Understanding Hydrological Sensitivities Induced by Various Forcing Agents with a Climate Model

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Abstract

The apparent hydrological sensitivity, defined as the global-mean precipitation change per increase of the global-mean temperature, is investigated for scenarios induced by different forcing agents. Simulations with a climate model driven individually by four different climate forcers, i.e. sulfate, black carbon, solar insolation and carbon dioxide (CO₂), are analyzed in the context of energy balance controls on global precipitation to explore how different forcing agents perturb different energy components grouped into fast and slow responses. Similarities and differences among the forcing agents are found in ingredients of the tendency contributing to the hydrological sensitivity from various energy budget components. Specifically, the sulfate and solar forcings induce the hydrological sensitivity of ~2.5%°K⁻¹ due to the slow response of radiative cooling whereas the black carbon induces a significantly negative hydrological sensitivity (~6.0%°K⁻¹) due to the strong atmospheric heating. The CO₂-induced hydrological sensitivity is found in between (~1.2%°K⁻¹) as a result from the slow response of radiative cooling and its partial compensation by the atmospheric heating. The findings provide a quantitative basis for interpreting climatic changes of global precipitation driven by a mixture of various natural and anthropogenic forcings.

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1. Introduction

Prediction of the global precipitation change is still subject to large uncertainty particularly when the climate change is driven by various forcing agents including different types of aerosols as well as long-lived greenhouse gases such as carbon dioxide (CO₂). The climatic change of global precipitation is often quantified by the hydrological sensitivity (HS), defined as the global-mean precipitation change per increase of the global-mean surface air temperature. The HS has earlier been studied for CO₂-induced global warming scenario based on the fact that the global-mean precipitation change is largely constrained by energy balance controls (e.g. Allen and Ingram 2002; Held and Soden 2006; Stephens and Ellis 2008; Pendergrass and Hartmann 2014; DeAngelis et al. 2015; Watanabe et al. 2018). The energy balance argument has more recently been extended to analysis of HS manifested in more realistic historical and future scenario simulations driven by a mixture of various forcing agents (Shiogama et al. 2010; Pendergrass and Hartmann 2012; Wu et al. 2013; Suzuki et al. 2017). These studies have pointed out that the global precipitation change contains a component that does not simply scale with the global-mean surface air temperature. In this context, the global-mean precipitation change containing the “temperature-independent” component simply divided by the global-mean surface air temperature is referred to as the apparent hydrological sensitivity (hereafter AHS) (Fläschner et al. 2016), which is convenient to estimate in historical and future scenario simulations. Factors influencing the atmospheric energy budget can contribute to AHS as argued by Stephens and Hu (2010) who highlight aerosol and cloud feedback as most uncertain factors. This study is intended to quantitatively understand AHS induced by various climate forcers.

A major factor making AHS different from the pure HS is the rapid adjustment (or the fast response) of precipitation to climate forcing. The rapid adjustment is particularly pronounced by atmospheric radiative heating of light-absorbing aerosols, such as black carbon (BC), which substantially deviates the historical precipitation change from the temperature-dependent trend (Suzuki et al. 2017) and is a major cause for the inter-model spread of AHS in future climate change scenarios (Pendergrass and Hartmann 2012). These studies underscore the importance of separating the fast and slow response components for better quantification of AHS.

These research needs motivate a recent community effort of the model inter-comparison called Precipitation Driver and Response Model Intercomparison Project (PDRMIP) (Samset et al. 2016; Myhre et al. 2017). This is coordinated to perform simulations with multiple global climate models individually driven by various forcing agents including sulfate (SF) and BC aerosols, solar insolation (Sol) and CO₂. The results from PDRMIP highlight how AHS differs among forcing agents (Samset et al. 2016) and how this difference is attributed to differing contributions from fast responses of energy budget components (Samset et al. 2018; Richardson et al. 2018). The relative contributions from fast and slow responses are better understood in a whole picture of global energy budget (Suzuki and Takemura 2019; hereafter ST19), which also explains stark differences in global-mean responses of temperature (Takemura and Suzuki 2019) and precipitation to BC and SF.

This study builds upon these previous studies to better understand AHS induced by various forcing agents through quantifying relative contributions of different factors to AHS. The factors influencing the atmospheric energy budget are identified in the manner tied to different physical processes. For this purpose, we employ climate model simulations individually driven by four major forcing agents (SF, BC, Sol and CO₂) in the way that extends PDRMIP. The results are analyzed in the context of atmospheric energy budget that is broken down into component fluxes corresponding to physical processes to quantify their corresponding contributions to AHS. The ingredients of AHS tendencies due to different factors are then compared among the forcing agents to characterize how different forcing agents induce various AHS values as a result from different compositions of energy balance component perturbed. As opposed to the multi-model analysis of PDRMIP, the single-model analysis of this study compares precipitation responses to different forcing agents under a common set up of model physics. This has an advantage of avoiding contaminations of the model-to-model discrepancy in representation of physical processes.

2. Model experiments

We perform and analyze the model experiments using MIROC5 (Watanabe et al. 2010) coupled with the SPRINTARS
aerosol model (Takemura et al. 2005, 2009). The model experiments are those extended from the PDRMIP protocol, which increased BC and sulfur dioxide (SO$_2$) emissions by ten times ($\times10$) and five times ($\times5$), respectively, relative to the present emission conditions (control experiment). In this study, the BC and SO$_2$ emissions are perturbed for their fuel sources by multiplying various globally uniform factors of 10, 5, 2, 1.5, 0.8, 0.5, 0.3, 0.1 and 0.0 to obtain more systematic and robust climate responses than PDRMIP (Methods in Takemura and Suzuki 2019) for these short-lived climate forcers with inhomogeneous spatial distributions. Simulations with increased solar insolation by $+2\%$ (denoted by Sol) and with CO$_2$ concentration doubled (denoted by CO$_2$) relative to the level in 2000 are also conducted but with no varying magnitudes for their relatively homogeneous nature. The change to quantity of interest caused by each of these forcings relative to the control experiment (denoted as $\Delta$) is analyzed throughout this paper.

For each of the forcing, sea surface temperature (SST)-prescribed and ocean-coupled simulations are conducted to decompose the total climate response into its fast and slow response components. Following PDRMIP, the fast response is estimated from the SST-prescribed run and is subtracted from the total response obtained from the ocean-coupled run to infer the slow response as residuals. The SST-prescribed and ocean-coupled runs are performed for 15 and 100 years, respectively, and the last 10 and 50 years are used for analysis, respectively, also following the PDRMIP analysis. For all the simulations of this study, horizontal and vertical resolutions of the model are T85 and 40 layers, respectively.

3. Analysis

3.1 Hydrological sensitivity for different forcing agents

Figure 1 shows how the global-mean precipitation change ($\Delta P$) is related to the global-mean surface air temperature change ($\Delta T_s$) in response to the four forcings. The statistics for the total response (Fig. 1a) show how diverse the AHS is among different forcing agents. The linear fittings to responses to varying SF and BC perturbations quantify their respective AHS to be $\sim+2.7\%K$ for SF and $\sim-6.0\%K$ for BC (as represented by blue and red lines in Fig. 1a). The substantial negative magnitude of the BC-induced AHS is consistent with PDRMIP (Sasmito et al. 2016). The response to increased solar insolation is located close to the blue line, suggesting the Sol-induced AHS ($\sim-2.4\%K$) is more or less similar to the SF-induced AHS. This is reasonable given that the two forcings have common characteristics of modulating the solar energy input through either changing the insolation or the planetary albedo. The CO$_2$-induced AHS is somewhat smaller than the SF and Sol cases although still positive.

To exclude the fast response contributions, the statistics for the slow-response component alone is shown in Fig. 1b. The comparison of Figs. 1a and 1b highlights that a vast diversity of HS for the total response to different forcing agents (Fig. 1a) is remarkably narrowed down to a common value across various forcings when the slow response component is isolated (Fig. 1b). This is also consistent with findings of Richardson et al. (2018) for PDRMIP multi-model ensemble. In the following analysis, the precipitation responses are investigated in the context of global energy budget depicted in Fig. 10 of ST19.

3.2 Atmospheric energy balance

The atmospheric energy budget is given as the balance between the atmospheric radiative cooling change ($-\Delta R_{\text{ATM}}$) and the latent ($\Delta P_L$) and sensible ($\Delta S$) heating change:

$$\Delta P_L + \Delta S = -\Delta R_{\text{ATM}},$$

(1)

Due to a relatively small heat capacity of atmosphere, the balance (1) also applies to each of the fast and slow response components as (see Fig. 10 of ST19)

$$\Delta P_{\text{fast}} + \Delta S_{\text{fast}} = -\Delta R_{\text{ATM}} \Delta \text{eff},$$

(2)

$$\Delta P_{\text{slow}} + \Delta S_{\text{slow}} = -\Delta R_{\text{ATM}} \Delta \text{eff},$$

(3)

where the subscript “fast” and “slow” denotes the fast and slow response components, respectively, of each quantity. $R_{\text{eff}}$ represents the effective radiative forcing (ERF) to atmosphere, which is obtained as the net radiative imbalance of atmosphere in the SST-prescribed simulations. When the sensible heat (SH) contribution is neglected, the energy balances (2) and (3) reduce to the radiative-convective equilibrium (RCE) given as

$$\Delta P_{\text{fast}} \sim \Delta R_{\text{eff}} \Delta \text{ATM},$$

(2)'

$$\Delta P_{\text{slow}} \sim \Delta R_{\text{eff}} \Delta \text{ATM},$$

(3)'

Figure 2 shows how these relationships apply to the model output for the fast and slow response components to the four different forcings. Figure 2a illustrates that the latent plus sensible heat changes balance the atmospheric radiative cooling change for the fast response component, following (2). The latent heat (LH) change has a major contribution to this energy balance as illustrated in Fig. 2c, which depicts how RCE given by (2)' applies to most of the forcing agents except BC. In the BC-forced scenarios, SH significantly decreases in response to the BC-induced stabilized atmosphere to substantially deviate the balance relationship from the RCE.

Figures 2b and 2d show the corresponding balance relationships (3) and (3)', respectively, for the slow-response component. Similar to the fast-response case, the latent plus sensible heat changes balances the atmospheric radiative cooling change (Fig. 2b). The RCE relationship is found to better apply to the slow-response component (Fig. 2d) for all the forcing agents including BC.
3.3 Scaling with global-mean temperature

a. Slow response

The slow response of atmospheric radiative cooling can further be decomposed into the clear-sky (denoted by the subscript "clr") and cloud radiative effect (CRE; denoted by $C_e$) components as

$$\Delta R_{\text{slow,ATM}} = \Delta R_{\text{slow,clr}} + \Delta C_{e,\text{ATM}}.$$

The clear-sky radiative cooling primarily comes from the column water vapor change (Stephens and Ellis 2008) as

$$-\Delta R_{\text{slow,ATM}} \sim \alpha \Delta W_{\text{slow}}/W,$$

where the coefficient $\alpha$ represents the radiative effect of water vapor as determined from the gas absorption parameterization of radiation physics (Stephens and Ellis 2008; Stephens and Hu 2010; Suzuki et al. 2017). This relationship is illustrated in Fig. 3a that provides an approximate estimate of $\alpha \approx 0.34 \text{Wm}^{-2}\%^{-1}$. The water vapor change then occurs with $\Delta T_s$ through the Clausius-Clapeyron (C-C) relationship as
The fast-response component, by its definition, has no direct dependency on the global-mean temperature. However, the fast-response component relates to the global-mean temperature indirectly through linkages of the fast response of energy budget to the top-of-atmosphere radiative forcing that somehow induces the global-mean temperature change via the climate response as typically represented by the so-called feedback parameter. For the purpose of interpreting AHS containing both fast and slow responses, it is useful to investigate how the fast-response components, represented by each term of (2), relate to the global-mean temperature change.

Figure 4a shows the correlation between the atmospheric ERF and $\Delta T_s$. The SF- and BC-induced ERFs are found to have starkly different correlations with $\Delta T_s$. The SF forcing exerts a small magnitude of the atmospheric ERF with a wide range of the temperature response whereas the BC-induced atmospheric heating exerts significant ERF on atmosphere for a small range of the temperature response. This difference can be primarily explained by different vertical structures of the instantaneous radiative forcing between the two aerosols although the ERF-$\Delta T_s$ correlations can also be influenced by aerosol impacts on clouds: BC heats atmosphere and cools surface whereas SF directly cools surface (ST19). The atmospheric heating of BC triggers rapid adjustment of atmosphere that weakens the global-mean temperature response (Stjern et al. 2017) whereas the SF forcing produces tiny magnitudes of atmospheric ERF accompanied by pronounced temperature responses. Such characteristics are also hinted in the CO$_2$ and Sol-induced responses in Fig. 4a where the Sol response is located closer to the SF relationship (blue line) than is the CO$_2$ case, reflecting their different energy redistributions into atmosphere and surface.

The corresponding relationships for the SH fast response also have starkly different relationships with $\Delta T_s$ between SF and BC (Fig. 4c). Reflecting a significant decrease of SH in response to BC that induces stabilized atmosphere and a small change of SH due to the tiny impact of SF on atmosphere. The SH fast responses to CO$_2$ and Sol are also found to be similar to those to SF.

\[
\Delta W_{\text{slow}}/W \sim \kappa \Delta T_s,
\]

where $\kappa \sim 7.6\% K^{-1}$ according to Fig. 3b. The clear-sky radiative cooling change therefore scales with the temperature change as

\[-\Delta R_{\text{slow}, \text{clear}} \sim \alpha \Delta W_{\text{slow}}/W \sim \alpha \kappa \Delta T_s.
\]

This provides a breakdown of the temperature-mediated slow response into components relevant to different physical processes.

\[\Delta W_{\text{slow}}/W \sim \kappa \Delta T_s\]

\[-\Delta R_{\text{slow}, \text{clear}} \sim \alpha \Delta W_{\text{slow}}/W \sim \alpha \kappa \Delta T_s.
\]

\[L \Delta P_{\text{slow}} \sim (\alpha \kappa - \mu + \nu) \Delta T_s.
\]

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\]
3.4 Contributions from various factors to AHS

Combining the fast and slow responses described above, the total response of the global-mean precipitation is expressed as

\[ \Delta P = \Delta P_{\text{fast}} + \Delta P_{\text{slow}} \approx -\Delta S_{\text{fast}} - \Delta T_{\text{ATM}}^{\text{fast}} + (\alpha \mu + v)\Delta T_s, \]

or dividing by \( \Delta T_s \) and decomposing \( \Delta T_{\text{ATM}}^{\text{fast}} \) into the clear-sky and CRE components as

\[ \Delta P/\Delta T_s \approx -\Delta S_{\text{fast}}/\Delta T_s - \Delta T_{\text{ATM}}^{\text{fast}}/\Delta T_s - \Delta C_{\text{fast}}^{\text{fast}}/\Delta T_s + \alpha \mu + v. \]

(4) provides a breakdown of AHS into contributions from different components of atmospheric energy budget relevant to different physical processes.

Figure 5 summarizes the AHS tendencies of different terms in (4) for the four forcing agents. It is found that SF and Sol have similar ingredients of contributions, which are dominated by the slow-response component of the clear-sky radiative cooling. This is mostly the only factor that determines AHS (~2.5%K\(^{-1}\)) for these two forcing agents and comes from the column water vapor change through the C-C relationship (Fig. 3). The values of \( \alpha \approx 0.34 \text{ Wm}^{-2}\%^{-1} \) and \( \kappa \approx 7.6\%\text{K}^{-1} \) result the AHS tendency due to this component of ~2.6 Wm\(^{-2}\)K\(^{-1}\) (or ~2.8%K\(^{-1}\)). This sets a component common among the forcing agents analyzed and dominating the slow response (Fig. 5), explaining a universal nature of the pure HS in Fig. 1b. This component is also found to exert a large contribution to the CO\(_2\)-induced AHS, which is partially offset by the negative tendency due to the clear-sky ERF induced by CO\(_2\) atmospheric heating to result a net positive AHS of ~1.2%K\(^{-1}\) that is somewhat smaller than the SF- and Sol-induced AHS (~2.5%K\(^{-1}\)).

The BC-induced AHS is dominated by a large negative tendency due to the clear-sky ERF component associated with the atmospheric heating. This negative tendency is partially offset by fast responses of CRE and SH as well as by the slow response of the clear-sky radiative cooling to result a pronounced net negative AHS of about ~6%K\(^{-1}\). The positive offset largely comes from the fast SH response, suggesting a significant role of SH in determining the precipitation response, as also pointed out by Myhre et al. (2018). The slow response of the clear-sky radiative cooling, common among the forcing agents, exerts the second largest compensation for the clear-sky ERF. The positive tendency due to the fast response of CRE is also not negligible, suggesting a significance of cloud responses to BC. The positive and negative tendencies represent two opposing pathways of precipitation responses to BC (Ming et al. 2010).

In MIROC, the fast response of CRE is negligible for forcing agents except BC but is subject to uncertainties arising from aerosol impacts on clouds for SF and BC cases. The slow-response component of CRE, representing the cloud feedback to the global precipitation, also has only a small negative contribution to AHS for all the forcing agents analyzed (Fig. 5). It should be noted, however, that there is no a priori reason that determines whether the cloud feedback on precipitation is positive or negative (Stephens and Hu 2010; Pendergrass and Hartmann 2014; Mauritsen and Stevens 2015). Also given the link of HS to the equilibrium climate sensitivity via the low-cloud feedback (Watanabe et al. 2018), the cloud feedback uncertainty and its influence on AHS warrant further investigations in future studies.

4. Conclusion

This study investigates how different forcing agents induce different AHS through different ingredients of contributions from various components of atmospheric energy budget. Relevance of energy budget components to global-mean temperature change is analyzed to quantify contributions of different components to AHS. Different forcing agents are found to have varying ingredients of the AHS tendencies due to different factors. In particular, SF and Sol primarily induce the slow response of radiative cooling that determines AHS of ~2.5%K\(^{-1}\) whereas BC induces a strong atmospheric heating, which is partially compensated for by the fast response of SH and CRE and the slow response of radiative cooling to result a significantly negative AHS (~6%K\(^{-1}\)). The CO\(_2\)-induced AHS is found in between (~1.2%K\(^{-1}\)) as determined by the slow response of radiative cooling and its partial compensation by the atmospheric heating. This study offers a theoretical basis for interpreting the historical and future climatic changes of global precipitation driven by a mixture of various forcings.

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