The sensitivity of domain-averaged solar fluxes to assumptions about cloud
geometry

By HOWARD W. BARKER$^{1*\dagger}$, GRAEME L. STEPHENS$^2$ and QIANG FU$^3$

$^1$Atmospheric Environment Service, Canada
$^2$Colorado State University, USA
$^3$Dalhousie University, Canada

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SUMMARY

The effects on domain-averaged broad-band solar fluxes due to assumptions about geometry of convective clouds are explored using a Monte Carlo algorithm and 3D distributions of water generated by a cloud-resolving model (CRM). Domains are (400 km)$^2$ with 2 km horizontal grid-spacing, $\Delta x$, and 35 layers of varying thickness. Optical properties are computed based on single-scattering parametrizations for hydrometeors and the correlated $k$-distribution method for gaseous absorption. Benchmark fluxes are established using the CRM fields at $\Delta x = 2$ km. Four plane-parallel versions of these fields (affected by letting $\Delta x \rightarrow \infty$) are considered which mimic 1D models: the independent column approximation (ICA) uses the full CRM fields; for the others, mixing ratios of cloudy cells are reset to associated layer-mean values thus conserving water mass and cloud fraction in each layer.

For the ICA, errors in reflected flux to space and surface irradiance rarely exceed 20 W m$^{-2}$. Total atmospheric absorption and heating rates are almost always within 5 W m$^{-2}$ and $\sim 3\%$, respectively. This demonstrates that cloud sides and horizontal fluxes are unimportant for averages over large domains. However, when clouds are homogenized horizontally yet exact overlap is retained, errors increase by almost an order of magnitude. This demonstrates the importance of horizontal variability. When the same clouds are randomly overlapped, errors in boundary fluxes can exceed 250 W m$^{-2}$ at high sun, and heating rates can be off by 50% to 100%. When these clouds follow maximal/random overlap, albedo is often underestimated because overlap of CRM liquid clouds falls between maximal and random. This demonstrates the importance of cloud overlap and ultimately the need for 1D models to account equally well for both subgrid-scale variability in cloud extinction and overlap.

KEYWORDS: Clouds Independent column approximation Short-wave radiation

1. INTRODUCTION AND EXPERIMENTAL DESIGN

Global climate models (GCMs) use one-dimensional (1D), multi-layer, plane-
parallel homogeneous (PPH) solutions of the radiative-transfer equation to predict the
distribution of solar heating (e.g. Wiscombe 1977; Fouquart and Bonnel 1980; Stephens
1984; Harshvardhan et al. 1987; Edwards and Slingo 1996). These are ideal for cloud-
less atmospheres which can be represented well as stratified and PPH. For domains the
size of GCM grid-cells, however, cloudy atmospheres violate key PPH assumptions as
they possess fluctuations over vast ranges of scales in all directions (Stephens and Platt
1987; Davis et al. 1994). Since, for the foreseeable future, horizontal grid-spacings, $\Delta x$, in
most GCM simulations will be at least 50 km, cloud fluctuations that are important for
solar transfer will remain unresolved. Moreover, since model tropospheres may soon be
partitioned into more than 30 layers, systematic application of extreme overlap assump-
tions may have dire cumulative effects on fluxes. Therefore, 1D algorithms must take on
a stochastic character (Stephens 1988b; Barker 1996) in order to deal with clouds and
thus minimize flux biases (Cahalan et al. 1994a).

With respect to horizontal variability, most 1D PPH models assume that clouds in
each grid-cell are homogeneous and occupy a fractional volume (e.g. Briegleb 1992;
McFarlane et al. 1992). However, when fluctuations in cloud extinction coefficient $I$
are neglected, domain-averaged fluxes can incur substantial systematic biases (Stephens

* Corresponding author: Atmospheric Environment Service, Cloud Physics Research Division (ARMP),
4905 Dufferin St, Downsview, ON, Canada M3H 5T4. e-mail: howard.barker@ec.gc.ca
$\dagger$ Additional affiliation: Dalhousie University, Canada.
et al. 1991; Cahalan et al. 1994a; Barker et al. 1996; Zuidema and Evans 1998). While methods that address this issue in 1D codes are beginning to emerge (Tiedtke 1996; Oreopoulos and Barker 1999), there are still several problems that must be addressed.

The layered structure of GCMs makes it necessary to address overlapping fractional cloud (Morcrette and Fouquart 1986; Stubenrauch et al. 1997; Liang and Wang 1997). Usually it is assumed that slabs of homogeneous clouds in adjacent layers are maximally overlapped and that separate layers are randomly overlapped (Geleyn and Hollingsworth 1979; Tian and Curry 1989; Ritter and Geleyn 1992). This was not the case, however, with cloud-resolving model (CRM) data used by Oreopoulos and Barker (1999). Moreover, when horizontal variability is admitted, the problem becomes general and includes overcast clouds.

For columns as wide as those in GCMs, convective clouds probably represent the greatest, and probably one of the most important*, challenges to 1D radiative-transfer modelling. This is because they exhibit extreme horizontal variability (Barker et al. 1998; Fu et al. 1999), have layer-cloud fractions generally $\leq 0.2$, and can extend through many contiguous model layers. Thus, it can be expected that domain-averaged solar fluxes for fields of convective clouds will depend much on assumptions made about horizontal variations in $\beta$ and overlap.

The main objective of this study is to demonstrate the impact that assumptions about convective cloud geometry have on domain-averaged, broad-band solar radiative fluxes produced by 1D algorithms. Such algorithms usually operate on profiles of cloud fraction, mean water path, and droplet effective radius. The experiments reported here reversed this by beginning with three-dimensional (3D) distributions of water predicted by a CRM. The idea is that while a typical GCM would not have resolved these fields, it would have, had its resolution allowed.

Benchmark solar fluxes and heating rates are obtained by applying a 3D Monte Carlo photon-transport algorithm to the CRM fields. Next, by setting $\Delta x$ arbitrarily large and homogenizing and rearranging cloudy cells within layers, four models are created that mimic 1D algorithms. In each model, profiles of cloud fraction and water mass are conserved. Hence, these experiments seek to demonstrate the sensitivity of domain-averaged fluxes to assumptions about, or neglect of, horizontal and vertical fluctuations of cloud.

The following section presents the CRM fields. Section 3 documents the Monte Carlo algorithm and the cloud-configuration (radiative transfer) models while section 4 discusses properties of the CRM fields and their simplified counterparts. Domain-averaged radiative fluxes are presented in section 5, followed by the conclusion and recommendations in section 6.

2. Cloud-resolving model data

Three 3D fields of water generated by an anelastic, bulk microphysical CRM (Clark et al. 1996) were selected for demonstration. These fields are from Grabowski et al.’s (1998) simulation of seven consecutive days (1–7 September 1974) during phase III of the GARP (Global Atmospheric Research Program) Atlantic Tropical Experiment (GATE). Domain size is $(400 \text{ km})^2$ and $\Delta x$ is 2 km. Originally there were 42 layers, varying in thickness from $\sim 0.1 \text{ km}$ near the surface to $\sim 1.2 \text{ km}$ near 26 km (only

* Cloud archives (Warren et al. 1988) show that cumuliform clouds occur very frequently, and analyses of satellite data at GCM grid-scales reveal that thick cumuliform clouds with small cloud fractions explain most of the variance in solar radiation budgets throughout warm climates (Okert-Bell and Hartmann 1992).
the lowest 35 layers or 20 km were used here). The simulation was forced by large-scale evolving fields of moisture, temperature, and horizontal winds measured within the region bounded by 7°N to 10°N and 22°W to 25°W.

Fields were sampled and saved every 20 model minutes. Only liquid droplets, slowly falling ice crystals (referred to as ice A by Grabowski et al.), and water vapour were considered. Rain and graupel were neglected because of their weak radiative impact and ambiguities in referring to them as cloud. More than one species of condensed water can occur in a single cell but all constituents are assumed to fill cells uniformly. Mixing ratios of condensed water less than 0.01 g kg⁻¹ were set to zero (Grabowski et al. 1998).

Figure 1 shows total cloud optical depth, \( \tau \), (for visible radiation) for liquid + ice and liquid only for the fields used here. The field referred to as nonsquall cluster (2 September) consists of several clusters of deep convection organized into approximate hexagons. The next field is a rapidly moving squall line (4 September), while the scattered convection field (7 September) is weaker convection with scattered cloud streets oriented parallel to low-level winds.

3. Radiative-transfer calculations

This section outlines the Monte Carlo algorithm that was used throughout this study. Also, it presents the procedures for creating various PPH counterparts for CRM fields.

(a) Monte Carlo algorithm

All radiative-transfer calculations were done with a broad-band, 3D Monte Carlo solar photon-transport algorithm. This algorithm is essentially that used by Fu et al. (1999). Fifty-four sets of effective optical properties for each cell were defined using the correlated \( k \)-distribution method for non-grey gaseous absorption (Fu and Liou 1992) and single-scattering parametrizations for cloud droplets and hexagonal ice crystals (Fu and Liou 1993; Fu et al. 1995). As such, each cell had 54 values of extinction coefficient, single-scattering albedo, and asymmetry parameter based on relative abundances of water vapour, cloud liquid, cloud ice, Rayleigh extinction, ozone (using the tropical profile of McClatchey et al. (1972)), and the uniformly mixed gases CO₂, CH₄, O₂, and N₂O. Attenuation by gases above 20 km was accounted for deterministically. The algorithm has been validated (Fu et al. 1999) against a 128-stream discrete-ordinate code (Stamnes et al. 1988) which uses the same description of optical properties, and has been cross-checked with numerous published results for conservative-scattering broken cloud fields (Barker 1991; Cribb (1997), personal communication).

Cloud droplet and ice effective radii were set to 10 µm and 50 µm, respectively. As only domain-averaged fluxes were of concern, the Henyey–Greenstein (1941) phase function was used. Unless stated otherwise, each photon was injected at a solar azimuthal angle, \( \phi_o \), selected at random so as to yield azimuthally-averaged fluxes. Cyclic horizontal boundary conditions were used as was a Lambertian surface. Solar irradiance at the top of the atmosphere (TOA) on a plane perpendicular to the earth–sun vector was 1370 W m⁻².

When only total atmospheric and surface absorptances, and TOA albedos were of interest, \( 2.5 \times 10^5 \) photons per experiment were used. This led to errors in these quantities of less than ±0.001. For computation of heating-rate profiles, \( 10^6 \) photons per simulation were used which limited errors to typically ±1%. Broad-band quantities were obtained by summing attenuation over all bands due to \( w_j N_p \) photons allocated to the \( j \)-th monochromatic band, where \( w_j \) is the weight obtained from the \( k \)-distribution \( (\sum_j w_j = 1) \) and \( N_p \) is the total number of photons (see Barker et al. (1998)).
Figure 1. Vertically-integrated visible optical depths for three cloud fields produced by Grabowski et al.'s (1998) cloud-resolving model simulation of seven days that occurred during phase III of GATE (north is towards the top of the plots). Top panels are when both liquid and ice cloud are considered while bottom panels are for liquid cloud only. Horizontal grid-spacing is 2 km and domain size is (400 km)$^2$. Note that the shade-bar for ‘scattered convection’ differs from the others.
(b) Cloud configurations (radiative-transfer models)

This subsection describes the five cloud configurations used here: one uses the 2 km CRM fields while the other four use altered versions. Since the altered cloud fields are supposed to represent different assumptions about cloud geometry made by 1D models, the term cloud configuration, as used here, is synonymous with radiative-transfer model. All four altered models use $\Delta x = 10^{10}$ km thus affecting plane-parallel conditions for each column.

(i) Full 3D. For the full 3D case, the actual CRM fields with $\Delta x = 2$ km are used by the Monte Carlo algorithm. Thus, results of these experiments provide benchmark estimates of domain-averaged transmittances, total atmospheric absorptances, TOA albedos, and heating-rate profiles.

(ii) Independent column approximation (ICA). ICA fields are simply the exact 3D CRM fields except $\Delta x$ is set to $10^{10}$ km. Thus, they have all available information about spatial distributions of cloud but they lack all indication that clouds have finite horizontal extent (and sides). In the past, the ICA has performed extremely well for both planar clouds (Cahalan et al. 1994b) and towering clouds (Barker et al. 1998) and there is no reason to assume a priori that it will perform poorly here.

(iii) Exact overlap. The exact-overlap model retains the exact position of cloudy cells as dictated by the CRM but all clouds in a layer have uniform optical properties. Therefore, it mimics a 1D model that is capable of handling a continuum of cloud overlap rates; assuming GCMs could predict the exact overlap structure of unresolved clouds. Hence, this model represents the ideal 1D PPH model.

To construct these fields, begin by computing layer-mean mixing ratios, for cloudy cells only, for the $m$th condensate as

$$
\bar{q}_m(k) = \frac{\sum_{i,j} \Phi(q_m(i, j, k))q_m(i, j, k)}{\sum_{i,j} \Phi(q_m(i, j, k))},
$$

where

$$
\Phi(x) = \begin{cases} 
1; & x > 0 \\
0; & x = 0,
\end{cases}
$$

and $q_m(i, j, k)$ is the mixing ratio in the $(i, j)$th cell of the $k$th layer. Next, letting $N_m(k)$ and $N_{tot}(k)$ denote, respectively, the number of cloudy cells for the $m$th condensate and the total number of cloudy cells in layer $k$, assign to each of the $N_{tot}(k)$ cells the value

$$
\bar{q}'_m(k) = \bar{q}_m(k) \frac{N_m(k)}{N_{tot}(k)}.
$$

Thus, on a per layer basis, the mass of each phase of water is conserved as is the total number of cells containing cloud. No distinction is made between fractional coverage by individual phases. This is consistent with GCMs that weight cloud optical properties by mass.

(iv) Maximal/random overlap. As with exact overlap, the maximal/random-overlap model uses both $\bar{q}'_m(k)$ and $N_{tot}(k)$. The working hypothesis here is that when clouds occur in adjacent layers, they are maximally overlapped but the excess portion is positioned at random across the layer. In addition, if a clear layer separates two cloudy layers, they are assumed to be randomly overlapped. This model is essentially that addressed by Tian and Curry (1989).
### TABLE 1. SUMMARY OF CLOUD FIELD (RADIATIVE TRANSFER) MODELS USED IN THIS STUDY

<table>
<thead>
<tr>
<th>Model</th>
<th>Unique</th>
<th>Proper cloud position</th>
<th>Variable ( \tau ) per layer</th>
<th>( \Delta x )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full 3D</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>2 km</td>
</tr>
<tr>
<td>Independent column approximation</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>( \infty )</td>
</tr>
<tr>
<td>Exact overlap</td>
<td>yes</td>
<td>yes</td>
<td>no</td>
<td>( \infty )</td>
</tr>
<tr>
<td>Maximal overlap</td>
<td>yes</td>
<td>no</td>
<td>no</td>
<td>( \infty )</td>
</tr>
<tr>
<td>Maximal/random overlap</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>( \infty )</td>
</tr>
<tr>
<td>Random overlap</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>( \infty )</td>
</tr>
</tbody>
</table>

The first column indicates the model; the second indicates whether the field is defined uniquely (i.e. 'no' implies dependence on random-number generation); the third tells whether cloudy cells are positioned as in the CRM ('yes' implies that total cloud fraction is as in the CRM field); the fourth column indicates whether clouds have been homogenized across layers; and the last column lists the horizontal grid-spacing. The 'maximal overlap' model was used only in Fig. 6 for visualization purposes.

To create these fields, begin with the uppermost cloud layer and randomly distribute \( N_{\text{tot}}(1) \) homogeneous cloudy cells. Moving down, if \( N_{\text{tot}}(2) < N_{\text{tot}}(1) \) then randomly position cloudy cells in the second layer beneath cloudy cells in the uppermost layer. If, on the other hand, \( N_{\text{tot}}(2) > N_{\text{tot}}(1) \), place \( N_{\text{tot}}(1) \) cells in layer 2 beneath all cloudy cells in layer 1, and randomly distribute the remaining \( N_{\text{tot}}(2) - N_{\text{tot}}(1) \) cloudy cells among the remaining \( N - N_{\text{tot}}(1) \) cloudless cells, where \( N \) is the total number of cells per layer. If a cloudless layer is encountered, position at random the cloudy cells of the next layer that contains cloud.

(v) Random overlap. Aside from the disastrous case of spreading clouds homogeneously across layers, the random-overlap model is the simplest. These fields are created by redistributing the \( N_{\text{tot}}(k) \) cloudy cells at random across the layer regardless of clouds in adjacent layers. Very similar results could have been obtained using either the exact or the maximal/random model and randomizing the horizontal position of photons as they cross model levels (see Barker et al. (1998) and Oreopoulos and Barker (1999)). Table 1 summarizes the models just presented.

4. RESULTS: CRM FIELDS AND THEIR PPH COUNTERPARTS

This section presents some characteristics of the three CRM fields shown in Fig. 1 and contrasts them with their altered versions as described in section 3(b).

The upper row of plots in Fig. 2 show profiles of layer-cloud fraction which is defined as

\[
C(k) = \frac{\sum_{i,j} \Phi[q(i, j, k)]}{N},
\]  

(3)

where \( q \) may represent the mixing ratio of either a single condensate or the sum of many. For liquid clouds, \( C(k) < 0.2 \) which is consistent with GCM convective-cloud parametrizations (e.g. Slingo and Slingo 1991). For ice clouds, \( C(k) \) are almost certainly too large. This is likely because of crude parametrization of microphysics (Fu et al. 1995) and cyclic boundary conditions which prohibited advection of cloud out of the domain (Grabowski et al. 1998). Therefore, consideration of fields with and without ice should bracket the best estimates.
Also shown in these plots is the fractional overlap of clouds in layer $k$ with those above in layer $k - 1$ which is defined as

$$\Theta_k^{k-1} = \begin{cases} \frac{\sum_{i,j} \mathbb{E}(q(i, j, k), q(i, j, k - 1))}{\min[\sum_{i,j} \Phi(q(i, j, k)), \sum_{i,j} \Phi(q(i, j, k - 1))]} & C(k) \text{ and } C(k - 1) > 0 \\ 0; & C(k) \text{ or } C(k - 1) = 0, \end{cases}$$

(4)
where
\[ \Xi(x, y) = \begin{cases} 1; & x \text{ and } y > 0 \\ 0; & x \text{ or } y = 0 \end{cases} \]

For the three idealized overlap scenarios, \( \Theta \) is defined as
\[
\Theta_k^{k-1} = \begin{cases} 
\text{minimal overlap} : & \begin{cases} 0; & C(k) + C(k - 1) < 1 \\
\frac{C(k) + C(k - 1) - 1}{\min\{C(k), C(k - 1)\}}; & C(k) + C(k - 1) \geq 1
\end{cases} \\
\text{maximal overlap} : & 1 \\
\text{random overlap} : & \max\{C(k), C(k - 1)\} \quad \text{as } N \to \infty.
\end{cases}
\]

For the liquid portions of the fields, \( \Theta \approx 0.7 \), which is between maximal and random overlap (i.e. clouds in adjacent layers overlap \( \sim 70\% \)). Barker et al. (1998) reported similar overlap rates for a case of intense tropical convection (Alexander 1995). Understandably, the precipitating ice portion of the fields resembles maximal overlap quite well, even when \( C(k) < 0.5 \). Clearly, \( \Theta \) depends on cloud type and both vertical and horizontal grid-spacing.

The result of having \( \Theta \approx 0.7 \) in conjunction with \( C(k) \approx 0.1 \) for about 20 layers of contiguous liquid cloud can be seen in Fig. 3 which shows cumulative downward (vertically-projected) cloud fraction \( \tilde{C}(k) \) for the CRM fields and their counterparts based on the assumptions of maximal/random and random overlap. For these cases, \( \tilde{C}(k) \) for the CRM fields are always between those for the maximal/random and random models. By the time the surface is reached, total cloud fractions differ greatly and this can be expected to impart a sizable impact on radiative fluxes. For liquid and ice together, differences in \( \tilde{C}(k) \) are not as large on account of \( C(k) \) being so large between 10 km and 12 km. For the squall line, note the similarity in \( \tilde{C}(k) \) for the CRM and the maximal/random model. This stems from \( \Theta > 0.9 \) between 4 km and 15 km for the CRM field.

The middle and lower rows of plots in Fig. 2 show profiles of horizontally-averaged cloud extinction coefficient \( \overline{\beta}(k) \). For ice, the cloudiest layers have \( \overline{\beta}(k) \approx 2 \text{ km}^{-1} \) whereas for liquid they have \( \overline{\beta}(k) \approx 70 \text{ km}^{-1} \). This implies that the choices of effective radii are reasonable (Stephens and Platt 1987; Liou 1992). These plots also show profiles of mean extinction \( \overline{\beta}'(k) \) for cells whose tops are exposed to space. For liquid clouds between 1 km and 5 km, \( \overline{\beta}'(k) \) are \( \sim 1/3 \) the corresponding \( \overline{\beta}(k) \), meaning that the densest cells are away from cloud edges and overlain by other cloudy cells. This has implications for understanding heating-rate differences between cloud fields with and without horizontal variability.

Also shown is the quantity \( v(k) \). This is the maximum likelihood estimate of the variance-related parameter in the gamma distribution which is defined as
\[
p_G(\beta) = \frac{1}{\Gamma(v)} \left( \frac{v}{\beta} \right)^v \beta^{v-1} e^{-v \beta / \beta}.
\]

It is shown because it is a convenient measure of horizontal variability of cloud (\( v \to 0 \) as variance diverges and \( v \to \infty \) as it collapses). For both liquid and ice, the cloudiest and densest layers (i.e. those having large effects on radiative transfer) have \( v(k) \approx 1 \), suggesting that probability density functions of \( \beta \) resemble decaying exponentials. Given this, and on the basis of results shown by Barker et al. (1998) and Oreopoulos and Barker (1999), one can expect horizontal variability to play an important role in
Figure 3. Solid lines represent cumulative total cloud fraction for the cloud-resolving model fields (shown in Fig. 1) as one progresses downward through the atmosphere to the surface. Dotted lines correspond to the same measure but using profiles of cloud fraction C, as shown in Fig. 2, and assuming that clouds in adjacent layers are maximally overlapped (with excess portions randomly positioned in available clear sky). Dashed lines are as the dotted lines except clouds in all layers are assumed to be randomly overlapped. Values at the surface are total cloud fraction.
Figure 4. Ensemble averaged 1D power spectral densities $E(k)$ of visible optical depths for the central $128 \times 128$ pixels in the liquid + ice fields shown in Fig. 1 as functions of frequency $k$ (all 256 N–S and E–W transects were used). Straight lines are shown for reference.

<table>
<thead>
<tr>
<th>Table 2. Summary of key properties that are important for domain-averaged radiative fluxes for the six cloud fields used</th>
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<tr>
<td></td>
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<td></td>
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<tr>
<td>----</td>
</tr>
<tr>
<td>$\bar{C}$</td>
</tr>
<tr>
<td>$\bar{\tau}$</td>
</tr>
<tr>
<td>$\bar{\sigma}$</td>
</tr>
<tr>
<td>$\nu$</td>
</tr>
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</table>

$\bar{C}$ is total cloud fraction, $\bar{\tau}$ is mean cloud optical depth, $\bar{\sigma}$ is its corresponding standard deviation, and $\nu = (\bar{\tau}/\bar{\sigma})^2$.

determining radiative heating for these fields. When $\nu(k) \gg 1$, horizontal variability of cloud is not important; but neither are clouds, for when $\nu(k) \gg 1$, almost without exception, either $C(k) \ll 1$ or $\bar{\gamma}(k) \ll 1$.

It is very difficult at this stage to assess the integrity of the 3D, or even 2D, structure of CRM fields though the fields shown in Fig. 1 could probably pass convincingly for satellite imagery. Indeed, Fig. 4 shows that the ensemble-averaged 1D power spectral densities of $\tau$ for the central $128 \times 128$ pixels in the liquid + ice fields resemble very closely those obtained from satellite imagery (Barker and Davies 1992b; Oreopoulos 1996). On a simpler level, histograms of $\tau$ were tabulated along with corresponding $p_\gamma(\tau)$ using the method of moments to estimate $\nu$. For the most part, agreement was excellent and consistent with the results of Barker et al. (1996; 1998). Table 2 summarizes some key overall properties of the fields.
Figure 5. 2D schematic representation of the random, maximal and maximal/random cloud overlap models. Profiles of layer-cloud fraction and extinction coefficient for the non-squall cluster field with liquid only (see Fig. 2) were used to derive these plots. Only 400 cells were used in this example (unlike 40000 in the cloud-resolving model fields). Listed at the top of each panel is total cloud fraction $\tilde{C}$, mean columnar cloud optical depth $\bar{\tau}$, and standard deviation $\tilde{\sigma}$ of optical depth.

Figure 5 shows a 2D schematic of the random and maximal/random-overlap models. For contrast with maximal/random overlap, pure maximal overlap (contiguous, left-justified slabs of cloud) is shown. The main difference between pure maximal and maximal/random overlap is cloud-top distribution. For pure overlap, cloud tops are at or above the layer with $\max\{C(k)\}$ while maximal/random cloud tops can be in any layer $k$ provided $C(k) > C(k - 1)$ (e.g. the 4th and 5th layers above the surface). Random overlap can have cloud tops in any layer. This example used profiles of $C(k)$ and $\bar{\theta}(k)$ for the liquid-only non-squall cluster case (see Fig. 2). For visualization, there are 400 columns rather than 40 000. Listed above each panel in Fig. 5 is total cloud fraction $\tilde{C}$. 

mean columnar cloud optical depth $\Tilde{\tau}$, and standard deviation $\Tilde{\sigma}$ of optical depth. As expected, $\Tilde{C}$ increases and both $\Tilde{\tau}$ and $\Tilde{\sigma}$ decrease with the degree of randomness. From Table 2, $\Tilde{C}$ is 0.46 and $\Tilde{\tau}$ is 63 for the CRM data; both values are between the random and the maximal/random values listed on Fig. 5.

Since the random and maximal/random models rely on random numbers to position clouds horizontally, they have multiplicities of configurations. If the distributions of key radiative properties are sufficiently narrow, one realization of the random process should yield an adequate representative of the population. Figure 6 shows distributions of $\Tilde{\tau}$ and $\Tilde{C}$ for 500 realizations of the liquid-only non-squall cluster field. Distributions for liquid plus ice are much narrower and so are not shown. Distributions for $\Tilde{\sigma}$ are about as wide

Figure 6. Normalized multiplicity histograms for total cloud fraction $\Tilde{C}$ and mean cloud optical depth $\Tilde{\tau}$ for the maximal/random and random-overlap models shown in Fig. 5. 40 000 cells were used here as in the cloud-resolving model fields.
as those for $\tilde{\tau}$ but centred on values roughly half as large. Clearly these distributions are extremely narrow and represent insignificant differences in radiative fluxes. As such, all results presented hereinafter used single realizations.

Correspondingly, the histogram of $\tau$ (not shown) for a single realization of the liquid-only non-squall cluster's random-overlap version has a mode near 33 with an exponentially-decaying tail that is essentially gone by 130. Conversely, the maximal/random model's distribution is very intermittent with several values up to $\sim 350$. This shows that multi-layer PPH atmospheres can have fairly broad implicit distributions of $\tau$.

Finally, for simplicity, all simulations used profiles of horizontally-averaged water vapour (and all other gases). This sidesteps ambiguities associated with some of the simplified atmospheres and treats clear skies equally in all experiments. Figure 7 shows profiles of domain-averaged water vapour mixing ratios. For many layers, water vapour mixing ratios are several times larger inside clouds than outside clouds. However, use of horizontally-averaged values had very little effect on domain-averaged fluxes and heating rates.

5. Results: Radiative Fluxes

Only domain-averaged results for broad-band TOA albedo $\alpha_p$, atmospheric absorptance $a_{\text{atm}}$, surface absorptance $a_{\text{sfc}}$, and heating rate (HR) profiles are presented. To highlight differences due to cloud geometry, most results presented here are for a non-reflecting surface.

Figure 8 shows full 3D (i.e. 2 km grid-spacing) values of $\alpha_p$ as functions of solar azimuth angle $\varphi_0$ at a solar zenith angle $\theta_0$ of 75° for the liquid-only fields (for $\theta_0 = 30°$ and when ice was included, fluctuations were much suppressed compared with those in
Fig. 8). Despite the high degree of anisotropy in the squall line relative to the nonsquall clusters, their estimates of $\alpha_p$ depend similarly on $\varphi_0$. This is because $\alpha_p$ is determined mainly by numerous small low clouds, with $\tau \lesssim 50$, that are distributed fairly isotropically across both domains. For scattered convection, however, surface winds were generally SW to NE (see Fig. 3 of Grabowski et al. (1998)) which probably explains why $\alpha_p$ is minimized and maximized for $\varphi_0$ near $\pi/4$ and $5\pi/4$. Barker (1994) demonstrated that for fields of systematically wind-sheared clouds, albedos tend to be slightly larger when the sun is coming in against ($\varphi_0 = 5\pi/4$ in this case) as opposed to with the direction of shearing. This is because cloud optical depth along the direct beam is slightly thicker for clouds sheared towards the sun. Intuitively, one may have expected $\alpha_p$ to maximize for $\varphi_0$ perpendicular to the cloud streets (i.e. $\varphi_0 = 3\pi/4$ or $7\pi/4$), as with Harshvardhan and Thomas's (1984) infinite bar cloud model, but it seems that the effects of shearing are stronger in this case. Since the $\varphi_0$-dependent signals shown in Fig. 8 are weak, only $\varphi_0$-averaged results are shown hereinafter.

For reference, Fig. 9 shows $\alpha_p$, $a_{\text{atm}}$, and $a_{\text{sfc}}$ as functions of the cosine of solar zenith angle $\mu_0$ for the full 3D simulations, while the plots in the left columns of Fig. 10 show corresponding HR profiles for $\mu_0$ of 0.5 and 1.0. The impact of thick, extensive anvils in the non-squall and squall cases is evident from the elevated $\alpha_p$, reduced $a_{\text{sfc}}$, and completely different $a_{\text{atm}}$ as functions of $\mu_0$ relative to the corresponding liquid-only cases. In terms of HRs for these fields, the difference between excluding and including ice is a shift in maximum heating from about 5 km to 10 km and a doubling in its magnitude. These shifts are accompanied, however, by reductions in $a_{\text{atm}}$ due to shielding of water vapour by ice cloud. Though the scattered convection's ice clouds are quite thin (see Fig. 2), they are thick enough and extensive enough to alter $\alpha_p$ and $a_{\text{sfc}}$ by about 40% and diminish greatly the dependence of $a_{\text{atm}}$ on $\mu_0$. Unlike the deep
Figure 9. Domain-averaged, broad-band top of atmosphere (TOA) albedo, atmospheric absorptance, and transmittance (surface absorptance) as functions of cosine of solar zenith angle $\mu_0$ for the fields shown in Fig. 1. These values are the full 3D benchmarks.
Figure 10. Left columns in both (a) and (b) contain plots of full 3D benchmark domain-averaged, broad-band heating-rate profiles (K day$^{-1}$) for two solar zenith angles (as listed). Centre and right columns show percentage differences in domain-averaged, broad-band heating rates between values for the four approximate models listed on the plot (see Table 1) and the full 3D benchmarks. Positive values represent overestimates by the models.

In convective cases, the heating profile for scattered convection is bimodal when ice is included; the relative maximum associated with liquid clouds at 5 km is still readily apparent though only \(\sim 80\%\) its value for liquid-only.

Figure 11 shows differences between various model estimates and full 3D reference values (based on data in Fig. 9) for reflected flux at the TOA, atmospheric absorption, and surface irradiance. Also, the middle and right columns in Fig. 10 are percentage differences in HRs between the four approximate models and full 3D results.

As expected (Barker et al. 1998), the ICA performs very well, regardless of whether ice is present or not, with errors for reflected and surface absorbed fluxes generally less than 20 W m$^{-2}$ and for total atmospheric absorption less than 4 W m$^{-2}$. Figure 10
shows that HR differences between the ICA and the full 3D are almost always less than ±5%. Moreover, cloud sides play an insignificant role as profiles of HR errors bear little dependence on $\mu_0$. Had this domain been $\sim (50 \text{ km})^2$ or smaller, however, the effects of cloud sides would have become apparent (Welch and Wielicki 1984, 1985; Barker and Davies 1992a; Fu et al. 1999).

When PPH clouds are used in conjunction with exact overlap, reflected and transmitted flux errors for $\mu_0 \gtrsim 0.7$ have little difficulty exceeding 50 W m$^{-2}$ for liquid clouds and 100 W m$^{-2}$ when ice is added. The magnitude of these biases can be explained not only in terms of simple horizontal variability but also because, more often than not, PPH clouds with tops exposed to space (i.e. direct incidence) are relatively thick. Profiles of exposed $\beta$ for the exact-overlap model are $\overline{\beta}(k)$, as shown in Fig. 2, whereas

Figure 10. Continued.
they are $\vec{\beta}(k)$ for the 3D and the ICA cases. Atmospheric absorption, however, differs from 3D values by at most 15 W m$^{-2}$ but is usually within ±5 W m$^{-2}$. Unlike the ICA, Fig. 10 shows that these errors in atmospheric absorption tend to be accompanied by cancellation of large positive and negative heating biases (especially for the liquid + ice profiles for the non-squall and squall-line cases).

Differences in errors associated with the exact-overlap model and the ICA represent the gap closed by inclusion of unresolved horizontal cloud fluctuations. For $\mu_0 \gtrsim 0.5$, this difference for reflected and transmitted fluxes usually exceeds 100 W m$^{-2}$ and indicates the overwhelming importance of horizontal fluctuations of cloud relative to the combined effects of horizontal transport of photons and cloud sides. This difference is maximized at $\sim 250$ W m$^{-2}$ for the squall line’s liquid + ice version since between
6 km and 10 km, \( \nu(k) < 1 \) for ice which is very inhomogeneous. Moreover, the large range of \( C(k) \) across this region contributes greatly to making the horizontal variability of vertically-integrated cloud much more powerful than any single layer (compare the profiles of \( \nu \) in Fig. 2 with the vertically-integrated values listed in Table 2).

When the maximal/random-overlap model is used for liquid cloud only, reflected fluxes are too small and transmitted fluxes are too large by \( \sim 55 \text{ W m}^{-2} \) for most \( \mu_0 > 0.5 \). This is because far too few clouds are exposed to radiation as anticipated from Fig. 3. When ice is included for scattered convection, the maximal/random model performs almost as well as the ICA. This is entirely fortuitous and arises via the countervailing effect of homogenized ice cloud above liquid cloud of too little areal extent. On the other hand, going from liquid to liquid + ice for the squall line, errors in reflected and transmitted fluxes reverse sign, increase in magnitude by a factor of \( \sim 4 \), and are almost the same as those for the exact-overlap model. This is testimonial to the
fact that the ice cloud is extremely thick and the overlapping structure, or even presence, of clouds beneath it is often irrelevant.

Regarding total atmospheric absorption, the maximal/random model absorbs too little but only by $\sim 10$ W m$^{-2}$ at most (Fig. 11). As with the exact-overlap model, these small errors are comprised of large HR errors (see Fig. 10). Note also that errors in HR are characterized by maximum underestimates between 1 km and 4 km and less severe error between the surface and 1 km (which translates into excessive heating for liquid-only). This shows the importance of getting the proper vertical distribution of irradiance onto clouds: clouds between 1 km and 4 km are largely shielded yet water vapour in the near-surface layers is over exposed. Furthermore, note the similarity in HR profiles for the exact and maximal/random-overlap models for deep convection cases of liquid + ice. This is again because the upper-level ice clouds are so thick and extensive that transmittance through them is very small.

Differences in reflected and transmitted fluxes estimated by the maximal/random and the exact-overlap models indicate the importance of distinguishing between what is considered by many to be a reasonable assumption about overlap and what overlap should be. As this difference can easily exceed 100 W m$^{-2}$, accurate estimates of overlap may be crucial for simulating the life cycle of convective clouds. The only time this difference was minor was for the squall line when, again, very thick and extensive ice clouds were considered.

The greatest errors are associated with the random-overlap model: at $\mu_0 = 1$ it reflects a staggering 200 W m$^{-2}$ to 375 W m$^{-2}$ too much to space. At $\mu_0 = 0.5$ these values have roughly halved due simply to less TOA irradiance. Similar numbers apply to surface irradiance. These extreme errors can be appreciated by examining cumulative downward cloud fractions shown in Fig. 3 where it is clear that far too much cloud is exposed to high energy direct-beam irradiance, in opposition to the maximal/random model.

Random overlap tends to overestimate atmospheric absorption by 20 W m$^{-2}$ to 30 W m$^{-2}$ at overhead sun and underestimate it slightly at very low sun. This is because at high sun there is too much absorption by cloud droplets through enhancements of both exposure to direct irradiance and internal multiple reflections, yet at low sun there is too little absorption by low-level water vapour. It should be stressed that this tendency to overestimate atmospheric absorption is erroneous absorption and not applicable to the debate over anomalous cloud absorption (Stephens and Tsay 1990; Cess et al. 1995; Li et al. 1995). Figure 10 shows that positive anomalies in heating near cloud tops (i.e. regions of maximal heating in the full 3D cases) can easily exceed 30% and extend for greater depths than do errors for the exact and maximal/random models. These are followed by extensive stretches of underestimation by often more than 40%. For a discussion on the applicability and incorporation of the random-overlap assumption in 1D models, see the appendix*. 

6. CONCLUSION AND RECOMMENDATIONS

Solar radiative-transfer models employed by GCMs neglect subgrid-scale cloud variability and make simple assumptions about overlapping fractional cloud. The main objectives of this study were: (i) to demonstrate the magnitude of broad-band flux errors set-up by these approximations; and (ii) to address the question: in order for

* While several experiments were performed for different values of surface albedo, they are not shown here as they revealed little beyond what has already been discussed.
GCMs satisfactorily and simultaneously, to model both cloud properties and solar fluxes, must unresolved horizontal variability of cloud and cloud overlap be addressed equally well by 1D models? To achieve these objectives, benchmark domain-averaged fluxes and HR profiles were generated by applying a Monte Carlo photon transport algorithm to three fields of convective clouds produced by a 3D CRM (Grabowski et al. 1998). Then, by restricting horizontal fluxes, and homogenizing and repositioning clouds horizontally, four 1D plane-parallel radiative-transfer models were mimicked. This demonstration was restricted to convective clouds to highlight errors for a cloud type that is important for climate because of high solar irradiance and high frequency of occurrence. Moreover, for convective clouds in GCM-sized grids, assumptions about subgrid-scale cloud properties are pushed to the extreme.

The vertical overlapping structure of CRM clouds was shown to differ from the random and maximal-overlap models as assumed for 1D models. Though this aspect of CRMs is untested, validation is likely forthcoming with ground- and space-borne cloud-profiling radars (Clothiaux (1998), personal communication). It was shown, however, that the degree of horizontal variabilty in cloud extinction for these fields is consistent with satellite imagery (Barker et al. 1996) and other CRM fields (Oreopoulos and Barker 1999). (See Grabowski et al. (1998) for other indications that the fields used here possess realistic features.)

The best possible plane-parallel model, the independent column approximation, produces flux errors that are generally much less than 20 W m\(^{-2}\) and HR errors that rarely exceed 5%. This is because all accessible horizontal and vertical fluctuations of cloud are considered. Moreover, this implies that for domain-averaged fluxes, the effects of cloud sides and horizontal transport of photons are of secondary importance (Cahalan et al. 1994b; Barker et al. 1998; Oreopoulos and Barker 1999) and not worth worrying about in the context of 1D parametrization given the complexity they are likely to entail.

It was also demonstrated that if a multi-layer, 1D PPH model was provided with, and could handle, profiles of the exact overlapping structure of fractional cloud, it could easily overestimate reflected flux to space and underestimate surface absorption by 100 W m\(^{-2}\). Also, HR errors in excess of 30% could often be expected. This demonstrates the importance of neglecting horizontal fluctuations in cloud extinction.

Due to vertical discretization of GCM atmospheres, simple assumptions regarding cloud overlap must be invoked. It was shown that when the familiar maximal/random-overlap model is used in conjunction with a 1D PPH algorithm, TOA albedos are often much lower than when exact overlap is used and can (when extensive ice clouds are minimized) be less than the 3D benchmarks. This is because, according to the CRM fields, the maximal-overlap assumption underestimates solar irradiance per unit area of cloud. Thus, even when profiles of cloud fraction and mean cloud optical depth are estimated perfectly, we expect 1D PPH models to yield errors in TOA and surface solar radiation budgets anywhere between ±50 W m\(^{-2}\) and ±200 W m\(^{-2}\). This should alarm GCM modellers for it implies, contrary to conventional wisdom, that use of the maximal/random model in a 1D PPH algorithm is not a satisfactory solution to the random-overlap problem. Moreover, if maximal overlap is used in conjunction with a method that attempts to account for unresolved horizontal fluctuations (e.g. Oreopoulos and Barker 1999), TOA reflectance would be underestimated even more (perhaps by up to 150 W m\(^{-2}\)). Therefore, to answer the question posed at the beginning of this section, it seems imperative that unresolved horizontal variability and overlap be treated together within 1D algorithms. Of course this banks on GCM parametrizations first producing realistic profiles of cloud fraction and condensed water mass.
Finally, it is important to note that all the simulations reported on here used CRM data with a horizontal grid-spacing of 2 km. Had the resolution been better, this would have only increased the discrepancies between the full 3D benchmarks and their PPH approximations (cf. Marshak et al. 1998).

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Appendix

Random overlap in 1D models

There is some ambiguity regarding the treatment of random overlap in 1D models. For simplicity, consider a two-layer cloud system in which the clear sky is perfectly transmissive. If it is assumed that either the radiation field between the layers does not vary horizontally or it is variable yet completely decorrelated with fluctuations in cloud (see Stephens (1988b)), overall albedo for monochromatic diffuse-beam irradiance is

\[
\bar{\tau}_{12} = c_1 r(\tau_1) + \frac{\left(1 - c_1 + c_1 t(\tau_1)\right)^2 c_2 r(\tau_2)}{1 - c_1 r(\tau_1) c_2 r(\tau_2)},
\]

where \(c_1\) and \(c_2\) are cloud fractions for the top and bottom layer, \(\tau_1\) and \(\tau_2\) are corresponding cloud optical depths, and \(r\) and \(t\) are albedo and transmittance respectively. This is equivalent to Morcrette and Fouquart’s (1986) SUNRAY model (Fouquart and Bonnel 1980). For the explicit random-overlap model, however, albedo of the combined layers is a weighted sum of (in this case) three distinct columns (e.g. Stubenrauch et al. 1997) and given by

\[
\bar{\tau}_{12} = c_1 (1 - c_2) r(\tau_1) + c_2 (1 - c_1) r(\tau_2) + c_1 c_2 \left( r(\tau_1) + \frac{r^2(\tau_1) r(\tau_2)}{1 - r(\tau_1) r(\tau_2)} \right)
\]

\[
= c_1 (1 - c_2) r(\tau_1) + c_2 (1 - c_1) r(\tau_2) + c_1 c_2 r(\tau_1 + \tau_2). \tag{A.2}
\]

It can be shown that (A.1) and (A.2) are not equal but that fractional differences between them are usually less than 5% with a maximum of \(\sim 12\%\) for \(c_1 = c_2 = 0.5\) and \(r(\tau_1) = r(\tau_2) \rightarrow 1.0\). For reasonable conditions and as more layers are added, differences between the two diminish markedly (Morcrette and Fouquart 1986). Therefore, which approach is most appropriate?

Figure A.1 is a schematic that depicts three cases of random overlap. First, two cloud layers are adjacent but randomly overlapped. Scenario (1) fits with (A.2) as there
Figure A.1. (1) Two plane-parallel clouds are randomly overlapped and in adjacent layers. The optical depth of the upper and lower clouds are \( \tau_1 \) and \( \tau_2 \) respectively. Thus, three distinct columns of cloud are formed. (2) Same as (1) but clouds are now separated by a cloudless layer. If photons are channelled vertically, the three columns in (1) are maintained. If photons are allowed to diffuse horizontally, the distinctiveness of the columns diminish. (3) Same clouds as in (2) but broken into many small clouds of finite horizontal extent and still separated by a clear layer with horizontal diffusion of photons. Clearly the concept of distinct columns of clouds has now broken-down entirely.

There are three distinct columns whose albedos can be weighted according to respective cloud fractions exposed to the incident beam and summed to give \( \bar{\tau}_{12} \). But, due to adjacency, most would classify this arrangement of cloud as maximal overlap, not random.

In scenario (2) the same clouds are separated vertically. This fits the usual model for random overlap as a cloudless layer exists between them; presumably, the thicker the
cloudless layer the better the assumption of random overlap. The radiation field exiting the base of the top layer is diffuse, so should a distinction be made for radiation incident on the lower cloud as to whether it came from the clear or cloudy portion of the top layer? Yes if the clouds are assumed to be plane-parallel, as photons do not diffuse horizontally; not necessarily if the plane-parallel restriction is relaxed, as it should be, for horizontally diffusing photons destroy the specific correlations set up by the explicit random-overlap configuration. Obviously, as the clear-sky separation increases, this decorrelation increases and (A.1) becomes increasingly appropriate. Moreover, the radiation field between clouds is spread horizontally via multiple internal reflections (Stephens 1988a).

In case (3) of Fig. A.1, clouds are no longer portrayed as plane-parallel plates but rather as numerous (identical) finite clouds. Now, the correlation between radiation incident on a unit area on the top of the lower cloud layer, and radiation emerging from the unit area directly above on the base of the upper cloud layer, will decrease rapidly as layer separation increases. In this case, (A.1) is the clear favourite (cf. Stubenrauch et al.'s (1997) Figs. 4 and 5).

A similar, though more complicated, argument holds for direct-beam irradiance, for it involves both more complex considerations of correlations between cloud and radiation (see Gabriel and Evans (1996) for an elaboration) and diffuse radiation at the same time. For direct beam, if clouds are horizontally finite and truly randomly overlapped, then only for overhead sun will (A.2) hold for sure. When the sun is not in the zenith, however, there is no reason to assume that the strict random-overlap scenario applies.

So, although it appears that a single description of random overlap for plane-parallel clouds cannot suit all conditions all the time, once horizontal variable cloud optical depth is admitted into each layer, which serves to decorrelate radiation onto the lower cloud even more, it becomes increasingly easy to make a case for general use of (A.1). Indeed, Oreopoulos and Barker (1999) found this to be an entirely satisfactory approximation for bounded cascade clouds (Cahalan et al. 1994a); even in ICA mode which neglects horizontal transport. Again, this was because the conditional distributions of irradiance onto cloudy cells in the lower layer for a given optical depth do not differ sufficiently, which is equivalent to saying that irradiance onto the lower cloud is horizontally homogeneous. As a final statement, (A.1) is more efficient to compute than (A.2), especially as the number of layers increases.

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