Diagnosing Cloud Feedbacks in General Circulation Models

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ABSTRACT

In this study, it is shown that the NCAR and GFDL GCMs exhibit a marked difference in climate sensitivity of clouds and radiative fluxes in response to doubled CO$_2$ and ±2-K SST perturbations. The GFDL model predicted a substantial decrease in cloud amount and an increase in cloud condensate in the warmer climate, but produced a much weaker change in net cloud radiative forcing (CRF) than the NCAR model. Using a multiple linear regression (MLR) method, the full-sky radiative flux change at the top of the atmosphere was successfully decomposed into individual components associated with the clear sky and different types of clouds. The authors specifically examined the cloud feedbacks due to the cloud amount and cloud condensate changes involving low, mid-, and high clouds between 60°S and 60°N. It was found that the NCAR and GFDL models predicted the same sign of individual longwave and shortwave feedbacks resulting from the change in cloud amount and cloud condensate for all three types of clouds (low, mid, and high) despite the different cloud and radiation schemes used in the models. However, since the individual longwave and shortwave feedbacks resulting from the change in cloud amount and cloud condensate generally have the opposite signs, the net cloud feedback is a subtle residual of all. Strong cancellations between individual cloud feedbacks may result in a weak net cloud feedback. This result is consistent with the findings of the previous studies, which used different approaches to diagnose cloud feedbacks. This study indicates that the proposed MLR approach provides an easy way to efficiently expose the similarity and discrepancy of individual cloud feedback processes between GCMs, which are hidden in the total cloud feedback measured by CRF. Most importantly, this method has the potential to be applied to satellite measurements. Thus, it may serve as a reliable and efficient method to investigate cloud feedback mechanisms on short-term scales by comparing simulations with available observations, which may provide a useful way to identify the cause for the wide spread of cloud feedbacks in GCMs.

1. Introduction

It has long been recognized that the radiative effects of clouds play an important role in regulating the earth’s energy budget and modulating anthropogenic climate changes. Although cloud–climate feedbacks have been intensely studied in the past decades, the sign of net cloud feedback is still a matter of uncertainty as concluded by the Third Assessment Report (TAR) of the Intergovernmental Panel on Climate Change (IPCC; Houghton et al. 2001). Understanding the mechanisms of cloud–climate feedbacks and reducing the uncertainties continue to be the toughest challenges in climate research.

Most of current knowledge of cloud–climate feedbacks is from three types of climate sensitivity experiments. The first two are the classic ±2-K sea surface temperature (SST) perturbation experiments (e.g., Cess and Potter 1988; Cess et al. 1990, 1996; Zhang et al. 1994) and doubling CO$_2$ experiments (e.g., Wetherald and Manabe 1988; Senior and Mitchell 1993; Williams et al. 2003). While the former provides the simplest way to measure the strength of cloud feedback, the latter further includes the complexity arising from a responsive ocean. While these experiments allow internally varied cloud fields in response to external forcings, the third type of experiments attempts to isolate
various feedback mechanisms by specifying cloud fields or cloud properties in GCM simulations (e.g., Taylor and Ghan 1992; Schneider et al. 1999).

Quantitatively climate feedback is measured by a feedback parameter defined as the ratio of the change in global mean net radiative flux at the top of the atmosphere (TOA) \( R \) to the change in global mean surface temperature \( T_s \) [i.e., \( \lambda = -(\partial R/\partial T_s) \); e.g., Wetherald and Manabe 1988; Soden et al. 2004]. To diagnose the feedback induced by clouds and calculate the cloud feedback parameter, corresponding to the various climate sensitivity experiments stated previously, different approaches have been developed. The partial radiative perturbation (PRP) approach pioneered by Wetherald and Manabe (1988) allows a quantification of all the possible feedback processes operating in a simulated climate system by explicitly computing the radiative perturbation (PRP) approach cannot completely separate cloud feedbacks from other feedbacks, such as water vapor and temperature feedbacks. The same argument was also made by Zhang et al. (1994). Based on their calculations, Soden et al. (2004) warned that there is a potential for the CRF approach to misinterpret a positive cloud feedback as a negative feedback. This finding suggests that the results from CRF analyses need to be interpreted with caution under certain circumstances. Leaving aside the possible “cloud masking” effect of CRF, which may be considered as a small flaw on a gem, the real limitation of CRF is that it lacks the ability to determine the individual contributions that result from different cloud processes to the total cloud feedback. Thus, the CRF approach provides little help to identify the cause for the wide spread of cloud feedbacks among GCMs.

Over the past few decades, both the CRF and PRP approaches have been widely applied to the analysis of cloud feedbacks in GCMs, which helps us to recognize the problems and gain some insight into the uncertainties of cloud feedbacks (e.g., Taylor and Ghan 1992; Zhang et al. 1994; Colman et al. 2001). However, the slow progress in reducing uncertainties associated with cloud feedbacks continues, which in part can be attributed to the methodological difficulty in evaluating cloud feedback processes (Bony et al. 2006), since the current approaches either cannot provide detailed information on various cloud feedback processes (e.g., CRF) or generate something that cannot be directly evaluated by observations (e.g., PRP). Over the past couple of decades, a great amount of satellite data of clouds and radiation has been collected. These data can be very useful for verifying model-simulated cloud feedback processes if the observed change in total radiative fluxes at TOA can be decomposed into individual components associated with different cloud processes. Unfortunately, the current methods, either PRP or CRF, cannot fulfill this task.

The need to develop novel feedback analysis approaches can be further demonstrated by the complexity of cloud feedbacks shown in the climate sensitivity tests performed by the GFDL and the National Center for Atmospheric Research (NCAR) GCMs. As shown in Fig. 1, the cloud properties and net CRF simulated by the NCAR Community Atmosphere Model version 3 (CAM3) and the GFDL AM2 have different responses to doubled CO\(_2\) and ±2-K SST perturbations at most latitudes. AM2 simulated a decrease in cloud amount and an increase in cloud condensate.
much stronger in magnitude than CAM3. The substantial reduction of cloud amount in the AM2 simulations appears to be largely compensated by the marked increase in cloud condensate, resulting in a net CRF change much weaker than that of CAM3. To fully understand the cause for this inconsistent response of clouds and radiation to climate change forcings shown in these sensitivity experiments, it is useful to decompose the change in total radiative fluxes into the individual components associated with different types of clouds (e.g., low, mid-, and high clouds) and different cloud properties (cloud amount and condensate). In this study, we propose a multiple linear regression (MLR) method for such a decomposition. The appropriateness and power of MLR in exploring the relationship between radiative fluxes and clouds have been demonstrated by Hartmann et al. (1992), who successfully decomposed the radiative fluxes observed by the Earth Radiation Budget Experiment (ERBE) in terms of the International Satellite Cloud Climatology Project (ISCCP) clouds using a linear stepwise regression. Here, the MLR approach is extended to analyze the cloud feedbacks in the ±2-K SST perturbation and doubling CO₂ experiments by decomposing the total cloud feedbacks into individual components. Although such a decomposition can also be done using the PRP approach, the main purpose to choose MLR is to test its performance in cloud feedback analysis since this method has a potential application to long-term satellite observations and the corresponding Atmospheric Model Intercomparison Project (AMIP) simulations by GCMs. If successful, the MLR approach can serve as a routine powerful supplement to CRF since it is easy to execute and yet retains the basic power of the PRP approach to quantify individual cloud feedback processes, an ability that the CRF approach lacks.

The paper is organized as follows. Section 2 describes the procedure of using MLR to diagnose feedback processes in the climate system and briefly reviews the climate sensitivity experiments used in this study. Section 3 presents the diagnosed individual cloud feed-
backs using the proposed method. A summary and discussion are presented in section 4.

2. Methodology

a. Multiple linear regression

The PRP approach is based on the assumption that the total change in the radiative budget can be broken down linearly into individual components (feedbacks). Considering the change in net radiative flux at TOA $\delta R = \delta F - \delta Q$ due to climate change, according to the linear assumption, $\delta R$ can be expressed as

$$\delta R = \delta R_1 + \delta R_2 + \cdots + \delta R_n = \frac{\partial R}{\partial x_1} \delta x_1 + \frac{\partial R}{\partial x_2} \delta x_2 + \cdots + \frac{\partial R}{\partial x_n} \delta x_n,$$

where, $F$ and $Q$ are the upward longwave and net downward shortwave radiative fluxes. Here $x_i$ is a generic variable representing surface temperature $T_s$, atmospheric temperature $T_a$, specific humidity $q_a$, clouds $c$, or any other quantity that may have a feedback on the climate system. The validity of the linear feedback assumption at the climate scale has been supported by previous studies (e.g., Wetherald and Manabe 1988; Zhang et al. 1994; Colman and McAvaney 1997) using offline radiative transfer calculations. The robustness of the linear relationship between total and individual feedbacks allows us to diagnose cloud feedbacks using the MLR approach. Considering the partial derivatives as the coefficients of a regression equation, Eq. (1) can be further written as

$$\delta R = \sum_{i=1}^{m} c_i \delta x_i + r_\epsilon; \quad c_i = \frac{\partial R}{\partial x_i},$$

where $m$ indicates the number of factors that may contribute significantly to the total feedback. $c_i$ represents the feedback coefficient associated with a particular feedback process, and $r_\epsilon$ is the residual. The PRP approach determines the partial derivatives using offline radiative transfer calculations, whereas for MLR if one has $n$ sets of samples of Eq. (2), the feedback coefficients $C = [c_1, c_2, \ldots, c_m]$ and the residual $r_\epsilon$ can be determined (see the appendix for details). There are two advantages of this method. First, it supports separating total cloud feedback in terms of cloud types (e.g., low, mid-, and high clouds) and cloud properties (cloud amount and optical thickness), similar to the PRP approach although they use different ways to accomplish the task. Second, this method provides a self-evaluation of regression performance. The significance of overall fitting regression and the significance of each independent feedback process in the linear model can be evaluated by the multiple correlation coefficient $\Gamma_{R,x_1, \ldots, x_m}$ and $t$ statistics $t_r$, respectively (see the appendix for details).

The core of the MLR approach is to obtain the samples of Eq. (2). Traditionally, a climate state is defined by the statistical mean over a sufficiently long period, say, 10 or 20 yr depending on the specific climate sensitivity experiment. However, any shorter time-scale mean (e.g., monthly or yearly mean) within the time series, although containing noise, includes the information of feedbacks. Thus, each monthly or yearly mean of model output can be considered as a sample of Eq. (2). Assuming that one has 20-yr data of two different climates for example, the present and doubled CO$_2$ climates, if the yearly mean is used, then the difference between the two climates yields 20 sets of samples of Eq. (2); if monthly mean is used, then the number of samples increases to 240. Note that in the latter case, the samples may contain seasonal signals, but they have been much reduced since only the difference, not the absolute value of each month, is considered. We have tested the regression using both yearly and monthly mean data. They basically produce similar results, but the estimation error is smaller when the monthly mean is used, apparently due to more sets of samples. For this reason, the diagnosed feedbacks shown in the following sections are computed using the monthly mean data obtained from the climate sensitivity experiments.

b. Climate sensitivity experiments

In this study, the proposed MLR methodology is used to analyze cloud feedbacks in the climate sensitivity experiments performed by NCAR CAM3 and GFDL AM2. The detailed description of the relevant model physics and the simulated climatology in CAM3 and AM2 are referred to Collins et al. (2004) and the GFDL Global Atmospheric Development Team (2004). Two types of experiments are analyzed in this study. The first is the $\pm2$ K SST perturbation experiments. Unlike the classic Cess experiments, which are the perpetual July simulations, here both models were forced by the observed monthly mean climatological SST with seasonal variation uniformly added by a perturbation of $\pm2$ K. AM2 was integrated for 9 yr for each run and the last 8-yr monthly mean data are used for the analysis, which gives 96 sets of samples of Eq. (2), whereas CAM3 was executed for 10 yr, thus, 108 sets (last 9 yr) of samples are available for the analysis. These two experiments hereafter are named as CAM3–CESS and AM2–CESS, respectively. We would like to
note that ±2-K SST perturbation forcing is highly unrealistic. The main purpose of including this type of experiments in this study is to show that the different cloud feedbacks between CAM3 and AM2 in coupled simulations (see below) also occur in the fixed SST perturbation experiments. This has an important implication that the cloud feedback issue can be properly accessible in an uncoupled atmospheric modeling system. More specifically, it means that we may use the AMIP simulations to identify the possible cause of the different cloud feedbacks among GCMs if the diagnosed cloud feedbacks from simulations can be compared directly with satellite observations.

The second type of climate sensitivity tests is the doubling CO$_2$ experiment. In this experiment, the atmospheric model is coupled to a slab ocean model (SOM). In the control simulation, the CO$_2$ concentration was fixed to the present climate value. This value was doubled at the beginning of integration for the sensitivity simulations. Since the ocean mixed layer temperature is a prognostic variable when the SOM is enabled, the model generally takes a much longer time to reach equilibrium than when SSTs are prescribed, so that both models were integrated for 50 yr, hereafter named as CAM3–2CO$_2$ and AM2–2CO$_2$, respectively. The last 20-yr monthly mean data are used for the analysis. Thus, 240 sets of samples are available for the regression analysis. Figure 2 compares the ISCCP annual mean total cloud amount and vertically integrated condensed water path [(CWP) i.e., liquid water path (LWP) + ice water path (IWP)] and the ERBE annual mean net CRF with those from the CAM3 and AM2 control simulations. Overall, there is fairly good agreement in cloud amount and CWP between observations and simulations in the Tropics and subtropics. However, large model biases are shown in the mid- and high latitudes. Both models significantly overestimate cloud amount beyond 70°. Serious positive biases in CWP are around 60° in both hemispheres. Despite the large biases in cloud properties, the simulated net CRF at TOA matches the ERBE observations unexpectedly well at most latitudes, especially for CAM3. The most likely explanation for this agreement is that the radiative biases generated at different levels due to incorrect cloud properties cancel each other to result in a radiative forcing superficially right at TOA although fundamen-
3. Regression results

Cloud–climate feedback is determined by many processes. Theoretically, any possible feedback process can be explicitly analyzed using Eq. (2) as long as enough sets of samples are available. However, in this study we only focus on cloud feedbacks. All the other noncloud feedbacks are grouped into the residual term in Eq. (2). The net cloud feedback is further divided into the contributions from cloud amount and cloud condensate (taken as CWP in this study) of low \( P > 680 \text{ hPa} \), mid-\( 440 \text{ hPa} < P < 680 \text{ hPa} \), and high \( P < 440 \text{ hPa} \) clouds in a total of six categories. In CAM3, the cloud vertical overlap follows Collins (2001), while AM2 uses a resolution-invariant overlap scheme (Pincus et al. 2003).

a. Regression significance and the change in clear-sky radiative flux and CRF

If Eq. (2) does represent the feedback processes in the cloud system in response to climate change forcings, then it can be used to deduce the change in clear-sky radiative flux and CRF from the change in full-sky radiative fluxes. Considering the previously classified three cloud types (low, mid, and high) and two cloud properties (amount and CWP), applying Eq. (2) to longwave and shortwave radiative fluxes, respectively, yields

\[
\delta F = \left( \sum_{i=1}^{6} c_{F_i} \delta x_i \right)_{\text{cloud}} + r_{F_c}, \tag{3}
\]

\[
\delta Q = \left( \sum_{i=1}^{6} c_{Q_i} \delta x_i \right)_{\text{cloud}} + r_{Q_c}. \tag{4}
\]

Physically, \( r_{F_c} \) and \( r_{Q_c} \) should represent the change in clear-sky longwave and shortwave radiative flux, respectively, and \( r_{F_c} - r_{Q_c} \) is the net clear-sky flux change if MLR forms a good approximation of the effect of clouds on the radiation balance (Hartmann et al. 1992). Following Ramanathan (1987), the longwave, shortwave, and net CRF are defined \( f_{\text{clr}} = F_{\text{clr}} - F \), \( f_{\text{scrf}} = -(Q_{\text{clr}} - Q) \), and \( f_{\text{fcrf}} = (F_{\text{clr}} - F) - (Q_{\text{clr}} - Q) \), respectively, where \( F_{\text{clr}} \) and \( Q_{\text{clr}} \) are the clear-sky upward longwave and net downward shortwave radiative fluxes. Thus, the change in CRF due to external forcing can be represented by

\[
\begin{align*}
\delta f_{\text{fcrf}} &= (F_{\text{clr}} - F)_{2} - (F_{\text{clr}} - F)_{1} \\
\delta f_{\text{scrf}} &= -(Q_{\text{clr}} - Q)_{2} + (Q_{\text{clr}} - Q)_{1}, \\
\delta f_{\text{clr}} &= \delta f_{\text{fcrf}} + \delta f_{\text{scrf}},
\end{align*}
\]

where subscript 1 and 2 indicate two different climates. In the regression formulation, terms \( \left( \sum_{i=1}^{6} c_{F_i} \delta x_i \right)_{\text{cloud}} \) and \( \left( \sum_{i=1}^{6} c_{Q_i} \delta x_i \right)_{\text{cloud}} \) in Eqs. (3) and (4) represent the change in longwave and shortwave radiative fluxes due to clouds. In accordance with the definition of CRF, the values of \( -(\sum_{i=1}^{6} c_{F_i} \delta x_i)_{\text{cloud}} \), \( (\sum_{i=1}^{6} c_{Q_i} \delta x_i)_{\text{cloud}} \), and their difference in the regression relations should be close to the change in longwave, shortwave, and net CRF. But they are not exactly the same because of the slight difference in their definitions. In the MLR approach, the change in longwave and shortwave radiative fluxes due to the cloud change is directly regressed from the change in full-sky radiative fluxes. In some sense, the regressed radiative flux change associated with the cloud change is similar to that derived from the PRP approach. However, if the change in noncloud properties such as temperature and moisture is strongly correlated to the cloud change, then the MLR approach will not separate them as cleanly as the PRP approach, an effect similar to cloud masking of the CRF approach. In the worst situation, the cloud masking of MLR may be comparable to that of CRF, but should be no more than that. Thus, like the CRF approach, the results from the MLR analysis should be also interpreted bearing the possible cloud masking effect in mind. We shall further investigate this issue in our future studies when the MLR approach is applied to long-term satellite observations and the corresponding AMIP simulations.

Although the MLR approach has been applied to the entire globe, in this paper we only show the results between 60°S and 60°N. One reason is that the clear-sky shortwave radiative fluxes in a narrow band around Antarctica simulated by CAM3–2CO2 show a significant bias compared with the ERBE satellite observations (Fig. 3). No substantial bias, however, is found in the full-sky shortwave radiative fluxes. Thus, the shortwave CRF in this band simulated by CAM3–2CO2 must have an equivalent bias with an opposite sign in order to offset the bias in clear-sky shortwave flux. The reason for this bias may have to do with the incorrect sea ice cover prediction in this latitude band. Thus, we discard the regression analysis beyond 60°S and 60°N, and focus on cloud feedbacks in the low and midlatitudes. Another reason for limiting our analyses to 60°S–60°N.
is that the multiple correlation coefficient (Fig. 5) goes down beyond there. Details of regression significance will be discussed shortly.

To the first-order approximation, the MLR-deduced clear-sky radiative flux change and the cloud radiative flux change should be close to those directly simulated by the models; thus, the comparison between them provides a way to measure the fidelity of MLR in decomposing the total cloud feedback. Figure 4 compares the zonally averaged change in annual mean net CRF and clear-sky radiative flux in response to doubled CO\textsubscript{2} and ±2-K SST perturbations simulated by CAM3 and AM2 with the corresponding change deduced from MLR. Note that the radiative flux change has been normalized by the corresponding surface temperature change. First, this figure shows that the clear-sky radiative feedback behaves quite differently in the doubling CO\textsubscript{2} experiment and the ±2-K SST perturbation experiment. There is a nearly 2 W m\textsuperscript{-2} K\textsuperscript{-1} difference in clear-sky radiative flux change between the two experiments at most latitudes between 60°S and 60°N. A likely explanation for this difference is that the direct radiative forcing that resulted from doubled CO\textsubscript{2} has not been subtracted from the change in radiative fluxes in the CO\textsubscript{2} experiment. But we will not rule out the possibility that this difference reflects the different clear-sky feedback that resulted from the doubled CO\textsubscript{2} and the ±2-K SST forcings since the latter is much stronger and unrealistic.

Second, the most promising result shown in the figure is that CAM3 and AM2 predicted a fairly consistent change in clear-sky radiative fluxes in both the doubling CO\textsubscript{2} and the ±2-K SST perturbation experiments, indicating the robustness of clear-sky feedback simulated by the two models. This result is consistent with previous studies (e.g., Cess et al. 1990).

Third, in contrast to the consistent change in clear-sky radiative fluxes, the two models predicted a rather different change in cloud radiative fluxes in both types of sensitivity experiments. CAM3 predicted a decrease in net CRF in the Tropics and subtropics but an increase in the midlatitudes, which is almost opposite to the change simulated by AM2. Such an inconsistent change in CRF reflects the uncertainty and complexity of cloud feedbacks simulated by the current GCMs. In the following sections, we will break down the net CRF change in terms of different cloud types and cloud properties.
Fourth, the MLR-deduced change in net cloud and clear-sky radiative fluxes is in fairly good agreement with the corresponding simulated change in all the experiments performed by CAM3 and AM2, indicating that this method performs sufficiently well in analyzing and interpreting cloud feedback processes. There are some noticeable differences here and there between the simulations and the estimations, which in part can be attributed to the slightly different definition between the change in CRF [Eq. (5)] and the cloud radiative flux change deduced from MLR [Eqs. (3) and (4)], and in part reflect the estimation error of MLR. For example, in our MLR analysis we did not consider the effect of cloud height and cloud phase on the radiative fluxes at TOA, which was shown to be important especially for the longwave radiation according to Colman et al. (2001). However, these effects do not seem to be significant enough to affect the performance of MLR considering the general agreement between the simulated and regressed change in cloud radiative fluxes (Fig. 4). The agreement, in a way, suggests that the effect of cloud height and cloud phase might not be as important as it was expected to be. But there is also a possibility that the errors generated in different layers have been cancelled out. We note that the regression analysis done by Hartmann et al. (1992) also neglected the possible effect from cloud height and cloud phase. This issue will be further investigated using the long-term satellite observations and the AMIP simulations in our future research.

To give an evaluation of the overall performance of the MLR analyses, Fig. 5 shows the multiple correlation coefficients (similar to the correlation coefficient in the simple linear regression with one independent variable) of the four climate sensitivity experiments. The MLR analysis works well in most places, especially at the low latitudes. This is different from the analysis done by Hartmann et al. (1992), who showed that their regression analysis fails to represent the ERBE clear-sky radiative fluxes using the ISCCP clouds in the tropical convection regime where the sky is overcast since the regression is overwhelmed by the cloudy radiances and it receives little information on what clear-sky radiiances are. But this problem no longer exists in our analysis: first, the radiances in our analysis were not measured but explicitly calculated by models and, second, our regression is applied to the difference between the two climates. For overcast conditions, even though
the cloudy radiances dominate the clear-sky radiances, their difference between the two climates may not. The large value of multiple correlation coefficient suggests that the MLR analysis receives sufficiently strong signals in both clear-sky and cloudy radiances.

The significance of individual terms in the regression equation (2) can be evaluated by $t$ statistics (see the appendix). A term in Eq. (2) is considered to be significant in the regression when the following condition is met:

$$ t_i^2 > F_{\alpha}, $$

where $t_i^2$ is defined by Eq. (A9), $\alpha$ is the confidence level (in some textbooks, $1 - \alpha$ is used and refers to significance level), and $F_{\alpha}$ satisfies

$$ \int_{F_{\alpha}}^{\infty} F(\eta, \nu) \, d\eta = \alpha, $$

where $F(\eta, \nu)$ is the F distribution defined by Eq. (A11). The $t$ statistics was performed during the MLR calculation at confidence levels $\alpha = 0.9$ and $\alpha = 0.7$. Figure 6 shows the values of $t_i^2$ and $F_{\alpha}$ of six cloud properties associated with the regression analysis of the net radiative fluxes. In most cases, $t_i^2$ is greater than $F_{0.9}$, indicating that the change in six cloud properties has significant contributions to the change in net radiative fluxes at a confidence level of $\alpha = 0.9$. Some variables such as the midcloud amount change appear to be less significant than other variables at some latitudes, but their significance is still above the confidence level of $\alpha = 0.7$. There is a good agreement on the $t_i^2$ value of high clouds between CAM3 and AM2, but substantial differences are shown in low and midclouds. In the CAM3 simulations, the change in CWP appears to be more significant than the cloud amount change, while the opposite is true for the AM2 simulations. The exact reason is not clear, but since all these cloud properties show their significance above the confidence level of $\alpha = 0.9$ at most latitudes, none of them can be neglected in the regression analysis.

In short, the significance tests and the general agreement between the regressed and simulated change in cloud and clear-sky radiative fluxes at TOA suggest that the MLR approach performs sufficiently well and provides an appropriate way to interpret the cloud feedbacks in the climate system. In the following sections, the regression analysis on cloud feedbacks will be discussed in detail.

b. Total cloud radiative feedbacks

In this section, we examine the MLR-deduced radiative flux change at TOA associated with the change in total cloud amount and vertically integrated CWP. Figure 7 shows the zonally averaged change in longwave, shortwave, and net radiative fluxes at TOA due to the change in total cloud amount and CWP in response to doubled CO$_2$ and ±2-K SST perturbations, where the radiative flux change has been normalized by the surface temperature change. Significant differences between the two models are shown at most latitudes. The cloud amount change in the AM2 simulations causes a larger change in longwave and shortwave radiative fluxes than that in the CAM3 simulations. This appears to be consistent with the larger cloud amount change in AM2 shown in Fig. 1. But since the change in longwave and shortwave radiative fluxes due to cloud amount change has a different sign, the cancellation results in a net radiative flux change equivalent to that of CAM3. In contrast, the large CWP change in AM2 does not result in a large flux change as expected. In particular, the AM2–CESS experiment simulates a much smaller change in shortwave fluxes than that of CAM3–CESS at the low latitudes. This inconsistency may be related to the cancellation between different cloud feedback processes, which we will show in the following sections.

The averaged (60°S–60°N) longwave, shortwave, and net cloud feedback parameters associated with the change in total cloud amount and CWP in response to doubling CO$_2$ and ±2-K SST perturbations are shown in Fig. 8, where the total longwave and shortwave cloud feedback parameters are defined as $\lambda_{LW} = \Sigma_x - (\partial F/\partial x)(\partial x/\partial T_s)$ and $\lambda_{SW} = \Sigma_x (\partial Q/\partial x)(\partial x/\partial T_s)$, respectively, where $x$ denotes individual cloud property. Despite the differences in many aspects, CAM3 and AM2 do produce the same sign of individual longwave and short-
wave feedbacks associated with the change in cloud amount and CWP. For example, they both agree on a negative longwave feedback and a positive shortwave feedback due to the cloud amount change, and a positive longwave feedback and a negative shortwave feedback due to the CWP change. The cancellation between them determines the sign and magnitude of net cloud feedback. CAM3 produced a negative net cloud feedback mostly due to the strong negative shortwave feedback caused by the CWP change, whereas the net positive cloud feedback in AM2 results mainly from the stronger positive shortwave feedback associated with the cloud amount change.

**c. Low cloud radiative feedbacks**

To identify the cause for the different cloud feedbacks shown in the CAM3 and AM2 simulations, we further examine the cloud feedbacks associated with
individual cloud types. This section focuses on low clouds. Figure 9 shows the change in low-cloud amount and CWP in response to doubled CO$_2$ and ±2-K SST perturbations. AM2 predicted an overall low-cloud amount decrease with the maximum reduction roughly at 40°S and 40°N. The reduction of low-cloud amount between 35° and 60° in the two hemispheres is also seen in the CAM3 simulations, but the reduction in the
Northern Hemisphere is much smaller than that of AM2. Large increase of low-cloud amount in the Tropics and subtropics is shown in the CAM3 simulations. The increase and decrease of low-cloud amount at different latitudes tend to cancel each other. As a result, CAM3 predicted a weak overall low-cloud amount increase between 60°S and 60°N.

Both CAM3 and AM2 predicted a small change of CWP in the Tropics and subtropics. But beyond 35°S and 35°N, CAM3 simulated a CWP decrease, which is approximately in phase with the cloud amount change. In contrast, AM2 produced a substantial increase of CWP in this region, which is almost off-phase with the cloud amount change, indicating clouds shrink and thicken in the warmer climate. We will show later that such an opposite change in cloud properties (i.e., decrease in cloud amount and increase in CWP) also occurs in mid- and high clouds. We shall discuss this issue later. Overall, we see an opposite sign in low-cloud change between 60°S and 60°N in the CAM3 and AM2 simulations, and the AM2 predicted low-cloud change is much stronger in magnitude than that of CAM3.

As we previously showed in the total cloud feedback, a large change in cloud properties may not lead to a large change in radiative fluxes because of the possible cancellation between individual cloud feedbacks. To see if this is the case for low clouds, we plotted the regression-deduced low-cloud longwave, shortwave, and net feedback parameters in Fig. 8. AM2 predicts a strong positive shortwave feedback due to the large low-cloud amount decrease and a strong negative shortwave feedback due to the low-cloud CWP increase. But they tend to cancel each other out and result in a weaker positive net shortwave feedback. In the mean-
time, AM2 simulated a negative longwave feedback, but it is too weak to offset the positive net shortwave feedback. As a result, the residual gives a weak net positive feedback of low clouds in the AM2 simulations. On the other hand, cancellation is not a big factor in the CAM3 simulations. CAM3 simulated a negative shortwave feedback due to the CWP change, which seems to dominate other feedbacks. Thus, the resultant negative net feedback of low clouds in CAM3 is equivalent in magnitude to the positive net low-cloud feedback in AM2.

d. Midcloud radiative feedbacks

Figure 11 shows the change in cloud amount and CWP of midclouds in response to doubled CO$_2$ and ±2-K SST perturbations simulated by CAM3 and AM2. Again, marked differences are shown in the simulations. AM2 predicted a substantial decrease in cloud amount and an increase in CWP. The maximum reduction of cloud amount occurs approximately at 40°S and 40°N. But there is only a weak change in cloud amount in the Tropics. The change in CWP does not appear to be correlated to the cloud amount change. The increase of CWP is fairly uniform in the warmer climate at most latitudes.

In the CAM3 simulations, the cloud amount increase is seen in the Tropics, while the cloud amount decrease occurs in the wide range of subtropics and midlatitudes. The CWP change appears to be weakly correlated to the cloud amount change. Since the increase and decrease of cloud amount and CWP at different latitudes tend to cancel each other out, the resultant mean cloud change between 60°S and 60°N in CAM3 is much weaker than that in AM2. In particular, the overall CWP change in CAM3 is nearly tenfold weaker than that in AM2.

Figure 12 shows the longwave, shortwave, and net feedback parameters associated with the midclouds. First, individually the longwave and shortwave feedbacks associated with the cloud amount change are stronger than those associated with the CWP change. However, since there is a strong cancellation between the longwave and shortwave cloud amount feedbacks, the resultant net cloud amount feedback is equivalent to that of the CWP feedback. Second, the strong individual feedbacks in AM2 seem to be consistent with their large change in cloud properties (Fig. 11). However, the large cancellation between them causes AM2 to produce a weaker net midcloud feedback than that of CAM3. This is similar to what we have seen in low-cloud feedback. Since the net feedback is usually much weaker than individual feedbacks because of the strong
cancellation between them, the sign of net feedback may strongly depend on the estimation error even if the error is proven to be negligible to the individual feedback. Third, in the doubling CO$_2$ experiment, both CAM3 and AM2 predict a positive net midcloud feedback; while in the CESS experiment a negative net feedback is produced by CAM3, indicating that net cloud feedback may also depend on the types of external forcings.

e. High cloud radiative feedbacks

Figure 13 shows the change in high-cloud amount and CWP in response to doubled CO$_2$ and ±2-K SST perturbations. AM2 predicted a decrease in cloud amount at most latitudes between 55°S and 55°N except a slight increase in cloud amount just north of the equator shown in the doubling CO$_2$ experiment. Cloud amount increase is seen at high latitudes beyond 55° in both hemispheres. CAM3, on the other hand, predicted a much complicated high-cloud amount change. Generally, high-cloud amount increases in the Tropics and high latitudes but decreases in the subtropics. There is a large reduction of cloud amount at 15°N in the CAM3–2CO$_2$ experiment. The cancellation gives a small total high-cloud amount increase between 60°S and 60°N in the two CAM3 experiments.

It is interesting to see that both CAM3 and AM2 predicted an increase of high-cloud CWP at all latitudes in both doubling CO$_2$ and ±2-K SST perturbation experiments. This appears to be the only change in cloud properties that is agreed by both models, although the detailed variation at a specific latitude is different. The
optically thick high clouds formed in a warmer climate shown in the CAM3 and AM2 simulations may be considered to be a robust phenomenon between the two models since they are different in every aspect in the cloud parameterizations. In AM2, large-scale cloud water is parameterized based on the prognostically determined specific humidity of liquid and ice. Cloud microphysics are parameterized with an updated treatment of mixed-phase clouds (Rotstayn et al. 2000). Cloud amount is also treated as a prognostic variable following the parameterization of Tiedtke (1993). While in CAM3, the parameterization of large-scale cloud processes follows Rasch and Kristjánsson (1998) and Zhang et al. (2003) with a prognostic cloud condensate scheme combining a bulk microphysical representation of condensation and evaporation. Cloud amount is diagnostically determined based on relative humidity, atmospheric stability, and convective mass fluxes. With all these differences, both models are still able to predict the same trend of an increase in optical depth of high clouds in a warmer climate. From the water budget point of view, the potential condensate available in high clouds is determined by the thermodynamic properties of the boundary layer air, which contains more moisture in a warmer climate. Ramanathan and Collins (1991) argued that the enhanced moisture in the boundary layer air over warm oceans may enhance the convective system due to the increased parcel buoyancy associated with the increased contribution of water vapor to virtual temperature, and thus lead to thicker and more extensive anvil clouds. However, we point out that the total high-cloud amount may not increase since the thicker anvil clouds have a higher precipitation efficiency that is unfavorable to the formation of high thin cirrus. A negative correlation between thick cirrostratus and thin cirrus is often seen in the ISCCP observations (J. Lin 2005, personal communication). This phenomenon is also shown in the CAM3 simulations. In the CAM3–CESS experiment, the ISCCP simulator (Klein and Jakob 1999; Webb et al. 2001) was activated, which allows us to examine the climate sensitivity of a specific type of clouds. Figure 14 shows the change in cirrus and cirrostratus amount in response to ±2-K SST perturbations simulated by CAM3, where following the ISCCP convention, cirrus and cirrostratus are defined as the clouds within the range: \( P < 440 \text{ hPa}, \tau < 3.6, \) and \( P < 440 \text{ hPa}, 3.6 < \tau < 23, \) respectively. Apparently, the increase of high-cloud CWP shown in Fig. 13 is caused by the increase of thicker cirrostratus. However, the net change in total high-cloud amount is determined by the change of both cirrus and cirrostratus. In this case, the increase of cirrostratus amount is nearly canceled by the decrease of cirrus amount, which leads to a barely changed total high-cloud amount. If
such a cancellation mechanism also holds for the other experiments, it is most likely that the decrease of cirrus dominates the increase of cirrostratus in the AM2 simulations. Unfortunately, the ISCCP simulator was not activated in the AM2 simulations and the CAM3 doubling CO$_2$ experiment. Thus, we are unable to examine the detailed high-cloud change in these experiments.

Figure 15 shows the computed feedback parameters associated with high clouds. Compared with low- and midcloud feedbacks, a relatively consistent high-cloud feedback is shown in the simulations. Both CAM3 and AM2 predict the same sign of individual cloud amount feedback and cloud condensate feedback although the feedback strength in AM2 is much stronger. Both models agree on a positive net longwave feedback and a negative net shortwave feedback. In CAM3, the positive net longwave feedback is dominated by the negative net shortwave feedback, which results in a negative net feedback of high clouds. However, in AM2 the opposite net longwave and shortwave feedbacks have nearly the same magnitude, which leads to a very weak net high-cloud feedback. From a different angle, the weak net high-cloud feedback in AM2 also resulted from a strong cancellation between the negative cloud amount feedback and the positive cloud condensate feedback.

To examine whether the SOM-type coupled simulation produces similar cloud feedbacks to those generated by a fully coupled system, the regression analysis is also applied to the IPCC 1% increase CO$_2$ experiment (to doubling CO$_2$) performed by the fully coupled NCAR Community Climate System Model version 3 (CCSM3), which uses the same atmospheric model as CAM3. Note that this IPCC 1% increase CO$_2$ experi-

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**Fig. 12.** Same as in Fig. 10, but for midclouds.
ment was performed at a high resolution of T85, which is different from T42 resolution used by CAM3–2CO₂ simulations. Thus, it allows us to further examine the sensitivity of simulated cloud feedbacks to model resolution. The regression diagnosed cloud feedback in CCSM3 does not show substantial difference from that in CAM3–2CO₂. Thus, no further results are presented here.

4. Discussion and summary

Cloud–climate feedback simulated by GCMs strongly depends on the treatment of clouds and radiation in models. In this study, we have shown that the NCAR CAM3 and GFDL AM2 exhibit a wide range of sensitivity to doubled CO₂ and ±2-K SST perturbations although they produce a similar cloud climatology in their control runs. CAM3 predicts a weak increase in global-mean cloud amount and cloud condensate in the warmer climate. In contrast, a substantial decrease in cloud amount and an increase in cloud condensate are simulated by AM2. The substantial reduction of cloud amount in AM2 appears to be largely compensated by the increase in cloud condensate to result in a net CRF change much weaker than that of CAM3. To identify the cause for this important inconsistent change in clouds and radiation and explore the complicated cloud–radiation feedback shown in the climate sensitivity tests, it is useful to decompose the total cloud feedback into individual components associated with different cloud processes. To do so, we have developed a new

![Image of graphs showing changes in high-cloud amount and mean over 60°S–60°N for CAM3 and AM2.]

Fig. 13. Same as in Fig. 9, but for high clouds.

![Image of graphs showing change in cirrus and cirrostratus amount in the CAM3 CESS experiment.]

Fig. 14. Change in cirrus and cirrostratus amount (diagnosed by the ISCCP simulator) in response to ±2-K SST perturbation simulated by CAM3.
approach based on the MLR technique to diagnose various cloud feedback processes. It is showed that there is a general agreement between the regressed change in clear-sky and cloud radiative fluxes and the change directly simulated by the models. The statistic significance analysis also indicates the appropriateness of the MLR approach for diagnosing cloud feedbacks in the climate sensitivity experiments. Using this approach, this study specifically examines the cloud feedback process associated with the change in cloud amount and condensate change involving low, mid-, and high clouds between 60°S and 60°N. The analysis successfully reveals the important similarities and discrepancies of individual cloud feedback processes simulated by CAM3 and AM2, which are hidden in the total cloud feedback measured by the CRF approach. The following presents the major regression results and further discussions on some important issues.

First, the decomposed cloud feedbacks clearly indicate that both CAM3 and AM2 predict the same sign of individual longwave and shortwave feedback associated with the change in cloud amount and condensate for all three types of clouds (Figs. 10, 12, and 15) except the low-cloud and midcloud condensate longwave feedbacks, but they are much weaker than the other individual feedbacks. This consistency has important implications considering the different cloud and radiation parameterizations used by the two models. Our regression analysis supports previous studies (e.g., Colman et al. 2001) that the longwave and shortwave feedbacks or cloud amount and cloud condensate feedbacks generally have opposite signs. Thus, as a subtle residual of all, the net cloud feedback is very sensitive to a small change in any part of clouds, external forcings, or even a specific radiative transfer calculation. For example, the regression analysis yields strong individual feedbacks in the AM2 simulations, which appears to be consistent with its predicted large change in cloud prop-

![Diagrams](image-url)

Fig. 15. Same as in Fig. 10, but for high clouds.
properties. But the strong cancellation between them results in a very weak net cloud feedback. Based on this, we argue that until cloud and radiation parameterizations can sufficiently generate accurate individual cloud feedbacks, it is impossible for climate models to predict a consistent net cloud feedback since it is an extremely delicate process resulted from a large cancellation.

Second, despite the same sign of individual cloud feedback predicted by the two models, CAM3 and AM2 disagree on the relative importance of the three types of clouds in determining the total cloud feedback. In the AM2 simulations, the net feedbacks of mid- and high clouds are small; thus, the net low-cloud feedback determines the sign and strength of the total cloud feedback. The MLR analysis further indicates that the strong positive shortwave feedback from low-cloud amount dominates the other feedback processes. This is consistent with the large decrease in low-cloud amount simulated by AM2. The large increase in low-cloud condensate does induce a negative shortwave feedback, but it is not strong enough to offset the positive shortwave feedback due to the reduction of low-cloud amount. On the other hand, in the CAM3 simulations, the total cloud feedback appears to be largely determined by the low- and high-cloud condensate feedbacks. The different importance of cloud amount and cloud condensate feedbacks involving low, mid-, and high clouds simulated by CAM3 and AM2 raises a question for the radiative transfer calculation in models. With the same cloud loading, do the radiative transfer codes used in CAM3 and AM2 produce the same climate sensitivity of the radiative flux? This question could be answered by using the offline calculation provided that the detailed cloud information is available.

Third, the detailed examination indicates that the climate sensitivity of cloud amount simulated by CAM3 and AM2 at least shares certain similarities. For example, our analysis indicates that both models predicted a low-cloud increase in the subtropical subsidence regimes where SST is less increased in the doubling CO$_2$ experiment (not shown here). However, almost no similarity in the condensate change of low and midclouds is seen in the two models. We have executed a new experiment to force CAM3 using the climatological SST generated by the AM2 doubling CO$_2$ experiment. The basic feature of low-cloud amount change in response to doubled CO$_2$ simulated by AM2 is somewhat reproduced by CAM3 with such an SST forcing although with biases. Again, no common feature in cloud condensate change is seen in the two simulations. Thus, as an important step to understand the impact of clouds on climate sensitivity and reduce the uncertainty in cloud–climate feedbacks, more attention should be paid to improve the treatment of cloud microphysics that determines the amount and phase of cloud condensate. It is also important to develop a self-consistent cloud parameterization that can provide an internal mechanism to constrain the change in cloud amount and cloud condensate.

Fourth, the large cancellation between individual feedback processes suggests that quantifying the subtle global-mean cloud feedback may depend strongly on a particular analysis approach and the estimation error associated with the approach. This is because even if the estimation error is proven to be negligible to the individual cloud feedback, the globally accumulated estimation error is not necessarily negligible to the global net cloud feedback. In other words, an accurate measure of the global-mean net cloud feedback is difficult since the real signal of the weak net cloud feedback may be overwhelmed, or affected by the estimation error and “cloud masking” effect suggested by Soden et al. (2004). Thus, the results from feedback analyses should be interpreted with caution.

Finally, as indicated by this work and many previous studies, at the current stage diagnosing individual cloud feedback processes may be more useful than just examining the total cloud feedback since the former provides an efficient way to isolate differences and identify the cause for the widespread of cloud–climate sensitivities among GCMs. Fortunately, the signals of individual cloud feedback processes are usually strong; thus, the estimation error may not be as critical as it is to the total cloud feedback. In this study, we successfully decompose the total cloud feedback simulated by CAM3 and AM2 into individual components associated with low, mid-, and high clouds using the MLR approach. Such a decomposition can also be done by the PRP approach. The real problem of this kind of studies is that we have generated something that cannot be evaluated by observations. Thus, although the different cloud feedback processes between models have been clearly illustrated using the MLR approach or the PRP approach, we are unable to determine which is the right feedback and which might be the unrealistic one. It would be a great help if the diagnosed cloud feedback could be directly compared with observations. One advantage of the proposed MLR approach is that it can be applied to observations as illustrated by Hartmann et al. (1992) who have successfully regressed 1-yr ISCCP cloud data to the ERBE radiative flux data. Over the past few decades, a great amount of satellite data of clouds and radiation has been collected. With the MLR approach, these satellite data can be used to diagnose the individual cloud feedback processes associated with short-term scale climate anomalies, such as ENSO. The
derived result from observations can be used to evaluate the individual cloud feedback processes diagnosed from the corresponding AMIP simulation by GCMs. We believe that such a comparison between observations and simulations can shed some new light on cloud feedback issues and provide a useful guide to improve cloud and radiation parameterizations. This will be one of the aspects we focus on in our future research.

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APPENDIX

Multiple Linear Regression

The following briefly summarizes the basic procedures for the MLR calculations. For more details, readers may refer to statistical analysis textbooks (e.g., Afifi and Azen 1979). Assuming one has n sets of samples of Eq. (2), δR_k, δx_{1k}, δx_{2k}, ... , δx_{nk}, (k = 1, 2, ... , n), then the regression coefficient \( C = [c_1, c_2, ... , c_m] \) can be determined as

\[ C = L^{-1}b, \]  

(A1)

where \( L^{-1} \) is the reciprocal matrix of \( L \) represented by

\[
L = \begin{bmatrix}
  l_{11} & l_{12} & \cdots & l_{1m} \\
  l_{21} & l_{22} & \cdots & l_{2m} \\
  \vdots & \vdots & \ddots & \vdots \\
  l_{m1} & l_{m2} & \cdots & l_{mm}
\end{bmatrix},
\]

and

\[
L^{-1} = \begin{bmatrix}
  f_{11} & f_{12} & \cdots & f_{1m} \\
  f_{21} & f_{22} & \cdots & f_{2m} \\
  \vdots & \vdots & \ddots & \vdots \\
  f_{m1} & f_{m2} & \cdots & f_{mm}
\end{bmatrix}.
\]  

(A2)

The matrix elements of \( L \) can be calculated by

\[ l_{ij} = \sum_{k=1}^{n} (\delta x_{ik} - \bar{\delta x}_i)(\delta x_{jk} - \bar{\delta x}_j), \quad (i, j = 1, 2, \ldots , m), \]

(A3)

where the overbar denotes the mean of a variable over \( n \) sets of samples, for example,

\[ \bar{\delta x}_i = \frac{1}{n} \sum_{k=1}^{n} \delta x_{ik}, \quad (i = 1, 2, \ldots , m). \]

The same definition also holds for other variables. Vector \( b_i = [l_{i0}, l_{i2}, \ldots , l_{im}] \) in Eq. (A1) is calculated by

\[ b_i = \sum_{k=1}^{n} (\delta x_{ik} - \bar{\delta x}_i)(\delta R_k - \bar{\delta R}), \quad (i, j = 1, 2, \ldots , m). \]

(A5)

Once the coefficient \( C \) is determined, the regression residue \( r_e \) can be calculated as

\[ r_e = \bar{\delta R} - \sum_{k=1}^{m} c_i \bar{\delta x}_i. \]

The overall performance of regression determined by the previous procedures can be evaluated by the multiple correlation coefficient \( \Gamma_{R,x_1, \ldots , x_m} \) represented by

\[ \Gamma_{R,x_1, \ldots , x_m} = \left( \frac{1}{n-1} \sum_{i=1}^{m} b_i^2 \right)^{1/2}, \quad (i = 1, 2, \ldots , m), \]

(A7)

where

\[ b_i = \sum_{k=1}^{n} (\delta R_k - \bar{\delta R})^2. \]

(A8)

The significance of each independent feedback process in the linear regression equation (2) can be evaluated by \( t \) statistics \( t_i \) represented as

\[ t_i = \frac{(c_i^2 f_{ii})^{1/2}}{s}, \quad (i = 1, 2, \ldots , m), \]

(A9)

where \( f_{ii} \) is the diagonal element of matrix \( L^{-1} \) in Eq. (A2). Here \( s^2 \) is the residual mean square represented by

\[ s^2 = \frac{1}{n - m} \sum_{i=1}^{m} c_i^2 b_i, \quad (i = 1, 2, \ldots , m). \]

(A10)

The \( t \) statistics defined by Eq. (A9) follows the \( F \) distribution represented by

\[ F(\eta, v) = \frac{\chi^{n/2-1}}{B(\eta/2, v/2)} \left( \frac{\eta}{v} \right)^{\eta/2} \left( 1 + \frac{\eta}{v} \right)^{-\eta+v/2}, \]

(A11)

with the degree of freedom of \( \eta = 1 \) and \( v = n - m - 1 \). Here \( B(\eta/2, v/2) \) is the \( \beta \) function.

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