

# Cloud variability, radiative forcing and meridional temperature gradients in a general circulation model

By PETER L. LANGEN<sup>1\*</sup> and RODRIGO CABALLERO<sup>2</sup>, <sup>1</sup>*Centre for Ice and Climate, Niels Bohr Institute, University of Copenhagen, Copenhagen, Denmark;* <sup>2</sup>*Meteorology and Climate Center, University College Dublin, Dublin, Ireland*

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## ABSTRACT

Due to the non-linearity of cloud–radiation interaction in general circulation models (GCMs), the time-mean cloud radiative forcing (CRF) is in general different from the CRF of time-mean clouds. This implies that a change in temporal cloud variability induces a change in radiative forcing even if there is no change in time-mean cloud properties. Here we investigate this variability contribution to CRF quantitatively in the National Center for Atmospheric Research Community Climate Model 3.6 GCM. In a reference run, the variability contribution is found to account for 35% of the global-mean climatological CRF. The variability contribution peaks in the mid-latitudes and is shown to be driven by synoptic eddy activity. In a climate change experiment, where the atmospheric CO<sub>2</sub> is quadrupled, the change in cloud variability offsets 40% of the change in CRF due to the change in mean clouds. It is found that almost all of this effect is due to variability in cloud fraction rather than in cloud water content, and it is traced to the non-linearity introduced by the model's treatment of vertical cloud overlap. This study indicates the possibility of an eddy variability–climate feedback that has not been extensively studied and quantified in the past.

## 1. Introduction

Clouds are observed to have a strong impact on Earth's radiative budget (Ramanathan et al., 1989). Cloud feedbacks can, therefore exert potentially crucial influence on the climate system's response to external forcing, and may explain some outstanding features of ancient climates (Sloan and Pollard, 1998). However, the representation of cloud processes within general circulation models (GCMs) remains problematic, and is a leading source of uncertainty in estimates of climate sensitivity (Houghton et al., 2001; Bony et al., 2006). This reflects the almost overwhelming complexity of clouds and cloud–climate interaction (Randall et al., 2003; Stephens, 2005). The problem is rich enough that, despite several decades of research, many of its aspects have yet to be explored in detail.

The question of cloud–climate interaction in GCMs can be divided into two parts: one involving the way in which dynamics and thermodynamics create clouds, and the other concerning the way in which clouds interact with radiation and thus feed back on the thermodynamic and dynamic fields. Both are important, largely unsolved problems (Stephens, 2005). The scope of this paper falls into the second part; specifically, we analyze the vari-

ability effect of clouds on their time-mean radiative impact in the context of a particular GCM. A useful measure of cloud impact on radiative transfer is cloud radiative forcing (CRF), defined as:

$$\text{CRF} = R - R_{\text{clr}},$$

where  $R$  is the total downward top-of-atmosphere radiative flux at a given longitude–latitude point, and  $R_{\text{clr}}$  is what  $R$  would be if clouds were instantaneously removed (which can be explicitly done in models; in observations,  $R_{\text{clr}}$  may be estimated from nearby clear-sky pixels). CRF is a non-linear function of cloud properties (Harshvardhan and Randall, 1985; Taylor and Ghan, 1992), and as a consequence, the time-mean CRF is not the same as CRF by time-mean clouds:

$$\overline{\text{CRF}} = M(\bar{C}) + V(\bar{C}, C'), \quad (1)$$

where  $\bar{C}$  represents a time average and  $C'$  deviations therefrom,  $C$  collectively represents cloud properties in an atmospheric column,  $M$  is CRF due to time-mean clouds and  $V$  is the contribution to time-mean CRF due to temporal variability of clouds around the time mean.

As illustrated in Fig. 1, the non-linear dependence of CRF on  $C$  means that  $V$  is generally non-zero. It follows that a change in temporal cloud variability implies a change in radiative forcing even if clouds do not change in the mean. In the mid-latitudes, cloud variability is driven mostly by synoptic eddy activity. A

\*Corresponding author.  
 e-mail: plangen@gfy.ku.dk  
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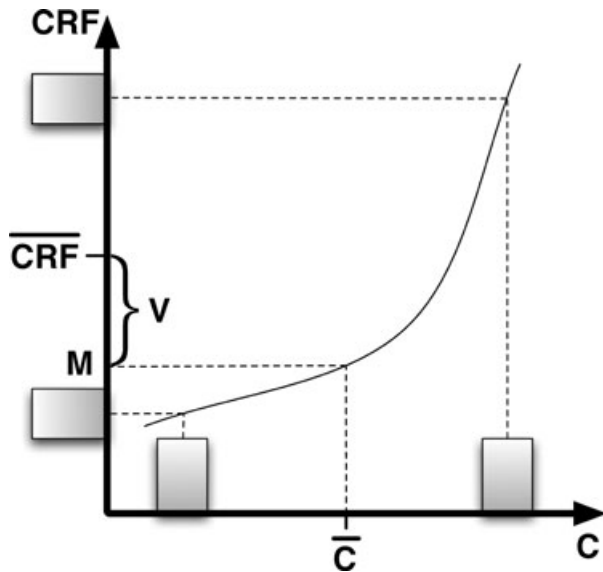


Fig. 1. Schematic illustrating the cloud variability effect. The bars on the  $C$ -axis denote the PDF of a simple form of variability, where the cloud properties attain only two values. The solid line illustrates a non-linear relationship between cloud properties and cloud radiative forcing, CRF. The bars on the CRF-axis give the PDF of the CRF resulting from the cloud distribution, and  $\overline{\text{CRF}}$  shows the mean of this distribution.  $\bar{C}$  is the mean of the cloud distribution and  $M$  is the CRF of this value. Due to the non-linearity of the relationship, there is a difference,  $V$ , between  $\overline{\text{CRF}}$  and  $M$ .

robust feature of GCM response to increased greenhouse forcing is a poleward shift of the mid-latitude storm tracks accompanied by a change in eddy activity (Yin, 2005). There is thus the potential for a cloud variability-climate feedback that has not been extensively documented and quantified in the past.

This is not to imply that previous studies have disregarded the  $V$  contribution. There are two widely used methods to quantify cloud feedback, one employing offline radiative calculations (Wetherald and Manabe, 1988) and another (Cess and Potter, 1987; Cess et al., 1996) based on changes in CRF driven by surface temperature perturbations (see Soden et al., 2004, for a discussion of the relative merits of the two methods). Cloud variability is automatically included in the Cess et al. approach, while studies using the offline approach are careful to include the variability contribution by computing feedbacks as averages over a large ensemble of instantaneous radiative calculations. Thus, feedback values published in the literature all include contributions from both  $M$  and  $V$ .

What has been missing is a detailed study of the *partitioning* between  $M$  and  $V$ , and of the underlying causes of  $V$ . The main goal of this paper is to go some way towards filling this gap, albeit for a single GCM in a specific, simplified setup. In previous work (Alexeev et al., 2005; Caballero and Langen, 2005) we have examined the effect of changed eddy activity on dynamic poleward energy transport and changes in mean meridional tem-

perature gradients. Here, we complement this earlier work by studying the effect of changed eddy activity on the meridional profile of cloud radiative forcing.

Some previous studies give an indication of the role played by  $V$ . Bergman and Salby (1997) used a single-column radiation model driven by observed cloud, temperature and humidity fields to diagnose the diurnal variability contribution to time-mean CRF, and found it could be as large as  $20 \text{ W m}^{-2}$ . Taylor and Ghan (1992), using an early version of National Center for Atmospheric Research's (NCAR) Community Climate Model (CCM1), compared a climate change experiment in which cloud water content was held fixed to another in which it was allowed to vary in time. Clouds in both cases gave a negative (cooling) feedback to global warming, with cloud variability adding about 13% to this cooling. Using a GCM derived from the NCEP forecast model, Schneider et al. (1999) found that fixing cloud fraction and optical properties at their time-mean values led to a drop of up to  $80 \text{ W m}^{-2}$  in absorbed insolation when compared to a reference run with interactive clouds. Conversely, a similar experiment using GENESIS2 (Vavrus, 2004) showed that fixing clouds led to a warming of up to several degrees at high-latitudes. These results show that  $V$  can be large and strongly model and climate state-dependent, and motivate further study.

The second aim of this paper is to identify the specific non-linearities that give rise to  $V$ . There are various candidates. One non-linearity is related to cloud water content: as the water content of a cloud increases from zero, the long-wave emissivity first increases rapidly but then, past a certain threshold, the cloud becomes a black body and the emissivity becomes constant and equal to 1. The short-wave albedo behaves similarly, though with a different threshold. Thus, a cloud whose water content fluctuates from near zero to above-threshold values will have a strongly non-linear impact on both long- and short-wave radiation.

Another important non-linearity is related to cloud overlap. The grid spacing in current GCMs is always much larger than individual clouds, so a cloudy grid cell will not in general be completely filled with cloud. Rather, the cloud parametrization predicts the fraction of the cell that is cloudy. This leaves the problem of how the cloudy fractions at different levels overlap. A variety of overlap schemes is used in current GCMs (Barker et al., 2003; Stephens et al., 2004). Among the simplest is the random overlap scheme, in which the horizontal disposition of cloud at one level is taken to be statistically independent from that at all other levels. As a result, the total cloud fraction  $c_{\text{tot}}$  is given by

$$c_{\text{tot}} = 1 - \prod_{i=1}^N (1 - c_i), \quad (2)$$

where  $N$  is the total number of model levels and  $c_i$  is the cloud fraction at level  $i$ . The product term in this expression introduces an obvious non-linearity which will make itself felt when cloud fraction varies in time. As an example, consider the simplest case with only two cloudy layers. With cloud fraction constant at 0.5

in both layers, total cloudiness is  $1 - (1 - 0.5)^2 = 0.75$ . If instead the two layers vary in phase, with cloud fraction of 0 half the time and 1 the rest of the time, the time-mean total cloud cover is decreased to 0.5 without changing the mean value in each layer. Conversely, if the same variability is used in antiphase the total cloud cover increases to 1. Thus, changes in cloud fraction variability can strongly affect CRF, the sign of the effect depending on the sign of the covariance between cloud fraction at different levels.

The random overlap method, first proposed by Manabe and Strickler (1964), is still in use in many modern GCMs; in particular, it is used in the long-wave component of the GCM used here. Another commonly used method is the maximum-random scheme (Geleyn and Hollingsworth, 1979; Collins, 2001), in which adjacent cloud layers are maximally overlapped while layers separated by clear air are randomly overlapped; the random component in this scheme introduces the same non-linearity discussed above. Yet another scheme (Briegleb, 1992) represents overlap effects by simply scaling the cloud layer optical depth by cloud fraction to the power  $3/2$ , thereby introducing an explicit non-linear dependence on cloud fraction. An important point is that, for a given level of cloud fraction variability, each of these schemes will give a different CRF response. Thus, the cloud variability contribution to CRF is likely to be highly model dependent.

The plan of the paper is as follows. The model setup and the details of our CRF calculations are described in Section 2. In Sections 3 and 4, the role of  $V$  in the GCM is analysed for the reference climate and a climate change experiment, respectively. Section 5 summarizes and concludes the study.

## 2. Model and methodology

The GCM employed in this study is the NCAR's CCM version 3.6.6 (Kiehl et al., 1996) with T21 horizontal resolution and 18 levels in the vertical. Keeping the experiment simple, we use an idealized model setup which simplifies the interpretation of the results: aquaplanet lower boundary conditions and an annually averaged diurnal cycle of solar forcing. This means that insolation and zenith angle have a diurnal cycle, but their daily-mean value is fixed and symmetric about the equator ('modified equinox' forcing; see Alexeev, 2003; Langen and Alexeev, 2004). We also exclude all effects of sea ice by fixing the surface albedo uniformly to 0.11 and treating subfreezing grid-points as open water. The solar constant has its current value of  $1367 \text{ W m}^{-2}$ .

We generated a reference climatology for this setup by setting  $\text{CO}_2$  concentration at 355 ppm and running the model, coupled to a 50 m deep slab ocean, until sea surface temperatures (SSTs) had reached a statistically steady state. The model was then run for a further 20 years in this state to obtain the reference climatology, which has a global-mean SST of  $15.3^\circ\text{C}$  and an equator-to-pole temperature gradient ( $\sim 40 \text{ K}$ ) similar to that of

the present-day northern hemisphere. This 'realistic' temperature gradient was achieved in spite of the lack of high albedo surfaces at high-latitudes by specifying a rather weak oceanic heat flux convergence corresponding to a maximum transport of only  $0.5 \times 10^{15} \text{ W}$ .

To study the role of cloud variability in the reference run, we use an approach that is a hybrid between the offline radiative calculation method and the CRF method (see Section 1). It may be summarized in the following steps.

(i) The full GCM is run with SST fixed at the time-mean, zonal-mean value taken from the reference run. The four cloud properties that affect cloud-radiation interaction in this GCM (cloud fraction, cloud water content, effective radius and ice fraction) are output every 2 hr for 200 d.

(ii) These cloud data are separated into time-mean and time-varying components:  $C = \bar{C} + C'$ , where  $C$  can represent any (or any combination) of the cloud parameters and synthetic data sets with any desired amplitude of variability are produced by scaling the variability component:

$$\tilde{C} = \bar{C} + q C'$$

with  $q$  a number between 0 and 1. Note that  $\tilde{C} = \bar{C}$  for all choices of  $q$ .

(iii) The GCM is then re-run, again with fixed SST, but with prescribed cloud properties read from the synthetic data set every 2 hr (linear interpolation is used for intervening time steps). These runs are 2 yr long, looping over and reusing the 200-d cloud data set.

The sensitivity of time-mean CRF in these fixed-SST runs to changes in  $q$  gives a quantitative measure of the role played by cloud variability in maintaining the climate of the reference run. A caveat of this method is that in the reference run, where clouds are fully interactive, the cloud and thermodynamic fields are closely correlated; this correlation is lost when using the resampled cloud data, and this can bias the CRF response, particularly in the long-wave (Schneider et al., 1999). A further bias will be introduced by the use of fixed SST, but we expect this to be small since there is actually little SST variability in the reference run. We can quantify the overall bias by comparing the time-mean CRF of the reference run and the resampled run using  $q = 1$ . As shown in the following section, the bias is very small (about  $0.02 \text{ W m}^{-2}$ ) when compared to CRF changes induced by changing  $q$ . We thus feel confident that the method is accurate enough for the purposes of this study.

## 3. Cloud variability in the reference climate

The cloud resampling method described in the previous section is used here to ascertain the importance of the cloud variability contribution,  $V$ , to the total CRF in the reference climate of our model. For later reference, we first briefly examine some cloud statistics from the reference run. Figure 2a presents

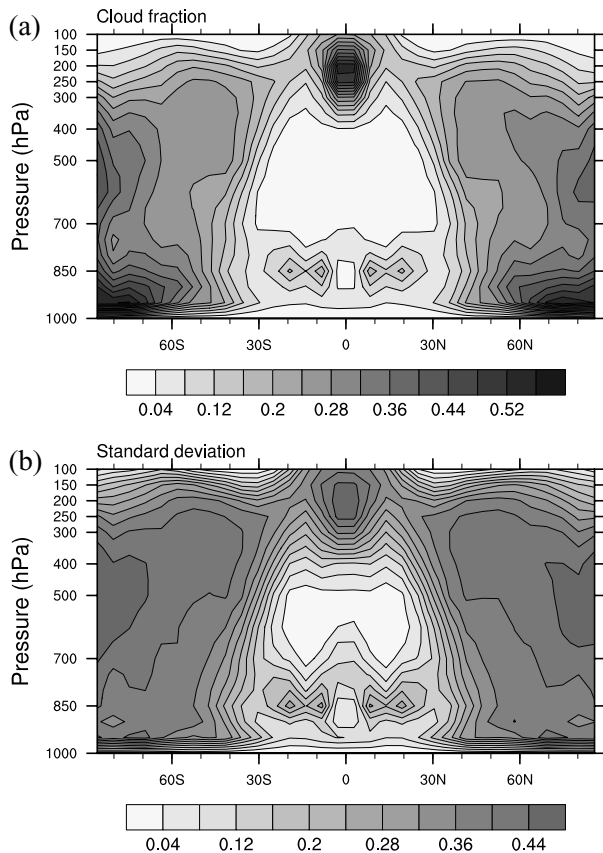


Fig. 2. (a) Zonal-mean, time-mean cloud fraction and (b) zonal-mean standard deviation of cloud fraction in the reference run.

time- and zonal-mean cloud fraction. The pattern in this figure compares well with those from GCM simulations of the modern climate, indicating that our idealized configuration is not in an unduly unrealistic regime. Cloud fraction variability (Fig. 2b) roughly follows the same pattern, with maxima at the equatorial tropopause, the low-level subtropics and the mid-troposphere in high-latitudes. Cloud water content (not shown) shows a rather different pattern, with a large maximum in the time-mean at low levels over the equator, and a single, high-latitude variability maximum in each hemisphere.

Figures 3a and b show the spectra of cloud fraction and vertical velocity ( $\omega$ ) at  $35^\circ\text{N}$  and 500 hPa determined from 200 d, two-hourly series. This is in the mid-latitude storm track region where the  $\omega$  variance maximizes in the reference run. The plots both show a broad peak in the synoptic range centred at a period of approximately 5 d. Panel (c) shows the coherence (squared) spectrum of the two time-series. This quantity would be identically 1 at all frequencies for two linearly related, noise-free series and vanish for uncorrelated series. We see statistically significant coherence (with 99% confidence) in broad parts of the spectrum, especially around the synoptic time-scale. Clearly, the cloud fraction variability (and the radiative effects thereof, which will be studied here) is associated with vertical velocity fluctuations due to synoptic eddy variability.

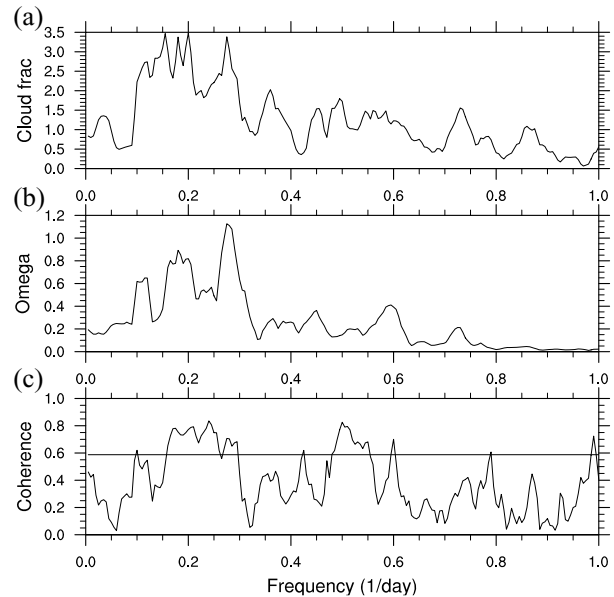


Fig. 3. Spectra of 200 day, two-hourly series of (a) cloud fraction and (b) vertical velocity,  $\omega$ , variability at  $35^\circ\text{N}$  and 500 hPa (arbitrary longitude). (c) Coherence spectrum of the two series. The straight line shows the coherence corresponding to the 99% level of confidence.

Figure 4a shows the global average top-of-atmosphere CRF as a function of the variability amplitude,  $q$ . Time-mean clouds ( $q = 0$ ) give a global-mean CRF of about  $-14.5 \text{ W m}^{-2}$ . This cooling tendency increases with increasing  $q$ , reaching  $-22.11 \text{ W m}^{-2}$  when full cloud variability is used ( $q = 1$ ). The large crossed-circle symbol in the figure shows time- and global-mean CRF in the reference run, which has a value of about  $-22.13 \text{ W m}^{-2}$ . The difference between this value and the  $q = 1$  fixed-SST value gives a measure of the bias inherent in our method, which is clearly very small. We conclude that, in this model,  $V$ , the variability contribution to CRF, plays a major role in the maintenance of the reference climate, accounting for about  $8 \text{ W m}^{-2}$  or 35% of total CRF.

These figures were obtained by scaling the variability in all cloud properties at the same time. Since the reference climate displays substantial variability in both cloud fraction and water content, it becomes interesting to determine the relative contributions of these variabilities to total CRF. This is addressed by conducting two additional fixed-SST runs, one with fixed cloud fraction and full water content variability, the other with these roles reversed. The two runs give a global-mean CRF of  $-14.8$  and  $-22.7 \text{ W m}^{-2}$ , respectively. Comparing these values with those in Fig. 4a, we see that cloud water content variability plays a negligible role. Furthermore, separate examination of short- and long-wave components of the water content contribution shows that they are both small, so this is not a case of cancellation between two large but opposite quantities. This implies that the radiative scheme in the model has an approximately linear response to changes in cloud water content, at least over the

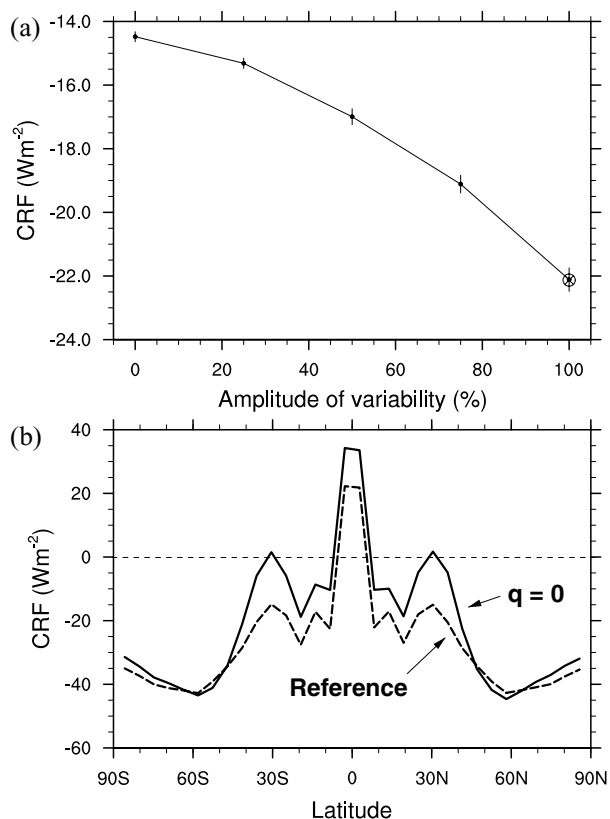


Fig. 4. (a) Global average top-of-atmosphere CRF as function of scaling employed. Vertical bars denote one standard deviation over the 2-yr integration and the crossed-circle shows the case of internally calculated clouds. (b) Latitudinal structure of CRF with  $q = 0$  (solid) and with internally calculated clouds (dashed).

range of values experienced in the present runs. Note, however, that a different cloud scheme or climate state may produce water content values in a range where the response is non-linear, so this result may not be robust.

Returning to our basic all-properties variability experiment, Fig. 4b compares the spatial structure of CRF in the no-variability ( $q = 0$ ) and full-variability cases. The  $q = 0$  curve corresponds to  $M$ , while the difference between the two curves is  $V$ , shown by the solid line in Fig. 5a.  $V$  peaks at  $30^\circ$  latitude, where it actually accounts for *all* of the cloud forcing. This region is at the boundary between the dry subtropics, essentially free of mid-level and high cloud, and the mid-latitude storm tracks where clouds are plentiful. At higher latitudes, the variability contribution is very small. As shown by the dashed and dotted curves, this is due to a cancellation between long- and short-wave components, which are large but of opposite sign.

The details of how this variability contribution comes about lie in the model parametrizations of the interactions of long- and short-wave radiation with the cloud field. We have examined this closely (Langen, 2005) but choose here, due to the model dependency, to merely summarize our conclusions. At

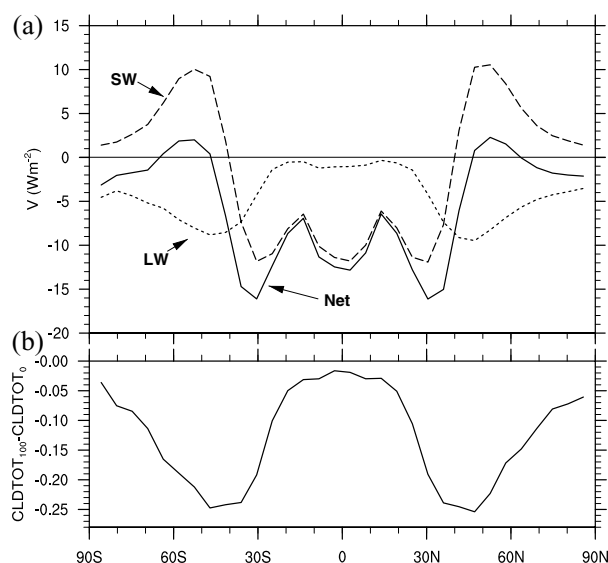


Fig. 5. (a) Latitudinal structure of  $V$  (solid) in the reference run and short-wave (dashed) and long-wave (dotted) contributions thereto. (b) The difference in vertically averaged (using random overlap) total cloud cover between the  $q = 100$  and  $0\%$  runs.

all latitudes, the dominant vertical pattern of cloud variability is single-signed, that is, low, medium and high cloud fractions tend to covary. The random-overlap assumption employed in the CCM3's long-wave cloud parametrization has the consequence (which can be shown analytically) that single-signed variability yields lower vertically averaged total cloud cover than do fixed time-average clouds. This effect strengthens with the number of layers with cloud variability, and the overall picture of negative long-wave contribution to  $V$  in Fig. 5a (dotted curve) is due to the decreased cloud-greenhouse effect accompanying the decreased total cloud cover seen in Fig. 5b. The mid- and high-latitudes have a thicker cloud deck and thus experience a larger effect.

In the short-wave part of the model's radiation code, overlap is parametrized by scaling the layer optical depth with the cloud fraction to the power  $3/2$  (Briegleb, 1992). We find that this has the consequence that in a high-transmission mean atmosphere (e.g. with little cloudiness or small zenith angle) variability will give short-wave cooling, while conversely, variability in a low-transmission mean atmosphere will lead to warming. This is reflected in Fig. 5a (dashed curve) where the low-latitudes, which have few cloudy layers and small zenith angles, experience a cooling effect. The mid- and high-latitudes, with more cloudy layers and larger zenith angles, experience a warming, which weakens with latitude due to decreasing cloud water content.

#### 4. Cloud variability and climate change

We saw above that a substantial part of the cloud forcing in the reference climate is due to cloud variability, and this forcing could be even larger were it not for a cancellation between

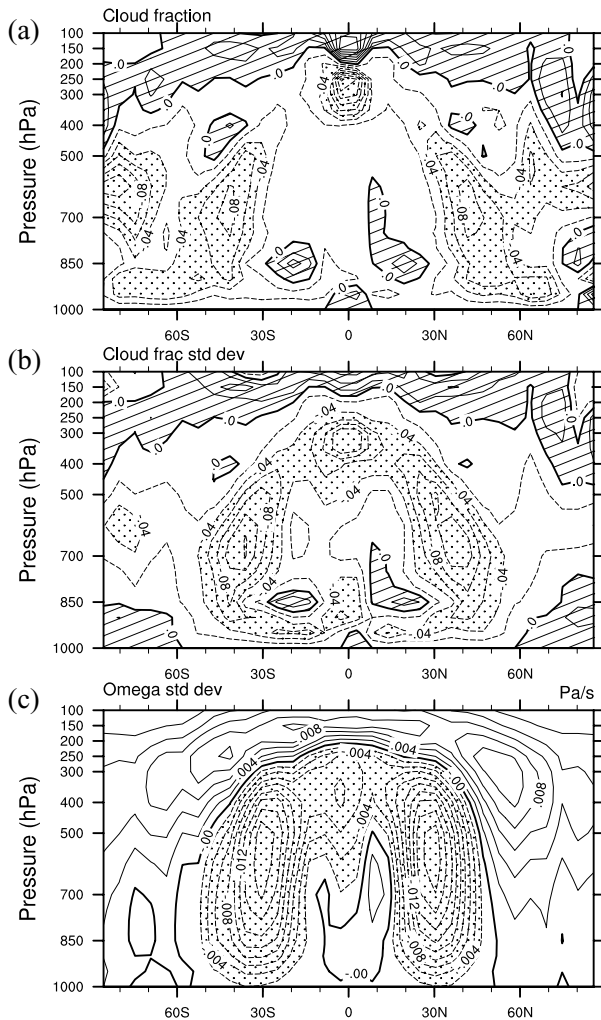


Fig. 6. (a) Time- and zonal-mean change in cloud fraction due to quadrupling  $\text{CO}_2$ . (b) As in (a) but for standard deviation. (c) As in (a) but for vertical velocity standard deviation. To ease readability, negative contours are dashed and in panels (a) and (b) positive contours are hatched while contours less than  $-0.04$  are stippled. In panel (c), contours less than  $-0.002$  are stippled.

the short- and long-wave effects. How the forcing changes and whether such a cancellation continues to hold in a changed climate is not obvious. To address these issues, we perform a model integration identical in every respect to the reference run but employing quadrupled  $\text{CO}_2$  concentration (' $4\times$ ' run). This run has a global-mean SST about  $5^\circ\text{C}$  higher than the reference run, which results in an elevated tropopause and hence greater upper-level mean cloudiness and variability (Fig. 6). There is also a  $6^\circ\text{C}$  reduction in equator-to-pole temperature difference, as well as a slight poleward shift and weakening of the mid-latitude storm tracks, resulting in reduced mean cloudiness and variability in the lower troposphere, especially in mid-latitudes. The horseshoe-shaped area of reduced cloud fraction variability is similar to the

area of reduced  $\omega$ -variability shown in Fig. 6c, a clear indicator of the reduction in the mid-latitude eddy activity. In general, the  $4\times$  run is associated with a reduced column-integrated cloudiness.

Our aim in this section is to assess the radiative impact of the cloud changes in Fig. 6. To do this, we again employ the cloud resampling method of Section 2. We output cloud data at 2 hr intervals from the  $4\times$  run, and then perform fixed-SST runs with clouds specified by reading from this data set. We emphasize that *all* fixed-SST runs here use SST and  $\text{CO}_2$  values taken from the *reference* run, that is, we use  $4\times \text{CO}_2$  clouds with  $1\times \text{CO}_2$  SSTs. Thus, changes in CRF are due solely to changes in clouds and not in clear-sky radiation.<sup>1</sup> Our method is thus closer to an offline radiation calculation than to the CRF approach of Cess and Potter (1987). Using the notation of eq. (1), we may formalize this as

$$\Delta \overline{\text{CRF}} = \overline{\text{CRF}}_4 - \overline{\text{CRF}}_1 \quad (3)$$

$$\Delta M = M_4 - M_1 \quad (4)$$

$$\Delta V = V_4 - V_1 = \Delta \overline{\text{CRF}} - \Delta M, \quad (5)$$

where  $\overline{\text{CRF}}_4$  is time-mean CRF in the fixed-SST run employing fully variable clouds ( $q = 1$ ) from the  $4\times$  run, while  $M_4$  is the same quantity for the case with fixed clouds ( $q = 0$ ). Index 1 indicates analogous quantities using clouds from the reference run.

Results are shown in Fig. 7a and summarized in Table 1.  $\Delta \overline{\text{CRF}}$  is weakly negative in the tropics and strongly positive in the extratropics. This latitudinal structure of total cloud feedback contributes towards reduced meridional temperature gradients in the warmer climate, exacerbating the effects of dynamic heat transports (see Alexeev et al., 2005).  $\Delta M$  gives the dominant contribution, but  $\Delta V$  also plays a significant role, offsetting much of the warming due to  $\Delta M$  in the mid-latitudes. Moreover, changes in cloud variability *reduce* the tendency to weaken the meridional temperature gradient in this experiment.

The reduction in  $V$  is closely related to changes in storm-track eddy activity: in the mid-latitudes,  $\omega$ -variability decreases (Fig. 6c) and eddy kinetic energy density (not shown) drops by about 15%. These amplitude changes are accompanied by a poleward shift which in Fig. 7b is seen to influence the  $V$  change. As shown in Caballero and Langen (2005), storm track eddy activity may either weaken or intensify with global warming, depending on the details of the reference climate: in general, cooler climates (with global mean temperatures less than  $\sim 15^\circ\text{C}$ ) will show intensified storm tracks as they warm, while climates that

<sup>1</sup> With the small caveat that since temperature and humidity are internally calculated in the fixed-SST runs, it can be argued that cloud changes may drive changes in these fields that will bias the clear-sky radiation. However, this caveat applies only to the long-wave component, and considering the very strong control that SST exerts on the climate, we expect the resulting bias to be small, on the order of the bias introduced by cloud decorrelation.

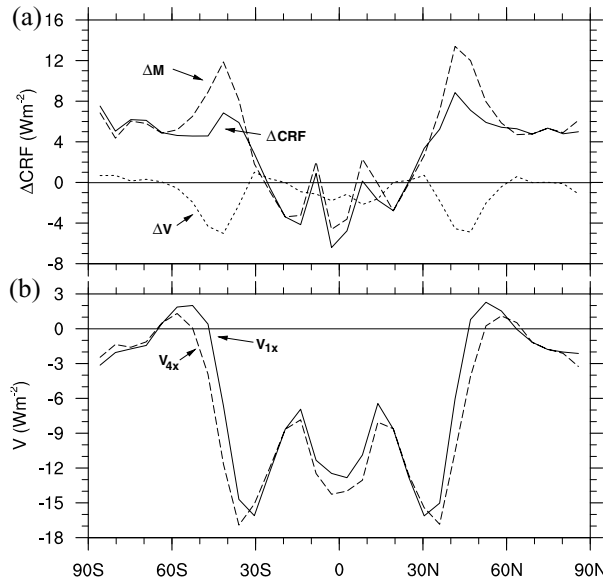


Fig. 7. (a) Cloud radiative feedbacks in the 4x run:  $\Delta CRF$  (solid),  $\Delta M$  (dashed) and  $\Delta V$  (dotted). (b)  $V$  contributions in the 1x (solid) and 4x (dashed) runs. The  $\Delta V$  in panel (a) is the difference between these two.

Table 1. Cloud radiative feedbacks (eqs 3–5) averaged globally and over the tropics (30°S–30°N) and extratropics (90°S–30°S, 30°N–90°N). Units are  $W m^{-2}$ .

	Global	Trop	Ex-trop
$\Delta CRF$	1.82	−1.92	5.55
$\Delta M$	3.06	−1.19	7.32
$\Delta V$	−1.25	−0.73	−1.77

are already warm will respond to further warming with a weakening of the storm tracks. In Caballero and Langen (2005), we speculate that the former is due to eddies being energized by latent heat release (as studied by Lapeyre and Held, 2004) while the latter is due to decreasing Eady growth rates accompanying increased static stability. Clearly, the particular case studied here falls in the latter category. However, the former category may be more appropriate for Earth's real climate: in a study of 15 GCMs used to simulate realistic 21st century global warming, Yin (2005) found a consistent increase in storm track intensity as the climate warmed. Thus cloud variability could be influencing meridional temperature gradients in those simulations.

## 5. Discussion and conclusions

We have investigated the impact of cloud variability on the top-of-atmosphere radiative budget of NCAR's CCM3.6 GCM, run in an idealized aquaplanet configuration with no seasonality. Using a cloud resampling method, we found that the cloud variability contribution  $V$  accounts for 35% of global-mean CRF in the

model's reference run. Geographically,  $V$  is highest in the mid-latitudes and is related to cloud variability driven by extratropical eddy activity. A fourfold increase in  $CO_2$  concentration resulted in a decrease and poleward shift of storm-track eddy activity and reduced  $V$  in mid-latitudes. Overall CRF change acts to reduce meridional temperature gradients in the warmer climate, but the change in  $V$  by itself tends to counter this effect.

The key conclusion of this paper is that changes in mid-latitude eddy activity can, through their effect on cloud variability, strongly impact the radiative response of a GCM to greenhouse gas increase. In the experiments analysed in this paper, the effect was due almost entirely to variability in cloud fraction, which brings into play the non-linearity in the cloud overlap scheme. Oreopoulos and Khairoutdinov (2003) studied cloud-scene snapshots from a cloud-resolving model and found that clouds spaced vertically by about 1 km were maximally overlapped, while clouds spaced by 5 km or more were randomly overlapped. Thus, some degree of random overlap seems inescapable, and this necessarily implies non-linearity (see Section 1). A wide variety of overlap schemes is used in current-generation GCMs (Barker et al., 2003); while the presence of some degree of non-linearity is a robust feature of such schemes, the details vary from scheme to scheme, and these differences will almost certainly have a large impact on  $V$ . In addition, two models sharing the same radiation and cloud overlap scheme but having different in storm track responses to climate change will also produce different values of  $V$ . Furthermore, there is no reason to think that the small role played by cloud water content variability in the present experiments is a robust feature. It is quite conceivable that a different cloud parametrization, or a different climate state, would give cloud water variability spanning the range over which non-linearity is important (see discussion in Section 1).

Overall, we conclude that  $V$  is likely to be a highly model-dependent quantity. Thus, much of the intermodel spread in cloud radiative feedbacks (e.g. Ringer et al., 2006; Soden and Held, 2006; Webb et al., 2006) may be due to differences in  $V$ . To underscore this point quantitatively, we can compute cloud feedback parameters for the present experiment, defined in the standard way (Bony et al., 2006) as  $\lambda_x = \partial R_x / \partial T_s \approx \Delta R_x / \Delta T_s$ , where  $\Delta T_s$  is the change in global-mean surface temperature and  $\Delta R_x$  is the resulting change in global-mean top-of-atmosphere radiative flux due solely to changes in variable  $x$ . Using the globally integrated values of  $\Delta CRF$ ,  $\Delta M$  and  $\Delta V$  given in Table 1 and  $\Delta T_s = 5$  K, we find an overall cloud feedback  $\lambda_{CRF} = 0.36 W m^{-2} K^{-1}$ , while the feedback due to change in mean clouds is  $\lambda_M = 0.62 W m^{-2} K^{-1}$ ; the difference is due to the negative cloud variability feedback,  $\lambda_V = -0.25 W m^{-2} K^{-1}$ . A recent study (Soden and Held, 2006, their fig. 1) shows that cloud feedback parameters in the IPCC AR4 (CMIP3) models range from 0.14 to 1.2  $W m^{-2} K^{-1}$ . Thus, the role of  $V$  in the present model is to bring cloud sensitivity from the middle to the bottom of this range.

This paper does not aim at comprehensiveness, but instead is meant as a pilot study aimed at drawing attention to this somewhat overlooked aspect and to spurring further research into it. Specifically, we suggest two directions for future work. First, it would be of obvious interest to quantify and intercompare  $V$  among a range of current GCMs run under given climate conditions and under standard climate change experiments. The cloud resampling methodology used here is simple and should be straightforward to implement in any GCM. Second, and perhaps of even greater importance, is the question of quantifying  $V$  for the real climate system directly from observations. It may be possible to do this using a combination of cloud amount data from the International Cloud Climatology Project (ISCCP, Rossow and Schiffer, 1991) and top-of-atmosphere radiative fluxes from the Earth Radiation Budget Experiment (ERBE, Barkstrom, 1984). For example, one could compare the time-mean CRF over a given area with the CRF computed for individual snapshots in which the cloud distribution happens to be close to the time-mean distribution. Though it may be difficult to find a statistically significant number of such analogues, this approach would be of great interest as it avoids all recourse to a radiation model and its attendant parametrization issues.

The very simple boundary conditions employed here obviously limit the direct applicability of the results to the real climate system. They were, nevertheless, used to isolate cloud effects from those of, for example, sea ice and geography and to complement our earlier work on energy transports and meridional temperature gradients in the same simple setting (Alexeev et al., 2005; Caballero and Langen, 2005). The SW shielding effect by clouds is reduced over high-albedo surfaces such as ice and snow and including these would thus likely reduce the role played by the SW component of  $V$  in the reference climate. This would, in turn, shift the cancellation between the LW and SW effects at high-latitudes in Fig. 5a and lead to an increased net cooling effect by  $V$ . In a climate warming experiment, melting sea ice would increase the shielding effect and thereby possibly negate some of the increase in high-latitude CRF change encountered in Fig. 7a. If seasons were included, the SW shielding would only be active during summer when the sun rises over the horizon. Thus, depending on the seasonality of both mean cloud and variability, the high-latitude cancellation between SW and LW would encounter large shifts over the seasons. Inclusion of realistic geography would not only produce hemispheric and zonal asymmetries in the cloud mean and variability and surface albedo; it would also enhance the tendency of seasonality and sea ice to create seasonal changes in mean temperature, meridional temperature gradients and thereby storminess. Such changes were in Section 4 seen to alter the role played by  $V$  relative to  $M$ .

As a final point, our results highlight an inconsistency often encountered in the cloud–radiation literature. As noted in Section 1, the non-linear nature of cloud–radiation interaction is well known, and all studies of CRF go to great lengths to include

cloud variability in their calculations. However, when it comes to *interpreting* these calculations and attributing changes in CRF to changes in clouds, it is very common to refer only to changes in mean cloud properties, ignoring changes in variability (e.g. Le Treut et al., 1994; Zhang et al., 1994; Colman et al., 2001; Ringer et al., 2006; Webb et al., 2006). However, as is apparent when comparing  $M$  and  $V$  in the reference climate [Fig. 4b (solid) and Fig. 5a (solid)] and the changes in  $M$  and  $V$  during climate change (Fig. 7a), the implicit assumption that changes in  $V$  are negligible or perhaps linearly related to  $M$  can be misleading. In fact,  $V$  was found to be of the same sign as  $M$  in the reference climate and account for 35% of the total CRF, while in the climate change experiment, its change was of the opposite sign and countered 40% of the CRF change due to  $M$ . Thus, ignoring the  $V$  contribution can be misleading. For example, while it may be possible to tune the radiation/cloud parametrization suite in a GCM so that it gives a reasonably realistic CRF in a reference climate, the results will likely be wrong in a changed climate with a different partitioning of  $M$  and  $V$ .

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