

On the range of future Sahel precipitation projections and the selection of a sub-sample of CMIP5 models for impact studies

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1 On the range of future Sahel precipitation projections and
2 the selection of a sub-sample of CMIP5 models for impact
3 studies

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12 **Abstract**

13 The future evolution of the West African Monsoon is studied by analyzing 32 CMIP5 models under the rcp8.5
14 emission scenario. A hierarchical clustering method based on the simulated pattern of precipitation changes is used to
15 classify the models. Four groups, which do not agree on the simple sign of future Sahel precipitation change, are
16 obtained. We find that the inter-group differences are mainly associated with the large spread in (i) temperature increase
17 over the Sahara and North Atlantic and in (ii) the strengthening of low and mid-level winds. A wetter Sahel is
18 associated with a strong increase in temperature over the Sahara ($>6^{\circ}\text{C}$), a northward shift of the monsoon system and a
19 weakening of the African Easterly jet. A dryer Sahel is associated with subsidence anomalies, a strengthening of the
20 600 hPa wind speed, and a weaker warming over the Northern Hemisphere. Moreover, the western (central) Sahel is
21 projected to become dryer (wetter) during the first months (last months) of the rainy season in a majority of models. We
22 propose several methods to select a sub-sample of models that captures both the ensemble mean pattern and/or the
23 spread of precipitation changes from the full ensemble. This methodology is useful in all the situations for which it is
24 not possible to deal with a large ensemble of models, and in particular most impact studies. We show that no
25 relationship exists between the climatological mean biases in precipitation and temperature and the future changes in
26 the monsoon intensity. This indicates that the mean bias is therefore not a reliable metric for the model selection. For
27 this reason, we propose several methodologies, based on the projected precipitation changes: The “diversity” method,
28 which consists in the selection of one model from each group is the most appropriate to capture the spread in
29 precipitation change. The “pattern selection” method, which consists in the selection of models in a single group allows
30 to select models for the study of a specific pattern of precipitation change, for example the one that is the most
31 representative of the full ensemble.

32

34 1. Introduction

35 Observational studies show that the 1970s and 1980s were abnormally dry in the Sahel (L'Hote et al., 2002;
36 2003; Dai et al., 2004; Nicholson et al., 2012ab). Since the 1990s, Sahel rainfall has experienced a limited precipitation
37 recovery (Ozer et al., 2003; Nicholson, 2005; Lebel and Ali, 2009), especially from August to October (Sanogo et al.,
38 2015). A recent study based on numerical modeling suggests that the recovery is due to changes in atmospheric
39 greenhouse gases (GHGs) and aerosols concentration (Dong and Sutton, 2015). It could thus be expected that the recent
40 Sahel precipitation intensification might continue as the GHGs concentration increases. Based on studies using the
41 CMIP3 and CMIP5 databases (Coupled Model Intercomparison Phase 3 and 5), the 4th and 5th IPCC (Intergovernmental
42 Panel on Climate Change) assessment reports however concluded that a high level of uncertainty in future changes in
43 Sahel climate exists (Solomon et al., 2007; Barros et al., 2015).

44

45 Sahel precipitation is inextricably linked to the West Africa Monsoon (WAM). Studies based on CMIP3/5
46 projections show that the WAM response to global warming is highly model-dependent. As a consequence, model based
47 projections of WAM and Sahel climate are highly uncertain. This is particularly problematic for the assessment of
48 socio-economic impacts, since in order to capture correctly the uncertainties (model formulation, internal variability,
49 emission scenario), a large ensemble of models is necessary, as well as different realizations and scenario emissions
50 should be considered. The CMIP5 multi-model ensemble consists in more than 40 climate models, with generally
51 several realizations (or members), and for 4 different Representative Concentration Pathways (RCPs). It is virtually
52 impossible for most groups working on dynamical downscaling and/or impacts, given limitations in computing
53 resources and/or data storage capacity, to deal with such a large ensemble. Sub-sampling is necessary and given the
54 major inter-model differences regarding the future evolution of Sahel precipitation, it is particularly complex in this
55 context.

56 The need for an adequate sub-ensemble of models is becoming more and more frequent, since in the recent years an
57 increasing number of multi-disciplinary impact studies have emerged: they are based on crop models (Sultan et al.,
58 2014); on hydrological models (Li et al., 2015); on land-cover and land use models (Xue et al., 2012); on malaria
59 (Caminade et al., 2014) and meningitis modeling (Abdussalam et al., 2014); among others. The African countries will
60 be indeed affected by global warming in many areas and will face important adaptation challenges. In this study, we
61 propose different approaches to define an optimal sub-sample of models (composed by a small number of models,

62 which is able to provide a mean pattern and inter-model spread of precipitation change close to them of the CMIP5
63 ensemble), based on the models response in Sahel precipitation under global warming.

64

65 The first step of the study is focused on the analysis of the diversity of CMIP5 future projections for Sahel
66 precipitation. Precipitation is projected to increase (decrease) over the central (western) Sahel in both CMIP3 and
67 CMIP5 multi-model ensembles (Fontaine et al., 2011b; Monerie et al., 2012; 2013; James and Washington, 2013;
68 Biasutti, 2013; James et al., 2015). In a recent study, Park et al. (2015) suggest that the discrepancies in future Sahel
69 projections can be explained by differences between Northern and Southern Hemisphere surface warming. Here, we
70 revisit this question with an original statistical approach, based on hierarchical clustering applied to the projected
71 patterns of Sahel precipitation change.

72

73 Sahel precipitation change uncertainty is caused by multiple competing physical mechanisms that impact the
74 interannual-to-multidecadal variability of Sahel precipitation. Additionally, the Tropical Atlantic is a region of large
75 model uncertainties: state-of-the-art climate models exhibit large systematic errors (Richter and Xie, 2008; Richter et
76 al., 2012) and large uncertainties exist in the relative roles of internal and external factors in shaping climate change.
77 The review of Druyan (2011) highlights that the studies based on CMIP3 projections often show opposite results,
78 ranging from a significant increase to a significant decrease in Sahel precipitation at the end of the 21st century.
79 Different physical mechanisms have been proposed to explain the opposite responses found in coupled models. On the
80 one hand, a wetter Sahel is associated with increased land-sea temperature contrast (Haarsma et al., 2005) between the
81 Gulf of Guinea and the Sahara, and with a strengthening of the Tropical North Atlantic/Tropical South Atlantic
82 temperature gradient (Hoerling et al., 2006; Park et al., 2015). On the other hand, the Tropical Ocean warming may
83 induce an increase in moist static energy at upper levels, affecting then the vertical stability of the atmosphere, leading
84 to a drying over the Sahel, in a way analogous to the impacts of El Niño Southern Oscillation on the global tropical
85 atmosphere (Giannini et al., 2010). Our objective is to better understand the physical mechanisms responsible for the
86 major inter-model spread in Sahel precipitation change. We also investigate whether the future model responses are
87 linked to present-day climatological biases in Sahel precipitation. This question is of interest, since some models sub-
88 sampling approaches are based on the models ability to simulate the mean historical climate (as in Buontempo et al.,
89 2015), making the implicit hypothesis that models with smaller biases provide more reliable future projections.

90

91 In a second step, we test several methods for the selection of a subset of CMIP5 models in the context of Sahel

92 precipitation changes. The main objective is to find a small subset of models that both reproduces the ensemble mean
93 and inter-model spread of the full CMIP5 ensemble.

94

95 The main scientific questions addressed in this study can be summarized as follows:

- 96 1. Which are the main responses in future Sahel precipitation and the associated physical mechanism in CMIP5 models
97 at the monthly time-scale?
- 98 2. Is the large inter-model spread in future precipitation changes linked to present-day climate characteristics?
- 99 3. Is it possible to define a subset of models, representative of the full ensemble in terms of ensemble mean and spread?

100

101 The paper is organized as follows: In section 2 we describe the methodology and the data used. The mean
102 changes in Sahel rainfall are analyzed in section 3. Section 4 focuses on models biases and proposes different methods
103 for model selection. Finally we conclude in section 5 with a summary and a discussion of our results.

104

105

106 2. Data and Methodology

107 2.1 Data

108 Observed precipitation for the 1979-2010 period from the GPCP v2.2 data set is used with a $2.5^\circ \times 2.5^\circ$
109 horizontal grid resolution. GPCP is a merged analysis that incorporates precipitation estimates from microwave data,
110 infrared data, and surface rain gauge observations (Adler et al., 2003). Surface temperature, wind and sea level pressure
111 for the period 1979-1999 come from the ERA-Interim (ERA-Interim) reanalysis (Dee et al., 2011). Compared to ERA-40
112 (Uppala et al., 2005), ERA-Interim provides an improved representation of the hydrological cycle over the tropics (Uppala et
113 al., 2008), a more realistic stratospheric circulation and better temporal consistency of the reanalysis fields (Dee et al.,
114 2011).

115

116 Two sets of numerical experiments from the CMIP5 archive (Taylor et al., 2012) are analyzed: the historical
117 ensemble (hereinafter HIST, forced by both historical natural and anthropogenic forcings); and the RCP8.5 ensemble
118 (noted RCP85, based on the most extreme scenario whose radiative forcing reaches 8.5 W/m^2 in 2100; see Meinshausen
119 et al., 2011). We selected the models for which the necessary variables to this study are available for both HIST and
120 RCP85, which leads to an ensemble of 32 models (see the figure 1 for the model names).

121

122 In this work, mean model biases are estimated from the JAS (July-August-September) differences between
123 HIST and GPCP or ERA-Interim on the 1979-1999 period. The models response to global warming is defined as the difference
124 between RCP85 in the 2060-2099 period and HIST on the 1960-1999 period. Models outputs, GPCP precipitation and
125 ERA-Interim variables have been interpolated on the same 2.5° latitude by 2.5° longitude grid to facilitate the analysis. One
126 member is considered for each of the 32 models for both the HIST and RCP85 experiments. Throughout this work, the
127 multi-model response is considered as robust if at least 80% of the models agree on the sign of the change.

128

129

130

131 2.2 Model classification

132 Future projected changes in Sahel precipitation from the 32 CMIP5 models are classified with a hierarchical
133 clustering algorithm (Jain et al., 1999). The spatial pattern to be classified is the JAS RCP85 - HIST differences in
134 precipitation over a Sahelian box defined as $20^\circ\text{West} - 20^\circ\text{East}$ and $10^\circ\text{North} - 20^\circ\text{North}$ (including both the Western
135 and Central box in Fig. 2a). The spatial correlation matrix is then computed (32×32 size). The hierarchical clustering is
136 performed following the ward minimum variance method (Ward, 1963), based on the spatial correlation amongst the

137 models. The position at which two models are connected on the tree characterizes their disagreement. Four groups of
138 models are empirically defined based on the classification shown in Figure 1, noted GR1, GR2, GR3 and GR4
139 hereinafter. The semi-empirical choice of the number of clusters rests on a compromise, aiming to avoid clusters of very
140 small size (whose properties could be strongly impacted by an outlier), and to have a sufficient number of groups to
141 capture correctly the discrepancies in Sahel precipitation changes.

142

143 Precipitation changes are expected to be consistent within each cluster, which is not the case for the full
144 ensemble. The goal of this classification is to facilitate the understanding of the diversity of projected precipitation
145 changes in the Sahel by CMIP5 models.

146

147 Two outliers are identified by the classification: two GFDL models (*gfdl_esm2g* and *gfdl_esm2m*), whose
148 responses are largely different from the other models, and finally they are included in any group. As in Pennell and
149 Reichler (2011), Masson and Knutti (2011) and Knutti et al. (2013), models from the same institution generally belong
150 to the same cluster (i.e. HADGEM, GFDL, IPSL, CMCC, MIROC, GISS, ACCESS and MPI). These similarities are
151 due to the fact that models from the same center sometimes only differ in resolution (*ipsl_cm5a_mr* and *ipsl_cm5a_lr*
152 for example), and generally share large portions of numerical code or even identical component (e.g. ocean, atmosphere
153 or land models) (Masson and Knutti, 2011).

154

155 In the following section, changes in precipitation, temperature, pressure and winds over West Africa for the four groups
156 of models defined above are studied.

157 3. Characterization of projected changes in the Sahel

158 3. 1. Water budget

159 Future changes in JAS Sahel precipitation (P), evaporation (E) and P-E budget for the four groups of models
160 identified by hierarchical clustering are depicted in Figure 2. The intra-cluster mean is computed and the result is
161 considered as robust when at least 80% of models within the cluster agree on the sign of the change. GR1 exhibits a
162 large increase in rainfall (> 2 mm/day) over the entire northern Sahel (Fig. 2a). Over the adjacent ocean, evaporation
163 slightly increases (Fig. 2e) yielding to a positive P-E budget, indicating an enhancement of moisture flux convergence
164 (divergence), over the Sahel (Gulf of Guinea). This pattern has been widely documented in the past, and is associated
165 with a strengthening of the land-ocean temperature contrast (Maynard et al., 2002; Haarsma et al., 2005; Skinner et al.,
166 2012), and inhomogeneous ocean temperature changes within the Tropical Atlantic basin (i.e. the Tropical North
167 Atlantic warms more than the Tropical South Atlantic, as reported in Hoerling et al., 2006). GR2 simulates a slight
168 increase in precipitation over the central Sahel, and a decrease in precipitation over the Senegal (Fig. 2b). An important
169 increase in precipitation along the maritime Inter-Tropical Convergence Zone (ITCZ) is also robust. GR2 also exhibits a
170 strong increase in E over the adjacent ocean and west of central Africa (Fig. 2f). The resulting P-E budget is strongly
171 negative over the Gulf of Guinea, and no robust changes are observed over the Sahel (Fig. 2j). Therefore, in GR2 the
172 change in precipitation over the Sahel is not associated with a change in moisture flux convergence, suggesting that it
173 might be linked to local changes in moisture recycling (the evaporation is moisture-limited rather than energy-limited in
174 the semi-arid Sahel). GR3, which is the most populated cluster, shows a robust increase in P over the north-central
175 Sahel and a decrease over its western part (Fig. 2c). The patterns for E and P changes are similar over the continent, but
176 differ over the ocean, where E increases more strongly (Fig. 2c and Fig. 2g). The P-E budget increases (decreases) over
177 the central (west) Sahel (Fig. 2k), indicating an increase (a decrease) in moisture flux convergence. These changes in
178 the water budget have been already documented by Fontaine et al. (2011b), Monerie et al. (2012; 2013), James and
179 Washington (2013), Biasutti (2013) and James et al. (2015): GR3 is the dominating response in the CMIP5 full-
180 ensemble. The response for GR4 consists in a slight decrease in P over both the continent and the ocean (Fig. 2d). E
181 decreases over the central Sahel but increases over the Gulf of Guinea area (Fig. 2h). No robust changes are found for
182 the P-E budget over the continent, whereas a robust decrease in P-E occurs over the Gulf of Guinea (Fig. 2l).

183 In summary, four main types of projected precipitation changes over the Sahel can be extracted from the
184 CMIP5 full-ensemble: a strong increase in precipitation (>2 mm/day, GR1), a zonal dipole with an increase (a decrease)

185 in precipitation over the western (central) part (GR2 and GR3, but with a small increase in precipitation over the central
186 Sahel in GR2); and finally a decrease in P over the entire domain (GR4). These patterns are consistent with the large
187 spread in the WAM changes simulated by CMIP3 models (Druryan, 2011), and illustrate the strong uncertainties in
188 Sahel precipitation projections. In the next section we analyze the atmospheric dynamics associated with the P, E and P-
189 E changes described above.

190

191 3.2 Atmospheric circulation and temperature

192 Figures 3a-d show the projected changes in 2m temperature (T2m hereinafter, shading), sea level pressure
193 (SLP, contours) and wind at 950 hPa (arrows) for the four groups of models. From Figure 3, it is evident that the
194 magnitude of T2m changes is different among the groups. However, the spatial patterns of warming present large
195 similarities, with stronger increases in temperature over the continent than over the ocean, which act to increase the
196 land-sea temperature gradients (Fig. 3a-d). The associated dynamics show a marked decrease in SLP over northern
197 Africa, together with a strengthening of the south-westerlies (as shown in Haarsma et al., 2005) for the 4 groups of
198 models. Over the Sahara, the SLP decreases, indicating a deeper heat low, which favors the strengthening of low-level
199 winds. The main inter-group differences concern the intensity of the warming and of the wind strengthening.

200 At global-scale, surface temperature increases more in the northern Hemisphere than in the Southern
201 Hemisphere for the four groups, which could act to enhance precipitation over the Sahel (Park et al. 2015). This inter-
202 hemispheric differential warming in JAS is considered here only over the Atlantic Ocean, and computed as the RCP85-
203 HIST difference of SSTs averaged between 75°W and 10°E, minus the global tropical SST change (the global tropical
204 domain is 180°W-180°E; 30°S-30°N). Results for the four groups of models are shown in Figure 4. The major
205 differences amongst the groups are located north of 40°N. GR1 and GR3 exhibit a stronger strengthening of the inter-
206 hemispheric SST gradient over the Atlantic than GR2 and GR4. Interestingly, GR1 and GR3 are the groups that project
207 an increase in Sahel precipitation (Fig2a and Fig2c). This result is consistent with Park et al. (2015), who have shown
208 that the strengthening of this inter-hemispheric gradient is one of the main causes of the models discrepancies in Sahel
209 precipitation changes.

210 The low-level warming leads to stronger temperature gradients in GR1 and GR3 than in GR2 and GR4. This is
211 consistent with a stronger increase in low-level winds and decrease in SLP, leading to larger increases in Sahel

212 precipitation in GR1 and GR3 than in GR2 and GR4. The land-ocean temperature gradient increases in all the group of
213 models and cannot explain the decrease in precipitation for GR4 and the very weak increase for GR2.

214 This difference in projected Sahel precipitation may be due to the upper-level wind dynamics, represented by
215 the Tropical Easterly Jet (TEJ) and the African Easterly Jet (AEJ), which are known to influence Sahel precipitation
216 (Nicholson, 2008). A southward shift of the AEJ displaces the rain-belt southward, reducing the rainfall over the Sahel
217 (Grist and Nicholson, 2001) and the TEJ strength is significantly correlated with Sahel precipitation (Grist and
218 Nicholson, 2001). According to Cook (1999) and Patricola and Cook (2008), the AEJ can also reduce rainfall by
219 transporting moisture away from the Sahel. The impact of the AEJ and TEJ on the precipitation change is however not
220 straightforward. Precipitation impacts soil moisture and surface warming, leading to a change of the meridional
221 gradients of surface moisture and temperature that displaces the AEJ (Thorncroft and Blackburn, 1999). More intense
222 precipitation also results in a stronger local deep meridional overturning circulation with upper-level northerlies that
223 accelerate the TEJ. A feedback therefore exists between the AEJ (TEJ) and Sahel precipitation. We thus do not
224 conclude on a direct impact of the jets on the precipitation change.

225 Following this, we investigate the low to upper levels dynamics considering the latitude-height cross-sections
226 of the zonal wind component. The Sahel domain (from 10°W to 10°E) is selected to compute longitudinal averages. The
227 intra-cluster mean for each group is shown in Fig. 3e-h. During the JAS rainy season, all the groups simulate a
228 strengthening of the surface winds (from equator to 15°N and between 1000 to 850 hPa) (Fig. 3e-h). The strengthening
229 of the westerlies is larger for GR1 and GR3, likely because of the greater warming over northern Africa (Fig. 3a and c).
230 The low-level winds also accelerate in response to increased latent heating due to the increased rainfall and low-level
231 moisture. At mid-level (600 to 400 hPa), the AEJ moves northward for GR1, as shown by the positive (negative)
232 anomalies south (north) of the wind core at 600 hPa and 15°N (Fig. 3e). No robust changes in the AEJ speed are
233 obtained for GR3 (Fig. 3g). This could be due to the choice of the cross-section, centered on the Greenwich meridian,
234 whereas for GR3 there is a zonal dipole of precipitation change and thus likely, a non-homogeneous zonal response.
235 The two others groups agree on an increase in the AEJ speed and on its southward shift (negative anomalies south of the
236 AEJ core) (Fig. 3f and h).

237 At upper level, the TEJ, whose core is located generally at 200 hPa, exhibits a strengthening and a
238 displacement southwards for GR1 and GR3 (Fig. 3e and Fig. 3g). For GR2 and GR4, the TEJ speed decreases at all
239 latitudes range. This is consistent with the increase in precipitation, as shown previously in the literature (Nicholson,
240 2008).

241 The projected responses in T2m, SLP and zonal wind vertical structure are generally consistent among the groups of
242 models in terms of spatial pattern, but with differing intensities (Fig. 3). The main differences are associated with
243 different changes in the vertically-integrated moisture flux convergence, represented by the P-E budget (Fig. 2i-l). The
244 latter are due to the competing effects of the feeding of moisture through the low-levels winds (Fig.3e-h) and the export
245 of moisture through the mid-level winds (Fig. 3e-h). GR1 models simulate a northward shift of the monsoon flow, a
246 weakening and a northward shift of the AEJ. On the contrary, GR2 and GR4 models simulate a strengthening of the
247 AEJ, in consistency with a decrease in precipitation in GR4 and with no northward displacements of the monsoon
248 system in GR2.

249 For GR3, there are no evident changes in mid-level winds. This group exhibits zonally contrasted changes in
250 precipitation (increase/decrease in the central/western Sahel) and the box centered on the Greenwich meridian is not
251 suitable for the analysis of this pattern. Therefore, in the following section 3.3, we consider two areas to characterize the
252 projected changes: the western and central Sahel (Fig. 2a, gray boxes).

253

254 3.3 Seasonal cycle

255 The increase in precipitation noted in Fig 2a-d may be associated with a change in the seasonal cycle of the
256 WAM. For example, Biasutti (2013) showed from an ensemble of CMIP5 models that a pattern of precipitation similar
257 to the one of GR3 is associated with a decrease in precipitation over the western Sahel in June-July, and an increase in
258 precipitation over the central Sahel in September-October. To investigate further this question, we analyze the latitude-
259 seasonal cycle diagrams of the water budget, zonal winds at 600 hPa (AEJ) and 400 hPa vertical wind velocity over the
260 western Sahel (20°W-0°E) and central Sahel (0°E-20°E) domains. Figures 5 and 6 show the projected changes in P (Fig.
261 5a-d, Fig. 6a-d) and P-E (Fig. 5e-h, Fig. 6e-h) over the western and central Sahel respectively. Zonal wind at 600 hPa
262 (Fig. 5i-l, Fig. 6i-l) and 400 hPa vertical wind velocity (Fig. 5m-p, Fig. 6m-p) changes are also displayed in the same
263 format.

264 First, we analyze the changes in the seasonal cycle over the western box (Fig. 5). GR1 simulates a strong
265 increase in precipitation from July to October over the Sahel and in boreal winter south of the equator (Fig. 5a). This
266 change is associated with an increase in moisture convergence (Fig. 5e), a monsoon system located northward in JAS,
267 as shown by the northward shift of the AEJ (Fig. 5i), and with ascending (subsiding) anomalies north (south) of 10°N

268 (Fig. 5m). GR2, GR3 and GR4 project a decrease in P over the Sahel (Fig. 5b-d), but the timing in P changes is
269 different, varying from the March to August period for GR2 to the July to October period for GR4. These changes are
270 associated with a decrease in moisture flux convergence (Fig. 5f-h) and with an increase in the AEJ strength (Fig. 5j-l).
271 There is an evident subsiding anomaly for GR2, GR3, and GR4 (Fig. 5n-p). These findings obtained for GR2, GR3 and
272 GR4 (i.e., a decrease in rainfall over western Sahel, subsidence anomalies and AEJ speed increases) are consistent with
273 Monerie et al. (2012; 2013) and James et al. (2015).

274 On the central Sahel, an increase in precipitation is seen from July to December for GR1 (Fig. 6a), GR2 (Fig.
275 6b) and GR3 (Fig. 6c). GR4 exhibits a decrease in precipitation from April to October and an increase at the end of the
276 year. A wetter Sahel during the late rainy season appears to be a robust feature of climate change, as shown in Biasutti
277 (2013), Seth et al. (2013) and Kitoh et al. (2013). The moisture flux convergence given by P-E is consistent with these
278 precipitation changes (Fig. 6e-h), except for GR2, for which there is no robust change, suggesting that precipitation
279 change is closely related to the change in local evapotranspiration and thus in moisture recycling (Fig. 6f). The increase
280 in precipitation at the end of the rainy season could also be associated with a delay in the phase of the Atlantic SST
281 seasonal cycle (Biasutti and Sobel, 2009; Dwyer et al., 2014).

282 The zonal wind associated with the AEJ weakens and shifts northward during the entire year for GR1. This is
283 consistent with an increase in Sahel precipitation, as shown in Grist and Nicholson (2001) for the anomalous wet years.
284 The AEJ also shifts northward in GR2, GR3 and GR4 from October to January (Fig. 6i-lf). The AEJ strengthens in JAS
285 for GR2 and GR4, which are projecting a decrease in precipitation during this season. GR3 does not exhibit any robust
286 change of the AEJ speed in JAS. The 400 hPa vertical velocity field shows a northward shift of the location of the air
287 ascendance, and thus of the monsoon system from August to September for GR1, GR2 and GR3 (Fig. 6mno). There is
288 also a weak negative anomaly of 400 hPa vertical velocity in September-October for GR4 (Fig. 6p).

289 In summary, three groups (GR2, GR3 and GR4) project a decrease in precipitation over the western Sahel
290 (associated with a strengthening of subsidence and AEJ speed), but the timing throughout the year is different. Three
291 groups (GR1, GR2 and GR3) also exhibit a northward shift and a strengthening of the monsoon system in September-
292 October. The decrease (increase) in precipitation over the western (central) Sahel is thus a robust behavior in the CMIP5
293 simulations. The precipitation change is more robust in May-June-July and September-October than in July-August-
294 September when focusing on a particular domain. The spread is thus stronger in JAS and for the entire Sahel.

295

296 4. Selecting a subset of models representative of the CMIP5 ensemble

297 In the previous sections, four groups of models have been defined and studied in terms of Sahelian
298 precipitation changes. They are characterized by very different precipitation responses, which indicate that it is not
299 straightforward to select a subset of few models representative of the full CMIP5 ensemble. This is of particular
300 importance from a practical point of view for many applicative studies (McSweeney et al., 2012; 2015; Buontempo et
301 al., 2015). It is indeed virtually impossible for most dynamical downscaling studies or impact studies, that generally
302 require high temporal and spatial resolutions, to deal with the entire CMIP5 ensemble, because of limitations in
303 computing resources and/or data storage and treatment capacity.

304 For example, Guan et al. (2015) have shown that daily values of precipitation are needed for impact studies on
305 crop yields since they strongly depend on the rainfall frequency and intensity, and on the timing and duration of the
306 rainy season. As in most impact studies, it is preferable in this case to use Regional Climate Models (RCMs) than
307 GCMs (Vizy and Cook, 2012; Crétat et al., 2014; Sylla et al., 2015) because of the higher spatial resolution (Wehner et
308 al. 2010; Li et al. 2011) and improved convective schemes (Li et al., 2012). Because RCMs are very computationally
309 expensive and require large amount of data as input, it is very difficult to downscale all the GCMs to take into account
310 all the uncertainties. It would also be difficult to deal with all the necessary associated simulations with crop models.

311 In practice, most impact or dynamical downscaling studies are therefore based on a limited sample of GCMs.
312 The choice of GCM is very important, in order to avoid biases in the characterization of the climate change signal
313 and/or the uncertainties due to climate models. The selection of GCMs is however in practice often ad-hoc and not
314 necessarily based on solid scientific ground.

315
316 In this section we propose and test several approaches to select a few models within the whole CMIP5
317 ensemble considered in this work. The selection of a sub-ensemble of models is often based on their performance in
318 simulating the mean climate in present conditions, characterized by a given metric, by comparing models to
319 observations (e.g. Lee and Wang, 2014). This approach assumes, at least implicitly, that the reliability of future
320 projections is linked to the accuracy of the models in simulating the current climate. However, this relationship is not
321 straightforward. To investigate this issue, we first focus on the model mean errors in Sahel precipitation and air surface
322 temperature.

323
324 In a second stage, we will also explore alternative methodologies for model selection, based only on the
325 models' projections (section 4.2 and section 4.3) and on the classification presented in Figure 1.

326

327 4.1 Relationship between the mean model biases and the projected response

328

329 In this section, we study whether the different groups of models that have been defined based on future
330 precipitation changes are characterized by different biases in the present climate.

331 Figure 7 shows the JAS differences between the observations (GPCP) or reanalysis (ERA-Interim) and the intra-group
332 mean for the four groups of models (Fig. 1). The differences with GPCP precipitation are computed on the 1979-1999
333 period and are shown in Figure 7a-d. The four groups show similar precipitation biases with the ITCZ located too south,
334 resulting in a positive (negative) bias of rainfall over the Gulf of Guinea (western Africa). GR1, GR2, GR3 and GR4 are
335 characterized by robust negative biases, with some differences in the magnitude of the biases.

336

337 Figure 7e-h shows the global T2m biases compared to ERA-Interim on the 1979-1999 period in JAS. In the Tropical Atlantic
338 region, biases are generally similar for each group of models. A cold bias is present over the Northern Hemisphere
339 oceans, and also over the north of Africa. The Tropical Atlantic ocean shows a strong bias ($>+3.5\text{degC}$ in the south-
340 eastern part), due to an incorrect representation of the Atlantic cold-tongue in JAS, as reported in Okomura et al. (2011)
341 and Richter and Xie. (2008), and also to deficiencies in simulating continental precipitation and surface winds (Richter
342 et al. 2012). It has been shown that the WAM is linked to the surface temperature gradient between the Sahara and the
343 Gulf of Guinea (Nicholson et al., 2013), which is too weak in climate models and this forces the WAM system to be
344 located too southward. Warm North Atlantic SSTs are also linked to larger precipitation (Martin et al., 2014). The
345 biases are spatially similar in the four groups of models, but with different intensities. In particular, a colder North
346 Atlantic is depicted by GR2 models, consistent with a stronger dry bias over the Sahel (Fig. 7f).

347

348 In summary, slight differences in mean biases in precipitation and T2m can be found among the four groups of models,
349 in particular over the Atlantic Ocean and the Sahel. It is however difficult to interpret the inter-group differences in
350 terms of response (characterized in section 3) to global warming based on present-day biases. Figure 8 shows an
351 alternative classification of the 30 CMIP5 models considered in this work (32 climate models minus the two outliers),
352 but in this case based on the correlation amongst the 30 spatial patterns of present-day errors in Sahel precipitation
353 using GPCP as reference. Models belonging to the same group for the projections-based classification (Fig. 1) are
354 indicated by the same color code in Figure 8. The two classifications lead to very different clusters, suggesting that the
355 spatial structure of the projected changes are not directly related to the model mean biases for Sahel precipitation, as

356 also found in Knutti et al. (2010) in a different context. This analysis confirms that the present-day biases in
357 precipitation and temperature are not good metrics of the respective credibility of the models in terms of future
358 precipitation changes, for this particular case.

359

360 The intensity of the biases might be different with another references. The warm bias in the equatorial Atlantic
361 and the cold bias in the North Atlantic are however systematic (Roehrig et al., 2013) and are partly responsible for the
362 systematic southward shift of the ITZC in coupled models (Richter and Xie, 2008). We thus argue that the main
363 conclusion of the this section is not sensitive to the choice of the reanalysis.

364

365 It has been shown that variations in Sahel precipitation are related to SSTs anomalies over the North Atlantic
366 (Knight et al., 2006; Zhang and Delworth, 2006; Ting et al., 2009; Mohino et al., 2011; Martin et al., 2014), the Indian
367 Ocean (Bader and Latif, 2003), and the Mediterranean Sea (Rowell, 2003; Fontaine et al., 2010; Gaetani et al., 2010;
368 Polo et al., 2011). It is also known that future precipitation changes in Sahel may be influenced by changes in SST
369 (Hoerling et al., 2006; Giannini et al., 2010; Park et al., 2015). Sahel precipitation change in a given model might
370 therefore be affected by how this particular model simulates the teleconnections with SSTs over near and remote
371 oceans. This metric has already been used to select the “best” models in larger ensemble (Gaetani and Mohino, 2013;
372 Martin et al., 2014). However, this methodology presents a caveat: Sahel-SSTs teleconnections are not stationary
373 (Fontaine et al., 2011a), and the results may depend on the reference period used to compute the teleconnection.
374 Furthermore, the teleconnections can be also affected by global warming. For this reason, we have decided not to use
375 this metric for model selection.

376

377

378 4.2 Model selection based on the classification of the projected response

379

380 The metrics based on models present-day performances tested in section 4.1 are not suitable to select a sub-
381 sample of models to study future precipitation changes in the Sahel, as the responses to anthropogenic forcing are not
382 necessarily connected to present-day biases. Here we propose other approaches that only use the information from
383 future climate projections. The aim of the model selection is then to select a sub-sample of models considered more
384 realistic: i) to define a small sub-ensemble of models, ii) with an ensemble mean of precipitation changes in the Sahel
385 comparable to the one of the full ensemble and/or iii) that correctly captures the inter-model spread of the full CMIP5

386 ensemble. Two metrics are thus defined: the mean precipitation change in the Sahel, computed as the multi-model
387 ensembles average, and the inter-model spread, defined as the multi-model standard deviation computed locally for
388 each grid point within the domain.

389

390 Based on the previous classification (section 2.2), we propose three different approaches for model selection:

391

392 (1) A “pattern selection” method that consists in the selection of models that simulate a pattern of precipitation
393 change of particular interest. For example, it may be useful to select a sub-sample of models whose precipitation change
394 pattern is as close as possible to the CMIP5 multi-model mean. Models in GR3 match this condition, since the GR3
395 intra-group mean is the dominant response in the full CMIP5 ensemble. We therefore test this method with the GR3
396 models.

397

398 (2) A “diversity” method based on the random selection of models within the four groups, with the same
399 number of models selected in each group. This method aims to keep the large range of responses from the full CMIP5
400 ensemble.

401

402 (3) - A “random” method that consists in the simple random selection of a subset of models from the entire
403 CMIP5 ensemble, without taking into account the classification in four groups. Contrary to (1) and (2), this approach
404 does not require a preliminary analysis and is not associated with particular variables and/or domains of interest. It
405 could be used as a baseline selection approach to assess the improvement of the other subsampling methods based on
406 the model classification described above (the “pattern selection” and “diversity” method).

407

408 The three approaches are tested for sub-samples of 4 and 8 models respectively. The results are compared to
409 the CMIP5 multi-model mean change (computed from the RCP85-HIST differences of the 30 CMIP5 models). To
410 ensure the robustness of the results, the model selection is carried out n times following a Monte Carlo procedure; hence
411 n ensemble means are computed. Here we chose $n = 30000$ for the subsample of 4 models (there are 27405
412 combinations of 4 models selected within 30); and $n = 500\,000$ for 8 models (there are almost 6 million combinations of
413 8 models but n is kept lower for computational reasons). From the n realizations, we can then build a probability
414 distribution function that determines if the new sub-ensemble averages present an anomaly of the same sign as the
415 whole CMIP5 multi-model mean. The anomaly is considered as robust when at least 95% of the n ensemble-means

416 (from 4 or 8 models) agree on the sign of the whole CMIP5 multi-model mean change.

417

418 The results of the 3 sub-sampling approaches for 4 and 8 models are shown in Figure 9. With 4 models, the “pattern
419 selection” method reproduces fairly well the pattern of precipitation change of the full ensemble (Fig. 9a). Less
420 successful, the “diversity” and the “random” methods reproduce the increase in precipitation only over the central Sahel
421 (Fig. 9bc). The same conclusions can be drawn for the sub-ensemble of 8 models, but with an agreement on more grid
422 points compared to the 4 models sub-ensemble (Fig. 9d-f).

423

424 After this first analysis, the “pattern selection” method (based on GR3) is the most successful since it reproduces both
425 the increase in precipitation over the central Sahel and the decrease in precipitation over Senegal.

426

427 We investigate now whether it is also the case for the inter-model spread, by computing the difference between the
428 average of the n spreads from the n Monte Carlo tests and the full CMIP5 inter-model spread (in color in Fig. 9g-l). The
429 “diversity” and the “random” methods lead to a spread very similar to the one of the full CMIP5 ensemble, both for the
430 4 models (Fig. 9gi) and 8 models (Fig. 9jl) subsets. The “pattern selection” clearly underestimates the spread of the full
431 CMIP5 ensemble (more than 30% over West Africa), and especially over the Western Sahel and the Gulf of Guinea
432 (more than 60%). This could be expected since the “pattern selection” approach only selects the models whose
433 precipitation change pattern is similar to the one of the full CMIP5 ensemble, which leads to a large underestimation of
434 the full inter-model spread.

435

436 The standard deviation of the n spreads is also shown (purple contours). This is a measure of the robustness of the
437 spread generated by all the Monte Carlo realizations for the 3 approaches. Figure 9g-l shows that the “spread of the n
438 spreads” is similar among the methods (none of the methods produces dramatically stronger inter-ensemble spread).

439

440 In summary, the most successful approach turns out to be the “diversity” method that i) captures correctly the mean
441 precipitation changes over the Sahel of the full ensemble with only 4 models and ii) leads in average to an inter-model
442 spread comparable with the one from the full CMIP5 ensemble.

443

444

445 4.3 Selection of an optimal sub-sample of models

446 We have shown that our model classification can be useful as a basis of the “diversity” method for model
447 selection. However, this does not guarantee that a particular sub-sample of either 4 or 8 models obtained with the
448 “diversity” approach would be the optimal one to capture both the mean pattern and inter-model spread of the whole
449 CMIP5 ensemble. In this section we provide the optimal sub-sets of models (4 or 8) representative of the full CMIP5
450 ensemble. As previously discussed, this could be very practical for dynamical downscaling studies on the Sahel
451 interested by precipitation changes, and also impact-oriented analyzes. It is also interesting to investigate if the 4 or 8
452 models from the optimal ensemble belong to the same group, or to different groups amongst the 4 identified in this
453 work.

454 To find the optimal subsets we use the “random” selection approach described in section 4.2 in which n random
455 selections of 4 or 8 models (30000 for 4 models and 500000 for 8 models) are done. We define a metric that evaluates
456 both the similarity of each sub-sample of models with the full ensemble in terms of mean precipitation change pattern
457 (M_{CMIP5}) and spread (SP_{CMIP5}) in JAS. For each random sample of 4 or 8 models we calculate the mean precipitation
458 change (RCP85-HIST, named M_n) and its inter-model spread (SP_n). We consider a Sahelian box (gray box in Fig. 10a)
459 as a target to evaluate the similarity to M_{CMIP5} and SP_{CMIP5} the ensemble mean and spread of the full ensemble. Then we
460 compute the spatial root-mean-square error (RMSE) between M_n and M_{CMIP5} and SP_n and SP_{CMIP5} within the Sahelian
461 box. This leads to $RMSE(M_n)$ and $RMSE(SP_n)$ respectively. The metric (F_n) is then defined as the sum of both
462 standardized $RMSE(M_n)$ and $RMSE(SP_n)$. The final metric, F_n , allows sorting the n sub-ensemble of models from the
463 “best” sub-ensemble of models that exhibits the minimum value of F_n to the “worst” sub-ensemble of models.

464 Figure 10 shows the $M_{CMIP5} - M_n$ and $SP_{CMIP5} - SP_n$ differences for the “best” and “worst” sub-ensemble of 4 (left) and
465 8 models (right). Fig. 10a-d shows that the “best” sub-set of 4 (Fig. 10ac) and 8 (Fig. 10bd) models simulates future
466 changes much closer to M_{CMIP5} than the “worst” sub-ensemble. This is also the case for the inter-model spread, when
467 comparing Figures 10eg and 10.fh. The results are better with 8 models than with 4 models (Fig. 10ab and Fig. 10ef)
468 indicating that a too small sub-sample of models could limit the possibility of representing accurately M_{CMIP5} and
469 SP_{CMIP5} .

470 The “best” (in the very limited sense previously described) sub-ensembles are composed by `bnu_esm`, `mpi_esm_mr`,
471 `giss_e2_r` and `hadgem2_cc` for 4 models; and by `giss_e2_r_cc`, `ccsm4`, `mpi_esm_lr`, `cnrm_cm5`, `bcc_csm1_1`,
472 `miroc_esm`, `cesm1_bgc` and `haadgem2_cc`. The worst sub-set of models are `miroc_esm`, `miroc_esm_chem`, `miroc5` and
473 the `csiro_mk3_6_0` for 4 models, and `gfdl_cm3_0`, `csiro_mk3_6_0`, `cnrm_cm5`, `miroc_esm`, `bnu_esm`, `fgoals_g2`,
474 `miroc_esm_chem` and `miroc5` for 8 models.

475 Based on Fig. 1 the “best” sub-ensemble of 4 models contains one model from GR2, two from GR3 and one from GR4,
476 whereas the “best” sub-ensemble of 8 models is built from 2 models from GR1, 1 from GR2, 3 from GR3 and 2 from
477 GR4. This may seem contradictory to the results from the previous section, which concludes that the “diversity”
478 approach is the more appropriate to define a sub-ensemble of models. This can be explained by the fact that we have
479 selected in this section only the optimal sub-sets with the best performing F_n metric. However, if we examine the
480 probability density function of F_n , we find that most subset of models associated with values of F_n included in the tenth
481 percentile correspond to subset of models in which one model of each of the 4 groups is selected (not shown). On the
482 contrary, regarding the 90th percentile of F_n , the worst sub-ensembles are generally obtained when there is an over-
483 representation of one group of models (for example, the “worst” ensemble of 8 models is composed by the five GR1
484 models).

485 5. Conclusion

486 Current climate models show large uncertainties in future projections of the WAM and Sahel precipitation, sometimes
487 even opposite responses. In the first part of this work, we classified the future Sahel precipitation projections from 32
488 CMIP5 models to define four groups of models, which allowed us to extract the main types of model responses to
489 facilitate their physical characterization and analyze their robustness. In the second part of the study, we used the
490 previous classification and different methodologies to identify sub-sets of 4 or 8 models (amongst 30 CMIP5 models)
491 representative of the full ensemble, in terms of the ensembles mean and inter-model spread. The aim is to be able to
492 provide to other communities (e.g. statistical and dynamical downscaling, impact modelers) a reduced but meaningful
493 set of models, much more easy to manage, to facilitate their applicative research.

494 Concerning the CMIP5 models classification and the characterization of the main responses over the Sahel, our findings
495 can be summarized as follows:

- 496 • The methodology for model classification is based on a hierarchical clustering algorithm (Jain et al. 1999). The
497 similarity criterion is based on the spatial pattern of precipitation change, defined as the differences RCP85
498 (2060 -2099) minus HIST (1960-1999) in JAS. We obtained four groups of models (GR1-GR4) with robust
499 intra-group pattern of precipitation changes. They are characterized by robust and specific changes in
500 precipitation, water budget, temperature and atmospheric dynamics.

- 501 • GR1 shows a large and robust increase in precipitation over the entire Sahel in JAS. GR2 exhibits a moderate
502 increase in precipitation over the central Sahel. GR3 projects a decrease in precipitation over the western Sahel
503 and an increase over the central Sahel. Finally GR4 projects drier conditions over the entire Sahel. This large
504 variety of precipitation changes is consistent with other studies based on CMIP-type ensembles, as summarized
505 in the review of Druryan (2011) for the CMIP3 models. We show that, in the climate change context, the Sahel
506 precipitation response is not spatially homogeneous. The western Sahel is projected to become drier in three
507 groups of models (GR2, GR3 and GR4) for the whole JAS period. Projections for the central Sahel show an
508 increase in precipitation, especially during the months of the monsoon withdrawal (September-October) in
509 three groups of models (GR1, GR2 and GR3).

- 510 • The increase in precipitation in the central Sahel is explained by a strong warming over the Sahara ($> 6^{\circ}\text{C}$) and
511 a strengthening of the North-Tropical Atlantic SST gradient. In GR1 and GR3 the heat low is deeper, pushing

512 the monsoon system northward along with a strengthening of the southwesterly winds. In GR2 the monsoon
513 circulation strengthens but does not move northward. A drier western Sahel is associated with less moisture
514 convergence and more subsidence.

515 • During the latest months of the rainy season (SON), the increase in precipitation over the central Sahel is
516 driven by changes in SSTs (Biasutti and Sobel, 2009) and by an increase in local moisture recycling (that
517 dominates the P-E change in October) (Monerie et al., 2016). The CMIP5 models are more or less influenced
518 by either of these mechanisms, as suggested by the large discrepancy in the contribution of P-E changes in the
519 total precipitation change (Fig. 6a-h).

520 • We suggest that the inter-model differences can be explained by two factors: (i) the amplitude of the surface
521 meridional land-ocean and North Atlantic-tropical Atlantic temperature gradients; and (ii) the strengthening of
522 the low and mid-level zonal wind. It is however difficult to determine the role of the AEJ, since there is a
523 positive feedback between the AEJ and precipitation over the Sahel. Therefore, further work is necessary to
524 address the respective roles of changes in the surface temperature gradient between the Sahara and the North
525 Atlantic, and the changes in the mid-level zonal wind. This can be helpful for improving the WAM
526 representation in models and to reduce the uncertainties in models responses under global warming.

527 The CMIP5 atmosphere-ocean-general circulation model (AOGCM) simulations used in this study do not take into
528 account the dynamic vegetation and land use feedback. We should keep in mind that the Sahel experiences strong
529 feedbacks between land and precipitations (Koster et al. 2004). This can potentially lead to a miss-estimation of
530 projected precipitation changes, especially during the late rainy season (Wang and Alo, 2012).

531 Furthermore, the CMIP5 climate models suffer from several biases due to the models coarse resolution and
532 underestimation of regional orography (Wehner et al. 2010; Li et al. 2011). The present results have thus to be
533 confirmed with RCMs and global GCM simulations using finer grids. To do so, it is first necessary to select the GCM
534 simulations that will be used to force the RCMs (dynamical downscaling) or that will be statistically downscaled. The
535 selected set of global simulations has to be representative of the full CMIP5 in terms of ensemble mean and spread in
536 Sahel precipitation change, otherwise the impact studies can not document and explore the signal and uncertainty
537 provided by the ensemble of CMIP5 climate models. The methods for the selection of sub-sample of models tested in
538 this study are of interest in this context.

539

540 Regarding the model selection, the approaches that we propose can be applied to other areas and variables of interest. In
541 our particular case, our conclusions are:

542 • We show that over the Sahel, future precipitation changes in summer are not strongly associated with present-day
543 biases. For this reason, we propose a selection criterion based on the projections instead of on the mean historical
544 climate simulations. The objective is then not to select a subset of models judged to be more realistic, but to select a
545 small subset of models representative of the full ensemble. This could be particularly useful for studies in which
546 computational resources and/or data storage and/or treatment capacity are a limiting factor, which is the case for most
547 dynamical downscaling or impact studies.

548 • The “best” sub-ensemble of models, in terms of similarity with the full CMIP5 ensemble mean and spread, turns out to
549 be composed by the `bnu_esm`, `mpi_esm_mr`, `giss_e2_r` and `hadgem2_cc` models.

550 • In section 4.3, we propose alternative solutions that may be useful for example if data from the above mentioned
551 models are not available at the time frequency necessary for the study of interest. They are based on the model
552 classification presented in this work. The best method basically consist of selecting one or two models in each of the
553 four groups, which allows more freedom in the choice of the models, and ensure a good representation of both the mean
554 and spread of the full ensemble. When using the methods described in the section 5 for impact studies it is crucial to use
555 consistent physical packages between RCM and the forcing GCM to ensure that the downscaled field will not be the
556 result of a change of the parametrization but of the forcing field with a higher resolution (Saini et al., 2015). If not the
557 downscaled fields will not be representative of the CMIP5 ensemble.

558

559

560

561

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570

571

572

573 Captions

574

575 Figure1: The model “family tree” from CMIP5 models for the RCP85-HIST change in Sahel precipitation, shown as a
576 dendrogram (a hierarchical clustering of the pairwise distance matrix for precipitation, see text). Models on the same
577 branch simulate similar patterns in precipitation changes. Models from the same group share the same color.

578

579 Figure2: Projected changes in JAS (a-d) precipitation (mm.day^{-1}), (e-h) evaporation (mm.day^{-1}) and (i-l) P-E budget
580 (mm.day^{-1}) for the four groups of models (one group per column) identified by the clustering. The present climatology
581 (HIST) is displayed with red contours and the RCP85-HIST differences by color shading. Hatching represents the grid-
582 points where at least 80% of the models agree with the sign of the intra-group ensemble mean within each groups (5 for
583 GR1; 7 for GR2; 13 for GR3; 5 for GR4)

584

585 Figure3: Projected changes RCP85-HIST in JAS (a-d) 2m temperature ($^{\circ}\text{C}$) (shading), sea level pressure (hPa) (blue
586 contours) and 950 hPa winds (m.s^{-1}) (green arrows) for the four groups of models. The winds anomalies are displayed if
587 at least 80% of the models agree on the sign of the intra-cluster mean. (e-h) Latitude-height cross section (average from
588 10°W to 10°E) of zonal winds (m.s^{-1}) for the RCP85-HIST projected changes (shading). The present climatology
589 (HIST) for zonal winds is displayed with red contours. Hatching represents the grid-points where at least 80% of the
590 models agree with the sign of the intra-cluster mean (5 for GR1; 7 for GR2; 13 for GR3; 5 for GR4).

591

592 Figure 4: Changes in Atlantic SST gradient, computed as the zonally-averaged RCP85-HIST difference over the
593 Atlantic Ocean ($75^{\circ}\text{W} - 10^{\circ}\text{E}$) minus the SST tropical warming ($180^{\circ}\text{W}-180^{\circ}\text{E}$; $30^{\circ}\text{S}-30^{\circ}\text{N}$) in JAS. The intra-cluster
594 mean is computed for GR1 (brown line), GR2 (blue line), GR3 (green line) and GR4 (red line). Shadings represent the
595 intra-cluster standard deviation.

596

597 Figure5: Time-Latitude diagram from January to December for RCP85-HIST projected changes averaged over the
598 western Sahel ($20^{\circ}\text{W}-0^{\circ}\text{W}$) in (a-d) precipitation (mm.day^{-1}), (e-h) P-E (mm.day^{-1}), (i-l) 600 hPa zonal wind (m.s^{-1}) and
599 (m-p) 400 hPa omega (Pa.s^{-1}) for the four groups of models. The present climatology (HIST) is displayed with red
600 contours and the HIST-RCP85 differences by the shading. Hatching represents the grid-points where at least 80% of the
601 models agree with the sign of the intra-cluster mean (5 for GR1; 7 for GR2; 13 for GR3; 5 for GR4).

602

603 Figure6: Same as the figure 5 but for the central Sahel (from 0° to 20°E).

604

605 Figure7: Mean model bias in JAS (a-d) precipitation computed as HIST-GPCP (in mm.day^{-1}) represented by the
606 shading. Observed precipitation (GPCP) is also displayed (red contours). Mean model bias of global T2m in JAS
607 computed as HIST-ERA-Interim reanalysis (e-h) (in $^{\circ}\text{C}$). Hatching represents the grid-points where at least 80% of the models
608 agree with the sign of the intra-cluster mean bias.

609

610 Figure8: The model "family tree" from the CMIP5 models for biases in Sahel precipitation, shown as a dendrogram (a
611 hierarchical clustering of the pairwise distance matrix for precipitation). The spatial pattern used to compute the
612 correlation matrix is the JAS precipitation bias (HIST-GPCP). Models on the same branch simulate similar biases in
613 precipitation. Colors indicate models belonging to the clusters defined in Fig.1 according to the classification on the
614 projected response.

615

616 Figure9: Mean precipitation changes (mm.day^{-1}) of the 30 CMIP5 models (models in color in Figure 1b, shading) and
617 the probability to reproduce its sign, when randomly selecting (a-c) 4 models and (d-f) 8 models (hatching). The
618 probability is computed with a Monte Carlo approach. Hatching shows the points where at least 95% of the n draws
619 agree on the sign of the CMIP5 pattern. Here, n is equal to 30 000 (500 000) for 4 models (8 models). The spread of the
620 intra-group precipitation change is computed when using (g-i) 4 models and (j-l) 8 models, the difference (in %)
621 between the mean spread computed from the n draws and the spread of the full CMIP5 ensemble is displayed in colors
622 and the spread computed from the n values of spread is indicated by the purple lines (mm.day^{-1}). The “pattern selection”
623 method consists of selecting 4 or 8 models in GR3, the “random” method randomly selects 4 or 8 models within the full
624 CMIP5 ensemble, and the “diversity” method selects 1 or 2 models from each group of models in Fig.1.

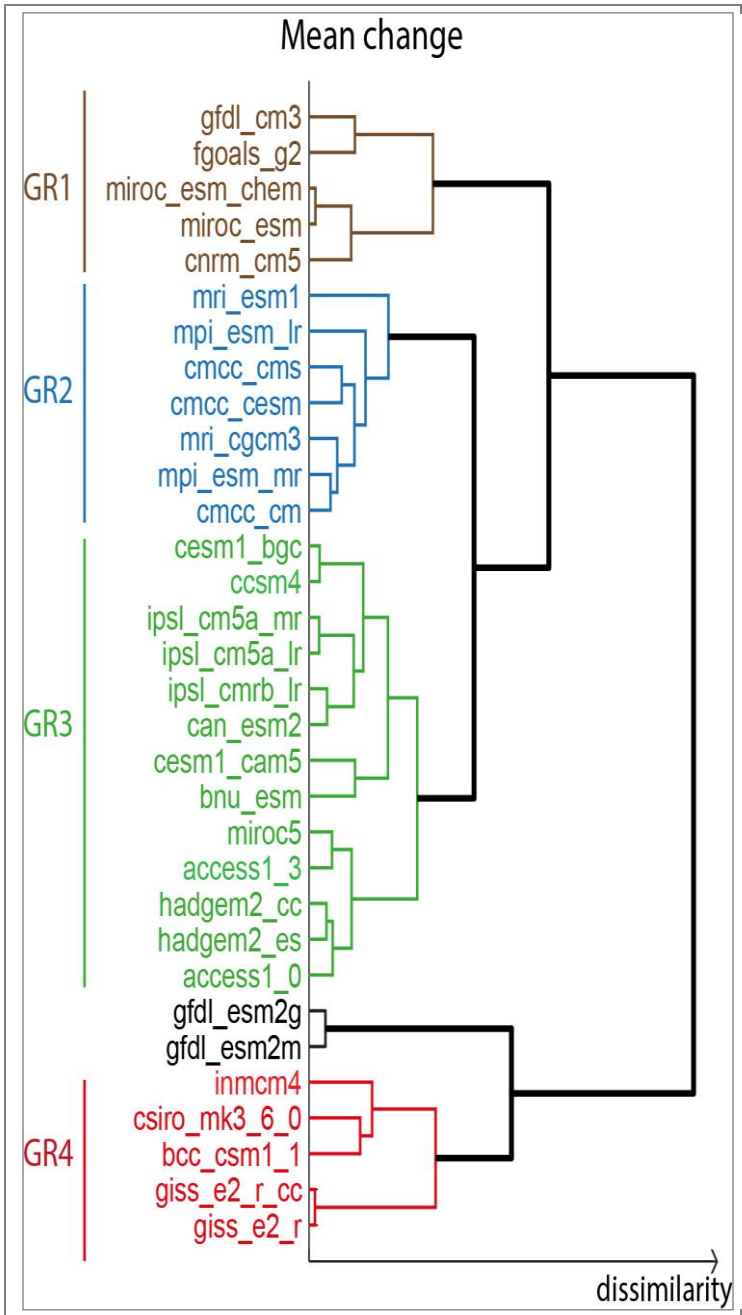
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626 Figure10: Differences of ensemble mean JAS precipitation changes (RCP85-HIST; mm.day^{-1}) between the full CMIP5
627 ensemble, and the best ensemble of (a) 4 models, (b) 8 models, and the “worst” ensemble of (c) 4 models and (d) 8
628 models. Differences of JAS mean precipitation (mm.day^{-1}) between the spread of the RCP85-HIST CMIP5 data-set
629 projection minus the spread of RCP85-HIST projection of the “best” ensemble of (e) 4 models, (f) 8 models and the
630 “worst” ensemble of (g) 4 models and (h) 8 models.

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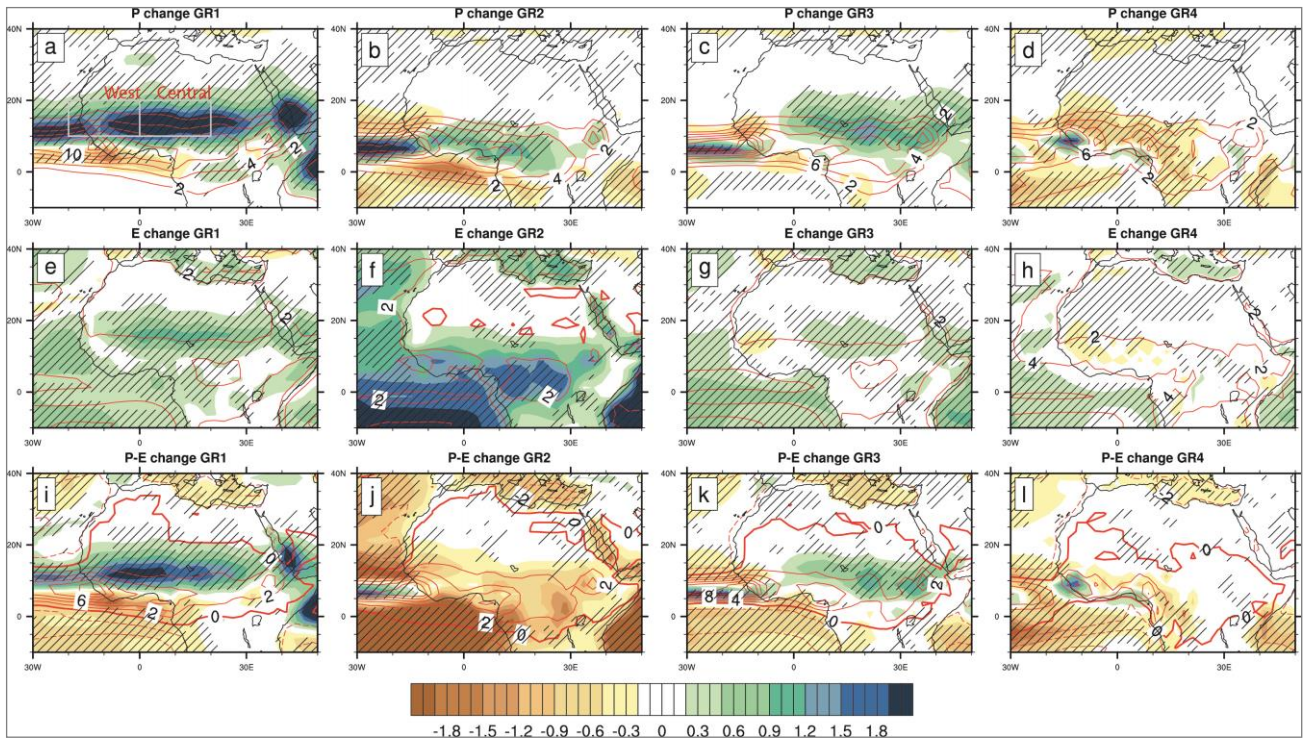
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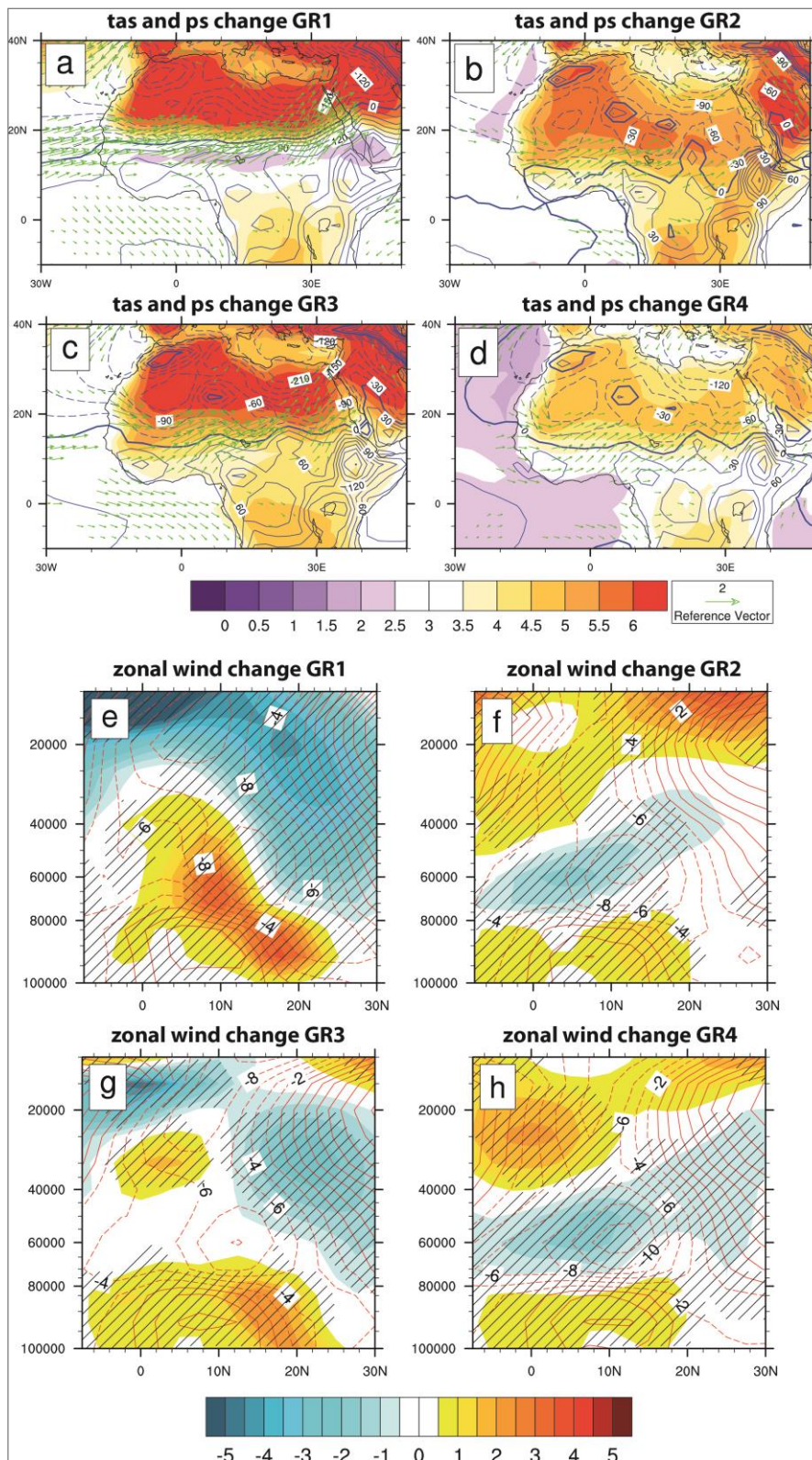
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Figure1: The model “family tree” from CMIP5 models for the RCP85-HIST change in Sahel precipitation, shown as a dendrogram (a hierarchical clustering of the pairwise distance matrix for precipitation, see text). Models on the same branch simulate similar patterns in precipitation changes. Models from the same group share the same color.



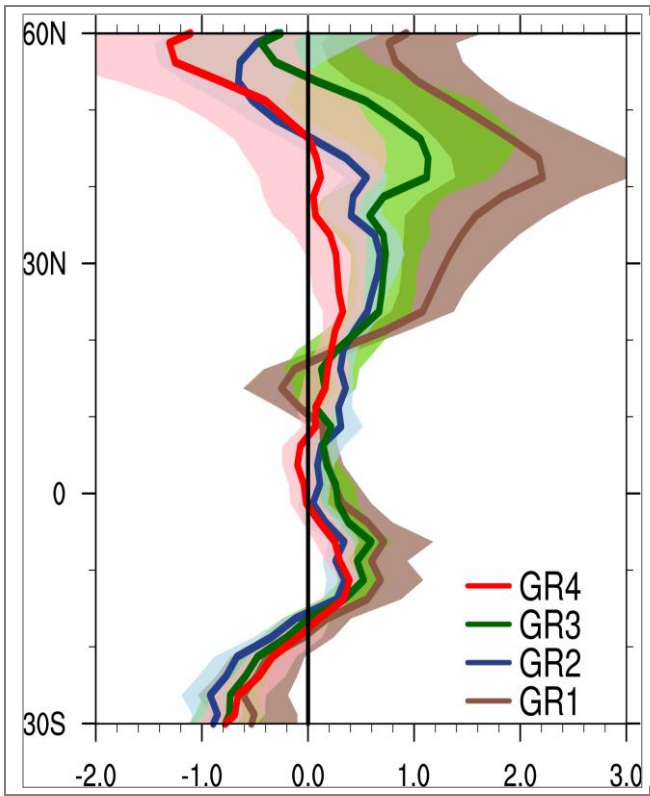
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Figure2: Projected changes in JAS (a-d) precipitation ($\text{mm}\cdot\text{day}^{-1}$), (e-h) evaporation ($\text{mm}\cdot\text{day}^{-1}$) and (i-l) P-E budget ($\text{mm}\cdot\text{day}^{-1}$) for the four groups of models (one group per column) identified by the clustering. The present climatology (HIST) is displayed with red contours and the RCP85-HIST differences by color shading. Hatching represents the grid-points where at least 80% of the models agree with the sign of the intra-group ensemble mean within each groups (5 for GR1; 7 for GR2; 13 for GR3; 5 for GR4)



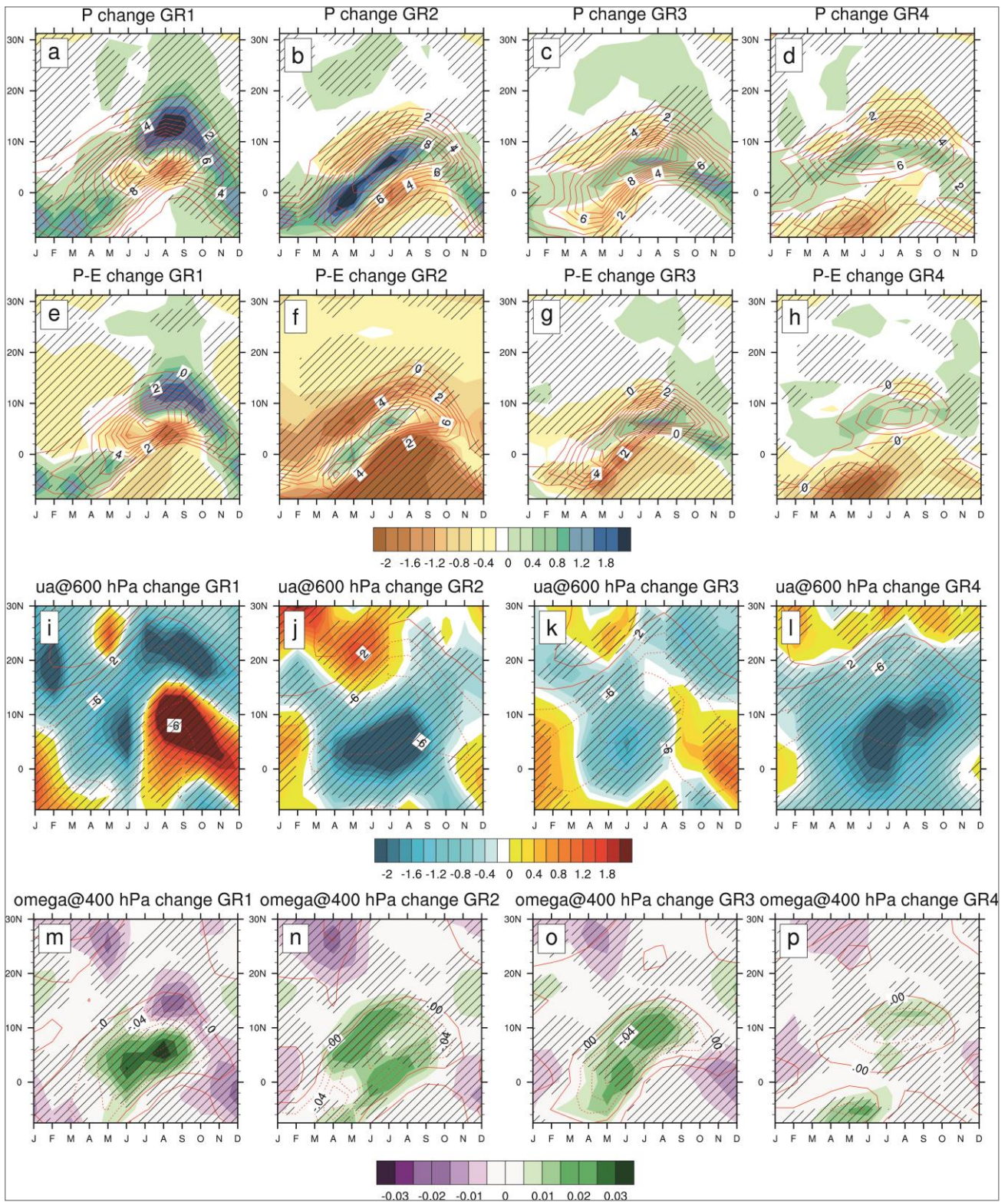
725 Figure3: Projected changes RCP85-HIST in JAS (a-d) 2m temperature (°C) (shading), sea level pressure (hPa) (blue
 726 contours) and 950 hPa winds (m.s⁻¹) (green arrows) for the four groups of models. The winds anomalies are displayed if
 727 at least 80% of the models agree on the sign of the intra-cluster mean. (e-h) Latitude-height cross section (average from
 728 10°W to 10°E) of zonal winds (m.s⁻¹) for the RCP85-HIST projected changes (shading). The present climatology
 729 (HIST) for zonal winds is displayed with red contours. Hatching represents the grid-points where at least 80% of the
 730 models agree with the sign of the intra-cluster mean (5 for GR1; 7 for GR2; 13 for GR3; 5 for GR4).
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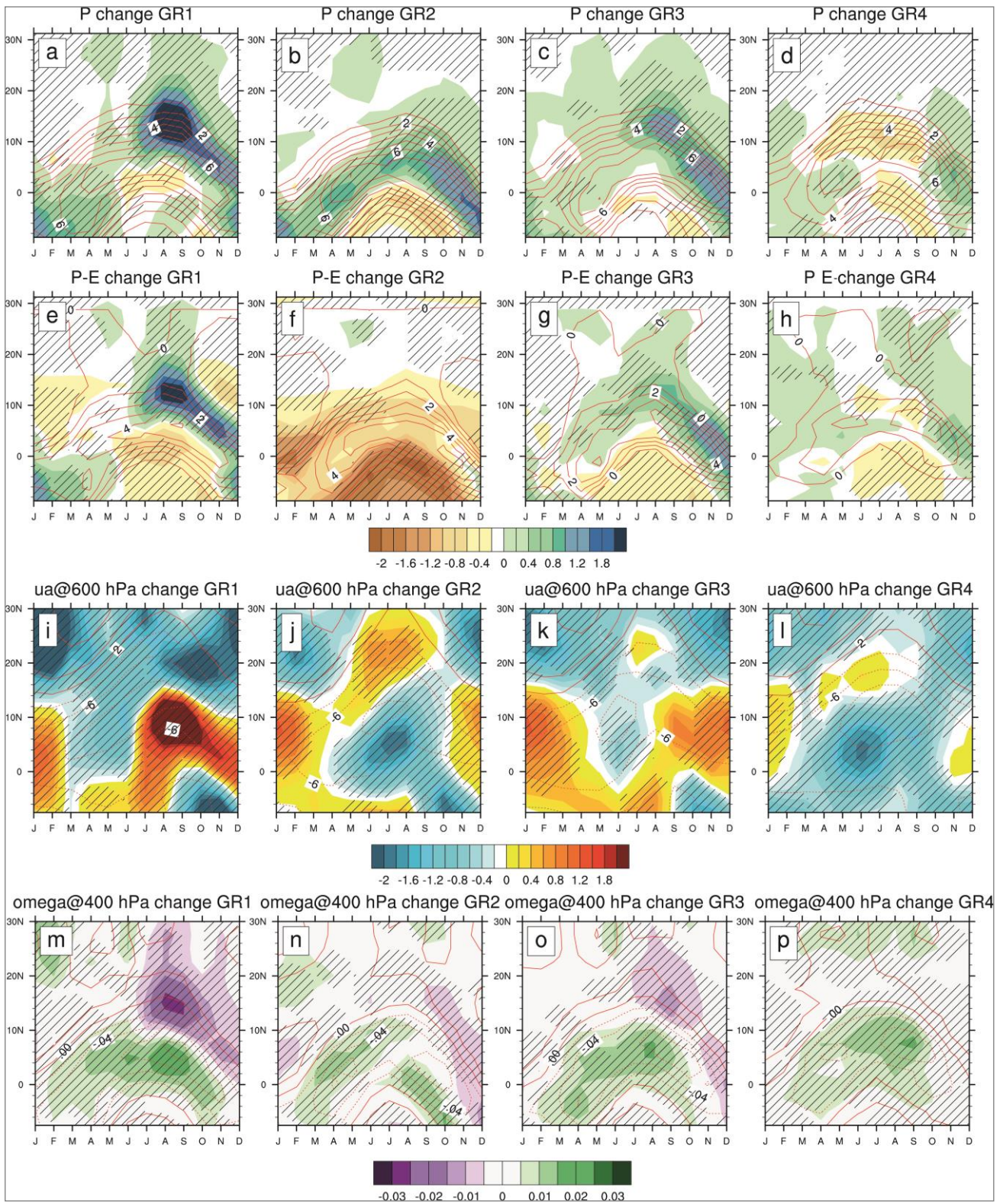
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Figure 4: Changes in SST Atlantic gradient, computed as the zonally-averaged RCP85-HIST difference over the Atlantic Ocean (75°W – 10°E) minus the SST tropical warming (180°W-180°E; 30°S-30°N) in JAS. The intra-cluster mean is computed for GR1 (brown line), GR2 (blue line), GR3 (green line) and GR4 (red line). Shadings represent the intra-cluster standard deviation.



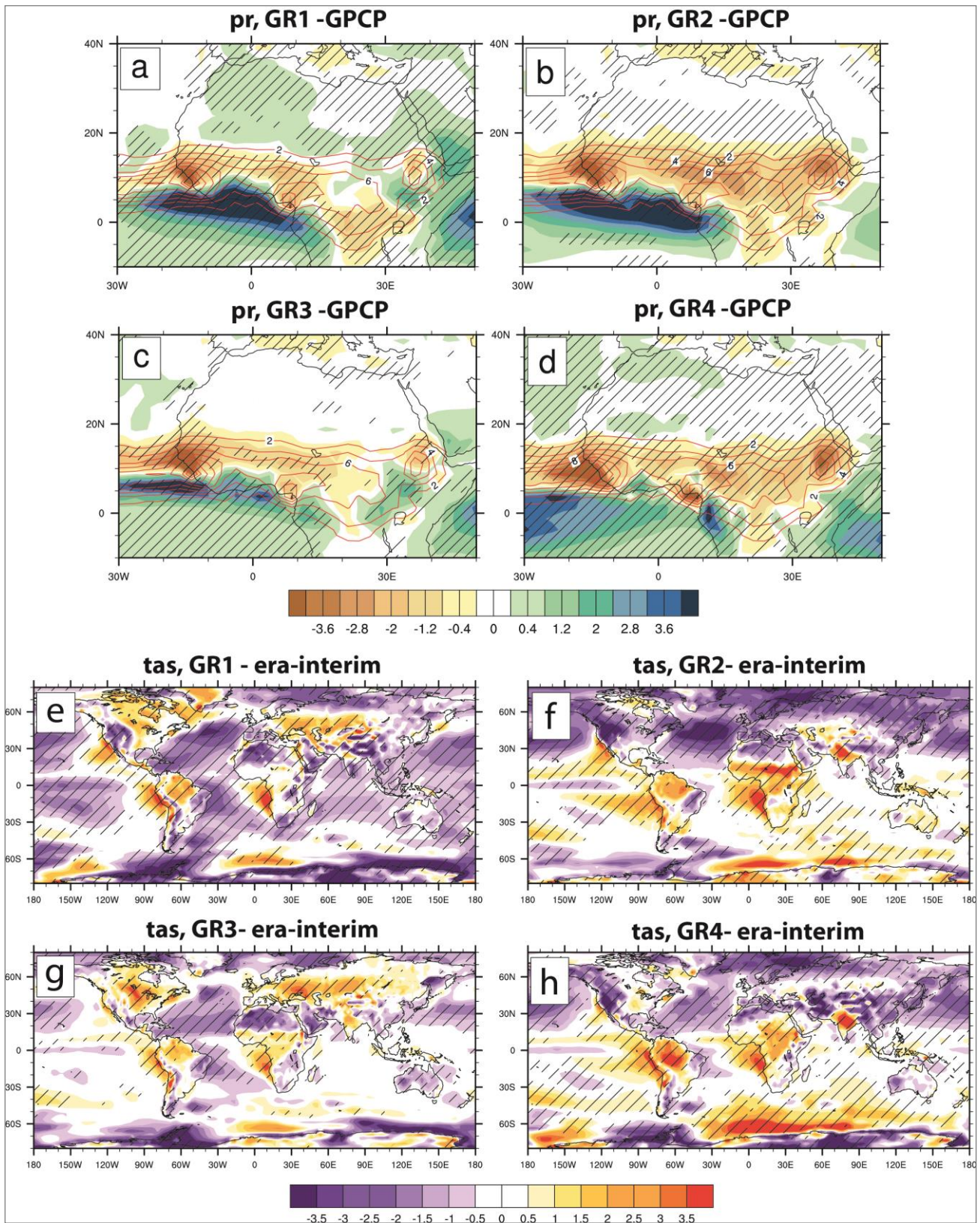
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Figure5: Time-Latitude diagram from January to December for RCP85-HIST projected changes averaged over the western Sahel (20°W-0°W) in (a-d) precipitation (mm.day⁻¹), (e-h) P-E (mm.day⁻¹), (i-l) 600 hPa zonal wind (m.s⁻¹) and (m-p) 400 hPa omega (Pa.s⁻¹) for the four groups of models. The present climatology (HIST) is displayed with red contours and the HIST-RCP85 differences by the shading. Hatching represents the grid-points where at least 80% of the models agree with the sign of the intra-cluster mean (5 for GR1; 7 for GR2; 13 for GR3; 5 for GR4).



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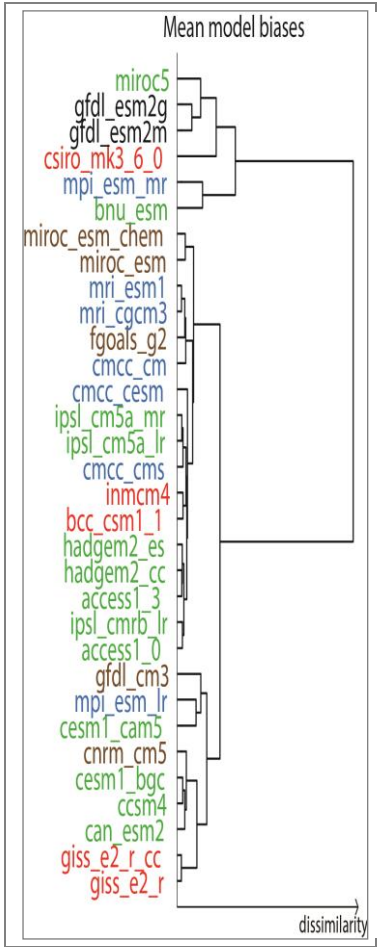
Figure6: Same as the figure 5 but for the central Sahel (from 0° to 20°E).



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Figure7: Mean model bias in JAS (a-d) precipitation computed as HIST-GPCP (in mm.day⁻¹) represented by the shading. Observed precipitation (GPCP) is also displayed (red contours). Mean model bias of global T2m in JAS computed as HIST-ERA-Interim reanalysis (e-h) (in °C). Hatching represents the grid-points where at least 80% of the models agree with the sign of the intra-cluster mean bias.

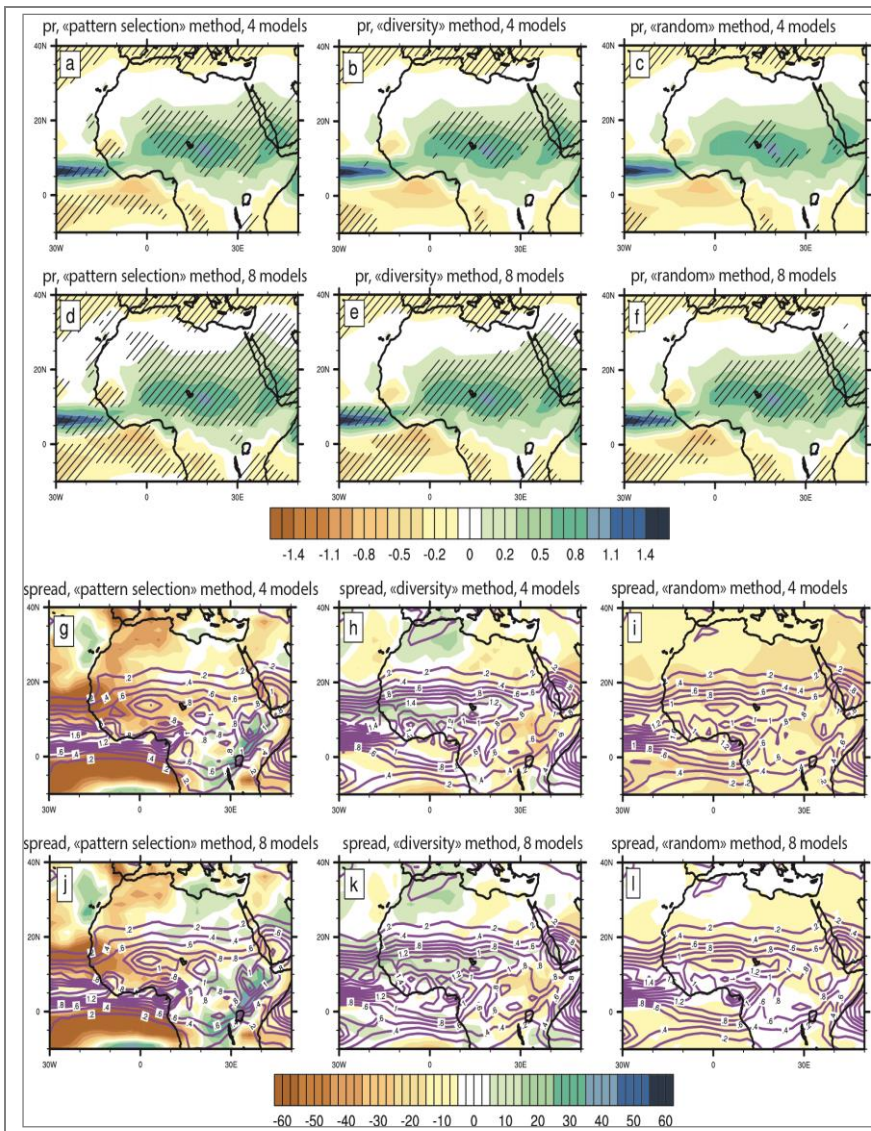
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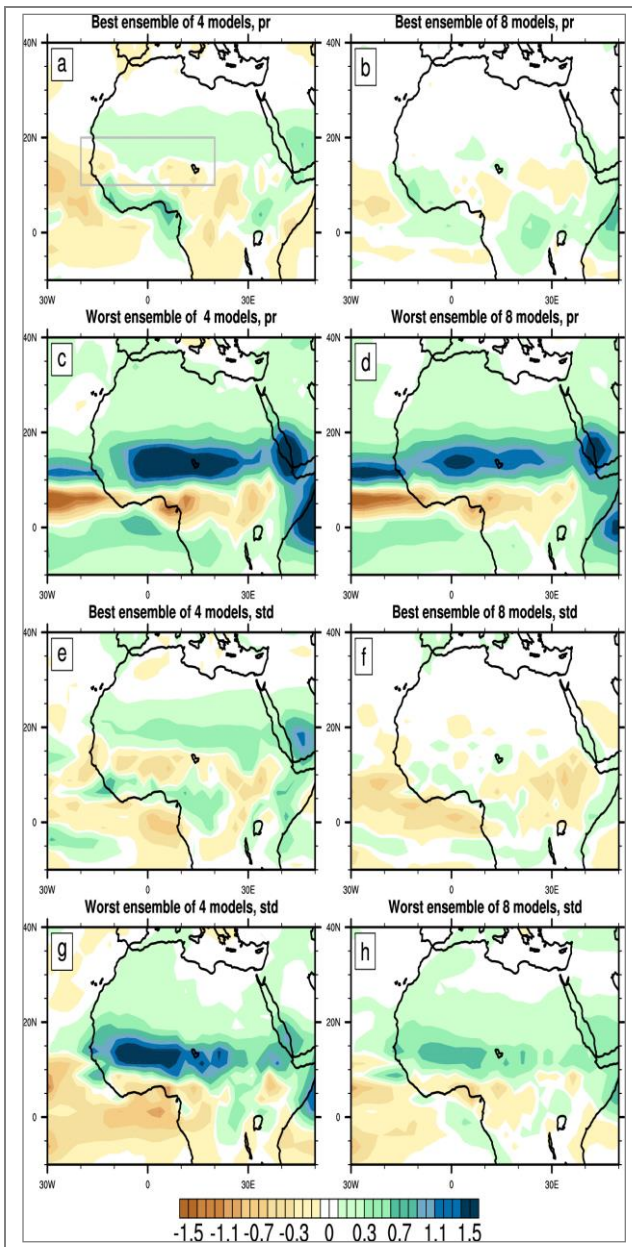
771 Figure8: The model "family tree" from the CMIP5 models for biases in Sahel precipitation, shown as a dendrogram (a
772 hierarchical clustering of the pairwise distance matrix for precipitation). The spatial pattern used to compute the
773 correlation matrix is the JAS precipitation bias (HIST-GPCP). Models on the same branch simulate similar biases in
774 precipitation. Colors indicate models belonging to the clusters defined in Fig.1 according to the classification on the
775 projected response.

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798 Figure9: Mean precipitation changes (mm.day⁻¹) of the 30 CMIP5 models (models in color in Figure 1b, shading)
 799 and the probability to reproduce its sign, when randomly selecting (a-c) 4 models and (d-f) 8 models (hatching). The
 800 probability is computed with a Monte Carlo approach. Hatching shows the points where at least 95% of the n
 801 draws agree on the sign of the CMIP5 pattern. Here, n is equal to 30 000 (500 000) for 4 models (8 models). The spread of the
 802 intra-group precipitation change is computed when using (g-i) 4 models and (j-l) 8 models, the difference (in %)
 803 between the mean spread computed from the n draws and the spread of the full CMIP5 ensemble is displayed in colors
 804 and the spread computed from the n values of spread is indicated by the purple lines (mm.day⁻¹). The “pattern selection”
 805 method consists of selecting 4 or 8 models in GR3, the “random” method randomly selects 4 or 8 models within the full
 806 CMIP5 ensemble, and the “diversity” method selects 1 or 2 models from each group of models in Fig.1.
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810 Figure10: Differences of ensemble mean JAS precipitation changes (RCP85-HIST; $\text{mm}\cdot\text{day}^{-1}$) between the full CMIP5
 811 ensemble, and the best ensemble of (a) 4 models, (b) 8 models, and the “worst” ensemble of (c) 4 models and (d) 8
 812 models. Differences of JAS mean precipitation ($\text{mm}\cdot\text{day}^{-1}$) between the spread of the RCP85-HIST CMIP5 data-set
 813 projection minus the spread of RCP85-HIST projection of the “best” ensemble of (e) 4 models, (f) 8 models and the
 814 “worst” ensemble of (g) 4 models and (h) 8 models.

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Figure1

Mean change

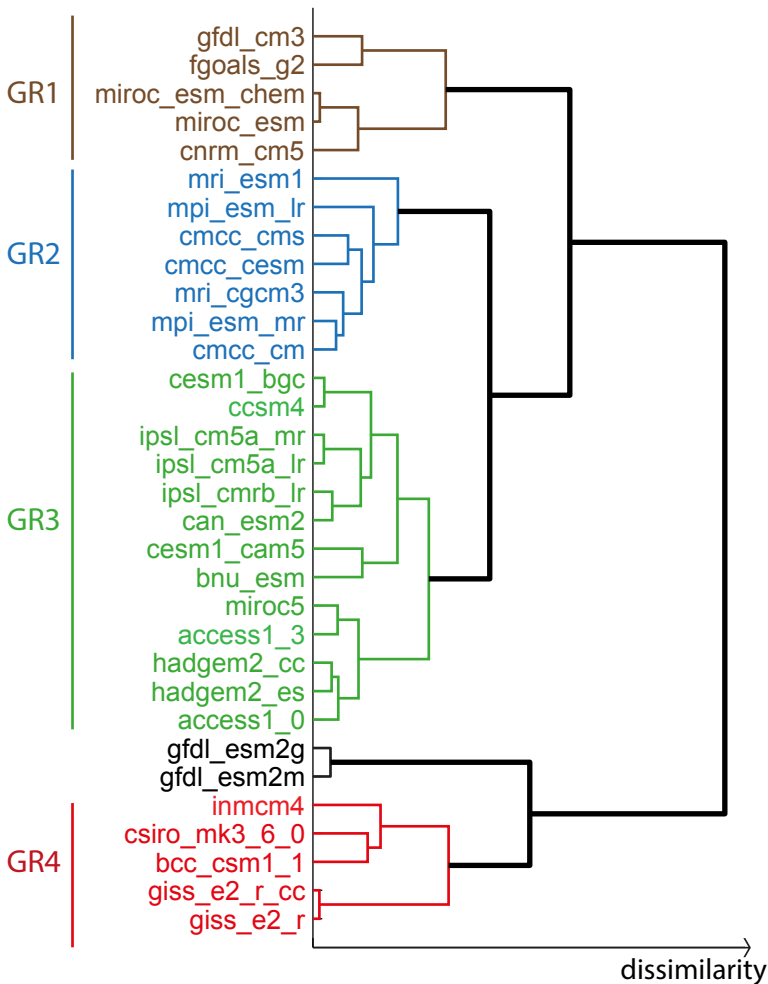


Figure2

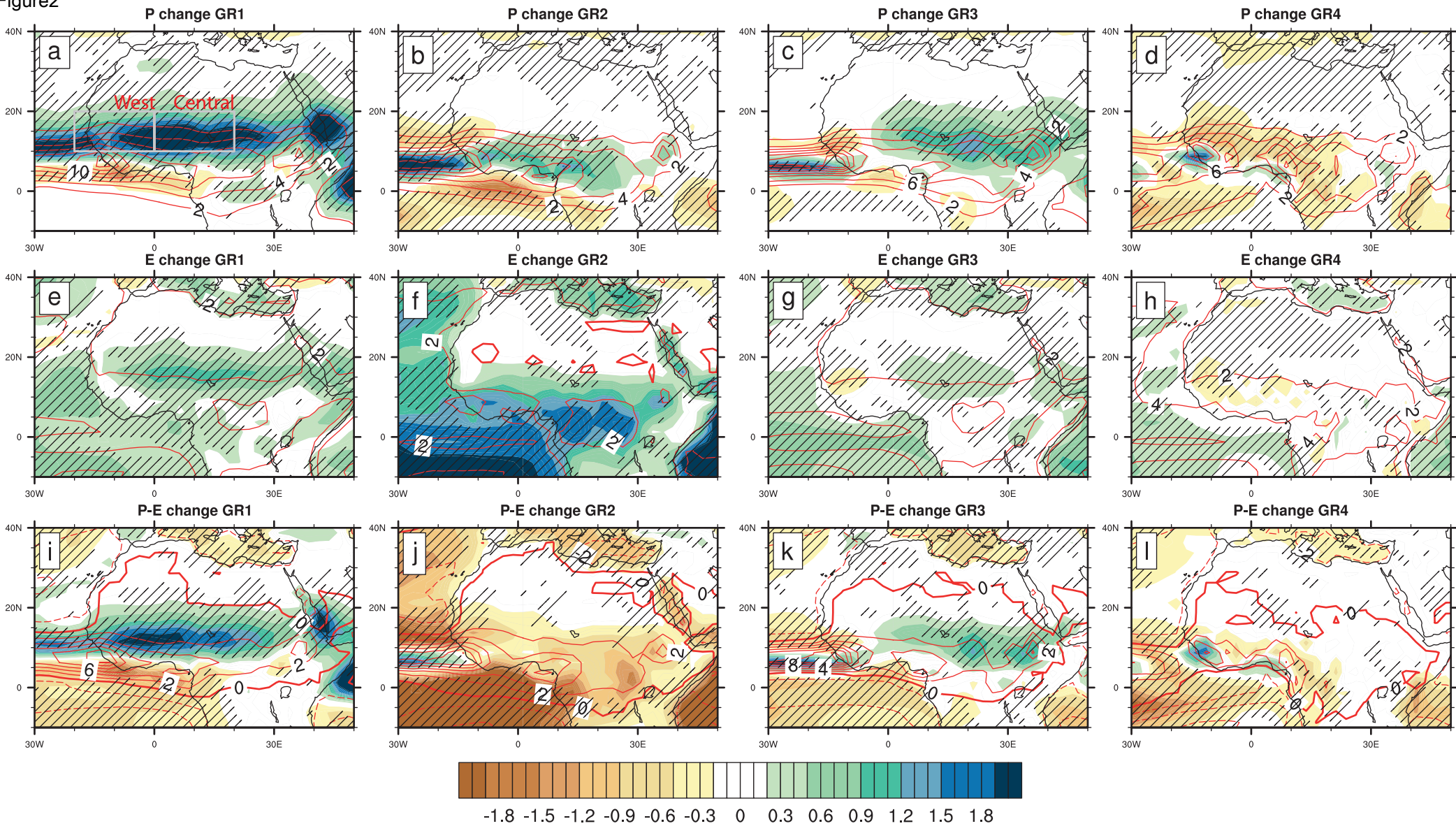
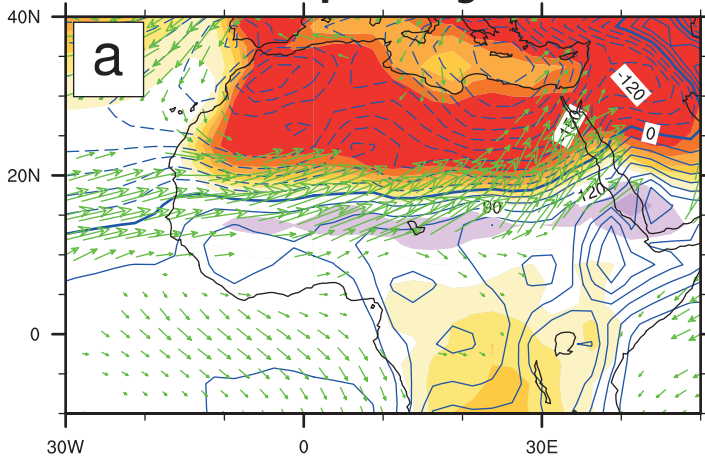
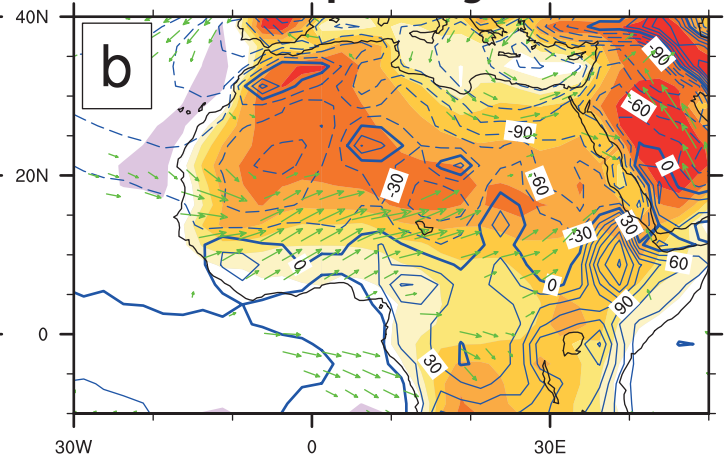


Figure3

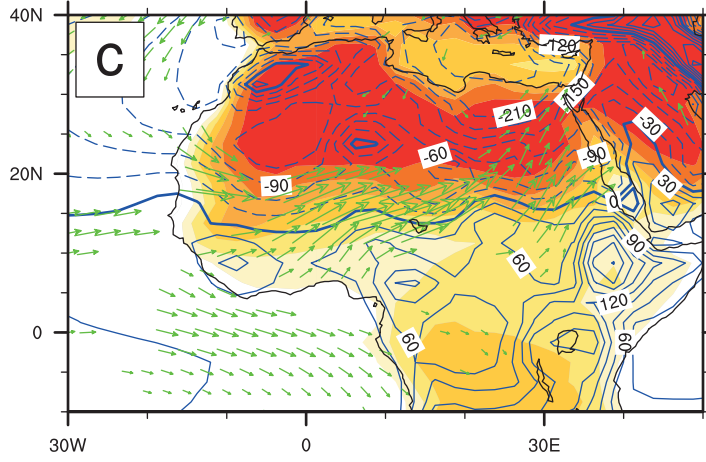
tas and ps change GR1



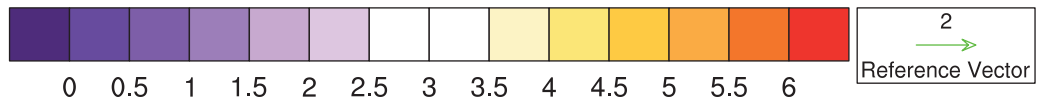
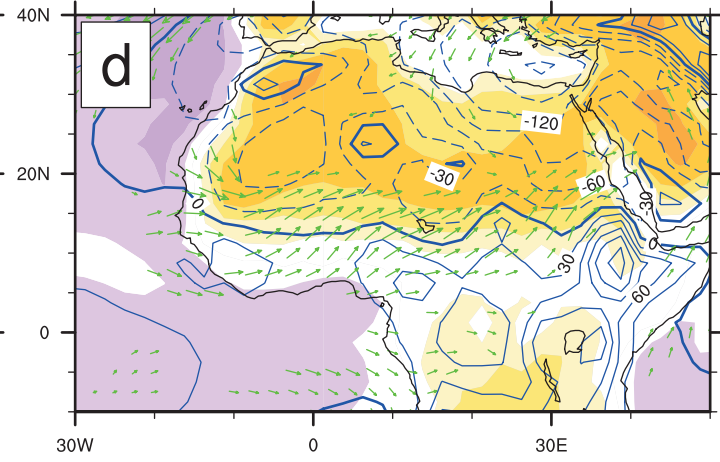
tas and ps change GR2



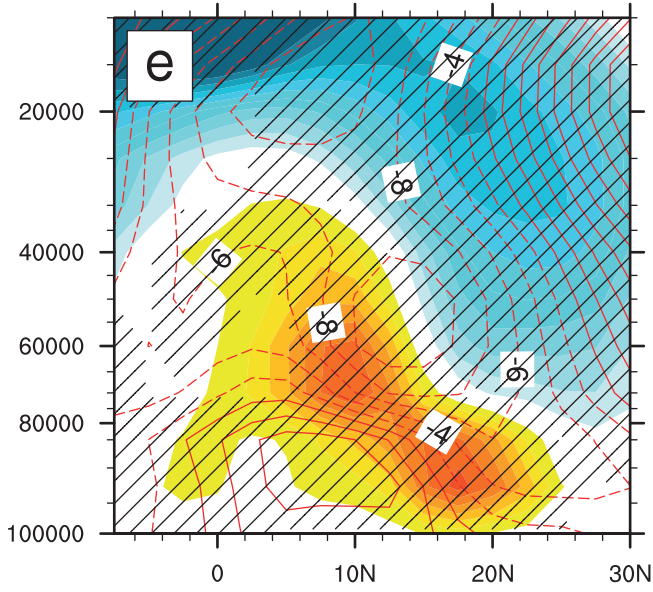
tas and ps change GR3



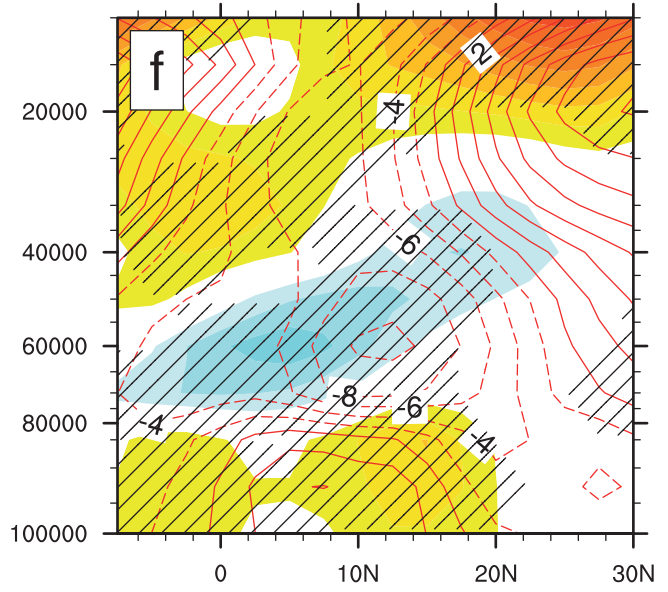
tas and ps change GR4



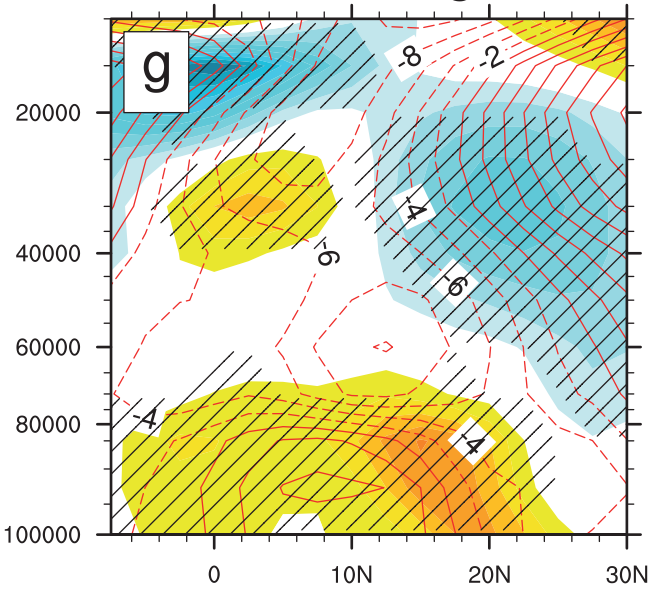
zonal wind change GR1



zonal wind change GR2



zonal wind change GR3



zonal wind change GR4

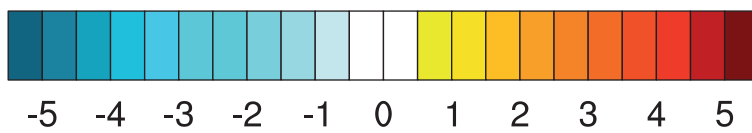
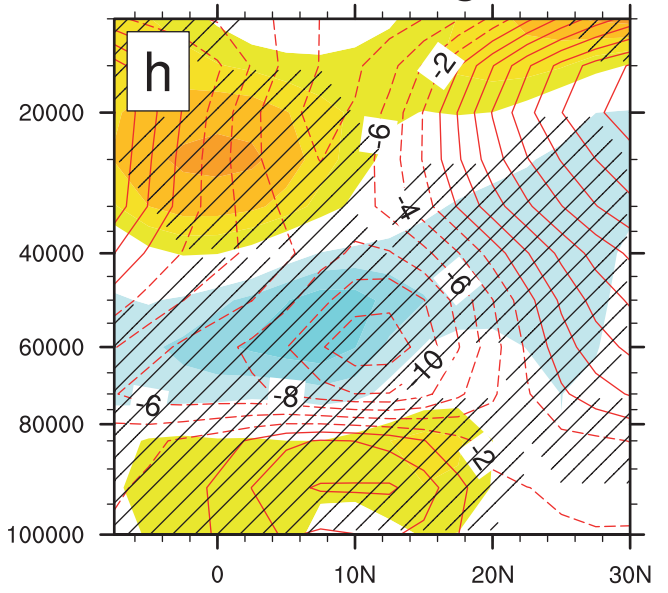
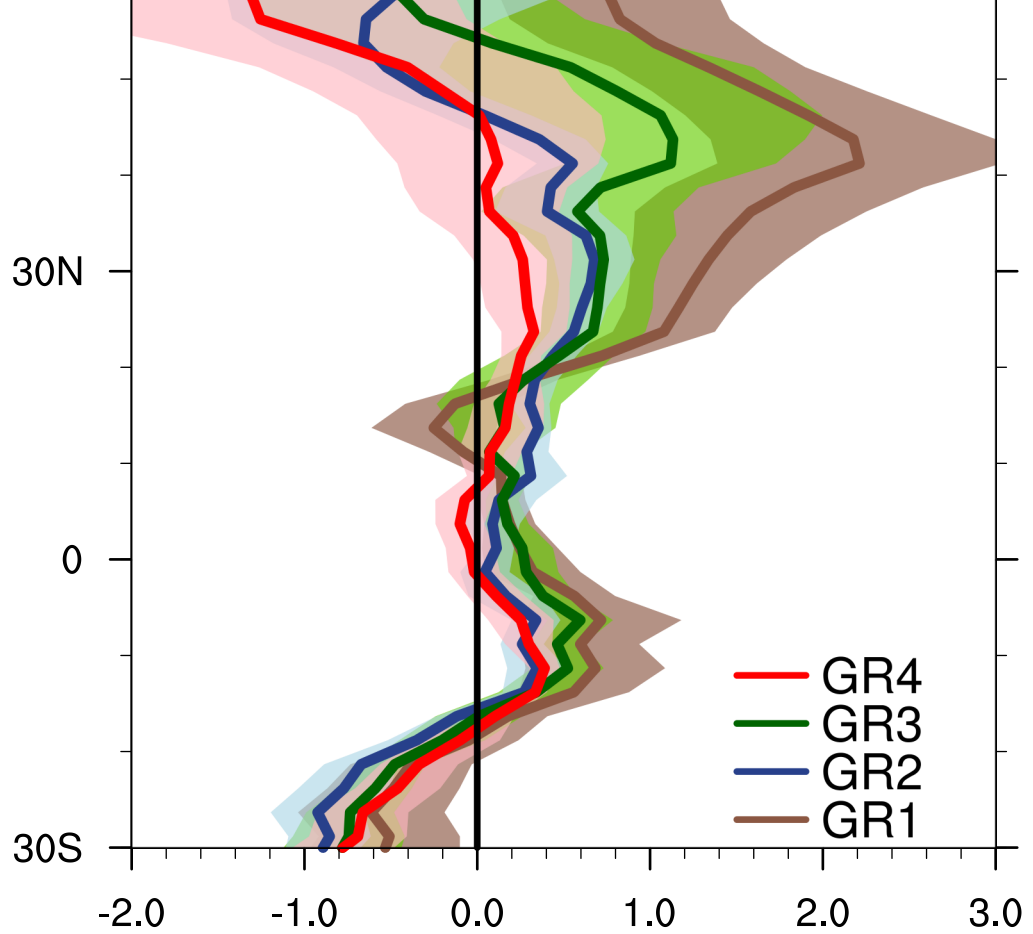
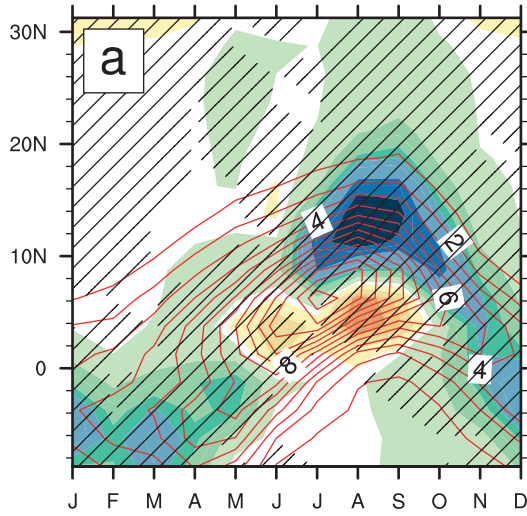


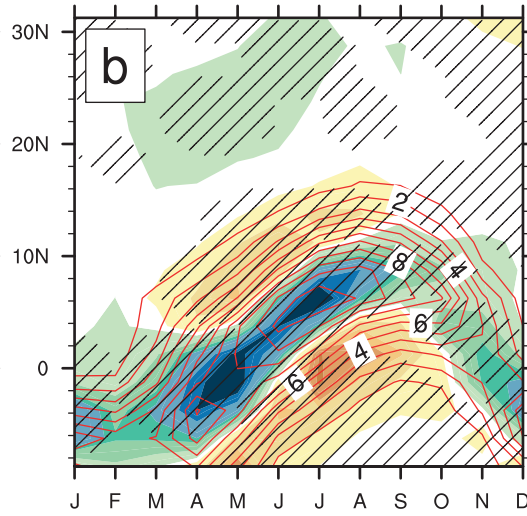
Figure4
60N



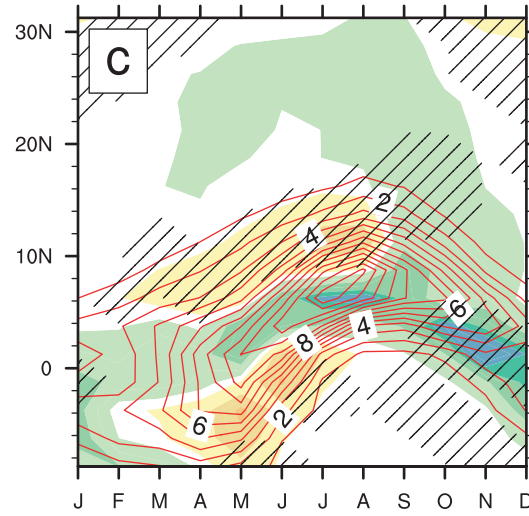
P change GR1



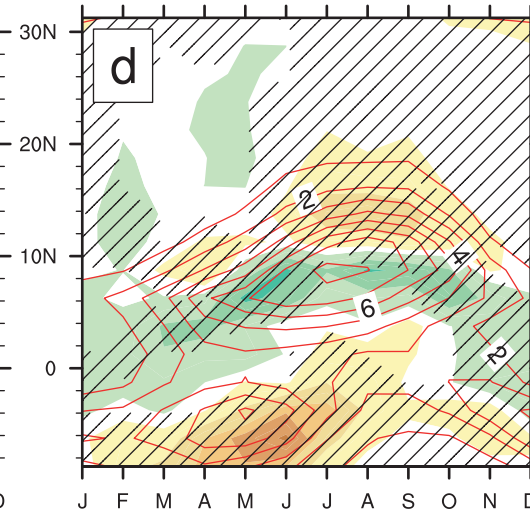
P change GR2



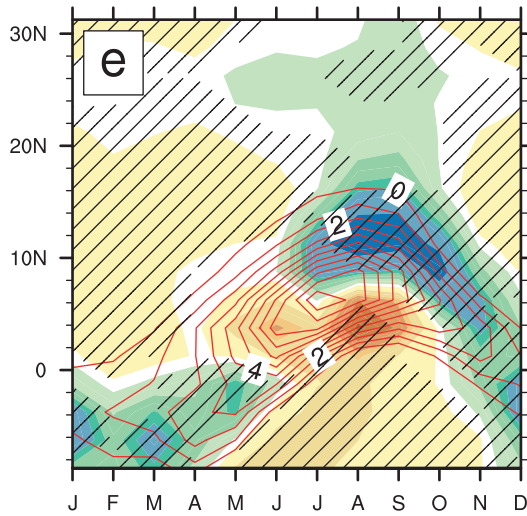
P change GR3



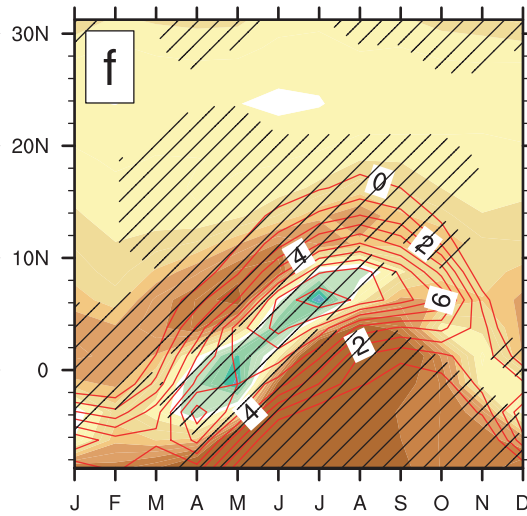
P change GR4



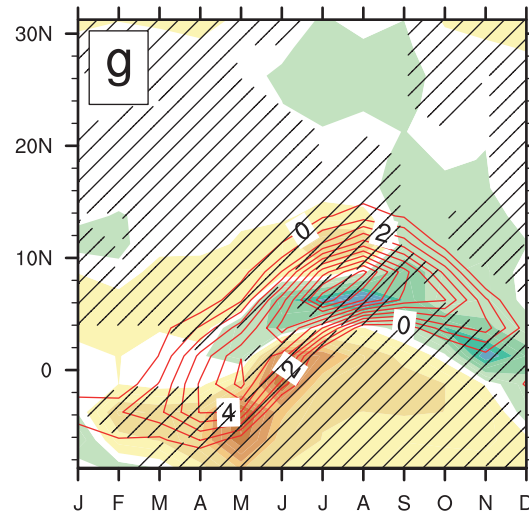
P-E change GR1



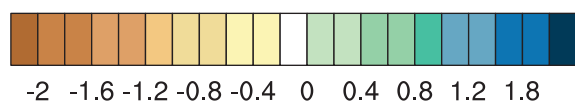
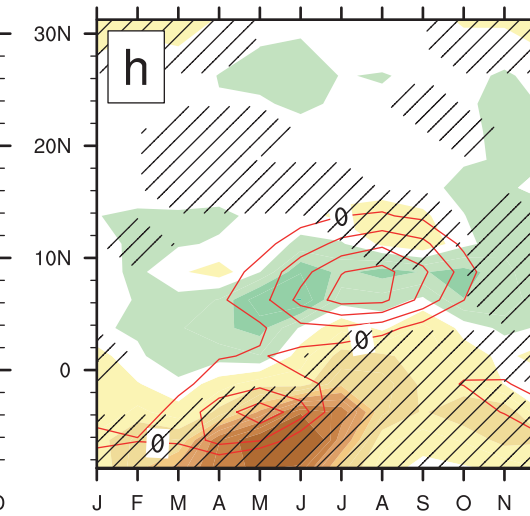
P-E change GR2



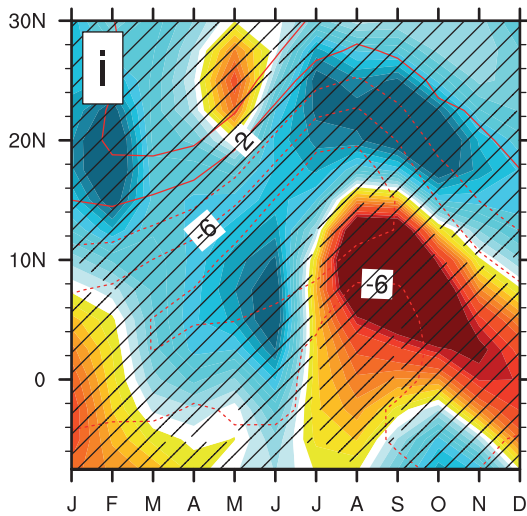
P-E change GR3



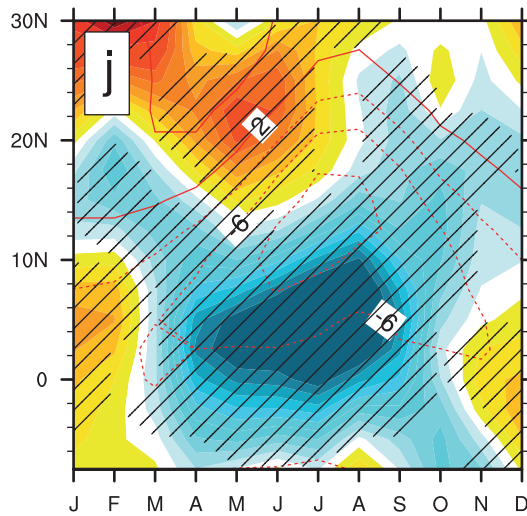
P-E change GR4



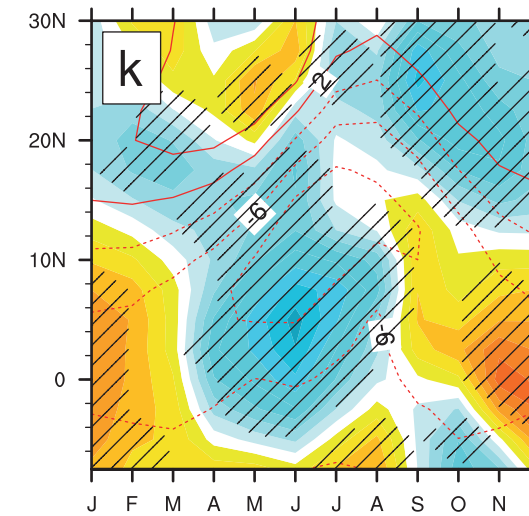
ua@600 hPa change GR1



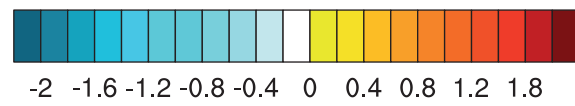
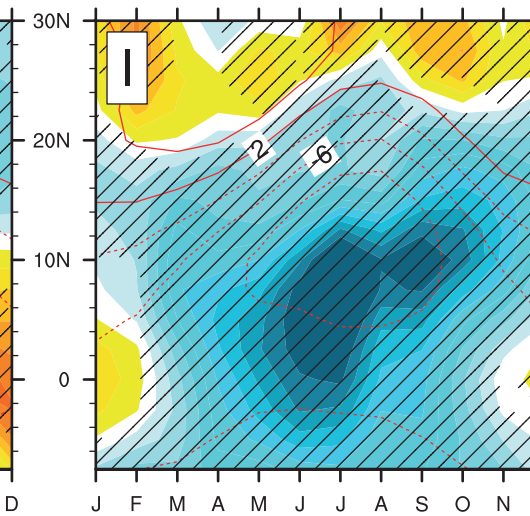
ua@600 hPa change GR2



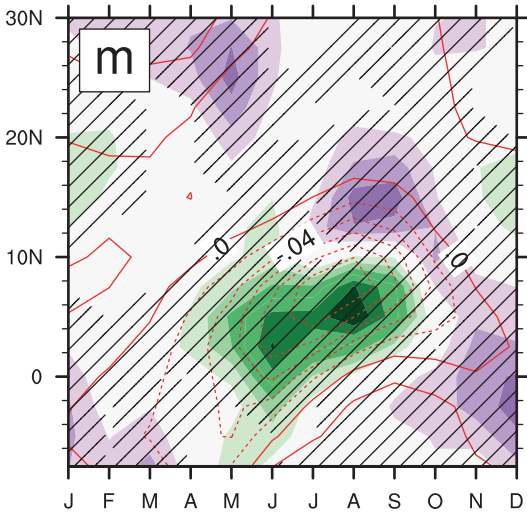
ua@600 hPa change GR3



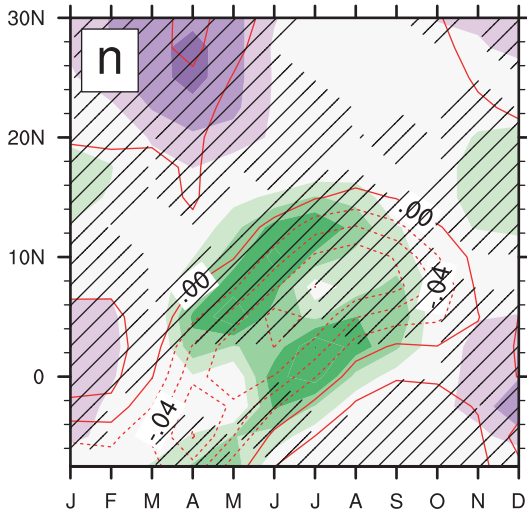
ua@600 hPa change GR4



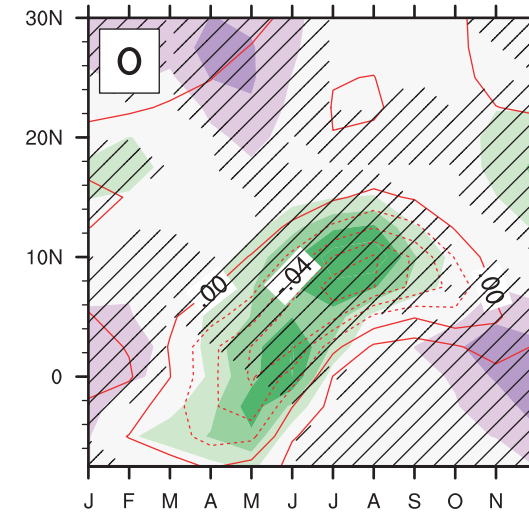
omega@400 hPa change GR1



omega@400 hPa change GR2



omega@400 hPa change GR3



omega@400 hPa change GR4

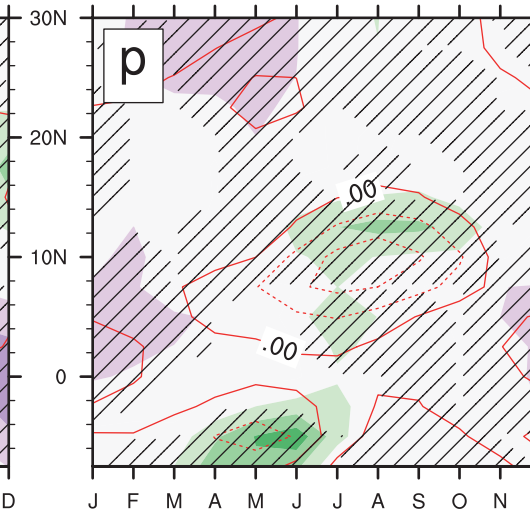


Figure 6

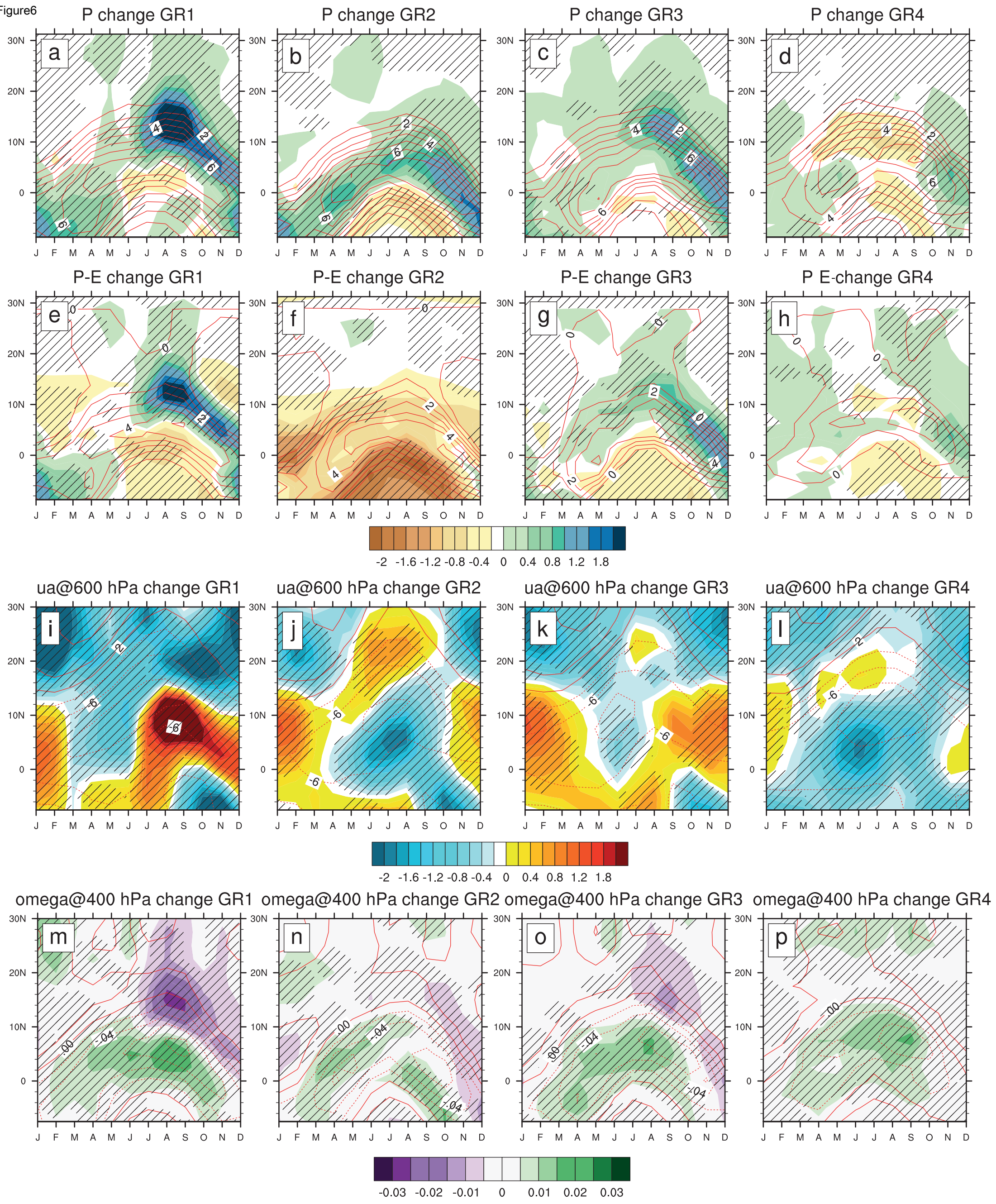
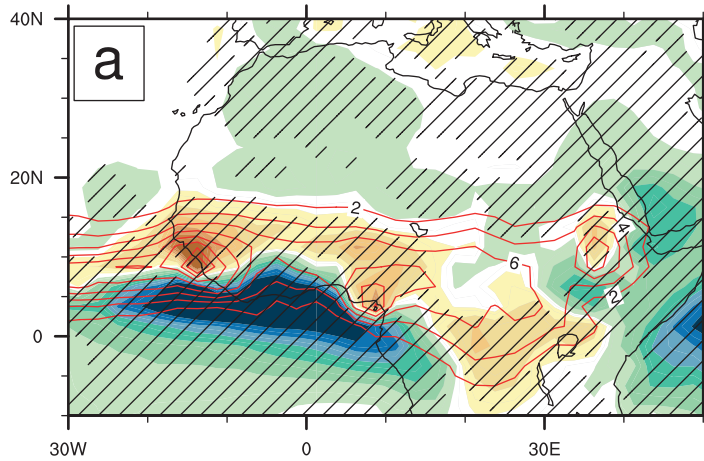
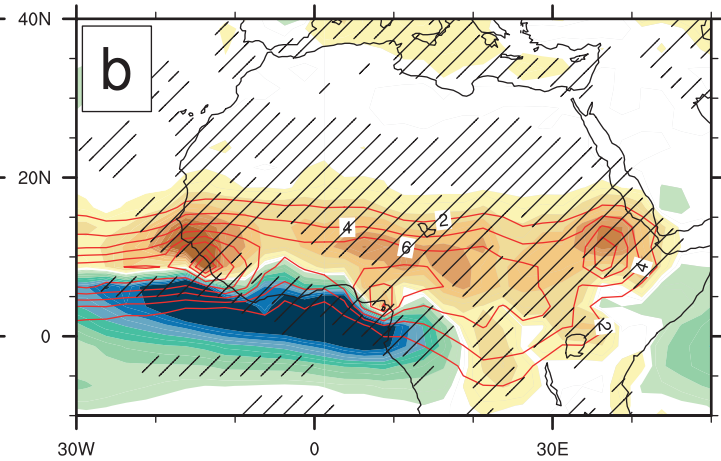


Figure7

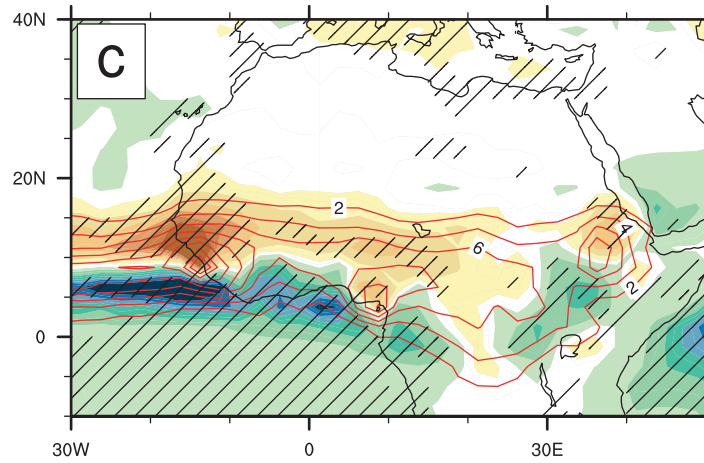
pr, GR1 -GPCP



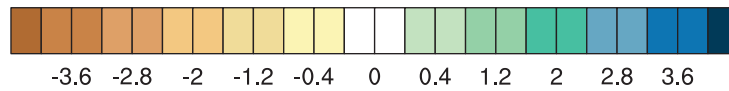
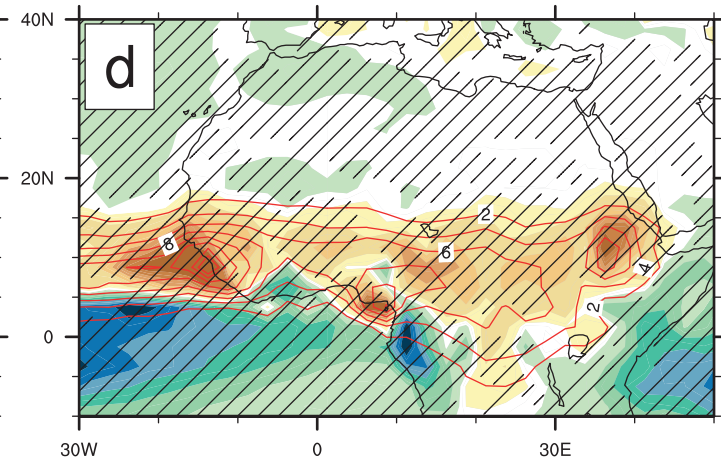
pr, GR2 -GPCP



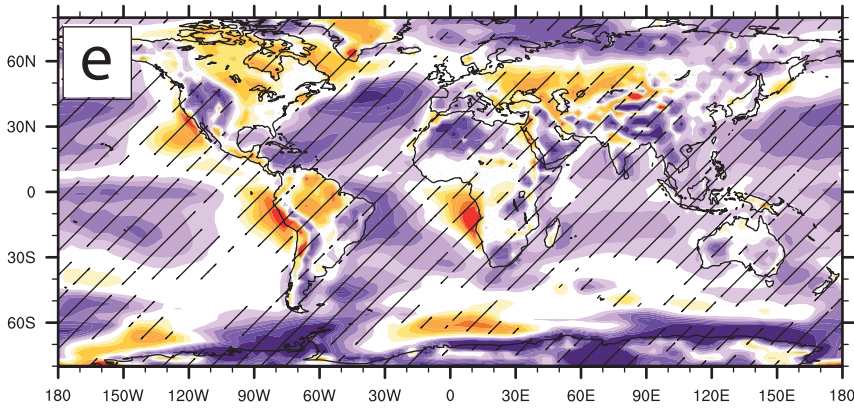
pr, GR3 -GPCP



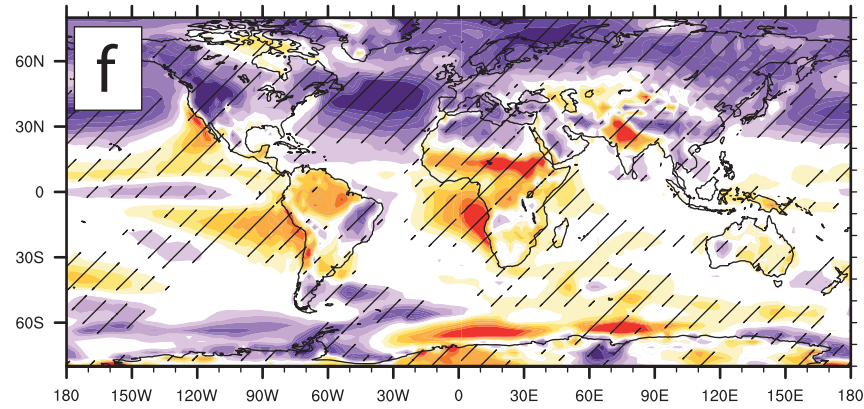
pr, GR4 -GPCP



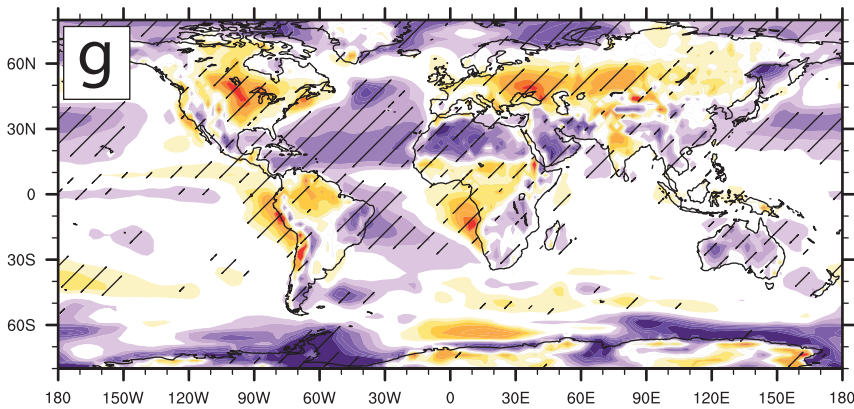
tas, GR1 - era-interim



tas, GR2- era-interim



tas, GR3- era-interim



tas, GR4- era-interim

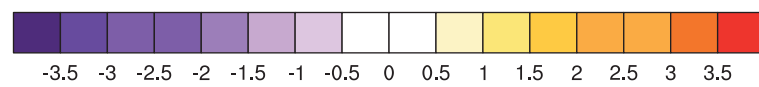
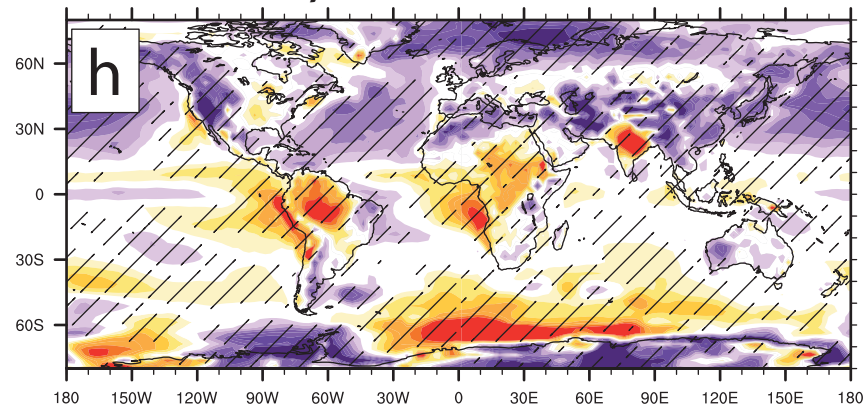


Figure8

Mean model biases

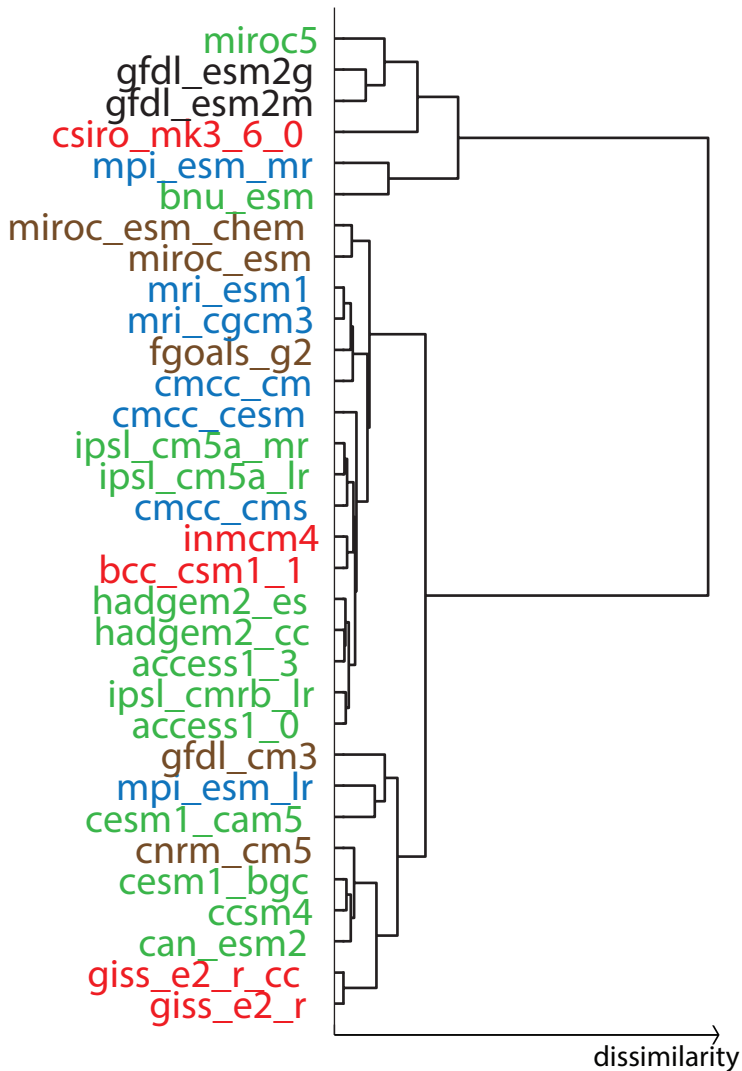
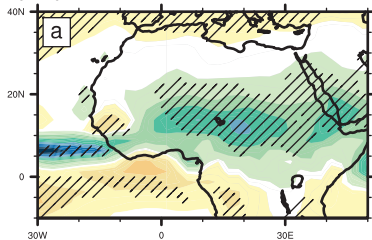
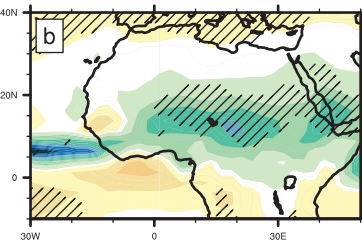


Figure9

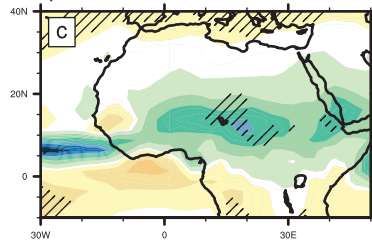
pr, «pattern selection» method, 4 models



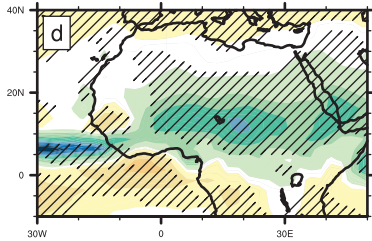
pr, «diversity» method, 4 models



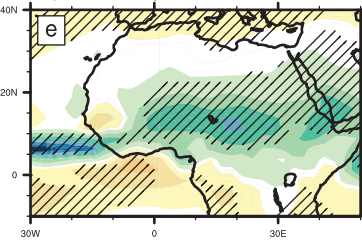
pr, «random» method, 4 models



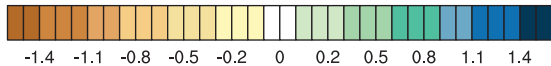
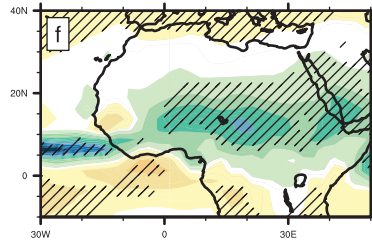
pr, «pattern selection» method, 8 models



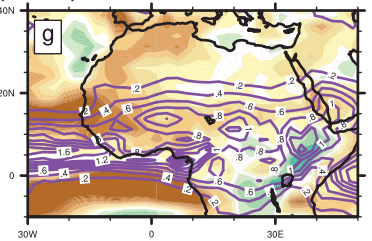
pr, «diversity» method, 8 models



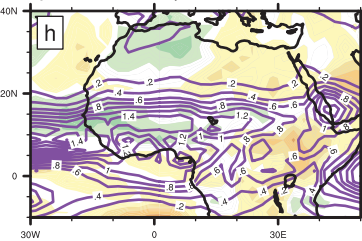
pr, «random» method, 8 models



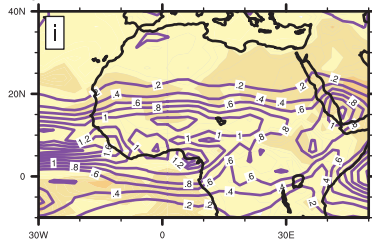
spread, «pattern selection» method, 4 models



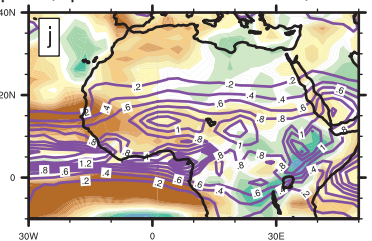
spread, «diversity» method, 4 models



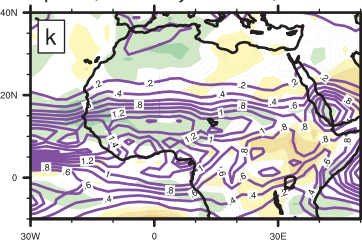
spread, «random» method, 4 models



spread, «pattern selection» method, 8 models



spread, «diversity» method, 8 models



spread, «random» method, 8 models

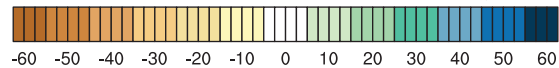
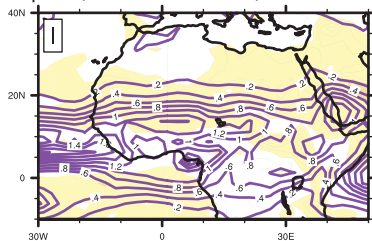
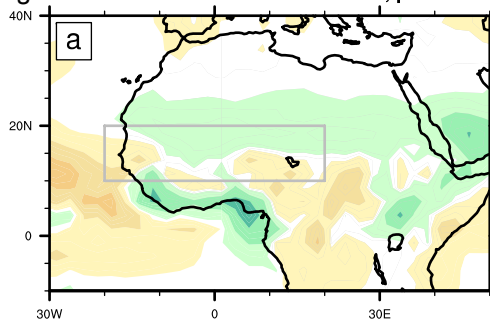
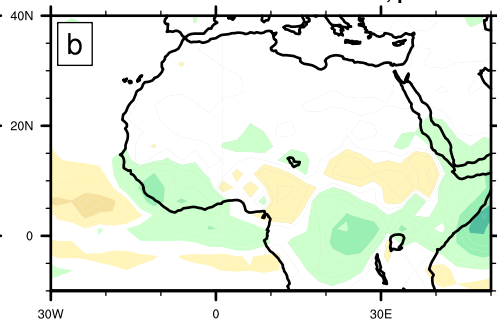


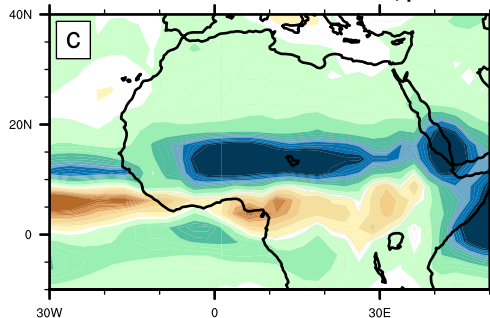
Figure 10 Best ensemble of 4 models, pr



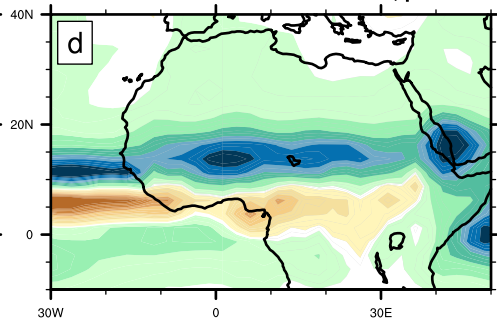
Best ensemble of 8 models, pr



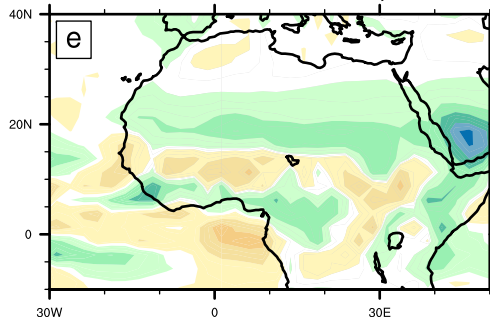
Worst ensemble of 4 models, pr



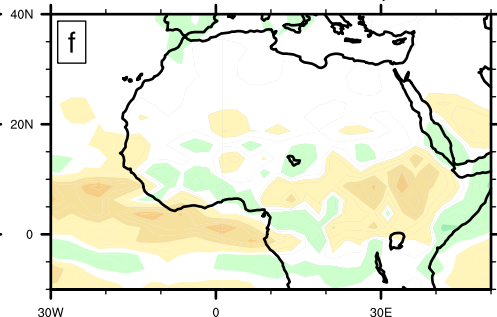
Worst ensemble of 8 models, pr



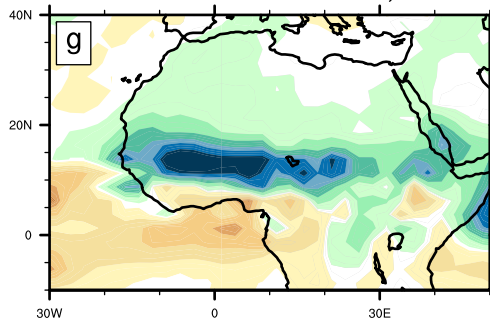
Best ensemble of 4 models, std



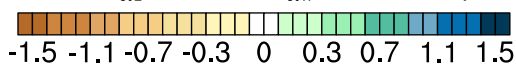
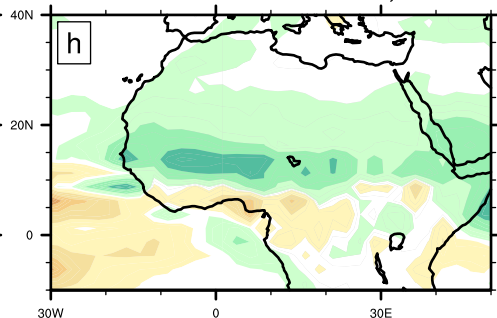
Best ensemble of 8 models, std

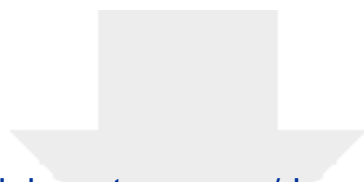


Worst ensemble of 4 models, std



Worst ensemble of 8 models, std





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Electronic Supplementary Material
Monerie_etal_with_track_changes.doc

