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- Slow and fast responses differ for changes in mean versus extreme precipitation
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Slow and fast responses of mean and extreme precipitation to different forcing in CMIP5 simulations

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Abstract We are investigating the fast and slow responses of changes in mean and extreme precipitation to different climate forcing mechanisms, such as greenhouse gas and solar forcing, to understand whether rapid adjustments are important for extreme precipitation. To disentangle the effect of rapid adjustment to a given forcing on the overall change in extreme precipitation, we use a linear regression method that has been previously applied to mean precipitation. Equilibrium experiments with preindustrial CO_2 concentrations and reduced solar constant were compared with a four times CO_2 concentration experiment for 10 state-of-the-art climate models. We find that the two forcing mechanisms, greenhouse gases and solar, impose clearly different rapid adjustment signals in the mean precipitation, while such difference is difficult to discern for extreme precipitation due to large internal variability. In contrast to mean precipitation, changes in extreme precipitation scale with surface temperature trends and do not seem to depend on the forcing mechanism.

1. Introduction

The response of mean and extreme precipitation to changes in global mean temperature is crucial for our understanding of the hydrological impacts of climate change. Previous studies have shown that the response of mean precipitation strongly depends on the forcing mechanism, such as changes in solar irradiance, greenhouse gases (GHG), or aerosols [*Andrews et al.*, 2010 *Fläschner et al.*, 2016]. For changes in mean precipitation, models agree on the overall direction of change, whereas large uncertainty exists in the simulations of the geographical pattern of changes in extreme precipitation [*Tebaldi et al.*, 2006; *Min et al.*, 2011; *Sillmann et al.*, 2013]. These uncertainties arise from parametric and structural model uncertainties and from internal variability, whereas models do agree on the forced signal [*Fischer et al.*, 2014]. *Pendergrass et al.* [2015] discussed that unlike for mean precipitation, extreme precipitation is nearly independent of the emission scenario as it depends on the total amount of warming at the surface in most models. This was recently debated by *Lin et al.* [2016], who find that the rate of change in precipitation extremes is significantly different in response to aerosol forcing than GHG forcing. Their findings, however, are based on ensemble simulations of only one model (Community Earth System Model version 1) and a set of more moderate extreme precipitation indices in addition to the extreme index used in *Pendergrass et al.* [2015] and in our study.

In this study, we concentrate on disentangling the effect of GHG versus solar forcing on mean versus extreme precipitation on a global scale. We use equilibrium simulations of the preindustrial climate and a climate with quadrupled CO_2 concentrations as well as a solar forcing scenario as prescribed in the Geoengineering Intercomparison Project (GeoMIP) [*Kravitz et al.*, 2011]. Some climate forcing mechanisms cause changes in atmospheric absorption of shortwave and/or longwave radiation, which may influence the lapse rate in the atmosphere, water vapor, and clouds. These rapid adjustments [*Boucher et al.*, 2013; *Sherwood et al.*, 2015] occur on a fast time scale. The current understanding of precipitation changes from different climate forcing mechanisms has been aided by separation into a fast response in precipitation, with time scales on the order of days to weeks, and a slower response on time scales of several years [*Andrews et al.*, 2010; *Ming et al.*, 2010; *Frieler et al.*, 2011; *Fläschner et al.*, 2016]. As described in *Bala et al.* [2010], "fast response or rapid adjustment refers to the adjustment of the stratosphere, troposphere, and the land surface before any change in global- and annual-mean surface temperature (ΔT) occurs. The response that depends on ΔT is called the slow response or feedback and is usually represented as change in the respective variable per unit ΔT." For mean precipitation, previous studies [e.g., *Andrews et al.*, 2010; *Kvalevåg et al.*, 2013;

He and Soden, 2016] have found a strong relationship between atmospheric absorption and the fast precipitation response, whereas the top-of-atmosphere (TOA) radiative forcing is strongly linked to the slow response of precipitation change. For change in the mean precipitation, the release of energy associated with condensation must be balanced by changes in the atmospheric radiative cooling and sensible heat to conserve energy balance [*Allen and Ingram*, 2002; *O'Gorman et al.*, 2012]. Therefore, atmospheric absorption will reduce the radiative cooling and thus the precipitation, whereas temperature increase of the surface-troposphere system leads to enhanced atmospheric radiative cooling and precipitation.

Changes in CO_2 and solar irradiance have been shown to have distinctly different influences on fast changes in mean precipitation due to their diverse impacts on atmospheric absorption [*Andrews et al.*, 2010; *Kvalevåg et al.*, 2013; *Samset et al.*, 2016]. The overall mean precipitation response depends, hence, on the forcing mechanism as well as the magnitude of TOA forcing. Here we will investigate whether rapid adjustments to CO_2 and solar forcing affects the extreme precipitation response.

2. Model Experiments and Methods

We use model simulations from the Coupled Model Intercomparison Project Phase 5 (CMIP5) [*Taylor et al.*, 2012] from 10 model centers (see Table S1 in the supporting information) that have also provided simulations for the GeoMIP experiment G1 [*Kravitz et al.*, 2011]. The latter is a highly idealized experiment in which the global mean radiative forcing from a quadrupling of the atmospheric CO_2 concentration $F_{4\times CO2}$ is balanced by a specified decrease of the solar irradiance δS_0, with the latter estimated for each model individually as $\delta S_0 \simeq -4F_{4\times CO2}/(1-\alpha)$, where α is the planetary albedo [*Schmidt et al.*, 2012]. This experiment is initiated from each model's preindustrial control run (hereafter piControl) prescribed with preindustrial GHG concentrations.

Both experiments, G1 and piControl, are compared to the equilibrium simulations of an abrupt increase of CO_2 concentration to 4 times the concentration of piControl (hereafter abrupt4xCO_2). We concentrate on two cases:

1. The first case is the difference between abrupt4xCO_2 and G1, which will be equivalent to an increase in the solar constant and representative for changes in the solar forcing only (hereafter SOL), and
2. The second case is the difference between abrupt4xCO_2 and piControl, which will be representative for a predominantly CO_2-driven forcing (hereafter CO2). Changes in CO_2 and solar irradiance act as very different climate forcing mechanisms and therefore result in different fast and slow responses of precipitation changes.

According to *Andrews et al.* [2010], we expect for mean precipitation that SOL will be dominated by the slow response, while the fast response should also be determinable in the CO2 case together with the slow response.

The length of the simulations for each experiment varies across the 10 models, which we utilize according to the specific analyses as described below, and we take that multiple ensemble members of each model and experiment were available. Details about available time periods and ensemble members used can be found in the Table S1.

To analyze extreme precipitation, we make use of indices for climate extremes as defined by the Expert Team for Climate Change Detection and Indices [*Zhang et al.*, 2011]. In particular, we calculated the annual maximum 1 day precipitation amount (rx1day) and annual maximum 5 day precipitation amount (rx5day) as indicators for extreme precipitation, which are reasonably robust indicators for the scales that can be addressed with the coarse spatial resolution of the global climate models used in this study. The performance of the CMIP5 models in simulating these indices is assessed in *Sillmann et al.* [2013].

For each model and experiment, we use linear regression (equation (1)) to analyze the change in globally averaged annual mean precipitation (ΔP) and extreme precipitation (Δrx1day) per degree change in globally averaged annual mean surface temperature (ΔTs).

$$\Delta P \ (\text{or } \Delta \text{rx1day}) = \eta \Delta Ts + A \qquad (1)$$

To disentangle the effect of slow and fast responses of precipitation to a given forcing, we consider the slope η of this linear regression to indicate the slow response and the intercept A to indicate the fast response (see

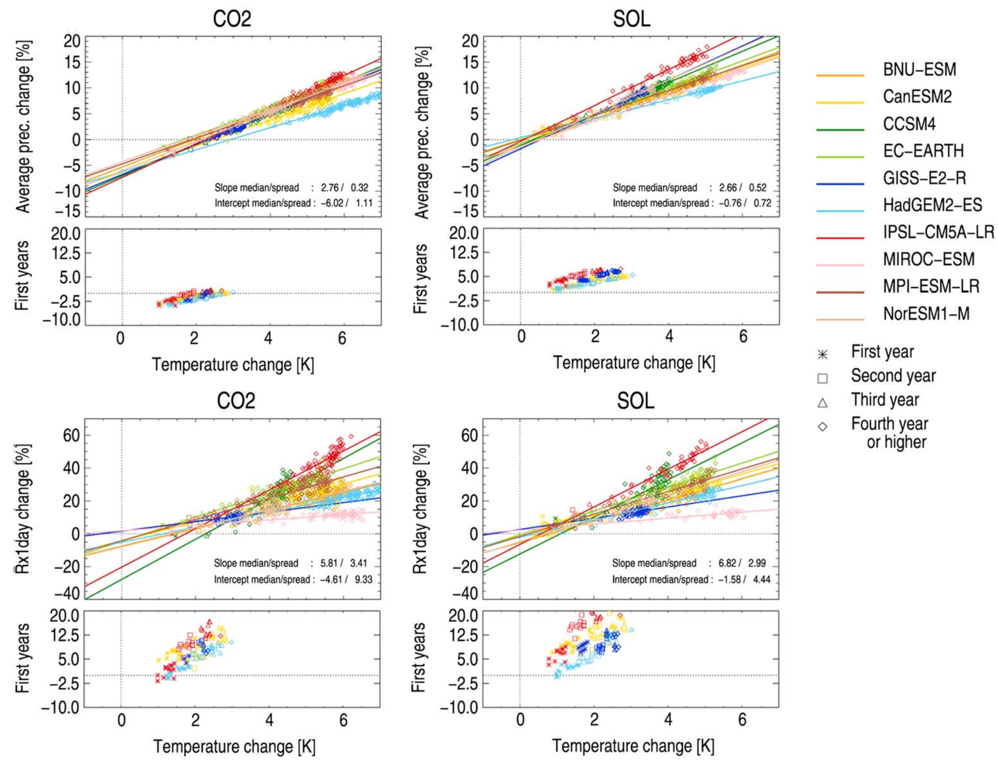

Figure 1. Changes in (top row) average and (bottom row) extreme precipitation (rx1day) per °K of global temperature change for two climate forcing mechanisms, CO2 (abrupt4xCO_2 − piControl) and SOL (abrupt4xCO_2 − G1), using the 20 first year of simulations from 10 CMIP5 models. The squares indicate individual model years, which were used to calculate the parameters of the linear regression (see equation (1)) and fit the corresponding regression lines for each model. Intermodel model median and spread (defined as one standard deviation) are given as text within each panel. Subpanels show changes for the first 4–5 years, for four models for which additional ensemble members were available (Canadian Earth System Model version 2, HadGEM2-ES, IPSL-CM5A-LR, and GISS-E2-R; see also Table S1).

also *Gregory et al.*, 2004). For this regression analysis, we utilize the first 20 years of each experiment in order to capture the rapid adjustment of precipitation to a change in the forcing. We follow the terminology from *Fläschner et al.* [2016] of η as the hydrological sensitivity and the apparent hydrological sensitivity as the ratio of ΔP to ΔTs. Since the estimates of the regression slope and intercept are particularly sensitive to the values in the first years (about 1–3) after quadrupling CO2, we further used the first 5 years of the abrupt4xCO_2 experiment, which were available for up to 12 ensemble members of three different models (see Table S1).

3. Results

We first show results from the linear regression analysis for each individual model to illustrate the effect of CO_2 and solar forcing on mean and extreme precipitation. In general, the total change in precipitation per degree of global warming, also referred to as global apparent hydrological sensitivity, differs between climate drivers such as CO_2 and solar insolation [*Andrews et al.*, 2010]. *Fläschner et al.* [2016] found a hydrological sensitivity of 2.6% K^{-1} in mean precipitation for the CO2 case for 30 CMIP5 models. We obtain a similar rate of change for mean precipitation of 2.8% K^{-1} using 10 CMIP5 models as indicated by the median slope in the CO2 case with a spread of 0.3% K^{-1} among models in Figure 1. The spreads indicated in the figure legend are given as one standard deviation based on the 10 model values. For the SOL case, we see a slightly lower rate of change (i.e., median slope of 2.7% K^{-1}) in mean precipitation with a larger spread among models (i.e., 0.5% K^{-1}). In general, the small differences between the median slope in CO2 and SOL indicate that the slow response to the different forcing mechanisms is similar for mean precipitation changes in accordance with previous findings [*Andrews et al.*, 2010; *Samset et al.*, 2016].

A larger difference can be seen for the median intercept, an indicator for the fast response in mean precipitation changes. For the CO2 and SOL cases, the intercepts are −6.0% and −0.8% with intermodel standard deviations of 1.1% and 0.7%, respectively. This is consistent with our expectation that the fast response to mean precipitation is negligible under solar forcing but plays a notable role for the CO_2 forcing. For changes in mean precipitation, the models seem to agree well on the response to the different climate forcings as indicated by the small spread among them.

Next we investigate if this holds also for changes in extreme precipitation as expressed by rx1day. The median slope of the rate of change in rx1day is 5.8% K^{-1} for CO2 and 6.8% K^{-1} for SOL with a considerable spread among the models (3.4% K^{-1} and 3.0% K^{-1} for CO2 and SOL, respectively). *Kharin et al.* [2013] estimated a similar rate of change (i.e., 5.9% K^{-1}) in 20 year return values of rx1day by using Representative Concentration Pathways (RCP) emission scenarios [*Moss et al.*, 2010] compared to the historical simulations by using up to 32 CMIP5 models. This is also supported by observations as described in *Westra et al.* [2013]. We further looked at rx5day (Figure S1 in the supporting information), which is an indicator for extended periods of extreme rainfall. Because rx5day represents an accumulation of rainfall over several days, it is not as extreme as rx1day that can pick up very heavy daily rainfall events. The slope and respective model spread in rx5day is smaller than for rx1day, and as for the mean precipitation, the intercept of rx5day for the SOL case is close to zero. Similar to the findings in *Lin et al.* [2016], we see that changes in rx5day lie in between of those seen for rx1day and annual mean precipitation, both in terms of magnitude of change and importance of rapid adjustment. Nevertheless, the spread is comparable to that of rx1day, reflecting that rx5day is, after all, a measure of extreme rainfall, with larger interannual variability than mean precipitation.

In order to provide a robust assessment considering the large role of internal variability for the fast and slow response estimates for extreme precipitation, we extended our analysis to different members of the abrupt4xCO_2 experiment. In the subpanels of Figure 1 for both SOL and CO2 cases, we can see that the change in extreme precipitation (rx1day) per °K is very close to zero or positive (i.e., above zero) in the first 5 years for the majority of ensemble members of different models. This means that extreme precipitation exhibits no fast response for either forcing mechanism. The Institut Pierre-Simon Laplace-Climate Model version 5A-low resolution (IPSL-CM5A-LR) model constitutes an obvious outlier in these plots, showing negative changes in the very first year for some ensemble members in the CO2 case.

Kharin et al. [2013] also point out a large intermodel uncertainty in the relative changes of extreme precipitation per unit of warming and note that the changes are not homogenously distributed across the globe, with lower rates of changes in extreme precipitation relative to the local temperature change over land. Therefore, we show spatial patterns of multimodel changes in mean and extreme precipitation per degree global warming in Figure 2. Since in this analysis we are interested in the changes between experiments at equilibrium, we are concentrating on the last 40 years of each experiment given that the G1 simulations are only available for approximately 50 years for some of the models (see Table S1).

The spatial patterns are very similar for the two forcing mechanisms, CO_2 and SOL. In particular, the CO_2 case compares well with results discussed in *Fischer et al.* [2014] for changes in rx1day in the RCP8.5 scenario using 5 CMIP5 models, as well as in *Pendergrass et al.* [2015] for changes in mean and extreme precipitation in RCP8.5 for 16 CMIP5 models. It is important to note that *Fischer et al.* [2014] and *Pendergrass et al.* [2015] look at total responses to a mixture of climate forcings, while in our analysis we are separating by climate forcing to look into rapid adjustment and slow responses of precipitation to temperature changes.

In general, changes in mean and extreme precipitation per degree global warming are greatest along the equator, particularly over the ocean and over higher latitudes. Mean and extreme precipitation are decreasing in regions between 10 to 40° southern and northern latitudes, mostly over the ocean, but also, for instance, around the Mediterranean Sea, Central America, and the Caribbean islands. The reduction in mean precipitation is larger in spatial extent than for extreme precipitation. *Sillmann et al.* [2013] further discuss seasonal aspects of changes in extreme precipitation over land for the RCP scenarios.

Especially when looking at changes in extreme precipitation at the regional scale (Figure 2), the patterns appear more “patchy” compared to changes in mean precipitation as discussed also in *Fischer et al.* [2014, and references therein]. This is a result of higher spatial heterogeneity in the physical processes leading to intensified heavy precipitation or a result of strong internal variability.

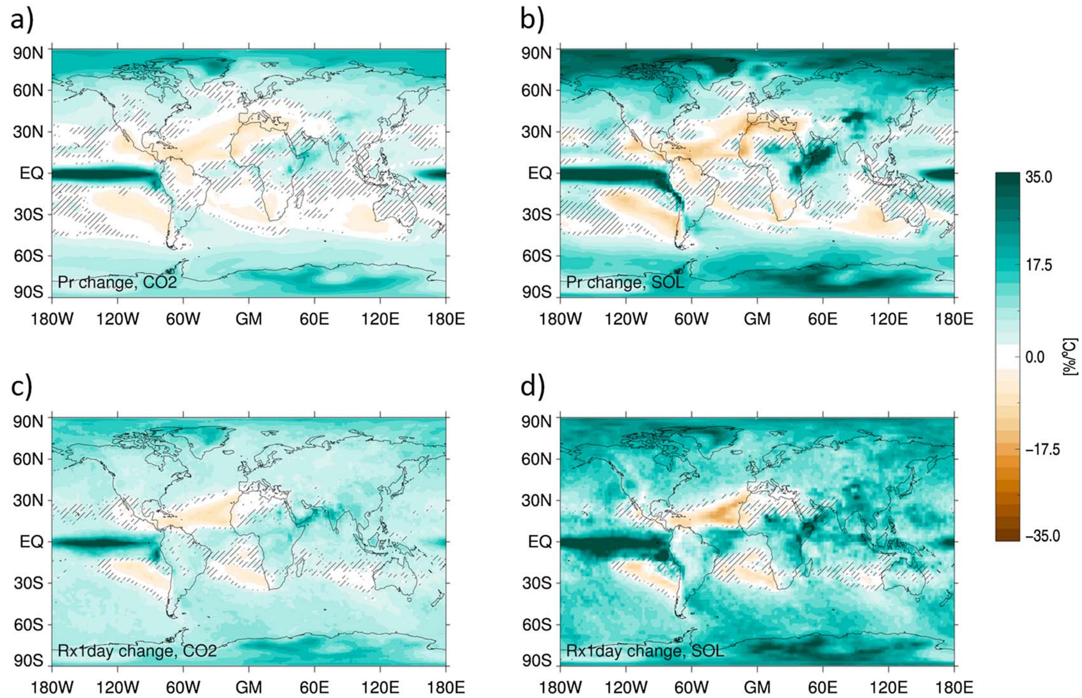

Figure 2. Multimodel mean change for 10 CMIP5 models in (a and b) average and (c and d) extreme precipitation regressed against the average global mean surface temperature change for two climate forcing mechanisms, CO2 and SOL. The hatching indicates areas where less than seven models agree on the sign of change to be significant.

We assess the effect of internal variability on the estimation of slope and intercept from the regression analysis (cf. equation (1)) by utilizing the long piControl simulations in the estimates of intercepts and slopes for the CO2 case (abrupt4xCO_2 $-$ piControl). We subtracted a moving 20 year period in 5 year intervals of piControl from a fixed 20 year period of abrupt4xCO_2 (i.e., the first 20 years of the time series), which resulted in 13–50 estimates of intercept and slope for each model and variable, depending on the exact number of years available from each model. These numbers are the basis for the box and whisker plots in Figure 3. For the SOL case, calculated as abrupt4xCO_2 $-$ G1, the short simulation periods of the G1 experiment did not allow for such statistics, but we have included the estimate based on the 20 first years of abrupt4xCO_2 minus the first 20 years of G1 as crosses in Figure 3, for comparison to the CO2 case.

The slope estimated from each model is very close to the multimodel average slope of 2.8% K^{-1} for CO2 and 2.7% K^{-1} for SOL for changes in mean precipitation per degree warming (i.e., apparent hydrological sensitivity as shown in Figure 1), with very small internal variability indicated by the narrow boxes and whiskers in Figure 3a (orange colors). This is consistent with previous findings, demonstrating that the slow response in mean precipitation is relatively well constrained [e.g., *Andrews et al.*, 2010; *Fläschner et al.*, 2016]. Note that there is no clear difference between the CO2 estimates and the SOL estimates the slope, as also seen in Figure 1.

For extreme precipitation (Figure 3a, blue colors), the models tend to deviate from each other in their slopes, with some models showing very small slopes (e.g., Goddard Institute for Space Studies E2 (GISS-E2-R) and Hadley Centre Global Environmental Model version 2 Earth System (HadGEM2-ES)) and some models showing large slopes (e.g., Community Climate System Model version 4 (CCSM4) and IPSL-CM5A-LR). These models also reveal relatively large internal variability in their slope estimates for CO2. Again, there is no clear difference between the median slope values for the CO2 and SOL cases, although the average difference between the CO2 and SOL median slopes is larger for extreme than for mean precipitation. The difference between medians of slope estimates is not statistically significant on the 99% level using a paired two-sample Student's *t* test. While the global mean changes in rx1day for CO2 and SOL are similar, Figure 2 further illustrates that the magnitude of the spatial changes in rx1day is somewhat larger for SOL compared to CO2.

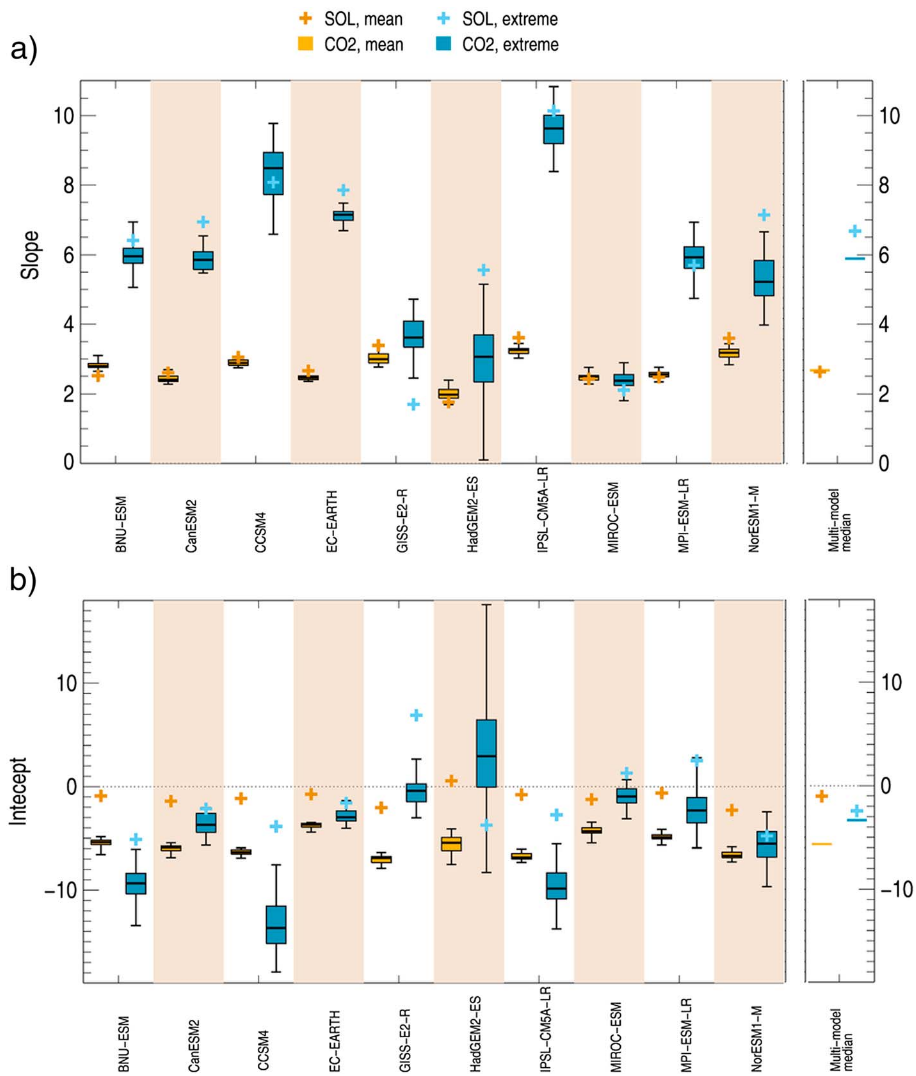

Figure 3. The parameters of the linear regression (equation (1)) for the two cases CO2 and SOL, for each model, where (a) the slope is an indicator for the slow response of changes in precipitation and (b) the intercept is an indicator for the fast or rapid adjustment of precipitation changes to the forcing (see also text). The box and whiskers show the internal variability in the estimates of the respective parameter as derived from the piControl simulations (as described in the text). Estimates for mean precipitation are indicated in orange and for extreme precipitation in blue. The boxes give the interquartile range, the whiskers indicate maximum and minimum values, and the solid lines indicate the medians for the CO2 case.

A different picture emerges for the fast response or rapid adjustment, indicated by the intercept estimates of Figure 3b. Here we find large differences between CO2 and SOL for changes in mean precipitation, as also seen in Figure 1, and the difference in the medians of intercepts are statistically significant on the 99% level. The intercept estimates in SOL are close to zero for all models, indicating no fast precipitation responses to solar forcing, but a rather robust intercept across models (around the multimodel mean of −6.0% as in Figure 1) pointing to relevant fast responses of mean precipitation changes to CO_2 forcing.

For changes in extreme precipitation, the intercept estimates vary substantially across models for SOL and CO2, and differences in the intercepts between the two forcing mechanisms vary for individual models (Figures 3b and 1, subpanels, for the first 5 years of simulations). In addition, we find that to a much larger extent than for mean precipitation and for rx1day in SOL, the quantification of the rapid adjustment for rx1day in CO2 is very sensitive to the number of years used for the regression (i.e., 5, 10, or 20 years). For the assessment of the rapid adjustments, the first 5 years of the simulations are most relevant. While for mean precipitation change, all models except HadGEM2 show values below zero in the first years; for extreme precipitation changes this is just the case for a couple of models (CCSM4 and IPSL-CM5A) and with the negative values being close to zero (see Figure 1, subpanels).

The internal variability in the estimates of the intercepts for CO2 is large, with HadGEM2-ES showing the largest (Figure 3b). For most models, except HadGEM2-ES, the intercept for the CO2 case is more negative than for SOL. Some models, such as Beijing Normal University Earth System Model (BNU-ESM), CCSM4, GISS-E2-R, IPSL-CM5A-LR, and Model for Interdisciplinary Research on Climate-ESM (MIROC-ESM), show an intercept for SOL that is not overlapping with the box and whiskers of the CO2 case. However, the intercepts derived from the multimodel median show no clear differences between the SOL and CO2 and are close to zero. Adding more ensemble members for the G1 experiment (available for only two models; see Table S1) moves the median value of the intercept even closer to zero as illustrated in Figure S3. This confirms our results that although model uncertainty and internal variability is large, on average, there is no discernible effect of rapid adjustment on the changes in extreme precipitation for both forcing mechanisms (SOL and CO2). This further underlines the need for generating several ensemble members for each model experiment to be able to assess uncertainties related to model differences and internal variability.

4. Conclusion

We were interested in investigating the fast and slow responses of changes in mean and extreme precipitation to different climate forcing mechanisms, such as CO_2 and solar forcing, to understand whether rapid adjustments are important for extreme precipitation. We compared the equilibrium experiments with preindustrial CO_2 concentrations (piControl) and a reduced solar constant (G1) with a four times CO_2 concentration experiment (abrupt4xCO_2) for 10 CMIP5 models. We analyzed the changes in annual mean precipitation and annual maximum 1 day and 5 day precipitation per degree change in global average temperature.

We were able to show that the rapid adjustment is more important or detectable for changes in mean precipitation than in extreme precipitation with the regression method used in this study. This is consistent with larger changes found for extreme precipitation per temperature change than for mean precipitation, because extreme precipitation depends largely on surface temperature changes [e.g., *Pendergrass et al.*, 2015]. We also point out that for detecting the latter, the choice of extreme metrics is important as for more moderate extreme precipitation a more pronounced dependence on the emission scenario and forcing can be found [see *Lin et al.*, 2016].

Our results imply that changes in extreme precipitation will be seen faster than for mean precipitation, because changes in the latter due to global warming can be masked on short time scales by rapid adjustment mechanisms. *Shine et al.* [2015] also find a global mean precipitation reduction limited to the first few years after applying pulse CO_2 emissions in their approach using metrics of global precipitation changes from climate models. Such a signal from the rapid adjustment on the global mean precipitation should not be expected for extreme precipitation, because the latter follows closely the change in surface temperatures [*Pendergrass et al.*, 2015].

In agreement with previous studies, we found a much larger intermodel and internal variability in the estimation of extreme precipitation compared to mean precipitation [e.g., *Kharin et al.*, 2013; *Pendergrass et al.*, 2015]. This large variability also imposes challenges to the applied regression method. Looking at fixed sea surface temperature (SST) experiments compared to coupled ocean experiments with different forcings as done, for instance in *Andrews et al.*, 2010, could provide a better basis for improving the method with regard to extreme precipitation as well as relaxing the linearity assumption for the regression analysis. This also requires that the SST simulations are available for longer time periods (e.g., 30–50 years) for obtaining robust results in the extreme value analysis.

In future studies, we will extend our analysis of fast and slow responses of changes in precipitation to other forcing mechanisms, such as aerosols. This will be possible through the Precipitation Driver and Response Model Intercomparison Project in which model uncertainties with regard to different climate forcings, model setup, and parameterization can be studied in more detail [*Samset et al.*, 2016; *Myhre et al.*, 2017].

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