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2 **Impacts of convection schemes**
3 **on simulating tropical-temperate troughs**
4 **over southern Africa**

5
6 **Tomoki Tozuka¹, Babatunde J. Abiodun²,**
7 **Francois A. Engelbrecht³**

8
9 ¹ *Department of Earth and Planetary Science, Graduate School of Science, The*
10 *University of Tokyo, Tokyo, Japan*

11 ² *Climate System Analysis Group, University of Cape Town, Cape Town, South*
12 *Africa*

13 ³ *CSIR Natural Resources and the Environment, Climate Studies, Modelling*
14 *and Environmental Health, Pretoria, South Africa*

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23 *Corresponding author address: Tomoki Tozuka, Department of Earth and Planetary*
24 *Science, Graduate School of Science, The University of Tokyo, 7-3-1 Hongo, Bunkyo-*
25 *ku, Tokyo 113-0033, Japan. E-mail: tozuka@eps.s.u-tokyo.ac.jp. Tel: +81-3-5841-*
26 *4288. Fax: +81-3-5841-8791.*

27 **Abstract**

28 This study examines southern African summer rainfall and tropical temperate
29 troughs (TTTs) simulated with three versions of an atmospheric general circulation
30 model differing only in the convection scheme. All three versions provide realistic
31 simulations of key aspects of the summer (November-February) rainfall, such as the
32 spatial distribution of total rainfall and the percentage of rainfall associated with TTTs.
33 However, one version has a large bias in the onset of the rainy season. Results from
34 self-organizing map (SOM) analysis on simulated daily precipitation data reveals that
35 this is because the occurrence of TTTs is underestimated in November. This model
36 bias is not related to westerly wind shear that provides favorable conditions for the
37 development of TTTs. Rather, it is related to excessive upper level convergence and
38 associated subsidence over southern Africa.

39 Furthermore, the model versions are shown to be successful in capturing the
40 observed drier (wetter) conditions over the southern African region during El Niño (La
41 Niña) years. The SOM analysis reveals that nodes associated with TTTs in the
42 southern (northern) part of the domain are observed less (more) often during El Niño
43 years, while nodes associated with TTTs occur more frequently during La Niña years.
44 Also, nodes associated with dry conditions over southern Africa are more (less)
45 frequently observed during El Niño (La Niña) years. The models tend to perform
46 better for La Niña events, because they are more successful in representing the
47 observed frequency of different synoptic patterns.

48 **1. Introduction**

49 Tropical-temperate troughs (TTTs) provide a substantial portion of summer
50 rainfall over southern Africa (Africa south of 12.5°S). During a TTT event, tropical
51 convection is linked with a transient system in the mid-latitudes (e.g. Vigaud et al.
52 2012), and a band of cloud and rain extending from the northwest to the southeast is
53 formed (Harrison 1984; Todd and Washington 1999; Washington and Todd 1999; Todd
54 et al. 2004; Ratna et al. 2012). The positioning of the Angola Low or related troughs
55 over the northwestern part of the subcontinent plays an important role in the formation
56 of TTTs over southern Africa (Lyon and Mason, 2007, 2009; Vigaud et al. 2008).

57 The interannual variation of rainfall in this region has been shown to be
58 influenced by El Niño-Southern Oscillation (ENSO) (e.g. Lindsay and Vogel 1990;
59 Richard et al. 2000; Cook 2000, 2001; Manhique et al. 2011) and sea surface
60 temperature (SST) anomalies in the surrounding oceans (e.g. Mason 1995; Rouault et
61 al. 2003; Washington and Preston 2006; Williams et al. 2008; Vigaud et al. 2012),
62 including those associated with the subtropical dipole modes (Reason 2002;
63 Fauchereau et al. 2009; Morioka et al. 2010, 2011, 2012). To mitigate impacts of the
64 above-mentioned interannual variations, skillful predictions are required (Behera and
65 Yamagata 2001; Reason et al. 2006; Landman et al. 2009). Landman and Beraki
66 (2012) conducted retroactive multi-model forecasts over southern Africa, and found
67 that their forecasts had relatively good skill during El Niño and La Niña years, but
68 performed poorly during neutral years (years without either El Niño or La Niña events).
69 Also, Yuan et al. (2013) showed that a coupled general circulation model (CGCM) with

70 high skills in predicting ENSO and the subtropical dipole modes had relatively high
71 skills in predicting southern African precipitation anomalies in a broad region south of
72 10°S. Although these studies have illustrated some useful skill in forecasting summer
73 rainfall over southern Africa, the simulation and prediction of rainfall over this region still
74 faces numerous deficiencies. For example, Kataoka et al. (2012) showed that almost
75 all CGCMs that participated in the third phase of the Coupled Model Intercomparison
76 Project (CMIP3; Meehl et al. 2007) failed to simulate the relationship between the
77 precipitation anomaly over southern Africa and global SST anomalies. Also, Lyon and
78 Mason (2009) showed that both atmospheric general circulation models (AGCMs)
79 forced by the observed SST and hindcast seasonal forecasts from CGCMs were
80 unable to reproduce atmospheric circulation anomalies over southern Africa during the
81 strong El Niño event of January-March 1998.

82 Realistic simulations of summer rainfall are important to obtain plausible
83 projections of future climate change over southern Africa, which may in turn be helpful
84 for adaptation (e.g. Thomas et al. 2007). The projection of Engelbrecht et al. (2009)
85 suggested a general decrease in rainfall over southern Africa, but with more frequent
86 occurrence of TTTs over the southeastern part of the subcontinent during mid-summer.
87 The latter resulted from the intensification of the Mascarene High over the
88 southwestern Indian Ocean under global warming. On the other hand, Shongwe et al.
89 (2009) have shown that in the CMIP3 models, the rainfall onset over southern Africa is
90 delayed under global warming, owing to a significant reduction in moisture supply from
91 the southwestern Indian Ocean. Also, Lyon (2009) showed a future drying trend in

92 austral summer rainfall, although this was found to be a model-dependent result, and
93 the experiments of Tadross et al. (2005) indicated that choice of cumulus convection
94 scheme may be regarded as an important source of uncertainty in regional projections
95 of future rainfall over southern Africa. The identification of model biases associated
96 with a particular convection scheme, and the eventual improvement or optimal
97 selection of schemes, may contribute to a reduction in uncertainties associated with the
98 projection of future climate change over this region.

99 Realistic modeling of the basic climatic state is the first step towards the realistic
100 simulation of interannual variations, accurate seasonal prediction, and more reliable
101 projections of future climate change. However, realistic simulations of the southern
102 African rainfall climatology remain a big challenge, partly because of the interaction of
103 tropical and extra-tropical processes over this region. In this regard, van den Heever
104 et al. (1997) used a regional atmosphere model and successfully simulated many
105 aspects of two TTT events. More recently, several studies have attempted to improve
106 the simulation of the rainfall over southern Africa (Crétat et al. 2012; Ratnam et al.
107 2012). Crétat et al. (2012) conducted 27 sensitivity experiments using three different
108 kinds of parameterizations for cumulus convection, planetary boundary layer, and
109 microphysics in a regional atmospheric model. Ratnam et al. (2012) compared results
110 from the same regional model, which was forced by observed SSTs or coupled with an
111 ocean mixed-layer model. However, these regional models depend heavily on the
112 lateral boundary conditions provided by global models or reanalysis data, making it
113 somewhat difficult to determine the relative contribution of convection schemes in

114 causing model biases. Therefore, we here analyze three versions of the same AGCM
115 differing only in the convection scheme, in light of obtaining more realistic simulations
116 of precipitation over the southern African region. Such an approach was useful for
117 understanding of precipitation in other regions such as in India (e.g. Singh et al. 2011;
118 Sinha et al. 2012).

119 This paper is organized as follows. A brief description of the model, convection
120 schemes, data, and methodology is given in the next section. In section 3, we
121 compare seasonal variations in precipitation over the southern African region and TTTs
122 simulated by three versions of our AGCM, and discuss possible causes of model
123 biases. We further evaluate model performances in simulating interannual variations,
124 with a special focus on the relation with ENSO, in section 4. Summary and
125 discussions are provided in the final section.

126

127 **2. Model, data, and methodology**

128 *2.1 Model and data*

129 The AGCM used in this study is the Frontier Atmospheric General Circulation
130 Model (FrAM; Guan et al. 2000). Influences of climate variability related to Indian
131 Ocean Dipole and ENSO on regional climate is relatively well captured by the FrAM
132 (Chakraborty et al. 2005; Yuan et al. 2012). It is the atmospheric component of the
133 University of Tokyo Coupled general circulation model (Tozuka et al. 2006, 2011; Doi
134 et al. 2010). The model equations are solved on 28 hybrid levels in the vertical, from
135 the surface up to 10 hPa level, by using the spectral transform method with triangular

136 truncation at wavenumber 42 (T42). The longwave radiation scheme is based on the
137 multiple parameter random model of Shibata and Aoki (1989) and Shibata (1989). In
138 this scheme, H₂O, CO₂, and O₃ are considered as absorbers of the longwave radiation
139 and the cloud emissivity is estimated as a function of temperature. The shortwave
140 radiation scheme is based on Lacis and Hansen (1974), except for the calculation for
141 partially cloudy skies. Here, H₂O and O₃ are considered as absorbers of the
142 shortwave radiation. The cloud fraction is assumed to be a function of relative
143 humidity and calculated following Slingo and Slingo (1991). The assumption of
144 random overlapping is used for both longwave and shortwave radiation. For the land
145 surface model, we used that of Viterbo and Beljaars (1995). The surface eddy fluxes
146 of momentum, heat, and moisture are calculated using bulk formula (Louis et al. 1982),
147 and the effect of subgrid-scale orography induced by the gravity wave drag is
148 parameterized after Palmer et al. (1986).

149 For the parameterization of cumulus convection, schemes developed by Kuo
150 (1974), Emanuel (1991), and Tiedtke (1989) are used in this study (see Stensrud, 2007
151 for a review). Briefly, Kuo (1974) formulated a parameterization in which convective
152 precipitation is proportional to total column moisture convergence and it is regarded as
153 a deep-layer control scheme. The parameterization proposed by Tiedtke (1989) is a
154 mass flux scheme with updraft plume, downdraft plume, and environmental subsidence.
155 Entrainment of the updraft plumes is assumed to be proportional to the large-scale
156 moisture convergence, while downdraft plumes are assumed to start at the level of free
157 sink and proportional to the upward mass flux. The precipitation rate is equal to

158 condensed liquid water in the above plume model. Emanuel (1991) developed a
159 parameterization categorized as a mass flux scheme that takes into account the
160 collective effects of the various subparcels in the cloud. A specified fraction of
161 condensed water from the subparcels falls as precipitation. We call these three
162 experiments FrAM_Kuo, FrAM_Emanuel, and FrAM_Tiedtke, respectively. We note
163 that we do not intend to discuss superiority of a particular scheme in this study.
164 Rather, the three experiments should be considered as sensitivity experiments of a
165 single AGCM. Also, their performance depends on the resolution of the model, and
166 the parameterization of Kuo (1974) tends to perform better with larger grid size (Singh
167 et al. 2011).

168 This model is integrated from 1981 to 2008 using monthly SST and sea ice cover
169 data from Hurrell et al. (2007). This dataset has been used in the Atmospheric Model
170 Intercomparison Project (AMIP) simulations. For each experiment, five different initial
171 conditions are used to generate five ensemble members, and outputs after 1982 are
172 used for the present analysis. To generate initial conditions, we have spun up the
173 model from a calm and isothermal atmosphere for about three years (the spin-up time
174 varies slightly for the five different ensemble members, being three years for one
175 member with the others 5, 10, 15, and 20 days shorter, respectively), using the monthly
176 climatologies of SSTs as a lower boundary forcing. The CO₂ concentration was set to
177 the AMIP-specified value of 348 ppmv, and the solar constant was set to AMIP-
178 specified 1365 W m⁻².

179 We also use the Global Precipitation Climatology Project (GPCP) data (Adler et

180 al., 2003) for precipitation, and the National Centers for Environmental Prediction
181 (NCEP)/National Center for Atmospheric Research (NCAR) reanalysis data (Kalnay et
182 al., 1996) for wind, sea-level pressure (SLP), temperature, and specific humidity, to
183 validate the model simulations. We note that we obtained qualitatively similar results
184 even when we used the NCEP-DOE reanalysis 2 data (Kanamitsu et al. 2002) and
185 ECMWF reanalysis data (Uppala et al. 2005), instead of the NCEP/NCAR reanalysis
186 data.

187

188 *2.2 Methodology: Self-organizing maps*

189 To capture synoptic precipitation patterns, we have applied self-organizing map
190 (SOM) analysis (Kohonen 2001) to daily rainfall anomaly data from November to
191 February (Fig. 1). This method has been successfully used to study climate variations
192 (Tozuka et al. 2008; Morioka et al. 2010) and synoptic weather patterns (Nicholls et al.
193 2010; MacKellar et al. 2010). In this study, we use a software package called
194 SOM_PAK 3.1 (Kohonen et al. 1995), and readers are referred to Kohonen (1982,
195 2001) for more details about the SOM.

196 The input data is first prepared from both observed and simulated daily rainfall
197 anomalies, by interpolating the observed data into the T42 grid of the AGCM over the
198 southern African region (43.254°S-12.558°S, 0°-50.625°E). Since the daily rainfall
199 data of the GPCP is available only from 1997 to 2008, we focus on the rainy seasons
200 (November to February) from 1997/98 to 2007/08. As a result, the input matrix
201 consists of 228 grids points with 19 grids in the zonal direction and 12 grids in the

202 meridional direction, and 21120 days of data (1320 days of data for the observations
203 and five ensembles of 1320 days of data for each version of the AGCM). We note
204 that simulated daily precipitation data are used without taking the ensemble mean
205 when we perform the SOM analysis. Then, the dimension of the two-dimensional
206 SOM array is chosen to be 5 nodes x 4 nodes. The topology of the array is selected
207 to be rectangular, and the reference vectors are initialized to random values. We
208 have chosen to use a “bubble” function for the neighborhood function. The training is
209 undertaken in two steps; we use a larger initial learning rate and a neighborhood radius
210 for the first phase to put reference vectors in an order, and a smaller rate and radius to
211 tune the values of reference vectors in the second phase. As a result, we have
212 obtained 20 different daily precipitation patterns, which will be discussed in Sections 3
213 and 4.

214

215 *2.3 Methodology: Equitable Threat Score*

216 Skills of the model in simulating interannual variations of precipitation are
217 measured using equitable threat score (ETS), which is defined as

$$218 \quad ETS = \frac{H - C}{F + A - H - C}$$

219 (Rogers et al. 1996; Chakraborty and Krishnamurty 2009). Here, F and A are
220 number of grids with simulated and observed precipitation exceeding a specified
221 threshold, respectively, H is the number of grids with both simulated and observed
222 precipitation exceeding the threshold or number of hit, $C = F \cdot A/T$ is the expected

223 number of hit by chance, and T is the total number of grids. Values of ETS may vary
224 from $-1/3$ to 1 and an ETS of 1 signifies that the simulation is perfect. We calculate
225 the ETS for an area that covers African continent south of 15°S (11.25°E - 42.1875°E ,
226 15.348°S - 34.883°S).

227

228 **3. Seasonal variation**

229 The mean precipitation patterns over the southern African region during mid-
230 summer (November-February) are shown in Fig. 2. Areas with high rainfall totals
231 extend southeastward from the equatorial region to around 15°S , and then extend
232 southward along the east coast of Mozambique and South Africa. There is a marked
233 west-east gradient in rainfall over the southern part of the subcontinent, with
234 precipitation less than 2 mm day^{-1} in the southwest. Over eastern South Africa, mid-
235 summer rainfall rates exceed 4 mm day^{-1} . A relatively dry region extends along 20°S ,
236 from the western subcontinent towards the east. These observed features are well
237 captured by all three versions of the model. The feature of the dry slot extending
238 eastwards along 20°S , and the precipitation maximum over eastern South Africa, are
239 better captured in FrAM_Tiedtke and FrAM_Kuo. However, the precipitation in the
240 equatorial Africa and the southwestern tropical Indian Ocean to the north of
241 Madagascar is too high in all three versions. Also, the precipitation maximum over
242 northern Madagascar is missing in FrAM_Tiedtke.

243 Figure 3 shows the mean SLP around the southern African region. All versions
244 provide satisfactory simulations of the relative positions of the subtropical highs in both

245 the South Atlantic and the southern Indian Oceans, and the heat low over the
246 subcontinent. The maximum SLP in St. Helena High is overestimated by 2 hPa, whilst
247 the heat low is simulated to be too deep, by about 5 hPa in all three versions. Since
248 these subtropical highs and the heat low play an important role in the formation and
249 distribution of precipitation over the southern African region (Reason et al. 2006), the
250 model's realistic representation of these highs and the low may be one of the reasons
251 for the reasonably realistic simulation of mid-summer precipitation patterns over the
252 region.

253 Next, to examine the seasonal evolution of precipitation, observed and simulated
254 monthly mean precipitation patterns are presented in Fig. 4. From May to September,
255 the region is dry in the observations and all three versions. However, by November,
256 the Inter-Tropical Convergence Zone (ITCZ) has progressed to the south of the equator,
257 and precipitation greater than 2 mm day^{-1} occurs over vast areas of the subcontinent.
258 The rainfall maximum over eastern South Africa is linked to that in the tropics by a
259 band-like structure. This large-scale pattern is well-captured in FrAM_Kuo and
260 FrAM_Emanuel, although both of these versions exhibit a wet bias that is particularly
261 strong in the tropics. However, in FrAM_Tiedtke, the precipitation maxima over
262 southern Africa and the tropics are not linked, and the region between 10°S and 25°S
263 is relatively dry. From January to March, most regions are observed to experience
264 precipitation greater than 2 mm day^{-1} with the exception being the dry southwestern
265 subcontinent. The highest rainfall totals occur in a band in the vicinity of 15°S ,
266 indicative of the position of the ITCZ. All three versions capture this broad-scale

267 pattern, although the precipitation maximum in March occurs too far south in
268 FrAM_Kuo. The observed feature of a dry slot extending eastward in the observations
269 is well represented in FrAM_Emanuel and FrAM_Tiedtke. In general, the seasonal
270 evolution of rainfall is relatively well captured by all three versions, with the most
271 significant bias in the delayed onset of the rainy season in FrAM_Tiedtke.

272 To understand the seasonal variation in the rainfall and its biases, it is convenient
273 to check the vertical stability. Following Ninomiya (2008), we have calculated the
274 vertical stability in the 850-500 hPa layer (Fig. 5), which is given by

$$275 \quad (\theta_{e500} - \theta_{e850}) / 3.5,$$

276 where θ_{e500} and θ_{e850} are equivalent potential temperature at 500 and 850 hPa,
277 respectively. In both the observation and the model, the southern African region is
278 convectively unstable from November to March and convectively stable from May to
279 September, in agreement with the rainy season in this region. Furthermore, Fig. 6
280 shows vertical velocity at 500 hPa. In general, the models are successful in
281 simulating the seasonal march of the vertical velocity. However, the upward motion is
282 too strong in all three versions in the tropics, which may be related to too much
283 precipitation there. Also, upward motion prevails in the southeastern part of South
284 Africa throughout the year in the models, even though downward motion is seen in May
285 and July in the observation. This is related to the wet bias in the southeastern corner
286 of the subcontinent, particularly in FrAM_Kuo.

287 For quantitative comparison, we have calculated spatial correlation coefficients of
288 rainfall over 0-60°E, 45°S-15°S between the GPCP observations and the three

289 versions of FrAM for each month (Fig. 7). Generally, the correlation coefficients are
290 high for all three versions throughout the year. In particular, the correlation coefficient
291 is higher than 0.79 (0.70) for all months in FrAM_Emanuel (FrAM_Kuo). However, the
292 correlation coefficient takes a minimum in all three versions in November, and as
293 expected from Fig. 4, it becomes lower than 0.5 for FrAM_Tiedtke.

294 One contributing factor for this dry bias in FrAM_Tiedtke may stem from a bias of
295 simulating subsident conditions over southern Africa in November. Figure 8 shows
296 the velocity potential along with divergent wind at 200 hPa in November. Spuriously
297 strong upper level convergence extends from the southwestern Indian Ocean into the
298 subcontinent in FrAM_Tiedtke, a feature that is likely to inhibit the formation of TTTs
299 during this month. It may also be noted that in FrAM_Emanuel, upper level
300 divergence is simulated over southern Africa, rather than the relatively weak
301 convergence present in FrAM_Kuo and in the observations.

302 To investigate how well synoptic precipitation patterns are reproduced by the
303 various AGCM versions, and whether the occurrence of TTTs in November is reduced
304 in FrAM_Tiedtke, we have applied the SOM analysis to daily rainfall anomaly data.
305 Twenty different precipitation patterns captured by the SOM are shown in Fig. 9. The
306 precipitation patterns that exhibit marked northwest to southeast alignments over
307 southern Africa, with rainfall rates of more than 4 mm day^{-1} over some areas, are
308 assumed to be associated with the formation of TTTs over this region. Such patterns
309 are found in the bottom row (nodes D1-D5) and left column (nodes A1-D1). We note
310 that our results are not very sensitive to the designation of additional nodes that exhibit

311 some TTT-like characteristics (e.g. node C5), since the qualitative results remains
312 almost the same even if we add or remove one node. The frequency map for both the
313 observation and the model versions (Fig. 10) indicates that all 20 precipitation anomaly
314 patterns seen in the observations are captured by the three versions (since a node with
315 frequency of 0% does not exist in the model frequency maps). The frequency of
316 occurrence of TTT nodes is overestimated by FrAM_Kuo, whilst FrAM_Emanuel and
317 FrAM_Tiedtke provide more realistic representations of these frequencies. Also, as
318 revealed by Figs. 11b, c, d, as much as 70% of simulated precipitation over 30°E-45°E,
319 15°S-30°S is associated with TTTs. This is in agreement with observations (Fig. 11a).
320 However, FrAM_Kuo exhibits a bias in this regard, in that too high percentage of
321 rainfall over the eastern part of the subcontinent occur in association with TTTs. One
322 possible reason for this bias is that the vertical stability over southern Africa is relatively
323 weak in FrAM_Kuo, especially during the early part of the rainy season, and this may
324 provide more favorable conditions for the development of TTTs in this version of the
325 model (Fig. 5).

326 Figure 12 shows how frequently each daily precipitation pattern appears each
327 month from November to February. In November, nodes A1-D1 and D2-D5 appear
328 less frequently compared with other months in the observation. This indicates that the
329 occurrence of TTTs is lower during this month. This tendency is exaggerated in
330 FrAM_Tiedtke; nodes D1-D4 appears less frequently in November. Therefore, the
331 model bias as suggested earlier by Figs. 4 and 7 for FrAM_Tiedtke is indeed due to an
332 underestimation in the occurrence of TTT events. Also, nodes that represent TTTs

333 appear too frequently in FrAM_Kuo (also see Fig. 10b) and this explains why it
334 overestimates the percentage of precipitation associated with TTTs (Fig. 11b).

335 Figure 12 also serves to illustrate the sensitivity of TTT formation in the AGCM to
336 various choices of convection schemes. It is illuminating to investigate whether the
337 differences in the simulated TTT frequencies are due to extra-tropical, or tropical
338 processes. The vertical shear in the zonal wind is displayed in Fig. 13, because
339 westerly shear is known to provide a favorable condition for the development of TTTs
340 (Todd and Washington 1999). Since all three versions show strong westerly shear of
341 about 30 m s^{-1} between 200 hPa and 850 hPa, which is slightly larger than the
342 NCEP/NCAR reanalysis data, model biases in the westerlies do not seem to explain
343 the different simulated frequencies of TTTs, and the less frequent occurrence of TTTs
344 in FrAM_Tiedtke in November. This result suggests that it is primarily the simulated
345 tropical circulation that is sensitive to the choice of convection scheme.

346

347 **4. Interannual variation**

348 The correlation coefficients between the observed and simulated precipitation
349 anomalies for November-February for the period of 1982-2008 are shown in Fig. 14.
350 In all three versions, the model has the highest skills in the equatorial East Africa, and
351 FrAM_Tiedtke has a correlation coefficient of above 0.6. The precipitation in this
352 region is strongly influenced by the Indian Ocean Dipole (Behera et al. 2005), and it
353 may be relatively easy for the AGCM to reproduce rainfall anomalies forced by
354 anomalous zonal SST gradient across the equatorial Indian Ocean. Also, the

355 correlation coefficient is relatively high in the southern African region with the maximum
356 correlation of 0.4 for FrAM_Kuo and 0.5 for FrAM_Tiedtke and FrAM_Emanuel.

357 Also, we have evaluated the performance by calculating the ETS for both dry and
358 wet conditions (Fig. 15). In general, the model tends to have higher skill for dry
359 conditions. This is particularly true for FrAM_Tiedtke, which has an ETS of 0.16 with -
360 0.4 and -0.8 mm/day thresholds. Among the three versions, FrAM_Tiedtke has the
361 highest score, except for the 0.0 mm/day threshold for wet conditions. However, the
362 ETS is below 0.2 for all versions regardless of threshold values. This suggests that
363 we need a higher resolution model, or additional model improvements, to more
364 faithfully simulate precipitation anomalies at a grid scale. Indeed, Chakraborty and
365 Krishnamurti (2009) revealed that downscaled forecasts show marked improvements
366 compared with their coarse resolution forecasts for the Indian summer monsoon.

367 Since the interannual variation in the southern African region is known to be
368 influenced by ENSO (e.g. Lindesay and Vogel 1990; Richard et al. 2000), the
369 difference in the skill levels mentioned above may be closely linked with that of the
370 model to simulate the impacts of ENSO. To examine influences of ENSO, we have
371 defined ENSO years based on the Niño-3.4 index (Fig. 16), which is computed by
372 taking an area-average of SST anomalies over the tropical eastern-central Pacific
373 (120°W-170°W, 5°S-5°N). Here, if the index is above (below) 1 standard deviation,
374 we define the year as an El Niño (a La Niña) year. As a result, we have two El Niño
375 years (1997/98 and 2002/03), three La Niña years (1998/99, 1999/2000, and 2007/08),
376 and six normal years (2000/01, 2001/02, 2003/04, 2004/05, 2005/06, and 2006/07).

377 Figure 17 shows composites of precipitation anomalies for ENSO years. As has
378 been shown to be typical by previous studies (e.g. Lindesay and Vogel 1990; Richard
379 et al. 2000), the observation shows negative (positive) precipitation anomalies over the
380 southern African region during El Niño (La Niña) years. East Africa exhibits
381 precipitation anomalies opposite to that of the southern African region. This general
382 pattern is well captured by all three versions, but there are some differences between
383 the observation and the simulations. The strongest negative precipitation anomalies
384 during El Niño are found over Mozambique and in Zimbabwe in the observations, but in
385 FrAM_Kuo, wet anomalies extend from the north into Mozambique. In
386 FrAM_Emanuel, the largest negative anomalies occur somewhat to the south than is
387 observed. Although negative precipitation anomalies extend too far into the Indian
388 Ocean, FrAM_Tiedtke simulates the location of largest negative precipitation anomalies
389 over Mozambique relatively well, and this explains why it has the best ETS (Fig. 15a).
390 Also, the strongest positive precipitation anomalies during La Niña is found over
391 Mozambique in the observation, but all versions of the model displaces this maximum
392 to the south over southeastern South Africa. This is why the ETS for the wet
393 conditions tends to be lower compared with that in the dry conditions (Fig. 15b.)

394 To examine interannual variations in the synoptic precipitation patterns, we have
395 checked how frequently each precipitation pattern appears compared with the
396 climatology during El Niño, normal, and La Niña years in the GPCP observation and
397 three versions of FrAM (Fig. 18). For quantitative comparison of the three versions'
398 performance, phase synchronization (ps) is calculated as:

399 $ps = (n-n')/n * 100$

400 (Misra 1991). Here, n is the total number of nodes and n' is the number of nodes for
401 which the anomalies in the observation and the model have opposite signs (out of
402 phase). Therefore, $ps = 0$, if signs of anomalies simulated by one version of our
403 AGCM are opposite to those of the GPCP observation for all 20 nodes, and $ps = 100$, if
404 signs of anomalies in a version are consistent with the observation for all 20 nodes.

405 During El Niño years, nodes associated with TTTs in the southern (northern) part
406 of the domain appear less (more) frequently in the observations; nodes D1-D5 (A1-C1)
407 have negative (positive) anomalies. This is well captured by FrAM_Tiedtke, as is also
408 evident from the fact that this version has the highest phase synchronization among the
409 three versions. However, all versions fail to capture positive anomalies in nodes A2-
410 A5 that show dry conditions over southern Africa. This is one of the reasons why the
411 phase synchronization remains around 50 for the all three versions.

412 On the other hand, nodes representing TTTs are observed to occur more
413 frequently during La Niña years (note the positive anomalies for nodes A1, B1 and D2-
414 D5 in Fig. 18). FrAM_Emanuel best captures positive anomalies in these nodes with
415 three nodes showing positive anomalies. In contrast to the situation during El Niño
416 years, FrAM_Emanuel and FrAM_Tiedtke tend to perform better in capturing the
417 negative anomalies in Nodes A2-A5. Because these dry patterns appear less
418 frequently, the southern African region experiences more rainfall during La Niña years
419 in general. As a result, FrAM_Emanuel and FrAM_Tiedtke have a high phase
420 synchronization of 70 and 65, respectively, whereas FrAM_Kuo has a low phase

421 synchronization of 45.

422 As expected in the absence of strong influences from ENSO, the frequency
423 anomaly is within $\pm 1\%$ in more than 80% of the nodes during the normal years.
424 FrAM_Tiedtke (FrAM_Kuo) has the highest (lowest) skill with the phase
425 synchronization of 65 (35).

426 In summary, the model versions perform better in simulating the interannual
427 variations in the precipitation pattern for La Niña years compared to El Niño or normal
428 years, and FrAM_Emanuel and FrAM_Tiedtke have higher skills in general compared
429 with FrAM_Kuo.

430

431 **5. Summary and discussions**

432 Using three versions of the same AGCM differing only in the convection scheme,
433 we have evaluated skills of models in simulating southern African rainfall and TTT
434 attributes. All three versions have relatively good capabilities in simulating the
435 summer precipitation, although one version (FrAM_Tiedtke) has a serious bias in the
436 onset. This version simulates excessive upper level convergence and associated
437 subsidence over southern Africa. As a result, development of TTTs is suppressed
438 and connection of tropical and extra-tropical precipitation is delayed by about one
439 month. It is interesting to note that for all three versions, the ability to represent the
440 climatology of monthly rainfall patterns is lowest in November. Since the onset of
441 rainy season is very important for subsistence farming in the southern African region,
442 this model bias is potentially a limiting factor to the skill of early-season seasonal

443 forecasts over the region.

444 Regarding the simulation of interannual variation, all three versions have
445 relatively good skill, particularly in equatorial East Africa and South Africa. In addition,
446 they are successful in capturing negative (positive) precipitation anomalies over
447 southern Africa in El Niño (La Niña) years, although the exact location of peak
448 precipitation anomalies is slightly shifted. When synoptic precipitation patterns are
449 examined using SOMs, we have found that nodes associated with TTTs in the
450 southern (northern) part of the domain are observed less (more) often during El Niño
451 years. In contrast, nodes associated with TTTs occur more frequently during La Niña
452 years. Also, nodes associated with dry conditions over southern Africa appear more
453 (less) frequently during El Niño (La Niña) years.

454 Interestingly, the models have better skill in simulating precipitation anomalies
455 during La Niña years, and this may explain why forecast skills have been found to be
456 higher during La Niña years (Landman and Beraki 2012). Because of limitation in the
457 length of daily precipitation data, we note that there are only two (three) El Niño (La
458 Niña) events in the composites, and the analysis should be repeated after the
459 accumulation of observation data.

460 However, this study is the first to illustrate that the usage of different convection
461 schemes in an AGCM can have pronounced effects on the simulation of southern
462 African rainfall in austral summer. In fact, the study shows that the simulation of upper
463 level circulation and TTT attributes are sensitive to the choice of cumulus convection
464 scheme. We therefore expect that the results presented in this study may shed new

465 light on simulation and prediction of the precipitation over the southern Africa region.

466

467

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482

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671 **Figure captions:**

672

673 **Figure 1:** Schematic diagram showing how the SOM is applied.

674 **Figure 2:** Mean precipitation (in mm day^{-1}) around the southern African region during
675 the rainy season (November-February) in (a) GPCP, (b) FrAM_Kuo, (c)
676 FrAM_Emanuel, and (d) FrAM_Teidtke.

677 **Figure 3:** Mean sea level pressure (in hPa) during the rainy season (November-
678 February) in (a) GPCP, (b) FrAM_Kuo, (c) FrAM_Emanuel, and (d) FrAM_Teidtke.

679 **Figure 4:** As in Fig. 2, but for monthly climatology of precipitation (in mm day^{-1}) in
680 January, March, May, July, September, and November.

681 **Figure 5:** As in Fig. 4, but for the vertical stability (in K (100 hPa)^{-1}).

682 **Figure 6:** As in Fig. 4, but for the vertical velocity (in Pa s^{-1}).

683 **Figure 7:** Spatial correlation coefficient of rainfall over 0° - 60° E, 45° S- 15° S between the
684 GPCP observation and three versions of FrAM. All pattern correlation
685 coefficients are significant at 99% confidence level when tested by the Monte
686 Carlo method.

687 **Figure 8:** Velocity potential (in $\text{m}^2 \text{s}^{-1}$ as shown in the color bar) and divergent wind (in
688 m s^{-1} and its magnitude shown in the vector below the color bar) at 200 hPa in
689 November for (a) the NCEP/NCAR reanalysis data, (b) FrAM_Kuo, (c)
690 FrAM_Emanuel, and (d) FrAM_Tiedtke.

691 **Figure 9:** SOM array of daily rainfall anomalies (in mm day^{-1}). Each node represents
692 a synoptic precipitation pattern over the southern African region.

693 **Figure 10:** Frequency map of the SOM array showing how frequently each
694 precipitation pattern appears during the rainy season (November-February).

695 **Figure 11:** As in Fig. 2, but for percentage of precipitation in the rainy season
696 (November-February) associated with nodes representing TTTs.

697 **Figure 12:** (First row) Frequency map of the SOM array showing how frequently each
698 precipitation pattern appears from November to February in the observation.
699 (Second, third, and fourth rows) Model biases in frequency of each precipitation
700 pattern in FrAM_Kuo, FrAM_Emanuel, and FrAM_Tiedtke, respectively.
701 Positive (Negative) values signify that the pattern appears more (less) frequently
702 compared with the observation.

703 **Figure 13:** As in Fig. 2, but for the zonal wind shear (200-850 hPa; m s^{-1}) in November.

704 **Figure 14:** Correlation coefficients between the observed and simulated precipitation in
705 the southern African region for November-February for the period of 1982-2008:
706 (a) FrAM_Kuo, (b) FrAM_Emanuel, and (c) FrAM_Tiedtke.

707 **Figure 15:** Equitable threat score of precipitation during November-February of the
708 period of 1982-2008 for (a) dry and (b) wet conditions.

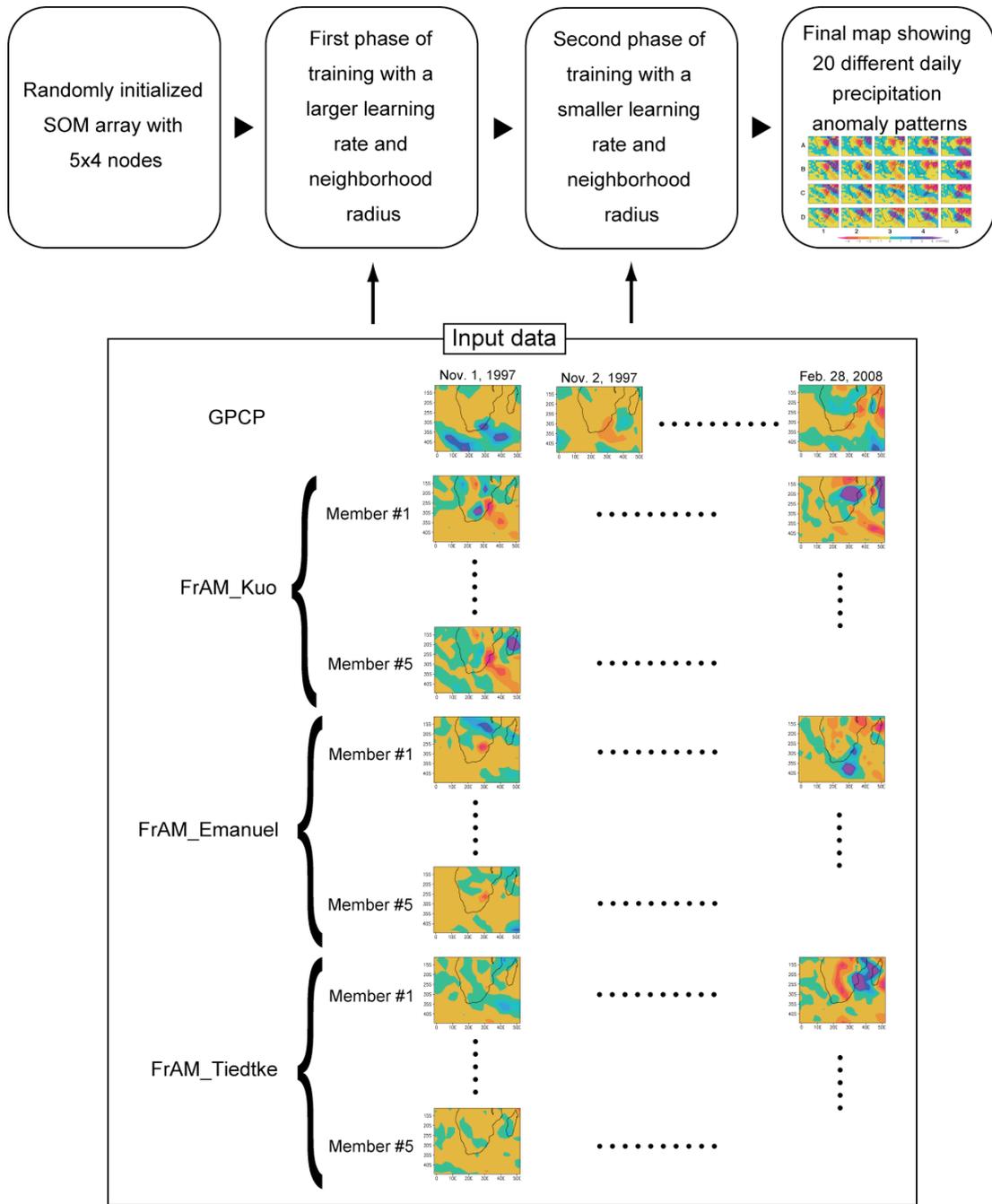
709 **Figure 16:** Normalized time series of Niño-3.4 index in November-February.

710 **Figure 17:** Composite of precipitation anomalies (in mm day^{-1}) in (upper panels) El
711 Niño and (lower panels) La Niña years.

712 **Figure 18:** Frequency map of the SOM array showing how frequently each
713 precipitation pattern appears during El Niño, normal, and La Niña years in the
714 GPCP observation and three versions of FrAM. Here, deviations from the

715 seasonal mean percentage are shown, and “ps” signifies phase synchronization.

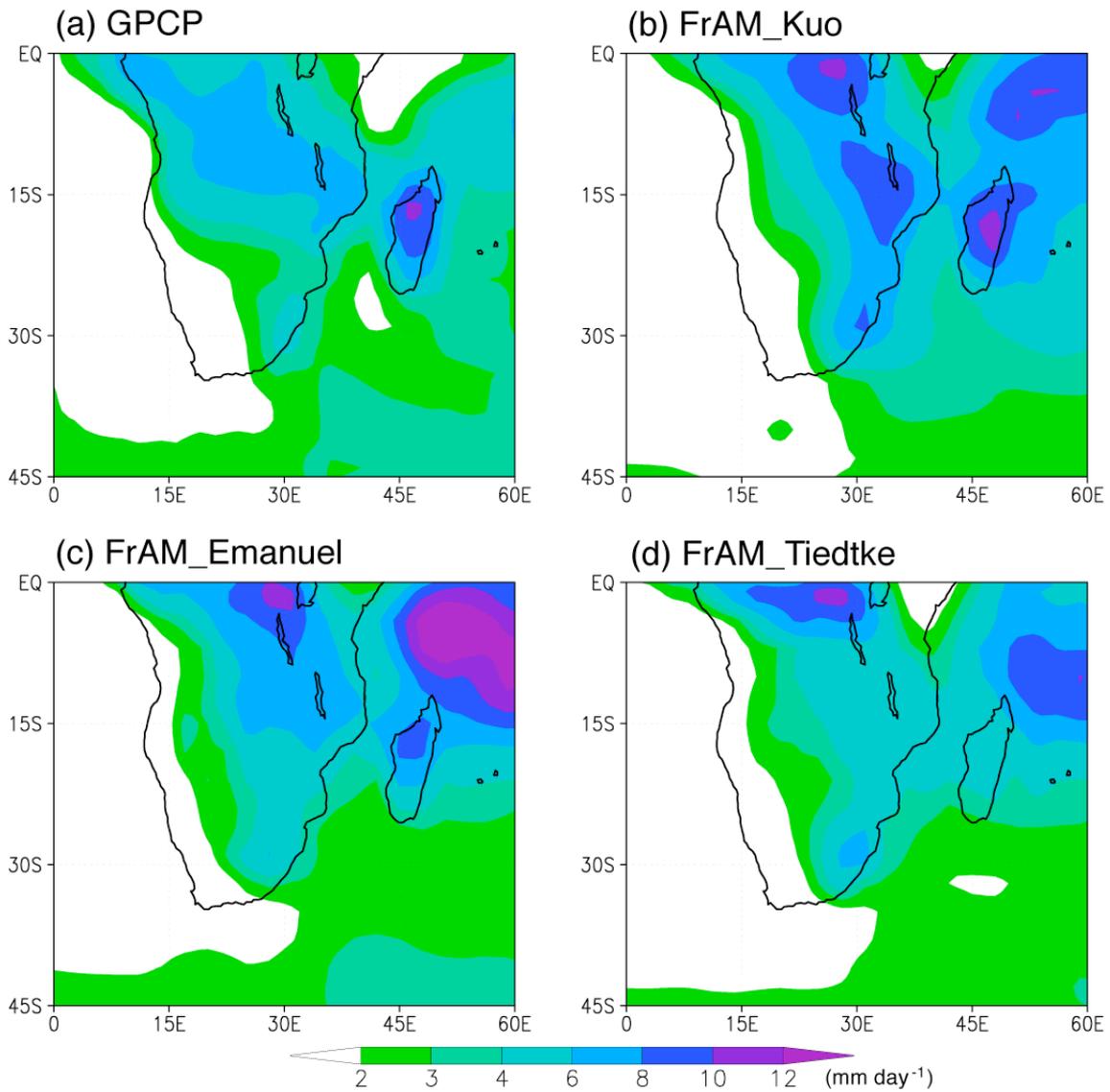
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719 **Figure 1:** Schematic diagram showing how the SOM is applied.

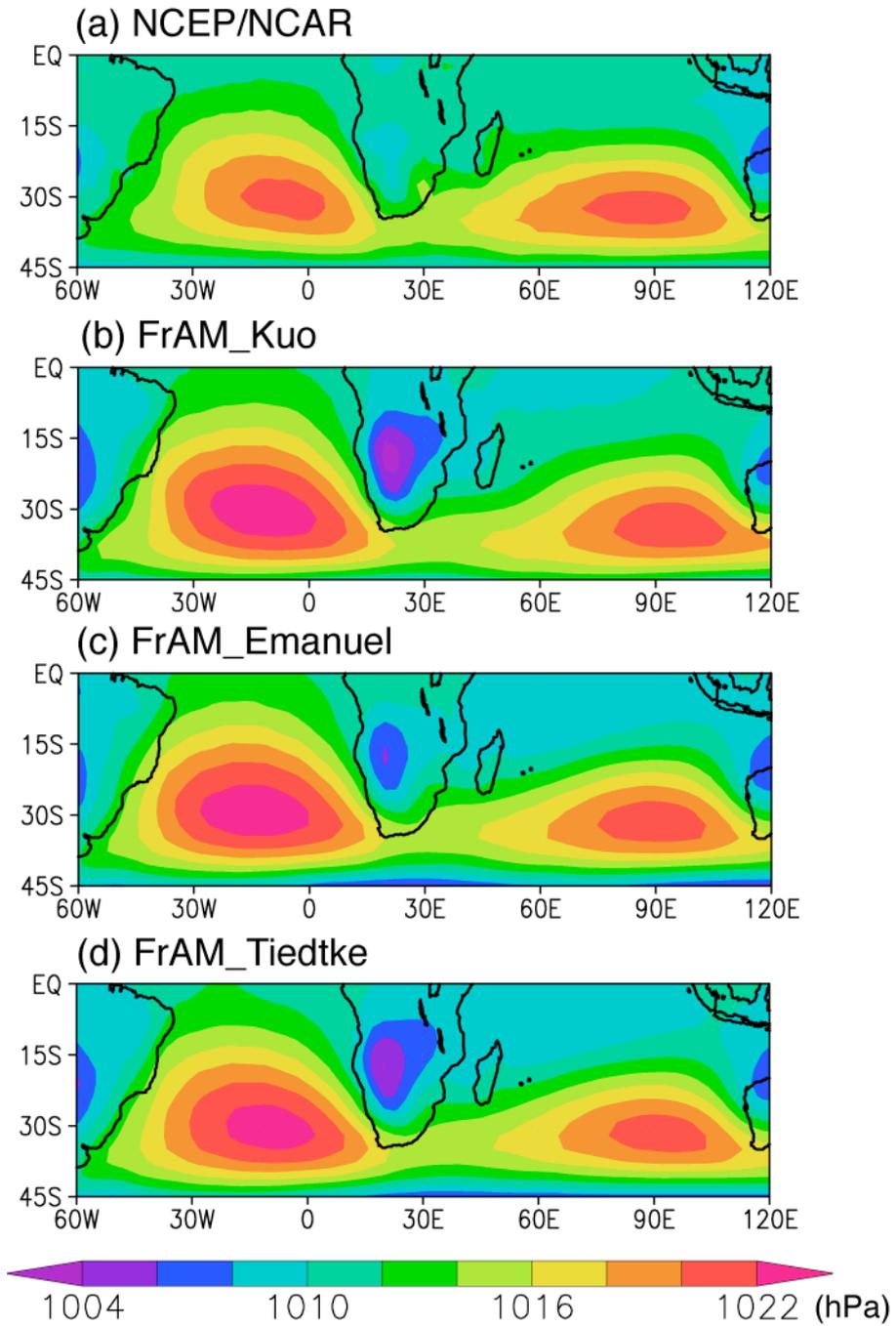
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 724 the rainy season (November-February) in (a) GPCP, (b) FrAM_Kuo, (c)
 725 FrAM_Emanuel, and (d) FrAM_Tiedtke.

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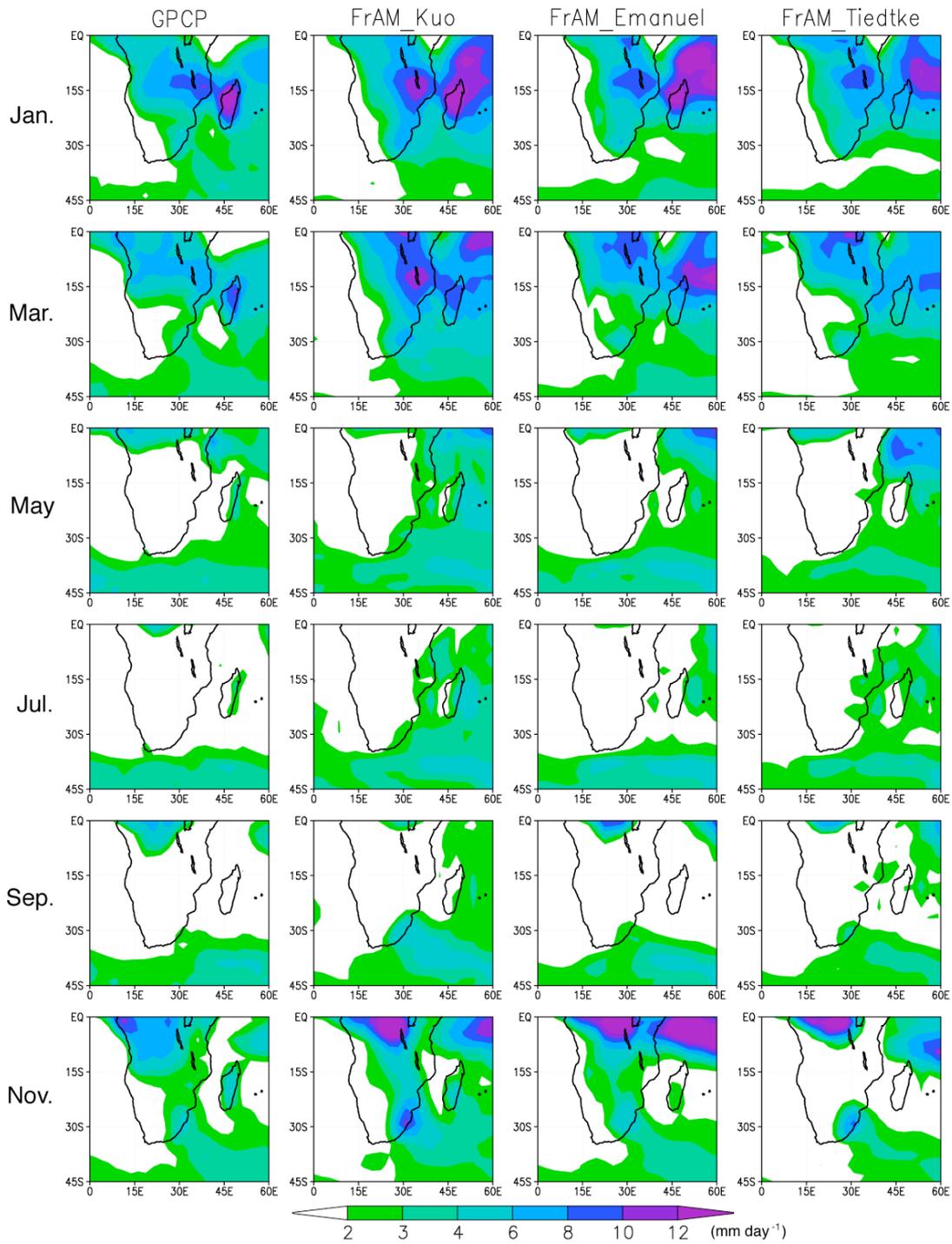


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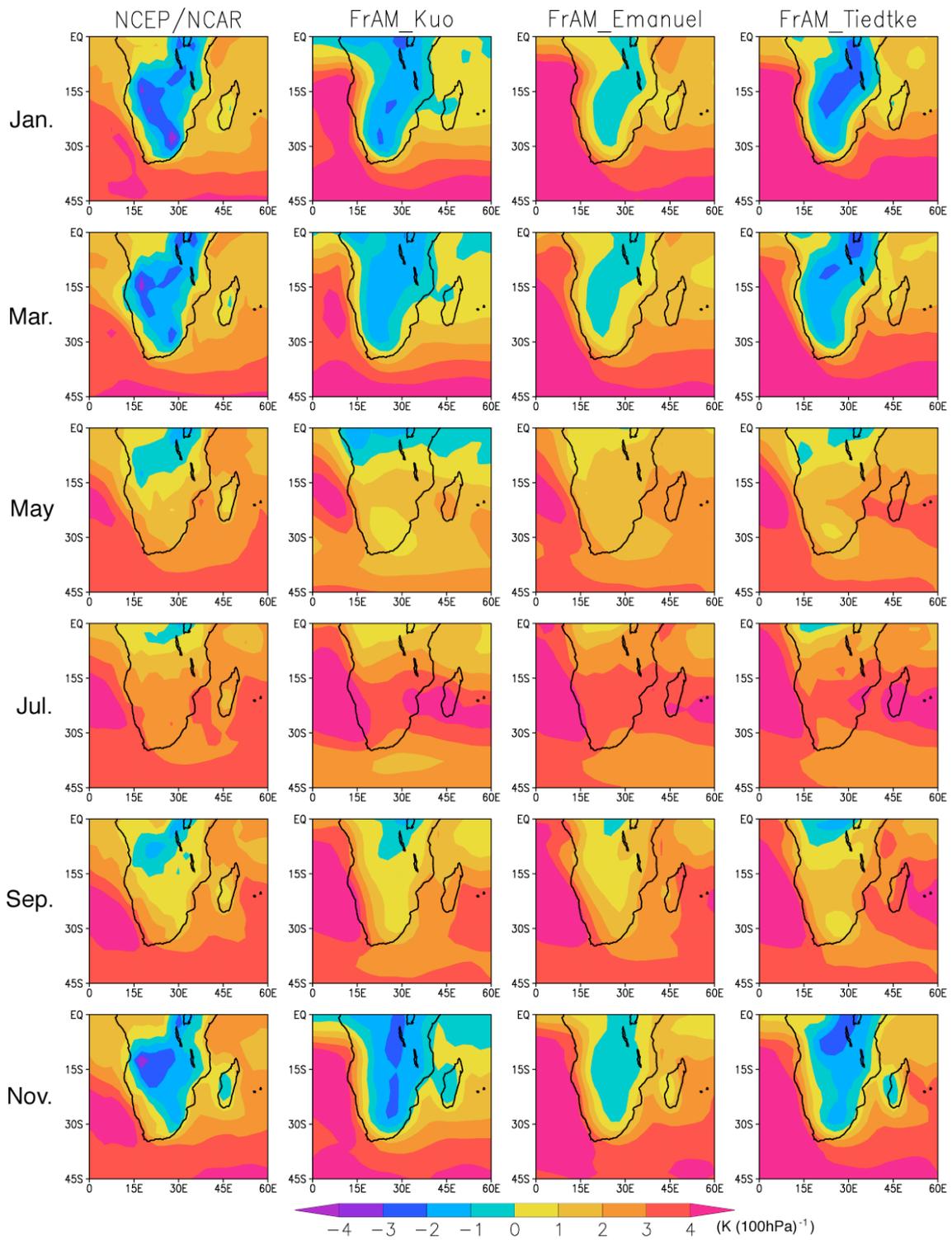


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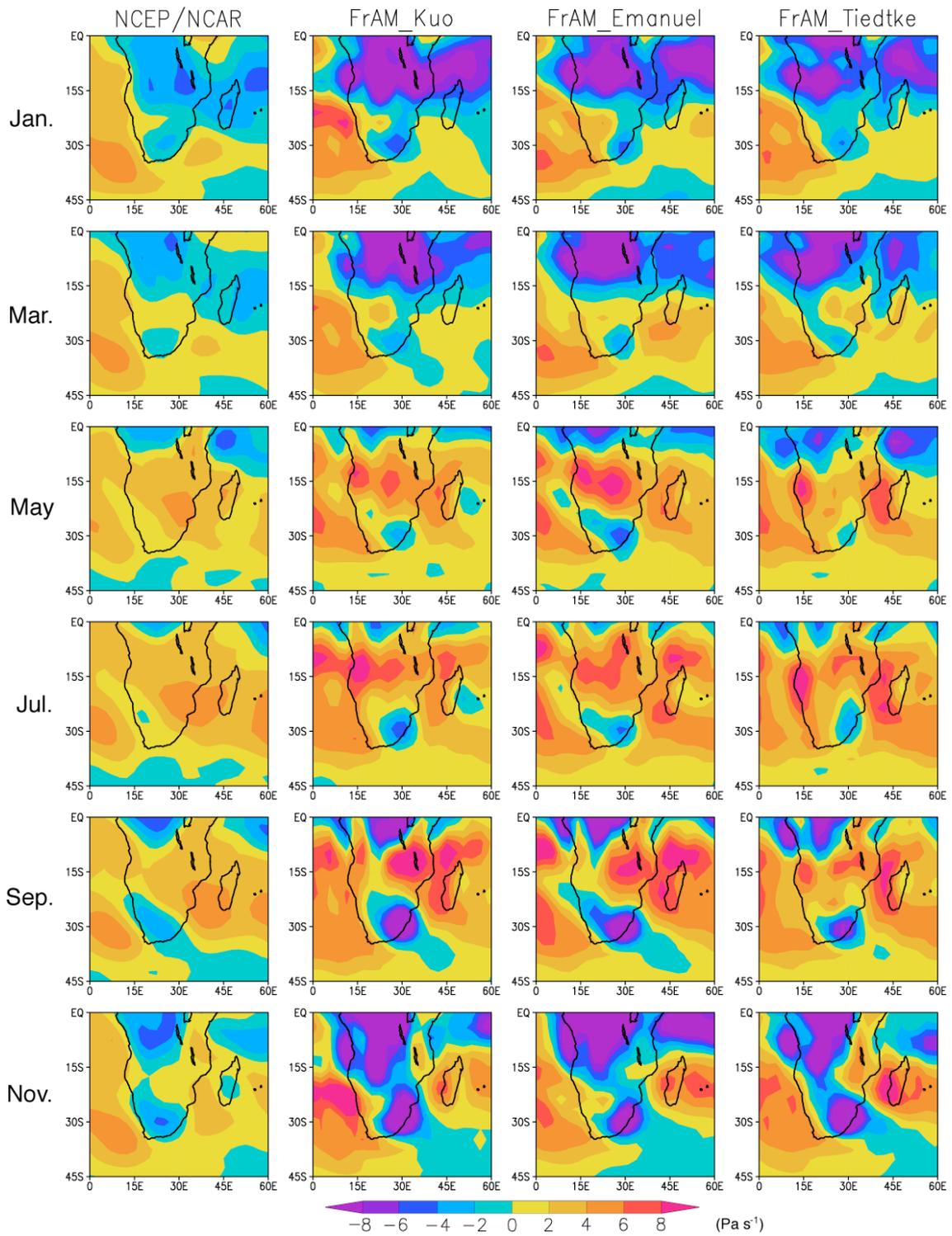
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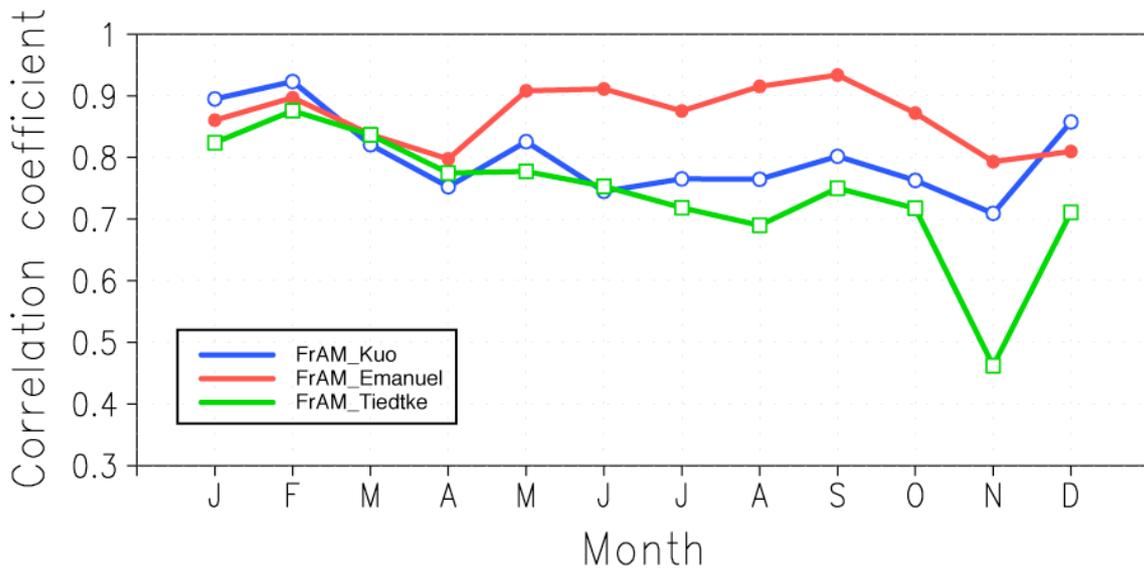
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739 **Figure 6:** As in Fig. 4, but for the vertical velocity (in Pa s^{-1}).

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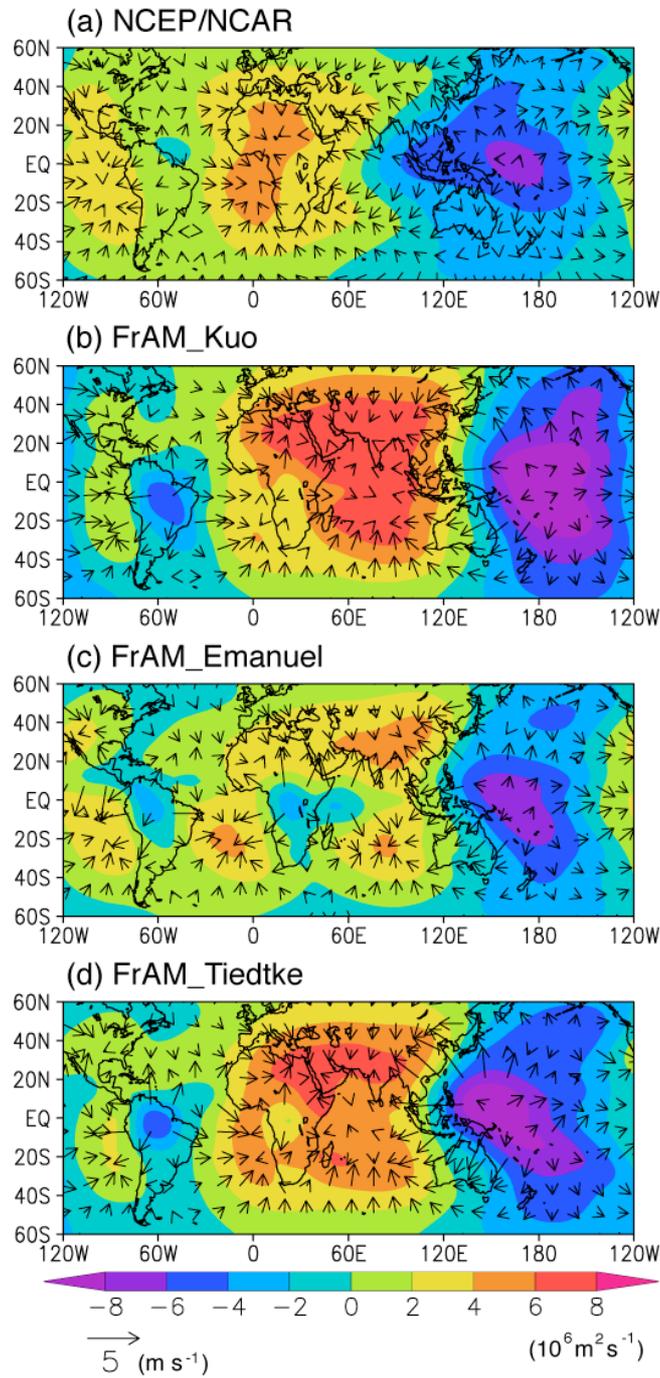


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744 GPCP observation and three versions of FrAM. All pattern correlation
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746 Carlo method.

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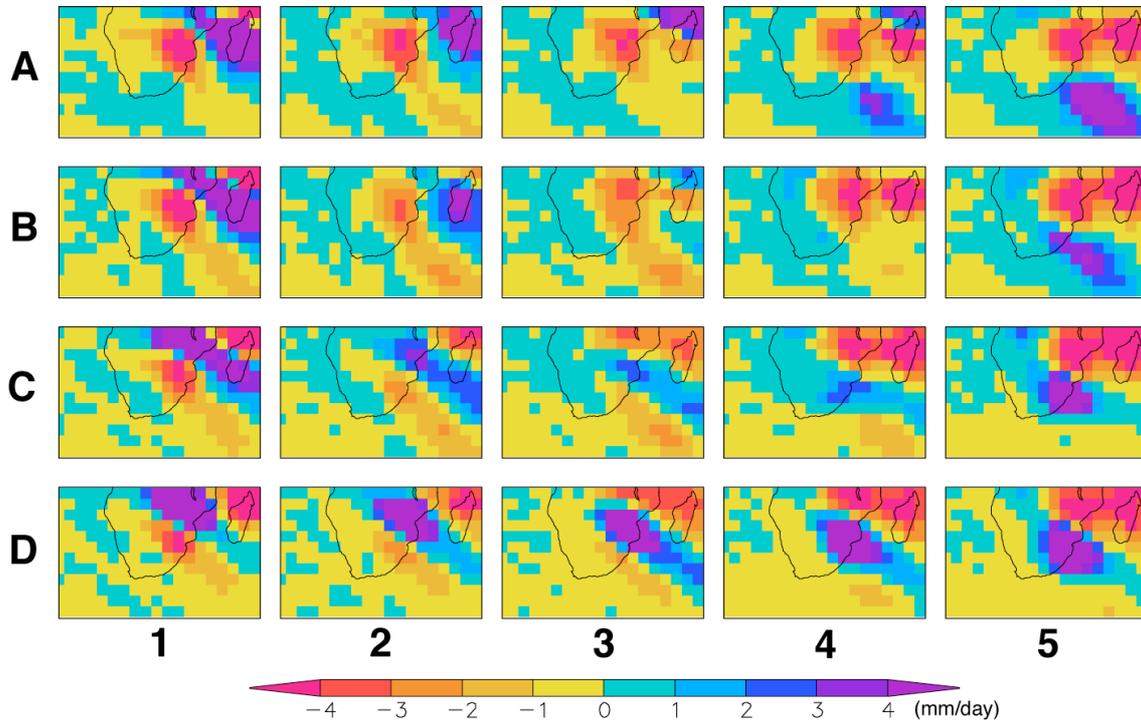
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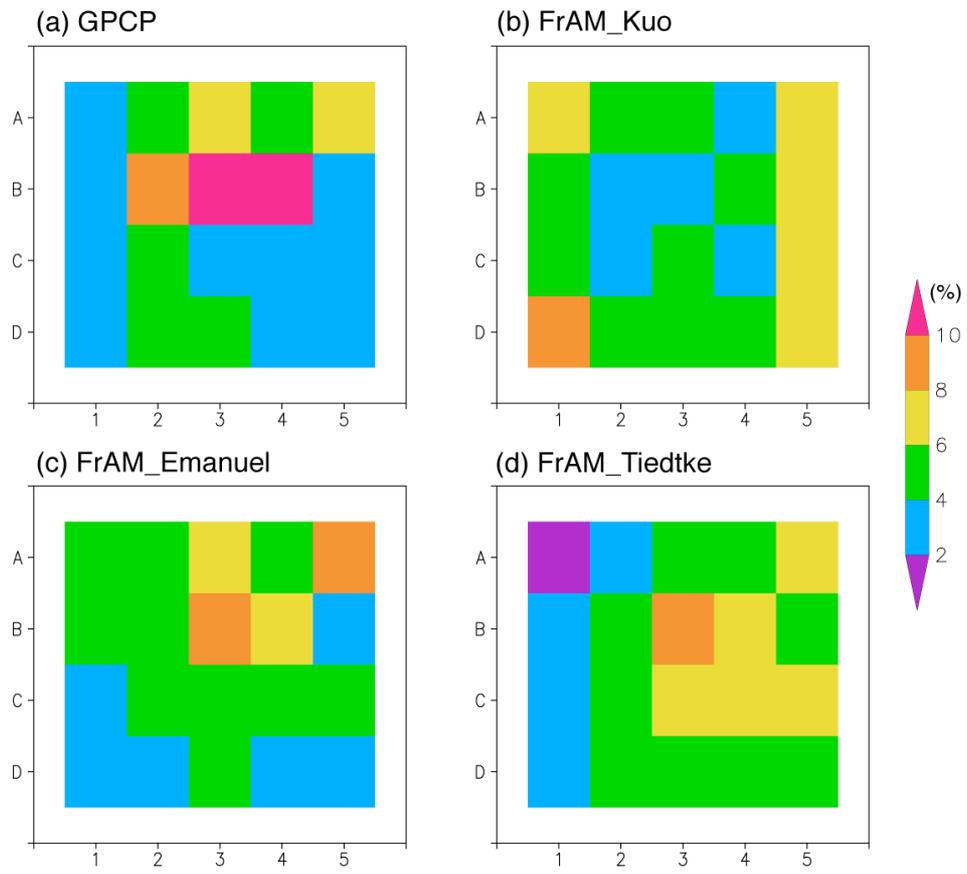
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758 a synoptic precipitation pattern over the southern African region.

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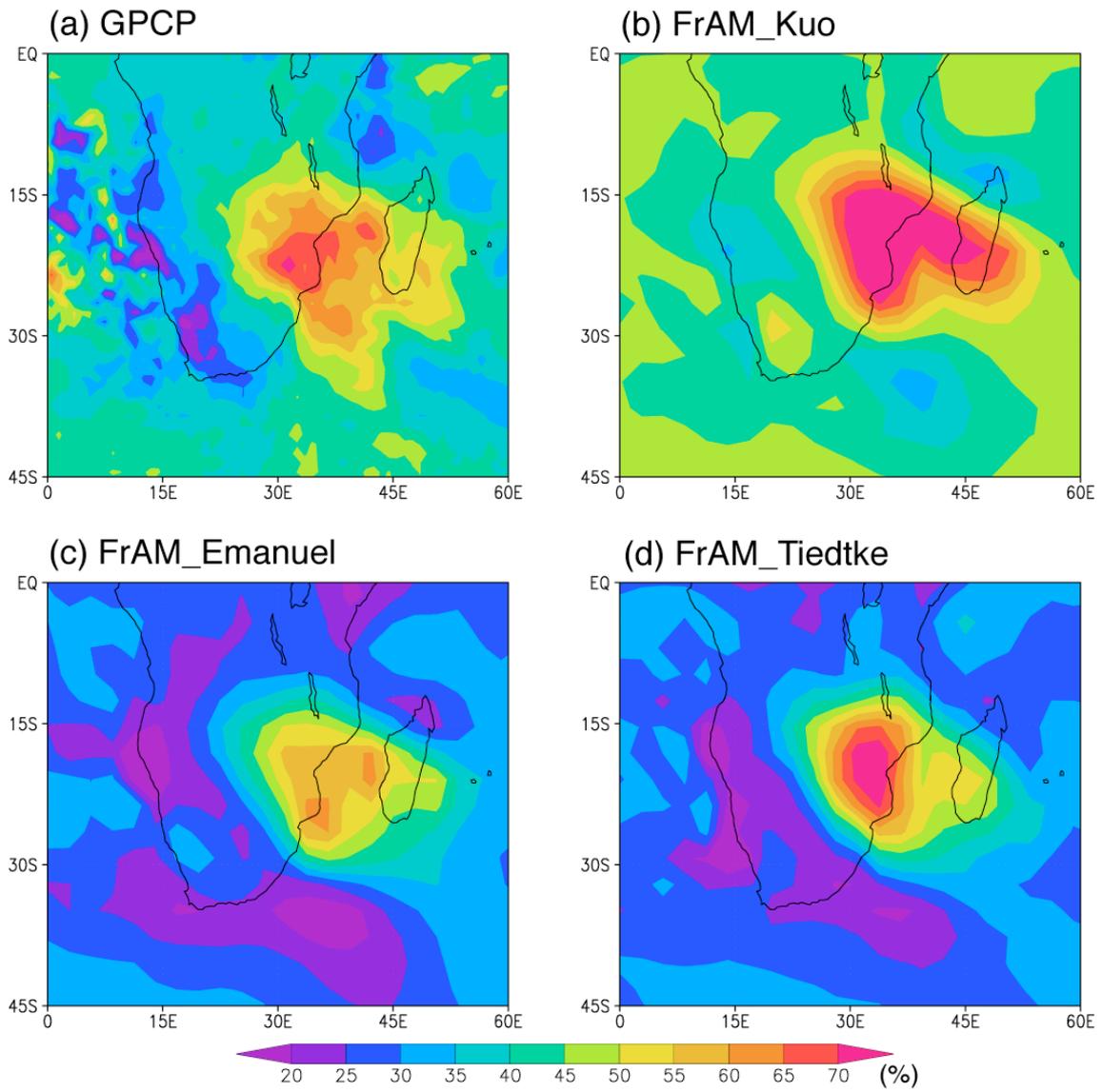
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763 **Figure 10:** Frequency map of the SOM array showing how frequently each
764 precipitation pattern appears during the rainy season (November-February).

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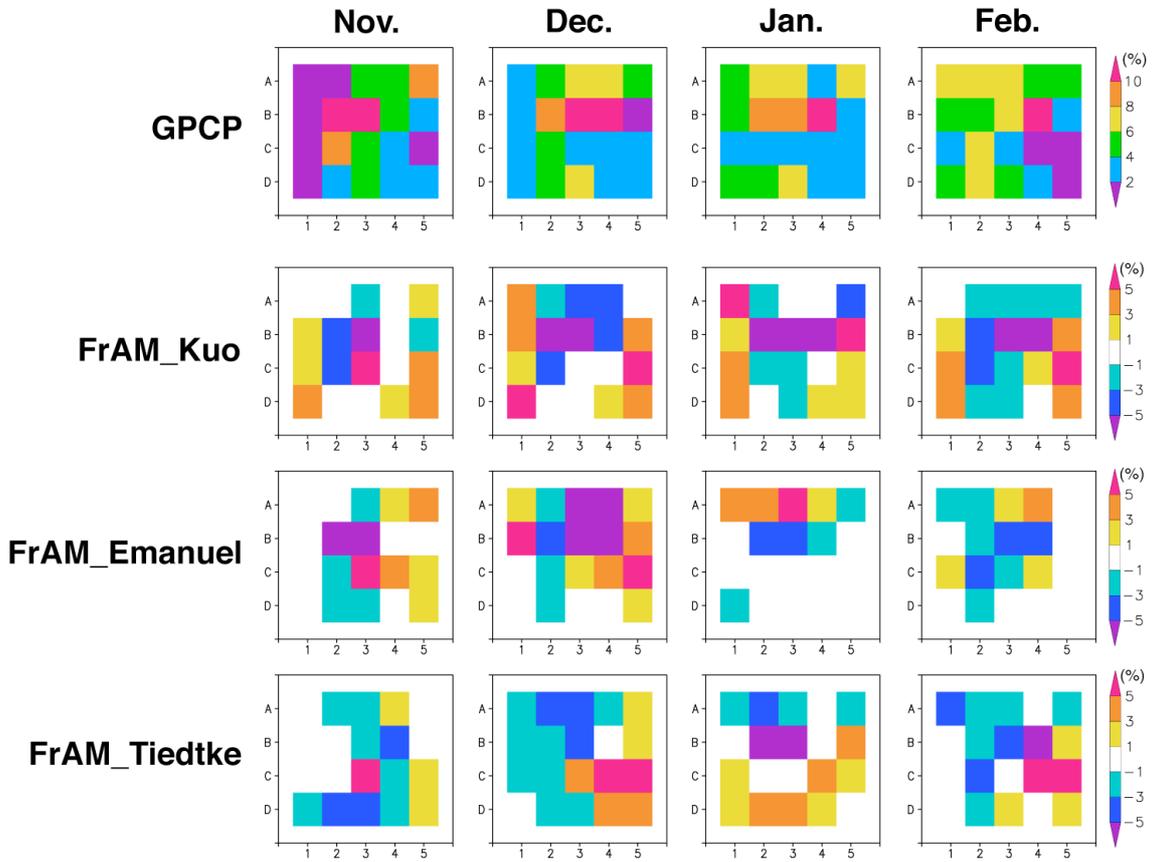
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769 **Figure 11:** As in Fig. 2, but for percentage of precipitation in the rainy season
770 (November-February) associated with nodes representing TTTs.

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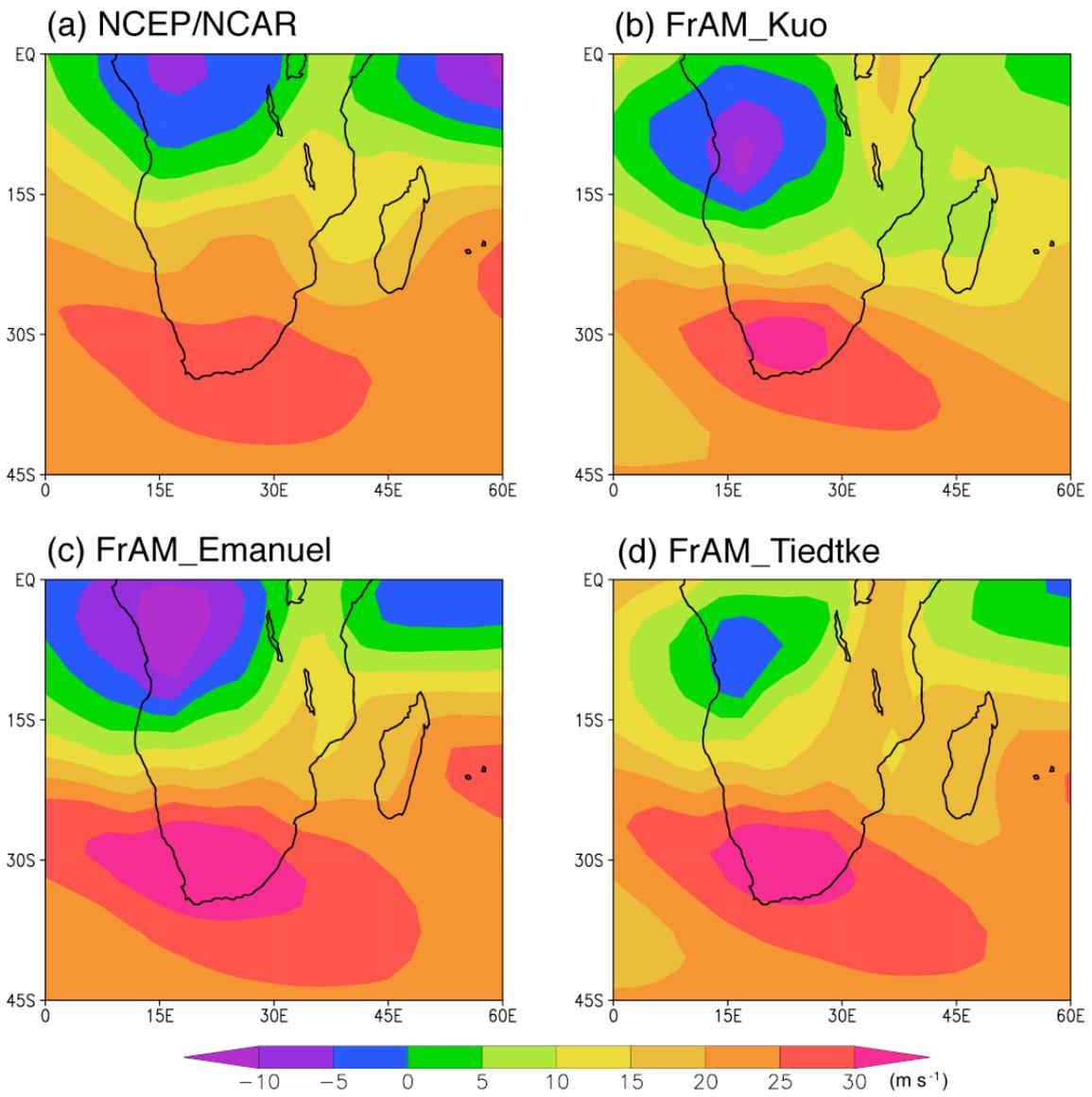
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776 precipitation pattern appears each month from November to February in the
777 observation. (Second, third, and fourth rows) Model biases in frequency of each
778 precipitation pattern in FrAM_Kuo, FrAM_Emanuel, and FrAM_Tiedtke,
779 respectively. Positive (Negative) values signify that the pattern appears more
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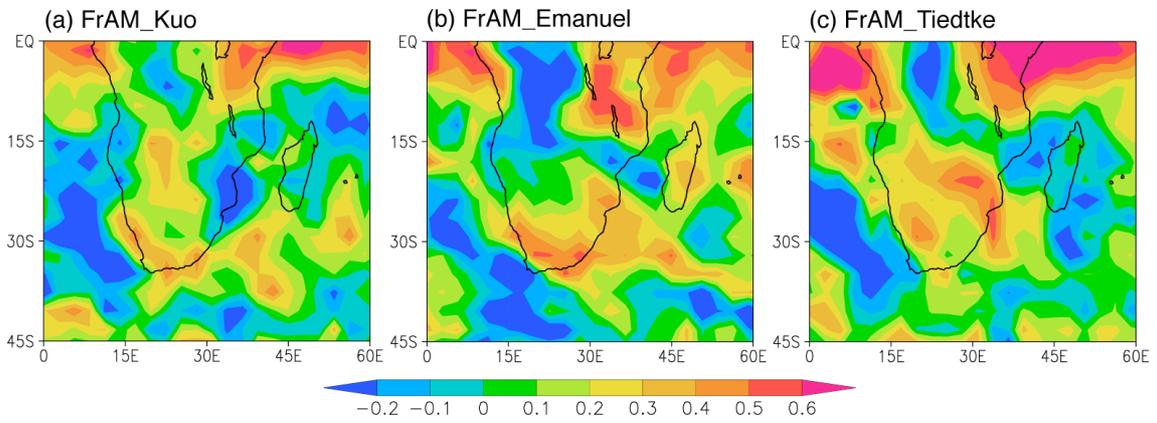
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785 **Figure 13:** As in Fig. 2, but for the zonal wind shear (200-850 hPa; m s^{-1}) in November.

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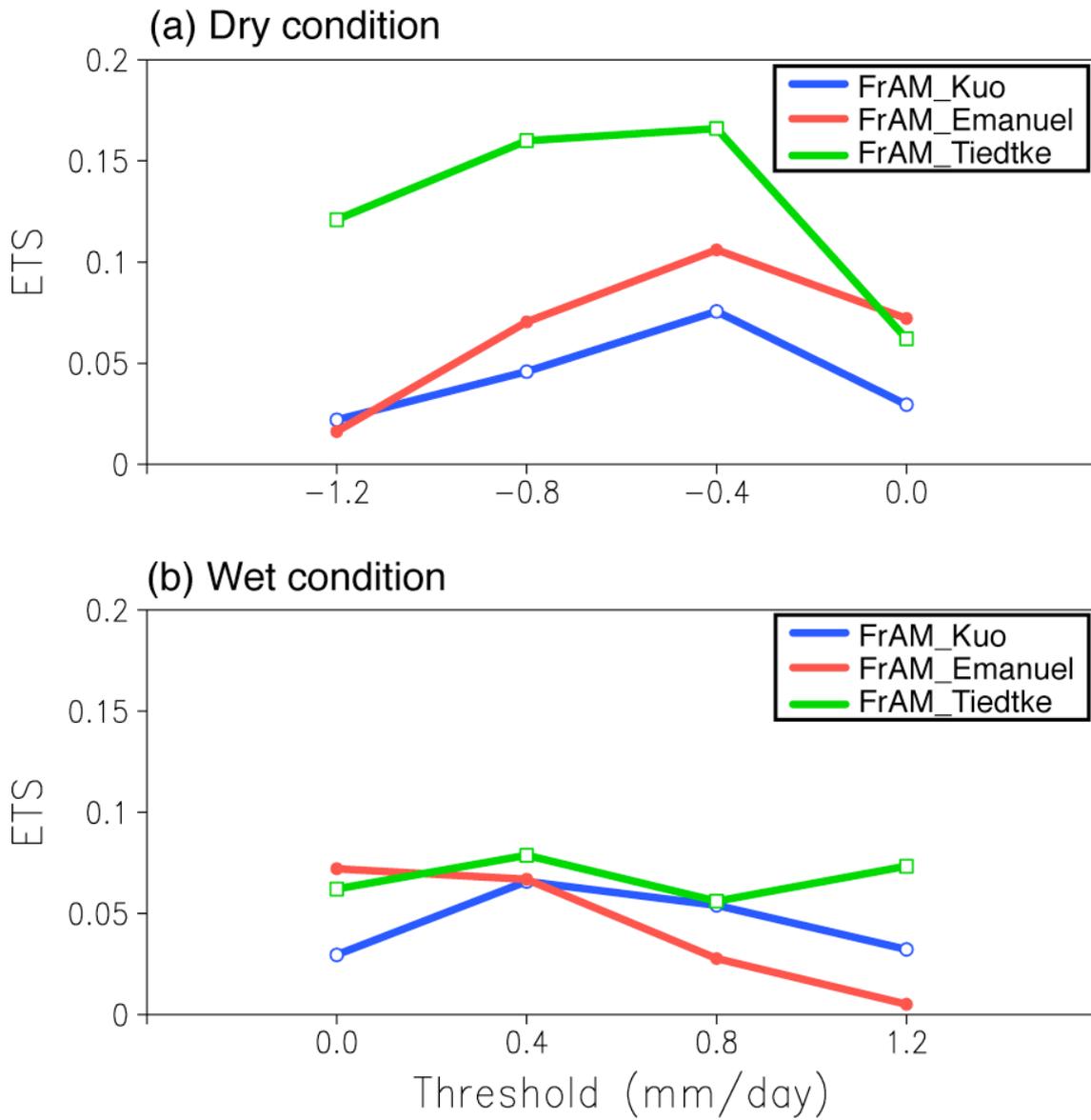
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790 **Figure 14:** Correlation coefficients between the observed and simulated precipitation in
791 the southern African region for November-February for the period of 1982-2008:
792 (a) FrAM_Kuo, (b) FrAM_Emanuel, and (c) FrAM_Tiedtke.

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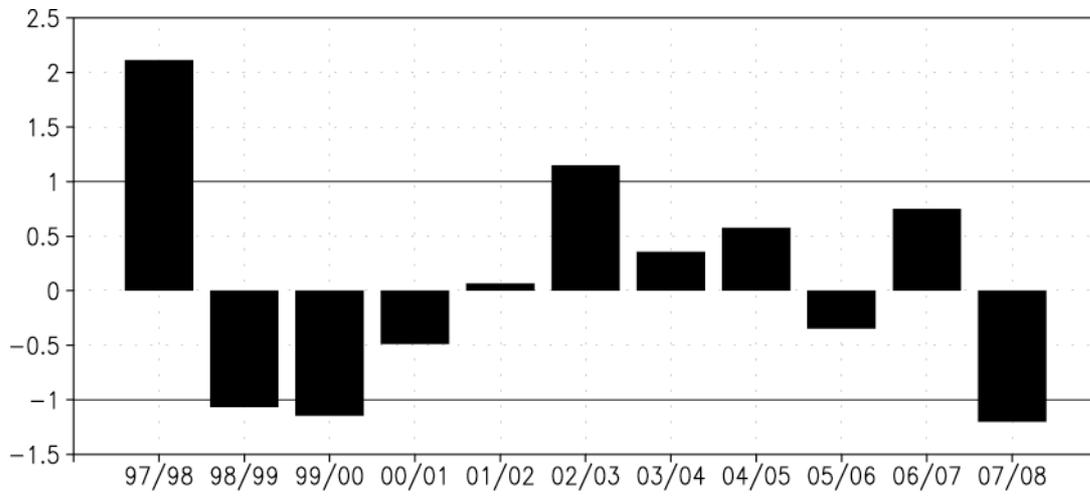
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797 **Figure 15:** Equitable threat score of precipitation during November-February of the
798 period of 1982-2008 for (a) dry and (b) wet conditions.

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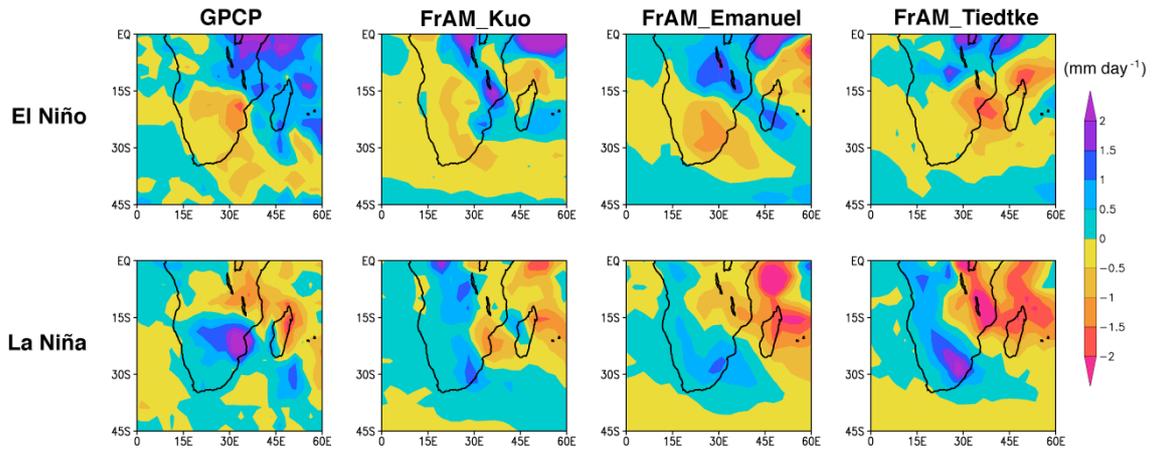
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803 **Figure 16:** Normalized time series of Niño-3.4 index in November-February.

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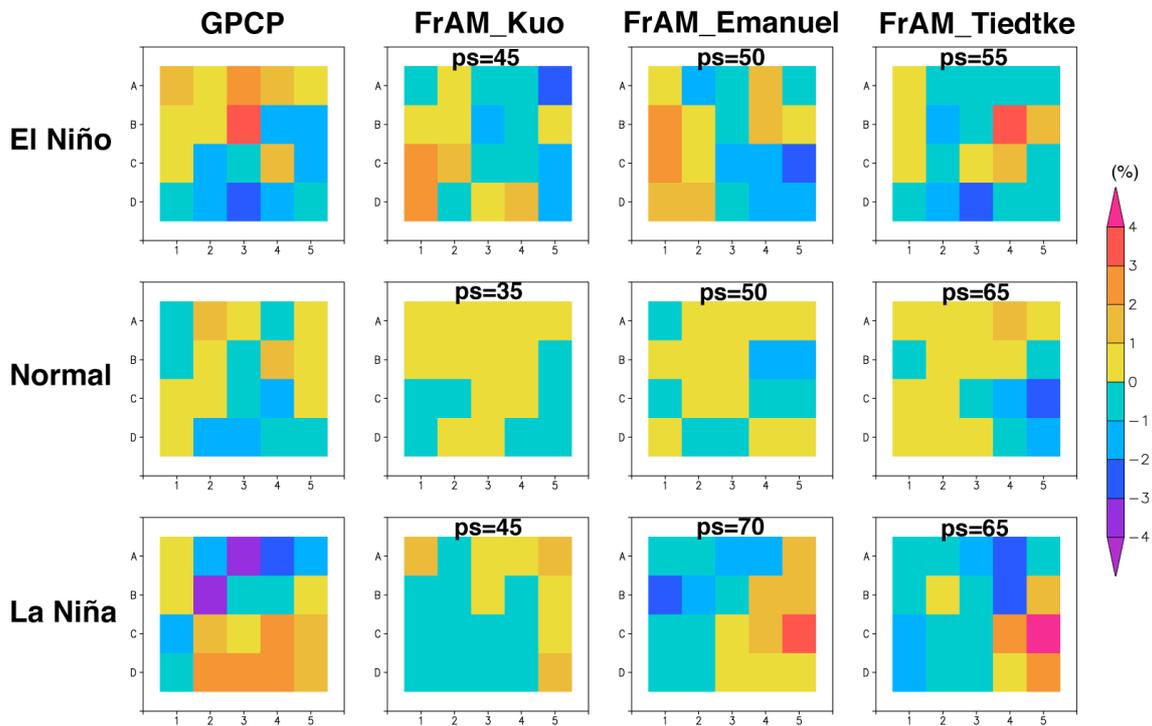
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808 **Figure 17:** Composite of precipitation anomalies (in mm day^{-1}) in (upper panels) El
809 Niño and (lower panels) La Niña years.

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814 **Figure 18:** Frequency map of the SOM array showing how frequently each
815 precipitation pattern appears during El Niño, normal, and La Niña years in the
816 GPCP observation and three versions of FrAM. Here, deviations from the
817 seasonal mean percentage are shown, and “ps” signifies phase synchronization.

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