



Fast and slow precipitation responses to individual climate forcers: a PDRMIP multi-model study

Article

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3 **FAST AND SLOW PRECIPITATION RESPONSES TO INDIVIDUAL CLIMATE FORCERS: A PDRMIP MULTI-MODEL**
4 **STUDY**

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22 Abstract

23 Precipitation is expected to respond differently to various drivers of anthropogenic climate change. We
24 present the first results from the Precipitation Driver and Response Model Intercomparison Project
25 (PDRMIP), where nine global climate models have perturbed CO₂, CH₄, BC, sulfate and solar insolation.
26 We divide the resulting changes to global mean and regional precipitation into fast responses that scale
27 with changes in atmospheric absorption, and slow responses scaling with surface temperature change.
28 While the overall features are broadly similar between models, we find significant regional inter-model
29 variability, especially over land. Black carbon stands out as a component that may cause significant
30 model diversity in predicted precipitation change. Processes linked to atmospheric absorption are less
31 consistently modeled than those linked to top-of-atmosphere radiative forcing. We identify a number of
32 land regions where the model ensemble consistently predicts that fast precipitation responses to
33 climate perturbations dominate over the slow, temperature driven responses.

34 Key points

- 35 - Precipitation response from five climate drivers shown for nine climate models
- 36 - Fast responses scale with atmospheric absorption, slow with surface temperature
- 37 - Over some land regions, fast precipitation responses dominate the slow response

38 Introduction

39 Global precipitation levels and patterns are changing in response to global warming [*Hartmann, 2013*].
40 Climate change is presently caused by the interaction of drivers such as changing concentrations of

41 greenhouse gases, natural and anthropogenic aerosol emissions, and changes to solar insolation [Myhre
42 *et al.*, 2013a]. While the connection between a changing temperature and the hydrological cycle may be
43 understood through energy balance analyses [Allen and Ingram, 2002; O’Gorman *et al.*, 2012], future
44 precipitation changes are poorly constrained in state of the art climate models [Collins *et al.*, 2013;
45 Knutti and Sedláček, 2012]. Present models also tend to underestimate the solar absorption response to
46 changes in water vapor following a climate perturbation, overestimating the resulting change in global
47 mean precipitation [DeAngelis *et al.*, 2015]. Even when identically perturbed by an ensemble of climate
48 forcings, differences in present models’ individual atmospheric responses to these forcings give rise to
49 significant uncertainties. Improving such precipitation forecasts, both globally and regionally, and on
50 short and long time scales, is an important topic in present climate research, since precipitation is one of
51 the climate factors that most closely affects human society.

52 The global apparent hydrological sensitivity, defined as the total change in precipitation per degree of
53 global warming, differs between climate drivers such as CO₂ and solar insolation [Allen and Ingram,
54 2002]. Further, the precipitation response to a climate forcing is usually thought to happen on two
55 timescales: A rapid adjustment of the atmosphere to the change in energy balance as a direct result of
56 the climate driver, and one slower response, scaling with the change in surface temperature (see e.g.
57 [Boucher, 2013; Cao *et al.*, 2012; Kamae and Watanabe, 2012; Myhre *et al.*, 2013a; Sherwood *et al.*,
58 2015]). The realization that these processes may be very differently represented in models led to the
59 suggestion [Bala *et al.*, 2010] that fast and slow responses be compared separately in multi-model
60 intercomparisons to uncover robust responses in the hydrological cycle. Other publications have noted
61 that the slow precipitation change per degree of warming is well constrained, indicating that the main
62 differences in apparent response lie in the rapid adjustments [Timothy Andrews and Forster, 2010;
63 Fläschner *et al.*, 2016].

64 Recently, several single model studies have investigated the response to climate drivers in isolation.
65 *Timothy Andrews et al.* [2010] forced the HadGEM1 model with greenhouse gas, aerosol, albedo and
66 solar insolation perturbations. They found strong correlations between the top of atmosphere forcing of
67 a perturbation and the slow, temperature driven precipitation change, and between the modeled
68 atmospheric absorption and the fast precipitation change. *Kvalevåg et al.* [2013] repeated the studies
69 using the NCAR CESM1 model and the CAM4 atmospheric component. They found very similar overall
70 results and correlations to *Andrews et al.* [2010], but a number of significant differences in response to
71 otherwise identical climate perturbations.

72 No coordinated effort has however yet been made to compare the precipitation response to identical
73 single driver perturbations across a broad range of models. To perform such a comparison was the
74 formative idea behind the Precipitation Driver and Response Model Intercomparison Project (PDRMIP).
75 In the following sections, we present the first results of the PDRMIP effort, based on results reported by
76 nine global climate models. The experiment design broadly follows that used in [*Timothy Andrews and*
77 *Forster, 2010*] and [*Kvalevåg et al., 2013*], but with some differences implemented in order to allow as
78 many models as possible to apply identical perturbations to their climate simulations. The details of the
79 PDRMIP setup, aerosol distributions and simulations will be covered in a separate publication. Here, we
80 present the first analysis of the PDRMIP precipitation responses to five climate drivers, and extend the
81 analysis to separate the responses over ocean and various land regions. Upcoming publications will
82 further explore the hydrological sensitivities, energy balances and circulation changes that underlie the
83 present results.

84 Methods

85 In PDRMIP, global coupled climate models have performed simulations with comparable configurations,
86 forcing baseline, equilibrated climates with individual drivers. In the following, we define the

87 perturbations, present the participating models, and show how the temperature, precipitation and
88 radiative forcing responses were calculated. The models used for the present analysis are CanESM2,
89 NorESM1, HadGEM2, HadGEM3-GA4, GISS-E2, NCAR CESM1 CAM4, NCAR CESM1 CAM5, MPI-ESM and
90 MIROC-SPRINTARS. (See Table S1 for details and model references.)

91 For the present analysis, five perturbations were simulated: A doubling of CO₂ concentration (hereafter
92 denoted *CO2x2*), tripling of CH₄ concentration (*CH4x3*), 2% increase in solar insolation (*Sol+2%*), ten
93 times BC concentration or emissions (*BCx10*) and five times SO₄ concentrations or emissions (*SO4x5*). All
94 perturbations were abrupt, relative to present day or preindustrial values. Greenhouse gas and solar
95 insolation perturbations were applied relative to the models' own baseline values. For the aerosol
96 perturbations, multi-model mean monthly present day concentrations were extracted from the
97 submissions to AeroCom Phase II (see e.g. [Myhre et al., 2013b; Samset et al., 2013]). To form
98 perturbations they were multiplied by the stated factor, and both baseline and perturbed fields were
99 regridded to the native resolution of the PDRMIP models. Some models were however unable to
100 perform simulations with prescribed concentrations. These models instead ran a baseline with present
101 day emissions, and then multiplied these emissions by the prescribed factors.

102 For the baseline and each perturbation, each model ran two sets of simulations: One keeping sea
103 surface temperatures fixed (hereafter denoted *fSST*), and one with a slab ocean or fully coupled ocean
104 (*coupled*). The *fSST* simulations were run for 15 years, and the *coupled* simulations for 100 years. Only
105 one ensemble member was used for each model. Note that for the present analysis, focusing on sub-
106 centennial responses, the use of a long simulation with constant forcings is equivalent to a perturbed
107 initial-condition ensemble.

108 Table S1 summarizes the nine models that were used for the present analysis, including their ocean
109 setup and native resolutions, and whether they used emissions or prescribed aerosol concentrations. All

110 models simulated all perturbations, except MPI-ESM which did not have the capability for performing
111 the aerosol perturbations. One model (CESM-CAM4) used a slab ocean setup for the *coupled* simulations,
112 the others used a full ocean representation.

113 Radiative forcing (RF) due to a climate perturbation was diagnosed using use the difference in global
114 mean flux for years 6-15 from the *fSST* simulations. The analysis was performed at top-of-atmosphere
115 (TOA, RF_{TOA}) and at the surface (RF_{surf}). The change in atmospheric absorption due to the climate
116 perturbation was then defined as $Atm.abs. = RF_{TOA} - RF_{surf}$. The run length was determined based on
117 earlier observations that the present models equilibrate well within 5 years of *fSST* running (see e.g.
118 [Kvalevåg *et al.*, 2013]). A Gregory-style regression was also performed [Gregory and Webb, 2008],
119 regressing the global, annual mean flux change relative to the baseline simulation against the change in
120 surface air temperature (ΔTS) in the *coupled* simulations. Both methods yield comparable results – see
121 Supplementary Information.

122 Temperature and precipitation responses to the perturbations were calculated as averages of annual
123 means from the last 10 years of *fSST* simulations, or the last 50 years of the *coupled* simulations. The
124 time windows were chosen to allow both for approximate model equilibration (see Discussion), and to
125 encompass internal annual and decadal variability. For the regional analyses, all modeled precipitation
126 responses were regridded to $1^\circ \times 1^\circ$ resolution.

127 To diagnose the fast precipitation response due to rapid adjustments, ΔP_{fast} , we used the response in the
128 *fSST* simulations. In the coupled simulations, we have assumed that the response over the last 50 years
129 is a linear combination of the fast response and a slow response due to surface temperature change.

130 Hence the slow response can be calculated as $\Delta P_{slow} = \Delta P_{total} - \Delta P_{fast}$.

131 Results

132 We first compare the near-surface temperature change and total (fast+slow) precipitation responses to
133 the five climate perturbations, regionally and globally averaged, for all participating models. We then
134 highlight similarities and differences across the multi-model ensemble and for each forcing agent; for RF,
135 fast and slow precipitation responses, and contrasts in behavior between land and ocean.

136 Figure 1 shows the global mean temperature and precipitation responses to the climate perturbations.
137 For $CO_2 \times 2$, the temperature response varies between about 2-4 K, consistent with the range in modeled
138 climate sensitivities found in CMIP5 [T. Andrews *et al.*, 2012]. We note, however, that most models have
139 not achieved equilibrium 100 years after the perturbation, and hence the full temperature response is
140 likely higher. The precipitation response to $CO_2 \times 2$ ranges from 1-6 %, correlated with the temperature
141 response. The bottom left panel of Figure 1 illustrates this, showing the hydrological sensitivity (HS) for
142 $CO_2 \times 2$ across the models. The HS, defined as $\Delta P_{\text{total}}/\Delta T$ (in recent publications termed the apparent
143 hydrological sensitivity parameter [Fläschner *et al.*, 2016], a terminology which we adopt here) shows
144 much less spread, with a multi-model mean HS of 1.4 ± 0.3 %/K for $CO_2 \times 2$. The error indicates one
145 standard deviation across the present model sample. One model (GISS-E2) stands out as having a
146 markedly lower response than the others, in temperature, precipitation and HS. This is consistent with
147 this model having amongst the lowest equilibrium climate sensitivities of the CMIP5 models [Forster *et*
148 *al.*, 2013], and being flagged as an outlier in another recent multi-model study investigating CO_2 forcing
149 in CMIP5 [DeAngelis *et al.*, 2015].

150 For $CH_4 \times 3$ and $Sol+2\%$ the pattern between models is qualitatively similar to $CO_2 \times 2$, although the
151 apparent HS is higher; 1.7 ± 0.4 %/K for $CH_4 \times 3$ and 2.4 ± 0.2 %/K for $Sol+2\%$. This is in line with earlier
152 modelling studies [Allen and Ingram, 2002].

153 Black carbon shows an opposite precipitation response to the other forcing agents, i.e. it has a negative
154 apparent HS, due to its strong atmospheric absorption of shortwave radiation. All models give a positive
155 temperature response in the *BCx10* case, but with a relatively large spread. The precipitation response is
156 consistently negative, except in one model (HadGEM3-GA4) where it is consistent with zero. The
157 apparent HS for *BCx10* shows sizeable spread.

158 The sulfate perturbation yields a negative response in both temperature and precipitation, across all
159 models. The HS for *SO4x5* is similar to that for *Sol+2%*, and stronger than for the greenhouse gases. One
160 model (HadGEM3-GA4) finds a markedly strong response to *SO4x5* in both temperature and
161 precipitation, but has a HS in line with the other models. This model version simulates a relatively high
162 sulfate aerosol optical depth per unit mass, and has previously been shown to have a strong indirect
163 aerosol effect relative to comparable models [Wilcox *et al.*, 2015]. NCAR CESM CAM4, which does not
164 include any indirect aerosol effects on clouds, has a sulfate response and a HS that is well within the
165 multi-model spread.

166 Inspired by earlier single model studies [Timothy Andrews *et al.*, 2010; Kvalevåg *et al.*, 2013], we
167 investigate correlations of precipitation changes with energetic quantities (Figure 2). The left panel
168 shows the regressed change in net atmospheric absorption against the global mean fast precipitation
169 response. RF values were calculated using the fSST method. Figure S1 shows the corresponding results
170 when using 20 year Gregory regressions. As in the previous single model studies, we find a strong
171 negative correlation. The main reason for this is that the greater change in absorption through the
172 atmospheric column, the more convection is suppressed, leading to reduced precipitation and latent
173 heating. All models show atmospheric absorption consistent with zero for *SO4x5* (except one model,
174 CAM5, which calculates 1 W m^{-2}), and around 0.5 W m^{-2} for *CH4x3* and *Sol+2%*. *CO2x2* results in around
175 2 to 3 W m^{-2} of atmospheric absorption for all models, with a corresponding fast precipitation response
176 of -20 to -40 mm/yr . *BCx10* displays significant absorption in all models, but with a very large range,

177 from 1 to more than 5 W m⁻². The resulting fast precipitation response however largely follows the
178 multi-model, multi-perturbation regression line. Deviations from this regression line can occur because
179 the change in the atmospheric energy budget also depends on changes in surface sensible heat flux, as
180 well as the radiative and latent-heat terms. See e.g. [Fläschner *et al.*, 2016].

181 The right panel of Figure 2 regresses the change in near-surface temperature (ΔT_S) against the slow
182 precipitation response. We find a strong positive correlation, again in line with previous single model
183 studies. The results for a single driver show a spread in accordance with the climate sensitivities of the
184 PDMIP model sample (generally the same versions as in CMIP5, see [Forster *et al.*, 2013]). For *BCx10* two
185 models (CanESM2, HadGEM2) fall well outside the correlation line, however the temperature change
186 due to the BC perturbation used here is also very low (<2K for all models). The HadGEM3-GA4 response
187 to *SO4x5* stands out as particularly strong, but still follows the general trend.

188 Broadly, Figure 2 confirms the physical picture drawn in [Timothy Andrews *et al.*, 2010] and [Kvalevåg *et al.*,
189 *et al.*, 2013]. The precipitation response to a global climate driver can be subdivided into two broad
190 components: A fast response, which scales with changes in the atmospheric absorption, and a slower
191 response related to changes in surface temperature, scaling with the surface temperature change (and,
192 more broadly, TOA RF). Inter-model differences are however significant. The scaling with climate
193 sensitivity in the right panel is far from perfect, and the left panel indicates a wide range of modeled
194 atmospheric absorptions and fast responses for comparable perturbations. Investigating the internal
195 processes that link TOA RF, surface temperature change and atmospheric absorption to precipitation
196 change in these models therefore is a promising way to understand inter-model spread and potentially
197 reduce multi-model uncertainty in precipitation.

198 Table S2 lists the multi-model average global mean responses to the five perturbations, for radiative
199 forcing, temperature, and total, fast and slow precipitation. The PDRMIP ensemble confirms earlier

200 model studies indicating a stronger apparent hydrological sensitivity for changes to solar irradiance
201 (2.4 %/K) relative to the greenhouse gases (1.4 %/K). Further, the modeled climates are also more
202 sensitive to aerosol perturbations than to forcing from greenhouse gases, albeit with a significantly
203 higher ensemble uncertainty for *BCx10*. Recent publications have studied how the precipitation
204 response to a climate driver scales with surface temperature change alone, termed the slow
205 hydrological sensitivity (e.g. [Timothy Andrews et al., 2010; Fläschner et al., 2016]), and found that it
206 varies less between models and drivers than the apparent HS. This will be explored for the PDRMIP
207 model ensemble in an upcoming publication.

208 Figure 3 shows the multi-model mean geographical patterns of the total, fast and slow precipitation
209 responses to the individual perturbations. For most regions and perturbations, the models do not all
210 agree on the sign of the responses, however some robust features are still apparent.

211 For *CO2x2* (top row), the total response is comprised of a negative fast response at most latitudes, and a
212 stronger positive slow response at all latitudes but with a few exceptions in the inter-tropical
213 convergence (ITCZ) regions. The former is mainly due to the stabilizing effect of the atmospheric
214 absorption of CO_2 , the latter due to the gradual increase in surface temperature. The total precipitation
215 change is strongest around the Equator, dominated by the slow change over the Pacific Ocean. Most
216 regions are dominated by the slow response, but some land regions are dominated by the fast changes.
217 (See below).

218 *CH4x3* and *Sol+2%* (second and third rows) show broadly similar total and slow precipitation response
219 features to *CO2x2*, except that *CH4x3* has lower absolute response due to the weaker RF (as also seen in
220 Figure 1). The model mean fast response to *CH4x3* is non-significant for all latitudes, as expected for
221 climate perturbations with low atmospheric absorption. *SO4x5* (bottom row) shows an inverted pattern
222 to the solar and greenhouse gas perturbations, with virtually no (significant) fast response in the zonal

223 mean. For $CO_2 \times 2$, $CH_4 \times 3$, $Sol + 2\%$ and $SO_4 \times 5$, there is a clear land/ocean difference, in line with earlier
224 analyses based on the CMIP5 model ensemble [Richardson *et al.*, 2016]. Tropical land areas generally
225 see a positive fast precipitation response, largely canceled out in the zonal and global means by a
226 corresponding negative response over tropical oceans.

227 $BC \times 10$ (fourth row) shows a markedly different response pattern to the other perturbations. There is
228 little slow response, except in the tropics where the zonal mean shows a small positive precipitation
229 change north of Equator and a smaller negative one south of Equator. The total is dominated by the fast
230 response, which is generally negative at most latitudes. The aerosol perturbations tend to shift the ITCZ
231 more (southwards for $SO_4 \times 5$, north for $BC \times 10$) than the solar and GHG changes, due to the more
232 hemispherically heterogeneous RF that they cause.

233 A common misconception about the change in precipitation caused by a given driver is that it is
234 composed of an initial, weak fast response due to rapid adjustments, which will over time be
235 overwhelmed by the slow, temperature driven response. Figure 3, however, indicates that in several
236 regions, the fast response may dominate even when the climate system approaches a new equilibrium,
237 in line with what has previously been observed for tropical precipitation under rising CO_2 concentrations
238 [Bony *et al.*, 2013]. In Figure 4, top row, we explore this by comparing the total, fast and slow
239 precipitation responses over land and ocean separately, and over six land regions: North America, South
240 America, Europe, Africa, South Asia and Australia (for region definitions, see Figure S2). There are clearly
241 large regional and inter-model differences, but some significant features still emerge. Over the ocean,
242 the climate drivers cause a fast response opposed by a slow response. Over some land regions, however,
243 the fast and slow responses have the same sign. This signature is particularly clear over South Asia.

244 To determine whether fast or slow precipitation responses dominate over years 51-100 of the PDRMIP
245 simulations, we define the response ratio $R_{resp} = (|\Delta P_{fast}| - |\Delta P_{slow}|) / (|\Delta P_{fast}| + |\Delta P_{slow}|)$. R_{resp} will be

246 positive when rapid adjustments dominate the long term precipitation response, and negative when the
247 slow response dominates. For the extreme cases of only fast or slow responses, R_{resp} will be +1 or -1
248 respectively. The lower panel of Figure 4 shows the multi-model mean R_{resp} for all PDRMIP drivers, for
249 land, ocean and the six regions defined above. For most regions and drivers, the models do not
250 consistently agree on the dominating response (not shown). The response over oceans is, however,
251 consistently dominated by the slow response for all drivers and models, except for *BCx10* where all
252 models but one predict that the fast precipitation response still dominates at near-equilibrium.
253 Considering land regions, South America and Africa are mainly dominated by the fast response for all
254 perturbations. Australia shows a similar pattern, albeit with a much larger intermodel spread. Southeast
255 Asia sees a dominance of the slow response, while North America and Europe have a more mixed
256 response to the different drivers. The latter mainly reflects a large inter-model spread in the results,
257 probably at least partly due to differences in aerosol treatment and lifetime (where emissions were used)
258 for the *BCx10* and *SO4x5* cases. For the *CO2x2* case, one factor likely contributing to the dominance of
259 fast responses over land is the physiological forcing from CO₂-induced stomatal response, which has
260 been shown to significantly affect both surface temperature response and water balance in previous
261 model studies [Cao *et al.*, 2010].

262 Discussion

263 Overall, the results presented in the previous section agree with earlier single model studies of the
264 precipitation impacts of individual forcings, and confirm our expectations based on simple energetics.
265 The internal mechanisms linking changes to the energy balance to altered precipitation rates however
266 differ between models, and we do see significant inter-model variability.

267 The hydrological sensitivity for a *BCx10* perturbation varies strongly between models. One model even
268 shows a positive (non-significant) apparent HS. This is likely due to the multiple ways in which BC can

269 affect climate – both directly, through absorption and scattering of incoming sunlight, indirectly through
270 modifications of cloud microphysical properties, and semidirectly, through heating ambient air and thus
271 altering stability and/or burning off clouds from within [Bond *et al.*, 2013; Samset and Myhre, 2015]. This
272 range of effects is much larger than e.g. for SO_4x_5 , where the additional particles mainly scatter
273 incoming sunlight and affect cloud microphysics. BC–climate interactions are treated very differently in
274 present global climate models, as are transport and removal processes, factors which cause strong
275 variations even for direct radiative forcing (see e.g. [Samset *et al.*, 2013]). E.g. it is interesting to note
276 that the responses for HadGEM2 and HadGEM3-GA4 are markedly different, even though they use the
277 same aerosol physics schemes. Also, some models have used prescribed concentrations based on
278 AeroCom Phase II, and some have used native emissions. As we have not attempted to normalize the
279 responses to the simulated aerosol burden, or to any differences in vertical profile, this is one likely
280 contributor to the observed diversity [Ban-Weiss *et al.*, 2011; Hodnebrog *et al.*, 2014; Samset and Myhre,
281 2015]. The precipitation response to BC perturbations in PDRMIP will be investigated in detail in a
282 follow-up publication. We note that the differences seen here will have been present for CMIP5,
283 meaning that BC is likely a strong contributor to the prediction diversity seen there.

284 As noted above, most PDRMIP models ran their *coupled* simulations with a fully coupled ocean. This
285 means that for strong perturbations like CO_2x_2 , they will likely not have reached their equilibrium
286 warming within the 100 years simulated here. Recently, Caldeira and Myhrvold [2013] found that in the
287 CMIP5 model ensemble, on average 80% of the equilibrium warming after a $4xCO_2$ perturbation had
288 been realized after the first 100 simulation years. One PDRMIP model (GISS-E2) ran an additional 250
289 years for our CO_2x_2 case, and found an additional 0.5K warming beyond the 1.5K realized over their first
290 100 years. Another (CanESM2) found an additional 0.6K beyond the 2.7K in the first 100 years when
291 running the model for 800 years. Both of these results are consistent with the Caldeira and Myhrvold
292 [2013] analysis, indicating that we could expect similar extra, long term warming for the other models in

293 the PDRMIP ensemble. For the present analysis, this non-equilibrium is not crucial for the main
294 conclusions, as models are then well within the regimes where changes to precipitation scale with the
295 slow increase in surface temperature. Hence, for fully equilibrated models both the temperature and
296 precipitation responses to the perturbations would have been stronger, but still follow the trends shown
297 in Figure 2. The ratio of fast to slow precipitation response would however likely change on such long
298 time-scales, changing the regional patterns found in Figures 3 and 4.

299 A further potential issue with the present analysis is the temperature response over land in the fSST
300 simulations. In principle, the fast response as diagnosed above could have a slow component, as the
301 land surface temperature may increase somewhat with time even if sea surface temperatures are kept
302 constant. We tested the impact of this by calculating the global mean temperature change over land in
303 the fSST case, assuming a resulting precipitation change of $(\Delta P_{\text{slow}} / \Delta T_{\text{land,coupled}}) \times \Delta T_{\text{land,fSST}}$, and
304 reinterpreting it as part of the slow response. While this procedure changes the results by up to 10% for
305 some models, the multi-model mean results presented above are not affected within the uncertainties
306 given.

307 Conclusions

308 We have presented the response to perturbations to five climate forcings (*CO2x2*, *CH4x3*, *Sol+2%*, *BCx10*
309 and *SO4x5*) across nine global climate models, as part of the PDRMIP project. As in previous single
310 model studies, we find that global mean precipitation responds on two timescales: One fast response,
311 acting on the timescale of months, that scales closely with the atmospheric energy net absorption due
312 to the forcing agent, and a slower response that scales with the long term change in global surface
313 temperature. All models show broadly similar responses to the perturbations, but beyond this there is
314 still significant inter-model variability, indicating differences in how the atmosphere reacts to altered
315 absorption and surface temperature. Black carbon stands out as the forcing agent with the largest inter-

316 model spread in hydrological sensitivity. The precipitation response over oceans is quite uniform
317 between models, and dominates the global mean values. Over land, where the precipitation response to
318 climate drivers is arguably much more relevant for human activities, we find large regions where the
319 rapid adjustments dominate over the slow response across the entire model ensemble, even 100 years
320 after the perturbation was applied. The main results in the present paper will be further explored in
321 upcoming PDRMIP publications, with emphasis on hydrological sensitivities, energy balances, circulation
322 changes and radiative forcing.

323

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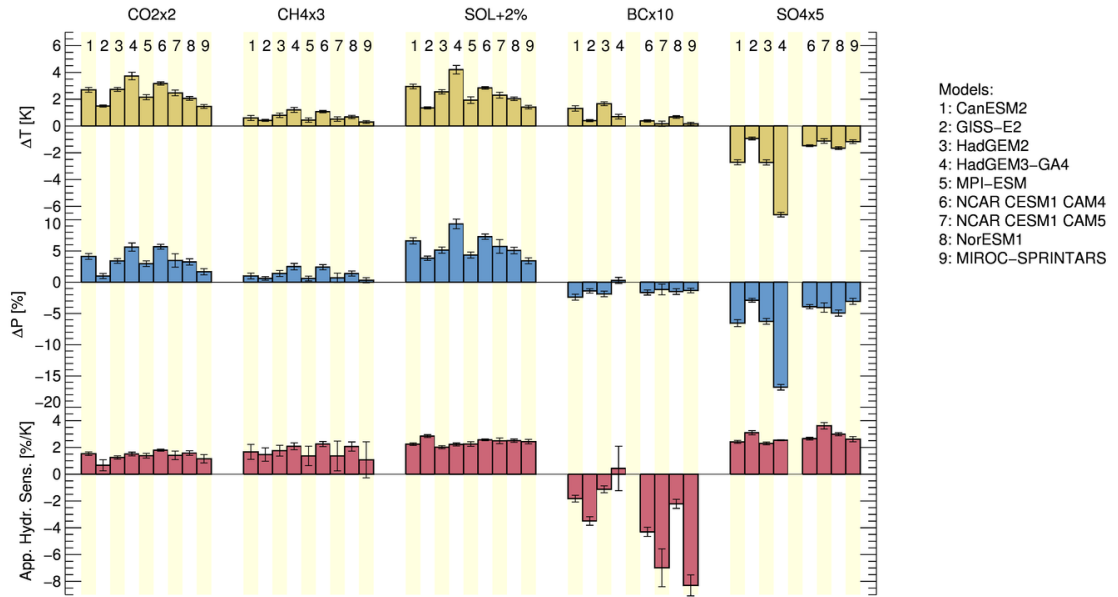
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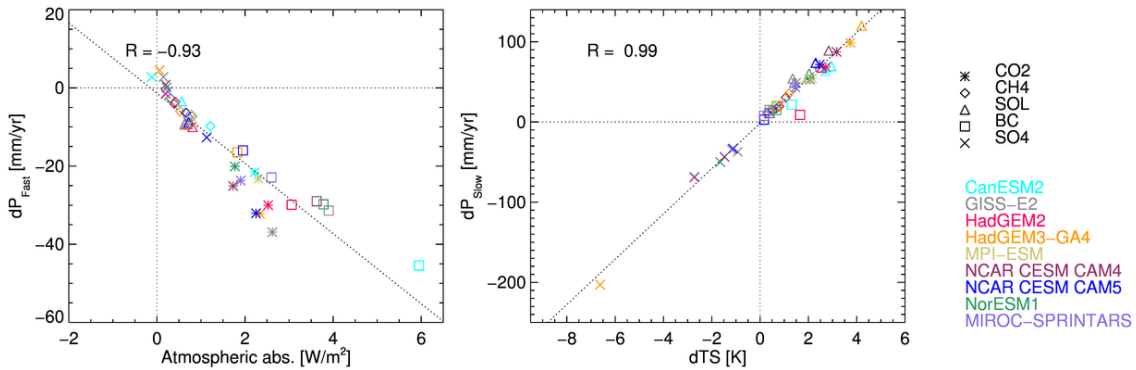
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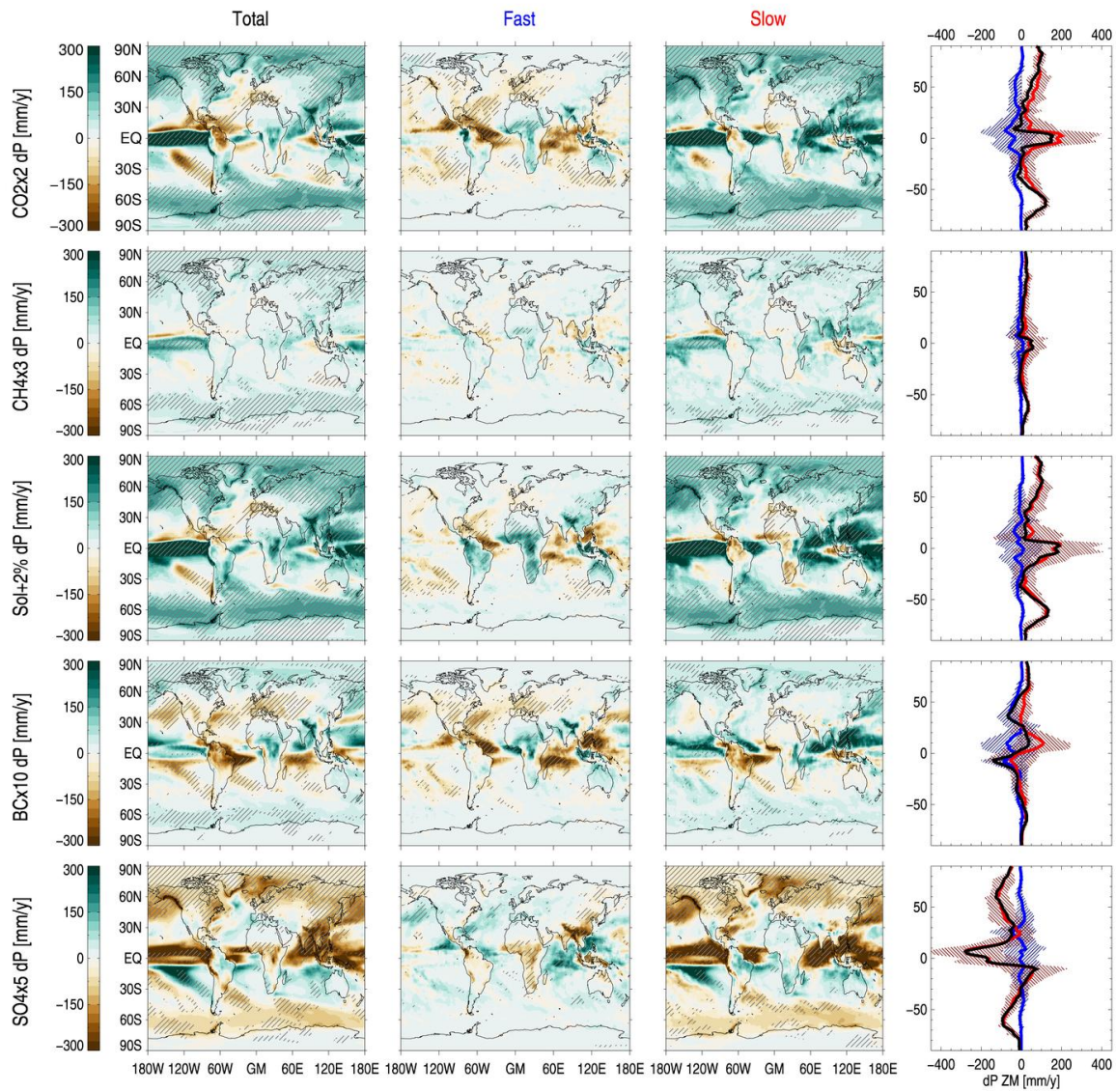
414 Figures



415
 416 *Figure 1: Global, annual mean temperature (top row) and precipitation (middle) change for years 51-100*
 417 *following a climate perturbation, and the resulting apparent hydrological sensitivity. The numbers*
 418 *indicate the participating models. Error bars indicate \pm one standard deviation of interannual variability.*



419
 420 *Figure 2: Regression of fast precipitation change vs. atmospheric absorption (left) and slow precipitation*
 421 *change vs. top-of-atmosphere radiative forcing (right). The shown regression lines and Pearson*
 422 *coefficients of correlation (R) are for the combined data from all models and climate perturbations.*

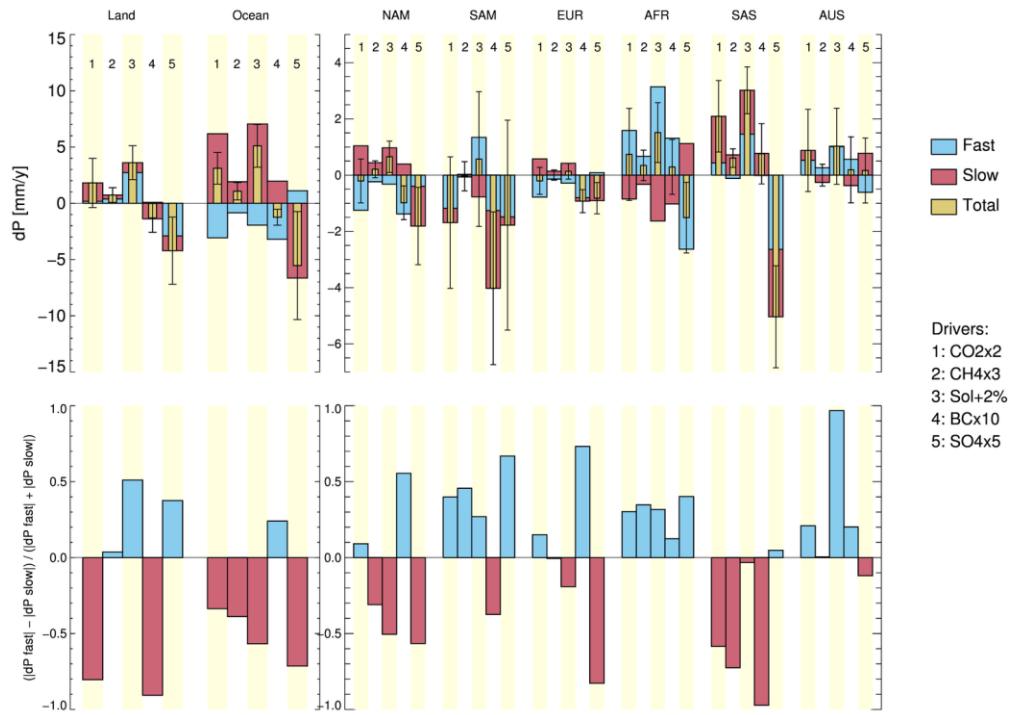


424

425 *Figure 3: Geographical patterns of multi-model mean precipitation change. Each row shows a different*
 426 *climate perturbation. Hatched regions indicate where the multi-model mean is more than one standard*
 427 *deviation away from zero. Left map column: Total change. Center map column: Fast change due to rapid*
 428 *adjustments. Right map column: Slow change due to surface temperature change. Rightmost column:*

429 Multi-model zonal means, showing fast (blue), slow (red) and total (black) precipitation changes. The
 430 shaded bands show $\pm 1\sigma$ of the 9-model ensemble.

431



432

433 *Figure 4: Top row: Regional precipitation response, divided into fast and slow components for 5 climate*
 434 *drivers. The left panel shows the land and ocean responses separately. The right panel shows the response*
 435 *for the land-only regions of North America (NAM), South America (SAM), Europe (EUR), Africa (AFR), the*
 436 *major aerosol emission regions of South Asia (SAS), and Australia (AUS). See Figure S2 for definitions.*
 437 *Bottom row: Response ratio (see text), calculated from the multi-model mean values in the top row.*

438