Using the Radiative Kernel Technique to Calculate Climate Feedbacks in NCAR’s Community Atmospheric Model

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Climate models differ in their responses to imposed forcings, such as increased greenhouse gas concentrations, due to different climate feedback strengths. Feedbacks in NCAR’s Community Atmospheric Model (CAM) are separated into two components: the change in climate components in response to an imposed forcing and the “radiative kernel,” the effect that climate changes have on the top-of-the-atmosphere (TOA) radiative budget. This technique’s usefulness depends on the linearity of the feedback processes. For the case of CO$_2$ doubling, the sum of the effects of water vapor, temperature, and surface albedo changes on the TOA clear-sky flux is similar to the clear-sky flux changes directly calculated by CAM. When monthly averages are used rather than values from every time step, the global average TOA shortwave change is underestimated by a quarter partially as a result of intra-month correlations of surface albedo with the radiative kernel. The TOA longwave flux changes do not depend on the averaging period. The longwave zonal averages are within 10% of the model-calculated values, while the global average differs by only 2%. Cloud radiative forcing ($\Delta$CRF) is often used as a diagnostic of cloud feedback strength. The net effect of the water vapor, temperature, and surface albedo changes on $\Delta$CRF is -1.6 Wm$^{-2}$, based on the kernel technique, while the total $\Delta$CRF from CAM is -1.3 Wm$^{-2}$, indicating these components contribute significantly to $\Delta$CRF and make it more negative. Assuming linearity of the $\Delta$CRF contributions, these results indicate that the net cloud feedback in CAM is positive.
1. Introduction

According to the Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC, Randall et al. 2007), the equilibrium sensitivities of atmospheric general circulation models (AGCMs) coupled to mixed-layer oceans range from 2.1 to 4.4 degrees C for a doubling of CO$_2$, despite many recent improvements in models. Climate feedbacks amplify or damp climate changes and thus influence the magnitude of the climate response to an imposed forcing. Differences in individual feedbacks account for much of the spread of climate responses of models (NRC 2003). Isolating the processes responsible for the differences in feedbacks in state-of-the-art climate models, along with improving our understanding of the physical feedback mechanisms and developing techniques to compare modeled feedbacks to observations, will lead to better climate models and, ultimately, improved estimates of the future climate (Bony et al. 2006).

When the Earth’s energy budget is modified, the climate changes in response to restore the energy balance. In a steady state, imposed top-of-the-atmosphere (TOA) radiative flux changes, $G$, must be balanced by changes in outgoing longwave radiation, $F$, and absorbed solar radiation, $Q$:

$$G = \Delta(F - Q)$$

The climate sensitivity determines how much the climate, represented by the surface temperature, $T_s$, needs to change in order for the TOA fluxes to return to equilibrium:

$$G = \frac{\Delta(F - Q)}{\Delta T_s} \Delta T_s = \gamma \Delta T_s$$

where $\gamma$ is the feedback parameter, the inverse of the climate sensitivity. From Zhang et al. (1994b), we can separate the feedback parameter into terms corresponding to the effects of
different climate components on the TOA budget:

\[
\gamma = \frac{\Delta (F - Q)}{\Delta T_s} = \frac{\partial (F - Q)}{\partial T} \frac{dT}{dT_s} + \frac{\partial (F - Q)}{\partial q} \frac{dq}{dT_s} + \frac{\partial (F - Q)}{\partial C} \frac{dC}{dT_s} + Re \tag{1}
\]

The feedback parameter is thus the sum of the feedback parameters related to atmospheric temperature \(T\), water vapor \(q\), and clouds \(C\), plus a residual term \(Re\), which is generally small (about 10 percent). Furthermore, we can split the feedback parameters into shortwave or long-wave components. Note that other feedback separations are also valid. For example, since \(q\) is strongly coupled to \(T\), another useful approach would be to replace the \(T\) and \(q\) terms with a constant relative humidity feedback and a relative humidity change feedback. Alternatively, it can be informative to combine the lapse rate and water vapor feedbacks, since the two tend to vary together (but are of opposite sign) due to the tight coupling of upper troposphere water vapor and temperature changes in models (Randall et al. 2007; Allan et al. 2002; Colman 2003; Soden and Held 2006). Hence, more negative lapse rate feedbacks tend to correspond to larger (positive) water vapor feedbacks. For the purposes of this study, though, we concentrate on the separation shown in Eq. 1.

One common method of calculating climate feedbacks is the partial radiative perturbation (PRP) method (Wetherald and Manabe 1988), which uses offline radiative transfer versions of AGCMs. First, control (e.g., present-day \(CO_2\)) and experimental (e.g., doubled \(CO_2\)) GCM simulations are performed. The offline model is then run using saved values from the control simulation for every variable except the one related to the particular feedback being examined. For this variable \(X\), the doubled \(CO_2\) values are used. The feedback is calculated by differencing the TOA fluxes from the offline model and the control GCM simulation. Thus, the PRP technique isolates the effect of a single variable \(X\) on the radiative budget \(\frac{\partial (F - Q)}{\partial X} \frac{dX}{dT_s}\).
man (2003) compares feedbacks generated using the PRP technique for different AGCMs with mixed-layer oceans.

Unfortunately, this method is very computationally expensive, since it requires that the radiative transfer portion of the model be run again for each feedback under consideration. In addition, the calculation must be repeated for every simulation and climate model version. Finally, errors related to the decorrelation of variables (for example, clouds and water vapor) may corrupt the results (Colman and McAvaney 1997; Soden et al. 2004).

Recently, Soden and Held (2006) and Soden et al. (2007) have proposed a new technique that decomposes each climate feedback into two parts. The first is the “radiative kernel” \( \frac{\partial (F - Q)}{\partial X} \), which describes the change in TOA fluxes for a standard change in property \( X \) and depends on the radiative properties and base state of the model. The second component is the climate response of the feedback variable \( \frac{dX}{dT} \), for example, the difference in \( X \) between a doubled CO\(_2\) CAM run and a present-day CAM run, normalized by the global average surface temperature change. These two values can be combined to determine the resulting feedback related to a particular variable. Since clouds are nonlinear, primarily due to their complicated overlap patterns, cloud feedbacks are calculated in a different way.

This technique facilitates comparison of the radiative responses of various models; it distinguishes between differences in feedbacks caused by differences in how the components respond to climate change and those due to differences in how the changed components affect the climate (that is, the radiative transfer portion of the model). We expect that the differences due to the spread of climate variables will be the dominant uncertainty, as radiative transfer schemes have been extensively tested against line-by-line calculations (e.g., Collins et al. 2002) as well as compared with each other. In fact, Soden et al. (2007) show that differences in radiative
kernels of three models (GFDL, BMRC, and NCAR) contribute less to the spread of climate feedbacks than differences in feedback variables from the IPCC AR4 coupled models, suggesting that a single kernel could be used to quickly and easily perform a first-order comparison of feedbacks across models. In addition, use of the radiative kernel technique decreases errors associated with the correlation of variables by using mean changes in feedback variables (Soden et al. 2007). Finally, while the method requires running the offline radiative transfer code once for each model level, the kernel can then be used for different climate experiments and models.

In order for the kernel technique to be useful, the non-cloud feedbacks must be relatively linear. To test this assumption, we utilize the clear-sky kernels $\frac{\partial F_c}{\partial X}$ and $\frac{\partial Q_c}{\partial X}$ (the $c$ subscript refers to clear-sky fluxes), which are calculated at the same time as the regular all-sky kernels and represent the effects climate component changes have on TOA fluxes when the model’s cloud fraction is set to zero (i.e., clouds are removed for the purposes of the radiative transfer calculations, but all other components remain the same). We compare TOA clear-sky longwave and shortwave flux changes calculated by an AGCM to the sum of the clear-sky flux changes for temperature, water vapor, and surface albedo, as determined using the kernel technique. After verifying that the kernel method captures most of the clear-sky feedback magnitude, we use the clear-sky and all-sky kernels to estimate the effect that changes in non-cloud climate components have on the change in cloud radiative forcing ($\Delta$CRF), a quantity which is often used as a diagnostic of the cloud feedback, to produce an “adjusted” $\Delta$CRF.
2. Methodology

For each major climate variable (other than clouds), we calculate both the adjoint radiative response (the kernel) and the climate response corresponding to a doubling of CO₂ ($\Delta X$). We then combine the two to obtain the contribution of each climate component to the change in longwave or shortwave TOA fluxes. To convert these flux changes to feedback values (such as those in Equation 1), we would divide the flux changes by the global average $T_s$.

The kernel ($\frac{\partial (F-Q)}{\partial X}$) is obtained from an offline radiative transfer version of the Community Atmospheric Model version 3 (CAM3) (Collins et al. 2006). The base state for the radiative transfer calculation is a year-long control run for present-day conditions, with instantaneous climate variables output every three hours. We begin by calculating the TOA longwave and shortwave fluxes corresponding to this control simulation. We save the all-sky fluxes as well as the clear-sky fluxes.

For each radiative feedback under consideration, we then modify the corresponding variable at each grid point, changing the values at one level at a time to determine the effect on the clear- and all-sky, longwave and shortwave TOA fluxes. The anomaly applied is the same for each grid point and level, though it varies based on the feedback under consideration. We examine feedbacks involving surface and atmospheric temperatures, water vapor, and surface albedo. The standard atmospheric temperature change is 1 K. The surface temperature is modified by increasing the upwelling longwave at the surface by 1 W m⁻². For water vapor, we compute (for every grid point, level, and time step) the specific humidity change corresponding to a 1 K increase in temperature, holding relative humidity constant. The four different shortwave surface albedos (longwave diffuse, longwave direct, shortwave diffuse, and shortwave direct) are all modified by 0.001. We average the 3-hourly kernels to obtain monthly averages. Both
clear-sky and all-sky fluxes are computed, resulting in four (longwave clear-sky, shortwave clear-sky, longwave all-sky, and shortwave all-sky) 3-dimensional kernels for each month and variable. Note that we do not calculate a cloud kernel. While the cloud feedback is very important for determining the climate sensitivity in climate models, it is unfortunately nonlinear and complicated by issues related to cloud overlap. Thus, rather than calculating cloud fraction and liquid or ice water kernels, we use a different method to determine cloud feedbacks (see Section 4).

To determine the climate response, we perform two GCM simulations with the mixed-layer ocean version of CAM, a present-day simulation and a doubled CO$_2$ simulation. Each version is run for 20 years, after an initial spin-up of 40 years, and we calculate averages for each variable $X$ (temperature, water vapor, and albedo) at every grid point and level (for the multi-level variables) for each month of the year. We also average fluxes from the first 10 years and compare them with those from the 20 year runs to verify that the length of the simulations does not influence the results presented here.

Finally, we multiply the monthly-average difference in $X$ between the doubled-CO$_2$ and present-day cases at each level and grid point by the corresponding monthly-average kernel values (normalized by the standard anomaly for that variable). The division by the standard anomaly is necessary because the kernels as implemented are technically the flux changes corresponding to a change of one standard anomaly ($\frac{\partial F}{\partial X} \Delta X_s$ and $\frac{\partial Q}{\partial X} \Delta X_s$, where $\Delta X_s$ is the standard anomaly for that variable). Thus, we combine the kernels with $\frac{\Delta X}{\Delta X_s}$. For the case of the water vapor feedback, we multiply the kernel by the change in the natural log of the water vapor, divided by the change in the natural log of water vapor using in the kernel calculation, since absorption of radiation by water vapor is roughly proportional to ln($q$). We sum the results
from all levels to obtain the clear- and all-sky, longwave and shortwave TOA flux changes for each point on the grid and calculate annual averages (for a total of four TOA flux changes). We also combine the anomalies and kernels for every 3-hourly time step before computing monthly averages to determine the effect of the averaging procedure.

We generate only one set of kernels, corresponding to the present-day climate. The kernels may be dependent on the base state used for the radiative transfer calculations. One option would be to use two sets of radiative kernels: one for the control simulation and one for the climate-change simulation. Differences between them would yield an error estimate, and the average of the two could be used to reduce errors associated with a changing base state, related to nonlinearity of the feedback processes. Rather than computing two sets of kernels, we recompute radiative kernels (and the corresponding TOA flux changes) for the present-day climate using different standard anomalies. For the range of climate responses seen in the doubled-CO$_2$ simulation, only the surface albedo change demonstrates a significantly different response. The influence of this nonlinearity will be seen in the next section. We prefer to focus on the nonlinearity from the present-day CO$_2$ simulation, since the radiative kernel technique is applicable to a range of climate experiments, and requiring the recalculation of the kernel for new simulations reduces the usefulness of the technique.

Figure 1 shows an example of this technique applied to outgoing longwave fluxes for the water vapor feedback. Figure 1a shows the zonally-averaged annual longwave kernel, the change in $F$ (outgoing longwave radiation). Since an increase in $F$ is a cooling effect, we show changes in $-F$ for this and all future plots. Thus positive values for the kernel correspond to locations (latitudes and heights) where an increase in water vapor results in a decrease in $F$ (increase in $-F$), a warming effect. Units are in W m$^{-2}$ per 100 mb of imposed specific humidity increase.
(corresponding to a 1 K increase in temperature assuming constant relative humidity). In general, increases in water vapor warm the climate, except at high latitudes and altitudes, where the lapse rate is negative. Water vapor increases are most effective at altering the TOA longwave flux in the tropical upper troposphere. Figure 1b shows the annual-average water vapor change from the doubled CO$_2$ experiment, divided by the specific humidity increase corresponding to a 1 K temperature increase and constant relative humidity (i.e., the specific humidity anomaly used to calculate the radiative kernel). Figure 1c shows the result from combining the kernel with the water vapor anomaly. The annual-average longwave water vapor feedback is positive everywhere. Although there are some high latitude heights where increases in water vapor result in decreases in -$F$, these decreases are more than compensated for by increases in -$F$ at other heights.

3. Linearity of clear-sky feedbacks

In order for the kernel feedback analysis method to be useful, the radiative changes must behave fairly linearly with respect to the magnitude of the climate response $\Delta X$. In addition, interactions between feedbacks must be small. Rather than performing a PRP calculation for each variable (as is done in Soden et al. (2007) for a different GCM), here we determine the accuracy of the net effect of the variables on TOA fluxes. Because the calculation of cloud feedbacks requires TOA fluxes from the GCM experiment (Section 4), we cannot test the technique by simply summing the individual all-sky feedback terms and comparing to the results from the GCM experiment. Thus, we consider the linearity of the water vapor, temperature, and surface albedo feedbacks with respect to clear-sky fluxes. We compare the sum of these flux changes to
the results of a clear-sky radiative transfer calculation which includes all three of these changes, namely the TOA clear-sky flux change produced by CAM during the doubled-CO$_2$ experiment. The difference between these two calculations will provide an estimate of uncertainty for the kernel technique.

To determine the linearity of these clear-sky feedbacks, we compare the sum of the longwave or shortwave clear-sky flux changes calculated using the kernel technique to the change in these clear-sky fluxes in the CAM simulations. Technically, we are comparing flux anomalies rather than feedbacks, which are normalized by the global average $T_s$, but since this affects feedbacks calculated with the kernel technique and the GCM in the same way, we omit this step from our calculations. Feedback values for the Community Climate System Model, the coupled version of CAM, are provided in Soden et al. (2007).

We include contributions from atmospheric temperature and water vapor and surface shortwave albedo and longwave emission (corresponding primarily to surface temperature). Note that, strictly speaking, the temperature response is not really a feedback, if we define a feedback as a process that amplifies or damps a climate response to an imposed forcing. Instead, the global increase in temperature associated with a doubling of CO$_2$ is generally considered the primary response of the system. However, we are interested in the total energy budget, and changes in temperature contribute to this energy budget. Therefore, we need to include the temperature “feedback” in order to calculate the new longwave flux changes. Similarly, we also include the longwave effect of the imposed CO$_2$ increase.

Note that other feedback separations are also valid. While we do not perform these calculations here, the kernel technique can easily be used to calculate a fixed relative humidity feedback (by summing the $T$ and $q$ kernels and then multiplying by the $T$ anomaly) and a rel-
ative humidity feedback (computed as the product of the $q$ kernel and the departure of $q$ from constant relative humidity), as is done for the GFDL model in Soden et al. (2007). Here, our primary goal is to test the technique, and thus we choose the simplest feedback separation.

If the two values (kernel and model) agree, then the feedbacks are relatively linear, and this offline radiative transfer technique can be a useful method for exploring clear-sky feedbacks in climate models. Figure 2 tests the ability of the kernel method to capture the changes in annual average clear-sky fluxes, as calculated by the 20-year GCM simulations. In general, the clear-sky fluxes calculated with the kernel technique agree with the “correct” values from the GCM simulations. Differences between the two techniques are due to nonlinear effects and interactions between components.

The pattern of clear-sky shortwave anomalies calculated using the kernel method (Figure 2a) is very similar to the pattern from CAM (Figure 2c). For both methods, the changes are almost entirely positive and largest over continents and high latitudes. However, the magnitude of the shortwave change is underestimated, by 23% for the global average. Since positive shortwave anomalies correspond to increases in absorbed solar radiation and a positive feedback, the monthly-average kernel technique underestimates the positive clear-sky shortwave feedback.

Most of the underestimation occurs at the edges of ice cover (Figure 3a). In these regions, the ice-albedo feedback is largest, and within-month correlations between the sea ice and incoming solar radiation result in an underestimation of $\Delta Q_c$ (the subscript $c$ is used to indicate a clear-sky flux) by 30-40%. In contrast, the kernel technique overestimates the tropical flux changes by 30%, but the magnitude of the tropical feedback is small. Outside of the high latitudes, errors in zonal-average $\Delta Q_c$ are only a few tenths of a W m$^{-2}$, and thus the global average is dominated by the high latitude changes.
The underestimation of the shortwave feedback is reduced when kernel and variable anomalies from every time step are combined (referred to in figures as the ETS kernel technique and indicated with dashed lines in Figure 3a), rather than monthly averages (dotted lines in Figure 3a). For the first year of the CAM experiment (the only year for which data was saved every three hours), calculating the $Q_c$ effect at every time step rather than monthly reduces the global-average error from 25% to 10%. The remaining error is due to the fact that the surface albedo feedback is somewhat nonlinear, as described earlier, and the radiative kernel calculation depends on the size of the standard anomaly used. Further refinement of the technique (for example, using different surface albedo anomalies in different regions) may reduce the error; however, the error associated with the averaging technique or interactions between components cannot be reduced in this way.

The annual-average clear-sky outgoing longwave change patterns are very similar (Figures 2b and 2d), and the error in the global-average value calculated with the kernel technique is 2% for the 20-year CAM experiment. Both methods indicate that the clear-sky longwave feedbacks are positive in the tropics and negative at high latitudes. The positive values in the tropics suggest the possibility of a regional runaway greenhouse, where the regions are less effective at cooling radiatively as the temperatures rise (Held and Soden 2000). The presence of clouds (Figure 2f) decreases the effects of non-cloud variable changes in these regions, and other regions exhibit increased longwave cooling, so the global-average longwave feedback is safely negative. Figure 3b shows that the kernel technique slightly overestimates the zonal-average positive feedback in the tropics as well as the negative feedback at higher latitudes. In other words, the kernel technique tends to produce the correct zonal-average feedback sign but overestimates the magnitude, by up to 12%. Combining the kernel and variable anomalies at every
time step before averaging does not significantly alter the results. The dashed and dotted lines in Figure 3b are essentially the same.

Figure 4 shows that the kernel technique captures most of the seasonal variation in feedbacks as well. Figures 4a and 4b show results for the first year of the simulation (when the every time step values are available), while Figures 4c and 4d show results for the entire 20-year simulations. Again, the shortwave results are improved when the kernel and variable differences are combined at every time step, while the longwave results are sometimes improved and sometimes worsened. The shortwave results are the most similar to the modeled changes in northern hemisphere summer, when no sunlight reaches the high southern latitudes and thus the albedo feedback is greatly reduced. The use of the longer averaging period reduces the noise due to interannual variability (especially in the longwave fluxes), but the correspondence between the kernel and model results does not change significantly.

Since the radiative kernel technique produces feedback estimates for every grid point, we can use it to compare the relative importance of different feedbacks regionally. Figure 5a shows the ratio of zonal clear-sky shortwave flux changes from surface albedo and water vapor anomalies to the total $Q_c$ change (calculated as the sum of the different contributions; see the dashed line in Figure 3a). The sum of both ratios is 1 everywhere; values close to 1 indicate that feedback is the dominant one at that latitude, while negative values indicate that the feedback is of the opposite sign to the net feedback (and thus the other feedback ratio must be greater than one). As expected, the water vapor feedback is the dominant feedback everywhere except in locations where the surface albedo change is large (i.e., in regions where sea ice or continental snow cover decreases). In the continental tropics and mid-latitudes, small regional surface albedo increases partially cancel the warming due to water vapor and result in a very slight dip
of the zonal average ratio below zero.

In contrast to the shortwave results, for the longwave clear-sky feedbacks, there is a large amount of compensation among the different components (Figure 5b). Magnitudes of ratios are generally larger than one, and the sign changes in $\Delta F_c$ result in ratio magnitudes of 20 to 40 close to the transitions. Water vapor and CO$_2$ changes tend to oppose temperature changes. (Strictly speaking, the CO$_2$ effect is not a feedback, but it does contribute to the changes in $F_c$ and is necessary for a complete TOA budget.) In particular, the water vapor and atmospheric temperature flux changes tend to cancel each other spatially, suggesting that the lapse rate and water vapor feedbacks operate in CAM as is found elsewhere (Randall et al. 2007; Allan et al. 2002; Colman 2003; Soden and Held 2006). Comparison with the total $F_c$ change (Figure 3b) shows that when the water vapor and CO$_2$ (i.e., greenhouse gas) ratios are positive, the change in $-F_c$ is positive, and when the temperature ratios are positive, the change in $-F_c$ is negative. This is an expected result, since the greenhouse gas effects are warming (positive), and the temperature effects are cooling. While the water vapor and CO$_2$ effects are similar in magnitude at high latitudes, the water vapor effect is much larger in the tropics. Of the temperature responses, the surface temperature response dominates at high latitudes, and the atmospheric temperature response is significantly larger in the tropics.

In this section, we compare clear-sky TOA flux changes from CAM with flux changes calculated using the kernel technique. The regional patterns and overall magnitude of the flux changes are similar between the two techniques, though the shortwave feedbacks are too small by about a fourth when monthly-average data is used. However, these clear-sky flux discrepancies will most likely be reduced for the all-sky fluxes. Clouds will mask some of the albedo, water vapor, and temperature feedbacks. Thus, comparing the clear-sky fluxes overemphasizes
the nonlinearities in the non-cloud feedbacks. The calculation of cloud feedbacks using the kernel technique requires additional steps. In the next section, we combine kernel results from non-cloud variables with information from the GCM experiment to estimate the model’s cloud feedbacks.

4. Impact of non-cloud variables on cloud radiative forcing

Differences in cloud feedbacks account for the largest portion of the spread in climate sensitivities among climate models (Randall et al. 2007; Cess et al. 1990; Webb et al. 2006; Colman 2003; Ringer et al. 2006; Soden and Held 2006). Because cloud feedbacks are nonlinear, we cannot simply apply the kernel technique to, for example, the cloud fraction and obtain the changes in TOA fluxes due to clouds. Here we introduce one method of estimating cloud feedbacks, which uses information from the non-cloud variables. Unlike some techniques, the method requires little computation, yet it separates the effects of clouds from those related to other variables.

Two methods are commonly used to calculate cloud feedbacks in climate models. The first is to use offline radiative transfer calculations with cloud fields from two model simulations to determine the change in TOA fluxes, and then divide by the global-average surface temperature change, as is done for other variables (Wetherald and Manabe 1988). A more computationally-efficient method is to calculate the cloud radiative forcing (CRF, the difference between the TOA all-sky and clear-sky fluxes) for each simulation. The difference in cloud forcing (ΔCRF), divided by the temperature change, is a useful diagnostic of the cloud feedback (Cess and Potter 1988). The shortwave and longwave ΔCRF from CAM are shown in Figures 6a and b.
The second method is easy to implement. Clear-sky and all-sky fluxes are generally calculated as part of normal model computations. However, $\Delta$CRF depends not only on cloud property changes, but also on other climate variables, such as water vapor. Cloud feedbacks calculated using the $\Delta$CRF method will not be the same as those calculated with the more accurate offline radiative transfer method (Soden et al. 2004). For example, if clouds are present over sea ice in the present-day, the present-day shortwave CRF will be small, since setting the cloud fraction to zero in the model will not significantly change the TOA albedo in that region. The surface albedo will still be high, resulting in about the same solar reflection when the sky is clear as when the sky is cloudy. In the doubled-CO$_2$ climate, however, the surface albedo decreases as sea ice melts. Now setting the cloud fraction to zero in the model will result in a large decrease in reflected sunlight compared to the cloudy case. Even if we keep the cloud fraction the same as the present-day value, $\Delta$CRF will not be zero, because the doubled-CO$_2$ CRF will be negative (cooling) and large, while the present-day CRF will be small.

The kernel technique can be used to estimate the effects that temperature, water vapor, and surface albedo have on $\Delta$CRF ($\Delta$CRF$_k$, the change in $\Delta$CRF caused solely by changes in the non-cloud variables, as calculated by the kernel technique). We subtract the change in $Q_c$ or $-F_c$ between the doubled CO$_2$ simulation and the present-day simulation ($\Delta Q_c$ or $-\Delta F_c$) from the change in $Q$ or $-F$ ($\Delta Q$ or $-\Delta F$), both calculated using the monthly-average kernel method for temperature, water vapor, and surface albedo:

$$\Delta CRF_{kSW} = \Delta Q - \Delta Q_c$$

$$\Delta CRF_{kLW} = -\Delta F + \Delta F_c$$

where the subscripts $_{SW}$ and $_{LW}$ refer to the shortwave and longwave components respectively. Figures 2c, e, d, and f show $\Delta Q_c$, $\Delta Q$, $-\Delta F_c$, and $-\Delta F$ due to changes in non-cloud variables
based on the kernel technique. If changes in temperature, water vapor, surface albedo, and CO\textsubscript{2} did not impact \( \Delta \text{CRF} \), all-sky and clear-sky plots would be identical. Differences between the all-sky and clear-sky flux effects “contaminate” the \( \Delta \text{CRF} \) values. Figure 7 shows the zonal average contributions to \( \Delta \text{CRF} \) by the individual components (i.e., \( \Delta \text{CRF}_k \)).

Changes in the non-cloud variables make \( \Delta \text{CRF}_{SW} \) more negative (Figure 7a). The global average \( \Delta \text{CRF}_{SW} \) from CAM is -1.2 W m\textsuperscript{-2}, while \( \Delta \text{CRF}_{kSW} \) is -0.4 W m\textsuperscript{-2}. The albedo changes contribute -0.6 W m\textsuperscript{-2} to \( \Delta \text{CRF}_{kSW} \). As described above, changes in the surface albedo (in particular, sea ice) result in a decrease in CRF, even if the cloud properties do not change. The water vapor effect is +0.2 W m\textsuperscript{-2}. Increases in water vapor are more effective at increasing the TOA absorbed solar radiation when clouds are present. Especially over low albedo surfaces, such as the ocean, increases in water vapor do not greatly alter the absorbed solar radiation when the cloud fraction is zero, since most of solar radiation that makes it through the atmosphere is absorbed by the surface (i.e., \( \Delta Q_c \) is small). However, when clouds are present, increases in water vapor lead to increased TOA solar absorption (\( \Delta Q \) is positive and larger), since additional water vapor absorbs additional solar radiation before it can be reflected to space by clouds.

In high latitudes, where the sea ice is changing (i.e., at the same latitudes where we see the difference in \( \Delta Q_c \) between the monthly-average kernel method and CAM), \( \Delta \text{CRF}_{kSW} \) is dominated by the albedo effect. The contribution of the water vapor changes, in contrast, is similar across all latitudes and generally of opposite sign. Thus, the water vapor effect dominates \( \Delta \text{CRF}_{kSW} \) outside of high latitudes.

The non-cloud variables also make \( \Delta \text{CRF}_{LW} \) more negative, except at high latitudes (Figure 7b). The effect is largest in the tropics. The global average \( \Delta \text{CRF}_{LW} \) from CAM is quite close
to zero (-0.06 W m$^{-2}$); $\Delta \text{CRF}_{kLW}$ -1.2 W m$^{-2}$. The atmospheric temperature contribution is -0.9 W m$^{-2}$; in a warmer climate, clouds are warmer and thus more effective at radiating to space, a cooling effect. The water vapor contribution is -1.3 W m$^{-2}$, and CO$_2$ contributes -0.7 W m$^{-2}$. When no clouds are present, water vapor and CO$_2$ absorb more longwave radiation in the doubled-CO$_2$ case than in the present-day simulation. Thus, the difference between all- and clear-sky fluxes (CRF) is reduced in the doubled-CO$_2$ case, resulting in a negative contribution to $\Delta \text{CRF}_{LW}$. The only positive contribution is from the surface temperature (+1.7 W m$^{-2}$). By trapping the upwelling longwave radiation from the surface, cloud decreases the outgoing longwave radiation. In a warmer climate, more longwave radiation is emitted by the surface, so clouds trap more radiation, leading to a larger positive CRF in the doubled-CO$_2$ climate.

The total $\Delta \text{CRF}_{kLW}$ is similar to the water vapor effect in low latitudes and becomes positive at high latitudes due to the surface temperature changes. However, there is cancellation between the surface temperature on one hand and the atmospheric temperature, water vapor, and CO$_2$ effects on the other, at all latitudes.

To determine the net effect of non-cloud variables on $\Delta \text{CRF}$, we add the longwave and shortwave effects. The net $\Delta \text{CRF}_k$ is -1.6 W m$^{-2}$, while the total $\Delta \text{CRF}$ from CAM is -1.3 W m$^{-2}$, indicating that changes in non-cloud components contribute significantly to $\Delta \text{CRF}$ and make it more negative. If we assume that the kernel technique adequately captures the effects of temperature, water vapor, surface albedo, and CO$_2$ changes, we can calculate the adjusted $\Delta \text{CRF}$ ($\Delta \text{CRF}_a$):

$$\Delta \text{CRF}_a = \Delta \text{CRF} - \Delta \text{CRF}_k$$

which should be a more accurate diagnostic of the cloud feedback than $\Delta \text{CRF}$. Figures 6c and d and Figure 8 show $\Delta \text{CRF}$ and $\Delta \text{CRF}_a$ for this climate change experiment. The global
average net $\Delta \text{CRF}_a$ is +0.3 W m$^{-2}$. $\Delta \text{CRF}_{a SW}$ is negative (-0.9 W m$^{-2}$), since tropical low clouds increase in CAM3, resulting in an increased planetary albedo. The negative $\Delta \text{CRF}_{a SW}$, however, is more than compensated for by the positive $\Delta \text{CRF}_{a LW}$ (1.2 W m$^{-2}$) resulting from the increased greenhouse effect of increased clouds.

However, from section 3, we know that the kernel technique does not capture the complete $\Delta Q_c$ or $\Delta F_c$. If we assume that the effects of nonlinearity are significantly reduced in the all-sky flux calculations, we can recompute $\Delta \text{CRF}_k$ using the model-calculated $\Delta Q_c$ and $\Delta F_c$ instead of the kernel-derived values. We still use the kernel-derived values for $\Delta Q$ and $\Delta F$. In this case, $\Delta \text{CRF}_{k SW}$ actually increases, from -0.4 W m$^{-2}$ to -0.8 W m$^{-2}$. On the other hand, the longwave effect is essentially the same, since the clear-sky longwave fluxes differ by only 0.01 W m$^{-2}$ between the kernel technique and CAM. In this case, $\Delta \text{CRF}_k$ is -2.0 W m$^{-2}$. These adjustments leave a positive $\Delta \text{CRF}_a$ of +0.7 W m$^{-2}$. Thus, the magnitude of the adjusted cloud feedback changes based on whether or not we assume similarity of the nonlinear effects on the clear-sky and all-sky shortwave fluxes. Since we expect clouds to partially reduce, but not eliminate, the error in the shortwave fluxes, the true value for CAM’s $\Delta \text{CRF}_a$ likely lies between these two values (+0.3 W m$^{-2}$ to +0.7 W m$^{-2}$).

To convert $\Delta \text{CRF}_a$ values (as well as the flux changes due to other climate components) into feedback values, we divide by the global average surface temperature change corresponding to a doubling of CO$_2$, 2.47 K. The net cloud feedback, based on $\Delta \text{CRF}_a$, is 0.1 W m$^{-2}$ K$^{-1}$ (-0.4 W m$^{-2}$ K$^{-1}$ shortwave, 0.5 W m$^{-2}$ K$^{-1}$ longwave), indicating that clouds are actually a slight positive feedback in CAM (i.e., changes in clouds in CAM lead to a net TOA heating in the doubled-CO$_2$ experiment) in contrast to the negative feedback which would be obtained using the non-adjusted $\Delta \text{CRF}$. Clouds reflect more sunlight, but they emit less longwave radia-
ation, with the longwave heating larger than the shortwave cooling. For comparison, the water vapor feedback is 1.4 W m$^{-2}$ K$^{-1}$; the albedo feedback is 0.2 W m$^{-2}$ K$^{-1}$; the atmospheric temperature feedback is -2.5 W m$^{-2}$ K$^{-1}$; and the surface temperature feedback is -0.7 W m$^{-2}$ K$^{-1}$.

5. Conclusions

A new technique to calculate feedbacks in climate models has recently been developed by Soden and Held (2006). This technique separates feedbacks into two components. One component, the radiative kernel, describes the change in TOA fluxes resulting from a standard change in a feedback variable at every grid point and level. The other component is the change in the particular feedback variable (e.g., water vapor or surface albedo) for a given climate experiment. Since the kernel is appropriate for any climate experiment with its corresponding climate model (assuming, of course, that the radiative transfer portion is unchanged), the same kernel can be used for multiple climate experiments. In addition, a comparison of kernels from three climate models indicates that, to first order, the same kernel can be used for different models (Soden et al. 2007). Thus, the kernel technique can be used to quickly compare feedbacks across various climate models, using data that has already been generated, without requiring computationally expensive offline radiative transfer calculations for all models.

The usefulness of the kernel technique depends on the linearity of the feedback processes. In order to test this assumption, we compare changes in TOA clear-sky fluxes calculated using the kernel technique with those obtained by a GCM for the case of CO$_2$ doubling. If the kernel technique accurately represents clear-sky feedbacks, these two values should be the same. We
find that these values are in fact similar. For the case of shortwave radiation, the global average TOA shortwave change is underestimated by a quarter partially as a result of intra-month correlations of surface albedo with the radiative kernel. When the kernel and variable anomalies are combined every three hours, rather than monthly, the error is reduced to 10%. The specifics of the averaging procedure do not significantly affect the TOA longwave fluxes calculated with the kernel technique. In addition, the longwave fluxes show better agreement overall, with a global-average error of 2%. These calculations provide an estimate of uncertainties associated with the technique related to the nonlinearity of feedbacks within a model.

Thus, the longwave clear-sky fluxes calculated using the kernel technique are in quite good agreement with those from CAM. The shortwave clear-sky fluxes capture much of the CAM behavior, but differ in overall magnitude. Using a different averaging procedure improves the results, but using three-hourly data is not practical for most model intercomparisons, since the vast majority of saved model data is on monthly timescales (or longer). However, we anticipate that errors will be less for all-sky fluxes, and using different surface albedo anomalies to calculate the kernel will likely reduce the errors. Furthermore, if the errors are similar across different climate models, the technique can still be useful in comparing feedbacks among the different models. In particular, this technique provides a computationally efficient method for obtaining longwave feedbacks, for which shortwave techniques such as those of Yokohata et al. (2005), Winton (2006), and Taylor et al. (2007) do not work. Outside of high latitudes, both the longwave and shortwave feedbacks calculated using the technique perform quite well.

Cloud feedbacks are often estimated as $\Delta$CRF, the change in cloud radiative forcing between the experimental and control simulations, divided by the global-average surface temperature. However, variables other than clouds may impact $\Delta$CRF. We use the kernel technique to
estimate the effect of water vapor, temperature, albedo, and carbon dioxide changes on $\Delta$CRF, demonstrating the problem with the standard $\Delta$CRF technique. Changes in non-cloud variables make $\Delta$CRF$_{SW}$ more negative. The positive shortwave contribution related to the water vapor change partially cancels the negative contribution due to the albedo change. Non-cloud variables also make $\Delta$CRF$_{LW}$ more negative, with atmospheric temperature, water vapor, and CO$_2$ all providing negative contributions and surface temperature providing a positive contribution.

The net effect of the non-cloud components ($\Delta$CRF$_k$) is -1.6 W m$^{-2}$, while the total $\Delta$CRF from CAM is -1.3 W m$^2$, indicating that surface albedo, temperature, and water vapor changes contribute significantly to $\Delta$CRF and make it more negative. Assuming linearity of the $\Delta$CRF contributions, these results indicate that the net cloud feedback in CAM is positive. Depending on our assumption about the similarity of the nonlinear effects on the clear-sky and all-sky shortwave fluxes, the value for CAM’s cloud feedback likely lies between 0.1 W m$^{-2}$ K$^{-1}$ and 0.3 W m$^{-2}$ K$^{-1}$. Calculating cloud feedbacks using the kernel technique addresses the problem of the standard $\Delta$CRF technique while retaining its computationally efficiency. Soden et al. (2007) continue the testing of this cloud feedback estimation technique.

So far, the technique has only been tested by comparison to other model results (using the clear-sky flux changes, as is done here, or by comparison to the partial radiative perturbation method, as is done in Soden et al. (2007)). It may be possible to use observational data, such as satellite data, to validate the radiative kernels (which correspond to the radiative transfer portions of GCMs) and then use observations of temperature, water vapor, and surface albedo changes to estimate feedbacks for the current climate. However, care must be taken, since clear-sky fluxes are calculated differently in models and satellite data sets (Zhang et al. 1994a). Comparison with observational results would be a useful way of extending this
computationally-efficient technique for model intercomparison to a more general applicability.

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