Radiative Transfer Diversity and its Influence on the Response of the Hydrological Cycle in Climate Models

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RADIATIVE TRANSFER DIVERSITY AND ITS INFLUENCE ON THE RESPONSE OF THE HYDROLOGICAL CYCLE IN CLIMATE MODELS

By

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RADIATIVE TRANSFER DIVERSITY AND ITS INFLUENCE ON THE RESPONSE OF THE HYDROLOGICAL CYCLE IN CLIMATE MODELS

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Due to considerable societal implications, accurately simulating the response of the hydrological cycle to climate change is an important focus of climate research. Currently, climate model simulations predict the hydrological cycle will strengthen globally with global warming, but the magnitude of this change remains highly uncertain. Here we identify sources of this uncertainty by diagnosing individual components of the radiative changes that constrain the hydrological cycle response. We show that the differing influences of CO$_2$ increases on long-term anthropogenic climate change versus short-term internal climate variability explains differences in precipitation sensitivity on these time scales. We investigate the response of the hydrological cycle to CO$_2$ increases further by using radiative kernels to quantify radiative forcing and feedbacks. We show instantaneous radiative forcing contributes substantially to the magnitude and inter-model spread of both hydrological cycle responses and climate projections more broadly. This indicates that diversity in the implementation of radiative transfer among climate models serves as an important source of uncertainty in climate change projections. This is confirmed in a comparison of radiative kernels, which are shown to differ more than previously documented, in part due to differences in radiative transfer modeling. We also
show that model bias in the distribution of climatological clouds is a substantial source of radiative kernel differences, which contributes to inconsistencies in estimates of cloud feedback. We introduce a new set of observation-based radiative kernels free from model bias in the base state, which will serve as a neutral radiative kernel for diagnosing radiative changes in models and observations.
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Chapter 1: Introduction

1.1 Motivation

Among the most societally impactful consequences of a warming climate will be an intensification of Earth’s hydrological cycle. Our ability to adapt to or mitigate this change relies on furthering our understanding of the physical processes controlling the hydrological cycle and identifying sources of uncertainty in projections of its changes.

While there is climate model consensus that global-mean precipitation, a proxy for hydrological cycle strength, will increase with surface warming, the projected magnitude of this change differs notably across models, ranging from 1-3%/K (Held and Soden 2006; Lambert and Webb 2008; Pendergrass and Hartmann 2014). Models also differ from observations (Wentz et al. 2007; Arkin et al. 2010; Kramer and Soden 2016). Energetic arguments provide a clear framework for diagnosing the causes of these differences (Mitchell et al. 1987; Allen and Ingram 2002). Unlike the energy budget at the top of the atmosphere (TOA), which is purely radiative, the budgets defined at the Earth’s surface and in the atmospheric column (TOA minus surface) include contributions from non-radiative latent heat flux from precipitation (LH) and sensible heat flux (SH) in addition to radiative terms. Due to the small heat capacity of the atmosphere, the atmospheric energy balance maintains equilibrium on annual and longer timescales. Under greenhouse gas induced global warming, changes in atmospheric radiative cooling are compensated for mostly by changes in LH associated with precipitation. Atmospheric radiative cooling is projected to increase, therefore precipitation will increase. Likewise, uncertainty in radiative responses begets uncertainty in hydrological cycle responses. Sensible heat flux also contributes to
changes the energy budget. Recent work indicates sensible heat flux changes have been an important driver of the magnitude of precipitation change since pre-industrial times, although its influence will lessen during future climate change (Myhre et al. 2018). Sensible heat flux may be an important source of uncertainty in these future changes, however (Flaschner et al. 2016; DeAngelis et al. 2016).

Numerous studies have addressed uncertainty in the hydrological cycle from the perspective of energetic constraints. Broadly speaking, recent literature has indicated that differences in the implementation of radiative transfer theory across models are an important source of uncertainty in hydrological cycle responses. For example, DeAngelis et al. (2015) suggests that inter-model spread in atmospheric shortwave absorption can partly be attributed to differences in shortwave radiative parameterization across models. This is in agreement with findings by Pendergrass and Hartmann (2014) and Pincus et al. (2015). While these studies highlight that radiative transfer differences impact hydrological cycle projections, this dissertation will investigate the details of this relationship and the full extent of its impact.

A common approach for diagnosing uncertainty in radiative responses is to decompose them into radiative forcing and feedback terms with radiative kernels (Soden et al. 2008). In response to a change in a forcing agent, such as an increase in CO₂, the net radiative flux response consists of two components: radiative forcing, a fast response (months or less) directly induced by the change in the agent and radiative feedbacks, a slow response (inter-annual and longer) mediated by surface temperature changes. Applied to the TOA radiative balance, this framework has proven extremely valuable to evaluating uncertainty in climate sensitivity, contributing to widely accepted conclusions,
such as that cloud feedback is the largest contributor to inter-model spread (e.g. Soden and Held 2006). When applied to the atmospheric energy budget to evaluate the hydrological cycle response, results have been less conclusive. As outlined in Chapter 2, for example, stark disagreements on the relative role of cloud and non-cloud feedbacks exist between studies (O’Gormann et al. 2012; Flaschner et al. 2016). Flaschner et al. (2016) posit that this discrepancy is due to differences between the radiative kernels used in each study to diagnose radiative feedbacks. Since radiative kernels are derived from an offline version of a climate model’s radiative transfer code, this disagreement further suggests that differences in radiative transfer modeling contribute to uncertainty in climate responses. Radiative kernels have not been extensively compared to confirm this, however.

Radiative forcing uncertainty is yet another example of how differences in the implementation of radiative transfer across models contributes to uncertainty in climate projections. Instantaneous radiative forcing (IRF), the radiative imbalance directly induced by changes in a forcing agent, is sensitive to a model’s radiative transfer parameterization and the model’s climatological state that initializes the radiative transfer calculations (Zhang and Huang 2014). Despite evidence that the fast response of the hydrological cycle is a substantial or even, depending on forcing scenario, dominant component of the magnitude and inter-model spread of the total response (Forster et al. 2016; Bala et al. 2010; Flaschner et al. 2016; Samset et al. 2016), the atmospheric and surface radiative forcing that constrains it has not been thoroughly diagnosed. In particular, IRF defined at the surface (ISRF) is rarely documented in model simulations and its inter-model spread is not known.
The purpose of this dissertation is twofold: to contribute to our understanding of radiative constraints on the hydrological cycle by decomposing radiative responses at the surface and in the atmospheric column and to investigate how radiative transfer differences in models contribute to uncertainty in hydrological cycle responses and climate projections more broadly.

1.2 Outline

This dissertation will consist of five research chapters. In the first research chapter (Chapter 2), we explore the causes of documented differences between modeled and observed hydrological cycle sensitivity and whether this disagreement denotes some fundamental difference in the radiative constraints on global-mean precipitation between long-term, anthropogenically forced climate change simulated by models and short-term, internal climate variability that dominates our relatively short observational satellite record (corresponds to Kramer and Soden 2016). In Chapter 3, we study radiative constraints on the hydrological cycle in further detail by decomposing surface radiative changes into its forcing and feedback components using radiative kernels (Kramer et al. 2018a). We highlight the important contributions of CO₂ ISRF to inter-model spread in the overall surface response. In Chapter 4 we diagnose instantaneous radiative forcing and its inter-model spread under multiple greenhouse gas and aerosol forcing scenarios, demonstrating the ubiquity of radiative transfer uncertainty in climate model projections (Kramer et al. 2018b). In Chapter 5 we inter-compare radiative kernels derived from different climate models to investigate methodological sources of bias in the diagnosis of radiative feedbacks and determine the relative role of radiative transfer, base state and vertical resolution differences to these biases (Kramer et al. 2018c). Finally, in Chapter 6
we introduce a new set of radiative kernels based on CloudSat satellite observations and explore how cloud feedback is sensitive to the distribution of clouds in the base state (Kramer et al. 2018d).
Chapter 2: The Sensitivity of the Hydrological Cycle to Internal Climate Variability versus Anthropogenic Climate Change

2.1 Background

Understanding the response of precipitation to climate change has become a topic of great focus in the climate science community, given the potential societal consequences. Climate models indicate that atmospheric water vapor will increase with warming at a rate consistent with that expected from the Clausius-Clapeyron equation (~7%K⁻¹). In contrast, results from modeling studies indicate that the increase of global-mean precipitation (\(P\)) with warming is much lower (~2%K⁻¹) and dictated by energetic constraints rather than moisture availability (Allen and Ingram 2002; Held and Soden 2006; Vecchi and Soden 2007; Stephens and Ellis 2008). This rate of change can be interpreted as the sensitivity of \(P\) to a change in global-mean near-surface air temperature (\(\Delta T_s\)). Herein, we use linear regression to quantify the sensitivity of a variable to changes in global-mean \(T_s\) and, for brevity, represent this sensitivity as a derivative (i.e., \(\frac{dP}{dT_s}\)) represents the linear regression slope of global-mean precipitation to changes in global-mean \(T_s\).

Changes to the globally averaged atmospheric energy budget can be expressed as:

\[
\Delta R = L \Delta P + \Delta S H, \tag{2.1}
\]

where \(\Delta R\) is the change in atmospheric radiative cooling (defined as positive for increased cooling), \(L \Delta P\) is the latent heat flux change, where \(L\) is the latent heat of vaporization, and \(\Delta S H\) is the sensible heat flux change. Calculated as the difference between the net radiation balance at the surface and at the top of the atmosphere (TOA), \(R\) increases as the surface warms, due to a growing energy loss from longwave (LW) emission. This increase in \(R\) must be balanced by an increase in \(LP\) in order to maintain
equilibrium in the atmosphere’s energy budget. The change in sensible heat ($\Delta SH$) also contributes to this balance, but is smaller in magnitude (Previdi 2010; Stephens and Ellis 2008).

Attempts have been made to quantify precipitation and water vapor sensitivity from observations. Water vapor increases are tightly coupled to surface warming in observations, and the sensitivity of water vapor is robustly observed to be 6-7 %K$^{-1}$ (Wentz and Schabel 2000; Trenberth et al. 2005; O’Gorman et al. 2012), in agreement with models. Precipitation and surface temperature change demonstrate weaker coupling in observations (O’Gorman et al. 2012; Allan et al. 2014), and more uncertainty in observed $\frac{dP}{dT_s}$. Wentz et al. (2007) determined that $P$ has increased at a rate of roughly 6 %K$^{-1}$ using observations from 1987-2006, much larger than modeled sensitivities. Other studies have shown observed $\frac{dP}{dT_s}$ to be 2-3 %K$^{-1}$ (Arkin et al. 2010, O’Gorman et al. 2012, Allan et al. 2014), in closer agreement with models. The sensitivity of $P$ is also dependent on the time period used (John et al. 2009). For example, the sensitivity obtained using data from the Global Precipitation Climatology Project (Huffman et al. 2009) and HadCRUT4 temperature measurements (Morice et al. 2012) is 3.4 %K$^{-1}$ for the years 1989-2010 (O’Gorman et al. 2012) and 2.8 %K$^{-1}$ for the years 1988-2010 (Allan et al. 2014).

It is well documented that precipitation is difficult to measure with confidence on a global scale and only a few decades of reliable data are available (see discussion in Stephens and Ellis 2008 and Arkin et al. 2010). Internal variability in these short record lengths may contribute to the uncertainties described above and limit the applicability of the observational data to understanding anthropogenic climate change. Without intending
to completely reconcile observations with model results, we investigate whether there is a fundamental difference between the constraints on $\Delta P$ under anthropogenic climate change and internal climate variability. This is not simply an academic question, but has important practical implications, since it is the shorter time-scale internal variability that frequently dominates the observational record.

Using a coordinated set of climate model simulations forced with increasing CO$_2$, we examine the energetic constraints on the hydrological cycle at both time scales by comparing $\frac{dR}{dT_s}$, $\frac{dP}{dT_s}$, $\frac{dSH}{dT_s}$, and the sensitivity of column-integrated water vapor ($\frac{dW}{dT_s}$) for changes on short (inter-annual) and long (multi-decadal) time scales. We also determine whether the balance between $\Delta R$ and $L\Delta P$ holds at these different time scales and assess the effects of clouds on these relationships.

### 2.2 Data and Methods

In this chapter we use monthly mean output from simulations conducted with 23 coupled ocean-atmosphere general circulation models (CGCMs) included in the Coupled Model Intercomparison Project phase 5 (CMIP5). In one set of simulations, CO$_2$ concentration in the atmosphere is increased 1% per year to a quadrupling from pre-industrial values (referred to as “1pctCO2”) (Taylor et al. 2012), however this study only uses output that extends to a doubling of CO$_2$ (years 1-70), since some models stop increasing CO$_2$ after this point. These 1pctCO2 experimental runs allow us to determine how the hydrological cycle responds to temperature change and how external forcing under transient climate conditions alters its response. In order to assess the direct response of the hydrological cycle to surface temperature change, separate from external forcing, we also use simulations where CO$_2$ is immediately quadrupled from pre-
industrial concentrations and then held fixed (referred to as “abrupt4xCO2”). In contrast to simulations of realistic climate projections, which include additional external forcings and account for climate mitigation efforts, 1pctCO2 and abrupt4xCO2 are idealized, experimental simulations, designed to isolate the effects of surface warming from the direct effects of CO₂. If multiple ensemble runs were conducted for a model, only the first realization is used. Models are listed in Table 2.1.

Table 2.1. CMIP5 models used in this study. Archived data from 1pctCO2 and abrupt4xCO2 experiments was used. Models have been identified with a number (#) used in multiple figures for identification.

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Each variable used in this analysis, besides \( R \), is available as direct model output. \( R \) is derived using modeled net LW and shortwave (SW) radiative fluxes at the surface and TOA. The monthly mean output is averaged to annual means and a time series of anomalies is calculated for each variable using the first ten years of data as a baseline. Many quantities are converted to percentage changes with respect to the mean of the baseline data, and results presented are areal-weighted global means, unless otherwise specified. In order to isolate longer scale variability, a ten-year moving average is applied to the time series of each globally averaged variable as a low-pass filter. We
consider the resultant low frequency variability to represent anthropogenic climate change (ACC). This data is compared to shorter scale variability, which is calculated by subtracting the ACC time series from the total time series. These shorter time scales of a year to a decade represent internal climate variability (ICV). The same methodology is applied to both the 1pctCO2 and abrupt4xCO2 simulations. On subannual timescales, the atmosphere is not subject to the same energy balance constraints discussed in Section 1 (Fasullo and Trenberth, 2008; Donahoe and Battisti, 2013), and therefore these timescales are not analyzed.

2.3 Results

2.3.1 Water Vapor, Radiative Cooling and Precipitation Changes

To assess whether the hydrological constraints on $\Delta P$ are timescale dependent, we calculate the sensitivity of each component of the atmospheric energy budget (and the sensitivity of $W$) by linearly regressing the time series of the respective variable to the time series of $\Delta T_s$. The linear regression slope represents the sensitivity. As an illustration, Figure 2.1 compares scatter plots of $\Delta W$ versus $\Delta T_s$, $\Delta P$ versus $\Delta T_s$, $L\Delta P$ versus $\Delta R$, $\Delta R$ versus $\Delta T$, and $\Delta SH$ versus $\Delta T_s$ for ACC (Fig. 2.1a-e) and ICV (Fig. 2.1f-j) from the 1pctCO2 simulation for the ACCESS1.3 model; the model whose behavior is closest to the ensemble-mean for each variable.

The correlation coefficient and linear regression slope is displayed for each relationship. All variable regressions in Figure 2.1 exhibit a linear relationship, but there are differences in the magnitude of the sensitivities, or slopes, between time scales. Although the correlation coefficients are generally lower for ICV, the reduced degrees of freedom for ACC likely contribute to its higher correlation coefficients. However, the
correlation of $\Delta SH$ versus $\Delta T_s$ for ICV is considerably lower than the correlations of the other relationships at this timescale and will be addressed in subsequent sections of this chapter.

**Figure 2.1.** Scatterplot of the global-mean change in quantities for the ACCESS1.3 model, using the 1pctCO2 simulation. Results are shown for column-integrated water vapor ($\Delta W$) vs. surface temperature ($\Delta T_s$), precipitation ($\Delta P$) vs. $\Delta T_s$, $L\Delta P$ (precipitation in energy form, latent heat flux) vs. radiative cooling ($\Delta R$) and $\Delta R$ vs. $\Delta T_s$ for anthropogenic climate change (a-e) and internal climate variability (f-j). Linear least-squares regression lines (black, dashed) and one-to-one lines (black, solid) are shown as necessary. Linear regression slope ($p$) and correlation coefficient ($r$) are displayed.

Figures 2.2 and 2.3 show sensitivities for the 1pctCO2 simulations from each model for ACC and ICV, respectively, calculated following the methodology outlined above. In
both figures, the red dashed lines indicate ensemble-means for ACC while the blue dashed lines indicate ensemble-means for ICV. Ensemble-mean $\frac{dW}{dT_s}$ (Figs. 2.2a and 2.3a) is nearly identical for ACC (7.4 %K$^{-1}$) versus ICV (7.6 %K$^{-1}$). Ensemble-mean $\frac{dP}{dT_s}$ (Figs. 2.2b and 2.3b) is less than $\frac{dW}{dT_s}$ for both ACC and ICV, in agreement with past studies (Allan and Ingram 2002; Held and Soden 2006 and others). Most importantly, we find that $\frac{dP}{dT_s}$ is systematically lower for ACC (1.5 %K$^{-1}$) compared to ICV (2.0 %K$^{-1}$).

Figure 2.2. Anthropogenic Climate Change global-mean a) column water vapor ($W$) sensitivity, b) precipitation ($P$) sensitivity c) ratio of latent heating change ($L\Delta P$) to radiative cooling change ($\Delta R$) and d) radiative cooling ($R$) sensitivity for each CMIP5 model listed in Table 2.1 for 1pctCO2 simulations. Dashed red line represents ensemble-mean (anthropogenic climate change). Ensemble-mean sensitivity for internal climate variability (blue dashed line) is displayed for comparison. Shaded regions of the same color show +/- 1 standard error of the mean.
As expected given the physical constraints outlined above, the ratio of $L\Delta P$ to $\Delta R$ maintains nearly a one-to-one relationship, however, on average $L\Delta P$ increases more than $\Delta R$ for ACC (Fig. 2.2c), and less than $\Delta R$ for ICV (Fig. 2.3c). This difference requires compensating differences in $\Delta SH$ in order to maintain equilibrium that is discussed in more detail below.

**Figure 2.3.** Internal Climate Variability global-mean a) column water vapor ($W$) sensitivity, b) precipitation ($P$) sensitivity c) ratio of latent heat flux change ($L\Delta P$) to radiative cooling change ($\Delta R$) and d) radiative cooling ($R$) sensitivity for each CMIP5 model listed in Table 2.1 for 1pctCO2 simulations. Dashed blue line represents ensemble-mean (internal climate variability). Ensemble-mean sensitivity for anthropogenic climate change (red dashed line) is displayed for comparison. Shaded regions of the same color show +/- 1 standard error of the mean.
Similar to $\frac{dP}{dT_s}$, $\frac{dR}{dT_s}$ is also smaller for ACC (Fig. 2.2d) compared to ICV (Fig. 2.3d), with ensemble-mean values of 0.8 Wm$^{-2}$K$^{-1}$ and 2.0 Wm$^{-2}$K$^{-1}$, respectively. Thus, $R$ increases more slowly with surface warming for ACC relative to ICV.

**Figure 2.4.** Sensible heat flux ($SH$) sensitivity for 1pctCO2 simulations for a) anthropogenic climate change and b) internal climate variability for each model listed in Table 2.1. Dashed black lines show ensemble-means.

In the 1pctCO2 simulations, $\frac{dSH}{dT_s}$ is robustly negative across models for ACC (Fig. 2.4a), in agreement with past studies of anthopogenically forced climate change simulations (Lambert and Webb 2008, Stephens and Ellis 2008). However, for ICV the sensible heat flux tends to increase with surface warming rather than decrease (Fig. 2.4b), and exhibits a less coherent relationship with temperature (Figure 2.1j, for example). The
different response of \( SH \) to warming is consistent with the findings in Figures 2.2c and 32.c that \( LP \) increases more than \( R \) for ACC, but increases less than \( R \) for ICV. For ACC, \( SH \) decreases with warming and \( R \) increases with warming, both contributing to increased atmospheric energy loss. Therefore, based on equation 2.1, \( LP \) must increase more than \( R \) to fully compensate for this energy loss (Fig. 2.2c). For ICV, however, \( SH \) increases with warming, offsetting some of the energy loss associated with increased \( R \). Therefore, \( LP \) increases less than \( R \) (Fig. 2.3c).

The effects of CO\(_2\) forcing are responsible for the differences in \( \frac{dP}{dT_s} \) and \( \frac{dR}{dT_s} \) between time scales (Figs. 2.2b,d and 2.3b,d). Increasing CO\(_2\) concentrations decreases the net outgoing TOA radiation more than it increases the downwelling surface radiation. This acts to heat the atmosphere, decreasing \( R \) and thereby suppressing the increase in \( P \) required to balance the energy budget (Allen and Ingram, 2002; Yang et al. 2003; Bony et al. 2013). This mechanism is effective for ACC but not for ICV, since the increases of CO\(_2\) are much larger on multi-decadal timescales (ACC) than inter-annually (ICV). Therefore, the response of \( R \) and \( P \) to direct CO\(_2\) forcing is greater on multi-decadal timescales, and consequently, both \( \frac{dP}{dT_s} \) and \( \frac{dR}{dT_s} \) is lower for ACC compared to ICV.

Under the 1pctCO2 simulations, \( R \), and therefore \( P \), respond concurrently to changes in CO\(_2\) concentrations and rising temperatures. When compared to the 1pctCO2 simulations, analysis of the abrupt4xCO2 simulations allows us to isolate each component and determine their relative contributions to the differences in sensitivity between ACC and ICV.

Figures 2.5 and 2.6 show sensitivities for ACC and ICV timescales, respectively, for the abrupt4xCO2 simulations. In contrast to the 1pctCO2 simulations, ensemble-
mean $\frac{dP}{dT_s}$ is nearly identical for ACC and ICV in the abrupt4xCO2 simulations (Figs. 2.5b and 2.6b). Similarly, the difference in $\frac{dR}{dT_s}$ between ACC and ICV that occurs in the 1pctCO2 simulations is almost completely absent in the abrupt4xCO2 simulations (Figs. 2.4d and 2.5d).

**Figure 2.5.** Same as Figure 2.2, but for abrupt4xCO2 simulations.

A slight difference between timescales does exist for ensemble-mean $\frac{dR}{dT_s}$ (and $\frac{dW}{dT_s}$) and likely reflects the unique aspects of the idealized abrupt4xCO2 simulations, such as rapid land-sea warming contrasts spurred by the instantaneous CO$_2$ quadrupling. Since $\frac{dP}{dT_s}$ and $\frac{dR}{dT_s}$ is reduced for ACC relative to ICV in the 1pctCO2 simulations, but not in the
abrupt4xCO2 simulations, this confirms that CO₂ effects are responsible for the difference between timescales.

**Figure 2.6.** Same as Figure 2.3, but for abrupt4xCO2 simulations.

Unlike \( \frac{dR}{dT_s} \) (and \( \frac{dP}{dT_s} \)), the difference in \( \frac{dSH}{dT_s} \) between timescales observed in the 1pctCO2 simulations also occurs in the abrupt4xCO2 simulations, where again \( \frac{dSH}{dT_s} \) is negative across most models for ACC (Fig. 2.7a) but tends to be positive for ICV (Fig. 2.7b). Because CO₂ does not change after the first day of the model integration, it is the temperature-dependent response of sensible heat flux, and not CO₂-induced changes, which is responsible for the differences in \( \frac{dSH}{dT_s} \) between timescales. Changes in sensible heat flux are strongly related to changes in the surface-air temperature difference, \( \Delta(T_{sk}) \).
$T_s$, where $T_{sk}$ is skin temperature, or sea surface temperature over oceans, and $T_s$ is the near-surface air temperature. This relationship is explored in Figure 2.8, which displays the linear regression slope of local changes in sensible heat flux ($\Delta SH$) to changes in global-mean near-surface air temperature $\Delta T_s$ for ACC (Fig. 2.8a) and ICV (Fig. 2.8b) for 1pctCO2 simulations. Maps of the regression between local changes in surface-air temperature difference $\Delta (T_{sk} - T_s)$ to changes in global-mean near-surface air temperature $\Delta T_s$ are also presented for ACC (Fig. 2.8c) and ICV (Fig. 2.8d).

**Figure 2.7.** Same as Figure 2.4, but for abrupt4xCO2 simulations.

For ACC, the sensitivity of $SH$ is uniformly negative over oceans, and tends to be positive over land. This is consistent with the spatial pattern of $\Delta (T_{sk} - T_s)$. Positive $\frac{dSH}{dT_s}$ over land can be explained by moisture constraints (Sherwood and Fu, 2014). $L\Delta P$ is
restricted by limited moisture availability over land; therefore $\Delta SH$ must be positive to maintain atmospheric energy demands. The positive $SH$ sensitivity requires enhanced warming at the surface, which the positive $(T_{sk}-T_s)$ sensitivities over land reflect.

![Figure 2.8](image)

**Figure 2.8.** Ensemble-mean linear regression of local changes in sensible heat flux ($\Delta SH$) to global-mean changes in near-surface air temperature difference ($\Delta T_s$) (local $SH$ sensitivity) for 1pctCO2 simulations for a) anthropogenic climate change and b) internal climate variability. Ensemble-mean linear regression of local changes in surface-air temperature difference ($\Delta(T_{sk}-T_s)$) to global-mean changes in near-surface air temperature ($\Delta T_s$) (local $(T_{sk}-T_s)$ sensitivity) for c) anthropogenic climate change and d) internal climate variability. All models are interpolated to a standard $2^\circ \times 2^\circ$ grid. Note, contours differ for each plot and are saturated at the minimum and maximum color bar values.

We are unaware of a similar hypothesis that explains the negative $\frac{dSH}{dT_s}$ over ocean. The difference in the response of sensible heat flux between ACC and ICV suggests that the reduction in $SH$ is not an intrinsic response of the ocean-atmosphere interface to
surface warming. For ICV, $\frac{dSH}{dT_s}$ is highly nonuniform over ocean, exhibiting a spatial pattern that is closely tied to the local changes in surface-air temperature difference (Figs. 2.8 b,d). This is consistent with the lack of coherence of global-mean $\Delta SH$ to $\Delta T_s$ displayed in Figure 2.1.

Additionally, from a subset of models, we make use of simulations where landmasses are removed (a so-called “aquaplanet” simulation) and a uniform surface warming of 4K is applied. Ensemble-mean $\frac{dSH}{dT_s}$ is negative in these simulations for most locations locally (not shown) and for the global average (-0.45 Wm$^{-2}$K$^{-1}$). This suggests that the $SH$ decrease with warming is not dependent on the presence of land.

2.3.2 Effects of Clouds on RadiativeCooling and Precipitation Changes

Clouds play a significant role in the atmospheric energy budget, and therefore are worthy of discussion in the context of precipitation changes, especially with regards to inter-model spread, which is notably greater in both $\frac{dP}{dT_s}$ and $\frac{dR}{dT_s}$ for ICV compared to ACC (Figs. 2.2b,d and 2.3b,d). We can consider the total-sky atmospheric radiative cooling, $R$, to be comprised of clear-sky ($R_{clr}$) and cloud contributions to atmospheric heating and cooling ($R_{cld}$) defined as:

$$R_{cld} = R - R_{ctr}, \quad (2.2)$$

The sensitivities of $R_{clr}$ and $R_{cld}$ are compared to the sensitivity of $R$ in Figure 2.9, where each point represents the global-mean for a single model. The figures, and all remaining analysis below, are shown for the 1pctCO2 simulations, but the results are nearly identical for the abrupt4xCO2 simulations. In agreement with previous studies (Stephens and Ellis 2008; Lambert and Webb 2008; Previdi 2010; Lambert et al. 2014),
ensemble-mean \( \frac{dR_{cld}}{dT_s} \) is negative, indicating that the global and column-averaged effect of warming induced changes in cloudiness and cloud forcing is to reduce radiative cooling (i.e., heat the atmosphere). This holds for both ACC (Fig. 2.9a) and ICV (Fig. 2.9b). Ensemble-mean \( \frac{dR_{cld}}{dT_s} \) for ACC, -0.42 Wm\(^{-2}\)K\(^{-1}\), is comparable to the ensemble-mean “cloud radiative forcing change” (0.55 Wm\(^{-2}\)K\(^{-1}\)) in Figure 2.6d from Previdi (2010), a synonymous quantity defined in that work to be positive for atmospheric heating.

Previdi (2010) considered timescales representative of ACC and concluded that cloud feedback is significantly responsible for inter-model spread in \( \frac{dR}{dT_s} \), with a contribution (standard deviation of 0.20 Wm\(^{-2}\)) to the spread comparable to the non-cloud component (standard deviation of 0.22 Wm\(^{-2}\)), represented as the combined lapse rate plus water vapor feedback contribution. In a similar analysis, O’Gorman et al (2012) concluded that cloud feedback was the largest contributor to inter-model spread in \( \frac{dR}{dT_s} \). In
contrast, our results show that for ACC, the inter-model spread of the clear-sky component accounts for a much greater portion of the model spread in $\frac{dR}{dT_s}$ than cloud effects do. This is consistent with findings by Pendergrass and Hartmann (2014).

Since the inter-model spread of $\frac{dR_{clr}}{dT_s}$ and $\frac{dR_{cld}}{dT_s}$ sum to the inter-model spread of $\frac{dR}{dT_s}$, the linear regression slopes listed in Figure 2.9 are a measure of each component’s contribution to the spread in $\frac{dR}{dT_s}$. Standard error is used as a measure of slope uncertainty. For ACC, spread in $\frac{dR_{clr}}{dT_s}$ accounts for 78%+/-15% of the inter-model spread in $\frac{dR}{dT_s}$, while $\frac{dR_{cld}}{dT_s}$ accounts for the remaining 22%+/-15% (Fig. 2.9a). In contrast, for ICV, $\frac{dR_{cld}}{dT_s}$ spread accounts for the majority (60%+/-12%) of the spread in $\frac{dR}{dT_s}$. Additionally, the range of $\frac{dR_{clr}}{dT_s}$ is similar for ICV and ACC time scales (1.6 Wm$^{-2}$K$^{-1}$ and 1.3 Wm$^{-2}$K$^{-1}$, respectively), while the range of $\frac{dR_{cld}}{dT_s}$ is much larger for ICV (2.0 Wm$^{-2}$K$^{-1}$), compared to ACC (1.0 Wm$^{-2}$K$^{-1}$). Therefore, the increased inter-model spread in $\frac{dR}{dT_s}$, and subsequently $\frac{dP}{dT_s}$, for ICV compared to ACC is due largely to increased inter-model spread in cloud radiative effects. The increased spread in $\frac{dR_{cld}}{dT_s}$ for ICV relative to ACC suggests that cloud feedbacks and their coherence with temperature change may differ between timescales, which warrants further investigation.

It is important to note that our methodology is not identical to that of Previdi (2010) and O’Gorman et al. (2012), since those studies made additional adjustments to cloud radiative forcing calculations that account for cloud masking effects (Soden et al. 2004; Soden et al. 2008). Accounting for cloud masking in our work would increase the
magnitude of $\frac{dR_{clld}}{dT_s}$ for each model, but since the bias is systematic across models (Soden et al. 2004), it would not change the conclusion that spread in $\frac{dR}{dT_s}$ is heavily influenced by spread in $\frac{dR_{clr}}{dT_s}$, especially for ACC.

Additionally, calculations by Previdi (2010) and O’Gorman et al. (2012) are produced from a single radiative transfer scheme, through the radiative kernel technique (Soden et al. 2008), while we use radiative fluxes produced from the unique radiative transfer scheme of each model. It has been shown that differences in model radiative parameterization contributes to inter-model spread in the SW component of $\frac{dR_{clr}}{dT_s}$ (Collins et al. 2006; Pendergrass and Hartmann 2014; DeAngelis et al. 2015; Fildier and Collins 2015). Based on methodology, our results may include this contribution to inter-model spread, while the findings by Previdi (2010) and O’Gorman et al. (2012) do not.

We further investigate $\frac{dR}{dT_s}$ spread by separating $\frac{dR_{clr}}{dT_s}$ and $\frac{dR_{clld}}{dT_s}$ into SW-only and LW-only components, indicated in the variable name with a corresponding subscript (i.e. $\frac{dR_{clld-LW}}{dT_s}$ for cloud-sky, LW radiative cooling sensitivity). In Figure 2.10, $\frac{dR_{clr-LW}}{dT_s}$ and $\frac{dR_{clr-SW}}{dT_s}$ for each model are plotted against $\frac{dR_{clr}}{dT_s}$ for ACC (Fig. 2.10a) and ICV (Fig. 2.10b). The same comparisons are made for the cloud-sky components (Fig 10c,d). As evident by the linear regression slopes displayed in the figure, the spread in the LW component accounts for the majority of the inter-model spread in $\frac{dR_{clr}}{dT_s}$, with some contribution from spread in the SW component. DeAngelis et al. (2015), studying the radiative response to surface warming in isolation, found a more equal inter-model spread contribution from $\frac{dR_{clr-LW}}{dT_s}$ and $\frac{dR_{clr-SW}}{dT_s}$, but in agreement with our study, the former
dominated. We find that inter-model spread in $\frac{dR_{cld}}{dT_s}$ is accounted for almost entirely by spread in the LW component, which is greater for ICV (~2.2 Wm$^{-2}$) compared to ACC (~1.2 Wm$^{-2}$). The influence of clouds on SW absorption is small, explaining the lack of contribution from the SW component to spread in $\frac{dR_{cld}}{dT_s}$ (Lambert and Webb 2008).

**Figure 2.10.** Model comparison of clear-sky radiative cooling ($R_{clr}$) sensitivity versus clear-sky, longwave ($R_{clr,LW}$) (blue) and clear-sky, shortwave ($R_{clr,SW}$) (red) radiative cooling sensitivity for 1pctCO2 simulations for a) anthropogenic climate change and b) internal variability. Model comparison of cloud-sky radiative cooling ($R_{cld}$) sensitivity versus cloud-sky, longwave ($R_{cld,LW}$) (blue) and cloud-sky, shortwave ($R_{cld,SW}$) (red) radiative cooling sensitivity for c) anthropogenic climate change and d) internal climate variability. Linear least-squares regression lines are shown along with corresponding slopes and +/- 1 standard error. Each point represents a single model.
The linear regression slope for each SW component is negative, or smaller than the uncertainty in the clear-sky ACC case, suggesting that $\frac{dW}{dT_s}$ is a dominant source of inter-model spread in the SW component of $\frac{dR}{dT_s}$. Water vapor enhances radiative cooling in total and in the LW, but also acts to increase SW absorption.

The magnitude of spread in $\frac{dR_{clr}}{dT_s}$, and dependency on LW versus SW components, is similar between ACC and ICV, and for both the 1pctCO2 and abrupt4xCO2 simulations (not shown), indicating that climate feedbacks and not external forcing are mainly responsible for the inter-model spread in $\frac{dR}{dT_s}$. Past studies have demonstrated that $\frac{dR_{clr}}{dT_s}$ is heavily dependent on water vapor (Stephens et al. 1994; Allan 2006; Stephens and Ellis 2008). The presence of water vapor increases LW emission to the surface, which is only partially compensated for by increased SW absorption (Mitchell et al. 1987; Allan 2006). With respect to inter-model spread, however, the relationships of $\frac{dW}{dT_s}$ to spread in $\frac{dR_{clr-LW}}{dT_s}$ and $\frac{dR_{clr-SW}}{dT_s}$ offset each other, limiting the dependency of $\frac{dR_{clr}}{dT_s}$ spread on $\frac{dW}{dT_s}$ spread for ICV, and almost eliminating the dependency entirely for ACC (not shown). Further investigation of the radiative cooling response to climate feedbacks, over both ACC and ICV time scales, using a technique like radiative kernels (Soden et al. 2008) is the next logical step toward defining the root causes of $\frac{dR}{dT_s}$ inter-model spread. This will be explored in later chapters.

2.4 Summary and Discussion

Using simulations from 23 CMIP5 models where CO2 is increased 1% per year, and simulations where CO2 concentration is instantaneously quadrupled from pre-industrial
values and then held fixed, we have analyzed the physical constraints on the global hydrological cycle and the response of $P$ to anthropogenic climate change (ACC) versus internal climate variability (ICV). We have done so by comparing $\frac{dW}{dT_s}$, $\frac{dP}{dT_s}$, $\frac{dR}{dT_s}$, $\frac{dSH}{dT_s}$, and the ratio of $L\Delta P$ to $\Delta R$ at annual-to-decadal versus multi-decadal time scales. We show that the ensemble-mean $\frac{dW}{dT_s}$ is close to values predicted by the Clausius-Clapeyron equation, and similar between ACC (7.4 $\%K^{-1}$) and ICV (7.6 $\%K^{-1}$) and that $\frac{dP}{dT_s}$, is similar in magnitude to $\frac{dR}{dT_s}$, supporting the argument outlined in previous studies that $\Delta P$ is constrained by the atmospheric energy budget.

Importantly, in the simulations with exponentially increasing CO$_2$, $\frac{dR}{dT_s}$, and subsequently $\frac{dP}{dT_s}$, is smaller for ACC compared to ICV due directly to the effects of the increasing CO$_2$ concentrations. $\Delta SH$ contributes to the atmospheric energy balance as well, and $\frac{dSH}{dT_s}$ also differs between timescales, but due to temperature-dependency alone and not CO$_2$ forcing. Differences in inter-model spread between timescales are addressed, with clouds shown to be responsible for increased spread in $\frac{dP}{dT_s}$ at ICV compared to ACC timescales.

The constraints of $\Delta P$ in a warming climate include two distinct components: a “slow” direct response of $P$ to $\Delta T_s$ on time scales of years and a “fast” response of $P$ directly to external forcing, such as CO$_2$, on time scales of weeks to months (Andrews et al. 2009; Bala et al. 2010; Frieler et al. 2011; Allan et al. 2014). Our finding that the largest CO$_2$ effect on $P$ occurs on multi-decadal time scales is not at odds with this concept. Rather, it shows that in a transient climate, the response of $P$ depends on the
magnitude of CO₂ concentration change, and not just on the presence of CO₂ forcing. Larger CO₂ increases occur with ACC, leading to a reduction in \( \frac{dP}{dT_s} \) compared to ICV. While separating the temperature and external forcing components as previous studies have done offers valuable insights into the constraints on \( \Delta P \), understanding how the two components evolve together is of equal importance in a climate where \( P \) continuously responds to both internal climate variability and externally forced change.

Our results ultimately highlight that the role of CO₂ on limiting \( \Delta R \) is minimal at sub-decadal time scales; therefore short-term trends in \( \Delta P \) with warming are a poor indicator of long-term change. This underlines the importance of developing an observing system capable of detecting low frequency climate variability. It is possible that other climate processes constrained by atmospheric radiative cooling change includes a response to CO₂ that is unobservable in the short term. We have identified important distinctions between ACC and ICV, and related responses of \( P \), that have implications on how we interpret both model results and our relatively limited record of global precipitation observations.
Chapter 3: Evaluating Climate Model Simulations of the Radiative Forcing and Radiative Feedbacks at the Earth’s Surface

3.1 Background

Changes to the Earth’s surface energy budget will have important effects on a warming climate, with significant societal implications. Changes to surface energy budget components influence, among other processes, the hydrological cycle (Andrews et al. 2009; Previdi 2010), land-sea temperature contrast (Joshi et al. 2008), soil moisture and aridity (Sherwood and Fu 2014), and vegetation physiology (DeAngelis et al. 2016).

Consisting of a radiative component and turbulent latent (LH) and sensible (SH) heat fluxes, the surface energy balance, $N$, can be written:

$$N = R_{LW} + R_{SW} + SH + LH,$$

(3.1)

where $R_{LW}$ and $R_{SW}$ are net downward longwave and shortwave radiative fluxes at the surface, respectively. Through analysis of the atmospheric energy budget, non-radiative terms are known to have considerable inter-model spread in the current generation of climate models (Allen and Ingram 2002; Stephens and Ellis 2008; Kramer and Soden 2016). However, differences in the surface radiative changes across models have received less attention.

The forcing-feedback framework for understanding top-of-atmosphere (TOA) radiative changes (e.g. Sherwood et al. 2015) can also be applied to radiative changes at the surface (Andrews et al. 2009; Colman 2015). A change in a forcing agent, such as CO$_2$ concentration, causes an instantaneous radiative perturbation at the surface, herein referred to as an instantaneous surface radiative forcing (ISRF). In response to the ISRF, rapid radiative adjustments in variables including air temperature, water vapor, and clouds can occur in direct response to the forcing, before any change in surface
temperature \((T_s)\). These further modify the initial surface radiative imbalance. We define the sum of these rapid radiative adjustments and ISRF as effective surface radiative forcing (ESRF).

Evaluating radiative forcing is crucial for interpreting climate responses in models and understanding why those responses differ across models. Spurred by efforts like the Radiative Forcing Model Intercomparison Project (Pincus et al. 2016), radiative forcing defined at the TOA has received increased attention in recent years. However, surface radiative forcing and its effects have been largely ignored, due in large part to the lack of quantitative diagnostics of ISRF. To the best of our knowledge, only Collins et al. (2006) has documented inter-model differences in ISRF, evaluating offline double-call radiative transfer calculations to do so. However, since these calculations are conducted separately from the model simulations, this limits the ability to draw conclusions regarding inter-model differences in ISRF and their connection to associated climate responses. Previdi and Liepert (2012) also computed ISRF in multiple models from double-call calculations, but only analyzed the ensemble mean. Colman (2015) evaluated surface radiative adjustments using the two-sided Partial Radiative Perturbation (PRP) Approach (Colman and McAveney 1997), but only in a single model. Inter-model differences in surface radiative adjustments have never been assessed.

Surface temperature responds to the ESRF, inducing temperature-mediated radiative feedbacks, which act to enhance or oppose the ESRF. While Colman (2015) isolated this surface radiative process from forcing components in a single model, inter-model differences have not been evaluated.
Here, for the first time, we will evaluate inter-model differences in ISRF, radiative adjustments and ESRF, using the radiative kernel technique combined with linear regression (Chung and Soden 2015a,b) applied to a large group of global climate models (GCMs) participating in the Coupled Model Intercomparison Project phase 5 (CMIP5; Taylor et al. 2012). We will also estimate radiative feedbacks with this methodology and identify sources of uncertainty that are particular to surface radiative changes.

3.2 Methods

3.2.1 Radiative Kernel-Regression

The radiative kernel technique (Soden and Held 2006; Soden et al. 2008) was developed to serve as a computationally efficient method for analyzing radiative changes across multiple models. Radiative Kernels ($K_x$) are the direct radiative response to a small perturbation of a radiatively-relevant state variable $x$ (e.g. temperature, water vapor, surface albedo). They are computed with an offline version of a model’s radiative transfer code, using model data from a simulation as input. To produce $K_x$, radiative fluxes are calculated at a high frequency (e.g. 3-hourly by Soden et al. (2008)) with a small perturbation in $x$ (at one vertical level for 3-d variables), while all other surface and atmospheric variables required to produce the fluxes remain unperturbed. The calculations are carried out again with no perturbations as a control. The radiative kernel is defined as the residual between the perturbed state and control radiative fluxes at the TOA or surface, herein referred to as TOA radiative kernels (TOA $K_x$) or surface radiative kernels (surface $K_x$), respectively. The latter will be used in this study.
Radiative kernels allow one to decompose the total change in radiative flux into contributions from each radiatively-relevant state variable. For small perturbations, the change in radiative flux for each variable \( x \) can be estimated as the product of \( K_x \) and its climatic response (\( \Delta x \)) as simulated by the model. In this study, we separate the climatic response of each variable into a temperature-mediated component and a rapid adjustment following Chung and Soden (2015a). To compute the temperature-mediated component, a timeseries of \( x \) at each latitude-longitude point and vertical level is regressed against a timeseries of global-mean \( T_s \) (specifically, near-surface air temperature in this study; results using skin temperature differ by less than 2.5\%). This temperature-mediated response multiplied by the appropriate radiative kernel constitutes the radiative feedback:

\[
\lambda_x = K_x \left( \frac{dx}{dT_s} \Delta T_s \right), \tag{3.2}
\]

where \( \lambda_x \) is a function of latitude, longitude, level and month of year. The rapid radiative adjustment is diagnosed by first subtracting the temperature-mediated component in equation 3.2 from the total change of the variable, calculated using finite differencing and then multiplying this difference by the appropriate radiative kernel:

\[
A_x = K_x (\Delta x - \frac{dx}{dT_s} \Delta T_s), \tag{3.3}
\]

where \( A_x \) is a function of latitude, longitude, level and month of year. For brevity, herein we refer to rapid radiative adjustments simply as radiative adjustments.

Due to nonlinearities in cloud-induced radiative changes, cloud radiative kernels cannot be quantified in same manner as temperature, moisture, and surface albedo kernels (Zelinka et al. 2012 offer an alternative cloud radiative kernel method, however). Instead, \( A_C \) and \( \lambda_C \) are estimated from changes in Cloud Radiative Effect (CRE) in model output,
and adjusted for cloud masking (Soden et al. 2008). We define $\lambda$ and $A$ as the sum of all individual radiative responses ($\lambda_i$) and radiative adjustments ($A_i$), respectively.

Clear-sky ISRF (ISRF$^{\text{clr}}$, whereby superscript $\text{clr}$ denotes clear-sky) is determined by subtracting the radiative responses and radiative adjustments from the clear-sky net radiative flux change ($\Delta R^{\text{clr}}$), which is estimated by finite differencing direct model output of radiative fluxes:

$$ISRF^{\text{clr}} = \Delta R^{\text{clr}} - (\lambda^{\text{clr}} + A^{\text{clr}}).$$  (3.4)

From an ensemble-mean of a small number of CMIP5 models where offline double-call radiative transfer calculations are available, we find that the presence of clouds reduces ISRF$^{\text{clr}}$ by (ISRF$^{\text{clr}}$-ISRF)/ISRF $\sim 0.37$, greater than the corresponding reduction at the TOA (Soden et al. 2008). We assume that the proportion of total-sky IRF to clear-sky conditions is constant (following Soden et al. 2004; Soden et al. 2008) and estimate total-sky ISRF by multiplying surface ISRF$^{\text{clr}}$ by 0.63 for all models.

### 3.2.2 Model Simulations and Radiative Kernels

Surface radiative forcing and responses are evaluated in 18 CMIP5 GCMs, using monthly mean data from simulations where CO$_2$ is abruptly quadrupled from preindustrial concentrations and then held constant (“abrupt4xCO$_2$”). Climatic responses in these simulations are estimated relative to a control simulation where a preindustrial forcing scenario is imposed (“piControl”). This allows for a clear separation of the fast (i.e. subannual) radiative forcing associated with the CO$_2$ perturbation, and the slow (i.e. years to decades), radiative responses to subsequent surface temperature increase. All models used in this study are listed in Table 3.1. Only the first realization is used if multiple ensemble members were run for a single model.
Following the methodology described in section 3.2.1, ISRF, $A_x$ and $\lambda_x$ at the surface are evaluated using surface radiative kernels generated from version 1.1 of the NCAR Community Earth Systems Model (CESM1.1), configured with version 5.0 of the Community Atmosphere Model (CAM5) (Pendergrass et al. 2018). These surface radiative kernels were developed following the methodology outlined by Soden et al. (2008). Specifically, they are the differential radiative response to a 1K warming at the surface and at each atmospheric level (temperature radiative kernel, $K_T$), an increase in atmospheric specific humidity anticipated from 1K warming with constant relative humidity (water vapor radiative kernel, $K_q$), and a 1% increase in surface albedo (albedo radiative kernel, $K_a$). Table 3.2 outlines key notation used throughout the study to describe the radiative kernels and associated radiative calculations.

<table>
<thead>
<tr>
<th>#</th>
<th>Model</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>ACCESS1.0</td>
<td>Bi et al. (2013)</td>
</tr>
<tr>
<td>2</td>
<td>BNU-ESM</td>
<td>Ji et al. (2014)</td>
</tr>
<tr>
<td>3</td>
<td>CanESM2</td>
<td>Arora et al. (2011)</td>
</tr>
<tr>
<td>4</td>
<td>CCSM4</td>
<td>Meehl et al. (2012)</td>
</tr>
<tr>
<td>5</td>
<td>CNRM-CM5</td>
<td>Voldoire et al. (2013)</td>
</tr>
<tr>
<td>6</td>
<td>GFDL-CM3</td>
<td>Donner et al. (2011)</td>
</tr>
<tr>
<td>7</td>
<td>GFDL-ESM2G</td>
<td>Dunne et al. (2012)</td>
</tr>
<tr>
<td>8</td>
<td>GFDL-ESM2M</td>
<td>Dunne et al. (2012)</td>
</tr>
<tr>
<td>9</td>
<td>HadGEM2-ES</td>
<td>Collins et al. (2011)</td>
</tr>
<tr>
<td>10</td>
<td>INMCM4</td>
<td>Volodin et al. (2010)</td>
</tr>
<tr>
<td>11</td>
<td>IPSL-CM5A-LR</td>
<td>Dufresne et al. (2013)</td>
</tr>
<tr>
<td>12</td>
<td>IPSL-CM5A-MR</td>
<td>Dufresne et al. (2013)</td>
</tr>
<tr>
<td>13</td>
<td>MIROC5</td>
<td>Watanabe et al. (2010)</td>
</tr>
<tr>
<td>14</td>
<td>MIROC-ESM</td>
<td>Watanabe et al. (2011)</td>
</tr>
<tr>
<td>15</td>
<td>MPI-ESM-LR</td>
<td>Stevens et al. (2013)</td>
</tr>
<tr>
<td>16</td>
<td>MPI-ESM-P</td>
<td>Giorgetta et al. (2013)</td>
</tr>
<tr>
<td>17</td>
<td>MRI-CGCM3</td>
<td>Yukimoto et al. (2012)</td>
</tr>
<tr>
<td>18</td>
<td>NorESM1-M</td>
<td>Betsen et al. (2013)</td>
</tr>
</tbody>
</table>
Table 3.2. A description of key notation used to describe radiative kernels and associated calculations throughout the text.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K_x$</td>
<td>Radiative kernel corresponding to a perturbation in state variable $x$, where $x$ is temperature ($T$), water vapor ($q$), or surface albedo ($a$)</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Total temperature-mediated radiative response</td>
</tr>
<tr>
<td>$A$</td>
<td>Total radiative adjustment</td>
</tr>
<tr>
<td>$\lambda_x$</td>
<td>Temperature-mediated radiative response to a change in $x$, where $x$ is temperature ($T$), water vapor ($q$), surface albedo ($a$) or clouds ($C$)</td>
</tr>
<tr>
<td>$A_x$</td>
<td>Radiative adjustment to a change in $x$ where $x$ is temperature ($T$), water vapor ($q$), surface albedo ($a$) or clouds ($C$)</td>
</tr>
<tr>
<td>ISRF</td>
<td>Instantaneous Surface Radiative Forcing</td>
</tr>
<tr>
<td>ESRF</td>
<td>Effective Surface Radiative Forcing</td>
</tr>
<tr>
<td>$\lambda_K$</td>
<td>Total temperature-mediated radiative response estimated using radiative kernels</td>
</tr>
<tr>
<td>$\lambda_G$</td>
<td>Same as above, but estimated from Gregory Regression</td>
</tr>
<tr>
<td>ISRF$_K$</td>
<td>Instantaneous Surface Radiative Forcing estimated from the radiative kernel residual method (Eq. 4), using $\lambda_K$ to account for $\lambda$</td>
</tr>
<tr>
<td>ISRF$_G$</td>
<td>Same as above, but using $\lambda_G$ to account for $\lambda$</td>
</tr>
<tr>
<td>ISRF$_D$</td>
<td>Instantaneous Surface Radiative Forcing estimated from offline double-call calculations</td>
</tr>
</tbody>
</table>

Figure 3.1a shows the atmospheric component of the total-sky zonal-mean, annual-mean surface $K_T$. For clarity, only the response to perturbations in the lowest one-tenth of the atmosphere is shown, since, above this point, the zonal mean magnitude is negligible. Importantly, surface $K_T$ has a large vertical gradient in these lowest layers of the atmosphere. The atmospheric values are positive, therefore an increase in temperature in the atmospheric column increases net radiation into the surface. In contrast, the surface component of surface $K_T$ ($K_{Ts}$) is negative (Fig. 3.1b), as warming of the surface decreases net radiation into the surface (increases net outgoing from the surface). Due to the large contribution from the surface component, the vertically integrated, global, annual mean surface $K_T$ is negative.
In principle, the surface $K_{Ts}$ response should stem entirely from a change in upwelling LW radiation, approximately equal to the first derivative of the Stephan-Boltzmann equation. Assuming realistic climatological surface temperatures and surface emissivity, global-mean surface $K_{Ts}$ should be about -5.5 Wm$^{-2}$K$^{-1}$. Since atmospheric temperature is not perturbed in this calculation, there should be no change in surface downwelling LW flux. Contrary to these expectations, the global-mean surface $K_{Ts}$ from this set of kernels is only -3.78 Wm$^{-2}$K$^{-1}$, including an increase in downwelling LW flux of 1.7 Wm$^{-2}$K$^{-1}$ at the surface (accounting for the reduced magnitude of surface $K_{Ts}$ relative to Stephan-Boltzmann scaling). The downwelling LW flux is slightly smaller for clear-sky conditions, so total-sky surface $K_{Ts}$ is 0.03 Wm$^{-2}$K$^{-1}$ smaller than the clear-sky counterpart. The clear-sky and total-sky surface temperature kernels would be identical were it not for this unexpected change in LW downwelling. This feature is an artifact of the methodology used to calculate the radiative fluxes in radiative transfer models (RTM). When computing the radiative fluxes, the contributions from each model layer mid-point are determined using average temperatures between adjacent level interfaces. In the course of this conversion to the RTM vertical grid, a prescribed temperature increase at the surface also affects the lowest-layer air temperature, inducing a change in the downwelling radiation at the surface. When the lowest atmospheric layer is perturbed 1 K in surface $K_T$, a corresponding and compensating additional upwelling LW flux from the surface is induced. This downwelling LW feature also occurs in surface radiative kernels generated from some other RTMs (Previdi 2010; Previdi and Liepert 2012; Soden et al. 2008), but has not been previously documented. It will be discussed version in Chapter 5.
Figure 3.1. Zonal, annual-mean surface radiative kernels, including: a) total-sky temperature surface radiative kernel (surface $K_T$) in Wm$^{-2}$K$^{-1}$100hPa$^{-1}$, b) the surface-temperature component of surface $K_T$ (surface $K_{Ts}$) in Wm$^{-2}$K$^{-1}$ for total-sky (solid line) and clear-sky (dashed line) conditions, and total-sky c) longwave (surface $K_{q,LW}$) and d) shortwave (surface $K_{q,SW}$) water vapor radiative kernels in Wm$^{-2}$K$^{-1}$100hPa$^{-1}$. For clearer visualization of low-level features, the atmospheric column is only shown below $\sigma=0.9$ for surface $K_T$ and only below $\sigma=0.5$ for surface $K_{q,LW}$ and $K_{q,SW}$.

Figure 1b,c shows total-sky longwave (LW) and shortwave (SW) components of the water vapor surface radiative kernel (surface $K_{q,LW}$ and $K_{q,SW}$, respectively), similar to Figure 1a, but shown for the lowest half of the atmosphere. Surface $K_{q,LW}$ is positive almost everywhere, and a maximum in the tropical boundary layer. The contribution from high latitudes is small, due to lack of moisture. The shortwave (SW) water vapor kernel $K_{q,SW}$ is negative, as increased SW absorption in the atmosphere leads to decreased SW absorption at the surface.
Since high water vapor concentrations in the boundary layer absorb much of the downwelling radiation emitted from the middle and upper troposphere, the surface radiative kernels are dominated by the very lowest layers of the troposphere, where large vertical gradients in moisture are present. Consequently, estimates of surface radiative responses are quite sensitive to the magnitude of the radiative kernels at these levels, and thus, how vertical interpolation is applied to the radiative kernels. Radiative kernels are typically interpolated to standard pressure levels to match model output, but this results in undefined values at grid points with a surface pressure less than the lowest standard pressure level (1000 hPa), missing part of the near-surface kernel response, which makes a substantial contribution to the radiative flux at the surface. To preclude this problem, in this study, all radiative kernels with a vertical dimension are used on the original CESM hybrid-sigma coordinates, and the accompanying CMIP5 model output used to compute forcings and radiative responses are interpolated to the same vertical coordinate.

3.2.3 Gregory Regression

The total surface radiative feedback, $\lambda$, is calculated as the sum of individual radiative feedbacks derived from radiative kernel-regression technique (Eqs. 3.2 and 3.4). It can also be obtained more directly from model output using linear regression following Gregory et al. (2004), where $\lambda$ is defined as the slope of the linear regression of net surface radiative imbalance against global-mean $\Delta T_s$. In Figure 3.2, $\lambda$ is shown for each CMIP5 model, estimated using the radiative kernel-regression method ($\lambda_K$) and Gregory regression ($\lambda_G$). The linear relationship and strong agreement ($r = 0.86$, RMSE = 0.17 W/m$^2$/K) suggests that the radiative kernel-regression method produces a reasonable estimate of $\lambda$ at the surface. Additionally, the difference between the clear-sky radiative
responses ($\lambda_{K}^{clr}$ and $\lambda_{G}^{clr}$) is <10% for 14 of the 18 models (not shown). This percent error benchmark, termed the clear-sky linearity test, has been used in previous studies to assess the effectiveness of radiative kernels to quantify individual radiative responses in a given model (Vial et al. 2013; Jonko et al. 2012).

![Figure 3.2](image_url)

**Figure 3.2.** Global-mean sum of surface radiative feedbacks estimated from the radiative kernel-regression method versus that estimated from the Gregory regression method. Numbered markers correspond to the CMIP5 models listed in Table 3.1.

We note, however, that this test evaluates not only the linearity assumption, but also the consistency between the differential behavior of radiative transfer models. The fact that there are 3 noticeable outliers seems more likely to result from bias between the transmittance calculations of the RTMs, rather than non-linearities in radiative perturbations that are unique to only those 3 models.
3.3 Results

3.3.1 Surface Radiative Forcing

If a perturbation of a forcing agent is prescribed identically across models, one may expect the resulting radiative forcing to also be identical. However, recent work has indicated that model differences in TOA ERF are an important source of uncertainty in climate projections (Forster et al. 2013, Vial et al. 2013), and that TOA IRF accounts for a substantial portion of that inter-model spread (Chung and Soden 2015a,b). Inter-model differences in ESRF and ISRF have not been previously quantified.

Offline double-call calculations of the instantaneous surface radiative forcing (ISRF_D) are not typically performed and are only available for a small subset of models. Instead, we use radiative kernels to estimate ISRF^clr as a residual calculation (Eq. 3.4) and then apply a proportionality constant to retrieve total-sky ISRF in all models, following the methodology used by Chung and Soden (2015a,b) for the TOA. Error in the radiative kernel calculation of λ^clr, which is typically an order of magnitude larger than ISRF^clr (see Figure 3.4), can contribute to error in this residual calculation. However, as noted above, λ^clr can be estimated using the Gregory regression method (λ_G^clr) instead of the radiative kernel-regression method (λ_K^clr), reducing the potential for radiative kernel error in the calculation of λ to be aliased into ISRF. Hereafter, we refer to ISRF estimated using λ_K^clr or λ_G^clr as ISRF_K or ISRF_G, respectively. In Figure 3.3, ISRF_D, ISRF_K and ISRF_G are compared for the 6 CMIP5 models where double call calculations are available. The difference between ISRF_K and ISRF_D is large (RMSE = 0.94 Wm⁻²), especially for 4 of the 6 models shown. The agreement is better between ISRF_G and ISRF_D (RMSE = 0.35 Wm⁻²), suggesting that errors in the residual calculation of ISRF mostly stem from the
radiative kernel calculation of $\lambda_{K}^{clr}$. Furthermore, it indicates that this error can be reduced by using $\lambda_{G}^{clr}$ (and thus ISRF$_{G}$), instead.

**Figure 3.3.** Global-mean instantaneous surface radiative forcing (ISRF) computed from double-call calculations versus that estimated using radiative kernels. Each numbered marker corresponds to a CMIP5 model listed in Table 3.1. For black markers, radiative kernels were used to estimate both the radiative feedback and radiative adjustment term. For red markers, the Gregory regression method was used to estimate the radiative feedback, while radiative kernels were used to estimate radiative adjustment. Results are shown only for those models where data for all three methods are available.

The disagreement between ISRF$_{K}$ and ISRF$_{D}$ compared to ISRF$_{G}$ also implies that there are systematic differences in the transmittance calculations between the RTMs of the model and the kernel. Differences in the treatment of water vapor are one possible explanation, which has been noted previously for the shortwave radiative fluxes (Collins et al. 2006; DeAngelis et al. 2015). For CanESM2, global-mean ISRF$_{D}$ (1.74 Wm$^{-2}$) differs substantially from both ISRF$_{K}$ (1.1 Wm$^{-2}$) and ISRF$_{G}$ (0.99 Wm$^{-2}$), while the latter
two are much more similar. This is a sole outlying case, and suggests that ISRF_D is inconsistent with the simulated fluxes from the CanESM2 abrupt4xCO_2 simulation, potentially due to the details of this particular double-call calculation.

![Figure 3.4](chart.png)

**Figure 3.4.** Global, ensemble-mean of surface radiative feedbacks (left), surface radiative adjustments (middle) and instantaneous surface radiative forcing (right) for clear-sky conditions.

Even though radiative kernels are also used to estimate A_{cline}, uncertainty in ISRF_K is mostly associated with λ_{cline}. This occurs because absolute λ_{cline}, expressed in Wm^{-2}, is considerably larger than A_{cline}, as in Eq. 3.3 and 3.4. Our explanation is as follows: radiative adjustments occur before any surface warming response, so associated temperature and water vapor changes in the boundary layer are minimal. Since the
surface radiative imbalance is insensitive to perturbations above the boundary layer (Fig 3.1), $A^{clr}$ is relatively small. Figure 3.4 shows the global, ensemble-mean of the clear-sky radiative feedbacks ($\lambda_x^{clr}$), radiative adjustments ($A_x^{clr}$), and instantaneous surface radiative forcing ($ISRF_K^{clr}$). The radiative feedbacks are substantially larger than the corresponding adjustments. Accordingly, the large $\lambda_x^{clr}$ can translate to a large absolute error between surface $\lambda_K^{clr}$ and $\lambda_G^{clr}$.

$ISRF_G$ is also more accurate than $ISRF_K$ spatially, compared to $ISRF_D$. While ensemble-mean $ISRF_G$ is near zero or positive everywhere, in agreement with $ISRF_D$, $ISRF_K$ is large and negative in the Arctic (Fig. 3.5). In this region, ensemble-mean $\lambda_K^{clr}$ is greater than both $A^{clr}$ and $dR^{clr}$ (not shown), mostly due to the clear-sky surface albedo radiative feedback ($\lambda_a^{clr}$), which is the largest radiative feedback north of 65$^\circ$ N by a factor of ~3. Similarly, Chung and Soden (2015a) estimated TOA IRF$_K$ to be negative in the Arctic. This discrepancy is due to the inability of radiative kernels to capture nonlinearity in $\lambda_a^{clr}$, which weakens as the amount of sea-ice decreases (Colman and McAveney 2009). Previous work shows that TOA $K_a$ derived from a base climate at 1xCO$_2$ is larger than one derived from a climate with elevated CO$_2$ concentrations, especially in the Arctic (Jonko et al. 2012; Block and Mauritsen 2013). Although these analyses examine the TOA, this finding should also apply to the surface. Since clear-sky SW absorption in the atmospheric column is small, $K_a$ is very similar for the TOA and surface. Consistent with $\lambda_a^{clr}$ overall, the magnitude of surface $K_a$ is smaller when less sea-ice is present in the baseline climate, like under elevated CO$_2$ compared to 1xCO$_2$ (Jonko et al. 2012). Therefore, the 1xCO$_2$ kernel used here should overestimate $\lambda_a^{clr}$ in the abrupt4xCO$_2$ simulations. $ISRF_G$ is not subject to this kernel-related bias in $\lambda_a^{clr}$, and
therefore is positive in the Arctic. Hereafter, for analyses of ISRF across all 18 models, we focus our attention on ISRF

Figure 3.5. Zonal, ensemble-mean total-sky instantaneous surface radiative forcing (ISRF) in which total surface radiative feedback component is quantified using the radiative kernel-regression method (ISRF\textsubscript{K}), the Gregory Regression method (ISRF\textsubscript{G}), and offline double-call calculations (ISRF\textsubscript{D}).

Global-mean ISRF\textsubscript{G} is shown in Figure 3.6 for the full suite of CMIP5 models used in this study. The inter-model spread in ISRF\textsubscript{G} is 2.30 Wm\textsuperscript{-2}, similar to the spread in ISRF\textsubscript{D} (2.16 Wm\textsuperscript{-2}). Among the subset of models where both estimates are available (red numbers in Figure 3.6a), the inter-model spread in ISRF\textsubscript{G} (1.83 Wm\textsuperscript{-2}) is slightly smaller than ISRF\textsubscript{D}, suggesting that the kernel residual calculation underestimates the model spread.
Figure 3.6. Global-mean inter-model comparison of total-sky instantaneous surface radiative forcing (ISRF) estimated using radiative kernels and double-call calculations in a subset of CMIP5 models. Numbered markers correspond to the CMIP5 models listed in Table 3.1. For models where both methods are available, markers are red.

In addition to spread across models, the ensemble-mean of ISRF\textsubscript{G}, ISRF\textsubscript{K} (not shown) and ISRF\textsubscript{D} are very similar. This result may not hold at the TOA, however, as Chung and Soden (2015b) found disagreement between the magnitudes of TOA IRF\textsubscript{K} and TOA IRF\textsubscript{D}. That study used a different set of radiative kernels developed from the GFDL model (Soden et al. 2008), which is a potential factor in the difference.

In a different, larger ensemble of ISRF\textsubscript{D,clr} calculations forced by instantaneous doubling of CO\textsubscript{2}, Collins et al. (2006) found a range of ~1.3 Wm\textsuperscript{-2} in the LW and ~3.5 Wm\textsuperscript{-2} in the SW. They only evaluated clear-sky fluxes, not total-sky. Assuming ISRF\textsubscript{D,clr} for a doubling of CO\textsubscript{2} is twice as large for a quadrupling, the spread in the Collins et al. ensemble would translate to a range of ~2.6 Wm\textsuperscript{-2} in the LW and ~7.0 Wm\textsuperscript{-2} in the SW.
under 4xCO$_2$. This is in close agreement with our estimates of spread in LW ISRF$_G$ and ISRF$_D$$_{clr}$, but more than twice as large for the SW components. The reduced SW spread would suggest modeling groups have addressed sources of uncertainty in SW parameterization schemes in response to the findings by Collins et al. Additionally, in the Collins et al. ensemble from the Radiative Transfer Model Intercomparison Project, each double-call calculation includes a different RTM, but an identical base climate used to initialize the simulations. The ensemble of CMIP5 ISRF$_D$$_{clr}$ used here contains differences in both components across models. Therefore, another explanation for the smaller SW range in the CMIP5 models is that spread associated with RTM and base climate differences may compensate to some degree, which may have been introduced in the model tuning process (Mauritsen et al. 2012; Hourdin et al. 2017).

Variability in ISRF is substantial; however, it does not fully account for the model differences in ESRF. Inter-model spread in ESRF is 3.5 Wm$^{-2}$ when estimated as the sum of kernel-derived radiative adjustments and ISRF$_G$. This spread is further decomposed in Figure 3.7, which compares global-mean ESRF to ISRF$_G$ for each model. There is a strong, linear relationship under total-sky conditions ($r = 0.90$, RMSE = 0.82 Wm$^{-2}$), indicating that much of the inter-model spread in ESRF can be attributed to inter-model differences in ISRF and thus, differences in radiative transfer algorithms across CMIP5 models, or model differences in base climate state. However, the agreement is stronger under clear-sky conditions ($r = 0.95$, RMSE = 0.39 Wm$^{-2}$), indicating that cloud adjustments also contribute significantly to the spread of ESRF.
Additionally, the magnitude of ESRF is systematically larger than ISRF under total-sky conditions (Fig 3.7a, positive bias of 0.68 Wm\(^{-2}\)) but similar under clear-sky conditions, indicating that cloud adjustments also contribute significantly to the magnitude of ESRF, while non-cloud radiative adjustments do not.

3.3.2 Radiative Adjustments and Radiative Feedbacks

For each model, Figure 3.8a displays the global-mean surface radiative adjustments. The cloud radiative adjustments have the dominant (1.83 Wm\(^{-2}\)) inter-model spread among the total radiative adjustment at the surface, and also have the largest ensemble-mean of any adjustment (0.77 Wm\(^{-2}\)). Radiative adjustments should be independent of surface temperature change. However, most models exhibit a nonzero, slightly negative Planck adjustment, even though the Planck effect is entirely surface-temperature-dependent by definition. Also, surface albedo adjustment is negative (an increase in upwelling SW) in all but one model, which is unphysical, since there is no process that would lead to sea ice becoming more reflective under rising CO\(_2\) concentrations (Block and Mauritsen 2013). These findings, along with similarities in the
horizontal spatial structure between ensemble-mean $A_x$ and $\lambda_x$, and between $A_x$ and initial surface warming patterns (not shown) suggest that some of temperature-driven response is aliased into $A_x$, an artifact of the regression method. This supports conclusions drawn by Chung and Soden (2015a), who found similar artifacts in the magnitude and spatial structure of $A_x$ at the TOA.

The radiative kernel-regression technique also affords the opportunity to estimate surface radiative feedbacks in isolation. Inter-model differences in these feedbacks are displayed in Figure 3.8b. The water vapor radiative feedback ($\lambda_q$) has an ensemble-mean of 1.31 Wm$^{-2}$K$^{-1}$, the largest feedback at the surface. The lapse rate feedback ($\lambda_{LR}$) is small in both magnitude and inter-model spread, unlike the analogous $\lambda_{LR}$ at the TOA. The surface does not respond radiatively to a change in lapse rate. The cloud radiative feedback ($\lambda_C$) exhibits the largest inter-model spread, but the ensemble-mean is small (0.06 Wm$^{-2}$K$^{-1}$) and there is an even distribution of positive and negative $\lambda_C$ across models.

Previously, Previdi and Liepert (2012) used ECHAM5-based radiative kernels to evaluate $\lambda_x$ in simulations where CO$_2$ was instantaneously doubled (they did not make a distinction between $\lambda_x$ and $A_x$, since finite differencing was used to compute $\Delta x$). They similarly found that $\lambda_q$ is the largest radiative feedback at the surface. However, they estimated $\lambda_T$ (sum of $\lambda_{LR}$ and Planck effect, $\lambda_{Pl}$) and $\lambda_q$ responses to be comparatively smaller in magnitude across models, with an ensemble-mean of -0.60 Wm$^{-2}$K$^{-1}$ and 0.89 Wm$^{-2}$K$^{-1}$, respectively.
Figure 3.8. Inter-model comparison of global-mean a) surface radiative adjustments and b) surface radiative feedbacks estimated using surface radiative kernels. Each point represents a single model. Ensemble-means are marked with a black dash. Results are averaged over the 140-year time period of the integration.

To better match their methodology, we estimate the same radiative responses using finite differencing for $\Delta x$, and still find estimates that are substantially larger ($-1.06 \text{ Wm}^{-2}\text{K}^{-1}$ and $1.35 \text{ Wm}^{-2}\text{K}^{-1}$) than those of Previdi and Liepert (2012). This indicates $\lambda_x$ may be particularly sensitive to the choice of radiative kernels used. The magnitudes $\lambda_T$ and $\lambda_q$ in
our study agree more closely with findings by Colman (2015), who combined regression with the Partial Radiative Perturbation (PRP) approach to evaluate \( \lambda \) in a single model.

At the TOA, \( \lambda_{LR} \) and \( \lambda_q \) are anticorrelated (Soden and Held 2006), and multiple studies have shown that the sum of the TOA \( \lambda_{LR} \) and \( \lambda_q \) exhibits less inter-model spread than the individual components. Previous literature is inconsistent on whether this compensation also applies to atmospheric (TOA minus surface) radiative responses that constrain the hydrological cycle. O’Gorman et al. (2012), using radiative kernels developed from ECHAM5 (Previdi 2010), found there is compensation between inter-model spread in atmospheric \( \lambda_{LR} \) and \( \lambda_q \), while Flaschner et al. (2016), using radiative kernels developed from ECHAM6, found that summing the two components does not markedly reduce inter-model spread. The latter was in agreement with findings by Pendergrass and Hartmann (2014), which diagnosed radiative responses but did not use radiative kernels. Flaschner et al. (2016) show that almost all of the inter-model spread in the sum of atmospheric \( \lambda_{LR} \) and \( \lambda_q \) stems from model disagreement in the lower troposphere, where the magnitude of the ECHAM5 and ECHAM6 radiative kernels are noticeably different. We find no compensation in surface \( \lambda_{LR} \) and \( \lambda_q \). Since these responses are almost solely related to changes in the lower troposphere (Figs. 3.1 and 3.2), this implies compensation does not occur for atmospheric radiative responses either, consistent with Flaschner et al. (2016). Chapter 5 will offer further support that anticorrelation is not present in the atmospheric response.
3.4. Summary

In this study we have documented sources of inter-model spread in the net surface radiative flux response to a quadrupling of CO$_2$ concentration. Using the radiative kernel technique combined with linear regression, we have decomposed the total surface response into instantaneous surface radiative forcing (ISRF), radiative adjustments ($A_x$) and temperature-mediated radiative feedbacks ($\lambda_x$) in an ensemble of CMIP5 model simulations. These radiative changes influence a range of climate processes, including the intensification of the hydrological cycle. Using the surface radiative budget to characterize inter-model spread in the fast response of the hydrological cycle to effective surface radiative forcing (ESRF), we find that ISRF exhibits an inter-model spread of 2.3 Wm$^{-2}$ and accounts for most of the inter-model spread in ESRF. This suggests that differences in the transmittance algorithms between models contributes to inter-model spread in fast hydrological cycle changes. This is consistent with other recent work indicating that this uncertainty associated with radiation schemes contributes to inter-model spread in the temperature-mediated hydrological cycle changes (DeAngelis et al. 2015; Fildier and Collins 2015; Pincus et al. 2015). On this basis, we would expect improvements in the accuracy of radiative transfer in climate models that lead to the convergence of estimates of ISRF will also lead to convergence among models in the projected response of hydrological cycle to forced change.

Beyond the initial forcing and adjustment, as surface temperature responds to the ESRF, water vapor change spurs the dominant linear, temperature-dependent radiative feedback at the surface, while the ensemble-mean cloud feedback is small. It has previously been shown that at the TOA, inter-model spread of the sum of non-cloud
feedbacks is reduced relative to individual non-cloud feedbacks, since water vapor and lapse rate responses at the TOA are highly anticorrelated. The surface signature of the lapse rate feedback is negligible, so this compensation does not play a role in the surface radiative response. As a result, cloud and non-cloud radiative feedbacks both contribute substantively to inter-model spread in total radiative response at the surface ($\lambda$).

The difference in surface radiative forcing and feedback across models contributes to uncertainty in projections of a wide range of climate change processes, including intensification of the hydrological cycle. This evaluation of ISRF, radiative adjustments and radiative feedbacks, and the associated inter-model spread, is an important step towards reducing that uncertainty.
Chapter 4: Inter-model Spread in Instantaneous Radiative Forcing Across Multiple Climate Drivers

4.1 Background

The effective radiative forcing (ERF) is a widely used concept for diagnosing the response of the climate to different forcing agents and has proven to be important for understanding why climate models respond differently to identical emission scenarios (Houghton et al. 2001; Gregory et al. 2004; Forster and Taylor 2006). The ERF consists of two parts - the instantaneous radiative forcing (IRF), which measures the perturbation in top-of-atmosphere radiative fluxes due solely to a change in the forcing agent, and radiative adjustments, which measure the radiative perturbations induced by the atmosphere’s response to the IRF (Boucher et al. 2013; Forster et al 2016). Recent efforts to diagnose uncertainty in ERF have largely focused on radiative adjustments, in part because IRF is not routinely calculated in climate model simulations. Here we use a multi-model ensemble of climate model simulations under various idealized forcing scenarios to show that differences in IRF, not radiative adjustments, are the dominant contributor to inter-model spread in ERF. Because IRF is relatively well constrained by radiative transfer theory, it provides a tractable solution to reducing the intermodel spread and error in ERF and, consequently, future climate change projections.

Instantaneous radiative forcing (IRF) quantifies the imbalance in the Earth’s top-of-atmosphere (TOA) energy budget induced directly from variations in a forcing agent. Climate change occurs in response to this imbalance, as the climate system attempts to restore equilibrium. While ERF is representative of the total radiative forcing that drives the climate response (Sherwood et al. 2015), findings by Chung and Soden (2015b) indicate that the differences in IRF account for a substantial amount of the intermodel
spread in ERF for an increase in CO\textsubscript{2} and results in Chapter 3 suggest this also holds for the analogous components of the surface radiative budget. Soden et al. (2018) recently highlighted that this spread in CO\textsubscript{2} IRF has been largely unchanged for decades, despite it being well constrained by both laboratory measurements and radiative transfer theory (Collins et al. 2006). Because the IRF has not been routinely evaluated in global climate models (GCMs) for other forcing agents, the full contribution of radiative transfer diversity to uncertainty in climate change projections is not known.

Here we use the radiative kernel technique (Soden et al. 2008; Chung and Soden 2015b) to diagnose the IRF and ERF in 11 GCMs participating in the Precipitation Driver Response Model Intercomparison Project (PDRMIP) (Myhre et al. 2017), which was designed to further understanding of the hydrological cycle response to changes in various relevant forcing agents.

4.2 Methods

4.2.1 Climate Model Simulations

Simulations from 11 PDRMIP models are used (CanESM, ECHAM6-HAM2, GISS ModelE, HadGEM2-ES, HadGEM3, IPSL-CM5A, MIROC-SPRINTARS, MPI-ESM, NCAR CESM1/CAM4, NCAR CESM1/CAM5, NorESM1). For each forcing scenario, results are presented for all models where necessary output is available. Not all forcing scenarios are available for each model. Further details are provided in Table 4.1 as well as Table 3 of Myhre et al. (2017). Models are run in a fixed-SST configuration (minimum 15 years long) and a fully coupled climate configuration (100 years long). Effective radiative forcing (ERF) and radiative adjustments are estimated by differencing
years 6-15 of the fixed-SST perturbed and base integrations. Global-mean surface temperature change is estimated from the change in the last 50 years of the fully coupled simulations. The forcing scenarios evaluated in this study include a doubling of carbon dioxide (CO$_2$x2), a tripling of methane (CH$_4$x3) a tenfold increase in Black Carbon (BCx10), a fivefold increase in sulphates (SO$_4$x5) and a 2% increase in solar irradiance (solar+2%). For the scaling of IRF in Figure 4.1, global-mean present-day radiative forcing estimates from Chapter 8 of Working Group I from the IPCC Fifth Assessment Report (Myhre et al. 2013) are used. For CO$_2$, CH$_4$ and solar irradiance,
observations and reconstruction were used to estimate the present-day radiative forcing, while estimates of BC and SO$_4$ radiative forcing relied on chemistry-climate models. In this Chapter, inter-model spread is quantified with the range.

### 4.2.2 The Radiative Kernel Technique with Fixed-SST Simulations

While traditionally used to quantify radiative feedbacks in coupled model simulations (e.g. Soden et al. 2008) the radiative kernel technique can also be applied to fixed-SST simulations to quantify radiative adjustments and instantaneous radiative forcing (IRF). Radiative kernels ($K_x$) represent the direct radiative response at the TOA to a small perturbation in surface temperature ($T_s$), atmospheric temperature ($T$), specific humidity ($q$) or surface albedo ($a$). They are developed by initializing an offline version of a climate model’s radiative transfer code with output from the base climate of that model and then performing radiative transfer calculations with small perturbations in individual state variables. The difference in net TOA fluxes between perturbed and control calculations is $K_x$, defined in the latitudinal, longitudinal, vertical and time dimensions, averaged to monthly means. Clear-sky radiative kernels ($K_x^0$) are calculated by setting cloud properties to zero. A more detailed description of the radiative kernel methodology is presented in Chapter 6. In this study, we use radiative kernels developed from four climate models: CESM (Pendergrass et al. 2018), ECHAM6 (Block and Mauritsen 2013), GFDL (Soden et al. 2008), and HadGEM2 (Smith et al. 2018), and present IRF averaged over the radiative kernels for a robust evaluation.

In fixed-SST simulations where radiative feedbacks are nonexistent, clear-sky instantaneous radiative forcing (IRF$^0$) is given by
\begin{equation}
IRF^0 = ERF^0 - \left( K_{T_s}^0 \Delta T_s + K_T^0 \Delta T + K_q^0 \Delta q + K_a^0 \Delta a \right). \tag{4.1}
\end{equation}

where ERF$^0$ is clear-sky effective radiative forcing calculated from TOA model fluxes, and the terms in the parenthesis are individual radiative adjustments, calculated by multiplying rapid adjustments in $T_s$, $T$, $q$, and $a$ by the corresponding clear-sky radiative kernel and vertically integrating when applicable. The methodology for quantifying radiative adjustments with kernels is described in more detail by Smith et al. (2018). Calculating IRF from the difference of ERF and radiative adjustments is referred to in this chapter as the kernel-differencing method.

### 4.2.3 Cloud Masking of the Instantaneous Radiative Forcing

Since clouds scatter, emit and absorb radiation, their presence modifies the TOA radiative imbalance relative to clear-sky conditions. This is known as cloud masking (Soden et al. 2008) and explains the difference between all-sky instantaneous radiative forcing (IRF) and IRF$^0$. The kernel-differencing method cannot be used to estimate IRF directly, because cloud adjustments must be considered in the calculation, which requires IRF to already be known. Instead IRF is estimated by multiplying IRF$^0$ by a constant that corrects for cloud masking (Soden et al. 2008; Chung and Soden 2015). For CO$_2$x2 and CH$_4$x3, we calculate this constant (0.831 and 0.832, respectively) by dividing offline radiative transfer calculations of IRF and IRF$^0$ conducted by Smith et al. (2018) and averaging over 8 PDRMIP models where these calculations were possible. Inter-model spread in cloud-masking is found to be less than 15% of the model mean for these forcing scenarios, but since a single radiative transfer model is used for these calculations, only cloud masking differences due to base state diversity are accounted for, not differences in radiative transfer parameterization across climate models. For BCx10 and SO$_2$x5, the
cloud masking constant (1.661 and 0.571, respectively) is quantified by dividing IRF and IRF\(^0\) diagnosed from a limited number of double call calculations archived by PDRMIP modeling groups. Inter-model spread, expressed as the range, is 8.5 % of the model mean for BCx10 and 17% for SO\(_4\)x5, but this is only based on 3 models and 2 models, respectively. The all-sky IRF for solar+2% is not evaluated in this study, but can be calculated from model output of planetary albedo.

4.2.4 Approximate Partial Radiative Perturbation Method

Adding aerosols to the atmosphere brightens clouds by increasing the concentration of cloud condensation nuclei and decreasing cloud droplet effective radii (Twomey 1977). This encapsulates the aerosol-cloud interaction component of instantaneous radiative forcing (RFaci), where total IRF is the sum of RFaci and a component associated with aerosol-radiation interactions (RFari) (Boucher et al. 2013). Under greenhouse gas forcing, the RFaci term is zero.

Since the kernel-differencing method only accounts for the presence of clouds and not cloud changes, only RFari is quantified with this technique. Alternatively, we use the Approximate Partial Radiative Perturbation (APRP) method to diagnose RFaci, whereby a simple one-layer model of the atmosphere is tuned to mimic a climate model’s full radiative transfer code and parameters are perturbed according to the climate responses of each PDRMIP model (Taylor et al. 2007; Zelinka et al. 2014). The APRP method is only recommended for quantifying shortwave (SW) responses, so the longwave is not analyzed here. Furthermore, non-cloud adjustments can be aliased into the RFaci with this method, reducing the accuracy for BCx10 in particular where such adjustments are large. We therefore only apply the APRP method to the SO4x5 forcing scenario.
4.3 Results

Since the kernel-differencing method for estimating IRF does not, alone, account for the component associated with aerosol-cloud interactions (ACI), we focus first on clear-sky results, but later show that conclusions are similar for all-sky conditions, especially when alternative methods are used to account for ACI. The IRF$^0$ and its spread exhibits considerable diversity across the five perturbation scenarios. Scaled by the ratio of present-day radiative forcing for each forcing agent to that of historical CO$_2$ forcing (IPCC AR5 WG I Chapter 8 [Myhre et al. 2013]) for more straightforward comparison (Figure 4.1 only), the weighted IRF$^0$ is largest in magnitude for CO$_2$x2 and largest in inter-model spread for SO$_4$x5 (or second largest to CO$_2$x2 when ignoring an outlying model).

Figure 4.1. Global, ensemble-mean clear-sky instantaneous radiative forcing (IRF$^0$) in W/m$^2$ weighted by the ratio of historical radiative forcing to that of historical CO$_2$ forcing (bars) and the global-mean weighted IRF$^0$ of each model (red markers) for the five forcing scenarios analyzed in this study.
For CH$_4$x3, BCx10 and SO$_4$x5, the inter-model spread is roughly equal to or larger than the ensemble-mean. In contrast, spread in the Solar+2% weighted IRF$^0$ is just 4% of its ensemble-mean, and exhibits the smallest absolute spread among the forcing scenarios. Radiative kernel estimates of longwave (LW) IRF$^0$ for Solar+2% are near-zero for all models (Figure 4.2). Since it is known that solar irradiance has no LW component, this result provides validation of the radiative kernel technique for diagnosing IRF$^0$.

The IRF$^0$ is positive for all individual models and the ensemble-means, except for SO$_4$x5, which is uniformly negative. For CH$_4$x3 and SO$_4$x5, and to a lesser extent BCx10, the magnitudes of IRF$^0$ and ERF$^0$ are similar (Figure 4.3), since non-cloud radiative adjustments are small or cancel out (Smith et al. 2018). This does not hold for CO$_2$x2 where strong stratospheric adjustments contribute to the magnitude of ERF$^0$ (Chung and Soden 2015b). Importantly, for all four of these forcing scenarios, model spread in IRF$^0$ and ERF$^0$ exhibits a strong, linear relationship (Figure 4.3), highlighting that IRF$^0$ contributes substantially to the spread in ERF$^0$ for these forcing scenarios.
Figure 4.2. Global-mean clear-sky shortwave (orange) and longwave (blue) instantaneous radiative forcing (IRF$^0$) estimated using radiative kernels for the models with necessary output.

As an alternative to the radiative kernel-differencing method, Smith et al. (2018) estimated IRF$^0$ from offline radiative transfer calculations where the base state variables from each PDRMIP model were run through the SOCRATES radiative transfer model (Manners et al. 2015).
Figure 4.3. Global-mean clear-sky instantaneous radiative forcing (IRF$^0$) versus clear-sky effective radiative forcing (ERF$^0$) for a) CH$_4$x3, b) CO$_2$x2, c) BCx10 and d) SO$_4$x5. Each marker represents a different model listed in Supplementary Table S1. For c) and d) red markers are used for models with prescribed aerosol concentrations and blue markers for models with prescribed aerosol emissions. The one-to-one line is shown.

Since a single radiative transfer model was used for all calculations, the estimates only account for spread due to model base state differences, not differences in radiative transfer parameterization. In contrast, the kernel-differencing method includes both sources of uncertainty. For CH$_4$x3, the spread in IRF$^0$ from Smith et al. (0.37 W/m$^2$) is just 37% of the spread estimated from the kernel-differencing method shown in Figure 4.3 (1.00 W/m$^2$), suggesting that differences in radiative transfer parameterization accounts for most of the spread in IRF$^0$, not base state differences. For CO$_2$x2, the IRF$^0$
spread from Smith et al. (0.76 W/m²) is more comparable to spread from kernel-differencing estimates (0.95 W/m²), indicating that base state differences explain more of the spread in IRF₀ for CO₂x2 than for CH₄x3. Due to technical limitations and a lack of data availability, the offline SOCRATES calculations were not possible for BCx10 or SO₄x5.

Some PDRMIP models performed baseline simulations with prescribed aerosol emissions, while others included prescribed aerosol concentrations (Myhre et al. 2017). This divide is evident in the forcing spread. For SO₄x5, the concentration models (Figure 4.3d, red markers) exhibit smaller IRF₀ and ERF₀ than the smallest emission model (blue markers). For BCx10, the concentration models generally have smaller forcing as well, and exhibit notably less spread than the emission models (Figure 4.3c). It is evident that the level of experimental control in a given model intercomparison project will impact evaluations of radiative forcing model spread.

All-sky IRF and ERF (herein just IRF and ERF) exhibit a strong, linear relationship for CH₄x3, and CO₂x2 (Figure 4.4a,b), albeit slightly weaker than their clear-sky counterparts. This may be a byproduct of our assumption that the cloud masking of IRF is the same for all models, thus introducing error when converting from IRF₀ to IRF. Double-call radiative transfer calculations under clear- and all-sky conditions from each model would be necessary to evaluate this. Similarly, spread in the IRF calculations from Smith et al. accounts for diversity in cloud masking, while the kernel-differencing method does not. Therefore, while spread in IRF is more comparable between the two methods than for IRF₀, this may be due to the kernel-differencing method underrepresenting cloud climatology diversity, not an inference about the relative
contribution of base state versus radiative transfer parameterization diversity to uncertainty in IRF.

Figure 4.4. Same as Figure 4.3 but for all-sky conditions. For d) SO$_4$x5, IRF is the sum of net IRF estimated from the kernel-differencing method and shortwave RFaci estimated from the Approximate Partial Radiative Perturbation method (see text). For all other forcing scenarios, IRF is solely from the kernel-differencing method.

Despite that the kernel-derived IRF only accounts for RFari and not RFaci, kernel-derived IRF and ERF are well correlated for BCx10 ($r = 0.71$, including a single outlying model) (Figure 4.4c) suggesting that the spread in ERF is mostly dictated by spread in RFari. For SO$_4$x5 however, kernel-derived IRF (RFari) and ERF are weakly related (Figure 4.5a, for instance), indicating that RFaci plays a greater role in overall spread. The Approximate Partial Radiative Perturbation (APRP) method can be used to
diagnose RFaci for the shortwave (Methods; [15,16]). When used for the 7 models with necessary output the sum of SW RFaci from APRP and the net RFari estimated from kernels is highly correlated with ERF (Figure 4.4d). There is also a near one-to-one relationship, indicating that radiative adjustments and LW RFaci are small. When SW RFaci is accounted for, it is evident that IRF dictates spread in ERF for all-sky SO₄x5.

![Graphs showing SW RFari and SW RFari + RFaci versus ERF](image)

**Figure 4.5.** a) The global-mean all-sky shortwave (SW) component of instantaneous radiative forcing (IRF) from aerosol-radiation interactions (RFari) versus SW effective radiative forcing (ERF) for SO₄x5 and b) the sum of SW RFari and the component of SW IRF from aerosol-cloud interactions (RFari+RFaci) versus SW ERF. Red markers are used for models with prescribed aerosol concentrations and blue markers for models with prescribed aerosol emissions. The one-to-one line is shown.

### 4.4 Summary

We have found that spread in ERF can mostly be explained by spread in IRF for idealized greenhouse gas and aerosol forcing scenarios, highlighting that radiative transfer implementation is a substantial and ubiquitous source of uncertainty in climate change projections, while model spread in radiative adjustments is less so. For BCx10 specifically, spread in surface temperature change estimated from fully coupled simulations can be directly traced to spread IRF (Figure 4.6). This is expected given that BC-induced warming is strongly dictated by radiative forcing compared to other climate
drivers, where feedbacks dominate (Samset et al. 2016; Myhre et al. 2017; Stjern et al. 2017).

Figure 4.6. Global-mean all-sky instantaneous radiative forcing (IRF) versus the change in global-mean surface temperature ($\Delta T_s$) for the models where fully-coupled simulations were available to estimate $\Delta T_s$.

It is disconcerting that IRF contributes so considerably to uncertainty in climate responses and while activities aimed at reducing spread in IRF present many technical challenges, there is no uncertainty in our knowledge of radiative transfer that would inhibit an ability to make progress. IRF is known from accurate line-by-line calculations, for example. Therefore, efforts to reduce uncertainty in climate change projections by addressing the spread in IRF should be a high-yield endeavor compared to addressing the plethora of other sources of uncertainty where considerable gaps in our knowledge exist.
Chapter 5: An Inter-comparison of Radiative Kernels

5.1. Background

Diagnosing radiative forcing and feedbacks in climate models, and more recently in observations, has become a cornerstone of modern climate science. This exercise is used, as in previous chapters, to describe the energetic processes that dictate the sensitivity of the Earth’s climate and highlight sources of uncertainty in projections of future climate change. The approaches for doing so each have unique strengths and limitations (Soden et al. 2004; Bony et al. 2006). For example, the Partial Radiative Perturbation approach (Colman and McAvaney 1997) is highly accurate and allows for the isolation of individual forcing and feedback terms, but it is computationally intensive and thus cannot be used to systematically evaluate radiative responses over multiple models. The sensitivity of the climate can also be quantified directly from changes in radiative fluxes (Cess et al. 1990, Gregory et al. 2004). While the calculations are straightforward, they do not allow for decomposition into individual forcing and feedbacks terms.

First formally outlined by Soden et al. (2008), the radiative kernel technique is both computationally efficient and allows individual feedback and forcing terms to be quantified (Chung and Soden 2015a). Consequently, the method is highly popular for diagnosing the magnitude of radiative responses and inter-model spread. In this approach, radiative feedbacks are assumed to be a product of the climate response of a state variable and the direct radiative response to an incremental perturbation in that variable. The latter term is the radiative kernel, derived from offline radiative transfer calculations initialized with climatological state variables and cloud information. Perturbations are made in
surface temperature (Ts), atmospheric temperature (T), humidity (q) or surface albedo (a) to quantify the differential radiative responses.

Traditionally the offline radiative transfer code and climatological data are sourced from a climate model. Therefore, the radiative kernel is subjected to biases in the model’s base climate and to errors associated with the unique configuration of the radiative transfer code, such as the radiative parameterization. The computational efficiency and consequent popularity of the radiative kernel technique stems from the notion that these biases are small, so a single radiative kernel can be used to systematically diagnose radiative forcing and feedbacks in an ensemble of climate models to evaluate model spread. Soden et al. (2008) found that radiative feedbacks quantified with three different radiative kernel sets agreed within 10% when zonally averaged and 5% when globally averaged. However, since the comparison by Soden et al. the number of radiative kernel sets developed from different climate models has grown considerably, as has the diversity of applications for the radiative kernel technique. Results from more recent studies indicate that radiative kernel sets differ more than first noted by Soden et al. For example, Smith et al. (2018) found inter-kernel differences in radiative adjustments to stratospheric cooling. Soden et al. (2008) only evaluated responses in the troposphere.

It has also recently been argued that disagreement in the literature regarding the contribution of non-cloud atmospheric radiative responses to total inter-model spread may stem from differences in the atmospheric (TOA-surface) radiative kernels used in the studies. O’Gorman et al. (2012), using radiative kernels developed from ECHAM5 (Previdi 2010), found that while lapse rate and water vapor atmospheric feedbacks
exhibit large inter-model spread, that spread is reduced when the two components are summed. Such compensation is exhibited in TOA feedbacks (e.g. Bony et al. 2006). In contrast, Flaschner et al. (2016), using radiative kernels developed from ECHAM6, found that summing the two components does not reduce inter-model spread. Additionally, Flaschner et al. (2016) found longwave atmospheric water vapor feedback is positive while O’Gorman et al. (2012) found it to be negative. Flaschner et al. attributes these disagreements to differences in the spatial structure and magnitude of the longwave water vapor radiative kernels used in the two studies. In Chapter 3 of this dissertation, we also noted that disagreement between our estimates of temperature and water vapor surface feedbacks and those of Previdi and Liepert (2012) may stem from differences in radiative kernels.

No comprehensive inter-comparison of radiative kernels has been conducted since the earlier work by Soden et al. (2008), so little is known about potential sources of error in the radiative kernel technique. To address this, we conduct an inter-comparison of 6 different radiative kernel sets provided by the research groups who developed them. For each set, we quantify radiative feedbacks in a suite of models participating in the Coupled Model Intercomparison Project phase 5 (CMIP5) (Taylor et al. 2013) to document methodological sources of uncertainty in the diagnosis of radiative responses that are associated with radiative kernels. Also, to determine the contribution of climatological biases, vertical resolution and radiative transfer diversity to differences in radiative kernels, we evaluate an ensemble of new radiative kernels derived from the base states of multiple CMIP5 models with a single radiative transfer code.
5.2. Methods

5.2.1 Radiative Kernel Methodology

The existing radiative kernel sets compared in this study were all developed following the methodology of Soden et al. (2008). In this approach, subdaily state variables and cloud information are input into an offline radiative transfer model and shortwave (SW) and longwave (LW) radiative fluxes are saved from the top of the atmosphere (TOA) and the surface (SFC). Radiative transfer calculations are repeated for each time step with small, successive perturbations in a single state variable at each horizontal and vertical grid point. This includes a 1 K increase in air temperature, a 1 K increase in surface temperature, an increase in specific humidity corresponding to a 1 K temperature increase with constant relative humidity and a 1 % additive increase in surface albedo. The difference in fluxes between the perturbed and control calculations, averaged to monthly means, is the TOA or SFC radiative kernel for air temperature (K$_T$), surface temperature (K$_{Ts}$), water vapor (K$_q$) and surface albedo (K$_a$), respectively. The radiative kernels for the atmospheric column (ATM) are defined as the difference between the TOA and SFC radiative kernels. Clear-sky radiative kernels (K$_x^0$) are generated following the same methodology described above but with cloud properties set to zero in all radiative transfer calculations.

5.2.2 Existing Radiative Kernel Ensemble

Table 5.1 lists 6 sets of radiative kernels developed from different climate models by the research groups referenced therein and collected for this inter-comparison. We only consider radiative kernels developed from a climatological base state, as opposed to kernels from a state with elevated CO$_2$ concentrations, for example (Jonko et al. 2012;
Block and Mauritsen 2013). All groups provided TOA and SFC radiative kernels on the climate model’s native vertical and horizontal coordinates.

**Table 5.1.** List of existing radiative kernel sets derived from GCMs that are compared in this study.

<table>
<thead>
<tr>
<th>Radiative Kernel – Model</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>BMRC</td>
<td>Soden et al. (2008)</td>
</tr>
<tr>
<td>CESM</td>
<td>Pendergrass et al. (2018)</td>
</tr>
<tr>
<td>ECHAM5</td>
<td>Previdi (2010)</td>
</tr>
<tr>
<td>ECHAM6</td>
<td>Block and Mauritsen (2013)</td>
</tr>
<tr>
<td>GFDL</td>
<td>Soden et al. (2008)</td>
</tr>
<tr>
<td>HadGEM2</td>
<td>Smith et al. (2018)</td>
</tr>
</tbody>
</table>

By comparing radiative kernel sets developed outside of this study, we lose some level of experimental control. While all radiative kernel sets in this ensemble were developed following the methodology of Soden et al. (2008), any small deviations from this approach may be a source of kernel difference that will be difficult to diagnose. In order to identify sources of kernel uncertainty more systematically, we will also assess additional ensembles of new radiative kernels developed with a consistent methodology specifically designed to isolate individual contributions to radiative kernel differences.

### 5.2.3 CMIP5 Radiative Kernel Ensembles

We develop new radiative kernels using climatological base states from 6 climate models participating in CMIP5 (Table 5.2), following the methodology of Soden et al. (2008). We use the final year of daily mean data from pre-industrial control simulations to establish the base state. While it is common to derive radiative kernels from a single
year of data (e.g. Soden et al. 2008; Pendergrass et al. 2018), daily-mean data is coarser in temporal resolution than usual. It is used here to maximize the number of CMIP5 models with necessary data to compute radiative kernels with. In the next chapter we will show there is a negligible difference between radiative kernels developed on 6 hourly timesteps and those developed using a single time step per day.

**Table 5.2.** List of CMIP5 models used to develop radiative kernels described in Section 5.2.3.

<table>
<thead>
<tr>
<th>Radiative Kernel – Model</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>CanESM2</td>
<td>Arora et al. (2011)</td>
</tr>
<tr>
<td>HadGEM2-ES</td>
<td>Collins et al. (2011)</td>
</tr>
<tr>
<td>IPSL-CM5A-LR</td>
<td>Dufresne et al. (2013)</td>
</tr>
<tr>
<td>MIROC5</td>
<td>Watanabe et al. (2010)</td>
</tr>
<tr>
<td>MIROC-ESM</td>
<td>Watanabe et al. (2011)</td>
</tr>
<tr>
<td>MPI-ESM-LR</td>
<td>Stevens et al. (2013)</td>
</tr>
</tbody>
</table>

Instead of using the radiative transfer model native to each CMIP5 GCM, all calculations use the offline broadband SOCRATES radiative transfer model (Manners et al. 2015). For each CMIP5 model, three different sets of radiative kernels are generated: calculations conducted a) on the native vertical coordinates of each model using the base state of each model, b) on the native vertical coordinates of CanESM2 with the base state of each model and c) on the native vertical coordinates of CanESM2 with non-cloud base state fields from each model but cloud fields from CanESM2. Comparing these ensembles of CMIP5 kernel sets with each other and with the ensemble of existing kernels allows us to diagnose the contribution of base state biases to radiative kernel
uncertainty, the relative contribution of cloud versus non-cloud fields, and the role of vertical resolution diversity.

5.2.4 Quantifying Feedback Terms

To further evaluate uncertainties in the radiative kernel technique, we use the radiative kernel sets to quantify radiative feedback in 18 CMIP5 coupled model simulations with an instantaneous quadrupling of CO$_2$ (abrupt4xCO2), listed in Table 3.1 of Chapter 3. Non-cloud radiative feedbacks are diagnosed by multiplying $K_x$ by the climate response of $x$ from each model, where $x$ is temperature, specific humidity or surface albedo. In Chapter 3, we separated the feedback and adjustment components using linear regression. Here the climate response is diagnosed from finite differencing between model output under a perturbed and control state so, accordingly, all radiative adjustment and feedback terms are included in the same response, herein referred to as a feedback.

Due to the nonlinear response of overlapping clouds, there is no radiative kernel specific to cloud perturbations in the standard radiative kernel technique. Alternatively, cloud feedbacks are diagnosed from changes in cloud radiative effects (CRE), estimated from the difference of all-sky and clear-sky model fluxes. The change in CRE is corrected for cloud masking using the difference between kernel-derived all-sky and clear-sky non-cloud feedback terms (Soden et al. 2008; Chung and Soden 2015a).

5.3 Results

Figure 5.1 shows the ensemble-mean of CMIP5 atmospheric (ATM) radiative feedbacks computed with different existing radiative kernel sets listed in Table 5.1. The vertical distribution of points illustrates inter-kernel differences in the estimate of each
feedback. ATM water vapor feedback exhibits the largest inter-kernel spread. This is mostly due to the fact that the ECHAM5 kernel is a substantial outlier, supporting the conclusions by Flaschner et al. (2016) that differences in the longwave atmospheric water vapor feedback between their calculations and O’Gorman et al. (2012) are due to kernel differences. Furthermore, ECHAM5 is the only kernel where the sum of ATM lapse rate and water vapor feedbacks are positive. ATM cloud feedback also exhibits notable inter-kernel spread. This spread stems from differences in kernel estimates of cloud masking and thus differences in the cloud climatologies of each model used to derive the radiative kernels.

Planck feedback exhibits the second most inter-model spread of all individual terms, while the ATM lapse rate feedback estimate is consistent across kernels. This is because lapse rate response is largest in the free troposphere, while ATM temperature radiative kernel differences are most prominent in the boundary layer. This is consistent with Figure 5.2, which shows that surface (SFC) Planck feedback (Fig. 5.2b) exhibits more than twice as much inter-kernel spread than TOA Planck feedback (Fig. 5.2a). The former is calculated with SFC $K_T$, which is comprised almost entirely of radiative responses to temperature perturbations in the lowest atmospheric layers (Figure 3.1, for example). Inter-kernel spread is also larger for SFC water vapor and cloud feedbacks compared to their TOA counterparts.
Figure 5.1. Ensemble-mean, global-mean atmospheric (TOA-SFC) feedbacks diagnosed with different radiative kernels listed in the legend and in Table 5.1. Terms include Planck, lapse rate (LR), water vapor (WV), the sum of lapse rate and water vapor, surface albedo, and cloud feedback as well as the sum of feedbacks due to changes in the stratosphere (Strato) and due to changes throughout the column (Sum). The vertical distribution of points shows inter-kernel differences in the feedback estimates.

In addition to diagnosing mean radiative feedback differently, we find that radiative kernels diagnose feedback inter-model spread differently. In Figure 5.3, each point shows the inter-model spread of an atmospheric feedback across 18 CMIP5 models, diagnosed using one of six radiative kernel sets. The vertical distribution of points is therefore inter-kernel differences in estimates of inter-model spread.
Figure 5.2. Same as Figure 5.1 but for a) TOA and b) surface (SFC) feedbacks.

In absolute terms, estimates of inter-model spread in ATM cloud feedback (Figure 5.3) exhibits the largest inter-kernel differences. If considered relative to the average inter-model spread, however, ATM Planck feedback exhibits the largest kernel differences. When the ECHAM5 kernel is used, inter-model spread in the sum of ATM lapse rate and
water vapor feedback is substantially smaller than spread in the individual components. This is a unique case. For all other kernels, inter-model spread in the combined feedback is roughly equal to or larger than model spread in the individual components. This confirms arguments by Flaschner et al. (2016) that radiative kernel differences explain why O’Gorman et al. (2012) found reduced spread in the sum of ATM lapse rate and water vapor feedback, while they did not. Given that most radiative kernels in our analysis show that summing the two feedbacks does not reduce inter-model spread, our findings suggest an anticorrelation between lapse rate and water vapor feedback found at the TOA is not present in the atmospheric column, as alluded to in Chapter 3.

![Figure 5.3](image). Inter-model spread in atmospheric (ATM) feedbacks diagnosed with different radiative kernels listed in the legend and in Table 5.1. Each point represents the inter-model spread (expressed as a range) diagnosed using a given radiative kernel.

Taking into consideration that ATM radiative kernels are the difference of TOA and SFC radiative kernels, we find that most of the kernel disagreement in the diagnosis
of ATM feedback inter-model spread is associated with differences in SFC radiative kernels, not TOA kernels. This is evident in Figure 5.4, which shows that inter-model spread is more consistently diagnosed across kernels for TOA feedbacks (Fig. 5.4a) than for SFC feedbacks (Fig 5.4b). One notable exception is TOA cloud feedback, where estimates of inter-model spread range from ~ 1.2 to 1.5 W/m²/K. In contrast SFC cloud feedback inter-model spread is robustly ~ 1 W/m²/K across kernels.

While the magnitude of inter-model spread for a given feedback term is kernel dependent, relative to other terms spread is consistent across kernels, with the exception of ECHAM5. For instance, regardless of kernel used, TOA cloud feedback exhibits the largest inter-model spread of any individual TOA feedback term, followed by roughly equal spread in lapse rate and water vapor feedback, while TOA Planck feedback exhibits the smallest inter-model spread.

Radiative kernel uncertainty can stem from three sources: biases in the model’s climatological base state, differences in radiative transfer modeling, or differences in the vertical resolution. We assess multiple radiative kernel ensembles that, when compared, will isolate the relative contribution of each source to the overall uncertainty. For each type of TOA and SFC radiative kernel (K_x), Figure 5.5 shows the spread (equivalent to the range) in the globally and annually averaged, and vertically integrated radiative kernels for the ensemble of 6 existing kernels shown in Figures 5.1 through 5.4. Spread is also shown for the three ensembles of 6 new radiative kernels where members are: a) calculated with the same offline radiative transfer model (RTM) but different CMIP5 base states (Table 5.2) and on each model’s native vertical coordinates (herein the NATIVE ensemble), b) calculated with the same RTM and different base states but on
the same vertical coordinates (COORD), and c) calculated with the same RTM, same vertical coordinates, same climatological cloud fields but different non-cloud variables (COORD-CLD).

Figure 5.4. Same as Figure 5.3 but for a) TOA and b) surface (SFC) feedbacks.

For each TOA $K_x$, inter-kernel spread is nearly identical for the ensemble of existing radiative kernels and the NATIVE ensemble. Members in the former ensemble are derived with a different RTM and different base state, while members in the latter are derived from the same RTM. The similarity in spread would therefore suggest that TOA
radiative kernels are not sensitive to discrepancies in radiative transfer modeling. In contrast for SFC $K_x$, the NATIVE ensemble has considerably smaller spread than the existing kernels, with the exception of SFC SW $K_q$ (Fig. 5.5d). This suggests that much of the uncertainty in SFC $K_x$ can be attributed to differences in radiative transfer modeling.

With the exception of SW $K_q$ (Fig. 5d), spread in the COORD ensemble is roughly half or less the size of the spread in the NATIVE ensemble for each TOA and SFC $K_x$. This suggests a substantial amount of the inter-kernel differences in NATIVE are associated with vertical resolution diversity and not bias in model base states. This is especially apparent in SFC $K_{Ts}$ (Fig. 5.5a) and SFC $K_T$ (Fig 5.5b) where inter-kernel spread in COORD is 75% and 85% smaller than the spread in NATIVE, respectively.

It is noteworthy that SFC $K_{Ts}$ is sensitive to vertical resolution in the atmosphere despite, in theory, being an entirely surface-based response. It reveals that radiative transfer modeling and vertical resolution are not entirely independent sources of uncertainty. As discussed in Chapter 3, since SFC $K_{Ts}$ is derived by perturbing surface temperature 1 K in isolation, the radiative response should stem entirely from a change in upwelling longwave radiation. However, in some radiative kernel sets, perturbing the surface also radiatively heats the atmospheric level just above it, inducing a change in downwelling radiation. This radiative transfer artifact accounts for the spread in SFC $K_{Ts}$ in the ensemble of existing kernels (Fig 5.5a) and is present in all kernels included in the three CMIP5-based ensembles. The fact that SFC $K_{Ts}$ spread is considerably larger in NATIVE than in COORD suggests the magnitude of the downwelling component is highly sensitive to the vertical placement of the near-surface atmospheric levels.
Figure 5.5. Spread across global, annually averaged and vertically integrated (when applicable) TOA and surface (SFC) a) surface temperature, b) air temperature, c) longwave (LW) water vapor, d) shortwave (SW) water vapor and e) surface radiative kernels from 4 different ensemble described in the text.

Inter-kernel spread in the COORD-CLD ensemble is roughly half the size of the spread in COORD across $K_x$. Since clouds are identical across kernels in the former ensemble but not latter, this indicates that roughly half of the uncertainty associated with base state biases is specifically associated with climatological cloud distribution. This holds for all TOA and SFC kernels except SW $K_q$, which exhibits the same, small inter-kernel spread for all four ensembles shown. Since the ensemble of existing kernels and COORD-CLD have similar spread in this case, biases in the non-cloud fields of the base
state account for most of the SW $K_q$ uncertainty, not radiative transfer modeling differences, vertical resolution or cloud fields. This is at odds with conclusions by DeAngelis et al. (2015) and Pendergrass and Hartmann (2014), who found that the parameterization of clear-sky shortwave water vapor absorption is a large source of uncertainty in the hydrological cycle response. It is important to note that since the ensemble of existing radiative kernels analyzed here is relatively small, it may not be representative of the diversity present in the larger suite of GCMs those studies analyzed.

5.4 Summary and Discussion

By comparing climate model-derived radiative kernel sets from the literature, we find notable inter-model spread in atmospheric (ATM) radiative kernels, confirming the conclusions by Flaschner et al. (2016) that radiative kernel differences account for discrepancies in recent literature regarding radiative feedbacks on the hydrological cycle. We also find that while surface (SFC) radiative kernels account for most of the spread in ATM, top-of-atmosphere (TOA) radiative kernels exhibit more differences than previously thought.

Furthermore, we find that radiative kernels diagnose inter-model radiative feedback spread differently, not just ensemble-mean feedbacks. For the TOA, this is most evident in estimates of cloud feedback spread, highlighting the sensitivity of radiative kernels to climatological cloud distribution biases.

By comparing ensembles of radiative kernels derived from the same radiative transfer model, we find that radiative transfer modeling is a substantial source of uncertainty in SFC radiative kernels but not TOA radiative kernels. We also find that both TOA and SFC radiative kernels are highly sensitive to the vertical resolution at
which the radiative transfer calculations were conducted. This is most evident in SFC $K_T$, which is only sensitive to perturbations in the boundary layer, suggesting that near-surface vertical resolution is an important source of uncertainty in surface flux responses.

The fact that radiative kernels differ suggests some amount of the inter-model spread in climate sensitivity or hydrological sensitivity may also be due to differences in radiative transfer modeling, since feedbacks are driven, in part by a “radiative kernel” response inherent to each model. A possible path forward is for more modeling groups to develop radiative kernels. If one is developed for each model, it would help define the contribution of radiative transfer diversity to climate sensitivity uncertainty more clearly.
Chapter 6: Observation-based Radiative Kernels from CloudSat/CALIPSO

6.1 Background

Climate change due to an external forcing is largely dictated by radiative feedbacks and uncertainty in model estimates of climate sensitivity is primarily attributable to inter-model differences in the representation of these feedbacks. Despite considerable advances in climate modeling, the inter-model spread in climate sensitivity has not changed since the late 1970s (Charney et al. 1979, Randall et al. 2007, Andrews et al. 2012). Furthering our understanding of radiative feedbacks in the climate system remains fundamental to improving prediction of future climate.

The radiative kernel technique (Soden et al. 2008) is a widely used and computationally efficient method for quantifying radiative feedbacks in global climate models (GCMs) and observations. Radiative kernels ($K_x$) represent the direct radiative response to a small, standard perturbation in state variable $x$ (e.g. temperature, water vapor, surface albedo) and are expressed as a function of latitude, longitude, altitude and month of year. Subsequently, radiative feedbacks ($\lambda_x$) can be computed as the product of $K_x$ and the climatic response of $x$.

Radiative kernels are computed from an offline version of a radiative transfer model initialized with state variable and cloud data typically sourced from the base climate of a GCM. Radiative fluxes at the top-of-atmosphere (TOA) and surface (SFC) are calculated with a small perturbation in $x$ applied individually at each latitude, longitude, vertical level and time step, while all other variables necessary for radiative transfer calculations remain unperturbed. Fluxes are then recomputed in a control case with no perturbations. The difference between the perturbed and control fluxes is $K_x$. Differencing the TOA and
SFC $K$, gives radiative kernels that represent the response in the atmospheric column (ATM). While TOA feedbacks regulate climate sensitivity, SFC and ATM feedbacks drive the response of the hydrological cycle to climate change (Manabe and Weatherald 1967; Held and Soden 2000; Andrews et al. 2009; Previdi 2010).

Radiative kernels have been developed using simulated climatological data from global climate models (GCMs) which, until recently, was the only practical source of the high vertical resolution cloud information required for the calculations. As discussed in Chapter 5, reliance on GCMs means the radiative kernel is subject to biases in the simulated base climate of the model used to develop it. As shown below, biases in the kernel can then, in turn, lead to systematic biases in the estimates of the radiative feedbacks.

Given advancements in satellite observing systems, we now have sufficient measurements to generate radiative kernels using observations. In particular, CloudSat (Stephens et al. 2002) provides the vertical distribution of cloud properties crucial for diagnosing TOA and SFC radiative fluxes (L’Ecuyer et al. 2008). Recently, Huang et al. (2017) introduced radiative kernels derived from reanalysis data. Here we build on that work to introduce the first ever set of observation-based radiative kernels, developed from the fifth release (R05) of the CloudSat level 2 fluxes and heating rates data set (2B-FLXHR-LIDAR) (Matus and L’Ecuyer 2017), which provides vertically resolved radiative fluxes using co-located measurements of the surface and atmosphere from multiple observing platforms in the A-train satellite constellation. Given their unique capabilities, observation-based radiative kernels are ideal for estimating climate feedbacks in the observed record, since they are free of bias associated with using a
model-derived base state. Observation-based radiative kernels are also ideal for quantifying feedbacks in an ensemble of GCMs, since they can serve as a “neutral” radiative kernel. In contrast, GCM-based radiative kernels bias the estimated feedbacks in each model towards the radiative kernel’s native GCM.

The CloudSat 2B-FLXHR-LIDAR product includes broadband longwave (LW) and shortwave (SW) fluxes produced using the vertical distribution of water content and cloud effective radii from the CloudSat 2B-CWC cloud water content product, along with cloud property data from the Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO) and the Moderate Resolution Imaging Spectroradiometer (MODIS). The profiles of cloud information are combined with temperature and humidity data from the European Centre for Medium-range Weather Forecasts (ECMWF) reanalysis, and surface albedo data from the International Geosphere-Biosphere Programme (IGBP) global land surface classification product to initialize a two-stream, adding-doubling radiative transfer model (Ritter and Geleyn 1992). Vertical profiles of radiative fluxes and heating rates are computed for each CloudSat footprint with a vertical resolution of 240 m and a horizontal resolution of 1.4 km across-track by 1.8 km along-track.

The methodology described above closely resembles the process by which fluxes are computed in GCMs; that is, from a broadband radiative transfer model initialized with cloud, surface albedo and atmospheric state variables. Additionally, cloud information can be omitted from the radiative transfer calculations in 2B-FLXHR-LIDAR to compute clear-sky radiative fluxes similar to a GCM. In other satellite-derived products, clear-sky irradiances are drawn from observations that lack clouds, thus subject to uncertainty in
the cloud-flagging algorithm. These similarities in methodology ensure that radiative kernels developed from 2B-FLXHR-LIDAR are appropriate for evaluating radiative feedbacks in GCMs, for quantifying observed feedbacks that are comparable to modeled feedbacks or for evaluating biases in the existing suite of GCM-based radiative kernels.

In this study, we detail the methodology used to compute the CloudSat radiative kernels and compare them to radiative kernels developed from the Geophysical Fluid Dynamics Laboratory (GFDL) model (Soden and Held 2006). As part of this comparison, we analyze estimates of TOA and SFC cloud feedbacks to discern their sensitivity to the distribution of clouds.

6.2 Methods

6.2.1 Radiative Kernel Perturbations

In order to generate radiative kernels from the 2B-FLXHR-LIDAR product, the existing algorithm is modified to include incremental radiative kernel perturbations in $x$ at the surface and in the atmospheric column. Following the methodology of Soden et al. (2008), the standard perturbations include: a 1% increase in surface albedo ($a$), a 1 K increase in temperature ($T$), and an increase in specific humidity ($q$) corresponding to a 1 K warming at fixed relative humidity (RH). The $q$ perturbation uses an eighth-order polynomial fit of Hyland-Wexler’s expression for saturation vapor pressure (Flatau et al. 1993). At extreme cold temperatures the expression is invalid, which leads to unrealistic changes in saturation vapor pressure in the upper stratosphere during polar winter. Therefore, at temperatures below 193 K, we assume a climatological temperature equal to 193 K and perturb $q$ accordingly. Error stemming from this approach is small compared to error associated with the polynomial fit.
Since the development of radiative kernels is computationally demanding, they are typically developed using just 1 year of data (Soden et al. 2008; Pendergrass et al. 2018). The CloudSat radiative kernels are based on data from 2009, with the exception of March and December, which use data from 2008 due to observing gaps in 2009 during those months. By using only a single year’s worth of data to compute radiative kernels, we are not accounting for inter-annual variability, thus introducing error. However, this error has been shown to be small (Pendergrass et al. 2018).

### 6.2.2 Post Processing and Interpolation

Although 2B-FLXHR-LIDAR provides a vertical profile of radiative fluxes, only fluxes at the TOA and SFC are used to develop the radiative kernels presented here. At each column boundary, we generate sets of along-track *control granules* of TOA or SFC radiative fluxes corresponding to a fully unperturbed base state and *perturbation granules* of TOA or SFC fluxes that correspond to perturbed values at each horizontal and vertical point.

To ensure consistent comparison between model and observational data, the control and perturbed fluxes must be interpolated to a standard grid. Monthly-averaged fluxes from the control and perturbation granules are first binned in $2^\circ \times 2.5^\circ$ resolution boxes and the average flux in each box is then interpolated onto a uniform latitude-longitude grid. Finally, the control fluxes are subtracted from perturbed fluxes corresponding to the surface and each vertical level to produce gridded, monthly mean radiative kernels, consistent with the format of most GCM output and therefore applicable to estimating radiative feedbacks.
6.2.3 Uncertainty and Limitations

6.2.3.1 2B-FLXHR-LIDAR Performance

Like any remote sensing product, each instrument contributing to 2B-FLXHR-LIDAR has known strengths and weaknesses. Numerous studies have evaluated uncertainty in 2B-FLXHR-LIDAR primarily by using CERES SW and LW fluxes as a source for validation. For version R05 of 2B-FLXHR-LIDAR used here, Matus and L’Ecuyer (2017) found net TOA clear-sky and all-sky fluxes are in close agreement with CERES, with an RMSE of ~3 %. Error is higher for SW-only fluxes (RMSE of 9% for all-sky), likely due to differences in cloud-detection methods between CloudSat/CALIPSO and CERES (Henderson et al. 2013; Matus and L’Ecuyer 2017). Scenes with mixed-phase clouds exhibit the largest RMSE for SW fluxes, but this has been greatly reduced compared to previous releases of 2B-FLXHR-LIDAR (Matus and L’Ecuyer 2017). It has also been shown that uncertainties in 2B-FLXHR-LIDAR decrease over larger temporal and spatial scales (L’Ecuyer et al. 2008; Kato et al. 2011). This is especially relevant for radiative kernels, which are generated after considerable averaging of individual scenes.

6.2.3.2 Use of Reanalysis Products

Henderson et al. (2013) found that ECMWF surface temperature and specific humidity profiles are the largest source of uncertainty in 2B-FLXHR-LIDAR LW fluxes, especially for the SFC. This raises important questions about the sensitivity of the radiative kernels to the choice of reanalysis product. Since it is not yet technically feasible to replace the ECMWF reanalysis data in the 2B-FLXHR-LIDAR algorithm with another reanalysis source, we address this by generating multiple sets of clear-sky
radiative kernels \( (K_x^0) \) from the offline broadband SOCRATES radiative transfer model (Manners et al. 2015), substituting in six-hourly temperature, humidity and surface albedo data from ERA-Interim (Dee et al. 2011), the Modern-Era Retrospective analysis for Research and Applications, version 2 (MERRA-2; Gelaro et al. 2017) and the Japanese 55-year Reanalysis (JRA-55; Kobayashi et al. 2015). The 2B-FLXHR-LIDAR radiative transfer model could not be used for this analysis due to technical limitations.

**Figure 6.1.** Ensemble mean (a,c,e) and 1 standard deviation (b,d,f) of clear-sky TOA temperature, \( (K_T^0) \), shortwave water vapor (SW \( K_q^0 \)) and longwave water vapor (LW \( K_q^0 \)) radiative kernels (Wm\(^{-2}\)K\(^{-1}\)100hPa\(^{-1}\)) generated from ERA-Interim, MERRA-2 and JRA-55 reanalysis data sets.

Figure 6.1 shows the ensemble-mean (Fig 6.1a,c,e) and 1 standard deviation (Fig. 6.1b,d,e) of the TOA temperature \( (K_T^0) \), longwave water vapor (LW \( K_q^0 \)) and shortwave
water vapor (SW $K_q^0$) radiative kernels generated from the three reanalysis sources. Spread is greatest in the topics, in the upper atmosphere for $K_T^0$ and LW $K_q^0$ and in the southernmost latitudes, but it is generally small relative to the mean. The standard deviation of the vertically-integrated, global-mean radiative kernel is less than 2.5% of the ensemble-mean for all TOA and SFC radiative kernels, with the exception of SW $K_q^0$, which is 31% and 6% of the ensemble-means, respectively. In this case, the TOA and SFC ERA-Interim kernels are notable outliers, while the MERRA-2 and JRA-55 kernels are nearly identical. Some of the differences are likely a consequence of interpolating the three reanalysis products to a common horizontal and vertical grid.

6.2.3.3 Diurnal Cycle

CloudSat completes a ~90 minute sun-synchronous orbit, crossing the equator at 0130/1330 local time and observing each location on the globe at the same local time with each pass. Therefore, the full diurnal cycle is not resolved in 2B-FLXHR-LIDAR. Given the relatively large diurnal range of solar insolation (Doelling et al. 2013), accounting for diurnal variability is especially important for shortwave (SW) radiative fluxes. We account for the SW diurnal cycle by using a special offline version of 2B-FLXHR-LIDAR designed to emulate Earth’s Radiation Budget (ERB). In this version, the solar zenith angle is manually adjusted over 12 consecutive along-track footprints to simulate the solar position over a 24-hour period.

While the ERB-related version does not explicitly account for the LW diurnal cycle, the impact of this on the radiative kernels are found to be negligible. To assess the impact of LW diurnal variability, all-sky radiative kernels are computed by running ERA-Interim cloud and non-cloud data through the SOCRATES radiative transfer model,
similar to the methodology outlined in Section 6.2.3.2. The calculations are repeated using ERA-Interim data interpolated to 0130 and 1330 local time for each grid point to closely match the CloudSat observing times. As illustrated in Figure 6.2, radiative kernels exhibit very similar structure in the zonal mean despite differences in the diurnal sampling. In fact, there is less than a 0.5% difference between the global-mean, vertically integrated radiative kernel developed using the full diurnal cycle versus the 0130 or 1330 sampling.

Figure 6.2. Zonal, annual mean TOA temperature radiative kernel (Wm⁻²K⁻¹100hPa⁻¹) from radiative transfer calculations initialized with ERA-I reanalysis data a) diurnally averaged, b) fixed to 0130 local time and c) fixed to 1330 local time.
6.3. Results

6.3.1 Spatial Distribution of the CloudSat Radiative Kernels

Figure 6.3 shows the zonal, annual mean air temperature ($K_T$), longwave water vapor (LW $K_q$) and shortwave water vapor (SW $K_q$) CloudSat radiative kernels under all-sky conditions. Radiative kernels are shown at the TOA, surface (SFC) and in the atmosphere (ATM), whereby ATM is defined as the TOA minus SFC radiative responses.

Figure 6.3. Zonal, annual-mean all-sky air temperature (a-c), longwave water vapor (d-f) and shortwave water vapor (g-i) CloudSat radiative kernels (Wm$^{-2}$K$^{-1}$100hPa$^{-1}$) for the top-of-atmosphere (a,d,g), the surface (b,e,h) and the atmospheric column (c,f,i).

There are substantial differences in the structure and magnitude of TOA (Fig 6.3a,d,g) versus SFC (Fig 6.3b,e,h) radiative kernels. TOA radiative kernels receive contributions from perturbations at nearly all levels of the atmospheric column, while SFC radiative kernels are largely confined to the boundary layer, since water vapor in the boundary
layer substantially absorbs net downwelling emissions from the middle and upper troposphere. Furthermore, SFC radiative kernels are generally larger in magnitude than their TOA counterparts, so, ATM (Fig 6.3c,f,i) radiative kernels are also dominated by contributions from the lower atmosphere. This indicates that changes in the free troposphere regulate climate sensitivity, while processes throughout the atmospheric column, including the boundary layer, drive hydrological sensitivity.

**Figure 6.4.** Same as Figure 6.3 but for clear-sky conditions.

Figure 6.4 shows the same radiative kernels as Figure 6.3 but for clear-sky conditions. Comparing the two figures reveals important effects of the distribution of clouds on TOA, SFC and ATM net radiative responses. While the clear-sky TOA radiative kernels exhibit strong sensitivity to low-level perturbations in T or q, clouds act to mask much of that response under all-sky conditions. For example, this shifts the
maximum sensitivities of TOA SW \( K_q \) to higher levels of the atmospheric column under all- versus clear-sky conditions (Figs 6.3g and 6.4g). Additionally, increased atmospheric emissivity in the upper troposphere due to the presence of clouds causes greater sensitivity to upper tropospheric temperature perturbations in TOA \( K_T \) under all-sky conditions relative to clear-sky. In contrast to the TOA, clouds act to enhance the magnitude of SFC radiative kernels near the surface, due to enhanced atmospheric emissivity from the presence of low clouds. In the case of SFC \( K_T \), the presence of low clouds acts to raise the largest sensitivities slightly higher into the boundary layer, while masking contributions from mid-tropospheric perturbations, relative to the clear-sky radiative kernel. This holds for ATM radiative kernels as well, since the ATM net radiative response is largely dictated by the SFC response.

**Figure 6.5.** Zonal, annual mean a) surface component of the CloudSat temperature radiative kernel (\( K_{Ts} \)) and b) surface albedo radiative kernel (\( K_a \)) at the TOA, SFC and in the ATM under all-sky (solid line) and clear-sky (dashed line) conditions.

While Figures 6.3 and 6.4 highlight the radiative responses to changes in atmospheric profiles, Figure 6.5 displays the zonal, annual mean TOA, SFC and ATM radiative response to perturbations at the surface. The surface component of the
temperature radiative kernel ($K_{Ts}$), or the net radiative response to a 1 K surface temperature increase, is small at the TOA due to the opacity of the atmospheric column to LW radiation. The response is smaller in the presence of clouds compared to clear-sky conditions. Radiative cooling at the surface results in a negative SFC $K_{Ts}$. It is larger in magnitude than TOA $K_{Ts}$, so ATM $K_{Ts}$ is positive. In contrast to the TOA, clouds act to increase the sensitivity of the ATM radiative budget to surface warming. The TOA and SFC surface albedo radiative kernels ($K_a$) are nearly identical. Accordingly, surface albedo perturbations have minimal impact on the atmospheric radiative budget. Clouds strongly mask the radiative effects of surface albedo changes, so $K_a$ is smaller under all-sky versus clear-sky conditions, especially in typically cloudy regions, such as the mid-latitude storm tracks.

6.3.2 Sensitivity of Radiative Kernels to Cloud Distribution

The distribution of clouds is also a key contributor to differences between radiative kernels developed from different sources, especially on a regional scale (Soden et al. 2008). This is visually evident in TOA $K_T$, which is highly sensitive to temperature perturbations located where cloud tops are exposed to space. Figure 6.6 shows the annual-mean cloud top pressure as observed by CloudSat (Fig. 6.6a) and, for each grid point, the pressure at which CloudSat TOA $K_T$ is at an absolute maximum value (Fig 5.6b) within the atmospheric column up to 200 hPa (thus disregarding large radiative responses to stratospheric perturbations unassociated with clouds). The spatial patterns are very similar, underlining the sensitivity of TOA $K_T$ to cloud distribution. Figure 6.6c shows the pressure map of maximum TOA $K_T$ from the GFDL model (Soden et al. 2008). The spatial pattern differs substantially from the CloudSat cloud top pressures and the
CloudSat kernel pressures, suggesting that biases in the distribution of clouds in the GFDL model introduce biases into the radiative kernels. For example, as reflected in GFDL TOA $K_T$, the simulated low clouds are too low in the marine boundary layer cloud regimes and cloud tops are too high over adjacent parts of the subtropical ocean.

**Figure 6.6.** Annual-mean a) observed Cloud Top Pressure (in hPa) measured by CloudSat and the spatial distribution of pressures at which the b) CloudSat and c) GFDL TOA temperature radiative kernel is an absolute maximum in each grid point’s atmospheric column.
We further isolate the influence of climatological clouds on radiative perturbations by calculating the cloud mask of the clear-sky radiative kernels, defined as the difference between radiative kernels under all-sky and clear-sky conditions. Zonal, annual-mean radiative kernel cloud masks from CloudSat are shown in Figure 6.7 for ATM. In ATM $K_T$, low-clouds outside of the tropics have the largest impact on the radiative response to temperature perturbations, with some contribution from mid-tropospheric clouds in the mid-latitudes and upper-tropospheric clouds in the tropics associated with deep convection (Fig. 6.7a).

Figure 6.7. Zonal, annual-mean ATM a) temperature radiative kernel ($K_T$) cloud mask (total minus clear-sky) from CloudSat and b) the difference between the ATM $K_T$ cloud mask from CloudSat versus GFDL (in Wm$^{-2}$K$^{-1}$100hPa$^{-1}$). The ATM CloudSat radiative kernel cloud mask and its difference from GFDL is also shown for longwave water vapor ($LW K_q$) and shortwave water vapor ($SW K_q$) (in Wm$^{-2}$K$^{-1}$100hPa$^{-1}$).

The difference between the CloudSat and GFDL cloud masks are also shown in Figure 6.7 (right) for the ATM kernel. For both the water vapor and temperature kernels, the largest differences are found in the boundary layer. In each case, the contribution of
near-surface clouds is larger for the GFDL radiative kernel than for CloudSat, as GFDL clouds are too low compared to the observed distribution. This bias is especially pronounced in the tropics for the LW $K_q$ cloud mask (Fig. 6.7d), where the difference between CloudSat and GFDL exhibits a dipole in sign near the surface, highlighting the difference in the altitude of low clouds between the two fields. This supports findings by Cesana et al. (2017) who compared cloud variables from an ensemble of GCMs against GCM-oriented CALIPSO Cloud Product observations (Cesana et al. 2016) and found that the heights of simulated low-level clouds were too low in nearly all models.

6.3.3 Cloud Masking and Cloud Feedbacks

To investigate the impact of differing cloud distributions between CloudSat and GFDL on the calculation of cloud feedbacks ($\lambda_C$), we analyze 18 CMIP5 models where CO$_2$ is instantaneously quadrupled and then held constant (“abrupt4xCO2”). At the TOA, $\lambda_C$ is the largest source of uncertainty in climate sensitivity (Soden and Held 2006; Andrews et al. 2012; Zelinka et al. 2013), and at the SFC the sign of $\lambda_C$ is inconsistent across models, as highlighted in Chapter 3. Ensemble-mean results are presented.

It is common to assess the ability of a particular set of radiative kernels to accurately estimate feedbacks in models by comparing the feedback parameter calculated from the sum of kernel-derived feedbacks versus the regression of model fluxes against global-mean $\Delta T_s$ (e.g. Vial et al. 2013). We find the ensemble-mean feedback parameter derived from CloudSat kernels agrees with the regression of model fluxes to within 17.5% for the TOA and 7.5% for the SFC. This is better agreement than is found in a similar comparison for the GFDL kernels (19.3% for TOA and 31.6% for SFC).
Following Soden et al. (2008), we infer $\lambda_C$ from changes in cloud radiative effect ($dCRE$) (Cess et al. 1990), but these terms are not equal as described in previous work (e.g. Soden et al. 2004). Since $dCRE$ is quantified by differencing changes in net all-sky and clear-sky radiative fluxes, it includes the difference in non-cloud feedbacks between the two climate states. Therefore to accurately compute $\lambda_C$ one must adjust $dCRE$ to account for the cloud mask of clear-sky feedbacks (herein feedback cloud mask) using radiative kernels. Accordingly, $\lambda_C$ is defined as:

$$\lambda_C = dCRE - \sum (K_x - K^0_x) dx = dCRE + \gamma$$

(5.1)

whereby the total feedback cloud mask ($\gamma$) is estimated from the product of the $K_x$ cloud mask and the climatic response of $x$, summed over all $x$ (Soden et al. 2008). Both $dCRE$ and $dx$ are estimated by linearly regressing anomalies of CRE and $x$, respectively, against global-mean $T_s$ anomalies to isolate the temperature-mediated feedback response (e.g. Chung and Soden 2015).

Figure 6.8 shows the ensemble-mean global SW and LW $\lambda_C$ at the TOA and at the SFC for each month of the year, estimated using the GFDL and CloudSat radiative kernels. The ensemble-mean $dCRE$ is also displayed for each month. Since $dCRE$ is calculated independent of radiative kernels, any difference in the two estimates of $\lambda_C$ is entirely from differences between estimates of $\gamma$. The largest $\gamma$ occurs for the LW component. At the surface, large negative $dCRE$ are actually indicative of near neutral LW $\lambda_C$, while at the TOA near neutral $dCRE$ are indicative of positive LW $\lambda_C$. Thus $\gamma$ is critical to accurately interpreting the sign of LW $\lambda_C$ at both the TOA and SFC.

The SW $\lambda_C$ at both the TOA and SFC exhibits a strong seasonal cycle: positive in late spring through early fall, and negative or near-zero in late fall through early spring.
This is in agreement with findings by Colman (2003) who evaluated the seasonal cycle of feedbacks in a single model. The SW $dCRE$ has a slightly different seasonal cycle phase than SW $\lambda_C$, indicating that $\gamma$ also has a unique seasonal cycle that is important for interpreting the amplitude of SW $\lambda_C$.

**Figure 6.8.** Global-, monthly-, ensemble-mean cloud feedback estimated using the GFDL and CloudSat radiative kernels for the a) LW TOA b) SW TOA, c) LW Surface (SFC) and d) SW SFC. Ensemble-mean change in cloud radiative effect ($dCRE$) is also shown.

To highlight the regional contributions to the global seasonal cycle of SW $\lambda_C$, Figure 6.9 shows the ensemble-mean spatial pattern of the local seasonal cycle regressed against the global-mean for SW SFC $\lambda_C$, $dCRE$, $\gamma$, and the surface albedo feedback cloud mask ($\gamma_a$). The pattern is nearly identical for the analogous responses at the TOA or when GFDL radiative kernels are used (not shown). Cloud changes associated with seasonal shifts of the ITCZ contribute largely to the seasonality of global-mean SW $\lambda_C$ and $dCRE$, as evidenced by the zonal bands of opposite sign that extend throughout the equatorial
Pacific and Indian oceans. In contrast, the seasonality of SW $\gamma$ is almost entirely driven by the polar regions due to the contributions of $\gamma_a$ (Fig. 6.9d).

**Figure 6.9.** Spatial pattern of the regression of the local seasonal cycle against the global mean for a) shortwave (SW) surface cloud feedback ($\lambda_C$), b) change in SW surface cloud radiative effect (dCRE), c) the total SW surface cloud mask ($\gamma$) and d) the SW surface albedo feedback cloud mask ($\gamma_a$). Units are dimensionless.

In the annual mean, LW SFC $\lambda_C$ exhibits the greatest sensitivity to the kernel choice. LW SFC $\gamma$ is systematically larger for CloudSat across all months, resulting in a negative LW $\lambda_C$ when GFDL $K_x$ is used (-0.09 Wm$^{-2}$K$^{-1}$) but positive LW $\lambda_C$ when CloudSat $K_x$ is used (0.06 Wm$^{-2}$K$^{-1}$). Figure 6.10 shows the annual mean distribution of LW, SW and net SFC $\gamma$ for the CloudSat $K_x$ (Fig. 6.10a,c,e) and the difference compared to the GFDL $K_x$ (Fig. 6.10b,d,f). In the LW, Cloudsat produces a larger SFC $\gamma$ over most of the globe. These differences are most pronounced over the ITCZ and mid-latitude
storm track regions. The former is due to differences in SFC \( \gamma_q \), possibly associated with known large inter-annual variability in that region, and the latter due to differences in SFC \( \gamma_T \) (not shown) and result from differences in the distribution of low clouds illustrated in Figure 6.7. In contrast, most of the difference in SW \( \gamma \) between radiative kernels is confined to the polar regions, where opposing effects largely cancel out.

![Figure 6.10. Annual-mean a) longwave, c) shortwave and e) net surface feedback cloud mask (\( \gamma \)) estimated using CloudSat radiative kernels and their respective difference (b,d,f) from \( \gamma \) estimated using GFDL radiative kernels. Units are Wm\(^{-2}\)K\(^{-1}\).](image)
6.4. Summary and Discussion

This study has introduced the first set of observation-based radiative kernels, developed from the CloudSat Level-2 fluxes and heating rates product (2B-FLXHR-LIDAR). In 2B-FLXHR-LIDAR, vertically-resolved radiative fluxes are calculated for each CloudSat observation by initializing a radiative transfer model with cloud information from CloudSat, CALIPSO, and MODIS, temperature and moisture profiles from ECMWF reanalysis and surface albedo from the International Geosphere-Biosphere Programme land classification product. We modify 2B-FLXHR-LIDAR to produce fluxes with and without standard radiative kernel perturbations in state variable $x$ (temperature, water vapor and surface albedo) (Soden et al. 2008). Fluxes from the two cases are then interpolated spatially, averaged temporally, and differenced to produce monthly-mean radiative kernels ($K_x$) on a uniform latitude-longitude grid. Unlike previous radiative kernels developed from GCMs, these CloudSat radiative kernels are not subject to model bias associated with the surface and atmospheric input data used in the calculations. These “neutral” radiative kernels are therefore ideal for estimating radiative feedbacks in an ensemble of models to evaluate inter-model spread.

Given the limited temporal sampling of polar-orbiting satellites, the standard 2B-FLXHR-LIDAR product does not capture the full diurnal cycle. We introduce a version that has been modified to account for the shortwave (SW) diurnal cycle of solar insolation by manually adjusting the solar zenith angle across consecutive points, but it does not account for the diurnal cycle of clouds, temperature, or humidity. We show this limitation has negligible impacts on radiative kernels. We separately develop LW radiative kernels from six-hourly ERA-Interim reanalysis data that represents the full
diurnal cycle and repeat the calculations using only data at 0130 or 1330 local times, representative of CloudSat temporal sampling. We find the three sets of radiative kernels are all nearly identical, indicating that realistic radiative kernels can be developed from data with coarser temporal resolution than has been the standard. More generally, these results further confirm that observing platforms developed to monitor climate variability in radiative balances are not hindered by the lack of temporal sampling inherent to a sun-synchronous orbit.

We compare the CloudSat radiative kernels to an existing set of radiative kernels based on the Geophysical Fluid Dynamics Laboratory (GFDL) model (Soden and Held 2006). While we find the two are generally comparable, we also highlight biases in the GFDL radiative kernels associated with inaccuracies in the simulated cloud fields they are based on. This is evident in the spatial structure of the TOA temperature radiative kernel ($K_T$), which is highly sensitive to the vertical position of cloud tops. Clouds also bias the net radiative response at the surface (SFC) or atmospheric column (ATM) to perturbations in the boundary layer, since low clouds from GFDL are too low compared to observations. Similar biases could partially explain discrepancies between two GCM-based ATM radiative kernels recently described by Flaschner et al. (2016).

Estimates of cloud feedback ($\lambda_C$) could be impacted by radiative kernel biases associated with cloud fields, since the difference between all- and clear-sky radiative kernels (radiative kernel cloud mask) is used in the estimate to quantify the radiative response to the cloud masking of non-cloud feedbacks. We investigate this by using the CloudSat and GFDL radiative kernels to estimate LW and SW TOA and SFC $\lambda$ in a suite of CMIP5 GCMs. We find that in general, the cloud-related biases do not greatly
influence estimates of ensemble-mean $\lambda_C$ except in the case of LW SFC $\lambda_C$, where climatological clouds lower in altitude than observations cause GFDL $K_\lambda$ to estimate too small of a total feedback cloud mask ($\gamma$), resulting in a negative $\lambda_C$, while the use of CloudSat $K_\lambda$ gives a positive $\lambda_C$.

The radiative kernel sets are found to produce a consistent seasonal cycle in SW $\lambda_C$ (the LW is invariant month-to-month), which reaches a maximum in spring and summer. Driven by the effects of clouds on the surface albedo feedback in particular, $\gamma$ strongly influences the seasonality of $\lambda_C$ in the polar regions. Given differences in the model treatment of ice processes in the polar regions and evidence that albedo radiative kernels are sensitive to their climatological fields (Jonko et al. 2012; Block and Mauritsen 2013), it is possible that a greater sampling of GCM-based radiative kernels may reveal more inconsistency in the seasonality of SW $\lambda_C$. However, even if a larger sample of radiative kernels reveals more differences, the seasonal cycle of $\lambda_C$ globally is not anticipated to be greatly impacted, since it is mostly driven by the change in cloud radiative effect, which is calculated independent of radiative kernels. Nonetheless, the role of cloud-masking in the polar regions warrants further investigation, given that important questions remain regarding the role of feedbacks on polar amplification.
Chapter 7: Conclusions and a Path Forward

Energetic balances in the climate system constrain many climate processes. Accordingly, uncertainty in climate change projections can be traced to differences in how models simulate energetic changes. While our understanding of radiative transfer theory is sound, our ability to accurately implement it in climate models is limited by the high computational expense of radiative transfer calculations. As a result, climate models rely on simplified and parameterized radiative transfer. Here we show these simplifications substantially influence simulations of the climate, contributing directly to inter-model differences in the radiative responses that drive climate processes with important societal impacts, such as the hydrological cycle.

Change in the hydrological cycle consist of two distinct regimes: a direct response to a perturbation in a forcing agent and a direct response to surface temperature change. Effective radiative forcing at the surface (ESRF) regulates the former while effective radiative forcing at the TOA (ERF), through its influence on surface temperature, regulates the latter. We showed that uncertainty in both ESRF and ERF is mostly accounted for by considerable inter-model spread in instantaneous radiative forcing (ISRF or IRF) under CO$_2$ increases. We showed that IRF is also the dominant contributor to ERF spread under increases in CH$_4$, BC and SO$_4$ - important drivers of the hydrological cycle. These results highlight that radiative transfer diversity is a substantial and ubiquitous source of uncertainty in climate model projections of the hydrological cycle.

Uncertainty in radiative kernels used to diagnose these radiative changes further highlights the important contribution of radiative transfer diversity to uncertainty in
climate projections. We compared radiative kernels developed from multiple climate models, showing that they differ more than previously documented. We demonstrated that surface (SFC) radiative kernels exhibit more inter-kernel differences than TOA radiative kernels, and that those large differences can specifically be traced to differences in the radiative transfer models used to develop the radiative kernels.

In addition to radiative transfer error, radiative kernel uncertainty also stems from differences in the model base states. In particular, we highlighted that the climatological distribution of clouds contributes to differences in the magnitude and spatial structure of radiative kernels. In response to this finding, we introduced a new set of radiative kernels based on satellite observations, using vertically resolved cloud information from CloudSat measurements. These radiative kernels are free from the base state model biases than impact radiative kernels derived from GCMs and thus are ideal for diagnosing radiative responses in models and observations.

We have demonstrated that inconsistency in radiative transfer modeling is a substantial contributor to uncertainty in climate change projections. This diversity is unnecessary, since our understanding of radiative transfer theory is robust, as evident by the strong agreement of highly accurate line-by-line radiative transfer calculations (e.g. Collins et al. 2006). We offer three recommendations that can contribute to reducing the associated uncertainty. First, as results in Chapters 3 and 5 show, while the radiative kernel technique is generally accurate, this method can introduce error into estimates of IRF. Furthermore, by using a single radiative kernel, the full contribution of radiative transfer diversity to IRF inter-model spread may not be fully represented. We encourage
more modeling groups to conduct and archive double-call radiative transfer calculations to provide a more accurate documentation of radiative forcing differences in models.

Second, near-surface radiative processes predominantly drive the energetic constraints on the hydrological cycle. It is evident from Chapter 5 these processes are sensitive to the near-surface vertical resolution. We encourage modelers to consider the effects of vertical resolution on the radiative transfer code and on differential radiative responses when selecting the concentration and placement of near-surface vertical levels. Currently these decisions are typically made with thermodynamic and dynamic processes in mind.

Finally, a potential path forward to narrowing the range of realistic projections of the hydrological cycle is to use line-by-line radiative transfer calculations to configure radiative parameterizations more accurately. These calculations can also be used as a benchmark for identifying models that already have realistic parameterization schemes. This information can then be used to identify models with the most realistic hydrological cycle sensitivities. While observations are commonly used as the benchmark in this manner, results in Chapter 2 highlight the difficulty of using short-term observations to make inferences about long-term precipitation changes. Furthermore, global satellite observations of surface or atmospheric fluxes also typically rely in part on simplified radiative transfer models (RTM), thus climate models in strong agreement with those observations may not be most realistic but rather just share similar biases associated with the RTM used in the observational calculation.

Uncertainties in projections of the hydrological cycle remain large, but addressing inconsistencies in radiative transfer is a promising path towards reducing them.
Bibliography


