Improving subgrid-scale clouds and precipitation in large-scale models: thesis proposal

Benjamin R. Hillman

10/12/14

## 1 Introduction

Clouds are a key piece of the global climate system, but accurate modeling of clouds in large-scale models is difficult, and cloud feedbacks in global climate models (GCMs) are recognized as a primary contributor to inter-model differences in responses to climate forcings (e.g., Cess et al., 1990; Bony and Dufresne, 2005; Williams and Webb, 2009; Medeiros et al., 2008).

The complexity of simulating the climate system with current computational resources limits GCM resolutions to tens or hundreds of kilometers, but clouds occur and vary on much smaller spatial scales. This means that traditional GCMs are unable to resolve individual clouds, and instead descriptions of clouds in GCMs are limited to large-scale statistical summaries of cloud properties on the scale of the model grid (Randall et al., 2003). But radiative fluxes depend on cloud properties in a non-linear manner and so the details of the unresolved structure and variability of clouds is important for model radiative transfer parameterizations (e.g. Barker et al., 1999). Most GCMs however, fail to completely account for unresolved cloud structure and variability in a sufficient manner.

The goal of this project is to reduce errors in radiative fluxes and simulated satellite-observable cloud diagnostics in large-scale models by improving the treatment of unresolved clouds and precipitation. The primary metric used in this study to evaluate improvements is the performance of simulated satellite-observable cloud diagnostics from the Cloud Feedback Model Intercomparison Project (CFMIP) Observation Simulator Package (COSP; Bodas-Salcedo et al., 2011) because this allows for evaluation of the simulated clouds themselves, but in so doing errors in radiative fluxes will be reduced because nominally the cloud diagnostics and radiative transfer use the same treatment of unresolved clouds and precipitation.

This project has four main objectives:

1. Quantitative evaluation of the sensitivity of COSP diagnostics to unresolved cloud and precipitation structure and variability
2. Quantitative evaluation of the uncertainties inherent in model to observation comparisons using COSP diagnostics
3. Develop improved treatment of subgrid-scale cloud and precipiation overlap and variability suitable for implementation in COSP and GCMs
4. Quantitative evaluation of the sensitivity of COSP diagnostics and associated radiative fluxes to improved treatment of subgrid-scale cloud and precipitation overlap and variability

The following section motivates the work by providing the background and context. Further motivation is provided by the Preliminary work section, which begins to address the first objective listed above. An outline for completing the last three objectives is then presented, followed by a timeline and summary.

## 2 Background

The description of clouds in GCMs typically includes profiles of partial cloudiness (cloud area fraction by level) and the in-cloud liquid and ice cloud condensate (e.g. Collins et al., 2004; Neale et al., 2010a). The gridbox mean description of clouds does not in itself specify how the clouds should be distributed horizontally and vertically within model gridboxes, and characterization of the unresolved structure depends on additional assumptions about how clouds in overlapping layers are aligned vertically and how cloud properties vary within model gridboxes.

Early radiative transfer parameterizations in large-scale models used relatively simple assumptions about how subgrid-scale overlapping cloudy layers align vertically (e.g. Collins, 2001). These include maximum overlap, in which the cloudy portions of overlapping cloudy layers are assumed to be perfectly correlated (i.e., vertically projected cloud area is minimized); random overlap, in which the cloudy portions of overlapping cloudy layers are uncorrelated; and the popularly used maximum-random overlap, in which adjacent cloudy layers are maximimally overlapped but layers separated by at least one clear layer are randomly overlapped (Geleyn and Hollingsworth, 1979). The maximal-random overlap assumption in particular has been used in a number of GCMs (e.g. Collins et al., 2004; Neale et al., 2010a, 2010b). However, these assumptions have been shown to be insufficient to capture the complexity of clouds seen in observations (e.g. Hogan and Illingworth, 2000; Mace and Benson-Troth, 2002; Barker, 2008), and sensitivity tests using high resolution model simuations have shown that unrealistic overlap assumptions can lead to instantaneous errors in calculated fluxes in excess of 50 W/m2 (Barker et al., 1999). Oreopoulos et al. (2012) demonstrate sensitivity in global cloud radiative effects due to the treatment of overlap that are on the order of 4 W/m2 in both SW and LW fluxes in a GCM.

Subgrid-scale variability in cloud condensate is often completely neglected in GCMs, despite the fact that clouds can exhibit large variability on scales much smaller than GCM gridboxes (e.g. Stephens and Platt, 1987). This is problematic because radiative fluxes and heating rates calculated from model radiative transfer parameterizations are sensitive to subgrid-scale variations in cloud condensate (e.g. Barker et al., 1999; Wu and Liang, 2005; Oreopoulos et al., 2012). Barker et al. (1999) demonstrate instantaneous errors due to unresolved horizontal cloud variability in excess of 100 W/m2. Oreopoulos et al. (2012) demonstrate global flux errors due to unresolved cloud variability The sensitivity to both cloud overlap and condensate variability emphasizes the need to provide descriptions of clouds in large-scale models radiative calculations that include both horizontal variability in cloud properties and more realistic cloud overlap.

One way to account for subgrid-scale variations in cloud structure and condensate amount is to actually generate ensembles of subcolumns from the gridbox mean properties and calculate the radiative fluxes and heating rates on each generated subcolumn independently using the independent column approximation (ICA; Cahalan et al., 1994). This can become computationally demanding due the need to integrate radiative transfer calculations over a large number of spectral intervals for each subcolumn, but Pincus et al. (2003) introduced an approach that reduces the computational burden substantially by stochastically sampling both cloud state and spectral interval simultaneously. This approach, known as the Monte Carlo Independent Column Approximation (McICA), allows for fast ICA-like radiative transfer calculations (at the cost of artifically increased random noise) that can treat inhomogeneous clouds and has been incorporated into the widely used RRTMG radiation package and used in a number of state-of-the-art models (Iacono et al., 2008; von Salzen et al., 2012; Neale et al., 2010a, 2010b; Donner et al., 2011; Hogan et al., 2014),

McICA separates the treatment of cloud structure and variability from radiative transfer parameterization, leaving the task of describing complex cloud structure and variability up to subcolumn sampling schemes. In principle, arbitrarily complex cloud geometries and condensate distributions can be generated by incorporating more sophisticated subcolumn schemes. However, the subcolumn schemes currently used in most GCMs make many of the same simplifications used by earlier models, including maximum-random overlap and homogeneous cloud properties (e.g. Neale et al., 2010a, 2010b). Improved subcolumn schemes are needed to take full advantage of the flexibility offered by McICA.

Unresolved cloud structure and condensate variability is important not only for calculations of radiative fluxes, but also for cloud diagnostics commonly used for evaluation of model cloud properties themselves. Satellite instrument simulators such as those provided by the CFMIP Observational Simulator Package (COSP; Bodas-Salcedo et al., 2011) are often used to remove ambiguities in model evaluation studies that arise from uncertainties and limitations in satellite retrievals of cloud properties by producing psuedo-observations from the model state that are more directly comparable to the satellite observations (e.g. Klein and Jakob, 1999; Webb et al., 2001; Zhang et al., 2005, 2010; Kay et al., 2012; Klein et al., 2013). A key first step in simulating satellite observations from GCM cloud properties is accounting for the mismatch in resolved scales between the satellite pixel and model resolution by downscaling the gridbox mean cloud properties. This is done in COSP by stochastically generating subcolumns consistent with an overlap assumption to account for correlations in overlapping cloudy layers in the same manner as described for McICA above. However, the current implementation of COSP allows for only the simple maximum, random, or maximum-random overlap, and treats subcolumn clouds and precipitation as homogeneous. Furthermore, while the subcolumn treatent in COSP is intended to account for the mismatch in resolved scales between satellite pixel and model resolutions, a specific spatial scale in terms of the number of subcolumns chosen is not defined within the COSP subcolumn treatment. This will need to be defined because any treatment of variability must be connected to an explicit scale. Previous studies have also shown that overlap statistics are dependent on resolution (e.g., Mace and Benson-Troth 2002), and so the treatment of overlap within COSP and the radiative transfer code should be consistent with the scale implied by the number of subcolumns..

To the extent that the simulated satellite-observables are sensitive to these assumptions, failing to accurately characterize the subgrid cloud structure and condensate variability potentially introduces ambiguities into satellite-model comparisons. This problem deserves a closer look to build confidence in conclusions derived from these evaluation efforts. A strategy for assessing these sensitivities and for improving the representation of subgrid scale cloud and precipitation overlap and variability is presented in the following sections.

## 3 Preliminary work

### 3.1 Sensitivity of simulated satellite-observable cloud diagnostics to unresolved clouds and precipitation

A straightforward analysis method is used to evaluate the sensitivity of COSP diagnostics to assumptions about subgrid-scale cloud and precipitation overlap and variability. The subcolumn sampling scheme within the COSP code can be bypassed by providing fields with resolved clouds and precipitation. Assumptions about variability and overlap can then be mimicked by modifying the resolved fields used as input to the simulators, and the differences in the outputs can be taken to represent sensitivities to the modeled assumptions.

Previous studies have used cloud resolving model simulations in a similar manner to evaluate the sensitivity of radiative fluxes and heating rates to overlap and unresolved variability (e.g. Barker et al., 1999; Wu and Liang, 2005). A more comprehensive sampling of different cloud regimes is obtained for this study by using output from the Multi-scale Modeling Framework (MMF; Khairoutdinov and Randall, 2001; Randall et al., 2003). The MMF replaces the cloud parameterizations in a traditional GCM with a 2D cloud resolving model in each gridbox. This provides global fields with resolved subgrid structure that can be passed directly to the individual instrument simulators within COSP.

In order to separately evaluate the sensitivity to overlap and heterogeneity, the following sets of modified fields are performed:

• CRM: The original CRM fields within each gridbox of the MMF are used as inputs to the individual instrument simulators in COSP.

• CRM-AVG: cloud mixing ratios are replaced with in-cloud averages (and precipitation mixing ratios with in-precipitation averages), but the locations of hydrometeors (both cloud and precipitation) are retained from the full CRM fields (i.e., occurrence overlap is retained from the CRM).

• CRM-RES: cloud and precipitation mixing ratios are re-sampled (with replacement) from the full CRM fields at each level within each gridbox, but the locations of these hydrometeors and their type are retained from the full CRM fields.

• MRO-AVG: hydrometeor mixing ratios and cloud optical properties are first averaged to produce gridbox means, similar to what a GCM would diagnose. Subcolumns are then regenerated consistent with the commonly used maximum-random overlap assumption, and homogeneous cloud properties (the gridbox means) are assigned to the cloudy subcolumns.

An example of these different fields obtained from a single grid cell from the MMF is shown in Figure . The only difference between the CRM and CRM-AVG fields is that the CRM-AVG fields have homogeneous cloud and precipitation properties, so differences in COSP diagnostics calculated from these two cases represent the sensitivity to unresolved variability in cloud and precipitation properties alone. Differences between the diagnostics calculated from the CRM-AVG and MRO-AVG fields represent errors arising due to assumptions about cloud (and precipitation) overlap. The CRM-RES modification destroys any correlation between condensate amount at different levels, so differences between the CRM and CRM-RES simulations represent errors arising due to condensate amount overlap and the overlap between hydrometeor condensate of different types (clouds and precipitation).

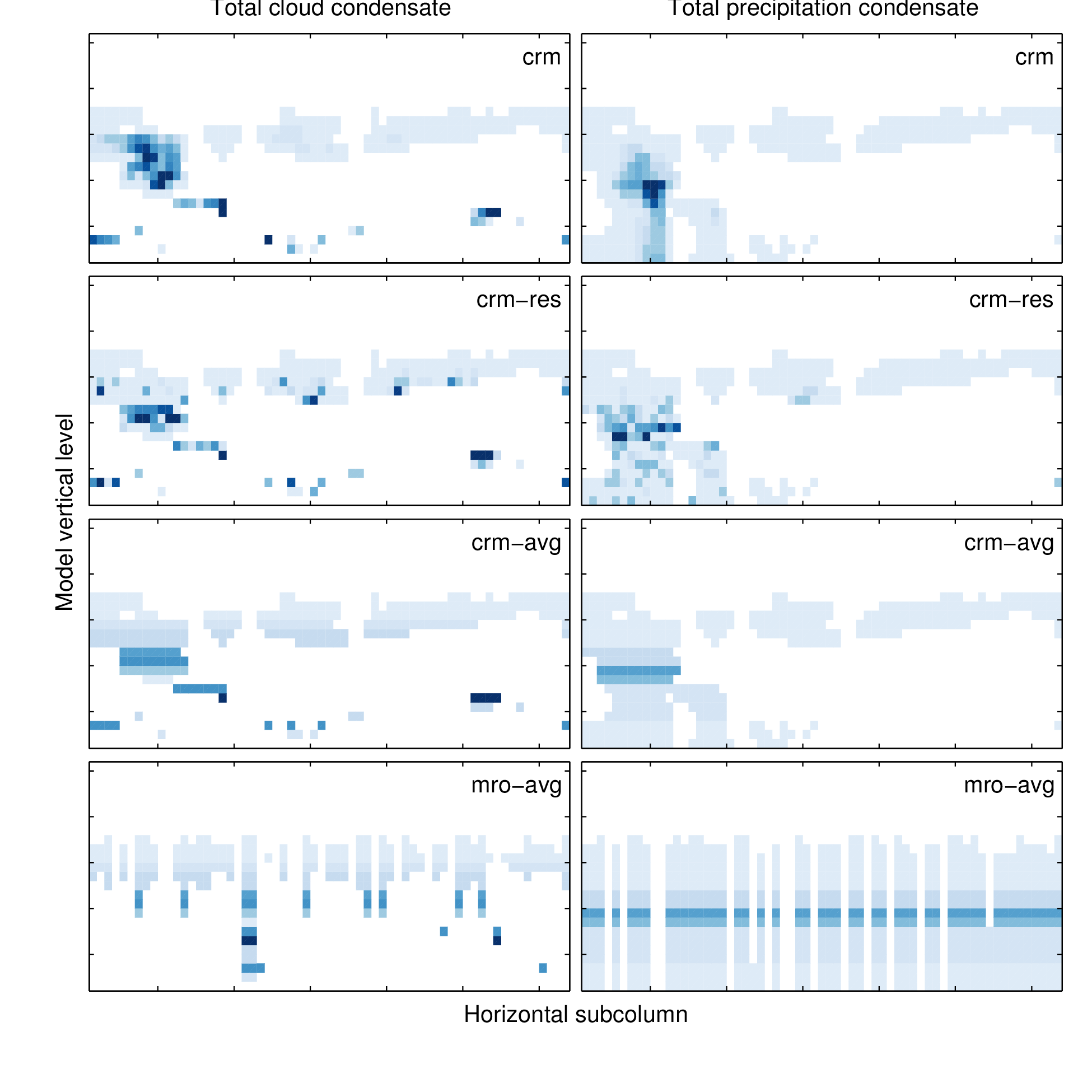


Figure 1: Total cloud and precipitation condensate mixing ratios modified from the embedded CRM condensate mixing ratios within a single MMF gridbox.

Simulated CloudSat (Stephens et al., 2002) radar reflectivity factor with height histograms from these four cases are shown in Figure . These histograms show a high frequency of hydrometeors along a “characteristic curve” in reflectivity-height space, with radar returns in four modes each dominated by a particular hydrometeor type (described in detail by Marchand et al. (2009)).

The CRM-RES simulation has more hydrometeors in middle levels above about 7 km with radar reflectivity factor between −20 and 10 dBZ than the CRM-full simulation. Because these cases have the same level-by-level PDF of condensate amount by construction, differences between these two cases arise due to differences in the vertical alignment of condensate amount between levels. Because the CloudSat radar simulator includes the effect of attenuation of the radar signal by upper level hydrometeors, the degree to which the condensate amounts are aligned in the vertical is important. For example, if hydrometeors are aligned such that the higher condensate parts of the horizontal distributions are correlated between layers to create “pockets” of high vertically integrated water path, then there will be a greater amount of attenuation of the radar beam by the upper levels and the signal returned from the lower levels will be reduced. Since the CRM-RES simulation removes any correlation between the condensate amounts between different levels, there is less attenuation of the radar beam and more hydrometeors are apparent throughout the vertical column. The differences shown here highlight the importance of accounting for this alignment in an improved subcolumn generator.

The CRM-AVG simulation has too many hydrometeors along the entire characteristic curve of the histogram relative to the CRM case, but this is especially evident at low levels and for radar reflectivity factor greater than 0 dBZ. Hydrometeros in this height and reflectivity range are attributed to low-level drizzle and rain (Marchand et al., 2009), and the overestimation of hydrometeor occurrence in this mode in the CRM-AVG simulation relative to the CRM case would imply that there is too much precipitation in the CRM-AVG case. However, these cases were drawn from the same CRM simulation and by construction the precipitation fraction at each level in each large-scale gridbox (number of subcolumns containing precipitation divided by total number of subcolumns) is consistent between the two cases. This emphasizes the need to account for subgrid variability in condensate amounts (especially precipitation) in order to be able to draw correct conclusions from simulator comparisons.

The MRO-AVG has even larger hydrometeor occurrence along the characteristic curve than the CRM-AVG simulation, especially for low-level hydrometeors with radar reflectivity greater than 0 dBZ. This suggests that the MRO-AVG simulation has even more widespread precipitation than the already too high CRM-AVG simulation. This is due to the simple treatment of precipitation subcolumn generation used in MRO-AVG, in which precipitation is not constrained by the actual precipitation fraction, but assigned to any level in a column in which the precipitation fraction is non-zero and contains cloud in the current column or precipitation in the column above. This likely leads to an overestimation of precipitation occurrence (suggested by the single-column example shown in Figure ), and this is consistent with the overestimation of hydrometeors with large radar reflectivity factor shown here. Di Michele et al. (2012) demonstrate considerable sensitivity of simulated radar reflectivity (using a different simulator) to different approaches of generating precipitation subcolumns. The bottom panel of Figure 2 also shows two additional methods of treating the generation of precipitation subcolumns. The MRO-AVG-PCLD simulation restricts precipitation to only those levels within each subcolumn that contain cloud (this is the current treatment in the operational COSP code), and the MRO-AVG-PADJ simulation first distributes precipitation in the same manner as the MRO-AVG simulation described above, and then either removes or adds precipitating cells as needed to match the prescribed precipitation fraction at each level. The MRO-AVG-PCLD simulation has less precipitating hydrometeors relative to the CRM and CRM-AVG simulations, consistent with the widespread removal of precipitation that results from only considering cloudy cells. The MRO-AVG-PCLD simulation appears to agree better with the full CRM simulation than the CRM-AVG simulation (which has exact overlap), but this is due to the cancellation of errors that result from too many hydrometeors along the characteristic curve due to the homogeneous condensate amounts and too few precipitating hydrometeors due to the removal of precipitation from non-cloudy levels. The adjustment of precipitating columns to match the precipitation fraction in the MRO-AVG-PADJ simulation reduces the differences relative to the full CRM simulation substantially. The sensitivity to the generation of the precipitation subcolumns demonstrated here highlight the importance of including a realistic treatment of precipitation in any subcolumn generation scheme used with the radar simulator.



Figure 2: Simulated CloudSat radar reflectivity factor with height histogram for the Tropical Warm Pool region. Two additional simulations are included here to demonstrate the sensitivity to the treatment of precipitation (see text).

Figure shows simulated ISCCP cloud top pressure and MISR cloud top height histograms for the same Tropical Warm Pool region from each of the subcolumn schemes. There are some noteworthy differences in the simulated cloud top height between the different cases, especially for the high-topped clouds. Cloud amount in the ISCCP highest cloud top pressure bin is underestimated while cloud in the second highest cloud top pressure bin is over estimated in both cases with averaged optical properties (CRM-AVG and MRO-AVG) relative to the cases without the averaging. These differences are up to about 5% in absolute cloud cover. The ISCCP simulator mimics the tendency for ISCCP to retrieve the radiative mean cloud top pressure in the case of multi-layer cloud profiles. If the upper layer is sufficiently thin so that a lower layer contributes to the emission seen by ISCCP, the cloud top pressure diagnosed by the ISCCP simulator will be placed lower in the atmosphere (high pressure). Because the optical depth distribution is peaked sharply at low optical depth values, averaging the optical depths input to the simulator algorithm removes a good deal of the larger values that would result from variability between gridboxes, so that on average there is greater penetration of the lower-level emission that lowers the retrieved cloud top pressure. It seems that this effect is lowered somewhat in the MRO-AVG simulation, suggesting that the maximum-random overlap assumption leads to some differences in the results as well. Others have shown (e.g., Mace and Benson-Troth, 2002) that the maximum-random overlap can actually overestimate the vertical correlation of contiguous cloudy layers. In the case of multi-layer profiles, this could cause the upper-level cloud to appear thicker to the simulator algorithm, reducing the penetration of emission from lower levels relative to the CRM-AVG simulation. This is consistent with the results shown here.

There are much larger differences are in the MISR-simulated cloud top height, and all of the modified cases overestimate clouds with top between 11 and 13 kilometers relative to the full CRM case. The MRO-AVG has the largest departure from the CRM case, with differences approaching 10% cloud cover and a concurrent underestimation of low-topped cloud cover. The MISR simulator mimics the tendency for the MISR retrieval to effectively see through thin upper level clouds and retrieve the cloud top height of the lower cloud layer in multi-layer profiles involving a sufficiently optically thin upper-level cloud layer and an optically thicker lower-level cloud layer. This is sensitive to the penetration depth from the top of the column at which the integrated optical depth reaches a nominal value of 1, and integrated optical depths greater than this do not further affect the assignment of cloud top height to a profile. The overestimation of clouds with cloud top s between 11 and 15 km in the CRM-AVG and MRO-AVG simulations can be explained then by the averaging of optical depths actually increasing a sufficient number of very small optical depth values so that this integrated optical depth threshold of 1 is exceeded more frequently. This seems to occur more frequently in the MRO-AVG simulation, and this can again be explained by an overestimation of the vertical correlation of vertically contiguous layers by the maximum-random overlap assumption, which results in the optical depth threshold being exceeded more frequently due to clouds lining up more than they should. This shows that both overlap and variability are important in explaining these differences, but these interpretations will need to be evaluated by examining individual single-point cases.

The differences in the ISCCP cloud top pressure and the MISR cloud top height between the different subcolumn treatments described above show that both overlap and condensate variability can affect the results of comparisons, but it is not clear from this analysis whether or not these differences are significant. A more comprehensive analysis of these differences will be included as key part of this work in order to better understand the sensitivities and uncertainties in these diagnostics. The analysis presented here will be extended to include a larger subset of regions with different characteristic cloud regimes to evaluate the importance of subgrid effects under different conditions.

It is also unclear to what extent observational uncertainty and the sensitivities of the simulators themselves (aside from subgrid effects) may affect conclusions drawn from comparisons between models and observations using these simulators. The proposed work discussed in the following section includes an analysis to quantify uncertainties in comparisons using the ISCCP and MISR simulators by comparing ISCCP and MISR data to simulated diagnostics calculated using profiles derived from observations from active profiling instruments.



Figure 3: Simulated ISCCP cloud top pressure and MISR cloud top height histograms for the Tropical Warm Pool region.

The sensitivities identifed in this section motivate improvements to the treatment of subgrid variability and overlap for use in COSP.

## 4 Proposed work

### 4.1 Evaluation of simulated satellite-observable cloud properties from COSP

### 4.2 Improving treatment of cloud and precipitation overlap and subgrid scale variability

Räisänen et al. (2004) present the details of a scheme that can generate cloudy subcolumns with more flexible occurrence overlap and variable in-cloud condensate. Their scheme allows for overlap that is a combination of maximum and random (e.g. Hogan and Illingworth, 2000), which has been demonstrated to better fit both observations and high resoluation model simulations than simple maximum-random overlap (Hogan and Illingworth, 2000; Mace and Benson-Troth, 2002; Pincus et al., 2005; Barker, 2008). The weighting between maximum and random overlap is determined by a decorrelation length scale that describes how overlap changes from maximum to random with separation distance. Variable in-cloud condensate for subcolums is possible if the probability distribution function (PDF) of condensate can be input to the subcolumn generator. The vertical alignment of condensate amount is determined by a separate decorrelation length scale that describes how the rank correlation of condensate amount between layers varies with separation distance. Räisänen et al. (2004) demonstrate improvements in radiative fluxes calculated using their improved subcolumn generator by resampling subcolumns from high-resolution model output with decorrelation depths and condensate distribution derived directly from the high-resolution model output.

Oreopoulos et al. (2012) tested the sensitivity of a global climate model to improved subgrid clouds using the Räisänen et al. (2004) generator. They derive approximate decorrelation depths that vary with latitude and season from an analysis of CloudSat data (Stephens et al., 2002), and use beta distributions to describe the variability of in-cloud condensate. Their results suggest that improvements in radiative fluxes due to implementation of this scheme may be significant, but their simple latitude and seasonal dependence of decorrelation depths are not guaranteed to hold in a changing climate, and parameterization of these quantities in terms of model fields is probably a better approach for operational use in a model intended to aid understanding of the climate system in response to changes. Pincus et al. (2005) derive decorrelation depths from cloud resolving model data, and suggest parameterizing these in terms of large-scale fields such as wind shear and convective strength. They provide such a parameterization, but limited to a single domain over the ARM SGP site. Nonetheless, this is a good start, and this is an attractive avenue for further parameterization of these quantities. A major contribution of the present work will be to provide a more comprehensive characterization of the subgrid-scale structure of clouds and precipitation.

I propose a characterization of overlap statistics using output from the MMF and to separately diagnose overlap of clouds and precipitation, which our senstivity test show will be important and is difficult to do using only CloudSat radar observations. The advantage of using the MMF for these studies is that it provides a complete description of subgrid-scale clouds and precipitation across all regimes and inludes the large-scale fields available in a traditional GCM, which will likely be useful for parameterizating the overlap characteristics. The limitation with this approach is that the MMF is still a model, and may not completely capture the complexity of the real atmosphere. In order to address this issue, I also plan to use hydrometeor occurrence profiles derived from CloudSat (Stephens et al., 2002) and CALIPSO (Winker et al., 2007) observations to independently derive overlap statistics in a similar manner as done by Barker (2008) to compare with my characterization of overlap derived from MMF output. The goal is for this analysis to result in a parameterization of decorrelation lengths for both cloud and precipitation occurrence and condensate overlap based on large-scale fields. As suggested in the previous section, treating the precipitation in a more realistic manner will be important in accurately simulating radar reflectivities.

Subgrid-scale variability of cloud and precipitation condensate amount will also need to be characterized. With recent interest in PDF-based cloud parameterizations (e.g. Tompkins, 2002), it makes sense to connect the subcolumns used by the radiative transfer and COSP modules to those used in the cloud physics parameterizations directly. There is an on-going project to implement the Cloud Layers Unified By Binormals (CLUBB Golaz et al., 2002) into the National Center for Atmospheric Research (NCAR) Community Atmosphere Model (CAM), which would naturally provide the subgrid-scale variability in total water and rain water mixing ratios needed. Work as already been done to pass PDFs of condensate from CLUBB to the radiation code in the development version of CAM5 (Andrew Gettelman, personal communication), and it would likely be straightforward to extend this to either pass the subcolumns generated by the McICA code to COSP, or to similarly pass the PDFs of condensate to an improved COSP subcolumn sampler to include the subgrid variability.

In the interest of also providing a stand-alone parameterization for use in offline calculations of simulator diagnostics using COSP, I also propose to develop an independent characterization of subgrid-scale cloud and precipitation variability. I plan to base this on output from both the MMF and available observations. The basic outline of this is to use the MMF to provide a first-guess at the distribution, and then to compare that to observations where possible. CloudSat reflecitivies have been used by others to derive variability parameters (Oreopoulos et al., 2012), but these carry large uncertainties due to the strong sensitivity to precipitation and difficulty in separating clouds from precipitation using radar reflectivity alone. Because of this, it might be necessary to look at variability derived from in-situ measurements as an additional check of variability derived from MMF output.

### 3.3 Sensitivity of radiative fluxes and COSP simulator diagnostics to improvements in the treatment of cloud and precipitation overlap and subgrid-scale variability

Following the characterization of overlap statistics and subgrid-scale variability, the next step is to implement the improved scheme into COSP and into a GCM and test the sensitivity of the fluxes and simulated satellite-observables to the improvements.

Implementation of the improved subgrid treatment is relatively straightforward in the stand-alone COSP code, and the new subcolumn generator can just replace the “SCOPS” and “PREC\_SCOPS” modules in that code. For use in CAM5, however, these modules should be bypassed and common subcolumns between COSP and the McICA radiative transfer code should be used to enforce consistency between the radiative transfer and the (radiatively-important) satellite-observable cloud diagnostics.

As mentioned above, the infrastructure to sample subcolumns with variable condensate from CLUBB PDFs has already been implemented in the development version of the CAM5. It should then be straightforward to either pass subcolumns with subgrid variability generated for the radiation code to COSP, or to pass CLUBB PDFs of condensate to COSP for generation of the subcolumns. This will allow for concurrent evaluation of the sensitivity of both radiative fluxes and COSP diagnostics to changes in the treatment of the subgrid cloud and precipitation structure and variability, with variability specified by the CLUBB physics parameterization. It is not clear yet whether or not their implementation generates subcolumns of precipitating hydrometeors. This will be important for the COSP diagnostics, and may need to be added or improved depending on what they have done.

Sensitivity of the COSP diagnostics will be tested alongside the radiative fluxes and heating rates in the context of the CAM5 implementation. The stand-alone COSP subcolumn scheme will be tested using MMF output and a similar framework as described above for the baseline sensitivity tests of the COSP outputs.

## 4 Expected outcomes and timeline

The following outcomes are expected from this work:

* Quantitative evaluation of the uncertainties in model to observation comparisons using COSP simulators
* Quantitative evaluation of the sensitivity of COSP diagnostics to unresolved cloud and precipitation structure and variability (Fall 2014)
* Characterization of subgrid-scale cloud and precipitation structure and variability (Winter and Spring 2015)
* Quantitative evaluation of the sensitivity of COSP diagnostics and radiative fluxes in CAM5 to improved treatment of subgrid-scale cloud and precipitation overlap and variability (Spring and Summer 2015)

## 5 Summary and impacts

Subgrid-scale variability in cloud structure and cloud properties have been shown by others to affect radiative fluxes and heating rates calculated by 1D radiative transfer codes in large-scale models, and are shown in the first part of this work to affect calculations of simulated satellite-observable cloud diagnostics. The latter are commonly used to assess the fidelty of models in simulating cloud properties consistent with present day observations, and so ambiguities arising due to neglect of important subgrid structure and variability potentially weaken some of the conclusions reached with these studies. The results of the present work will improve the representation of the subgrid-scale structure and variability of clouds and precipitation, and thereby lead to improved simulation of fluxes and heating rates and simulated satellite observerable cloud diagnostics in models. The improvement in fluxes and heating rates may reduce compensating errors in cloud properties, where tuning efforts have historically been needed to adjust cloud properties away from reasonable values in order to obtain radiative balance in climate simulations. The improvement in simulated satellite-observable cloud diagnostics will reduce ambiguities and uncertainties in comparisons between modeled and observed clouds and lead to more robust model evaluation.

References

Barker, H. W., 2008: Overlap of fractional cloud for radiation calculations in GCMs: A global analysis using CloudSat and CALIPSO data. *J. Geophys. Res.*, **113 (D00A01)**, 10.1029/2007JD009677.

Barker, H. W., G. L. Stephens, and Q. Fu, 1999: The sensitivity of domain-averaged solar fluxes to assumptions about cloud geometry. *Q. J. R. Meteorol. Soc.*, **125 (558)**, 2127–2152, 10.1256/smsqj.55809.

Bodas-Salcedo, A., et al., 2011: COSP: Satellite simulation software for model assessment. *Bull. Amer. Meteor. Soc.*, **92 (8)**, 10.1175/2011BAMS2856.1.

Bony, S. and J.-L. Dufresne, 2005: Marine boundary layer clouds at the heart of tropical cloud feedback uncertainties in climate models. *Geophys. Res. Lett.*, **32 (20)**, 10.1029/2005GL023851.

Cahalan, R. F., W. Ridgway, W. J. Wiscombe, T. L. Bell, and J. B. Snider, 1994: The albedo of fractal stratocumulus clouds. *J. Atmos. Sci.*, **51 (16)**, 2434–2455, 10.1175/1520-0469(1994)051<2434:TAOFSC>2.0.CO;2.

Cess, R. D., et al., 1990: Intercomparison and interpretation of climate feedback processes in 19 atmospheric general circulation models. *J. Geophys. Res.*, **95 (D10)**, 16 601–16 615, 10.1029/JD095iD10p16601.

Collins, W. D., 2001: Parameterization of generalized cloud overlap for radiative calculations in general circulation models. *J. Atmos. Sci.*, **58 (21)**, 3224–3242, 10.1175/1520-0469(2001)058<3224:POGCOF>2.0.CO;2.

Collins, W. D., et al., 2004: Description of the NCAR Community Atmosphere Model (CAM 3.0). NCAR Technical Note TN-464+STR, NCAR.

Di Michele, S., M. Ahlgrimm, R. Forbes, M. Kulie, R. B. M. Janisková, and P. Bauer, 2012: Interpreting an evaluation of the ECMWF global model with CloudSat observations: ambiguities due to radar reflectivity forward operator uncertainties. *Q. J. R. Meteorol. Soc.*, **138**, 2047–2065.

Donner, L. J., et al., 2011: The dynamical core, physical parameterizations, and basic simulation characteristics of the atmospheric component AM3 of the GFDL global coupled model CM3. *J. Climate*, **24 (13)**, 3484–3519, 10.1175/2011JCLI3955.1.

Geleyn, J. F. and A. Hollingsworth, 1979: An economical analytical method for the computation of the interaction of between scattering and line absorption of radiation. *Contrib. Atmos. Phys.*, **52**.

Golaz, J.-C., V. E. Larson, and W. R. Cotton, 2002: A PDF-based model for boundary layer clouds. part I: Method and model description. *J. Atmos. Sci.*, **59 (24)**, 3540–3551, 10.1175/1520-0469(2002)059<3540:APBMFB>2.0.CO;2.

Hogan, R. J. and A. J. Illingworth, 2000: Deriving cloud overlap statistics from radar. *Q. J. R. Meteorol. Soc.*, **126**, 2903–2909, 10.1256/smsqj.56913.

Hogan, T. F., et al., 2014: The navy global environmental model. *Oceanography*, **27 (3)**, 10.5670/oceanog.2014.73.

Iacono, M. J., J. S. Delamere, E. J. Mlawer, M. W. Shephard, S. A. Clough, and W. D. Collins, 2008: Radiative forcing by long-lived greenhouse gases: Calculations with the AER radiative transfer models. *J. Geophys. Res.*, **113 (D13103)**, 10.1029/2008JD009944.

Kay, J. E., et al., 2012: Exposing global cloud biases in the Community Atmosphere Model (CAM) using satellite observations and their corresponding instrument simulators. *J. Climate*, **25**, 5190–5207, 10.1175/JCLI-D-11-00469.1.

Khairoutdinov, M. F. and D. A. Randall, 2001: A cloud-resolving model as a cloud parameterization in the NCAR Community Climate System Model: Preliminary results. *Geophys. Res. Lett.*, **28**, 3617–3620.

Klein, S. A. and C. Jakob, 1999: Validation and sensitivities of frontal clouds simulated by the ECMWF model. *Monthly Weather Review*, **127 (10)**, 2514–2531, 10.1175/1520-0493(1999)127<2514:VASOFC>2.0.CO;2.

Klein, S. A., Y. Zhang, M. D. Zelinka, R. Pincus, J. Boyle, and P. J. Gleckler, 2013: Are climate model simulations of clouds improving? an evaluation using the ISCCP simulator. *J. Geophys. Res.*, **118 (3)**, 1329–1342, doi:10.1002/jgrd.50141.

Larson, V. E., J.-C. Golaz, H. Jiang, and W. R. Cotton, 2005: Supplying local microphysics parameterizations with information about subgrid variability: Latin hypercube sampling. *J. Atmos. Sci.*, **62**, 4010–4026.

Larson, V. E. and D. P. Schanen, 2013: The Subgrid Importance Latin Hypercube Sampler (SILHS): a multivariate subcolumn generator. *Geosci. Model Dev.*, **6**, 1813–1829, 10.5194/gmd-6-1813-2013.

Mace, G. G. and S. Benson-Troth, 2002: Cloud-layer overlap characteristics derived from long-term cloud radar data. *J. Climate*, **15**, 10.1175/1520-0442(2002)015<2505:CLOCDF>2.0.CO;2.

Marchand, R., J. Haynes, G. G. Mace, and T. Ackerman, 2009: A comparison of simulated radar output from the multiscale modeling framework global climate model with CloudSat cloud radar observations. *J. Geophys. Res.*, **114**, 10.1029/2008JD009790.

Medeiros, B., B. Stevens, I. M. Held, M. Zhao, D. L. Williamson, J. G. Olson, and C. S. Bretherton, 2008: Aquaplanets, climate sensitivity, and low clouds. *J. Climate*, **21 (19)**, 4974–4991, 10.1175/2008JCLI1995.1.

Neale, R. B., et al., 2010a: Description of the NCAR Community Atmosphere Model (CAM 4.0). NCAR Technical Note TN-485+STR, NCAR.

Neale, R. B., et al., 2010b: Description of the NCAR Community Atmosphere Model (CAM 5.0). NCAR Technical Note TN-486+STR, NCAR.

Oreopoulos, L., D. Lee, Y. C. Sud, and M. J. Suarez, 2012: Radiative impacts of cloud heterogeneity and overlap in an atmospheric General Circulation Model. *Atmos. Chem. Phys.*, **12**, 9097–9111, 10.5194/acp-12-9097-2012.

Pincus, R., H. W. Barker, and J.-J. Morcrette, 2003: A fast, flexible, approximate technique for computing radiative transfer in inhomogeneous cloud fields. *J. Geophys. Res.*, **108 (D13)**, 10.1029/2002JD003322.

Pincus, R., C. Hannay, S. A. Klein, K.-M. Xu, and R. Hemler, 2005: Overlap assumptions for assumed probability distribution function cloud schemes in large-scale models. *J. Geophys. Res.*, **110 (D15S09)**, 10.1029/2004JD005100.

Räisänen, P., H. W. Barker, M. F. Khairoutdinov, J. Li, and D. A. Randall, 2004: Stochastic generation of subgrid-scale cloudy columns for large-scale models. *Q. J. R. Meteorol. Soc.*, **130**, 2047–2067, 10.1256/qj.03.99.

Randall, D., M. Khairoutdinov, A. Arakawa, and W. Grabowski, 2003: Breaking the cloud parameterization deadlock. *Bull. Amer. Meteor. Soc.*, **84 (11)**, 1547–1564, 10.1175/BAMS-84-11-1547.

Stephens, G. L. and C. M. R. Platt, 1987: Aircraft observations of the radiative and microphysical properties of stratocumulus and cumulus cloud fields. *J. Climate Appl. Meteor.*, **26**, 1243–1269, 10.1175/1520-0450(1987)026<1243:AOOTRA>2.0.CO;2.

Stephens, G. L., et al., 2002: The CloudSat mission and the A-Train. *Bull. Amer. Meteorol. Soc.*, **83 (12)**, 1771–1790, 10.1175/BAMS-83-12-1771.

Tompkins, A. M., 2002: A prognostic parameterization for the subgrid-scale variability of water vapor and clouds in large-scale models and its use to diagnose cloud cover. *J. Atmos. Sci.*, **59**, 1917–1942, 10.1175/1520-0469(2002)059<1917:APPFTS>2.0.CO;2.

von Salzen, K., et al., 2012: The Canadian fourth generation atmospheric global climate model (CanAM4): Simulation of clouds and precipitation and their responses to short-term climate variability. *Atmos.-Ocean*, submitted.

Webb, M., C. Senior, S. Bony, and J.-J. Morcrette, 2001: Combining ERBE and ISCCP data to assess clouds in the Hadley Centre, ECMWF and LMD atmospheric climate models. *Clim. Dyn.*, **17 (12)**, 905–922, 10.1007/s003820100157.

Williams, K. D. and M. J. Webb, 2009: A quantitative performance assessment of cloud regimes in climate models. *Clim. Dyn.*, **33 (1)**, 141–157, 10.1007/s00382-008-0443-1.

Winker, D. M., B. H. Hunt, and M. J. McGill, 2007: Initial performance assessment of CALIOP. *Geophys. Res. Lett.*, **34 (L19803)**, 10.1029/2007GL030135.

Wu, X. and X.-Z. Liang, 2005: Radiative effects of cloud horizontal inhomogeneity and vertical overlap identified from a monthlong cloud-resolving model simulation. *J. Atmos. Sci.*, **62**, 4105–4112.

Zhang, M., et al., 2005: Comparing clouds and their seasonal variations in 10 atmospheric general circulation models with satellite measurements. *J. Geophys. Res.*, **110 (D15)**, 10.1029/2004JD005021.

Zhang, Y., S. A. Klein, J. Boyle, and G. G. Mace, 2010: Evaluation of tropical cloud and precipitation statistics of Community Atmosphere Model version 3 using CloudSat and CALIPSO data. *J. Geophys. Res.*, **115 (D12205)**, 10.1029/2009JD012006.