Evaluation of Subgrid-Scale Hydrometeor Transport Schemes Using a High-Resolution Cloud-Resolving Model

MAY WONG* AND MIKHAIL OVCHINNIKOV
Pacific Northwest National Laboratory, Richland, Washington

MINGHUAI WANG
Institute for Climate and Global Change Research, and School of Atmospheric Sciences, Nanjing University, and Collaborative Innovation Center of Climate Change, Nanjing, China

(Manuscript received 27 February 2015, in final form 8 May 2015)

ABSTRACT

Potential ways of parameterizing vertical turbulent fluxes of hydrometeors are examined using a high-resolution simulation of continental deep convection. The cloud-resolving model uses a double-moment microphysics scheme that contains prognostic variables for four hydrometeor types: rain, graupel, cloud ice, and snow. The benchmark simulation with a horizontal grid spacing of 250 m is analyzed to evaluate three different ways of parameterizing the turbulent vertical fluxes of hydrometeors: an eddy-diffusion approximation, a quadrant-based decomposition, and a scaling method that accounts for within-quadrant (subplume) correlations. Results show that the downgradient nature of the eddy-diffusion approximation enforces transport of mass away from concentrated regions, whereas the benchmark simulation indicates that the vertical transport often moves mass from below the level of maximum concentration to aloft. Unlike the eddy-diffusion approach, the quadrimodal decomposition is able to capture the signs of the flux gradient but underestimates the magnitudes. The scaling approach, which accounts empirically for within-quadrant correlations, improves the representation of the vertical fluxes for all hydrometeors except snow. A sensitivity study is performed to illustrate how vertical transport effects on the vertical distribution of hydrometeors are compounded by accompanying changes in microphysical process rates. Results from the sensitivity tests show that suppressing rain or graupel transport drastically alters vertical profiles of cloud ice and snow through changes in the distribution of cloud water, which in turn governs the production of cloud ice and snow aloft. Last, a viable subgrid-scale hydrometeor transport scheme in an assumed probability density function parameterization is discussed.

1. Introduction

Clouds and precipitation play an important role in our climate system—for example, through their direct impact on surface hydrology, radiative feedbacks by high clouds, and on atmospheric stability through vertical redistribution of heat and moisture. Convective storms that are associated with deep clouds and heavy precipitation are especially efficient at transporting moisture and heat in the atmosphere. Unfortunately, because of the low model resolution used in current global models (with typical horizontal grid spacings from approximately 25 km in operational numerical weather prediction models to 100 km in climate models), these convective storms are largely unresolved and therefore need to be parameterized.

Model precipitation can be categorized into two types: stratiform (large scale) and convective (shallow and deep convection) precipitation. Although prognostic microphysics schemes are commonly used in mesoscale models, in global models precipitation is typically diagnosed; that is, the scheme assumes that the time tendency of precipitation is zero over one time step. All precipitation is formed and depleted completely by rainout or evaporation within one time step. In deep convection schemes, diagnostic relationships related to

* Current affiliation: National Center for Atmospheric Research, Boulder, Colorado.

Corresponding author address: May Wong, Mesoscale and Microscale Meteorology Laboratory, National Center for Atmospheric Research, 3450 Mitchell Lane, Boulder, CO 80301. E-mail: mwong@ucar.edu

DOI: 10.1175/JAS-D-15-0060.1

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precipitation efficiency (e.g., approximated using the vertical flux of cloud condensate, diagnosed updraft mixing ratio of cloud condensate, downdraft mixing ratio of cloud condensate, and/or some critical cloud condensate threshold) were developed to determine the amount of precipitating condensates formed (e.g., Fritsch and Chappell 1980; Emanuel 1991; Zhang and McFarlane 1995; Bechtold et al. 2001; Walters et al. 2014). These schemes neglect the transition between different hydrometeor types.

Recent developments have included more microphysical details in both cumulus and microphysics schemes in global models. Song and Zhang (2011) implemented a diagnostic double-moment microphysical scheme that includes hydrometeor transformation processes (among cloud water, cloud ice, rain, and snow) in the deep convection scheme of Zhang and McFarlane (1995) and have found that including the new microphysics in the deep convection scheme improved stratiform precipitation amounts and the vertical cloud ice water content structure. Gettelman and Morrison (2015) added prognostic double-moment rain and snow microphysics (MG2, where “2” refers to version 2 of this global model two-moment microphysics scheme) into the originally diagnostic precipitation microphysics scheme of Morrison and Gettelman (2008) [MG1.5, where “1.5” refers to a modified version from version 1; see Gettelman and Morrison (2015)]. In Gettelman and Morrison (2015), they compared MG2 with two other prognostic microphysics schemes commonly used in mesoscale models (one of which was used as the basis of their work) and found that for warm-rain cases, the vertical cloud water and rainwater distributions in MG2 resembled those from the mesoscale microphysics schemes better than MG1.5. Surface rain rates, increased as a result of more efficient accretion rates, and the evolution of the event were closer to the other microphysics schemes.

The aforementioned studies showed that more detailed microphysics certainly have an impact on the vertical structure of precipitation process rates. Cloud dynamics can also influence the formation of clouds and precipitation, especially within strong convective updrafts and downdrafts. In Song and Zhang (2011), convective microphysics were found to be highly sensitive to the convective vertical velocity, especially for cloud ice water content. In the same study, convective detrainment, a process related to the vertical transport, was found to be an important term in better predicting cloud ice content aloft. Suspended liquid and frozen condensates in the air column can have a thermodynamical impact on the development of convective storms. For instance, ice hydrometeors in the anvil of a deep convective storm can lead to a destabilizing effect in the system by radiative cooling at the cloud top and warming near the cloud base. As hydrometeors form by condensation/deposition, the subsequent release of latent heat enhances convective motion. The net effect of the convective mixing induced by these deep convective systems tends to stabilize the atmosphere.

More sophisticated convection schemes in GCMs are emerging; in particular, schemes that solve prognostic turbulent budget equations can retain some memory of subgrid variability at each time step. For example, one can include a prognostic convective vertical momentum equation to increase the memory of subgrid-scale convective motion (Donner 1993; Donner et al. 2001; Gerard et al. 2009). In Gerard et al. (2009), the authors included cloud microphysical effects in the cumulus scheme, as described in Piriou et al. (2007). Like in most other cumulus schemes, only vertical convective transport of cloud water was considered.

Another type of cumulus scheme uses higher-order turbulence closure (e.g., Lappen and Randall 2001a; Larson and Golaz 2005). In a particular scheme called Cloud Layers Unified by Binormals (CLUBB), joint assumed probability density functions (PDFs) were utilized to represent subgrid-scale variability of vertical velocity, liquid-water potential temperature, and total-water mixing ratio (sum of water vapor and liquid water) (Golaz et al. 2002; Larson and Golaz 2005). Prognostic precipitation microphysics can be coupled to these assumed PDF closure schemes (Larson and Griffin 2013; Griffin and Larson 2013). The scheme was recently tested for deep convection by Storer et al. (2015), unifying turbulence, shallow convection, and deep convection parameterizations with a single physics scheme. The authors utilized a subcolumn sampling generator (called SILHS) to handle the coupling to the microphysics. In CLUBB, the multivariate joint PDF provides subgrid-scale information including vertical velocity variance, skewness, and other higher-order moments. A lognormal assumed PDF is used to describe the subgrid-scale variability of hydrometeors (Larson and Griffin 2013; Griffin and Larson 2013). Such a scheme is able to provide spectral information of subgrid-scale variability and may be useful in improving the parameterization of subgrid-scale transport processes.

This study focuses on the parameterization of subgrid-scale transport processes of hydrometeors. We assume that the subgrid-scale PDFs of prognostic variables are given at each vertical level and time step by a scheme such as CLUBB. In the present diagnostic evaluation, we use a high-resolution cloud-resolving model (CRM), which provides the input to the subgrid-scale transport schemes, as well as the benchmark solution. We focus on the transport of hydrometeors for their increasingly important role in convection schemes.
Three subgrid-scale transport schemes—an eddy-diffusion approach, quadrimodal decomposition, and a quadrimodal decomposition with scaling—are taken from the literature and applied for hydrometeor transport. The last two schemes are applied on hydrometeors for the first time.

The paper is organized as follows. We begin by describing the cloud-resolving model simulations (section 2). Comparisons of the three approaches with the high-resolution CRM benchmark simulation are presented in section 3. A sensitivity study is also presented in section 3 to examine how vertical transport may affect the microphysical processes in deep convection. In section 4, potential implementation of a subgrid-scale transport scheme in a PDF-based convection scheme, based on the scaled quadrimodal analysis, is discussed. Finally, a summary is given in section 5.

2. Model description and evaluation method

We use the CRM called System for Atmospheric Modeling (SAM) (Khairoutdinov and Randall 2003) to produce high-resolution simulations of a series of deep convective storms. SAM is a nonhydrostatic anelastic model with periodic lateral boundary conditions. The dynamical core uses an Adams–Bashforth time-stepping scheme. The default advection scheme is an Eulerian second-order multidimensional positive definite advection transport algorithm (MPDATA; Smolarkiewicz and Grabowski 1990). The thermodynamic variable is the liquid-ice static energy, and the prognostic moisture variables native to SAM are the nonprecipitating (sum of cloud water and cloud ice) and precipitating (sum of rain, snow, and graupel) condensates. A double-moment microphysics scheme by Morrison et al. (2005) is used to compute cloud microphysics at each time step for cloud liquid water, rain, cloud ice, graupel, and snow. A 1.5-order turbulent kinetic energy (TKE) subgrid-scale closure is used, and the Rapid Radiative Transfer Models (RRTMs) are used for the short- and longwave radiation calculations (Iacono et al. 2008; Clough et al. 2005).

The simulated deep convection case is a 4-day period from the Atmospheric Radiation Measurement Program’s (ARM) 1997 intensive observation period (from 0000 UTC 27 June to 0000 UTC 1 July) at the Southern Great Plains (SGP) site (36.5°N, 97.5°W). Several model intercomparison studies have been done in the past for this midlatitude summertime continental convection observation period, including intercomparisons of single-column models and cloud-resolving models (Xie et al. 2002; Xu et al. 2002; Khairoutdinov and Randall 2003). The selected period includes a major precipitation event with a maximum precipitation rate of 84 mm h⁻¹ on 29 June and a series of weaker precipitation events on 27 June.

We run SAM in 3D at a uniform horizontal grid spacing of 250 m with stretched vertical grid spacings from 25 m closest to the surface to 250 m. The model domain has 512 × 512 × 128 grid points (128 km × 128 km × 28 km). A time step of 2 s is used. As in previous studies, horizontally homogeneous forcing is applied based on forcing data derived from an objective analysis of observations (Zhang et al. 2001). Surface latent heat and sensible heat fluxes are prescribed. The full CRM domain is designed to represent a single gridcell column in a coarser grid model.

This simulation serves two purposes: first, to provide high-resolution three-dimensional model output every 10 min for the evaluation of parameterization schemes, and second, to serve as a benchmark for coarser simulations performed for a sensitivity study. Domain-mean statistics of hydrometeor-related processes are sampled every 10 s to generate 10-min averages. These statistics include microphysical tendencies from the prognostic microphysics scheme, resolved vertical advection tendencies, sedimentation tendencies, and subgrid diffusion tendencies.

Because of the nonlinear interactions between transport, sedimentation, and the microphysical processes of the hydrometeor variables, it is difficult to disentangle the role of vertical transport from the others. Coarser-resolution sensitivity runs are performed with suppressed vertical transport of each hydrometeor type. The goal is to assess how vertical transport affects microphysical processes in a CRM, and analogously, in a subgrid-scale scheme.

The evaluation is based on the analogy between the high-resolution CRM domain and a coarse-grid column of a global atmospheric model. Assuming that the CRM explicitly resolves all the processes, the horizontally averaged statistics from the CRM are essentially the solutions the parameterization schemes aim to represent in a coarse-grid column. In a coarse-grid model with prognostic microphysics, resolved vertical advection of hydrometeors is handled by the scalar advection scheme. Because the CRM uses periodic lateral boundary conditions, the mean vertical velocity at each level is zero (analogous to no resolved vertical advection in a coarse-grid column). We can therefore focus our analysis on the subgrid-scale transport using the CRM results and compare the parameterized fields with those computed explicitly from the benchmark simulation.

Here, our goal is to find the best representation of the subgrid-scale vertical hydrometeor flux. Throughout the paper, we will use the term “vertical transport” to mean the parameterized subgrid-scale vertical fluxes in a coarse grid cell, which will be evaluated against the horizontal means of the vertical fluxes explicitly.
simulated by the high-resolution CRM. Evaluation is performed for the transport of rain, graupel, snow, and ice mass mixing ratios.

3. Subgrid-scale transport schemes

a. Eddy-diffusion approach

The time tendency due to subgrid-scale vertical transport of the hydrometeor mass mixing ratio \( q_x \) is defined as

\[
\left( \frac{\partial q_x}{\partial t} \right)_{\text{SGS transport}} = - \frac{1}{\rho} \frac{\partial}{\partial z} (\rho w q_x^L),
\]

(1)

where \( \rho \) is air density, \( z \) is the vertical height coordinate, and \( w \) is the vertical velocity. The overbar denotes the horizontal average at a specific height and the prime notation denotes perturbation from the horizontal mean. The parameterization of the covariance, or vertical flux, \( w q_x^L \) is key to representing subgrid-scale transport. We begin with a simple approximation of the covariance, namely the eddy-diffusion approximation,

\[
\overline{w q_x^L} \approx -K \frac{\partial q_x}{\partial z},
\]

(2)

where \( K \) is the eddy viscosity and typically parameterized as a nonnegative coefficient that increases with turbulent kinetic energy (Stull 1988). Storer et al. (2015) recently described a formulation for \( K \) that accounts for deep vertical motion in convective cases. Using their large-eddy-type benchmark simulation, the authors noted that, when compared to their previous formulation for shallow convection, they had to increase their eddy-viscosity coefficient by approximately a factor of 100. To work for both shallow and deep convection, their \( K \) parameterization depends on prognostic vertical velocity skewness and variances of the hydrometeor mixing ratios, which depend on convection strength.

Here, we evaluate their formulation, repeated below for clarity:

\[
\overline{w q_x^L} \approx -cK \frac{\partial q_x}{\partial z},
\]

(3)

where \( c = 0.75 \text{ m}^2\text{s}^{-1} \) is a tunable constant. Their definition of \( K \) is

\[
K = \sqrt{e L} \left( \frac{d q_x^L}{\overline{q_x^L}} \right) (1 + |\text{Sk}_w|),
\]

(4)

where \( e \) is the subgrid turbulent kinetic energy, \( L \) is CLUBB’s mixing length (Golaz et al. 2002; Larson et al. 2012), \( \overline{q_x^L} \) is the horizontally averaged mixing ratio, and \( \text{Sk}_w \) is the skewness of vertical velocity.

The subgrid-scale vertical flux in Eq. (1) can be evaluated using Eq. (3), where all the variables on the right-hand side can be obtained from the benchmark simulation. The horizontally averaged resolved turbulent kinetic energy from the 250-m simulation is used to represent the subgrid turbulent kinetic energy \( e \). The mixing length \( L \) is diagnosed as is done in the single-column model CLUBB but using horizontally averaged profiles from the benchmark simulation. The CLUBB mixing length depends on the vertical profiles of liquid-water potential temperature and its variance, total-water mixing ratio and its variance, virtual potential temperature, and pressure. Readers are referred to Golaz et al. (2002) and Larson et al. (2012) for more details on the diagnosis of the mixing length in CLUBB.

The temporal evolution of the domain-mean time tendencies due to resolved vertical advection from the 250-m benchmark simulation is shown in the top row of Fig. 1. Regions in blue (red) denote levels at which hydrometeor mass is being removed (deposited) by vertical motion. The mean mixing ratios at each vertical level and time (not shown) in the benchmark simulation represent the resolved field in a coarse grid cell. The black crosses indicate the level of maximum mean hydrometeor mixing ratio. Only vertical mass redistribution due to advection is shown here; sedimentation and subgrid diffusion are calculated separately from these time tendencies. The magnitudes of the subgrid diffusive fluxes are small relative to the resolved fluxes (approximately \( 10^{-2} - 10^{-3} \) of the total flux). We therefore use only the resolved fluxes in our analyses.

Strong convective motion tends to redistribute the frozen hydrometeors from altitudes below to above the peak amount. The level of maximum mean rain mixing ratio is dominantly from melting graupel and snow into rain at or below the freezing level.

The time tendencies of the parameterized transport using eddy diffusion for each hydrometeor are shown in the bottom row of Fig. 1, which illustrates that the eddy-diffusion transport scheme transports hydrometeors away from the peak level of hydrometeor mass. This behavior is, of course, expected from the downgradient nature of the scheme.

The downgradient formulation implies that for a positive-definite eddy viscosity \( K \) [e.g., Eq. (4)], the vertical flux is positive (negative) when \( q_x^L \) decreases (increases) with height. Figure 2 shows the mean hydrometeor mixing-ratio profiles at two specific times 4130 and 4180 min. The mean mixing ratios in updraft and downdraft regions (red and blue dashed lines, respectively) are diagnosed from the model simulation.
The downgradient formulation assumes positive fluxes above the level of maximum mixing ratio (horizontal dashed line), either from updrafts \(w_0^+ > 0\) associated with \(q_0^+ > 0\) or downdrafts \(w_0^- < 0\) associated with \(q_0^- < 0\). This assumption is potentially valid as vindicated by the mean updraft and downdraft mixing ratios above the horizontal dashed line, shown in Fig. 2. (In a more detailed analysis presented in the next section, it can be shown that negative fluxes above the level of maximum can exist as a result of the negative correlation between mixing ratio and downdraft velocity.)

Below the level of maximum mixing ratio, the downgradient formulation assumes negative fluxes, either from downdrafts associated with \(q_0^- > 0\) or updrafts associated with \(q_0^- < 0\). As shown in Fig. 2, at different times (4130 and 4180 min), the mean graupel mixing-ratio profiles show agreement and disagreement, respectively, with this assumption. Similar graupel mixing ratio profiles to that in Fig. 2a (at which time, the maximum \(\overline{w^2}\) is 1.2 \(\text{m}^2\text{s}^{-2}\)) are also found at other times, indicated by the white vertical lines in Fig. 3. At these times, the intersection of the mean updraft and downdraft mixing ratio profiles (e.g., near 7 km in Fig. 2a for graupel) occurs within 1 km in height from that of the maximum mean mixing ratio (horizontal dashed line). These profiles are found in between convective activities, where convective activities are characterized by an increase in vertical velocity variance (Fig. 3), whereas during these activities, profiles similar to that in Fig. 2b (when the maximum \(\overline{w^2}\) is 5.3 \(\text{m}^2\text{s}^{-2}\)) are found.

In ice and snow, updrafts generally carry greater-than-mean mixing ratios from below the level of maximum. The downgradient formulation may, however, be a valid approximation for rainwater fluxes. Below the level of maximum rain mixing ratio, downdrafts are found to be associated with greater-than-mean rain mixing ratios. These larger rain mixing ratios are likely associated with strong downdrafts partly induced by precipitation loading and microphysical processes such as rain evaporation and melting of graupel and snow. The level of maximum rain mixing ratio coincides with the freezing level; below which, the melting of precipitating graupel and snow in downdrafts also contributes to larger rain mixing ratios.

Past studies have shown that the eddy-diffusion approximation may not be appropriate for representing subgrid-scale heat and tracer transport in convection and proposed modifications to account for the countergradient transport in parameterizations (e.g., Deardorff 1972; Gidel 1983; Chatfield and Crutzen 1984; Holtslag and Moeng 1991). As we will demonstrate in the next section, updrafts and downdrafts both play an important role in redistributing the hydrometeors throughout the column, not only between adjacent layers. To account for the countergradient transport, a correction term may be added to the eddy-diffusion formulation—for example, as in the nonlocal transport schemes reviewed in Zilitinkevich et al. (1999). A generalized formulation of a correction term for all hydrometeors however is difficult. Alternative formulations are described next.

b. Quadrimodal decomposition method

The vertical hydrometeor flux in Eq. (1) can be approximated using a mass-flux formulation.
where $s_i$ is the fractional area of flux-type $i$ (to be interpreted as a population of plumes that satisfies a set of predefined criteria). The mass flux of each type $i$ is defined as

$$M_i = \rho w_i q_i,$$

and the sum of all $s_i$ equals to unity; that is, the set of $N$ flux types should represent the entire grid cell. Information on the subgrid-scale correlation between $q'_x$ and $w'$ is typically unavailable. When $N = 1$, no correlation information is included and Eq. (5) becomes highly inaccurate. When $N \to N X \times N Y$ (where $N X$ and $N Y$ are the CRM grid dimensions in the $x$ and $y$ directions, respectively), this is equivalent to explicitly calculating the vertical flux using $w'$ and $q'$ at every grid point, which implies knowing the subgrid-scale correlation that is precisely the parameterization problem. The decomposition into a reasonable number of flux types allows incorporation of some preexisting knowledge of the correlation. For example, updrafts tend to promote the growth of rain drops, so more positive $q'_x$ values are typically associated with more positive $w'$ values. Positive $q'_x$ that are associated with positive $w'$ values can be broadly defined as one flux type. The microphysical growth/decay rates may depend on the specific microphysics scheme, but the correlation or coupling between the dynamics (vertical velocity) and microphysics should remain similar.

Many conventional precipitating convection schemes use entraining plume models to estimate the mass fluxes [Eq. (6)] in subgrid-scale transport. Such schemes separate the fluxes into up- and downdraft mass fluxes, which are diagnosed based on assumptions of entrainment and detrainment rates. Moreover, the fractional area of the convective towers is often assumed to be negligible. Here, we assume that these updraft and downdraft mass fluxes within a coarse grid cell are known a priori and predetermined by the signs of the CRM gridpoint vertical velocity perturbation to the horizontal mean. We also use nonzero fractional areas for all decomposed fluxes.

In our analysis, we decompose the updraft and downdraft fluxes further into below-mean ($q'_x < 0$) and above-mean ($q'_x > 0$) quantities, such that $N = 4$ (or into quadrants),

$$w' q'_x = \sigma_1 (w' q'_{x,u})_{q'_x > 0} + \sigma_2 (w' q'_{x,u})_{q'_x < 0}$$

$$+ \sigma_3 (w' q'_{x,d})_{q'_x < 0} + \sigma_4 (w' q'_{x,d})_{q'_x > 0},$$

FIG. 2. Mean profiles of hydrometeor mixing ratio at time (a) 4130 and (b) 4180 min. Domain-averaged mixing ratios are plotted in black, with the height of the maximum indicated by the horizontal dashed line. Updraft ($w > 0$) and downdraft ($w < 0$) mean mixing ratio profiles are plotted in red and blue dashed lines, respectively.
where the subscripts \( u \) (\( d \)) denote updraft (downdraft) fluxes and the subscripts I, II, III, and IV indicate the quadrant that each right-hand-side term represents. The quadrimodal decomposition is essentially a bivariate conditional sampling of the vertical hydrometeor flux, and the analysis technique was used in the past to study sensible heat flux (e.g., Réchou and Durand 1997) and convective thermodynamic (potential temperature and water vapor) and momentum fluxes (e.g., Yano et al. 2004). Here, we apply the analysis technique on the study of the turbulent transport of microphysical variables.

The quadrimodal decomposition of the joint density function of rain mixing ratio and vertical velocity at 3.5 km (600 m below the freezing level) is shown in Fig. 4a. Log scales in the y axis and color bar are used for plotting purposes only. The horizontal dashed line marks the mean rain mixing ratio at that altitude. The vertical dashed line marks the mean vertical velocity (zero owing to periodic lateral boundary conditions). The numbered quadrants correspond to each of the right-hand-side terms in Eq. (7), respectively. The position of the quadrant means, \( \bar{w}^i \) and \( \bar{q}_{r}^i \), in each quadrant are shown as white crosses.

Vertical velocities associated with the most frequent rain mixing ratios are generally small and have a fairly Gaussian distribution (quadrants II and III in Fig. 4a). These normal distributions likely correspond to clouds that have a more stratiform characteristic (uniformly distributed). Quadrants I and IV show the convective transport associated with updrafts and downdrafts, respectively. To illustrate this, the joint density functions of grid points subsampled in the vicinity (within a 3-km radius) of strong updraft regions (defined as \( w > 5 \text{ m s}^{-1} \)) is shown in Fig. 4b. There is a large area fraction, away from the updraft regions (Fig. 4c), with greater-than-mean mixing ratios at that altitude. These mixing ratios are primarily associated with downdrafts where graupel melts into rain.

We note that although most of the points reside in quadrants II and III, the main contributing fluxes are in quadrants I and IV. Figure 4d shows the relative flux contribution (%) of each bin to the total flux, sampled over the whole horizontal domain. The relative contributions to the total flux of the defined updraft regions are shown in Fig. 4e and account for most of the updraft fluxes in quadrant I. The remainder is associated with extended downdraft regions farther away from the updraft cores.

At this altitude, the fractional area is larger for downdrafts (higher density). The fractional areas \( \sigma_i \) for quadrants I and IV are 0.0242 and 0.0728, respectively (whereas quadrants II and III occupy \( \sigma_i \) of 0.5020 and 0.4009, respectively). But the maximum absolute flux is greater in the updraft than in the downdraft, leading to a mean flux that is 4 times that of the downdraft.

We explicitly compute each of the four components—that is, \( \sigma_i(\bar{w}^i \bar{q}_{r}^i) \). Note this is different from the mass-flux representation of each vertical flux component, which is represented by the product of the means, \( \bar{w}^i \) and \( \bar{q}_{r}^i \), of each quadrant \( i \).

The decomposition is repeated at all levels and for all hydrometeors. The vertical profiles at time 4130 min of the vertical fluxes of rain, graupel, ice, and snow are shown in Fig. 5. The decomposed fluxes explicitly
computed from the benchmark simulation are shown in thin black solid lines (quadrants I and IV) and thin black dashed lines (quadrants II and III), and their sum (net flux) is shown in thick black solid line with diamond markers. Strong downdraft fluxes of rain below approximately 4 km are associated with the increase of rainwater from the melting of graupel and snow. For the other hydrometeors, the downdraft fluxes exist throughout the depth of hydrometeors. The magnitude of the vertical flux of ice is about an order of magnitude smaller than the other hydrometeors because of the small vertical motion at higher altitudes (near the tropopause). We also note that for rain and graupel, the fluxes associated with small \( q' \) (i.e., the thin dashed lines representing quadrants II and III) are small compared to the ones with large \( q' \). However, in ice and snow, those fluxes are closer in magnitude: the vertical motion variability in ice and snow is smaller than that in rain and graupel.

The mass-flux approximations [Eq. (7)] of the vertical hydrometeor fluxes are shown in blue in Fig. 5 (in a similar fashion as that for the benchmark fluxes). The quadrimodal decomposition, in general, is able to capture the changes in the sign of the fluxes with height. The local sign of the flux gradient is important in determining whether hydrometeor mass is being transported away or toward the region. However, the approach tends to underestimate the absolute fluxes in both quadrants I and IV, especially for rain and graupel. The error is smaller for ice and snow. The underestimation indicates that...
convective hydrometeor transport is too weak, compared to the benchmark calculations.

c. Scaling approach for within-quadrant correlations

Many existing convective transport schemes use a bulk mass-flux approach. The underlying assumption is that all scalar quantities are being transported within the same air parcels over a time step. The assumption may be justified for passive scalars with long residence and slow reactive times. However, for scalars of which the quantities are greatly modified along their trajectory, this assumption may become invalid. Hydrometeors fall within this category. The formation of rain, graupel, ice, and snow are correlated with regions of updrafts and downdrafts. This correlation is evident in the individual joint distribution in quadrants I and IV (Fig. 4a).

The conventional approach, such as that in Eq. (7), assumes that there is no correlation between the vertical velocity perturbations $w'$ and mixing ratio perturbations $q'_x$ within a quadrant. This within-quadrant correlation is equivalent to the subplume-scale variability discussed in Lappen and Randall (2001b). The zero-correlation assumption allows the use of the approximation

$$\langle w'q'_x \rangle_i \approx \langle w'q'_x \rangle^s_i.$$  

The decomposition of the net flux into several components allows a degree of correlation to be incorporated into the parameterization of subgrid-scale turbulent transport. However, the quadrimodal decomposition neglects the correlation within each quadrant. As shown in Fig. 5, the mean absolute flux of each component (dashed lines) of the subgrid-scale transport is too weak. Given that exact $\sigma_i$ values are used in Eq. (7), the underestimation of the decomposed fluxes is then due to the lack of intraquadrant correlation.

Quadrants I and IV of the joint density distribution (Fig. 4a) typically show positive and negative correlations, respectively, between the hydrometeor mixing ratio and vertical velocity. These within-quadrant correlations mean that stronger vertical motion is typically associated with greater hydrometeor mixing ratios and, therefore, with greater absolute fluxes. To account for this, the quadrant means of vertical velocity and mixing ratio can be scaled toward higher absolute values. A power-law relationship (e.g., Yano et al. 2004) can be used to scale the quadrant means

$$\bar{\bar{\phi}}^s_i = \left(\frac{\bar{\phi}^{n'}\phi_i^{n'}}{\bar{\bar{\phi}}^n_i}\right)_i,$$  

where $\phi = (w', q'_r, q'_g, q'_i, q'_s)$, and $\alpha$ is a parameter that scales the distribution such that larger absolute values contribute more weight to the flux estimate (whereas $\alpha = 0$ reduces $\bar{\bar{\phi}}^s$ to $\bar{\bar{\phi}}$; i.e., zero within-quadrant correlation). The normalization factor [denominator in Eq. (9)] ensures that the maximum/minimum scaled mean is within the limits of the original distribution. The scaled fluxes are then defined as

$$\langle w'q'_x \rangle^s_i = \langle w^{bs}q'^{bs}_x \rangle_i,$$  

and the net flux as before is the sum of the scaled decomposed fluxes.
Results from scaling the quadrant means with $\alpha = 0.25$ are shown in red in Fig. 5. The scaled quadrimodal fluxes are generally closer to the benchmark fluxes, comparing with those from the unscaled quadrimodal decomposition. For the time shown in Fig. 5, the scaled vertical fluxes of graupel between 7 and 10 km are still too weak. The scaled approach also tends to overestimate the vertical fluxes of snow, producing updraft fluxes that are too strong. Reducing the $\alpha$ parameter from 0.25 to 0.025 reduces the maximum errors by about 80%. These results indicate that there is likely a weaker intraquadrant correlation in snow. The joint density distribution for snow mixing ratio at time 4130 min (Fig. 6) shows supporting evidence that this is indeed the case. The vertical velocity distribution in regions of snow is dominantly Gaussian (normally distributed about zero). Vertical velocities ranging from $-10$ to $30 \text{ m s}^{-1}$ are also found to be associated with near-mean snow mixing ratio values (but the fractional area is much smaller). Because of the weak intraquadrant correlation in snow, a smaller $\alpha$ is recommended.

Using the 250-m benchmark simulation as reference, column-integrated errors in the quadrimodal fluxes and the scaled quadrimodal fluxes are calculated for the 4-day simulation (Fig. 7). Table 1 shows the errors in the net and decomposed fluxes integrated over the same period. While the scaled quadrimodal fluxes show overall reduced errors in the vertical fluxes of rain, graupel, and ice, the scaling approach degrades the vertical flux calculations of snow. Most of the improvement is seen in fluxes in quadrants I and IV. An increase in errors is found in quadrants II and III, but the magnitudes of the errors are often small compared to those in quadrants I and IV, and of similar magnitude to each other, which reduces their impact by cancellation.

The intraquadrant correlation of snow and vertical velocity is found to be weaker, comparing to the other hydrometeors, making the scaled means approach less appropriate for snow advection. Within-quadrant correlations may be enhanced by microphysical and sedimentation processes within updrafts and downdrafts. Vertical profiles of the three horizontally averaged sources and sinks in the hydrometeor budget equation—namely, vertical resolved advection, microphysical

![Fig. 6. Joint density distribution of snow mixing ratio (g kg$^{-1}$) and vertical velocity (m s$^{-1}$) at height 8 km and time 4130 min. Vertical dashed line marks zero vertical velocity. Horizontal dashed line marks mean mixing ratio at that height. White crosses and circles indicate the quadrant means and scaled means, respectively.](image)

![Fig. 7. Time series of vertical flux errors ($\alpha$ parameterized explicitly calculated) from the quadrimodal approach (blue) and the scaled quadrimodal approach (red) for four hydrometeor types (rain, graupel, ice, and snow). Errors are column integrated.](image)

| Table 1. Accumulated errors (m g kg$^{-1}$) and net improvement (%) of the vertical hydrometeor fluxes calculated using the quadrimodal (QM) and scaled QM approaches. Errors are calculated over the entire 4-day simulation. |
|---|---|---|---|
| Rain | Graupel | Ice | Snow |
| QM overall | $-119.86$ | $-617.13$ | $-32.66$ | $-31.52$ |
| Scaled QM overall | $-35.96$ | $-22.47$ | $-10.96$ | $85.76$ |
| Improvement | $+70\%$ | $+96\%$ | $+66\%$ | $-172\%$ |
| QM Q1 | $-186.91$ | $-760.74$ | $-59.81$ | $-55.11$ |
| Scaled QM Q1 | $64.50$ | $123.68$ | $-10.66$ | $134.71$ |
| QM Q2 | $-1.58$ | $-4.27$ | $-0.52$ | $-2.12$ |
| Scaled QM Q2 | $-18.00$ | $-49.71$ | $-6.63$ | $-21.39$ |
| QM Q3 | $1.25$ | $3.70$ | $0.32$ | $1.41$ |
| Scaled QM Q3 | $13.93$ | $42.1$ | $6.58$ | $16.74$ |
| QM Q4 | $67.37$ | $144.17$ | $27.34$ | $24.30$ |
| Scaled QM Q4 | $-24.47$ | $-13.85$ | $-0.25$ | $-44.31$ |
processes, and sedimentation—are shown in Figs. 8a, 8b, and 8c, respectively (Fig. 8a is the same as the top row of Fig. 1, but on a different scale).

Positive (negative) regions indicate net production (removal) due to the various processes. The black crosses indicate the level of maximum mean mixing ratio at that time (as in Fig. 1). Three inferences can be made from these budget terms: 1) vertical advection moves hydrometeors from their maximum growth locations to farther aloft (except for snow), 2) maximum microphysical production occurs just below the level of maximum mean mixing ratio (except for rain), and 3) sedimentation acts to remove the lofted hydrometeors. As discussed before, in rain, the maximum microphysical production rate coincides with the level of maximum mean mixing ratio as it is governed by melting of frozen hydrometeors into rain. The correlation between microphysical production rate and removal rate by advection is weaker in snow than for the other hydrometeors, which may be related to the degraded snow fluxes using the scaling approach.

Figure 8 also shows that the magnitudes of the time tendencies due to advection and sedimentation are comparable; that is, both are important components of hydrometeor transport in deep convection. In this study, only that by advection is examined, primarily because sedimentation is handled separately in our target model (CLUBB).

d. Sensitivity of microphysical processes to vertical transport

To examine the potential impact of neglecting or underpredicting subgrid-scale vertical transport of hydrometeors in deep convection, sensitivity tests are conducted by artificially suppressing vertical advection of one hydrometeor type at a time in the CRM. The suppression is carried out by setting the vertical advective tendencies of the hydrometeor mass and number mixing ratios to zero.

For computational efficiency reasons, a coarse-resolution SAM with a horizontal grid spacing of 4 km, lowest level at 63 m (vertical spacing increases with height), and a time step size of 10 s is used for the sensitivity experiment. The model domain has $32 \times 32 \times 28$ grid points. Aside from the grid resolution and suppressed hydrometeor transport, the rest of the model
setup is identical to that for the 250-m simulation. As a control, a 4-km simulation with full hydrometeor transport is also run.

Many studies have shown sensitivity of convection to horizontal grid spacing (e.g., Petch 2006; Bryan et al. 2003; Bryan and Morrison 2012). Likewise, discrepancies between the two simulations exist (e.g., development strength, timing of the events). The comparison is performed for the first event that lasted about 10 h in both simulations (1920–2500 min in the 250-m simulation and 1000–1600 min in the 4-km control simulation). We have compared the microphysical processes in the 4-km control run with the 250-m benchmark simulation (not shown). Despite the differences in both horizontal and vertical resolutions, the time-averaged vertical profiles of the microphysical processes from the two simulations share the same structure. The comparable microphysical processes seen in our two simulations are similar to those presented in Bryan and Morrison (2012), who tested with the same microphysics scheme. In their study, they concluded that the behavior of the microphysics scheme is qualitatively similar in their examined range of grid spacings (from 250 m to 4 km).

Sensitivity runs are performed separately for a weak (1000–2000 min) and a strong (3600–5200 min) convective event. In both cases, ice formation and strength of convective vertical motion are most sensitive when vertical transport of rain or graupel is suppressed. The increase of ice and snow aloft in those two simulations lead to strengthened vertical motion due to destabilizing effects, such as latent heat release and radiative feedback of the high clouds. Suppressing ice or snow transport has a weaker influence on the microphysical processes. We also note that the vertical structure of rain mixing ratios showed little sensitivity to suppressed vertical hydrometeor transport.

We now focus on how vertical transport of rain or graupel may have affected the microphysics, based on our simulations. Rain is first formed by autoconversion of cloud-liquid water. Without vertical transport of rain, accretion is slowed immediately above where the rain is initially formed (Fig. 9b), compared to the control run (Fig. 9a). The slower accretion rate reduces the depletion of cloud-liquid water (which would have converted into rain). Consequently, more cloud water is found aloft, likely causing the increase in accretion rate near 4–5 km. On average over the course of the event, comparable rain mixing ratios are found (Figs. 10b and 11b). The insensitivity is likely related to the compensated formation of rain aloft (by accretion) and by an increased melting of graupel (Fig. 9d).

Under weak conditions when rain vertical transport is suppressed, the rate of graupel mass production actually increases owing to a faster collection of cloud-liquid water aloft (Fig. 9f). This process is much slower in the control run (Fig. 9e). Under more intense convection, less graupel is found aloft than in the control run (Fig. 11c). As indicated by the microphysical processes of ice rates in the simulation (not shown), graupel formation in this scenario is primarily due to freezing of rain, which is sensitive to the drop radius. In the control run, strong updrafts help transport rain drops that have grown to a larger size. Drop sizes are inferred by comparing the mixing ratios with the number concentrations of rain (Figs. 11a and 11g, respectively). Larger drop sizes accelerate heterogeneous freezing of rain into graupel. In the suppressed transport case, rain drops formed aloft primarily by autoconversion and accretion are relatively small and, therefore, cannot produce as much graupel as in the control run (Figs. 9g, h).

Ice formation shows similar sensitivity to processes related to cloud-liquid water. The freezing rate of cloud-liquid water increases substantially by suppressing the vertical transport of rain or graupel. The maximum peak formation of ice particles due to freezing of cloud-liquid water (time averaged over 1000–2000 min) increased 100–200-fold with suppressed rain or graupel transport, remained unchanged with suppressed ice transport, and doubled with suppressed snow transport. Under suppressed rain or graupel vertical transport in both weak and strong convective events, snow formation rate is highly dependent on the amount of ice because production is dominated by depositional growth and autoconversion from and collection of cloud ice in the Morrison microphysics scheme.

Here, we have shown that the vertical advection of rain and graupel have a strong impact on accurately predicting ice and snow formation. On the other hand, the vertical advection of ice and snow has a weaker impact on the simulations. Also, accurately predicting rain amount does not necessarily mean that the dynamical processes are well represented. The microphysical processes that are most sensitive to vertical hydrometeor transport are the ones that are highly dependent on the vertical distribution of cloud-liquid water mass and number mixing ratios.

The implications of the results from the sensitivity study may extend beyond parameterized convection. In some cloud-resolving modeling studies (e.g., Weisman et al. 1997; Petch et al. 2002; Petch 2006; Bryan and Morrison 2012), total rainfall and updraft strengths were found to be sensitive to horizontal resolution. Their coarser-resolution simulations were found to exhibit weaker vertical velocities, which would effectively lead to suppressed hydrometeor advection. As our results show, suppressing hydrometeor transport may not necessarily
reduce surface rainfall; in some cases, it would lead to an increase in rain production, as was found in some coarser-resolution models in previous studies.

4. Extension of results to assumed PDF schemes

In section 3b, we briefly stated that the evaluation of the subgrid-scale transport schemes is based on the assumption that the updraft and downdraft bulk mass fluxes are known a priori. This assumption allows us to use the high-resolution benchmark simulation as input to the subgrid-scale transport schemes. We now elaborate on how one might acquire these bulk mass fluxes.

In a probability context, the subgrid-scale vertical flux of $q_x$, evaluated at each model level, can be written as

$$w^\prime q_x^\prime = \int_{-\infty}^{\infty} (w - w') (q_x - \bar{q}_x) p(w, q_x) \, dw \, dq_x.$$  \hspace{1cm} (11)

The joint probability density distribution can be decomposed into quadrants (for $N = 4$) based on some predefined thresholds of $w$ and $q_x$ (e.g., positive and negative perturbations as used in the previous section). The subgrid-scale vertical flux can then be rewritten (with no approximation applied yet) as

$$w^\prime q_x^\prime = \sum_{i=1,N} \int_{\Omega_i} (w - w') (q_x - \bar{q}_x) p(w, q_x) \, dw \, dq_x,$$  \hspace{1cm} (12)

where the integrand in each term of the summation is evaluated over subdomain $\Omega_i$ defined by the range of $w$.

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**Fig. 9.** Microphysical process rates (kg kg$^{-1}$ s$^{-1}$) of (a)–(d) rain and (e)–(h) graupel from the control run and suppressed vertical transport of graupel. Vertical profiles shown are averaged over different periods: (a),(b) warm-rain processes only (time 850–1000 min), (c),(d) mixed-phase processes during the weak event (time 850–1800 min), (e),(f) the first hour of graupel formation in the weak convection case (time 1000–1060 min), and (g),(h) the first 30 min of graupel formation in the strong convection case (time 4540–4570 min).
and \( q_x \) in each quadrant and \( p(w, q_x) \) is the joint probability density function that is precisely the unknown that leads to the parameterization problem. An approximation similar to Eq. (7) can be applied in each quadrant. By defining the (unscaled) mean in each quadrant,

\[
\overline{\phi_i} = \int_{\Omega_i} (\phi - \overline{\phi}) p_i(\phi) \, d\phi,
\]

where \( \Omega_i \) are defined by the \( \phi \) values in quadrant \( i \). Eq. (12) can be written as

\[
\overline{w^2 q_x} = \sum_{i=1}^{N} \int_{\Omega_i} (w - \overline{w})(q_x - \overline{q}_x)p(w, q_x) \, dw \, dq_x \\
= \sum_{i=1}^{N} \sigma_i^{w^2} \int_{\Omega_i} (w - \overline{w})p_i(w) \, dw \int_{\Omega_i} (q_x - \overline{q}_x)p_i(q_x) \, dq_x,
\]

where the overbar represents horizontal means (equivalent to resolved grid-scale means), and \( p_i(\phi) \) are the normalized probability distributions of the portion of \( p(\phi) \) that resides in quadrant \( i \). With this approximation, the double integral reduces to a sum of the product of two 1D integrals for each quadrant.

In an assumed PDF scheme such as CLUBB, the form of each marginal PDF in the joint distribution is assumed; for example, a double-Gaussian function is used to represent the subgrid-scale variability of vertical velocity, and the sum of two lognormal functions is used for that of hydrometeor mixing ratios and numbers (Larson and Griffin 2013; Griffin and Larson 2013). The subgrid-scale PDFs are prognostic in the sense that CLUBB solves a system of prognostic equations for higher-order moments, which are then used to determine the shape parameters of the assumed PDFs.
The approximation [Eq. (14)] would be true only if vertical velocity and mixing ratio are independent (i.e., uncorrelated). This is not the case with hydrometeors. With the marginal PDFs, one can then apply bivariate conditional sampling (as in sections 3b and 3c) and scale the means in each quadrant as described in section 3c. The scaled mean is

$$\frac{\Phi_i}{\Phi_j} = \frac{\int \phi_i^a \phi_j^b \phi_i p_i(\phi_i) d\phi_i}{\int \phi_j^a \phi_j^b \phi_j p_i(\phi_i) d\phi_i}.$$  \hspace{1cm} (15)

A parameterization scheme requires determination of the marginal PDFs $p(\phi)$, the values $\Phi_i$ in each quadrant (over which the marginal PDF is integrated), and the fractional area of each quadrant $\sigma_i$.

The “true” fractional area $\sigma_i$ depends on how the bivariate conditional sampling (selection of $\Phi_i$) of the joint distribution is done. If we know the joint distribution, this is easy to estimate. Unfortunately the joint distribution is precisely the parameterization problem, and we only have the prognostic marginal PDFs of vertical velocity and hydrometeor mass mixing ratios. One approach to estimating the quadrant fractional area is by using the prognostic PDF of vertical velocity from CLUBB. Since quadrants II and III typically have small vertical velocities and mixing ratios (Fig. 4), a very simple approach is to define constant vertical velocity thresholds (e.g., $-1.5 \leq w \leq 1.5$ m s$^{-1}$) to identify the velocity spectrum that accounts for the fluxes in those quadrants. The two remaining portions of the spectrum, those associated with large positive vertical velocities and large negative velocities are used for the flux calculations in quadrants I and IV, respectively. The threshold determines in effect the fractional area and the quadrant (scaled) mean velocity. Based on the benchmark simulation, the former is more sensitive to the threshold in both quadrants I and IV and leads to a decreasing estimated absolute flux as the absolute velocity threshold increases. Testing of such a parameterization is beyond the scope of this paper and will be addressed in a future study.

The approximation of splitting the 2D integral in Eq. (14) into the product of two 1D integrals of the marginal PDFs [rhs of Eq. (14)] requires further evaluation. Similar approximated PDF integrations of a joint PDF, but for a warm-rain microphysics parameterization, were explored by Kogan and Mechem (2014). In their results, they noted that the split-integral approximation worked well for accretion rates because of the weaker correlation between rainwater and cloud-liquid water mixing ratios; whereas for autoconversion rates, the approximation showed larger errors due to stronger correlation between cloud water mixing ratio and droplet number concentration. In their approach, conditional sampling was not performed, which may help in representing the correlation within the split-integral approach.

5. Summary

Subgrid-scale vertical fluxes of various types of precipitating condensate—namely, rain, graupel, cloud ice, and snow—are examined using a high-resolution cloud-resolving simulation of continental deep convection. An eddy-diffusion approximation to the vertical hydrometeor flux is evaluated against the benchmark simulation. Results show that the downgradient nature of the scheme tends to advect mass away from concentrated regions, whereas the benchmark simulation indicates that mass is often advected from below the level of maximum mean mixing ratio to aloft. For rain, graupel, and cloud ice, the benchmark simulation shows that vertical advection mainly removes the hydrometeors from altitudes of maximum microphysical formation. The snow mixing ratios, however, show a weaker relationship between advection and microphysical formation.

A quadrimodal analysis is then performed to quantify the contributions to the total flux from each of the quadrants of the joint probability density function. The quadrimodal decomposition, which accounts for inter-quadrant correlations, is found to correctly represent the sign of the flux gradients but underestimates the fluxes associated with above-mean quantities because within-quadrant correlations are not taken into account. Scaling applied to empirically adjust for these within-quadrant correlations is able to bring the approximated fluxes much closer to the benchmark fluxes for all hydrometeors except snow. Snow is found to have a weaker microphysical linkage to its vertical transport (weak correlation between snow mixing ratio and vertical velocity), which may explain the degradation. Results and statistics presented here are designed to represent a coarse gridcell size of approximately 100 km. The characteristics of these statistics may change depending on the target coarse-grid spacing. An additional analysis designed for reduced coarse gridcell sizes will be useful in guiding parameterization development for a global model on a refined grid.

A sensitivity study is carried out to examine how vertical transport of hydrometeors may affect the microphysics in deep convection. It is shown that cloud ice and snow formation are highly sensitive to the vertical advection of rain and graupel. On the other hand, the vertical advection of cloud ice and snow themselves
has a relatively weaker impact on the simulations. Also, the vertical structure of rain mixing ratio showed little sensitivity to suppressed hydrometeor transport, implying that accurately predicting rain amount does not necessarily mean that the dynamical processes are well represented. The microphysical processes that are most sensitive to vertical hydrometeor transport are the ones that are highly dependent on the vertical distribution of cloud water. Because of computational constraints, we used a 4-km grid spacing model. We note that sensitivity to suppressed vertical hydrometeor advection may differ for a finer-resolution model with more resolved dynamics.

Based on the scaled quadrimodal analysis, a way to conditionally sample and integrate marginal PDFs from an assumed PDF scheme (such as CLUBB) and parameterize subgrid-scale hydrometeor fluxes is proposed. Our preliminary tests based on the presented simulation of continental deep convection yield some encouraging results, but the robustness of the approach is yet to be demonstrated. Testing the scheme on other continental deep convection cases, as well as other precipitating event types such as tropical deep convection and drizzling stratocumulus, is needed. With increasing interest in two-moment bulk microphysics schemes (e.g., Gettelman and Morrison 2015; Song and Zhang 2011), which include hydrometeor number mixing ratios, the methodology presented here can also be used to analyze the covariances of vertical velocity and number mixing ratios.

This study demonstrates the importance of convective transport of hydrometeors and makes a step toward including this aspect of the dynamics–microphysics interaction in a convection parameterization. In the diagnostic evaluation presented in this study, we note that the convective microphysics are assumed to be predicted perfectly by the microphysics scheme in the CRM. Within the context of a convection scheme, this is equivalent to a perfect prediction of the subgrid-scale convective microphysics, which has much uncertainty especially in deep convection owing to the complex microphysical processes and their interactions. Although sophisticated convective microphysics are emerging, much development remains to incorporate the detailed convective microphysics into existing convection schemes. Because of the complex interactions between the subgrid-scale dynamics and microphysics, we advocate for more detailed and efficient methods to represent subgrid-scale variability of the microphysics to better represent these systems.

Acknowledgments. This research is based on work supported by the U.S. Department of Energy (DOE), Office of Science, Biological and Environmental Research (BER) under the Atmospheric System Research (ASR) Program. Computing resources for the simulations are provided by the National Energy Research Scientific Computing Center (NERSC). Pacific Northwest National Laboratory is operated by Battelle for the U.S. Department of Energy under Contract DE-AC06-76RL01830. Forcing data were obtained from the ARM program archive, sponsored by the DOE Office of Science. The authors thank Vincent Larson for many useful discussions. We also thank the reviewers for their careful reviews and helpful comments.

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