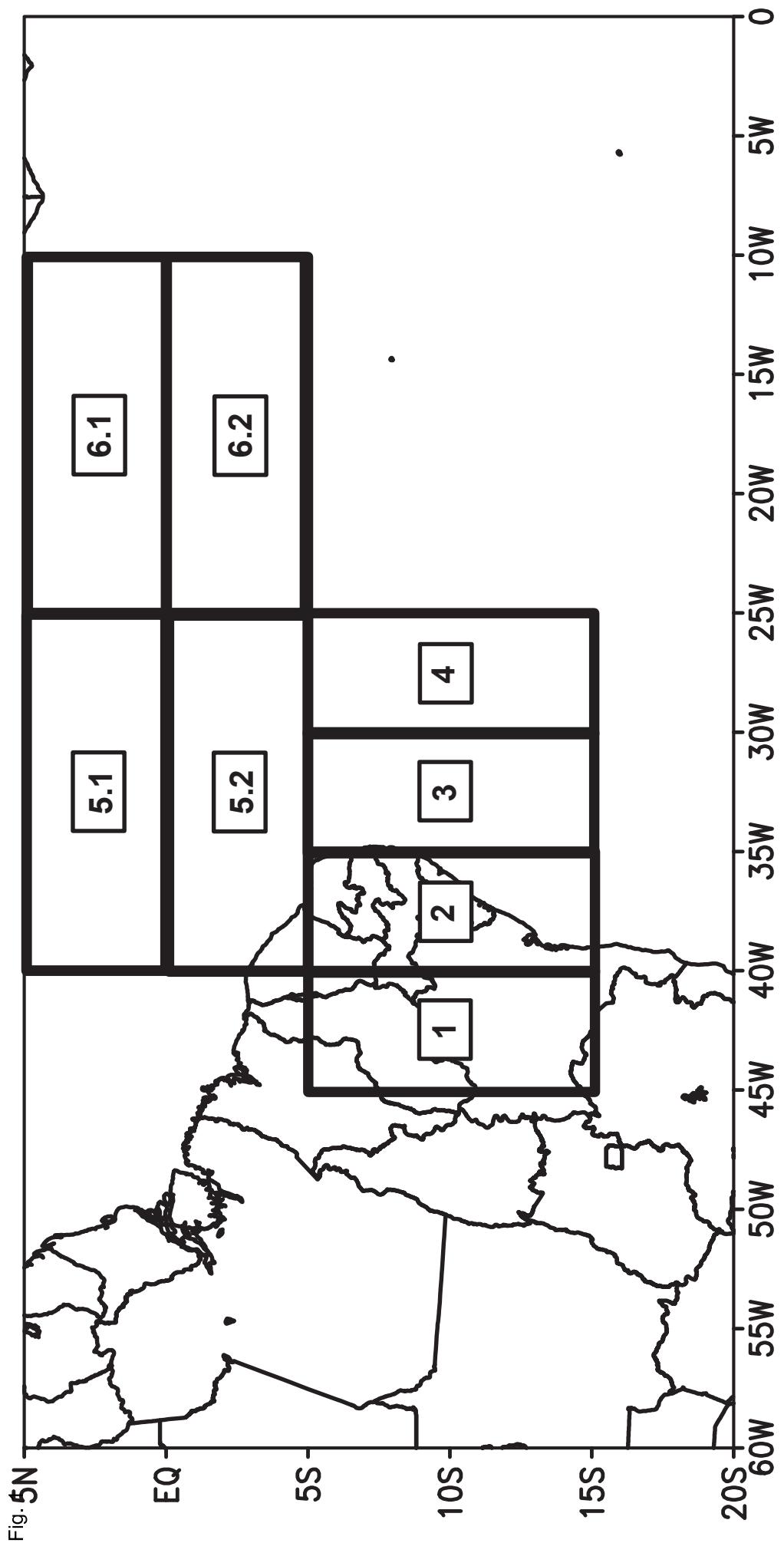
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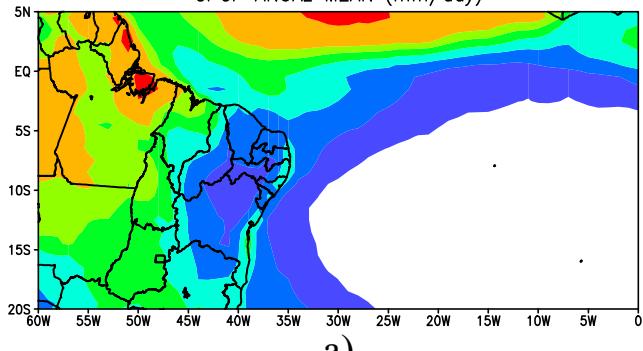
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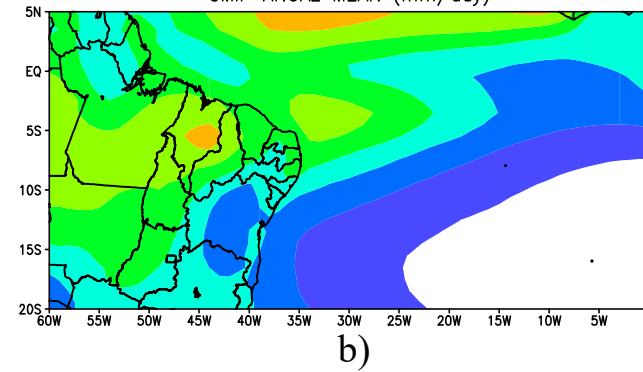


GPCP ANNUAL MEAN (mm/day)



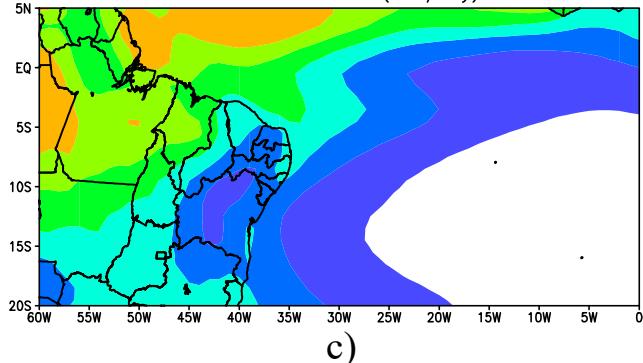
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CMIP ANNUAL MEAN (mm/day)



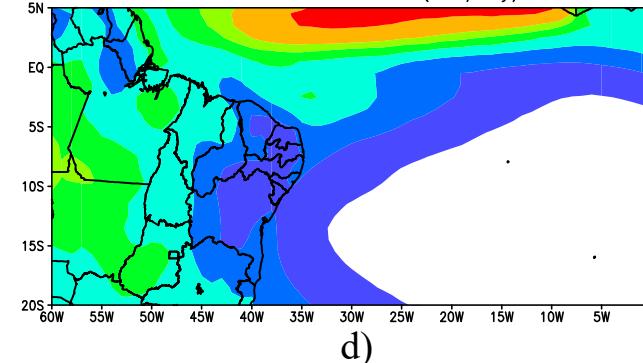
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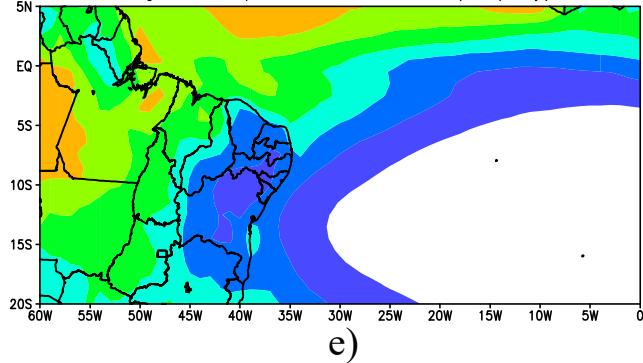
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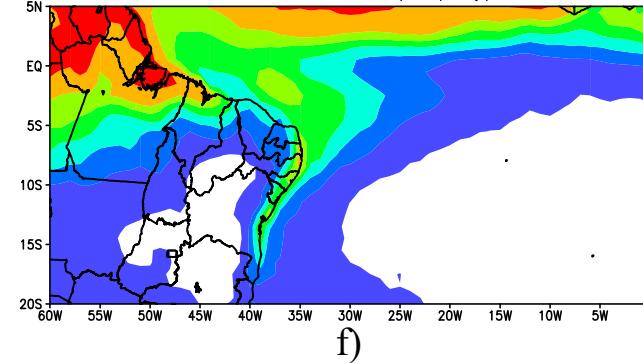
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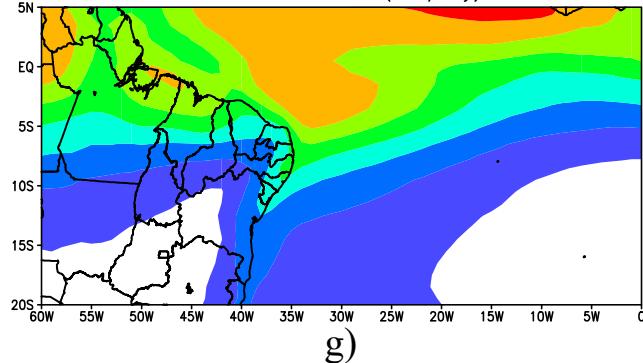
e)

GPCP AMJJA MEAN (mm/day)



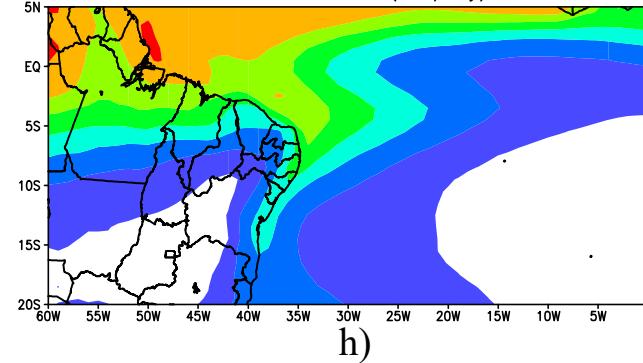
f)

CMIP AMJJA MEAN (mm/day)



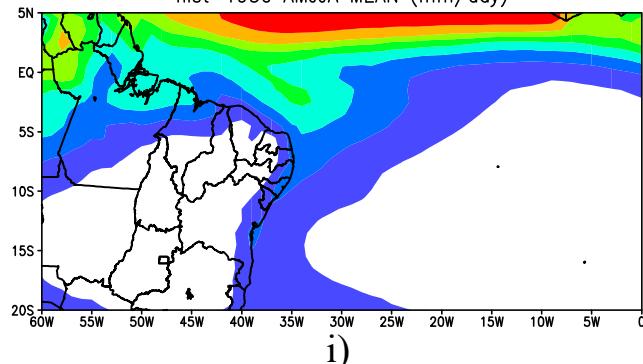
g)

AMIP AMJJA MEAN (mm/day)



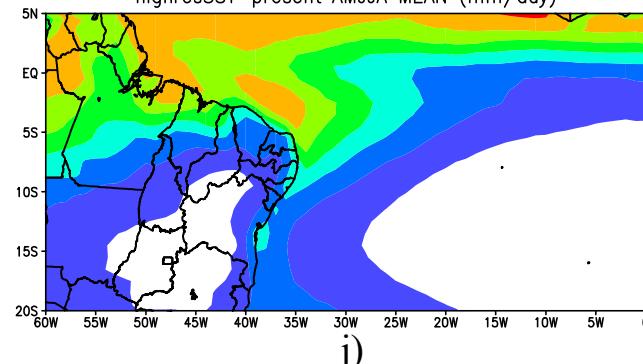
h)

hist-1950 AMJJA MEAN (mm/day)

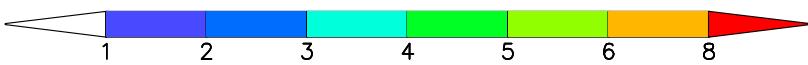


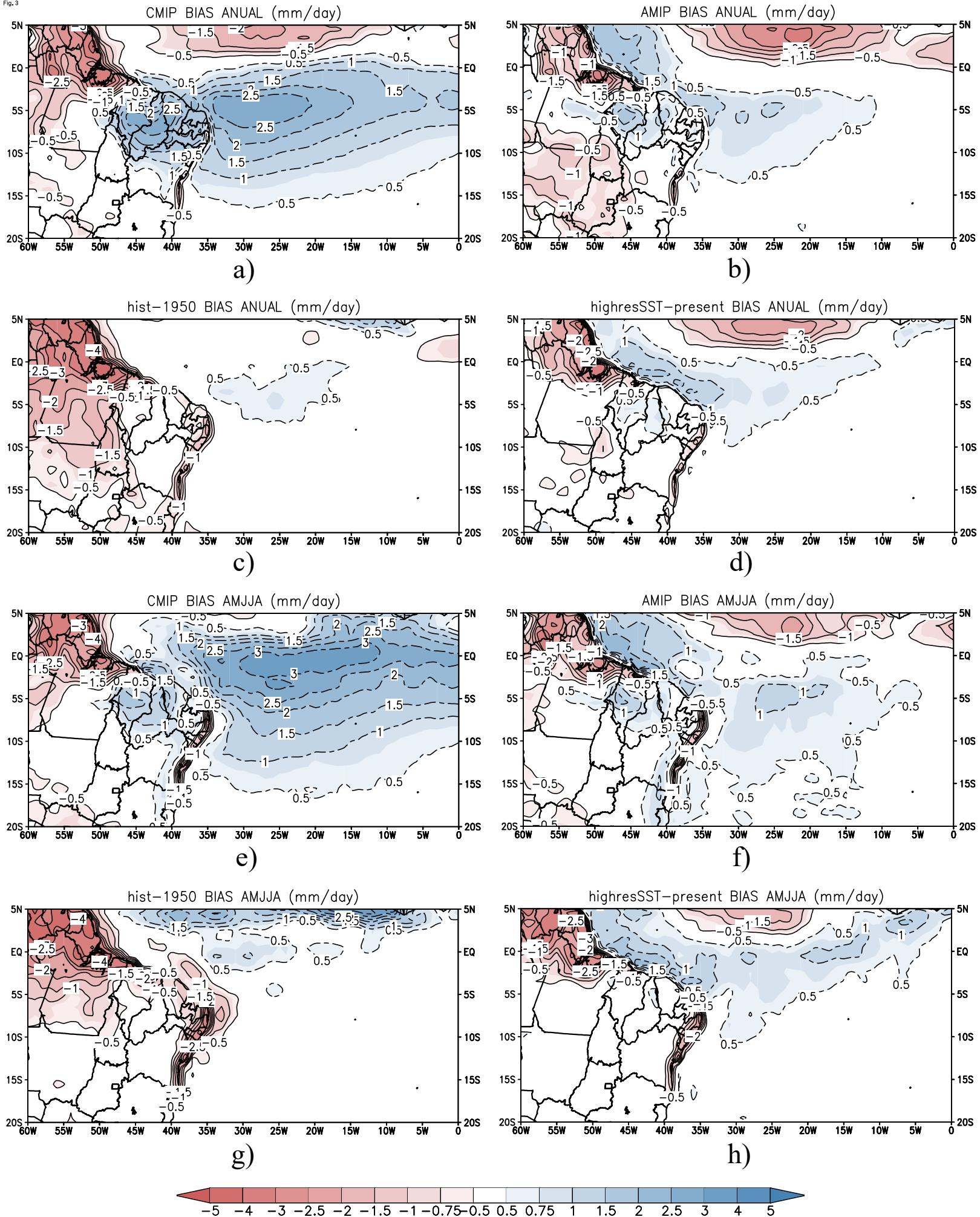
i)

highresSST-present AMJJA MEAN (mm/day)

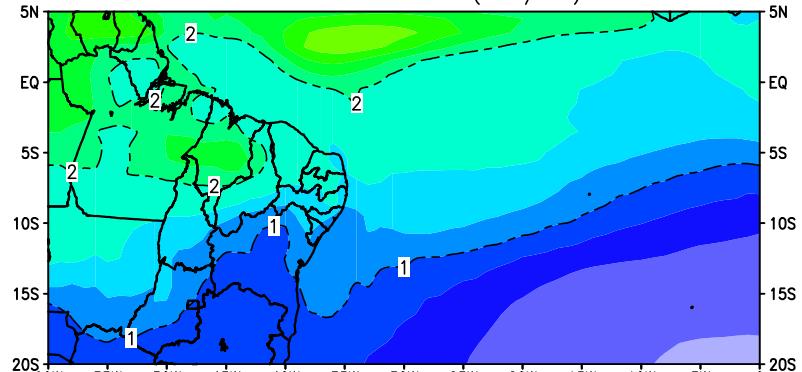


j)



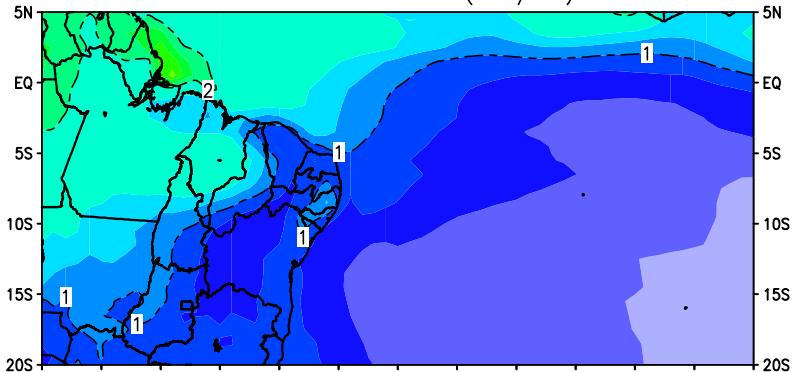


SPREAD CMIP ANUAL (mm/dia)



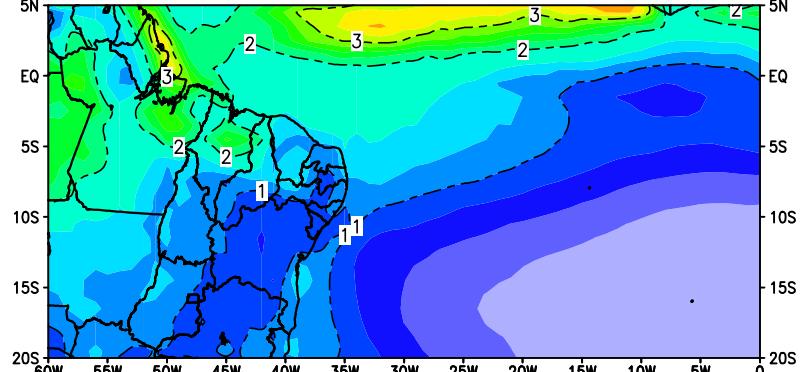
a)

SPREAD AMIP ANUAL (mm/dia)



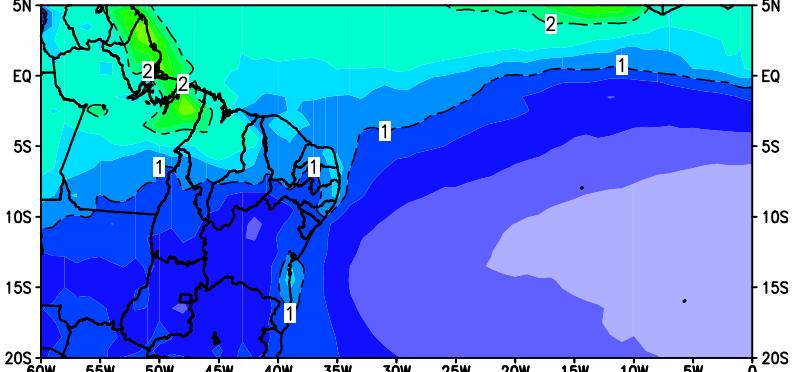
b)

SPREAD hist-1950 ANUAL (mm/dia)



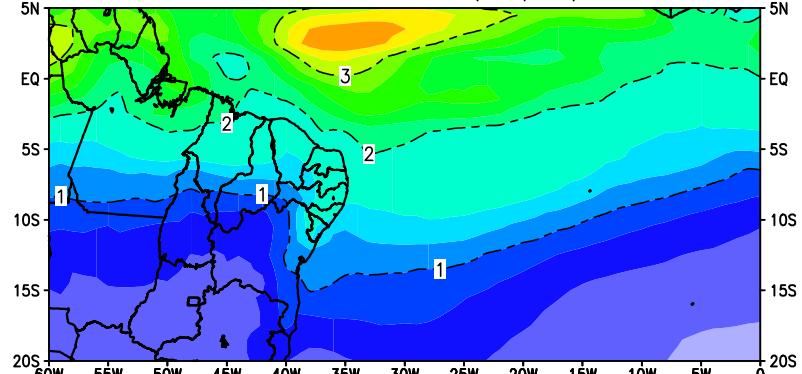
c)

SPREAD highresSST-present ANUAL (mm/dia)



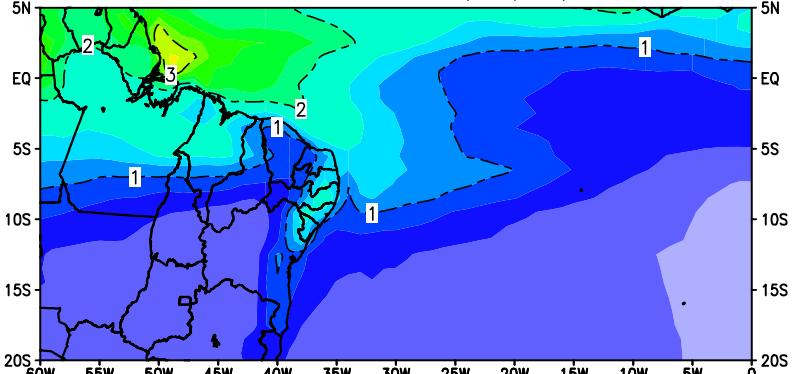
d)

SPREAD CMIP AMJJA (mm/dia)



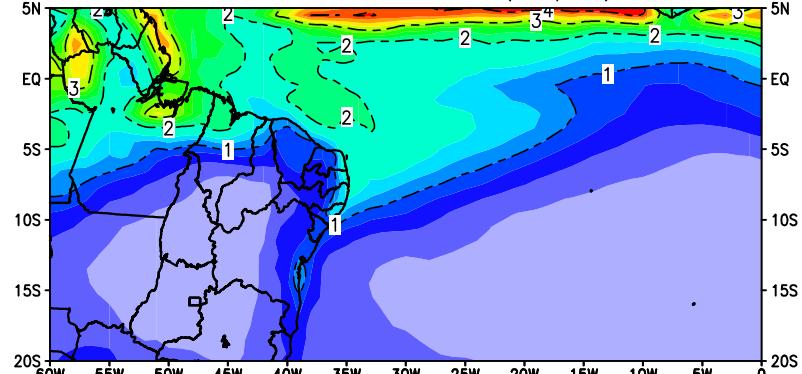
e)

SPREAD AMIP AMJJA (mm/dia)



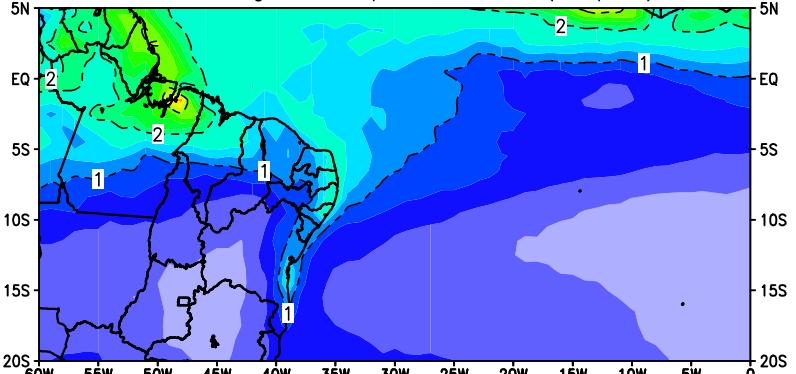
f)

SPREAD hist-1950 AMJJA (mm/dia)

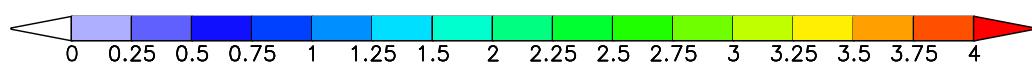


g)

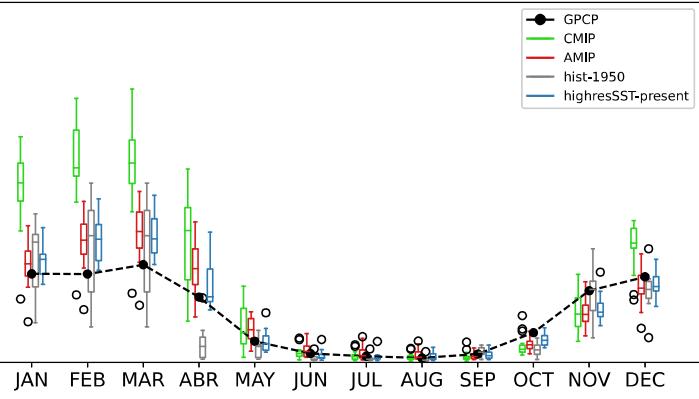
SPREAD highresSST-present AMJJA (mm/dia)



h)

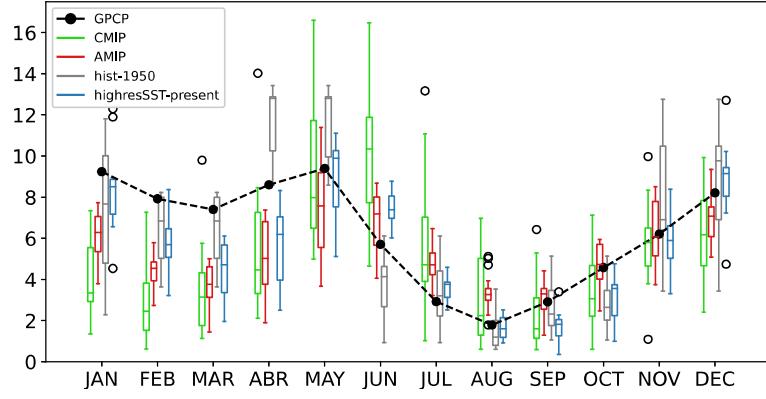


Boxplots AREA 1



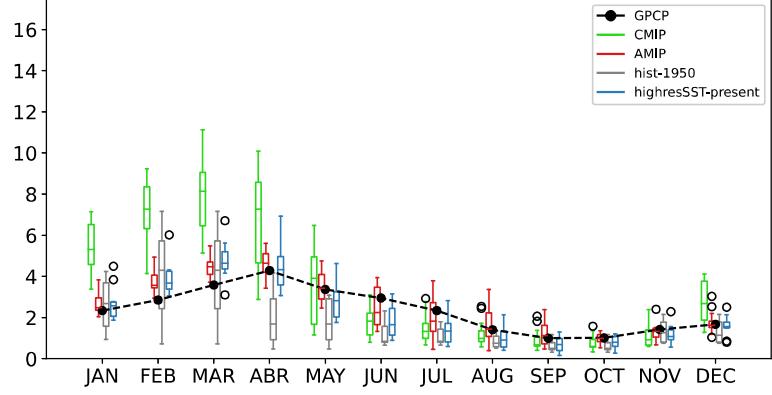
a)

Boxplots AREA 5.1



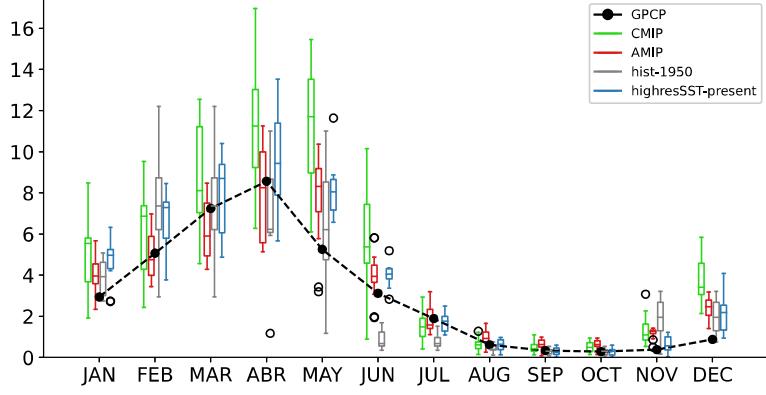
e)

Boxplots AREA 2



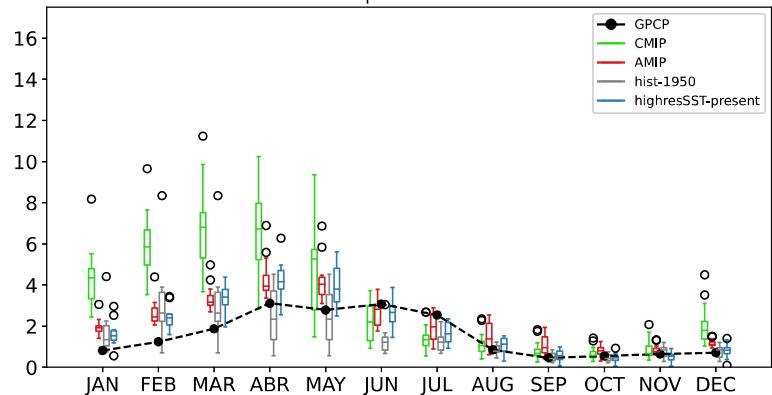
b)

Boxplots AREA 5.2



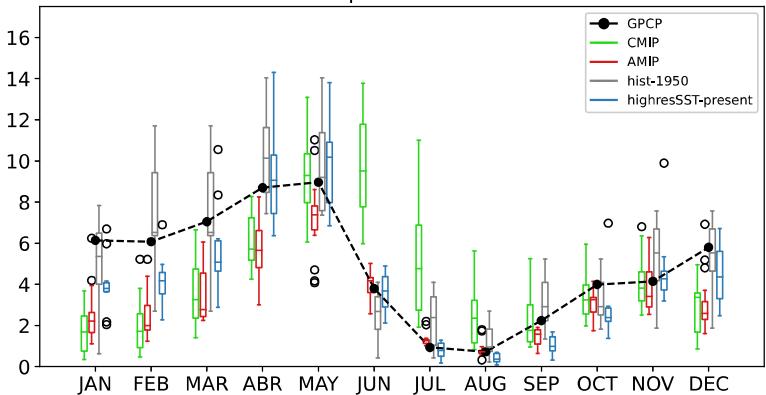
f)

Boxplots AREA 3



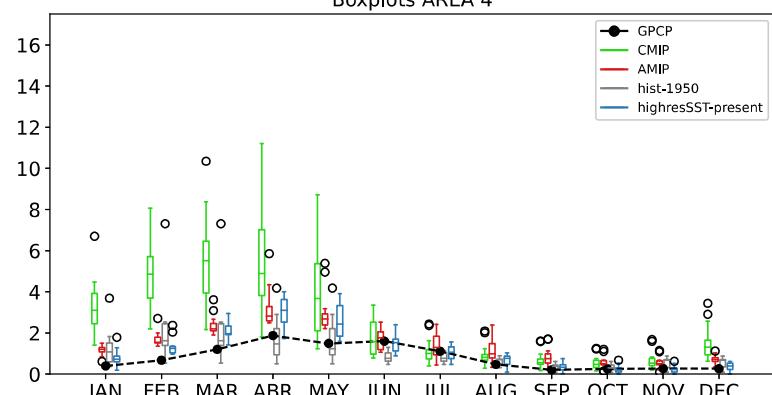
c)

Boxplots AREA 6.1



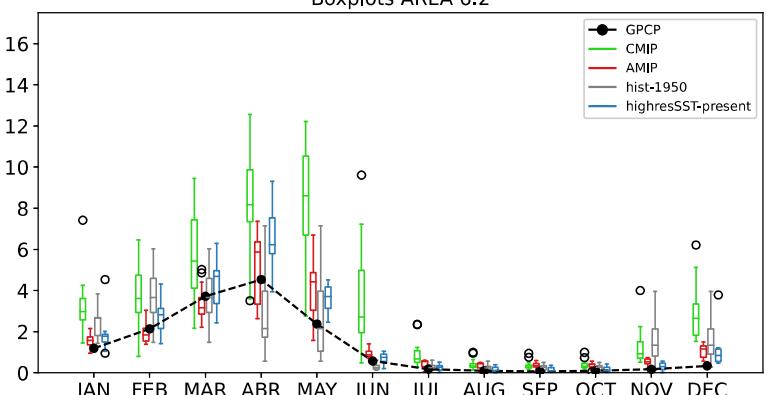
g)

Boxplots AREA 4



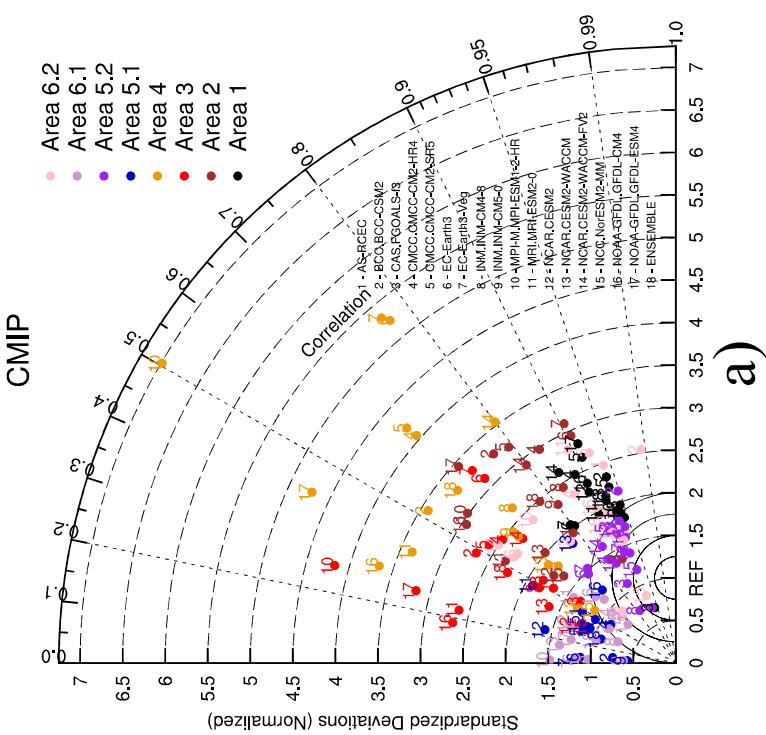
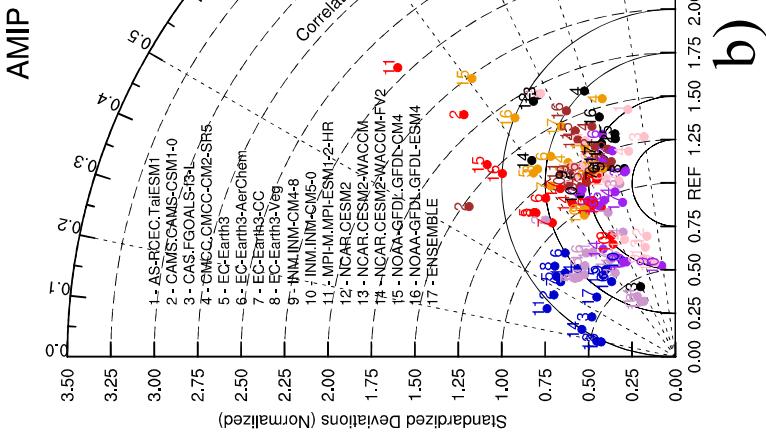
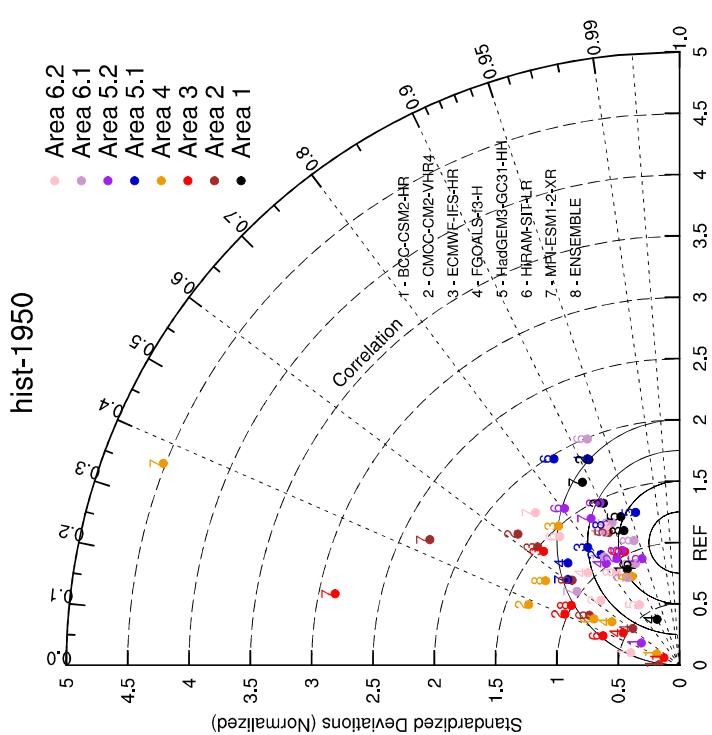
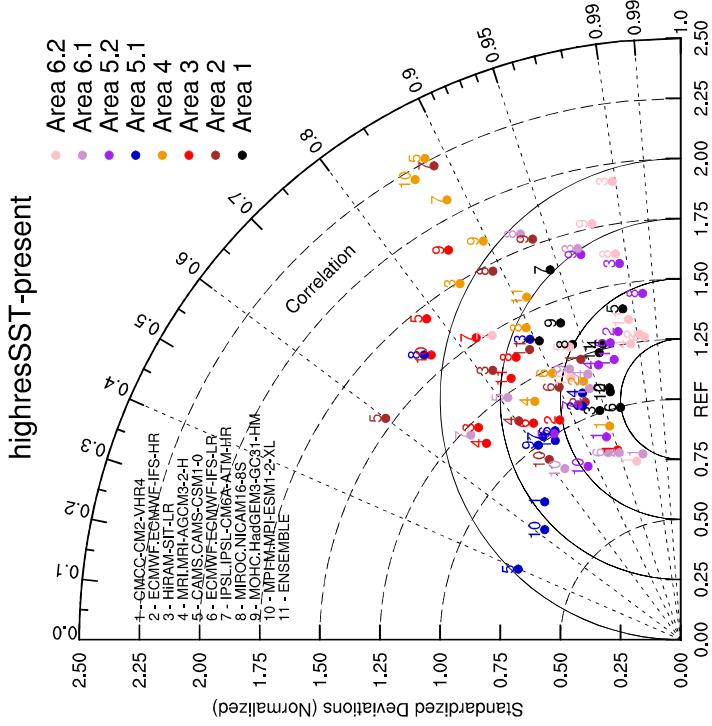
d)

Boxplots AREA 6.2

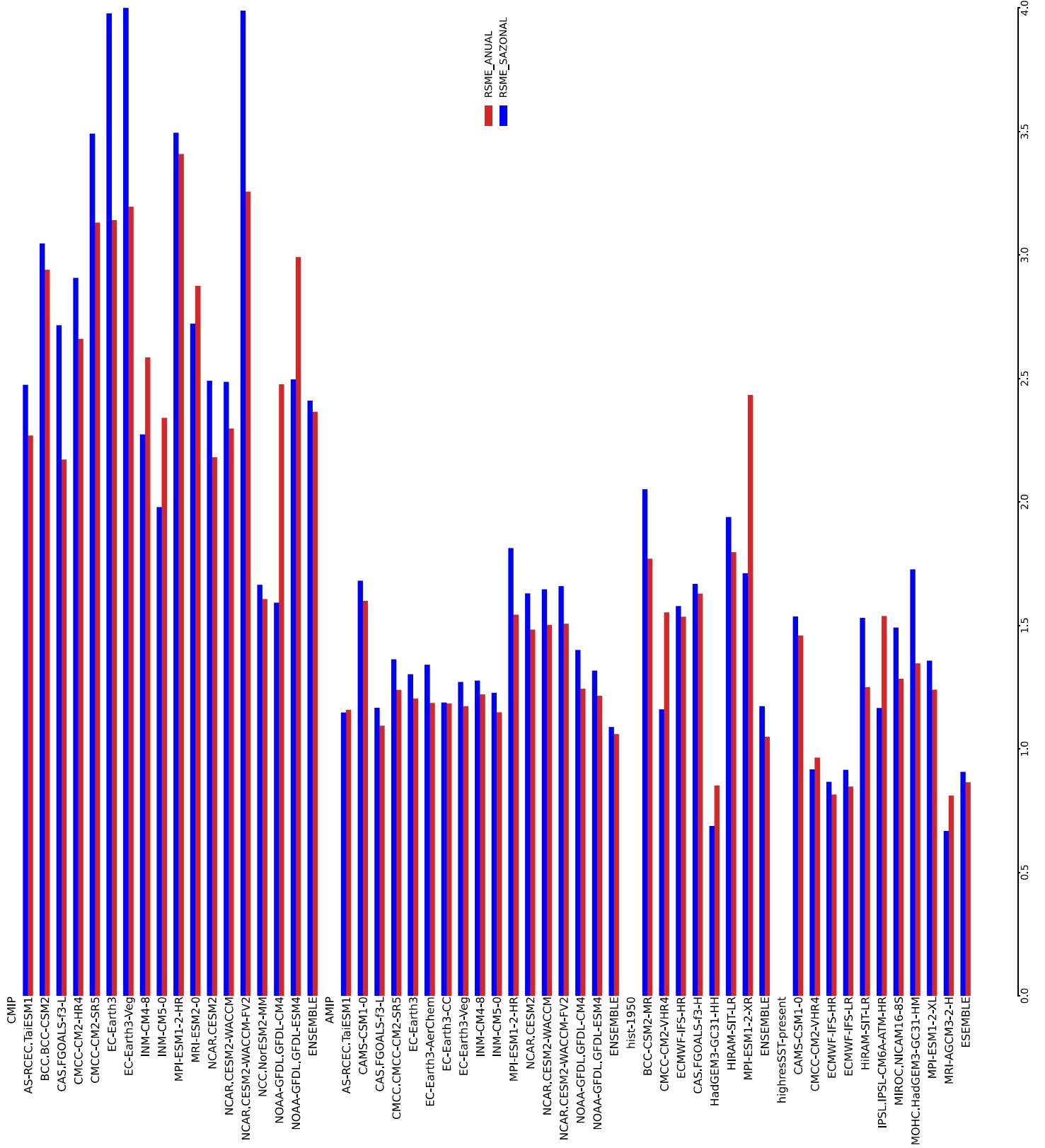


h)

Fig. 6

**a)****b)****c)****d)**

a)



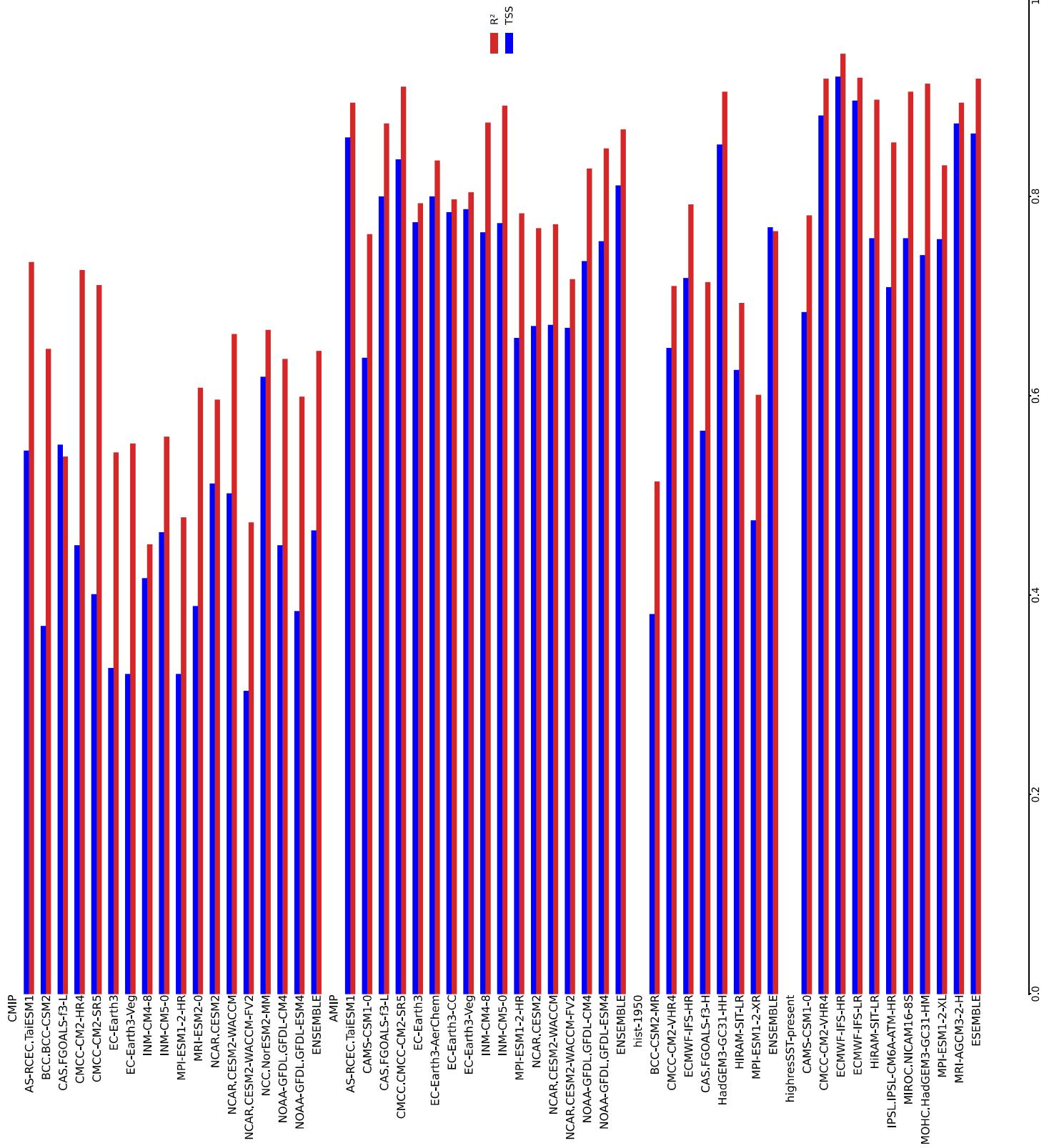
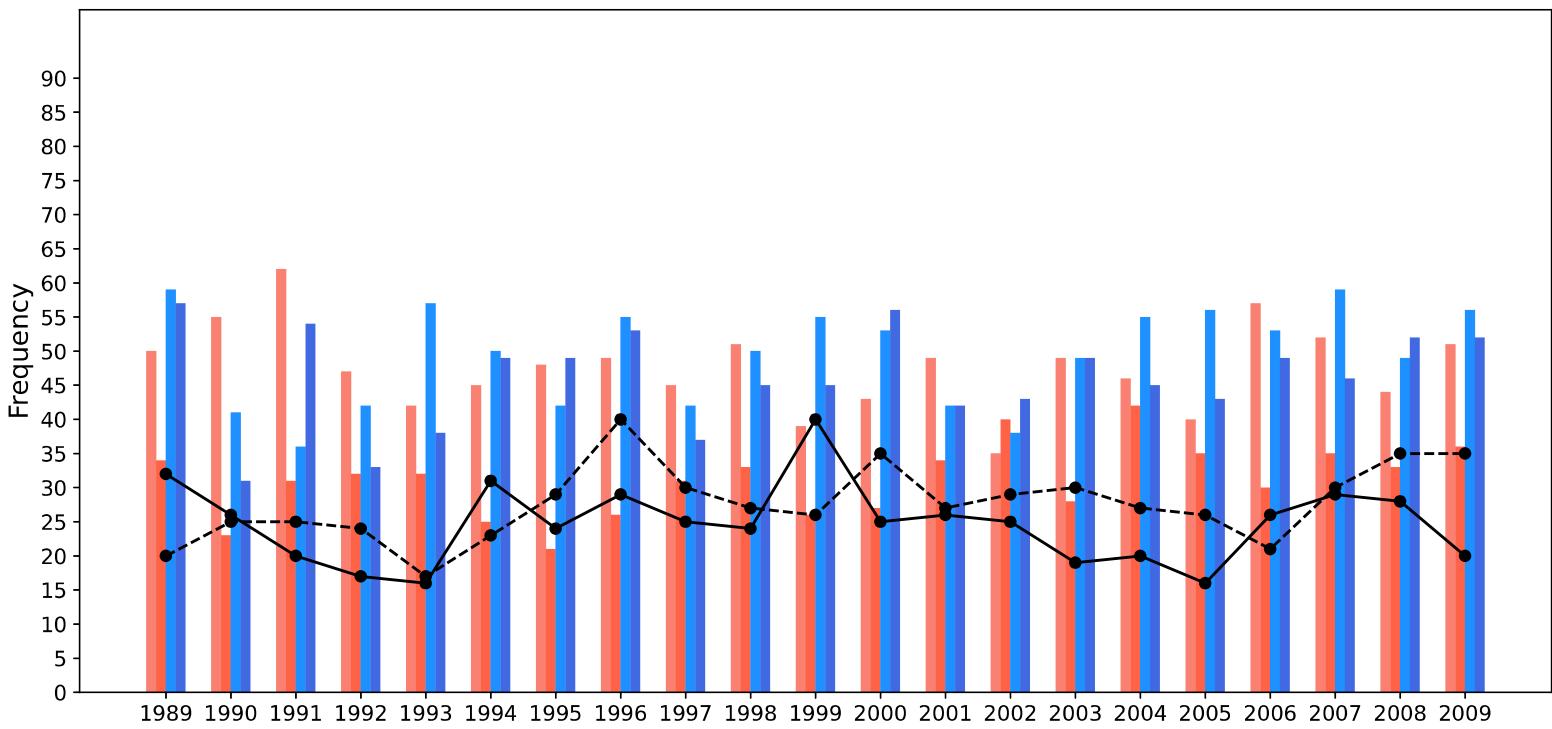
**b)**

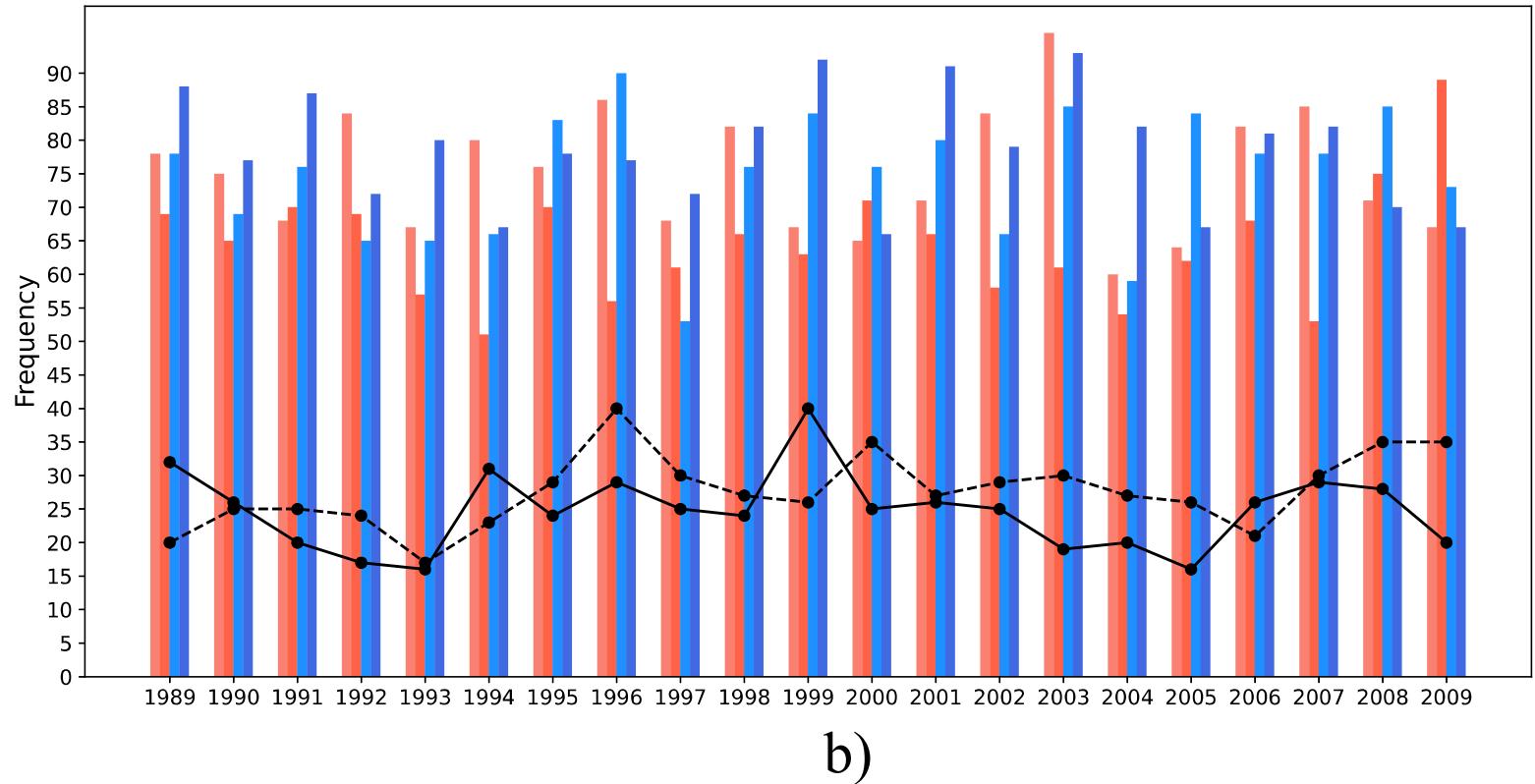
Fig. 8

● GOMES(2019)	TaiESM1_historical	CMCC-CM2-SR5_amip
● ERA5	NorESM2-MM_historical	TaiESM1_amip



a)

● GOMES(2019)	ECMWF-IFS-HR_hist-1950	ECMWF-IFS-HR_highresSST-present
● ERA5	CMCC-CM2-VHR4_hist-1950	CMCC-CM2-VHR4_highresSST-present



b)

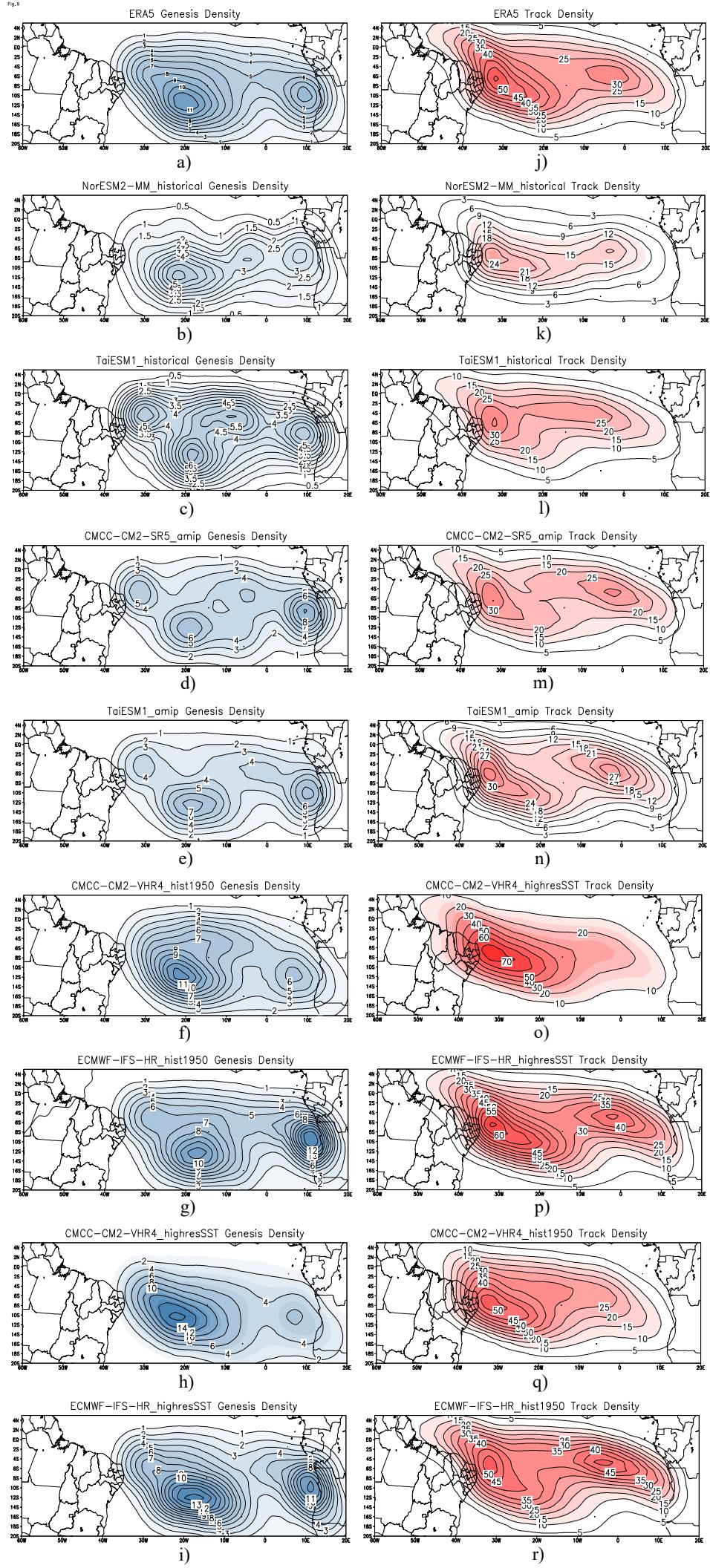


Table 1

Period (days)	Wavelength (km)	Phase velocity (ms <sup>-1</sup> )	Levels (hPa)	Methods/Data	References
4-6	6000	14	700-300	v, spectral analysis	Neiva 1975
4	4000	10	-	Satellite	Yamazaki 1975
3-5	-	12	-	Sounding	Kayano 1979
3-6	6200	12	850	v, ROLE, spectral analysis	Chou 1990
4	3500-4500	10-13	1000-500	v, EOF and EEOF	Espinosa 1996
3.5-3.8	2900-3800	9.8-11.6	700	v, composites, satellite	Mota 1997
3-6	-	-	850-500	v, sounding	Coutinho 2007
3-9	2000-4000	6-12	700	Spectral analysis, v, composites,	Diedhiou et al. 2010
5	4000	10	850 and 700	v, satellite, sounding	Torres 2011
5,3	4307	9.5	1000– 200	u, v, w, composites, synoptic analysis	Pontes da Silva 2011
5,5	4500	9.5	1000– 200	u, v, w, composites, Track	Gomes et al. 2015
4-6	4500	9.5	1000– 200	u, v, w, composites, Track	Gomes et al. 2019

Table 2

Research Centers/Groups	Institute (ID)	Model (Spatial Resolution latitude x longitude)
<b>CMIP (historical)</b>		
Research Center for Environmental Changes	AS-RCEC	TaiESM1 ( $0.94^\circ \times 1.25^\circ$ )
Beijing Climate Center, China Meteorological Administration	BCC	BCC-CSM2-MR ( $1.1^\circ \times 1.1^\circ$ )
Chinese Academy of Sciences	CAS	FGOALS-f3-L ( $1^\circ \times 1.25^\circ$ )
Centro Euro-Mediterraneo per I Cambiamenti Climatici	CMCC	CM2-SR5 ( $0.94^\circ \times 1.25^\circ$ ) CM2-HR4 ( $0.94^\circ \times 1.25^\circ$ )
EC-EARTH consortium	EC-EARTH	EC-Earth3 ( $0.7^\circ \times 0.7^\circ$ ) EC-Earth3-Veg ( $0.7^\circ \times 0.7^\circ$ )
Institute for Numerical Mathematics	INM	INM-CM4-8 ( $1.5^\circ \times 2^\circ$ ) INM-CM5-0 ( $1.5^\circ \times 2^\circ$ )
Max Planck Institute for Meteorology	MPI-M	MPI-ESM1-2-HR ( $0.9^\circ \times 0.9^\circ$ )
Meteorological Research Institute	MRI	MRI-ESM2-0 ( $1.1^\circ \times 1.1^\circ$ )
Norwegian Climate Centre	NCC	NorESM2-MM ( $0.9^\circ \times 1.3^\circ$ )
National Center for Atmospheric Research	NCAR	CESM2 ( $0.95^\circ \times 1.25^\circ$ ) CESM2-WACCM ( $0.95^\circ \times 1.25^\circ$ ) CESM2-WACCM-FV2 ( $1.95^\circ \times 2.5^\circ$ )
National Oceanic and Atmospheric Administration (NOAA) Geophysical Fluid Dynamics Laboratory	NOAA GFDL	GFDL-CM4 GFDL-ESM4 ( $1^\circ \times 1^\circ$ )
Seoul National University	SNU	SAM0-UNICON ( $0.9^\circ \times 1.3^\circ$ )
<b>AMIP</b>		
Research Center for Environmental Changes	AS-RCEC	TaiESM1 ( $0.94^\circ \times 1.25^\circ$ )
Chinese Academy of Meteorological Sciences	CAMS	CAMS-CSM1-0 ( $1.1^\circ \times 1.1^\circ$ )
Chinese Academy of Sciences	CAS	FGOALS-f3-L ( $1^\circ \times 1.25^\circ$ )
Centro Euro-Mediterraneo per I Cambiamenti Climatici	CMCC	CM2-SR5 ( $0.94^\circ \times 1.25^\circ$ )
EC-EARTH consortium	EC-EARTH	EC-Earth3 ( $0.7^\circ \times 0.7^\circ$ ) EC-Earth3-Veg ( $0.7^\circ \times 0.7^\circ$ ) EC-Earth3-AerChem ( $0.7^\circ \times 0.7^\circ$ ) EC-Earth3-CC ( $0.7^\circ \times 0.7^\circ$ )
Institute for Numerical Mathematics	INM	INM-CM4-8 ( $1.5^\circ \times 2^\circ$ ) INM-CM5-0 ( $1.5^\circ \times 2^\circ$ )
Max Planck Institute for Meteorology	MPI-M	MPI-ESM1-2-HR ( $0.93^\circ \times 0.93^\circ$ )
National Center for Atmospheric Research	NCAR	CESM2 ( $0.95^\circ \times 1.25^\circ$ ) CESM2-WACCM ( $0.95^\circ \times 1.25^\circ$ ) CESM2-WACCM-FV2 ( $1.95^\circ \times 2.5^\circ$ )
National Oceanic and Atmospheric Administration (NOAA) Geophysical Fluid Dynamics Laboratory	NOAA GFDL	GFDL-CM4 ( $1^\circ \times 1^\circ$ ) GFDL-ESM4 ( $1^\circ \times 1^\circ$ )
<b>hist-1950</b>		
European Centre for Medium-Range Weather Forecasts	ECMWF	ECMWF-IFS-HR ( $0.50^\circ \times 0.50^\circ$ )
Centro Euro-Mediterraneo per I Cambiamenti Climatici	CMCC	CM2-VHR4 ( $0.23^\circ \times 0.31^\circ$ )
Research Center for Environmental Changes	AS-RCEC	HiRAM-SIT-LR ( $0.5^\circ \times 0.5^\circ$ )
Chinese Academy of Sciences	CAS	FGOALS-f3-H ( $0.25^\circ \times 0.25^\circ$ )

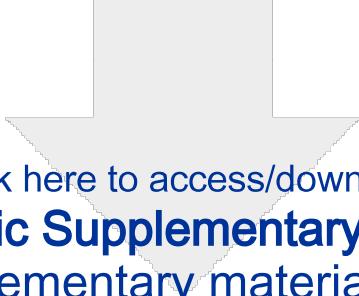
Beijing Climate Center, China Meteorological Administration	BCC	BCC-CSM2-HR ( $0.45^\circ \times 0.45^\circ$ )
Max Planck Institute for Meteorology	MPI-M	MPI-ESM1-2-XR ( $0.47^\circ \times 0.47^\circ$ )
Met Office Hadley Centre	MOHC	HadGEM3-GC31-HM ( $0.23^\circ \times 0.35^\circ$ )
<b>highresSST-present</b>		
European Centre for Medium-Range Weather Forecasts	ECMWF	ECMWF-IFS-HR ( $0.50^\circ \times 0.50^\circ$ ) ECMWF-IFS-LR ( $1.0^\circ \times 1.0^\circ$ )
Institut Pierre-Simon Laplace	IPSL	IPSL-CM6A-ATM-HR ( $0.50^\circ \times 0.70^\circ$ )
Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	MIROC	NICAM16-8S ( $0.28^\circ \times 0.28^\circ$ )
Max Planck Institute for Meteorology	MPI-M	MPI-ESM1-2-XR ( $0.47^\circ \times 0.47^\circ$ )
Centro Euro-Mediterraneo per I Cambiamenti Climatici	CMCC	CM2-VHR4 ( $0.31^\circ \times 0.23^\circ$ )
Research Center for Environmental Changes	AS-RCEC	HiRAM-SIT-LR ( $0.56^\circ \times 0.70^\circ$ )
Chinese Academy of Meteorological Sciences	CAMS	CAMS-CSM1-0 ( $0.46^\circ \times 0.46^\circ$ )
Met Office Hadley Centre	MOHC	HadGEM3-GC31-HM ( $0.23^\circ \times 0.35^\circ$ )
Meteorological Research Institute	MRI	MRI-AGCM3-2H ( $0.56^\circ \times 0.56^\circ$ )

Table 3

MODEL	TSS	RMSE_A (mm day <sup>-1</sup> )	RMSE_S (mm day <sup>-1</sup> )	BIAS_A (mm day <sup>-1</sup> )	BIAS_S (mm day <sup>-1</sup> )	R <sup>2</sup>	DV_norm (mm day <sup>-1</sup> )
<b>CMIP</b>							
AS-RCEC.TaiESM1	0.545	2.269	2.474	1.323	2.019	0.734	1.790
CAS.FGOALS-f3-L	0.551	2.338	2.715	1.245	2.873	0.539	1.293
NCC.NorESM2-MM	0.619	1.606	1.664	0.719	3.563	0.666	1.263
<b>AMIP</b>							
CAS.FGOALS-f3-L	0.800	1.094	1.166	0.667	2.740	0.873	0.980
AS-RCEC.TaiESM1	0.859	1.158	1.147	0.761	2.929	0.894	1.134
CMCC-CM2-SR5	0.837	1.239	1.362	0.934	2.849	0.910	1.184
<b>hist-1950</b>							
CMCC-CM2-VHR4	0.648	1.552	1.160	0.095	-0.345	0.710	2.095
ECMWF-IFS-HR	0.718	1.535	1.578	0.748	0.776	0.792	2.182
HadGEM3-GC31-HH	0.852	0.852	0.687	-0.028	0.036	0.905	1.871
<b>highresSST-present</b>							
MRI-AGCM3-2-H	0.873	0.810	0.667	0.381	0.285	0.894	1.178
CMCC-CM2-VHR4	0.881	0.964	0.917	0.572	0.508	0.918	0.954
ECMWF-IFS-HR	0.920	0.815	0.866	0.490	0.563	0.943	1.100

Table 4

MODELS	Mean phase speed (m/s)	Mean lifetime (day)	Mean frequency (EWD/year)	R <sup>2</sup> (ERA5)	R <sup>2</sup> (Gomes et al, 2019)
CMIP					
NCC.NorESM2-MM	6.65	6.51	31.1	-0.05	-0.05
AS-RCEC.TaiESM1	6.37	6.31	47.6	-0.10	-0.10
AMIP					
CMCC-CM2-SR5	6.62	6.42	49.5	0.01	0.01
AS-RCEC.TaiESM1	7.07	5.83	46.1	0.35	0.35
hist-1950					
CMCC-CM2-VHR4	6.90	6.12	64.5	0.23	0.23
ECMWF-IFS-HR	6.94	6.68	75.0	0.06	0.06
highresSST-present					
CMCC-CM2-VHR4	6.7	5.84	74.7	-0.31	-0.31
ECMWF-IFS-HR	7.07	5.99	78.6	0.34	0.34
ERA5					
ERA5	7.29	5.78	27.7		
Gomes et al (2019)	9.5	5	25		



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