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Effects of cloud condensate vertical alignment on radiative transfer calculations in deep convective regions

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Effects of cloud condensate vertical alignment on radiative transfer process were investigated using cloud resolving model explicit simulations, which provide a surrogate for subgrid cloud geometry. Diagnostic results showed that the decorrelation length L_{cw} varies in the vertical dimension, with larger L_{cw} occurring in convective clouds and smaller L_{cw} in cirrus clouds. A new parameterization of L_{cw} is proposed that takes into account such varying features and gives rise to improvements in simulations of cloud radiative forcing (CRF) and radiative heating, i.e., the peak of bias is respectively reduced by 8 W m^{-2} for SWCF and 2 W m^{-2} for LWCF in comparison with $L_{cw} =$ 1 km.

The role of L_{cw} in modulating CRFs is twofold. On the one hand, larger L_{cw} tends to increase the standard deviation of optical depth σ_τ, as dense and tenuous parts of the clouds would be increasingly aligned in the vertical dimension, thereby broadening the probability distribution. On the other hand, larger σ_τ causes a decrease in the solar albedo and thermal emissivity, as implied in their convex functions on τ. As a result, increasing (decreasing) L_{cw}leads to decreased (increased) CRFs, as revealed by comparisons among $L_{cw} = 0$, $L_{cw} = 1$ km and$L_{cw} = \infty$. It also affects the vertical structure of radiative flux and thus influences the radiative heating. A better representation of σ_τ in the vertical dimension yields an improved simulation of radiative heating. Although the importance of vertical alignment of cloud condensate is found to be less than that of cloud cover in regards to their impacts on CRFs, it still has enough of an effect on modulating the cloud radiative transfer process.

1. Introduction

Accurate parameterizations of clouds and their radiative properties are critical if numerical models are to produce realistic simulations of current climate or believable predictions of the future. Although this topic has received increased attention in recent decades (Lohmann et al., 1999; Bogenschutz and Krueger, 2013; Kuell and Bott, 2014), cloud representation in general circulation models (GCMs) is still in its infancy and contributes to one of the largest uncertainties in climate modeling (Bony and Dufresne, 2005). Apart from challenges in fractional cloudiness parameterization (Tompkins, 2002; Wang et al., 2015) and cloud cover overlap treatment (Wang et al., 2016), cloud representation is complicated by cloud hydrometeor inhomogeneity and associated vertical alignment.

Traditionally, GCMs represent clouds using grid-box means of a variable such as cloud liquid or ice water content (Zhang et al., 2013); however, this is far from realistic, as observed clouds exhibit dramatic variability at spatial scales smaller than the GCM grid (Tompkins, 2002). Remarkable errors can therefore occur in a series of physical processes, i.e., cloud autoconversion and radiative transfer (Pomroy and Illingworth, 2000; Larson et al., 2005). For instance, Cahalan et al. (1994a) found that the homogeneous assumption often yields overestimations in both shortwave and longwave cloud radiative forcings (CRFs). Pomroy and Illingworth (2000) obtained similar results and found the overestimation is essentially due to the non-linear relationship between cloud optical depth and solar albedo/thermal emissivity. There have been several attempts to remedy such biases. The simplest of these is to artificially scale down cloud optical depth. Cahalan et al. (1994a) suggested using a scaling factor of 0.7 based on maritime stratocumulus; however, they acknowledged the optimum value would vary in terms of time and location. Gu and Liou (2006) found that using a location-dependent inhomogeneity factor improved the global mean planetary albedo by 4%. Furthermore, Hill et al. (2012) proposed a parameterization of inhomogeneity that is suitable for inclusion in GCMs and obtained encouraging results. While the introduced inhomogeneity factor is beneficial in improving radiative budget simulations, it brings limited success in other aspects, i.e., radiative heating.

Another approach is the so-called stochastic independent column approximation (ICA), which generates subgrid-scale columns and allows each subcolumn to calculate radiative transfer independently (Cahalan et al., 1994b; Barker et al., 1999). The accuracy of this method

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depends on how closely the generated subcolumns resemble those in reality, in particular the vertical correlation relationship. Contrary to the scaling approach above, this method aims to resolve cloud geometry in a direct manner. The algorithm used to generate vertical correlation profiles is akin to that in cloud cover overlap but with a different decorrelation length L_{cw}(Raisanen et al., 2004). Hogan and Illingworth (2003) found L_{cw}typically varies between 0.5 and 2 km for a domain range of 2 to 300 km. Oreopoulos et al. (2012) fixed L_{cw}at 1 km and examined its impacts on radiative budgets in GEOS-5 (Goddard Earth Observing System Model, Version 5). These studies neglected the varying feature of L_{cw} in the vertical dimension; however, this was at the cost of accuracy, as will be shown later. The goal of this study was thus to propose a new parameterization of L_{cw} that accounts for vertically varying characteristics and to compare it with previous parameterizations.

This study, targeting cloud condensate vertical alignment, is a follow up to Wang et al. (2016), which focused on cloud cover overlap. The decorrelation length L_{cf} in Wang et al. (2016) is used to adjust the degree of cloud fraction overlap, while L_{cw}in this study is used to adjust cloud condensate vertical alignment. The paper is structured as follows. Section 2 details a new parameterization of L_{cw} based on cloud resolving model (CRM) simulations of two deep convective systems. Section 3 compares variousL_{cw}, including the new parameterization, in terms of simulated CRFs and radiative heating rates. Also explored in this section are reasons for the distinct behavior of different parameterizations and the role of L_{cw} in modulating these fields. Section 4 discusses the relative importance between cloud cover overlap and cloud condensate alignment. The last section summarizes the main findings of this study.

2. Diagnosis and parameterization of L_{cw}

2.1. Cloud condensate vertical alignment in CRM simulations

Cumulus clouds are usually associated with large subgrid horizontal variability because of intense turbulence inside the clouds (Wang et al., 2015). Fig. 1a shows the subgrid cloud water (liquid + ice) distribution for one snapshot simulation of deep convection by the SAM (System for Atmospheric Modeling) cloud-resolving model (Khairoutdinov and Randall, 2003). Technical details of the model configuration can be found in Wang et al. (2016). The subgrid in this study refers to the CRM grid at the resolution of 4 km, and any variability in the horizontal dimension is down to this scale. Fig. 1a indicates that cloudy cells are widely spread in the upper two layers (blue), whereas they are sporadically distributed in the middle layers (red). This is consistent with the fact that anvil clouds usually occupy a larger cloud fraction and convective cores occupy a smaller cloud fraction. A remarkable peak-to-peak correspondence is apparent between the two convective layers, even though they span as far as 3 km. However, such a clear correlation is not apparent in the two anvil layers, although they are adjacent to each other with an interval of <500 m. It is thus implied that vertical correlation and decorrelation length L_{cw}varies in different cloud regimes. Although the homogenous assumption excludes any variability at each level, variability remains in the cloud condensate path (CCP) (green line in Fig. 1b), which is also reflected in the cumulative condensate path (green line in Fig. 2b). It is important to remember the geometry of cloud hydrometeors is governed by that of cloud cover, in view of the fact that cloud hydrometeors can only exist within cloudy cells. Constrained by the same cloud cover geometry shown in Fig. 2a, the generated stochastic subcolumns under two L_{cw} extremes are shown in Fig. 1c and d. Details of the stochastic method will be provided in Section 3.1. We noticed that maximum overlap (MO,$L_{cw} = \infty$) produces higher peak-to-peak correlation, while random overlap (RO, $L_{cw} = 0$) generally weakens the correlation. As a result, the maximum value of CCP is increased under MO, whereas it is somewhat decreased under RO conditions.

2.2. Diagnosis of L_{cw}

First, to diagnose L_{cw} from CRM simulations, the correlation coefficient ρ is calculated for any two adjacent levels. Here, the correlation

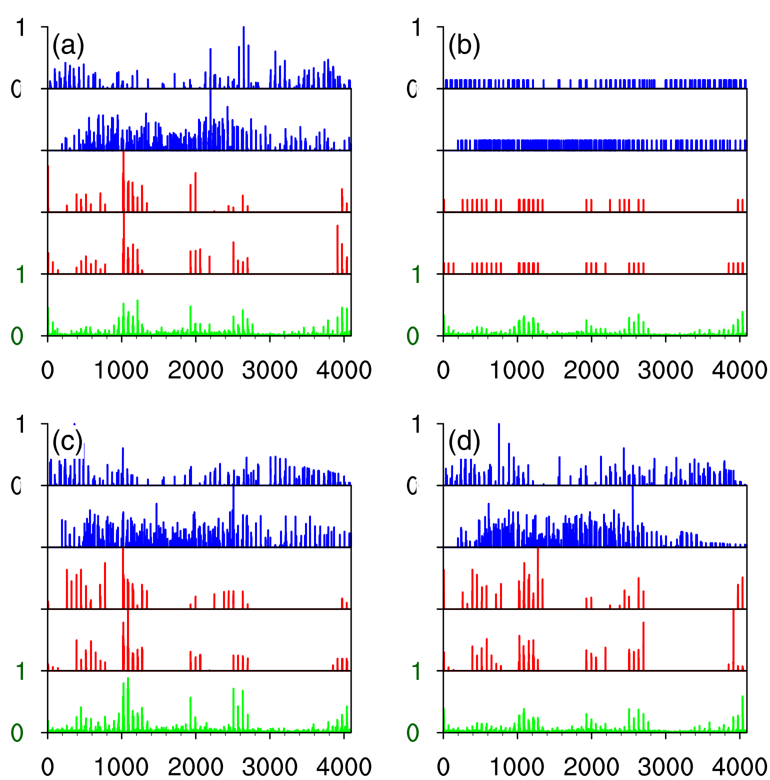

Fig. 1. Horizontal subgrid distribution and vertical alignment of cloud hydrometeors under (a) CRM output geometry, (b) PPH, (c) maximum overlap and (d) random overlap assumptions. The abscissa is the number index of CRM subcolumns and the ordinate is relative values of cloud hydrometeor amount (blue and red) and cloud condensate path (green).