The physical drivers of historical and 21st century global precipitation changes

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Abstract
Historical and 21st century global precipitation changes are investigated using data from the fifth Coupled Model Intercomparison Project (CMIP5) Atmosphere-Ocean-General-Circulation-Models (AOGCMs) and a simple energy-balance model. In the simple model, precipitation change in response to a given top-of-atmosphere radiative forcing is calculated as the sum of a response to the surface warming and a direct ‘adjustment’ response to the atmospheric radiative forcing. This simple model allows the adjustment in global mean precipitation to atmospheric radiative forcing from different forcing agents to be examined separately and emulates the AOGCMs well. During the historical period the AOGCMs simulate little global precipitation change despite an increase in global temperature—at the end of the historical period, global multi-model mean precipitation has increased by about 0.03 mm day\(^{-1}\), while the global multi-model mean surface temperature has warmed by about 1 K, both relative to the pre-industrial control means. This is because there is a large direct effect from CO\(_2\) and black carbon atmospheric forcing that opposes the increase in precipitation from surface warming. In the 21st century scenarios, the opposing effect from black carbon declines and the increase in global precipitation due to surface warming dominates. The cause of the spread between models in the global precipitation projections (which can be up to 0.25 mm day\(^{-1}\)) is examined and found to come mainly from uncertainty in the climate sensitivity. The spatial distribution of precipitation change is found to be dominated by the response to surface warming. It is concluded that AOGCM global precipitation projections are in line with expectations based on our understanding of how the energy and water cycles are physically linked.

Keywords: precipitation, radiative forcing, AOGCM

1. Introduction

The tropospheric energy budget provides a useful link between the global energy and water cycles since atmospheric radiative cooling is balanced by latent and sensible heat flux into the atmosphere. It provides a fundamental constraint on changes in global mean precipitation \(\Delta P\) (e.g. Mitchell et al 1987, Allen and Ingram 2002, Stephens and Ellis 2008, O’Gorman et al 2012) allowing us to write \(\Delta P\) (mm day\(^{-1}\)) in terms of perturbations to the tropospheric energy budget:

\[
L \Delta P = k \Delta T - F_{\text{ATM}}
\]

where \(k\) (Wm\(^{-2}\)K\(^{-1}\)) is the sensitivity of the sum of tropospheric radiative and sensible cooling to global mean surface air temperature change \(\Delta T\) (K), and \(F_{\text{ATM}}\) (Wm\(^{-2}\)) is any external tropospheric radiative forcing (such as decreased net tropospheric cooling due to increased CO\(_2\)). Note that we assume \(\Delta T\)-independent changes in tropospheric radiative cooling and sensible heat flux are small. \(L\) converts a heat flux in Wm\(^{-2}\) into precipitation in mm day\(^{-1}\), and is approximately equal to 29 Wm\(^{-2}\) mm day\(^{-1}\) (Muller and O’Gorman 2011); dividing equation (1) by \(L\) gives all terms in mm day\(^{-1}\). \(k/L\) (mm day\(^{-1}\)K\(^{-1}\)) is the ‘hydrological sensitivity’ (i.e. a scaling factor for the contribution to \(\Delta P\) that arises from \(\Delta T\)).
sensitivity of $\Delta P$ to $\Delta T$ is widely established in models as $\sim 1.4-3.4\% \text{K}^{-1}$ (e.g. Lambert and Webb 2008).

In this simple model there are two drivers of $\Delta P$: (i) the response of tropospheric radiative and sensible cooling to changes in $\Delta T$, and (ii) direct perturbations to the tropospheric radiative forcing. Black carbon aerosol provides a clear example of these two effects. Firstly, increasing black carbon causes a positive radiative forcing on the climate system as a whole, which induces a positive $\Delta T$ response that increases precipitation. Secondly, there is a radiative forcing that is largely felt in the troposphere (since increased black carbon will absorb more shortwave radiation in the troposphere), generating a positive $F_{\text{ATM}}$ term that reduces precipitation. These two opposing effects are well established in climate models (e.g. Ming et al 2010, Andrews et al 2010) for black carbon and other forcing agents such as CO$_2$. In contrast, an increase in the solar constant, while giving a positive radiative forcing on the climate system (and so a positive $\Delta T$ and $\Delta P$), does not induce a large opposing $F_{\text{ATM}}$ response since the atmosphere is largely transparent to shortwave radiation changes (Lambert and Faull 2007, Andrews et al 2009, Bala et al 2010).

While many studies have looked at these two opposing effects on precipitation in idealised climate model studies only a few have looked at the direct role of different forcing agents in historical and 21st century scenarios (e.g. Andrews 2009, Lambert and Allen 2009, Frieler et al 2011, Allan et al 2014, Andrews 2014). For example, both Allan et al (2014) and Andrews (2014) suggest that precipitation adjustments to radiative forcing may play a considerable role in opposing recent decadal precipitation trends in response to global temperature increases. Further research is needed on separating these two effects, particularly since precipitation adjustments first need to be removed before trying to estimate the sensitivity of the global hydrological cycle to surface warming using observations (e.g. Arkin et al 2010).

In this study we further explore the role of $F_{\text{ATM}}$ in historical simulations and 21st century projections of $\Delta P$. We combine the hydrological sensitivities of the individual models and estimated independent timeseries of $F_{\text{ATM}}$ with state-of-the-art Coupled Model Intercomparison Project phase 5 (CMIP5) (Taylor et al 2012) climate model simulations to reconstruct projections of $\Delta P$ based on equation (1). Our aims are (i) to determine the significance of precipitation adjustments in realistic transient scenarios, (ii) to evaluate the utility of the simple model of precipitation in emulating the behaviour of complex Atmosphere-Ocean-General-Circulation-Models (AOGCMs) and thus provide a check on our physical understanding of how the energy and water cycles are linked, and (iii) to provide physical insight on the main drivers of $\Delta P$ in realistic scenarios.

Section 2 describes the coupled atmosphere-ocean historical and 21st century projections of $\Delta P$ in the CMIP5 models and explores the uncertainty in these projections. Section 3 reconstructs the $\Delta P$ projections using $\Delta T$ and hydrological sensitivity values obtained from the coupled models alongside an independent estimate of $F_{\text{ATM}}$. Section 4 briefly looks at the main regional drivers of precipitation. Section 5 presents a discussion and summary.

2. Projections of global precipitation in CMIP5 models

2.1. Historical and 21st century projections

Figures 1(a) and (b) show the global-annual-mean $\Delta T$ and $\Delta P$ time series for the CMIP5 historical simulation—covering the period 1850–2005—and the four Representative Concentration Pathway (RCP) scenarios out to 2100: RCP8.5, RCP6, RCP4.5 and RCP2.6 (Meinshausen et al 2011). Anomalies are relative to the mean of each model’s pre-industrial control (at least 250 model years). Table 1 lists $\Delta P$ for each model at the end of the historical simulation (mean over 1986–2005) and at the end of the RCP projections (mean over 2079–2098).

We want to separate $\Delta P$ into a response to surface warming and an adjustment response to the atmospheric radiative forcing, as per equation (1). In order to calculate the precipitation response to surface warming (given by the first term on the right-hand side of equation (1)), we need to know the hydrological sensitivity, $k_L$. We determine the hydrological sensitivity for each CMIP5 model (see table 1) via standard linear regression techniques, as done by for example Lambert and Webb (2008) and Andrews et al (2009). We use data from the CMIP5 ‘abrupt4xCO2’ experiment where the CO$_2$ concentration is instantaneously quadrupled at the start of the simulation and then held constant. The hydrological sensitivity is then determined from the slope of the ordinary least square regression of $\Delta P$ against $\Delta T$. The magnitude of this term is mostly determined by a warmer atmosphere increasing atmospheric radiative cooling with $\Delta T$, with large but offsetting effects from water-vapour and lapse-rate feedbacks (e.g. Previdi 2010). While cloud feedbacks and sensible heat flux changes are smaller in magnitude, they are important contributors to the model spread (Previdi 2010, O’Gorman et al 2012).

Here we assume that the hydrological sensitivity in the ‘abrupt4xCO2’ experiment is the same as that in the historical and RCP simulations. However, we note that Good et al (2012) found that the hydrological sensitivity may somewhat depend on the amount of CO$_2$—the higher the CO$_2$ concentration, the smaller the hydrological sensitivity. However, we cannot calculate the hydrological sensitivity in the historical and RCP simulations directly, because precipitation in these simulations includes the adjustment to the atmospheric radiative forcing.

Figure 1(c) shows the component of $\Delta P$ we expect from each model’s hydrological sensitivity and $\Delta T$. Global annual mean $\Delta T$ at the end of the 21st century is 1.7 K, 2.5 K, 3 K and 4.5 K in RCP2.6, RCP4.5, RCP6 and RCP8.5 respectively (figure 1(a)), corresponding to multi-model mean increases in $\Delta P$ of 0.13 mm day$^{-1}$, 0.19 mm day$^{-1}$, 0.23 mm day$^{-1}$ and 0.34 mm day$^{-1}$ in RCP2.6, RCP4.5, RCP6 and RCP8.5 respectively. The residual, $\Delta P - k_\text{L} \Delta T$
(equivalent to figure 1(b) minus figure 1(c)), is given in figure 1(d). The fact that it is non-zero in CMIP5 model results implies either a breakdown of our simple model of \( \Delta P \) or a considerable role for radiative forcing in directly opposing \( \Delta P \) increases in both historical simulations and 21st century projections.

In the rest of this study, we independently estimate \( F_{\text{ATM}} \) and hence evaluate whether AOGCM projections of \( \Delta P \) are in line with our physical understanding of how the energy and water cycles are linked. But first we briefly consider the dominant sources of uncertainty in projections of global precipitation across the models.

2.2. Sources of uncertainty

The largest spread between models in \( \Delta T \) at the end of the 21st century occurs in RCPs with the greatest radiative forcing. For RCP8.5 the range between the minimum and maximum 2079–98 means is about 3.0 K, while for RCP2.6 the range is about 1.6 K (figure 1(a)). This spread can be understood as resulting largely from differences in modelled radiative forcings and climate sensitivities (Forster et al. 2013). But there is also considerable spread amongst models in the projections of \( \Delta P \) (table 1 and figure 1(b)), which has received less attention. As with \( \Delta T \), the spread between models is greatest for RCP8.5—the range at the end of the 21st century is about 0.24 mm day\(^{-1}\) for RCP8.5 and 0.13 mm day\(^{-1}\) for RCP2.6. This spread could come from three sources: uncertainty in (i) projections of \( \Delta T \), (ii) the hydrological sensitivity, or (iii) the adjustment to radiative forcing.

The spread between models for \( \Delta T \)-dependent precipitation, \( k\Delta T/L \), (figure 1(c)) is about twice as large as the spread between models for the residual, \( \Delta P - k\Delta T/L \), (figure 1(d)), indicating that most of the uncertainty across models in \( \Delta P \) comes from \( k\Delta T/L \) rather than the residual. Thus the dominant source of spread is from the uncertainty in \( \Delta T \) (climate sensitivity) or differences amongst models in their hydrological sensitivities \( k/L \).

In scatter plots of \( \Delta P \) at the end of the 21st century against \( \Delta T \) (figure 2(a)) and the hydrological sensitivity (figure 2(b)), the strongest correlation is found between \( \Delta P \) and \( \Delta T \) at the end of the 21st century (figure 2(a))—the correlation coefficients range from 0.805 in RCP8.5 to 0.924 in RCP6. The number of models used in calculating the correlation coefficients varies between RCP scenarios—see the legends in figure 1. The gradient of the line of best fit is shallower in the RCPs with greater radiative forcing. This means that precipitation does not increase as much per degree of warming, probably due to the greater tropospheric radiative forcings that suppress \( \Delta P \). In contrast, the correlation is weaker between \( \Delta P \) at the end of the 21st century and the adjustment \( \Delta P \) in the quadrupled CO2 experiment (not shown) —the correlation coefficients being in the range 0.276–0.442. The correlation is weaker still between \( \Delta P \) at the end of the 21st century and the hydrological sensitivity (figure 2(b)).
Hence we conclude that the largest source of spread between the CMIP5 models in 21st century projections of $\Delta P$ comes from differences in simulations of $\Delta T$—the proportion of variance explained in $\Delta P$ by $\Delta T$ is 0.801, 0.724, 0.854, 0.648 for RCP2.6, RCP4.5, RCP6 and RCP8.5 respectively. This can be further traced back in CMIP5 models to uncertainties in climate sensitivity (Forster et al 2013) and cloud feedback (Andrews et al 2012). We confirm this by demonstrating a reasonably strong correlation across models between 2100 $\Delta P$ projections (table 1) and the transient climate response (TCR) parameters given in Forster et al (2013) (figure 2(c)). The TCR is defined to be the global mean surface air temperature change in a 1%/yr CO2 increase experiment at the point where CO2 has doubled (Cubasch et al 2001). The correlation coefficients are 0.585, 0.602, 0.756, 0.564 for RCP2.6, RCP4.5, RCP6 and RCP8.5 respectively. We note an anti-correlation between the hydrological sensitivities and TCRs (figure 2(d)) which implies that models that warm the most have smaller $\Delta P/\Delta T$, though the correlation coefficient is only −0.42.

3. Radiative forcing as a direct driver of global precipitation

To estimate the precipitation adjustment to atmospheric radiative forcing, $\Delta P_{\text{adj}} = -F_{\text{ATM}}/L$, we use a top-of-atmosphere radiative forcing ($F_{\text{TOA}}$) timeseries and ratios of $F_{\text{ATM}}$ to $F_{\text{TOA}}$ that allow us to partition this forcing between the troposphere and the surface. This allows us to calculate the

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### Table 1. Hydrological sensitivities and mean precipitation anomalies at the end of the historical (mean over the period 1986–2005) and 21st century (mean over the period 2079–2098) scenarios. Mean precipitation anomalies are relative to the mean precipitation in the pre-industrial control run. The hydrological sensitivities refer to the temperature-dependent precipitation response only (using data from the abrupt 4xCO2 experiment), whereas the mean precipitation anomalies are the total precipitation response. The 90% uncertainty level is calculated as 1.64 standard deviations.

| Model               | Hydrological sensitivity (mm day$^{-1}$ K$^{-1}$) | Historical mean $\Delta P$ (mm day$^{-1}$) | RCP8.5 mean $\Delta P$ (mm day$^{-1}$) | RCP6 mean $\Delta P$ (mm day$^{-1}$) | RCP4.5 mean $\Delta P$ (mm day$^{-1}$) | RCP2.6 mean $\Delta P$ (mm day$^{-1}$) |
|---------------------|-----------------------------------------------|------------------------------------------|----------------------------------------|----------------------------------------|----------------------------------------|----------------------------------------|
| ACCESS1.0           | 0.0633                                        | −0.027                                   | 0.113                                  | —                                      | 0.084                                  | —                                      |
| BCC-CSM1.1          | 0.0758                                        | 0.041                                    | 0.203                                  | 0.139                                  | 0.132                                  | 0.098                                  |
| BCC                 | 0.0836                                        | 0.070                                    | 0.251                                  | 0.181                                  | 0.167                                  | 0.133                                  |
| CSIM1.1(m)          |                                              |                                          |                                        |                                        |                                        |                                        |
| CanESM2             | 0.0689                                        | 0.009                                    | 0.187                                  | —                                      | 0.128                                  | 0.104                                  |
| CCSM4               | 0.0824                                        | 0.039                                    | 0.218                                  | 0.142                                  | 0.132                                  | 0.101                                  |
| CNRM-CM5            | 0.0772                                        | −0.008                                   | 0.168                                  | —                                      | 0.112                                  | 0.071                                  |
| CSIRO-Mk3.6.0       |                                              | −0.016                                   | 0.205                                  | 0.122                                  | 0.132                                  | 0.100                                  |
| FGOALS-s2           | 0.0659                                        | 0.075                                    | 0.299                                  | 0.238                                  | 0.165                                  | 0.138                                  |
| GFDL-CM3            | 0.0765                                        | −0.059                                   | 0.188                                  | 0.119                                  | 0.112                                  | 0.076                                  |
| GFDL-ESM2G          | 0.0687                                        | 0.007                                    | 0.096                                  | 0.056                                  | 0.047                                  | 0.026                                  |
| GFDL-ESM2M          |                                              |                                          |                                        |                                        |                                        |                                        |
| GISS-E2-H           | 0.0855                                        | 0.005                                    | 0.141                                  | 0.100                                  | 0.095                                  | 0.054                                  |
| GISS-E2-R           | 0.0897                                        | −0.001                                   | 0.108                                  | 0.082                                  | 0.064                                  | 0.034                                  |
| HadGEM2-ES          | 0.0649                                        | −0.032                                   | 0.160                                  | 0.120                                  | 0.108                                  | 0.060                                  |
| INM-CM4             | 0.0828                                        | 0.031                                    | 0.143                                  | —                                      | 0.088                                  | —                                      |
| IPSL-CM5A-LR        | 0.0858                                        | 0.059                                    | 0.326                                  | 0.212                                  | 0.207                                  | 0.154                                  |
| IPSL-CM5B-LR        | 0.0772                                        | 0.033                                    | 0.178                                  | —                                      | 0.123                                  | —                                      |
| MIROC5              | 0.0835                                        | −0.006                                   | 0.126                                  | 0.085                                  | 0.093                                  | 0.048                                  |
| MIROC-ESM           | 0.0726                                        | −0.022                                   | 0.205                                  | 0.139                                  | 0.126                                  | 0.085                                  |
| MPI-ESM-LR          | 0.0718                                        | 0.018                                    | 0.176                                  | —                                      | 0.102                                  | 0.057                                  |
| MPI                | 0.0744                                        | 0.019                                    | 0.179                                  | —                                      | 0.109                                  | 0.065                                  |
| ESM-MR              | 0.0752                                        | 0.003                                    | —                                      | —                                      | —                                      | —                                      |
| MPI-ESM-P           | 0.0972                                        | −0.030                                   | 0.193                                  | 0.103                                  | 0.102                                  | 0.066                                  |
| MRI-CGCM3           | 0.0800                                        | 0.001                                    | 0.152                                  | 0.093                                  | 0.093                                  | 0.067                                  |
| NorESM1-M           | 0.0773                                        | 0.009                                    | 0.178                                  | 0.125                                  | 0.112                                  | 0.079                                  |
| Multi-model mean    |                                              |                                          |                                        |                                        |                                        |                                        |
| 90% uncertainty     | 0.0134                                        | 0.054                                    | 0.096                                  | 0.083                                  | 0.059                                  | 0.057                                  |
fraction of $F_{TOA}$ which directly perturbs the tropospheric radiative cooling. The forcing is calculated after allowing for any stratospheric adjustment so it can be interpreted as the forcing acting on the troposphere.

We cannot apply the simple model given by equation (1) to individual CMIP5 models because we do not have the individual atmospheric forcing estimates for the models. Instead, we use $F_{TOA}$ data for the historical and RCP scenarios from Meinshausen et al. (2011) (http://www.pik-potsdam.de/~mmalte/rcps/). This gives us top-of-atmosphere radiative forcing timeseries (figure 3, left column) for a number of forcing agents that potentially act on the tropospheric heat budget. We use the 1850 radiative forcing as a baseline, in order to be able to compare with the AOGCMs where we have used the mean of the pre-industrial control as a baseline. Alternatively, we could use a commonly defined period (say 1861–80) in both the CMIP5 historical AOGCMs runs and the simple model, but we found this choice had no qualitative impact on our conclusions.

We convert the $F_{TOA}$ timeseries into $F_{ATM}$ using published ratios that allows us to estimate the component of top-of-atmosphere radiative forcing that is acting on the tropospheric heat budget (e.g. Andrews et al. 2010, Kvalevåg et al. 2013). For example Andrews et al (2010) calculated the radiative forcing of many different forcing agents at both the top-of-atmosphere and surface, defining $R$ as the ratio of surface radiative forcing to that at the top-of-atmosphere. In this study, we are interested in the amount of radiative forcing in the atmosphere, so we define $R$ to be the ratio of atmospheric radiative forcing to that at the top-of-atmosphere (equal to 1 minus the ratio given in Andrews et al (2010)). Kvalevåg et al (2013) give the radiative forcings in the atmosphere and at the top-of-atmosphere, from which we calculate $R$. This means we can write $\Delta P_{adj}$ as follows:

$$\Delta P_{adj} = \frac{F_{ATM}}{L} = -\sum_i R_i \Delta F_{TOA} / L,$$

where $i$ indexes the different forcing agents.

A list of the forcing agents we have considered in the simple model is given in table 2, along with their values of $R$. Note that Andrews et al (2010) did not distinguish between tropospheric and stratospheric ozone, so here we have to sum the radiative forcings for stratospheric and tropospheric ozone. In addition, neither study distinguished between the direct and indirect effects of sulphate aerosol, so sulphate in this study is the sum of both the direct and 1st indirect effects. The Meinshausen et al (2011) dataset includes additional forcing agents, but we are only interested in those forcing agents that we consider to have an $F_{ATM}$ term (i.e. $R \neq 0$). There is some uncertainty in $R$ in the two studies owing to different models and different radiation codes. We try to account for this uncertainty in our analysis by using values that both maximise and minimize $F_{ATM}$, thereby sampling the full possible ranges of $F_{ATM}$ given the known uncertainty in $R$. We acknowledge that further uncertainty likely exists, which would broaden our estimates of $F_{ATM}$ and $\Delta P_{adj}$, and would encourage future work to perform targeted calculations to better constrain $R$, especially for ozone and biomass burning (where we are
relying on a single study) and sulphate and black carbon aerosol (where differences in $\mathcal{R}$ across the studies are large). There will also be uncertainty in the $\mathcal{F}_{\text{TOA}}$ dataset itself (Meinshausen et al. 2011) that we do not account for. The largest uncertainty will be for sulphate aerosol-cloud-interactions (e.g. Myhre et al. 2013) but we do not believe this will have a large impact on our results since sulphate aerosol has only a relatively small role in $\mathcal{F}_{\text{ATM}}$ (see below). Fortunately the dominating term in the 21st century is from CO$_2$, which is one of the most well understood forcings (Myhre et al. 2013).

Figure 3 (right column) shows the $\mathcal{F}_{\text{ATM}}$ timeseries (using the average $\mathcal{R}$, table 2) for the different forcing agents...
Table 2. Forcing agents included in the simple model and the corresponding ratios of atmosphere to top-of-atmosphere radiative forcing in Andrews et al (2010) and Kvalevåg et al (2013). Ozone includes both tropospheric and stratospheric ozone. Sulphate includes the direct effect and the 1st indirect effect.

\[ R = \frac{F_{\text{ATM}}}{F_{\text{TOA}}} \]

| Forcing agent       | Andrews et al 2010 | Kvalevåg et al 2013 |
|---------------------|---------------------|---------------------|
| Carbon dioxide (CO₂)| 0.8                 | 0.6                 |
| Other GHGs          | 0.5                 | 0.3                 |
| Ozone               | −0.3                | N/A                 |
| Sulphate            | 0.0                 | −0.4                |
| Black carbon        | 2.5                 | 6.0                 |
| Biomass burning     | −0.9                | N/A                 |
| Solar               | 0.2                 | 0.1                 |

as well as the corresponding \( \Delta P \). Since CO₂ has the largest \( F_{\text{TOA}} \) in the 21st century and a large \( R \) (i.e. most of its forcing is felt in the atmosphere), it contributes the most to the net \( F_{\text{ATM}} \) in the 21st century and hence has the largest negative \( \Delta P \) independent of \( \Delta T \). Black carbon strongly absorbs solar radiation in the atmosphere (\( R > 1 \)) giving rise to a strongly positive \( F_{\text{ATM}} \) term (and large negative \( \Delta P \)) in the historical simulation despite only a relatively small \( F_{\text{TOA}} \), but this declines in the 21st century scenarios. The next largest term arises from greenhouse gases other than CO₂ (figure 3, see Frieler et al 2011 also). Frieler et al (2011) and Lambert and Allen (2009) also found that historical precipitation is decreased in response to increased greenhouse gases and black carbon, independent of surface temperature change.

Andrews et al (2010) and Kvalevåg et al (2013) disagree as to whether sulphate aerosol contributes to tropospheric cooling. In Andrews et al (2010), \( R \) for sulphate aerosol is equal to zero, indicating that all \( F_{\text{TOA}} \) is absorbed at the surface and none in the troposphere, so there is no adjustment precipitation change. However, Kvalevåg et al (2013) have \( R \) equal to −0.4 for sulphate aerosol and so a non-zero \( F_{\text{ATM}} \) and a direct effect on precipitation. Figure 3 (right column) uses average \( R \), so sulphate aerosol has a non-zero precipitation adjustment. Kvalevåg et al (2013) note that the atmospheric absorption due to sulphate aerosol is larger than in other studies and suggest that enhanced absorption by atmospheric gases is the cause. Further targeted radiative transfer calculations are required to better understand and quantify the impact of sulphate aerosol changes on the atmospheric heat budget.

Figure 4 shows the CMIP5 \( \Delta P \) projections overlaid on the reconstruction based on the CMIP5-mean \( k\Delta T/L \) (figure 1(c)) plus the estimated precipitation adjustment (\( -F_{\text{ATM}}/L \)). The simple model \( \Delta P \) is in good agreement with the AOGCM simulations of \( \Delta P \), implying that the AOGCMs are simulating physically robust changes in global precipitation that are in line with our physical expectations. It is interesting that if we choose \( R \) for each forcing agent so as to minimise \( F_{\text{ATM}} \), then the simple model would be able to emulate the CMIP5 multi-model mean very well. As it is, the simple model results mostly fall within the spread of the CMIP5 models, albeit at the lower end of the CMIP5 range of AOGCM projections. This could be because the hydrological sensitivity is not exactly constant (e.g. Good et al 2012) or we have slightly overestimated \( \Delta P_{\text{adj}} \). For example, in equation (1), we make the assumption that the tropospheric radiative forcing, \( F_{\text{ATM}} \) is balanced by changes in precipitation (condensational heating, \( \Delta P') \). While this assumption is generally acceptable (e.g. Andrews et al 2010), O’Gorman et al (2012) suggested that it is more appropriate for the free troposphere (i.e. forcings applied above the boundary layer). For example Ming et al (2010) showed that black carbon aerosol forcing in the boundary layer was more effective at inducing sensible heat flux adjustments, whereas forcing applied in the free troposphere was mostly balanced by latent heat and precipitation adjustments. We do not have the sufficient information on the vertical profile of black carbon aerosol forcing to account for this in our simple model, which means we could be overestimating the precipitation adjustment to black carbon if a significant fraction of it resides in the boundary layer. This may explain why the simple model starts to drop relative to the CMIP5 results around 1900 and again around 1960 (figure 4), which we note is consistent with the time profile of black carbon aerosol forcing and its precipitation adjustment (figure 3).

Still, the broad agreement between the AOGCMs and our simple model is a useful result, not only for our physical understanding, but also from a simple modelling perspective. It means that if we diagnose radiative forcings in the atmosphere or at the surface, as well as at the top-of-atmosphere or tropopause, we can expand the radiative forcing concept to the water cycle and successfully predict projections of \( \Delta P \) without the need to resort to complex AOGCMs. Of course, in this study we use AOGCM output of \( \Delta T \) in our reconstruction of \( \Delta P \), but this need not be so. The simple model of precipitation could easily be coupled to simple models of \( \Delta T \), such as two-layer energy balance models (Allan et al 2014).

4. Regional precipitation changes

The previous sections highlighted the importance of precipitation adjustments to radiative forcing in opposing the global precipitation trends due to increases in surface warming. Bony et al (2013) recently suggested a dominant role for precipitation adjustments in tropical rainfall patterns, so next we briefly consider the regional pattern of the precipitation changes.

Figure 5(a) shows the regional change in precipitation in RCP8.5 at the end of the 21st century (mean over 2069–98) as simulated by HadGEM2-ES. To estimate the pattern of change associated with \( \Delta T \) versus that associated with precipitation adjustments we first calculate a regional hydrological sensitivity. In principle we could apply an analogous method to that used in the global-analysis, i.e. regress local precipitation change against global-mean \( \Delta T \). However we instead make use of the ‘amip’ and ‘amipFuture’ experiments: the difference (amipFuture—amip) represents a patterned
$+4\, \text{K}$ sea surface temperature (SST) forcing applied to an atmosphere-only model (Taylor et al., 2012, Bony et al., 2011). $F_{\text{ATM}}$ is zero by construction, and hence $\Delta P$ in this experiment comes about solely in response to surface warming (equation (1)). Since the experiments are run for 30 years this gives us a clean signal of the regional pattern of precipitation response to surface warming. In order to compare with RCP8.5, we normalise the regional precipitation change by the global mean $\Delta T$ (i.e. a regional hydrological sensitivity) and then scale the field by the global mean $\Delta T$ in RCP8.5.

Figure 5(b) shows the estimated change in regional precipitation due to surface warming for HadGEM2 in (a) RCP8.5, (b) ‘amipFuture’, a ‘$+4\, \text{K}$’ patterned surface temperature change (rescaled so that $\Delta T$ is equal to $\Delta T$ in RCP8.5) which we use to represent the precipitation response to surface warming, and (c) ‘amip4xCO2’, where carbon dioxide is instantaneously quadrupled and then held constant with fixed SSTs. (a) is a 30 year mean over the period 2069–98, relative to the mean of the preindustrial control. (b) and (c) are 30 year means over the period 1979–2008, relative to the mean of the ‘amip’ control.
strongly resembles many of the broad features simulated in the RCP8.5 change. Both show decreased precipitation just north of the equator in the Pacific, and increased precipitation just south of the equator, as well as increased precipitation in the mid to high latitudes and decreased precipitation over Southern Africa. This implies a dominant role for surface temperature change in determining the pattern of precipitation response. This is in contrast to Bony et al (2013), but in agreement with Chadwick et al (2014), who found that the Bony et al (2013) definition of precipitation adjustment included regional patterns of rapid surface temperature change. A recent study by He et al (2014) looked at the effect of SST pattern change on the atmospheric circulation and precipitation by contrasting the CMIP5 uniform and patterned +4 K SST increase AMIP experiments. They found the broad features of circulation and precipitation change to be robust across these experiments, suggesting that our large-scale precipitation changes to surface warming are largely independent of the actual pattern of SST change.

Figure 5(c) shows an estimate of the regional pattern of precipitation adjustment derived from the ‘amip4xCO2’ experiment whereby SSTs are prescribed and the CO2 concentration is quadrupled. $\Delta T \sim 0$ but $F_{ATM}$ is large in this case. Over most of the globe, precipitation is reduced so that this adjustment term cannot be used to describe the broad features of the RCP8.5 change. A comparison with RCP8.5 ignores contributions to $F_{ATM}$ from other forcing agents (though CO2 is by far the dominant $F_{ATM}$ term by 2100, figure 3) and will overstate the CO2 effect since CO2 levels do not quite reach four times the pre-industrial level by 2100. So this field should be scaled down, which would further reduce the impact of precipitation adjustments on the regional patterns. Although SSTs are prescribed in the 4xCO2 experiment, the land can still warm, causing increased precipitation that counteracts the effect of CO2 directly on precipitation. In addition, the land warming could lead to changes in monsoon circulations that will affect the spatial distribution of precipitation.

5. Summary and discussion

We have shown that a simple model of global mean precipitation based on the tropospheric energy budget can emulate the transient scenarios of more complex models. The precipitation timeseries from the simple model fall within the range of the CMIP5 models, albeit in the lower half of the models projections. The CMIP5 multi-model mean falls within the uncertainty we have in the simple model as to how top-of-atmosphere radiative forcing should be partitioned between the atmosphere and the surface. We used surface temperature anomalies from the CMIP5 models in our simple model, but one could instead use surface temperature anomalies calculated from simple energy balance models (Allan et al 2014).

The CMIP5 models show little or no increase in precipitation over the historical period, despite some increase in surface temperatures. We found that it is not that precipitation is insensitive to the changing surface temperature, but that the increase has been largely cancelled by the direct effects of the radiative forcing of the troposphere. We found that the regional pattern of precipitation change is dominated by the response to surface warming rather than the precipitation adjustment to radiative forcing in the atmosphere.

One of the difficulties in using the simple model approach is the lack of published values for the ratio $R$, which translates commonly reported top-of-atmosphere forcings into atmospheric and surface components. This means that we are limited to certain forcing agents and there is also uncertainty in the ratios that are published. We would encourage future studies to report radiative forcings at the surface as well as at the top-of-atmosphere. More focused calculations of the radiative forcings arising from different forcing agents (such as ozone and black carbon) would be useful and help expand the radiative forcing concept beyond energy and temperature to include the water cycle as well.

Still, our results point to AOGCM projections of global mean precipitation that are in line with our current knowledge of how the energy and water cycles are linked, providing a useful approach in emulating global mean precipitation changes in complex AOGCMs for any scenario.

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