Reducing errors in simulated satellite views of clouds from large-scale models

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A dissertation
submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

University of Washington

2016

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A fundamental test of the representation of clouds in models is evaluating the simulation of present-day climate against available observations. Satellite retrievals of cloud properties provide an attractive baseline for this evaluation because they can provide near global coverage and long records. However, comparisons of modeled and satellite-retrieved cloud properties are difficult because the quantities that can be represented by a model and those that can be observed from space are fundamentally different. Satellite simulators have emerged in recent decades as a means to account for these differences by producing pseudo-retrievals of cloud properties from model diagnosed descriptions of the atmosphere, but these simulators are subject to their own uncertainties as well that have not been well-quantified in the existing literature. In addition to uncertainties regarding the simulation of satellite retrievals themselves, a more fundamental source of uncertainty exists in connecting the different spatial scales between satellite retrievals and large-scale models. Systematic errors arising due to assumptions about the unresolved cloud and precipitation condensate distributions are identified here. Simulated satellite retrievals are shown in this study to be particularly sensitive to the treatment of cloud and precipitation occurrence overlap as well as to unresolved condensate variability. To correct for these errors, an improved treatment of unresolved
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ACKNOWLEDGMENTS

This work would not have been possible without tremendous support from a great number of people. I thank my advisers, Tom Ackerman and Roger Marchand, for giving me the opportunity to study atmospheric science at UW, for all of their support and guidance throughout the (many) long years of my graduate work, and for teaching me to find my way as a scientist. I thank Rob Wood, Daehyun Kim, and Curtis Deutsch for serving on my Ph.D. committee, and Cecilia Bitz and Dargan Frierson for serving on my masters committee. A very special thanks is due to Jen Kay, for not only sponsoring me for a summer at NCAR, but for continuing to serve as a mentor and a supporter of my work ever since. I owe a great deal of gratitude to many incredible teachers I have learned from, but especially to Stephanie Diemel at Shoreline Community College and to Brad Johnson at Western Washington University. I thank all of the friends I have made in the department, especially Stephen Po-Chedley, Stuart Evans, Aaron Donohoe, and Max Menchaca for all at one point sharing offices and numerous conversations about both science and life, and to all of Grads 08 for endless support and fun throughout our shared time at UW. I thank all of my friends outside the department, especially Mike Clawson, who has been my closest friend since as long as I can remember and even contributed science inspiration, enlightening discussions, and suggestions relevant to my graduate work. Most importantly, I thank my family for endless love, support, encouragement, and understanding throughout this whole journey, especially my parents Ed and Gretchen, my brother James, my nieces Lilli, Aria, and Scarlet, and my sweetheart Piper and her family; thank you all for supporting me and believing in me.
Chapter 1

INTRODUCTION

Large-scale (global) models of the atmosphere and climate system are fundamental tools that aid in our understanding of the climate system. They are used not only to study interactions between different components of the climate system, but also to perform simulations of future climate change relevant for informing societal policy decisions. The formulation of these models is evaluated using multiple approaches, including testing the individual components that go into the models (such as a particular physical process like convection) using case studies, idealized frameworks (such as aqua planets, in which land is removed) and idealized forcings. Climate models are often, if not always, evaluated by comparing simulations of present-day climate with observations of the present-day climate system. The sources for these observations are diverse, and depend on the particular aspect of the climate being evaluated.

Clouds are a critical piece of the climate system, and yet the simulation of clouds by global climate models (GCMs, also general circulation models) remains a challenge, and cloud feedback processes are well-known to be a primary source of uncertainty in projections of future climate (Cess et al., 1990; Bony and Dufresne, 2005; Williams and Webb, 2009; Medeiros et al., 2008; Dufresne and Bony, 2008; Bony et al., 2006). This makes evaluation of clouds in large-scale models of utmost importance.

Observational records of cloud occurrence and other properties from satellite imagers including the International Satellite Cloud Climatology Project (ISCCP; Rossow and Schiffer, 1999), the Moderate Resolution Imaging Spectroradiometer (MODIS; King et al., 2003), and the Multi-angle Imaging Spectroradiometer (MISR; Diner et al., 2002, 2005) provide a natural baseline for the evaluation of the large-scale cloud statistics simulated by these models.
because they provide near-global coverage and an increasingly long time-series. Comparisons of cloud amount (or cloud fraction) and cloud top height for various cloud types have long been used to evaluate models (Klein and Jakob, 1999; Webb et al., 2001; Norris and Weaver, 2001; Lin and Zhang, 2004; Zhang et al., 2005; Wyant et al., 2006; Gleckler et al., 2008; Marchand and Ackerman, 2010; Pincus et al., 2012; Kay et al., 2012; Klein et al., 2013), but comparisons between satellite-retrieved and modeled cloud properties are difficult because of fundamental differences between how clouds can be measured from space and how they are represented in large-scale models. These differences stem from both unavoidable limitations in the satellite retrieval process, as well as from limitations that arise due to the differences in scale between satellite retrievals and current GCMs. For example, cloud top height or cloud top pressure retrievals based on visible or infrared observations (e.g., ISCCP, MODIS, and MISR) are known to have significant problems when clouds with low amounts of condensate (i.e. non-opaque clouds or cloud-tops) are present, especially for scenes with multi-layer clouds where the upper layer cloud is optically thin (Marchand et al., 2010; Pincus et al., 2012). Fundamentally, the visible and infrared observations gathered by ISCCP, MODIS and MISR cannot fully constrain the vertical distribution of condensate, including discriminating between condensate types in differing layers, and this leads to uncertainties and systematic errors in the determination (retrieval) of cloud top height. Models, however, specify (or resolve) the vertical distribution of condensate to some degree. This fundamental difference between retrievals of cloud top height and the vertical distribution of clouds specified by a model makes direct comparisons between the two somewhat ambiguous. An alternative to this often ambiguous direct comparison between satellite-retrieved and modeled clouds is to first “simulate” the satellite view of clouds from the model-simulated atmospheric state. The goal with this approach is to account for some of the known errors in the satellite retrieval process by forward-modeling or emulating the retrieval technique used for a particular satellite instrument from the available model fields, with the goal of providing a description of what a given satellite instrument would see given the model-simulated atmosphere. These simulated or pseudo-retrievals are expected to be more directly comparable to the available
satellite retrievals than the raw model fields, thus enabling a more appropriate evaluation of model clouds against satellite observations.

The ISCCP simulator introduced by Klein and Jakob (1999) has been widely used in model comparisons with ISCCP observations (Webb et al., 2001; Norris and Weaver, 2001; Lin and Zhang, 2004; Zhang et al., 2005; Wyant et al., 2006; Klein et al., 2013). The ISCCP simulator produces joint histograms of cloud top pressure and cloud optical depth from model fields that can be directly compared with joint histograms produced from ISCCP retrievals. In effect, each bin in the ISCCP histogram is a cloud fraction that quantifies how often clouds within a certain range of cloud top pressures and cloud optical depths occur, and with the sum of all bins yielding the total cloud fraction. Because outgoing longwave radiation is strongly influenced by cloud top height (and cloud amount) and outgoing shortwave radiation is strongly influenced by cloud optical depth (and cloud amount), comparisons using the ISCCP joint histograms provide an evaluation of model cloud amount that is linked to the impact of clouds on the model radiation budget. This is extremely useful for assigning radiative importance to diagnosed errors in cloud properties, but is also useful for exploring cloud feedbacks associated with future climate change. Zelinka et al. (2012a) introduce a new framework for calculating cloud feedbacks by creating a radiative “kernel” from the ISCCP histogram output by the ISCCP simulator. This kernel represents the change in radiative forcing that results from changes in each of the ISCCP histogram components. Zelinka et al. (2012b) demonstrate the utility of this new approach by using the kernels to partition cloud feedbacks into feedbacks due separately to cloud amount, cloud top height, and cloud optical depth.

The utility of the ISCCP simulator has inspired efforts to construct simulators for additional satellite-based imagers, including MISR (Marchand and Ackerman, 2010) and MODIS (Pincus et al., 2012). Additional simulators have also recently been developed for the CloudSat (Stephens et al., 2002) cloud profiling radar (Quickbeam; Haynes et al., 2007), and for the Cloud-Aerosol Lidar with Orthogonal Polarization (CALIOP) lidar (Chepfer et al., 2008) onboard the Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observations
(CALIPSO; Winker et al., 2007) satellite.

With the goal of facilitating the implementation of these simulators into global climate models, the Cloud Feedback Model Intercomparison Project (CFMIP; Webb et al., 2016) has collected the ISCCP, MISR, MODIS, CloudSat, and CALIPSO simulators into a single software package with a common interface: the CMFIP Observation Simulator Package (COSP; Bodas-Salcedo et al., 2011). This has enabled both coordinated multi-model experiments comparing simulated cloud properties across models as well as innovative multi-sensor analyses of models (e.g., Bodas-Salcedo et al., 2011; Kay et al., 2012; Klein et al., 2013; Franklin et al., 2013b,a), nominally leading to more robust evaluation of clouds in climate models.

While the goal of the simulator approach is to remove ambiguities in comparisons between models and remote sensing observations of clouds, not all ambiguities in model-to-observation comparisons can be removed with the simulator framework. The presence of remaining uncertainties or ambiguities in simulated and retrieved cloud properties may undermine conclusions reached using this framework. It is therefore important to identify and understand the uncertainties and limitations of this framework in order to be able to confidently attribute differences between simulated and retrieved cloud properties unambiguously to model biases.

Simulating satellite retrievals from global model output is essentially a three-part process, involving 1) inferring pixel-scale cloud properties from the large-scale description provided by models, 2) simulating the pixel-scale satellite retrievals from the inferred pixel-scale (or subgrid-scale) cloud properties from the model, and finally 3) aggregating the simulated pixel-scale retrievals into statistical summaries consistent with the gridded, global summary products distributed by the satellite teams (often referred to as “Level 3” products in satellite retrieval nomenclature). This is illustrated in Figure 1 in Bodas-Salcedo et al. (2011), and also in Figure 1.1 here. In general, there can be errors associated with each of these three steps in the simulator process, and the primary goal of the present study is to identify and quantify these errors, and ultimately to present strategies for reducing these errors in order to enable more robust evaluation of models in the future.
Figure 1.1: Schematic of the simulator framework
The first of these steps, inferring subgrid-scale cloud properties, is necessary because the resolution of typical global models is much coarser than the scales at which satellite retrievals are performed. These bulk statistics at the gridbox scale imply a distribution of possible retrievals within each gridbox, each resulting from a different possible combination of subgrid-scale profiles. This is due to the fact that simple profiles of averaged quantities at larger scales do not in themselves fully constrain the distribution of profiles at smaller scales, and simulating the satellite views of clouds depends on detailed knowledge of the overlapping nature of clouds and precipitation at scales approximating satellite pixels. This is accounted for in the simulator framework by generating stochastic samples of “subcolumn” profiles, which reproduce the gridbox-averaged profiles in the limit of many samples and are consistent with some external assumption about how the cloudy parts of the gridbox overlap vertically (Klein and Jakob, 1999). This problem is not unique to simulating satellite-retrieved quantities, but is also important for simulating radiative fluxes and heating rates within models. In COSP, the assumption is made in the subcolumn sampling process that cloud occurrence obeys a conceptually simple combination of maximum and random overlap and that cloud (and precipitation) condensate is horizontally homogeneous on the scale of model gridboxes. These same assumptions are often (but not always) used in models for the simulation of radiative fluxes. It has been shown that these assumptions can lead to substantial errors in simulated radiative fluxes and heating rates in models (Barker et al., 1999; Oreopoulos et al., 2012); here, in Chapter 3, it is shown that these assumptions similarly lead to substantial errors in simulated satellite retrievals. In Chapter 4 an improved framework for sampling these subcolumns is presented that better represents the subgrid-scale cloud and precipitation properties; these improvements can substantially reduce the errors identified in Chapter 3.

Errors in the second step in the simulator framework (simulating the pixel-scale satellite retrievals), can arise due to incomplete or incorrect implementation of the retrieval process, even given perfect pixel-scale cloud properties as inputs. While every effort is made to build the simulators to account for as many features of the individual retrievals as possible, verifi-
cation of the simulators is difficult, and documented verification is limited in the literature. A fundamental question is, given perfect descriptions of the cloudy atmosphere as inputs, can the simulators reproduce pseudo-retrieved cloud properties consistent with actual retrievals? A theoretical framework for answering this question is to supply “observed profiles” of cloud properties as inputs to the simulators, and then to compare the simulated retrievals with coincident retrievals. Using this framework to answer this question is difficult because it requires some source for these “observed profiles”. Mace et al. (2011) use a multi-sensor approach combining ground-based remote sensing retrievals of cloud properties to derive inputs to the ISCCP simulator, run the ISCCP simulator directly on these inputs and then compare the simulated ISCCP cloud properties with actual coincident ISCCP retrievals. While the input profiles derived from the ground-based retrievals are likely imperfect and have their own associated uncertainties (which must be considered in the analysis), studies such as these are important for building confidence in the fidelity of the simulator framework itself. In Chapter 2, an evaluation of the MISR simulator is presented, using a conceptually similar framework to that used in Mace et al. (2011).
Chapter 2

EVALUATING THE MISR SIMULATOR USING INDEPENDENTLY RETRIEVED HYDROMETEOR PROFILES FROM ACTIVE SENSORS

The goal of the instrument simulator approach is to remove ambiguities in comparisons between models and observations such that remaining differences between the observed and simulated cloud properties can be interpreted unambiguously as model errors. However, the simulators themselves have seen little critical evaluation. Mace et al. (2011), hereafter M2011, performed an evaluation of the ISCCP simulator using thermodynamic and cloud property profiles derived from data collected at the Atmospheric Radiation Measurement Program (ARM; Ackerman and Stokes, 2003) Southern Great Plains (SGP) ground-based observing site located near Lamont, Oklahoma. In their analysis, M2011 compare ARM radar-and-lidar derived cloud properties directly to those retrieved from ISCCP to first assess the biases in the ISCCP retrieval relative to the ARM-derived cloud properties. They then apply the ISCCP simulator to the ARM-derived profiles of cloud extinction and compare the ISCCP-simulated cloud properties to ISCCP retrievals. They find that the simulator accounts for much of the bias in the ISCCP cloud top pressure ($p_c$) retrieval; that is, the ISCCP-simulated $p_c$ retrieval compares well with the actual ISCCP retrieval. However, mid-level cloud remained a problem with significantly less mid-level cloud in the simulated retrievals than in the ISCCP retrievals (6% relative to the total number of profiles, or equivalently, 23% relative to the amount of simulated mid-level cloud), suggesting that the simulator does not completely compensate for the well-known tendency of ISCCP retrievals to overestimate the amount of mid-level clouds (e.g., Marchand et al., 2010). More problematically, M2011 found large differences in optical depth between ISCCP and ARM retrievals. M2011 suggest this may be due to
a combination of sub-pixel variability in the clouds and limitations associated with the 1D radiative transfer used in the ISCCP retrievals. The simulators do not currently correct for any optical depth biases, and the potential exists for large biases in the comparisons for cases involving small, heterogeneous broken clouds where 3D effects are especially important. This topic is discussed in more detail later in this chapter, as it also affects the evaluation of the MISR simulator presented here.

The analysis by M2011 provides one of the few critical evaluations of the simulators documented in the available literature (see also, Mace et al., 2006; Di Michele et al., 2012). The lack of verification of the simulators severely undermines their credibility for use in the evaluation of climate models. The goal of this chapter is to perform a similar analysis to M2011 for the MISR simulator. Conceptually similar to the ISCCP simulator, the MISR simulator produces histograms of cloud optical depth and cloud top height. While the optical depth retrievals are similar, the MISR cloud top height is based on a geometric stereo-imaging technique that has different strengths and weaknesses than ISCCP. In particular, MISR provides more accurate retrievals of cloud top height for low-level and mid-level clouds, more reliable discrimination of mid-level clouds from other clouds, and is insensitive to the instrument calibration making the data well suited for examining variability on seasonal or longer time scales, while ISCCP provides a longer time record, diurnal sampling (MISR has a fixed equator crossing time near 10:30 am) and is able to better detect optically thin high-level clouds because of its use of thermal IR observations.

Again, the overall goal of this chapter is to advance understanding of uncertainties and limitations of the simulator framework by performing a critical verification for the MISR simulator. The fundamental question addressed in this chapter is, given observed profiles of visible extinction, can the MISR simulator accurately reproduce the features of the MISR retrieval?

Section 2.1, Section 2.2 and Section 2.3 describe the analysis approach and datasets, and comparisons between MISR-simulated cloud top height and MISR retrievals are shown in Section 2.4. Section 2.5 provides additional discussion of possible uncertainties that may arise
due to differences in diurnal sampling between the simulated and retrieved cloud properties. A summary of the results and additional discussion is presented in Section 2.6.

### 2.1 Framework for verification of MISR and ISCCP simulators

In contrast to the analysis performed by M2011, verification of the MISR simulator is challenged by the fact that MISR optical depth retrievals are not performed over land or ice surfaces (only over ice-free open ocean), which makes the kind of direct comparisons between ISCCP and ARM ground-based retrievals performed in M2011 impossible for comparisons involving MISR. Instead, the MISR simulator is tested here using profiles of cloud visible extinction derived from a combination of data from CloudSat, CALIPSO, MODIS, and AMSR-E, all flying within the A-Train constellation of satellites enabling nearly-coincident observations from a wealth of sensors.

While using extinction profiles derived from satellite observations provides nearly global sampling for this analysis, this approach is further challenged by the fact that the MISR instrument does not fly in constellation with the A-Train, but rather flies on-board the Terra platform, with an equator crossing time approximately three hours earlier in an entirely different orbit. This largely prevents a direct comparison of collocated retrievals as done by M2011, and instead only aggregated monthly statistics can be compared here. This also introduces the possibility for differences in the comparison of MISR and MISR-simulated retrievals due to differences in the diurnal cycle sampled by the different satellite platforms. These differences are expected to be small in most regions, with the likely exception of maybe marine stratocumulus clouds, but this will be examined in more detail in Section 2.5.

### 2.2 Retrievals of visible extinction using A-train measurements

The derived extinction profiles were graciously provided by Gerald G. Mace and Sally Benson at the University of Utah for this study. The retrievals are described briefly below, and more extensively in the provided references.

The retrieval approach used is essentially that used in Mace and Wrenn (2013) and
Berry and Mace (2014), with ice cloud microphysical properties taken from the CloudSat 2C-ICE product (Deng et al., 2010, 2013) following Berry and Mace (2014). Thermodynamic profiles are based on European Centre for Medium-Range Weather Forecasts (ECMWF) data mapped to the CloudSat track in the CloudSat auxiliary product known as ECMWF-AUX. Column visible optical depths from the CloudSat cloud optical depth product (2B-TAU, which uses MODIS radiances) are used. With the exception of the use of 2C-ICE, the most detailed description of this technique can be found in Mace (2010). Specifically, the hydrometeor layer occurrences from combined CloudSat radar and CALIPSO lidar data from the Radar-Lidar Geometrical Profile Product (RL-GEOPROF; Mace et al., 2009; Mace and Zhang, 2014) Version R04 defines the vertical hydrometeor occurrence. In RL-GEOPROF, CALIPSO lidar detections are mapped onto the coarser CloudSat grid (with an along track horizontal resolution of approximately 2 km, a horizontal grid spacing of about 1 km and vertical grid spacing of 240 m). Only radar volumes that are at least 50% filled by lidar detections are treated as having a lidar cloud detection on the CloudSat retrieval grid. This threshold has a notable affect on the resulting low-cloud fractions (see Section 2.4). The properties of warm liquid phase clouds are derived by combining CloudSat radar reflectivity factors with optical depths from 2B-TAU and liquid water paths from AMSR-E, applying essentially the Dong and Mace (2003) retrieval (see Mace, 2010, Appendix A). Radar volumes where condensate is only detected by the lidar assume a radar reflectivity value below the sensitivity of CloudSat (-35 dBZe) and a default liquid water path of 200g/m² is used in instances where neither optical depth nor liquid water path retrievals were successful. For radar volumes with temperatures colder than the freezing level an estimate is made of the liquid water path fraction that is above the freezing level to temperatures as low as 240 K as described in Mace et al. (2006) and is added to the 2C-ICE extinction.

These retrievals of visible extinction are used in this study as inputs to the MISR simulator to diagnose the cloud top heights that MISR would likely retrieve, given the input extinction profile derived from the A-Train data. These “MISR-simulated” cloud top heights are then compared with MISR-retrieved cloud top heights. The MISR retrievals used, and the method
Figure 2.1: Profiles of visible extinction $d\tau$ from the combined CloudSat/CALIPSO retrieval and estimates of cloud top height $z_c$ for a short orbit segment. Grey “x” markers indicate cloud top heights diagnosed by taking the highest altitude with non-zero extinction, and black “+” markers indicate cloud top heights diagnosed using the MISR simulator.

for simulating MISR cloud top heights from the input extinction profiles are described in the following section.

2.3 MISR-retrieved and MISR-simulated cloud top heights

The MISR cloud top height and optical depth (CTH-OD) data used here is the Version 6 product (Marchand et al., 2010), which is produced at the NASA Langley Distributed Active Archive Center (DAAC). In order to calculate sampling uncertainties at the monthly time scale, orbit-by-orbit data are used in this study, but for use with climate models these data have been aggregated into monthly summaries that are available from the Cloud Feedback Model Intercomparison Project (CFMIP; Webb et al., 2016) observational data archive\textsuperscript{1}.

The MISR simulator takes as a primary input a visible extinction profile (and temper-

\textsuperscript{1}http://climserv.ipsl.polytechnique.fr/cfmip-obs/
nature) and outputs the cloud top height that MISR would likely retrieve for that profile. The estimates of the cloud top height ($z_c$) that MISR would likely retrieve (from a given input profile of visible extinction) are based on a number of simple rules, described in detail in Marchand and Ackerman (2010) (see Appendix A therein) and briefly summarized here in the context of Figure 2.1. The shading in Figure 2.1 show an example of the combined CloudSat and CALIPSO (hereafter referred to as CC) cloud visible extinction retrieval for a short orbit section. The cloud top height estimated using two different methods is overlaid on the panel. First, cloud top height is estimated directly from the extinction profiles as the highest altitude for which the visible extinction is non-zero. This direct estimate of cloud top height (hereafter referred to as CC-dir) is indicated on the figure for each profile with a grey “x”. Next, the simulated cloud top height (hereafter referred to as CC-sim) is diagnosed by passing the profiles of visible extinction to the MISR simulator. This estimate of cloud top height is indicated on the figure for each profile with a black “+”.

The example shown in Figure 2.1 highlights several key aspects of how the MISR simulator works. For single-layer water clouds (which have optical depth $\tau > 1$ and high visible contrast), the MISR estimate of cloud top height is expected to be in good agreement with the “true” cloud top height, and thus CC-sim will agree well with CC-dir for these cases. For example, the extinction profile near 31.5 N shows a single low-level cloud layer with large optical depth, and the CC-dir and CC-sim estimates of cloud top height are similar. For multi-layer profiles where the upper cloud layer is sufficiently thin (nominally $\tau < 1$), MISR retrievals tend to effectively “see through” the upper-level, optically thin cloud, and retrieve the cloud top height of the lower cloud layer due to the fact that the lower cloud layer usually has more contrast in the scene and is preferentially picked up by the MISR pattern-matcher. The MISR simulator mimics this tendency (with again a nominal optical depth threshold for the upper layer of $\tau < 1$) and so the MISR simulator would return the cloud top height of the lower cloud layer in this case, even though the true cloud top height of the highest cloud in the column might be much higher in altitude, coinciding with the upper-level cloud. An example of this situation is seen in Figure 2.1 near 33.5 N, where the
CC-sim estimate returns the height of the lower cloud layer, but CC-dir returns the height of the upper cloud layer. For clouds with optically thicker ice-phase cloud tops, the MISR simulator penetrates down into the cloud layer to retrieve the cloud top height where the integrated optical depth reaches a nominal value of $\tau = 1$. In these cases (such as near 34.5 N in Figure 2.1), the simulated (CC-sim) cloud top height will also be lower than the true cloud top height, calculated directly by taking the highest level with non-zero extinction (CC-dir).

Figure 2.2 shows joint histograms of cloud top height and cloud optical depth for the example orbit segment shown above in Figure 2.1. The value of each element in the joint histogram is the relative frequency of occurrence of profiles within a certain cloud top height and optical depth range, and because each profile is assigned only one value of cloud top height and one value of cloud optical depth, the sum of the joint histogram values over all bins is equal to the total vertically projected cloud area. Likewise, the sum over all bins with cloud top height $z_c \leq 3$ km yields the low-topped cloud area, the sum over all bins with cloud top height $3 < z_c \leq 7$ km yields the mid-topped cloud area, and the sum over all bins with cloud top height $z_c > 7$ km yields the high-topped cloud area. Taking the sum across the columns of the joint histogram yields the marginal histogram of cloud top height, and taking the sum across the rows yields the marginal histogram of cloud optical depth.

The CC-sim joint histogram for this orbit has one low-topped mode with $0.5 < z_c < 2.0$ km (corresponding primarily to the low-level cloud at the far left of the top panel of Figure 2.1) and a mid-topped mode with $4.0 < z_c < 9.0$ km (corresponding to the mid-level and deep cloud layers at the right of the top panel of the figure). There is also a large amount of cloud in the CC-sim joint histogram with $z_c < 0.0$ km. This cloud top height bin is reserved for profiles for which the MISR simulator determines that MISR would fail to retrieve a cloud top height. This often occurs for columns with very low optical depths. These no-retrieval cases correspond to the section of the example orbit in the top panel of the figure with a single-layer thin high-level cloud, between 32 and 33 N. The CC-dir joint histogram is dominated by a high-topped mode with $11.0 < z_c < 15.0$ km. There is also a
Figure 2.2: Joint histograms of cloud top height and optical depth for the example orbit segment shown in Figure 2.1. The left panel shows joint histograms created using cloud top heights diagnosed using the MISR simulator (CC-sim), and the right panel shows joint histograms created using cloud top heights diagnosed by taking the highest altitude with non-zero extinction (CC-dir).
much smaller low-topped mode with $1.0 < z_c < 2.0$ km, corresponding to the short section of the orbit with single-layered low-level cloud around 31.5 N.

The following section presents comparisons for two separate months (January and June 2008) of aggregated MISR, CC-sim, and CC-dir retrievals.

### 2.4 Comparisons between MISR-retrieved and MISR-simulated clouds

Figure 2.3 and Figure 2.4 show maps of low-topped, mid-topped, high-topped, and total cloud cover from MISR retrievals and diagnosed from the CC visible extinction profiles with and without using the MISR simulator (CC-sim and CC-dir, respectively) for the months of January and June 2008. Data covers the domain with bounds -70N to 70N latitude and 100E to -70E longitude (this includes ocean surfaces beyond the Pacific Ocean, but we will refer to this domain as the “Pacific” for convenience). Boxes are drawn around five climatically distinct regions that will be investigated more closely below: the North Pacific (35N to 60N; 160E to -140E), Hawaiian Trade Cumulus (15N to 35N; 160E to -140E), California Stratocumulus (15N to 35N; -140E to -110E), Tropical Western Pacific (-5N to 20N; 70E to 150E), and the South Pacific (-60N to -30N; -180E to -80E).

These figures show that the cloud area by cloud type from the CC extinction retrieval using the MISR-simulator (CC-sim; middle panels) is broadly similar to the MISR-retrieved cloud area (left panels), especially as compared with the cloud area diagnosed from the CC extinction retrieval (CC-dir; right panels). This indicates that (at least qualitatively) the MISR simulator is working as intended. Differences between CC-dir and CC-sim (and likewise between CC-dir and MISR) are especially large in the Tropical Western Pacific, North Pacific, and South Pacific regions, owing to the large occurrence of optically thin high-altitude cloud in these regions. Averaged over the entire region shown in the figure, the occurrence of high-topped clouds differs by only 2% cloud area in January 2008 between CC-sim and MISR (16% in CC-sim and 14% in MISR retrievals), and by 1% cloud area in June, and the occurrence of mid-topped clouds differs by only 2% cloud cover in January (15% in CC-sim and 13% in the MISR retrievals), and by 3% in June (14% in CC-sim and
Figure 2.3: Maps of cloud area by cloud type for January 2008 retrieved by MISR (left), diagnosed using the MISR simulator on CloudSat/CALIPSO extinction profiles (middle), and diagnosed directly by taking the highest altitude with non-zero extinction from CloudSat/CALIPSO extinction profiles (right). Shown from top to bottom are total ($\tau > 0.3$), high-topped ($\tau > 0.3; z_c > 7$ km), mid-topped ($\tau > 0.3; 3 < z_c < 7$ km), and low-topped ($\tau > 0.3; z_c < 3$ km) cloud area. Area-weighted domain averages are indicated in the upper-right corner of each panel.
Figure 2.4: Maps of cloud area by cloud type for June 2008 retrieved by MISR (left), diagnosed using the MISR simulator on CloudSat/CALIPSO extinction profiles (middle), and diagnosed directly by taking the highest altitude with non-zero extinction from CloudSat/CALIPSO extinction profiles (right). Shown from top to bottom are total ($\tau > 0.3$), high-topped ($\tau > 0.3; z_c > 7$ km), mid-topped ($\tau > 0.3; 3 < z_c < 7$ km), and low-topped ($\tau > 0.3; z_c < 3$ km) cloud area. Area-weighted domain averages are indicated in the upper-right corner of each panel.
The largest difference between MISR and CC-sim is in low-topped cloud, where the low-topped cloud cover is smaller in CC-sim by 8% in January and 6% in June. However, much of this difference appears to be due to differences in low cloud detection between MISR and CC, rather than due to errors in the MISR simulator determination of cloud top height. This is supported by the estimates of total cloud cover, which also differ by 8% and 6% in January and June, respectively. This difference is due to differences in detection of low-level clouds by CC, which will be shown below.

The large impact the MISR simulator has on the estimate of cloud top height is clearly evident in the zonally-averaged cloud area by cloud top height, shown in Figure 2.5 and Figure 2.6 for low, mid, and high-topped cloud cover (limited to the domain shown in Figure 2.3 and Figure 2.4) for MISR, CC-sim, and CC-dir in January and June. Shaded regions show the 95% confidence interval (due to sampling), based on 1000 bootstrap resamples of the orbit-by-orbit zonal means. A large fraction of the high-topped cloud detected by CC is not identified by the MISR stereo height retrieval, largely because it is optically thin (as will be shown later). The MISR simulator corrects for this in the CC retrieval, and the MISR-simulated high-topped cloud cover is in good agreement with the MISR retrievals except at northern mid-latitudes in January (30-60 N) and at high southern latitudes in June (south of 50 S) where differences are about 10% and outside the range of sampling uncertainty indicated by the 95% confidence interval shading. This may be due to several factors, including MISR detecting thinner cirrus in these regions (that is, clouds with an optical depth \( \tau < 1 \)) because of contrast generated from long solar slant paths through the cirrus, or it may be due to limitations in the MISR stereo height algorithm. The MISR CTH-OD product uses the MISR stereo height retrieval with wind correction (the so-called “best-winds” retrieval) when cloud wind speed is successfully retrieved, and the stereo height “without wind” correction otherwise. The MISR stereo image matcher algorithm is in the process of being upgraded by the MISR Science Team, and the upgraded code (which will eventually lead to Version 7 of the MISR CTH-OD product) produces many more successful wind retrievals. Preliminary analysis of MISR CTH-OD Version 7 data indicates somewhat lower amounts
Figure 2.5: Zonally-averaged cloud area by cloud type from MISR-retrievals, MISR-simulated retrievals from CloudSat/CALIPSO extinction profiles, and directly inferred from the CloudSat/CALIPSO extinction profiles for the month of January 2008. Shown are total, high-topped, mid-topped, and low-topped cloud area. Shading indicates the 95% confidence interval obtained by bootstrap resampling the orbit-by-orbit zonal means.
Figure 2.6: Zonally-averaged cloud area by cloud type from MISR-retrievals, MISR-simulated retrievals from CloudSat/CALIPSO extinction profiles, and directly inferred from the CloudSat/CALIPSO extinction profiles for the month of June 2008. Shown are total, high-topped, mid-topped, and low-topped cloud area. Shading indicates the 95% confidence interval obtained by bootstrap resampling the orbit-by-orbit zonal means.
of high-topped cloud in the North Pacific (closer to the CC-sim results) suggesting that the 10% difference here may be at least partially due to incomplete wind speed correction, but a complete analysis of these errors is not possible until the new product is released.

The mid-topped MISR-simulated cloud area is also in very good agreement with the MISR retrievals, except for mid to high northern latitudes (north of 40 N in January and 50 N in June). Uncertainty bars are large at these latitudes because there is relatively little mid-topped cloud and relatively little ocean area at these latitudes. Nonetheless, it may well be that the MISR simulator is over-estimating the amount of MISR mid-topped cloud at these northern latitudes. The North Pacific is investigated in more detail later in this section.

There are large differences between MISR and CC-sim in the amount of both low-topped and total cloud. The occurrence of MISR low-topped cloud is much larger than CC-sim nearly everywhere except at high northern latitudes in January (north of 40 N) and at high southern latitudes in June (south of about 50 S) where CC-sim low-topped cloud exceeds MISR. This difference in low (and total cloud) area is likely due to differences in the instrument field-of-view or “pixel size”. Because the field-of-view of satellite instruments can be partially filled by clouds, the fraction of satellite pixels containing some amount of cloud (the retrieved cloud fraction) will be larger than the true fractional area covered by clouds, and this difference generally increases as the satellite pixel size is increased (Di Girolamo and Davies, 1997). Of course, satellite retrievals do not perfectly identify partially cloud-filled pixels as cloudy, and there is a partial cancellation of errors which typically results in the satellite-retrieved cloud fraction being closer to the true fractional area covered by clouds than would be produced by a perfect cloud detector with the same resolution (Wielicki and Parker, 1992). This resolution effect is particularly important for the small, broken clouds common in trade-wind cumulus in the subtropical dry zones, but applies to all broken boundary layer clouds (Zhao and Di Girolamo, 2006; Marchand et al., 2010).

The effect that the detection of sub-pixel-sized clouds has on the retrievals is approximated here by creating a new joint radar-lidar cloud mask, modifying the thresholds used to
identify cloudy versus clear profiles from the CloudSat and CALIPSO data. The CALIPSO data are mapped onto the coarser CloudSat grid in such a way that a combined retrieval (which uses the CloudSat grid) is only considered to have a lidar detection if 50% of the CloudSat volume is filled by lidar detections, and so clouds smaller than the 1 km scale of the CloudSat grid are sometimes missed. The joint radar-lidar mask is then constructed by setting CloudSat bins as cloudy if either the CloudSat cloud mask identifies cloud \( \text{CPR}_\text{Cloud\_mask} > 20 \) in the 2B-GEOPROF product or the lidar cloud fraction within that CloudSat bin is greater than 50% \( \text{CloudFraction} > 50 \) in the 2B-GEOPROF-LIDAR product. The sensitivity of the low-level cloud fraction (the fraction of profiles with any cloud below 3 km, not just profiles with cloud tops below 3 km as reported by MISR) to the lidar cloud fraction threshold is quantified here by adjusting the lidar cloud fraction threshold for which a CloudSat “1 km” volume is considered to be cloud to 0% and 10% and comparing the resulting low-level cloud fraction to that obtained using the 50% threshold used in the Mace scheme.

Figure 2.7 shows the zonally-averaged low-level cloud fraction from the joint radar-lidar mask for the same domain used in the MISR analysis (ice-free ocean between -70 to 70 N and between 100 E and -70 E) using the three threshold values for lidar cloud fraction, as well as the differences relative to using the 50% cloud fraction threshold. The domain-averaged difference in low-level cloud area is 12%, and differences in the zonally-averaged low-level cloud area are as high as 22% in the tropical Pacific. Differences are smaller at higher latitudes, and differences in the north Pacific are generally less than 5% cloud area. Nonetheless, this analysis shows there is a very large sensitivity in low-level cloud fraction based on the fraction of lidar-detected clouds kept, and suggests a large resolution dependence on the low-level (and total) cloud area in general. The resolution-driven increase in MISR-retrieved low-topped cloud due to this partially filled pixel problem is likely to be of a similar magnitude, and thus the large differences identified in Figure 2.5 and Figure 2.6 for total and low-topped cloud throughout the low latitudes is very likely due primarily to an overestimation by MISR of the cloud area. Sensitivities to this detection threshold are
Figure 2.7: Joint radar-lidar low-level cloud mask from 2B-GEOPROF and 2B-GEOPROF-LIDAR for different lidar cloud fraction thresholds over the Pacific domain. Height bins are considered “cloudy” if the radar cloud mask (CPR_Cloud_mask in 2B-GEOPROF) has a value greater than 20, or if the lidar cloud fraction (CloudFraction in 2B-GEOPROF-LIDAR) is greater than the selected threshold value (indicated in the legend). Plotted are the zonally averaged fraction of profiles with any cloudy height bins below 3 km (left), and differences relative to the default threshold of 50% (right). Numbers in parentheses in the legend indicate the average over the entire (Pacific) domain.
Figure 2.8: Joint histograms of cloud top height and cloud optical depth over the Pacific domain for January 2008 from MISR retrievals (left), MISR-simulated cloud top height retrievals performed on CloudSat/CALIPSO extinction profiles (middle), and cloud top heights directly inferred from CloudSat/CALIPSO extinction profiles.

much lower in the high latitudes, and the close agreement in total cloud fraction between MISR and CC at high-latitudes in the winter hemisphere demonstrated in Figure 2.5 and Figure 2.6 demonstrates the more horizontally continuous nature of low clouds during the winter season at these latitudes, especially in the southern hemisphere.

Cloud 3D structure and partially-filled satellite pixels are also well-known to affect imager retrievals of cloud optical depth, which are based on 1D radiative transfer and effectively assume homogeneous plane parallel clouds (Yang and Di Girolamo, 2008; Evans et al., 2008).
Figure 2.9: Joint histograms of cloud top height and cloud optical depth over the Pacific domain for June 2008 from MISR retrievals (left), MISR-simulated cloud top height retrievals performed on CloudSat/CALIPSO extinction profiles (middle), and cloud top heights directly inferred from CloudSat/CALIPSO extinction profiles (right).
Figure 2.8 and Figure 2.9 show the cloud top height and optical depth joint histograms for the entire analysis region for January and June 2008, respectively. The MISR retrieved joint histograms have a low-topped ($z_c < 3 \text{ km}$) maximum at low to moderate optical depths ($\tau < 23$), and a mid to high-topped maximum ($5 < z_c < 13 \text{ km}$) at moderate optical depths ($3.6 < \tau < 23$). The CC-sim joint histograms have a similar bimodal structure, but with considerably smaller amounts of cloud with low optical depth ($\tau < 3.6$) and large amounts of cloud with high optical depth ($\tau > 9.4$), consistent with expectations for errors due to partially filled pixels and reliance on 1D radiative transfer (Marchand et al., 2010). The large differences in the CC-dir histograms again illustrate the importance of accounting for the effects of multi-layered and optically thin cloud profiles in the distribution.

Figure 2.10 and Figure 2.11 show marginal histograms of cloud top height ($z_c$) for each of the regions outlined in Figure 2.3 and Figure 2.4. Regionally averaged cloud area by cloud type is summarized for each of these regions in Table 2.1 and Table 2.2 for January and June, respectively. The tables show the regionally averaged cloud area by cloud type for the MISR and CC-sim retrievals, the difference between CC-sim and MISR, and the significance level of the differences calculated using a Welch’s (two-sample, unequal size, unequal variance) Student $t$-test, treating each orbit as an independent sample. With the exception of the California Stratus region, the CC-dir results show large amounts of high-topped clouds in both January and June. Most of this high-topped cloud is optically thin, and the MISR simulator does a reasonable job matching the MISR retrievals. The good agreement between MISR and CC-sim mid and high-topped cloud is also evident in Table 2.1 and Table 2.2, which show that the more broadly defined mid and high-topped categories are in even better agreement than the profiles of cloud top height shown in Figure 2.10 and Figure 2.11, with differences generally less than 5%. The differences in the North Pacific in January may reflect biases due to incomplete wind correction in the MISR CTH-OD V6 product. Differences in the other regions are much smaller than those in the North Pacific (typically less than 5% cloud area) and are generally not statistically significant with respect to sampling.
Figure 2.10: Histograms of cloud top height for January 2008 from MISR retrievals, MISR-simulated cloud top height retrievals performed on CloudSat/CALIPSO extinction profiles, and cloud top heights directly inferred from CloudSat/CALIPSO extinction profiles.
Figure 2.11: Histograms of cloud top height for June 2008 from MISR retrievals, MISR-simulated cloud top height retrievals performed on CloudSat/CALIPSO extinction profiles, and cloud top heights directly inferred from CloudSat/CALIPSO extinction profiles.
Table 2.1: Regional mean cloud area by cloud top height for January 2008 from MISR retrievals and from MISR-simulated retrievals performed on CloudSat/CALIPSO extinction profiles (CC-sim). Also shown are the differences (CC-sim minus MISR) and the significance of the differences calculated using the Student t-test on the orbit-level means.

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</table>

Low-topped differences can be large even when using the simulator to correct for the effects of thin high-topped cloud on the retrievals due to differences in low-level cloud detection between the different observing platforms. This is especially true in the California Stratocumulus, Hawaiian Trade Cumulus, and North Pacific regions (in the NH summer) due to field-of-view issues, but these regions also have large variability in low-topped cloud amount, as indicated by the large sampling uncertainties for low-topped cloud bins in these regions. Table 2.2 shows that low-topped cloud differences in June are largest in the California SC region, where CC-sim low-topped cloud amount (using the 50% lidar cloud fraction threshold as discussed above in the context of Figure 2.7) is lower than MISR by 15% cloud area. While this region is well known for its extensive low cloud, this cloud often displays considerable spatial structure and broken cloudiness. Klein and Hartmann (1993) found using ship-based observer reports (following Warren et al., 1986, 1988) that low (stratus) cloud cover in this region can exceed 60% cloud area in summer months, reaching a peak value of 67%. This is consistent with the low-topped cloud cover found here from MISR retrievals. Low-topped cloud amounts are lower in this region in January, and the differences are much smaller and are not statistically significant with respect to sampling.
Table 2.2: Regional mean cloud area by cloud top height for June 2008 from MISR retrievals and from MISR-simulated retrievals performed on CloudSat/CALIPSO extinction profiles (CC-sim). Also shown are the differences (CC-sim minus MISR) and the significance of the differences calculated using the Student $t$-test on the orbit-level means.

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### Region Type MISR CC-sim Diff p-value Significance

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<th>CC-sim</th>
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<th>p-value</th>
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<td>81.5</td>
<td>2.7</td>
<td>0.024</td>
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</table>

### 2.5 Diurnal variations in cloud cover

Some of differences discussed in the previous section between MISR and CC-sim may arise due to diurnal differences in the true cloud height or cloud area since MISR overpass times (on the Terra platform; 10:30 AM local equatorial crossing time) are roughly three hours different (at the equator) than CloudSat and CALIPSO (in the A-train constellation; 3:30 PM local equatorial crossing time). There are MODIS instruments on both the Terra and Aqua (which is also in the A-train constellation) satellites, and in this section retrievals from the MODIS Terra and Aqua sensors are compared in order to provide a measure of the differences in cloud properties between the two overpass times. Of course, some of the difference between MODIS Terra and Aqua cloud cover may be due to differences in the sensors and their performance, but these are thought to be small (King et al., 2013). King et al. (2013) use this strategy to evaluate diurnal differences in cloud cover by comparing 12 years of MODIS Terra (MOD35) and 9 years of MODIS Aqua (MYD35) cloud masks. They find cloud cover over ocean is in general slightly greater in the Terra retrievals than in those from Aqua, suggesting a decrease in cloud cover from the morning to afternoon overpass. King et al. (2013) show that differences between Terra and Aqua are largest in regions dominated by coastal marine stratocumulus, and Terra to Aqua differences approach 20% cloud cover in the Peruvian and Angolan stratocumulus regions from September to February. However, zonal average differences are much smaller, and global averages agree
to within 5% cloud cover between Terra and Aqua. Meskhidze et al. (2009) similarly look at differences between Aqua and Terra liquid cloud amount and likewise find a reduction in both cloud amount and cloud optical depth in stratocumulus (and trade wind cumulus) regions between the morning and afternoon overpasses, with differences in the Peruvian and South African stratocumulus on the order of 20% cloud cover during the months of December to February. These results are consistent with the diurnal cycle in cloud amount expected from both modeling studies and field campaign studies, which show that cloud cover reaches a maximum in the early morning and decreases throughout the day, reaching a minimum in the early afternoon (Bretherton et al., 2004).

Terra to Aqua differences reported in King et al. (2013) and Meskhidze et al. (2009) for the regions studied here are more modest. King et al. (2013) show differences in June-July-August total cloud cover for the California Stratus region are about 10%, and differences in the North Pacific for these months is much less than 5%. Nonetheless, these differences in cloud cover are non-trivial, and are of the correct sign to explain at least some of the differences between MISR and CC-sim low cloud cover shown in the previous section.

Figure 2.12 and Figure 2.13 show zonally-averaged MODIS total, high-topped (cloud top pressure $p_c < 440$ hPa), mid-topped (440 < $p_c$ < 680 hPa) and low-topped ($p_c > 680$ hPa) cloud area using data from 12 years (2003 to 2014) and restricted to ocean areas in the Pacific analysis region shown in Figure 2.3 and Figure 2.4 for the months of January and June, respectively. The zonal mean total cloud cover (bottom right panels) are nearly indistinguishable between the Terra and Aqua retrievals (less than 2% cloud cover difference throughout most of the domain), and the small differences that do exist in total cloud cover are not statistically significant with respect to sampling. There are, however, noticeable differences between the Terra and Aqua low and mid-topped cloud cover, with the Terra mid-topped cloud cover being larger than Aqua. The differences are significant in the sense that they are larger than could be explained by sampling (as represented by the error bars showing the 95% confidence interval). The differences in mid-topped and low-topped zonal mean cloud area are a bit less than 6% and 5%, respectively, but this is comparable to the
Figure 2.12: January climatology of zonally-averaged cloud area from MODIS Terra and Aqua over the Pacific domain. Shading indicates 95% confidence interval obtained by bootstrap resampling individual monthly-means.
Figure 2.13: June climatology of zonally-averaged cloud area from MODIS Terra and Aqua over the Pacific domain. Shading indicates 95% confidence interval obtained by bootstrap resampling individual monthly-means.
difference between MISR retrieved and MISR-simulated mid-topped cloud amount found in Section 2.4, which suggests this difference may be near the limit of agreement that one should expect given our evaluation approach.

2.6 Summary and discussion

Increasingly, satellite instrument simulators are being used in model evaluation studies to account for known features, limitations, or errors in individual satellite retrievals (Webb et al., 2016). However, not all such errors or ambiguities have been (or likely can be) removed by this approach (Pincus et al., 2012; Mace et al., 2011), and critical evaluation of the simulators themselves is of the utmost importance if the simulator framework is to be used to quantify biases between satellite-retrieved and model-simulated cloud properties. This chapter presents an evaluation of the MISR simulator by comparing MISR retrievals to MISR-simulated retrievals based on extinction profiles derived from a combination of CloudSat, CALIPSO, and MODIS observations.

The results in this chapter show that mid and high-topped cloud cover is in good agreement between MISR and MISR-simulated retrievals from CC. Global, zonal and regionally-averaged mid and high-topped cloud cover differences are typically small (on the order of 5% cloud cover or less) and not statistically significant with respect to sampling. Marginal histograms of cloud top height capture the main features of the cloud top height distribution, including the altitude of peaks in cloud top height. The most notable exception to this is high-topped cloud amounts in the winter hemisphere poleward of 50 degrees, where differences are closer to 10% cloud area. It is expected that this problem will be at least reduced in the next release (Version 7) of the MISR CTH-OD dataset. An analysis of Version 7 results is not yet possible and will be the focus of future research for the MISR Science Team.

Uncertainties in low-topped cloud remain large in this comparison, with differences between MISR and CC-sim between 5 and 15% cloud area for the specific regions studied here, and with differences in MISR and CC-sim zonal means often exceeding 10% cloud area. This is likely due to differences in detection of partially filled cloudy pixels (sensor field-of-views)
between MISR and CC, rather than being indicative of a problem with the MISR simulator. Nonetheless, these errors need to be considered when comparing model-simulated cloud area with MISR-retrieved cloud area, as the MISR-retrieved cloud area is likely biased high in regions occupied by small broken boundary-layer clouds. This bias is of the correct sign to explain at least some (though certainly not all) of the ubiquitous “biases” in low-level cloud amount in current global climate models as compared with retrievals from MISR, ISCCP, and MODIS (e.g., Zhang et al., 2005; Pincus et al., 2012; Kay et al., 2012; Klein et al., 2013).

Differences in the full cloud top height and optical depth joint histograms for the whole domain have an absolute error of 4% or less for any particular cloud-type ($z_c$-$\tau$ bin). For comparison, M2011 looked at coincident ISCCP and ISCCP-simulated retrievals derived from ARM SGP data, and report absolute errors in the coarsened 9-bin ISCCP histograms that are typically under 4% as well, but can be as high as 8% for low, optically thick clouds (see Figure 4 in M2011). Much of the difference between the MISR-retrieved (or ISCCP-retrieved) joint histogram and that obtained from the simulator (using CC retrievals as input) is due to a systematic trend toward higher values of cloud optical depth in the CC retrieval than in MISR (or ISCCP) retrievals. While for low clouds the effect of sensor resolution and 3D effects on visible radiances may explain much or most of the difference, the situation is less clear for high and mid-level clouds, which tend to occur on larger horizontal scales. While 3D effects may still be significant for high and mid-level clouds, other factors may also be important. In particular, retrievals of optical depth from radar and lidar may be prone to overestimate optical depth for a variety of reasons including the strong sensitivity of radar to precipitating particles (which makes retrieval of small or non-precipitating particles that usually dominate the visible-extinction difficult and uncertain), especially at temperatures where both ice and water condensate may exists.
Chapter 3

QUANTIFYING SENSITIVITIES OF SATELLITE-SIMULATED CLOUD RETRIEVALS TO UNRESOLVED CLOUDS AND PRECIPITATION

The simulator framework is essentially a technique to account for uncertainties, biases, and limitations in satellite retrievals of cloud properties in order to make more consistent comparisons with modeled cloud properties. However, because the descriptions of clouds in GCMs are themselves limited and insufficient for directly simulating the satellite retrievals, the process of simulating satellite retrieval products relies on additional assumptions about the model clouds beyond the descriptions provided by the models themselves. This introduces another layer of complexity and another possible source for errors or ambiguities.

At the heart of this problem is the fact that while cloud properties in the physical atmosphere vary at all spatial scales down to (and below) those measured by satellite sensors, the current resolution of most global climate models is limited by computational expense and model infrastructure to about a hundred kilometers. For example, climate model simulations produced for the latest round of the Climate Model Intercomparison Project (CMIP5) and referenced in the Intergovernmental Panel on Climate Change (IPCC) AR5 used grids with typical resolutions of 1 to 2 degrees (Flato et al., 2013), which translates to about 100-200 km at the equator. Because of these coarse-scale grids, current large-scale models cannot explicitly resolve individual cloud elements at the scales observed by satellites (1-2 km for the MISR and CloudSat retrievals used predominantly in this study), but rather must rely on (often empirically-based) statistical parameterizations about the nature of clouds at these larger scales that summarize the aggregated properties of the smaller scales (Randall et al., 2003).
The relatively coarse resolution of GCMs is problematic because the gridbox-mean description of clouds implies a distribution of possible simulated retrievals within each gridbox (Pincus et al., 2012). The gridbox mean description of clouds does not in itself specify how the clouds should be distributed horizontally and vertically within model gridboxes, and thus 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.

The importance of unresolved cloud properties is not unique to the problem of simulating satellite retrievals, but is more generally important to the problem of calculating radiative fluxes and heating rates within models. This is due to the fact that radiative fluxes are non-local. That is, the radiative flux resulting from a combination of two cloud layers depends on the degree to which those two layers overlap vertically. Radiative transfer parameterizations in large-scale models typically account for the overlapping nature of clouds from partly cloudy layers by appropriately weighting clear and cloudy-sky flux calculations to satisfy a specific overlap assumption. These overlap assumptions are necessarily simply defined, and have included random overlap, in which clouds in different vertical layers are assumed to be completely uncorrelated, maximum overlap, in which clouds in different layers are assumed to be perfectly correlated (or “lined up”), and the popular maximum-random overlap, in which clouds in adjacent cloudy (or continuous) layers are maximally overlapped and clouds in layers separated by at least one clear layer are randomly overlapped (Geleyn and Hollingsworth, 1979; Tian and Curry, 1989). The maximum-random overlap in particular has been used in a number of GCMs (e.g., Collins et al., 2004; Neale et al., 2010a,b). That different overlap assumptions can significantly affect simulated radiative quantities is well established (e.g., Morcrette and Fouquart, 1986; Stubenrauch et al., 1997; Barker et al., 1999), and these overly simple assumptions have been shown to be insufficient in capturing the complexity of cloud overlap seen in observations (Hogan and Illingworth, 2000; Mace and Benson-Troth, 2002; Barker, 2008). Sensitivity tests using high resolution model simulations have shown that these unrealistic overlap assumptions can lead to instantaneous errors in
calculated fluxes in excess of 50 W/m² (Barker et al., 1999; Wu and Liang, 2005), suggesting that a more realistic treatment of cloud overlap should be sought for inclusion in GCMs. Additionally, horizontal variability on model gridbox scales is important in the calculation of radiative fluxes, but subgrid-scale horizontal variability in cloud condensate is often completely neglected in GCMs, despite the fact that clouds can exhibit large horizontal 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 flux errors due to unresolved horizontal cloud variability in excess of 100 W/m², and Oreopoulos et al. (2012) demonstrate global cloud radiative effect errors on the order of 5 W/m², with much larger regional errors. The sensitivity to both cloud overlap and condensate horizontal variability emphasizes the need to provide descriptions of clouds in large-scale model radiative calculations that include both horizontal variability in cloud properties and more realistic cloud overlap.

An alternative to the approach of weighting clear and cloudy sky fluxes is to generate stochastic samples of binary clear or cloudy “subcolumn” profiles, in which each subcolumn element has either unit or zero cloud fraction, and in the limit if many such samples the gridbox-mean partial cloudiness profile is reproduced and the subcolumn profiles are consistent with an assumed overlap. This approach, described by Klein and Jakob (1999) to generate stochastic subcolumns for use with the ISCCP simulator, provides pseudo-resolved cloud fields sufficient for not only simulating satellite retrievals, but also for performing radiative transfer calculations using the independent column approximation (ICA; Cahalan et al., 1994). Pincus et al. (2003) made this approach for calculating fluxes and heating rates much more tractable for use in large-scale models by introducing the Monte Carlo Independent Column Approximation (McICA), in which both cloud state (subcolumns) and spectral interval are stochastically sampled simultaneously, drastically reducing the computational burden associated with integrating calculations over a large number of spectral intervals for
each column. This allows for fast ICA-like radiative transfer calculations (at the expense of artificially increased random noise) and more flexible representations of subgrid-scale cloud structure, and has since 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,b; 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,b). Improved subcolumn schemes are needed to take full advantage of the flexibility offered by McICA.

The first step in simulating satellite retrievals from GCM output is to downscale the gridbox-mean quantities to scales approximating those at which the actual satellite retrievals are performed. In COSP, this is done by generating stochastic subcolumns following Klein and Jakob (1999), analogous to how subcolumns are generated for McICA, following the simple overlap assumptions described above with horizontally homogeneous cloud condensate. Horizontal variations in cloud and precipitation condensate amount are neglected because clouds are often treated as horizontally homogeneous in GCM radiative transfer calculations. Thus, the subcolumn generator in COSP is primarily a means to account for subgrid-scale variability in cloud occurrence overlap, but neglects to treat subgrid-scale variability in cloud condensate amount. Because many GCMs assume maximum-random overlap for radiative transfer calculations, maximum-random overlap is the default used in COSP (although COSP does include options to use random or maximum overlap as well). To the extent that the simulated satellite retrievals are sensitive to these assumptions, failing to accurately characterize the subgrid cloud structure (overlap) and condensate variability potentially introduces ambiguities into satellite-model comparisons. The sensitivity of the satellite-simulated cloud
properties to assumptions about unresolved cloud and precipitation are quantified here, and a framework for reducing errors due to these assumptions is presented in Chapter 4.

3.1 Generating stochastic subcolumns of cloud and precipitation

The individual instrument simulators in COSP require profiles or columns of cloud and precipitation in which cloud and precipitation fraction is either zero or one at each level, i.e., profiles of binary cloud and precipitation occurrence (Bodas-Salcedo et al., 2011). Because large-scale models do not resolve clouds, profiles of resolved cloud and precipitation occurrence must be inferred using an ensemble of subcolumns for each model gridbox. These subcolumns can be provided to COSP by the model if available, as may be the case if the model uses such subcolumns elsewhere in the code, such as in an implementation of McICA for calculating radiative fluxes as described above. But, if such subcolumns are not available, COSP contains code for generating subcolumns itself using the model large-scale (gridbox) mean profiles of cloud fraction and condensate amounts together with a specified overlap assumption. The overlap can be one of maximum, random, or maximum-random and should be selected to be consistent with the assumption used in the model radiative transfer calculations.

Generating stochastic subcolumns of cloud and precipitation properties is itself a multi-step process. First, stochastic subcolumns of binary cloud occurrence are generating using the Subcolumn Cloud Overlap Profile Sampler (SCOPS), described conceptually by Klein and Jakob (1999) and Webb et al. (2001). SCOPS can generate subcolumns obeying random, maximum, or maximum-random overlap, and can separately treat convective and stratiform cloud if such a distinction is made in the model. If the model distinguishes between convective and stratiform cloud, convective cloud is maximally overlapped and the remaining stratiform cloud may follow a separate overlap assumption (one of random, maximum, or maximum-random). SCOPS takes as input the gridbox-mean total cloud fraction profile $\bar{c}_k$ (the fraction of the gridbox at each level $k$ containing either stratiform or convective cloud) and the gridbox-mean convective cloud fraction profile $c_{conv}^k$ and then outputs an ensemble of $n_{col}$
binary subcolumn cloud occurrence profiles \( c_{i,k} \), where for each subcolumn \( i \) and at each level \( k \),

\[
c_{i,k} = \begin{cases} 
0 & \text{if subcolumn is clear} \\
1 & \text{if subcolumn is stratiform cloud} \\
2 & \text{if subcolumn is convective cloud}
\end{cases}
\]

Following the generation of subcolumn cloud occurrence profiles, subcolumn binary precipitation occurrence profiles are generated following the algorithm described by Zhang et al. (2010) and implemented in the PREC.SCOPS routine within COSP. PREC.SCOPS takes as input the subcolumn cloud occurrence (stratiform and convective) as determined by SCOPS and either the gridbox-mean precipitation condensate amount (mixing ratio) or the gridbox-mean precipitation fluxes. Again, PREC.SCOPS handles large-scale (resulting from stratiform cloud) and convective precipitation separately if the model distinguishes between the two. The approach works as follows. The algorithm steps down through model levels from the top of the atmosphere to the surface. At a given altitude where the domain-mean large-scale precipitation is non-zero, the precipitation is first assigned (and will be equally divided) across all subcolumns that have stratiform cloud (as determined by SCOPS) in the current level or large-scale precipitation in the level above. If large-scale precipitation is non-zero but there are no columns which meet either of these two criteria, the algorithm assigns precipitation to all subcolumns with stratiform cloud in the level below. Failing this, the precipitation is assigned to all subcolumns with stratiform cloud anywhere in the vertical column. If large-scale precipitation has still not been assigned by any of these criteria, it is assigned to all subcolumns in the current level. Most of the time, the first rule is sufficient to place the stratiform precipitation. This procedure is repeated for convective precipitation (replacing stratiform in the above rules with convective cloud), but in the case that precipitation is not assigned by the first four criteria it is assumed to only cover 5% of the subcolumns for convective precipitation, as opposed to filling all subcolumns in the case of large-scale precipitation.
Once subcolumn profiles of binary cloud and precipitation occurrence have been generated, condensate amounts (mixing ratios) are assigned to the cloudy and precipitating elements. The current implementation in COSP assumes a constant in-cloud (and in-precip) condensate mixing ratio at each level within each gridbox, so that each subcolumn at a given level within a gridbox is assigned the same in-cloud (or in-precip) condensate mixing ratio.

The in-cloud condensate mixing ratio for a specific hydrometeor type (i.e., stratiform cloud liquid, stratiform cloud ice, convective cloud liquid, or convective cloud ice) $\tilde{q}_k$ at level $k$ is calculated from the gridbox mean mixing ratio $\bar{q}_k$ by dividing the gridbox-mean condensate mixing ratio by the fraction of subcolumns containing cloud of that type (stratiform or convective) at that level, $a_k = \sum_{i=1}^{n_{col}} c'_{i,k} / n_{col}$, where $c'_{i,k}$ is the subcolumn binary cloud occurrence for the particular hydrometeor type ($c' = 1$ where either $c = 1$ for stratiform or $c = 2$ for convective, and $c' = 0$ otherwise) and $n_{col}$ is the number of subcolumns, so that

$$\tilde{q}_k = \bar{q}_k / a_k$$

This is then repeated for precipitation, using the precipitation subcolumn profiles generated by PREC_SCOPS.

The precipitation treatment described above associates precipitation with cloud, but fails to account for any estimate of precipitation fraction (the fraction of the gridbox that contains precipitation at any level) that may be diagnosed by the model. Furthermore, the precipitation treatment essentially assumes that once precipitation is diagnosed at a particular level in a subcolumn, it falls all the way down to the surface unless a precipitation-free layer (that is, a layer in which gridbox-mean condensate is equal to zero) is encountered. This can lead to a gross over-estimation of the number of precipitating subcolumns and, consequently, a gross over-estimation of the occurrence of large values of simulated radar reflectivity factor (the increase in radar reflectivity is mitigated somewhat by spreading the in-precipitation mean over a larger area, but this effect is secondary to the overestimate in precipitation occurrence). An adjustment to the subcolumn precipitation occurrence is added here, following the work of Di Michele et al. (2012), in which subcolumn precipitation
is either added or removed at each level until the fraction of subcolumns with precipitation at a given level matches the input precipitation fraction. Precipitation is added preferentially to columns with more (vertically integrated) cloudy levels, and removed preferentially to columns with less cloudy levels. This is similar to the “PEVAP” adjustment described by Di Michele et al. (2012), and the improvement to simulated radar reflectivity in response to this adjustment will be evaluated.

### 3.2 Framework for sensitivity tests

The simulation process assumes that gridbox-mean profiles of cloudiness and condensate are provided as inputs; however, the modular structure of COSP enables bypassing the sub-column generation step if resolved condensate fields with sufficiently high resolution (that approximate the scales at which the actual retrievals are performed) are available. This is done when using COSP with a cloud-resolving model (Marchand et al., 2009; Marchand and Ackerman, 2010). Using inputs with resolved cloud properties then enables testing arbitrary assumptions about small-scale variability and overlap simply by obtaining or creating condensate fields with differing properties, passing these directly to the individual simulator routines, and comparing the COSP-simulated outputs. A similar approach has been used by previous investigators to quantify sensitivities in radiative fluxes and heating rates using cloud-resolving models to provide the initial high resolution fields, and then modifying those fields to mimic large-scale model assumptions (Barker et al., 1999; Wu and Liang, 2005). In order to evaluate how assumptions about unresolved variability affect cloud diagnostics at both regional and global scales, a larger set of inputs is sought for this study, ideally, a set of cloud and precipitation fields with global coverage.

In the Multi-scale Modeling Framework (MMF; Randall et al., 2003) the convection and cloud parameterizations in a traditional GCM are replaced by a cloud-resolving model running within each model grid box. This concept was first implemented into the National Center for Atmospheric Research (NCAR) Community Atmosphere Model (CAM) using the System for Atmospheric Modeling (SAM) as the cloud resolving model (SP-CAM; Khairout-
dinov and Randall, 2001), but has also been implemented with a completely different GCM and CRM (Tao et al., 2009) and with a variety of different schemes for handling turbulence, clouds, and aerosols (e.g., Cheng and Xu, 2011, 2013). MMF model output provides sufficiently high resolution (approximating satellite fields of view) cloud and precipitation properties within each gridbox to run the simulators within COSP without using a subcolumn generator, and also provides the global coverage necessary to evaluate the impact of modifying the inputs on both the global and regional diagnostics typically used to evaluate the performance of clouds in global climate models (e.g., Gleckler et al., 2008). For this chapter, a single month (simulated July 2000) of 3-hourly output from the SP-CAM (version 3) is used to derive the inputs to the COSP simulators. The model was run using an east-west oriented 2-dimensional cloud-resolving model with 64 columns, a 4 km horizontal resolution with 26 vertical levels, and single moment bulk microphysics scheme. Further details of the model configuration are given by Khairoutdinov et al. (2005) and Marchand et al. (2009).

In order to separately evaluate the sensitivity of the COSP diagnostics to occurrence overlap and condensate heterogeneity, three versions of modified cloud and precipitation fields with incremental changes are created from the original CRM fields output from SAM running within SP-CAM. These modifications are described below; total cloud and precipitation condensate amounts for each modification are shown in Figure 3.1 for an example grid-box (00 UTC 01 July 2000, 10 N, 180 E) along with the original, unmodified CRM fields (top row in the figure).

First, a set of fields with homogenized condensate (referred to as “CRM-HOM”) is created by replacing the condensate amount in each cloudy CRM column in each gridbox with the gridbox in-cloud average (for each level). This is repeated for precipitation, and is done separately for each hydrometeor type (cloud liquid, cloud ice, precipitating liquid, precipitating ice). No change is made to the spatial (horizontal or vertical) location of cloud and precipitation or how cloud and precipitation overlap with one another, so this modification retains the exact cloud and occurrence overlap from the original CRM.

A second set of modified fields (referred to as “MRO-HOM”) is created by first calculating
Figure 3.1: Total cloud (left) and precipitation (right) mixing ratios from the original CRM fields (top), homogenized CRM fields (CRM-HOM, second row), regenerated using SCOPS and PREC_SCOPS (MRO-HOM, third row), and regenerated using SCOPS and PREC_SCOPS with precipitation adjusted to conform to the precipitation fraction from the CRM (MRO-HOM-PADJ, bottom row) for an example gridbox (00 UTC 01 July 2000, 10 N, 180 E).
the gridbox mean cloud fraction and cloud and precipitation condensate profiles (similarly to how a GCM would represent the clouds) and then regenerating cloud and precipitation subcolumns using SCOPS and PREC_SCOPS with maximum-random cloud overlap and homogeneous condensate, as described above. Because the embedded CRM in SP-CAM (SAM) does not distinguish between stratiform and convective cloud and precipitation, all cloud and precipitation is passed to SCOPS and PREC_SCOPS as if it were stratiform.

The simulators for the passive remote sensing instruments ISCCP, MODIS, and MISR take as input only the cloud properties, but CloudSat radar reflectivity is extremely sensitive to the presence of precipitation (because radar reflectivity depends on the sixth moment of the particle size distribution), and thus the treatment of precipitation is critical to the accurate simulation of radar reflectivity. The lack of a constraint in the PREC_SCOPS algorithm on the fraction of columns that are determined to be precipitating can lead to a gross over-estimation of precipitation occurrence. This is evident from Figure 3.1 for the example gridbox shown, and this leads to especially large errors in simulated CloudSat radar reflectivity and diagnostics calculated from it.

Precipitation fraction is easily calculated from the CRM fields in the SP-CAM model output used in this study. This enables the simple modification to the regenerated subcolumn precipitation condensate to force the fraction of precipitating subcolumns at any level within a gridbox to match the fraction of precipitating CRM columns at that level in the baseline CRM fields. An additional set of modified fields is created from the original CRM fields (referred to as “MRO-HOM-PADJ”) using SCOPS with MRO, homogeneous cloud and precipitation condensate, and this precipitation adjustment. This adjustment substantially reduces the errors in simulated CloudSat radar reflectivity (see Figure 3.8 and Figure 3.10).

The sensitivities of the COSP diagnostics to occurrence overlap, condensate subgrid-scale heterogeneity, and precipitation treatment can be separately quantified by calculating appropriate differences between the cases. Because the CRM-HOM case shares the exact occurrence overlap with the original CRM fields but uses homogenized condensate, differences in the COSP diagnostics between them show the sensitivity of the COSP diagnostics to the
assumption of homogeneous cloud and precipitation condensate. Because the MRO-HOM-PADJ fields share the same homogeneous condensate profiles as the CRM-HOM fields but with maximum-random occurrence overlap, differences between them show the additional impact of assuming maximum-random cloud occurrence overlap. Differences between MRO-HOM and MRO-HOM-PADJ show the impact of constraining precipitation fraction. Lastly, the differences between MRO-HOM and CRM cases show the total error due to using homogeneous cloud and precipitation condensate and maximum-random overlap with the default PREC_SCOPS precipitation treatment (i.e., the GCM-equivalent errors expected using both MRO and homogeneous condensate). Symbolically, for a COSP-simulated pseudo-retrieved quantity \(X\) (e.g., MISR cloud top height), the total error in using the subcolumn generator \(E_{\text{total}}\), the component of the error due to using homogeneous condensate \(E_{\text{hom}}\), the component of the error due to the overlap assumption \(E_{\text{mro}}\) and the component of the error due to the precipitation treatment \(E_{\text{precip}}\) are calculated as

\[
E_{\text{total}} = X_{\text{MRO-HOM}} - X_{\text{CRM}} \\
E_{\text{hom}} = X_{\text{CRM-HOM}} - X_{\text{CRM}} \\
E_{\text{mro}} = X_{\text{MRO-HOM-PADJ}} - X_{\text{CRM-HOM}} \\
E_{\text{precip}} = X_{\text{MRO-HOM}} - X_{\text{MRO-HOM-PADJ}}
\]

Note here that the sum of all of the components is equal to the total error, that is, \(E_{\text{total}} = E_{\text{hom}} + E_{\text{mro}} + E_{\text{precip}}\).

In order to more easily evaluate the properties of the modified fields, and to ensure a consistent treatment for each case, the modified cases are created outside of the COSP software infrastructure, and then fed into COSP via a standalone driver program. COSP is intended to be implemented directly into the source code of a model, but a minimal driver program capable of reading in archived large-scale model output in netCDF format and saving COSP outputs in CMOR-compliant netCDF files is distributed with the COSP source code. In order to run COSP on the SP-CAM output used in this study, this minimal example program was substantially rewritten and modularized, resulting in a stand-alone
Fortran 90 program that can read standard history files from SP-CAM and write COSP outputs in CMOR-compliant format as well.

3.3 Sensitivity of simulated passive remote sensing diagnostics

The MISR, ISCCP, and MODIS simulators estimate the cloud top heights (or cloud top pressures, in the case of ISCCP and MODIS) that would be retrieved by each instrument from the model input. These cloud top heights are aggregated together with the column cloud optical depth into joint histograms consistent with those produced by the individual instrument teams. These diagnostic summaries provide a description of cloud occurrence tied to their radiative impact, because the height of cloud top affects top of atmosphere outgoing longwave emission (and heating of the surface and atmosphere below the cloud top) and the optical depth or brightness of clouds affects the reflectance of shortwave energy to space (and cooling of the surface and atmosphere below cloud top). Cloud area for specific cloud types can be calculated from these joint histograms by summing appropriate bins in the joint histograms.

Figure 3.2 shows MISR-simulated monthly-mean total (optical depth $\tau > 0.3$), high-topped (cloud top height $z_c > 7$ km, $\tau > 0.3$), mid-topped ($3 < z_c < 7$ km, $\tau > 0.3$), and low-topped ($z_c < 3$ km, $\tau > 0.3$) cloud area simulated from the baseline CRM, CRM-HOM, and MRO-HOM cases. The spatial patterns and global means are similar between each of these cases, and global mean values agree to within 4% cloud area for all cloud types. While the differences in the global means appear small, it should be noted that this is on the order of the uncertainty in comparisons between MISR retrievals and MISR-simulated retrievals using CloudSat and CALIPSO-derived extinction profiles, as shown in Chapter 2.

Large regional errors emerge when differences are calculated, and when those differences are broken into components due to homogenizing the clouds and to the treatment of cloud occurrence overlap following the framework described in Section 3.2. Figure 3.3 shows the total error in regenerating condensate from gridbox-means using SCOPS and PREC_SCOPS (outputs from MRO-HOM minus outputs from CRM, left column), as well as the components of
Figure 3.2: From top to bottom, MISR-simulated total, high-topped, mid-topped, and low-topped cloud area using the (from left to right) CRM, CRM-HOM, and MRO-HOM fields as input to COSP.
Figure 3.3: Errors in MISR-simulated cloud area by cloud type for (from top to bottom) total, high-topped, mid-topped, and low-topped clouds. Shown are (from left to right) the total error in using SCOPS and PREC_SCOPS with homogeneous cloud condensate, the component of the error due only to homogenizing the condensate, and the component of the error due only to using SCOPS to regenerate subcolumns with maximum-random overlap.
these errors due separately to homogenizing the cloud condensate within each gridbox (HOM errors; CRM-HOM minus CRM, middle column), and using the maximum-random overlap assumption to re-generate subcolumns from the grid-box means (MRO errors; MRO-HOM minus CRM-HOM, right column). Errors in MISR-simulated total cloud area due to homogenizing the cloud and precipitation condensate (top row, middle panel) are everywhere positive. By homogenizing the cloud condensate, the total number of CRM columns that contain cloud condensate has not actually been changed, nor have those columns been re-arranged in any way. Rather, the increase in the simulated total cloud area is explained in terms of how “cloud” is defined using the MISR simulator outputs. In order to make more reasonable comparisons with satellite observations, which have finite detection capabilities, columns are considered cloudy only if the total column optical depth exceeds some threshold value, nominally $\tau > 0.3$. Homogenizing the condensate changes the distribution of optical depth. This happens because CRM columns with low condensate amounts (and thus lower resulting optical depths) often occur alongside columns with larger condensate amounts within the same gridbox, such that taking the average results in a squeezing of the distribution of condensate (less occurrence in the tails of the distribution and more near the mode), so a greater number of columns exceed the optical depth threshold. This effect is illustrated in Figure 3.4, which shows the distribution (histogram) of cloud optical depth for a single time-step of SP-CAM output. The increase in total cloud area due to this effect is modest, and only results in an increase of 2% cloud area in the global mean and regional errors on the order of 4-6% cloud area (Figure 3.3). These errors (and all errors discussed in this text) are absolute errors rather than relative errors; for example, in this case the homogenization results in an increase in the global-average cloud area from about 53% to 55%, for an absolute error of 2% cloud area. Errors due to this effect are larger for the diagnosis of high-topped cloud area, and can exceed 8-10% cloud area in the deep tropics, especially over the tropical warm pool region over the Maritime Continent and over the Indian Ocean. These regions are dominated by deep convective cloud systems with associated cirrus that often have very low optical depths. This situation is especially conducive to the effect illus-
Figure 3.4: Marginal (global) histogram of cloud optical depth from the CRM and CRM-HOM cases for a single SP-CAM snapshot.

trated in Figure 3.4, due to the increased likelihood of averaging columns with optical depths that would be below the threshold with those having much larger optical depths.

Figure 3.4 suggests that homogenizing cloud condensate increases not only the total cloud area relative to the baseline simulation, but also the diagnosis of optically thick cloud area (defined here as those gridboxes with column optical depth $\tau > 23$). That models tend to overestimate the occurrence of optically thick clouds (at the expense of underestimating the occurrence of cloud as a whole) is a commonly identified model “bias” often referred to as the “too few, too bright” problem (Zhang et al., 2005; Nam et al., 2012; Kay et al., 2012; Klein et al., 2013), but these results here suggest that at least part of this difference might
be explained simply by treating unresolved clouds as horizontally homogeneous. Figure 3.5 shows errors in optical thick cloud area, analogous to Figure 3.5. While it is clear that optically thick cloud is increased by homogenizing cloud condensate, the increase is mostly balanced by a corresponding decrease in optically thick cloud due to implementing MRO.

While errors due to homogenizing cloud condensate are primarily positive, the errors in total cloud area due to the maximum-random overlap assumption are negative nearly everywhere, showing that implementing maximum-random overlap tends to decrease the total vertically projected cloud area (top right panel of Figure 3.3). The decrease in cloud area is a result of the maximum-random overlap assumption tending to overestimate the vertical correlation in adjacent cloudy layers (e.g., Mace and Benson-Troth, 2002; Hogan and Illingworth, 2000; Barker, 2008). The decrease is only 3% cloud area in the global mean, but can reach values exceeding 10% regionally, especially in the tropics. The decrease is largest for the low-topped cloud area. This is easily interpreted as increased “shielding” of low-topped (and mid-topped) clouds by high-topped clouds due to the increased vertical correlation introduced using maximum-random overlap, such that low-topped clouds tend to more frequently exist beneath high-topped clouds. This has a minimal affect on the high-topped cloud area, and in fact high-topped cloud area actually increases slightly throughout some regions in middle to high latitudes. This is because the MISR simulator emulates the tendency for MISR to “see through” optically thin upper cloud layers and retrieve cloud top heights of optically thicker lower cloud layers when low-level clouds are present. Because increasing vertical correlation of cloudy layers tends to increase the cloud water path (and hence the cloud optical depth of those combined layers), the MRO assumption can inflate the high-topped cloud area by increasing the number of columns where the high-level cloud optical depth exceeds the threshold $\tau > 1$ (which MISR does not see through).

The errors in MISR-simulated cloud area due separately to homogenizing cloud condensate and using MRO are mostly compensatory in regards to total cloud cover, but produce noteworthy errors in high, middle, and low-topped cloud area. The effect on simulated high-topped clouds due to the two components of the error are both positive in sign, so that these
Figure 3.5: Errors in MISR-simulated optically thick cloud area ($\tau > 23$) by cloud type for (from top to bottom) total, high-topped, mid-topped, and low-topped clouds. Shown are (from left to right) the total error in using SCOPS and PREC,SCOPS with homogeneous cloud condensate, the component of the error due only to homogenizing the condensate, and the component of the error due only to using SCOPS to regenerate subcolumns with maximum-random overlap.
components of the error combine to produce much larger errors in simulated high-topped cloud, with almost a 5% cloud area increase in the global mean and an increase greater than 10% cloud area throughout much of the deep tropics. In regard to the total cloud area, the errors in high-topped cloud area are mostly compensated by a decrease in low-topped cloud, caused primarily by the errors due to using maximum-random overlap. The result is a decrease in simulated low-topped cloud of 4% cloud area in the global average that, combined with the 2% cloud area decrease in mid-topped clouds, nearly completely compensates the increase in high-topped cloud area.

Figure 3.6 shows errors in ISCCP-simulated cloud area by cloud type. These errors are similar to the errors shown in Figure 3.3 for the MISR simulated cloud area by cloud type, with again an overestimation of total and high-topped cloud area due to homogenizing cloud condensate and an underestimation of total and low-topped cloud area due to using maximum-random overlap. The errors in high-topped cloud area due to homogenizing condensate are similar to the errors in the MISR-simulated cloud area. The errors due to using MRO are somewhat different between the ISCCP and MISR-simulated high-topped cloud area; the MISR-simulated high-topped cloud area increased somewhat in some regions, but ISCCP-simulated high-topped cloud area is universally decreased. This is because ISCCP high-topped cloud area is based on IR detections and is not as sensitive as MISR to the increased cloud water path that results from the MRO approximation. This results in a lower net error in ISCCP-simulated high-topped cloud, albeit due to the cancellation of errors between the effects of homogenizing cloud condensate and using MRO.

### 3.4 Sensitivity of simulated CloudSat diagnostics

The 94 GHz radar reflectivity ($Z_e$) retrieved by the CloudSat Cloud Profiling Radar (CPR) is simulated in COSP using the Quickbeam (Haynes et al., 2007) radar simulator. Quickbeam accounts for attenuation due to both hydrometeors and gases in the atmosphere between the detector (radar) and the hydrometeors for which cloud properties are being “retrieved”. Because the CloudSat cloud radar has difficulty detecting hydrometeors with reflectivity
Figure 3.6: Errors in ISCCP-simulated cloud area by cloud type for (from top to bottom) total, high-topped ($p_c < 440$ hPa), mid-topped ($680 < p_c < 440$ hPa), and low-topped clouds ($p_c > 680$ hPa). Shown are (from left to right) the total error in using SCOPS and PREC_SCOPS with homogeneous cloud condensate, the component of the error due only to homogenizing the condensate, and the component of the error due only to using SCOPS to regenerate subcolumns with maximum-random overlap.
Figure 3.7: Zonal-mean CloudSat-simulated hydrometeor occurrence fraction by height for, from top to bottom, the CRM, CRM-HOM, MRO-HOM, and MRO-HOM-PADJ cases.
Figure 3.8: Errors in zonal-mean CloudSat-simulated hydrometeor occurrence fraction by height due to regenerating subcolumns from gridbox means using SCOPS and PREC_SCOPS with homogeneous cloud and precipitation condensate (top) and components of the error that arise separately due to homogenizing cloud and precipitation condensate (second panel), using SCOPS with maximum-random overlap (third panel), and using PREC_SCOPS without constraining the resulting precipitation fraction (bottom).
below -27.5 dBZ, this threshold is often used when comparing simulated reflectivity from models to CloudSat observations (Marchand et al., 2009). The fraction of profiles with radar reflectivity above this threshold can be taken as a measure of the “hydrometeor occurrence” (fraction of radar volumes containing either cloud or precipitation, or both).

Figure 3.7 shows simulated zonal-mean hydrometeor occurrence profiles (the sum of occurrences of radar reflectivity bins with reflectivity $Z_e > -27.5$ dBZ at a given height) from the CloudSat simulator using the CRM, CRM-HOM, MRO-HOM, and MRO-HOM-PADJ fields, and Figure 3.8 shows the errors in the MRO-HOM fields as well as the components of the errors due separately to homogenizing (both the cloud and precipitation) condensate amounts, using SCOPS and PREC_SCOPS with the maximum-random overlap assumption to regenerate hydrometeor occurrence with the precipitation adjustment (i.e., errors due to occurrence overlap alone, not conflated with precipitation fraction errors), and using the (biased) precipitation fraction that arises from PREC_SCOPS (i.e., errors that arise due to PREC_SCOPS inflating the precipitation fraction). Homogenizing the cloud and precipitation condensate amounts ($E_{\text{hom}}$) and using the full subcolumn generator in COSP ($E_{\text{total}}$) both result in an increase in simulated hydrometeor occurrence at all altitudes. These errors are especially large in the deep tropics in the ITCZ and in both northern and southern hemisphere mid-latitudes. The third panel of Figure 3.8 shows the component of the error due to the occurrence overlap of clouds and precipitation from SCOPS and PREC_SCOPS with the precipitation adjustment. That is, the component of the error due only to the treatment of cloud and precipitation overlap, without the errors in precipitation fraction that arise using the unadjusted PREC_SCOPS routine. Figure 3.8 shows that the errors due to occurrence overlap are extremely small relative to the other components, and do not show up at all on the color-scale used in the figure. The bottom panel of Figure 3.8 shows the component of the error due solely to using the unconstrained precipitation treatment in PREC_SCOPS, and it is clear that this error accounts for the majority of the error in generating subcolumns of cloud and precipitation occurrence in the tropical lower troposphere. The errors due separately to homogenizing cloud and precipitation and to using SCOPS and PREC_SCOPS
with MRO in COSP combine to produce larger total errors in hydrometeor occurrence than result from either component alone (top panel of Figure 3.8).

The causes of these errors in hydrometeor occurrence can be understood more easily by looking at the full reflectivity with height histograms. Figure 3.9 shows the simulated radar reflectivity with height histograms using the CRM, CRM-HOM, MRO-HOM, and MRO-HOM-PADJ cases for the northern hemisphere tropics (0 to 10 N latitude). This region is chosen because of the large errors evident in Figure 3.8. While the histograms all show similar patterns of high frequency along a characteristic curve typical of reflectivity with height histograms (e.g., Marchand et al., 2009), the homogenized cases show enhanced occurrence along the characteristic curve, and suppressed occurrence off of it where baseline occurrences are lower. This is clearer in Figure 3.10 (second panel from the left), which shows errors due to using homogeneous clouds and precipitation. Similar to the errors in MISR-simulated cloud area, the source of these errors is driven by the squeezing of the distribution of condensate that results from replacing the subgrid distributions of condensate with the gridbox averages, which effectively reduces the tails of the distribution by removing the within-gridbox variability. This explains the apparent shift in frequency of occurrence from low reflectivity to high reflectivity values, but while there is some decrease in the occurrence of large reflectivity, it is much smaller than one might expect from the decrease in occurrence of small reflectivity.

This apparent inconsistency is explained by considering the attenuation of the radar signal by hydrometeors existing between each radar volume and the detector. The presence of such hydrometeors tends to decrease the radar signal, with larger attenuation for larger condensate amounts. Thus, decreasing the occurrence of hydrometeors with larger condensate amount simultaneously decreases both the radar reflectivity and the attenuation. Below cloud top, the decrease in attenuation can offset the reduction in condensate, such that there tends to be little reduction in the occurrence of the largest reflectivity values. The result is that the occurrence is increased along the characteristic curve and decreased for lower simulated reflectivity values, but can be nearly unchanged for larger simulated reflectivity values. This
Figure 3.9: CloudSat-simulated radar reflectivity with height histograms for the NH tropics (0 to 10 N latitude) from the CRM, CRM-HOM, MRO-HOM, and MRO-HOM-PADJ cases.
Figure 3.10: Errors in CloudSat-simulated radar reflectivity with height histograms for the NH tropics (0 to 10 N latitude). Shown (from left to right) are the total errors due to using SCOPS and PREC,SCOPS with maximum-random overlap and homogeneous cloud and precipitation condensate (far left), the component of the error due to homogenizing cloud and precipitation condensate (second panel), the component of the error due only to the treatment of cloud and precipitation overlap (third panel), and the component of the error due to the overestimation of precipitation fraction using PREC,SCOPS (far right).
Figure 3.11: Differences in simulated reflectivity with height histograms between CRM and CRM-HOM cases for an example gridbox (the same gridbox shown in Figure 3.1), with attenuation turned on (left) and with attenuation turned off (right).

is demonstrated for a sample gridbox in Figure 3.11, which shows the simulated reflectivity from both the CRM and CRM-HOM fields, but with attenuation in the radar simulator turned on (left), and with attenuation turned off (right) for comparison. The histograms with attenuation turned off show precisely the squeezing of the distribution that we would have expected in the absence of attenuation at lower altitudes.

Errors in using SCOPS and PREC_SCOPS to overlap cloud and precipitation are small when constraining precipitation with the CRM precipitation fraction (third panel in Figure 3.10). However, the impact of constraining precipitation fraction is large, and failing
to faithfully reproduce the CRM precipitation fraction (fourth panel in Figure 3.10 leads to large increases in the occurrence of columns with especially large reflectivity. The effect is more pronounced at low to mid-levels (altitude $z < 5$ km). This error is not surprising given the discussion in Section 3.2 in the context of Figure 3.1, which shows that the PREC_SCOPS subcolumn precipitation generator can tend to overestimate the number of precipitating subcolumns. This suggests that the simulated CloudSat radar reflectivity is not sensitive to the cloud overlap, but is sensitive to the treatment of subgrid-scale precipitation, and shows that accurately reproducing the precipitation fraction when generating subcolumns is crucial to obtaining useful CloudSat-simulated diagnostics from model output. For models that diagnose gridbox-mean precipitation fraction, the precipitation adjustment used here is effective in reducing errors that arise due to using PREC_SCOPS to overlap precipitation with cloud. While precipitation fraction may not yet be predicted by all GCMs, it is predicted by some (e.g., CAM; Neale et al., 2010a,b).

### 3.5 Summary and discussion

Current global models do not resolve individual cloud elements, but rather represent most cloud-scale variability by way of parameterization. But simulated satellite diagnostics (and radiative fluxes and heating rates) depend on the small-scale characteristics of clouds. The common simplification made in large-scale models is that cloud (and precipitation) condensate is horizontally homogeneous on the gridbox scale, and that cloud occurrence follows maximum-random overlap. Because these assumptions are often used to infer subgrid-scale cloud structure in model radiative transfer codes, these assumptions have been adopted as defaults in COSP to generate stochastic subcolumns on which the individual satellite instrument simulators are performed. However, these assumptions lead to biases in calculated fluxes and heating rates, and these assumptions also affect simulated MISR and CloudSat satellite diagnostics.

The assumption of homogeneous cloud properties tends to inflate the simulated MISR cloud area (when counting all clouds with an optical depth greater than 0.3) because columns
with small optical depths in the tail of the distribution are sometimes shifted to values above the cut-off threshold by averaging with columns with larger optical depths. These errors occur primarily in high-topped clouds, and high-topped cloud occurrence can be overestimated by as much as 10% cloud area in regions with a lot of high-topped optically thin cloud, such as in the tropical western Pacific and other parts of the deep tropics. The global mean high-topped cloud error due to homogenizing the cloud properties is about 3% cloud area, and the effect on total cloud area is only 2%. The maximum-random overlap assumption tends to decrease the cloud cover because it overestimates the vertical alignment of vertically continuous clouds (Mace and Benson-Troth, 2002; Hogan and Illingworth, 2000; Barker, 2008). This leads to a global mean underestimate in total cloud area of only 3%, but with regional errors as large as 10% cloud area, especially in the deep tropics. The errors in cloud area due to homogeneous cloud properties and using the maximum-random overlap are generally opposite in sign, and result in a partial cancellation in the total error (that is, total vertically-projected cloud area that includes both high and low-topped clouds). The result is that the errors in total cloud area are less than 2% in the global average, and regional errors in total cloud area are much smaller than for either of the two components of the error. However, errors in high and low-topped cloud area due to the two components are additive, such that the total errors in high and low-topped clouds are larger than they are for either the homogeneous or MRO components. High-topped cloud is overestimated by 5% cloud area, and low-topped cloud is underestimated by 4% cloud area in the global mean. Regional errors are even larger, and high-topped cloud errors reach 10% cloud area or more, especially in the tropical western Pacific, the Indian Ocean, and throughout the tropics.

The sensitivity in MISR-simulated total cloud area identified here is generally less than errors in cloud area identified in current GCMs (Kay et al., 2012; Klein et al., 2013; Bodas-Salcedo et al., 2011), and on the order of the spread in estimates of total cloud area from satellite remote sensing retrievals (Marchand et al., 2010; Pincus et al., 2012). However, the regional errors in MISR-simulated cloud area by cloud top height identified here are large, and exceed the uncertainty in MISR-retrieved high-topped cloud area, which is estimated to
be on the order of 5% cloud area regionally, as shown in Chapter 2. Thus, the sensitivity of MISR-simulated cloud area to homogeneous cloud condensate and maximum-random overlap cannot be ignored, especially as representations of clouds in GCMs improve.

Simulated CloudSat radar reflectivity is found to be sensitive to the treatment of unresolved subcolumn cloud and precipitation condensate horizontal variability, but much less sensitive to the treatment of cloud overlap. Homogenizing the cloud and precipitation condensate leads to a narrowing of the distribution of simulated radar reflectivity, making the more frequently occurring reflectivity values in the baseline simulation even more frequently occurring in the homogenized simulation. This tends to decrease the occurrence of columns with small radar reflectivity, while increasing the occurrence of columns with large radar reflectivity. Similar to the MISR simulator, employing a reflectivity cut-off to determine hydrometeor occurrence (for the purpose of making consistent comparisons with CloudSat) results in an apparent increase in the hydrometeor occurrence when homogenizing the cloud and precipitation properties, and an apparent increase in precipitation occurrence. The increase in simulated hydrometeor occurrence fraction reaches a value of 10% in high altitudes in the tropics and in low altitudes in mid to high-latitudes.

Using the subcolumn generator currently implemented in COSP (as of version 1.4) leads to further errors in simulated CloudSat radar reflectivity and hydrometeor occurrence that combine with the errors due to homogenizing the cloud and precipitation condensate to produce even larger total errors that reach 10% frequency of occurrence at all altitudes throughout the tropics. Much of this error is due to the fact that precipitation has a relatively large reflectivity compared with clouds, and the subcolumn precipitation scheme implemented in COSP tends to overestimate the number of precipitating subcolumns. Using this subcolumn scheme then tends to increase the number of columns with large radar reflectivity, and thus increases the simulated hydrometeor occurrence. Constraining the number of precipitating subcolumns by the precipitation fraction greatly reduces errors in simulated hydrometeor occurrence. The ability to constrain the subcolumn precipitation by the precipitation fraction will be included in future versions of COSP (Y. Zhang, personal communication). The
remaining errors due to maximum-random cloud overlap alone are small, with hydrometeor occurrence errors everywhere less than 4% in the zonal mean.

The errors in simulated CloudSat radar reflectivity factor and hydrometeor occurrence due to the homogeneous cloud and precipitation assumptions are troubling, and show that subgrid-scale cloud and precipitation variability needs to be better represented in COSP in order to create more consistent comparisons between model-diagnosed and satellite-retrieved cloud statistics. The following chapter explores the possibility of reducing these errors with an improved subcolumn generator framework, which includes both a more realistic treatment of overlap and heterogeneous subcolumn condensate.
Chapter 4

AN IMPROVED FRAMEWORK FOR DOWNSCALING CLOUD PROPERTIES FROM LARGE-SCALE MODELS

The previous chapter identified errors in simulated satellite cloud diagnostics that arise from using unrealistic cloud overlap assumptions and horizontally homogeneous condensate. In this chapter, an improved subcolumn generator is presented, building on the work of previous investigators, to reduce those errors and enable more consistent and robust comparisons of modeled and satellite-retrieved cloud statistics.

The improved subcolumn generator described here uses a scheme developed by Räisänen et al. (2004) to generate subcolumn cloud condensate that both follows a more realistic and flexible cloud overlap assumption and allows for generating subcolumn condensate with horizontal variability. This scheme has been extended here to apply to precipitation as well. Using the same framework as in Chapter 3, the new subcolumn generator is shown to substantially reduce the identified errors that arise in using SCOPS and PREC_SCOPS to generate stochastic subcolumns of cloud and precipitation condensate.

The goal of this chapter is to demonstrate the sensitivity of simulated satellite diagnostics to the improved treatment of overlap and variability, and thus overlap and variability parameters for use in the subcolumn generator are derived directly from the SP-CAM simulation used as the baseline. Ultimately, inclusion of such a scheme in a GCM should use overlap and variability assumptions consistent with those used elsewhere in the model (e.g., radiative transfer calculations and cloud microphysics schemes), and so this study provides further motivation for improving the representation of subgrid-scale cloud and precipitation distributions not only in COSP but throughout GCMs.
4.1 Generating stochastic subcolumns of cloud and precipitation condensate

Räisänen et al. (2004) (hereafter R04) introduce a stochastic subcolumn cloud generator that can handle both horizontally variable cloud condensate and generalized cloud overlap. In the R04 scheme, subcolumn cloud occurrence is first determined by assuming that cloud overlap between adjacent layers is a linear combination of maximum and random overlap, such that the combined cloud fraction between two layers $k_1$ and $k_2$ is

$$c_{\text{gen}}^{k_1,k_2} = \alpha_{k_1,k_2} c_{\text{max}}^{k_1,k_2} + (1 - \alpha_{k_1,k_2}) c_{\text{ran}}^{k_1,k_2} \quad (4.1)$$

where $c_{\text{gen}}^{k_1,k_2}$ is the combined (vertically projected) cloud area (fraction) that would result from generalized overlap, $c_{\text{max}}^{k_1,k_2}$ is the cloud area that would result if the layers were maximally overlapped, $c_{\text{ran}}^{k_1,k_2}$ is the cloud fraction that would result if the layers were randomly overlapped, and $\alpha_{k_1,k_2}$ is the “overlap parameter” that specifies the weighting between maximum and random overlap. The theoretical combined cloud fractions $c_{\text{max}}^{k_1,k_2}$ and $c_{\text{ran}}^{k_1,k_2}$ are defined as

$$c_{\text{max}}^{k_1,k_2} = \max(c_{k_1}, c_{k_2})$$

$$c_{\text{ran}}^{k_1,k_2} = c_{k_1} + c_{k_2} - c_{k_1} c_{k_2}$$

where $c_{k_1}$ and $c_{k_2}$ are the partial cloud fractions of layers $k_1$ and $k_2$, respectively (i.e., the fraction of the gridbox at levels $k_1$ and $k_2$ that are cloudy).

In general, Equation 4.1 is assumed to apply to any two pairs of layers, but for the practical implementation of the subcolumn generator R04 consider only adjacent layer pairs. Given $\alpha_{k,k-1}$ and the gridbox-mean cloud fraction $\bar{c}_k$ at each layer $k$, R04 describe a straightforward algorithm to stochastically generate a binary subcolumn clear/cloudy flag with $n_{\text{col}}$ subcolumns that obeys the above overlap relationship by stepping down from the top of the atmospheric column and considering only adjacent layer pairs. First, for each subcolumn $i$ and at each level $k$, three random numbers on the interval $[0,1)$ are drawn, denoted $R1_{i,k}$, $R2_{i,k}$, and $R3_{i,k}$. A variable $x_{i,k}$ is then generated as follows. At level $k = 1$ (TOA), $x_{i,1}$ is set to $x_{i,1} = R1_{i,1}$. Levels $k$ and columns $i$ are then iterated over from $k = 2, \ldots, n_{\text{lev}}$ and
$i = 1, \ldots, n_{\text{col}}$, and $x_{i,k}$ is determined by

$$x_{i,k} = \begin{cases} x_{i,k-1}, & R2_{i,k} \leq \alpha_{k,k-1} \\ R3_{i,k}, & R2_{i,k} > \alpha_{k,k-1} \end{cases}$$

From this, the subcolumn cloudy/clear flag $c_{i,k}$ is determined from the value of $x_{i,k}$ and the partial cloud fraction $\bar{\tau}_k$ at level $k$ by

$$c_{i,k} = \begin{cases} 1, & x_{i,k} > 1 - \bar{\tau}_k \\ 0, & x_{i,k} \leq 1 - \bar{\tau}_k \end{cases}$$

Once the cloud occurrence subcolumns are created, cloud condensate is assigned to the cloudy elements by drawing from a specified probability distribution for condensate amount. The choice of distribution should be consistent with the given model assumptions about subgrid variability of condensate, if such exists. Traditionally models have assumed homogeneous subcolumn condensate (e.g., CAM4; Neale et al., 2010a), but some models have started to incorporate subgrid-scale variability into their cloud microphysics schemes. For example, the most recent version of the NCAR CAM assumes condensed cloud water follows a gamma distribution, but cloud ice and precipitation are still assumed to be homogeneous (CAM5; Neale et al., 2010b).

Condensate values are drawn such that the subcolumn condensate obeys a specified rank correlation $\rho_{k,k-1}$ for condensate amount between adjacent layers, where $\rho_{k,k-1}$ is the Pearson Product-Moment Correlation coefficient of the ranks $r_k$ and $r_{k-1}$ of condensate at levels $k$ and $k-1$, defined by

$$\rho_{k,k-1} = \frac{\text{cov}(r_k, r_{k-1})}{\sigma_{r_k} \sigma_{r_{k-1}}} = \frac{\sum_{i=1}^{n_{\text{col}}} (r_{i,k} - \overline{r}_k)(r_{i,k-1} - \overline{r}_{k-1})}{\sqrt{\sum_{i=1}^{n_{\text{col}}} (r_{i,k} - \overline{r}_k)^2} \sqrt{\sum_{i=1}^{n_{\text{col}}} (r_{i,k-1} - \overline{r}_{k-1})^2}}$$

(4.2)

where the overbars denote horizontal averages over all $n_{\text{col}}$ subcolumns. Condensate values are drawn to satisfy a specified $\rho_{k,k-1}$ by first generating a variable $y_{i,k}$ at each subcolumn $i$ and level $k$ analogous to the variable $x_{i,k}$ used to determine the binary occurrence flag. Again, three sets of random numbers $R4_{i,k}$, $R5_{i,k}$, and $R6_{i,k}$ on the interval $[0, 1)$ are drawn.
at each subcolumn $i$ and level $k$. The top ($k = 1$) layer is set to $y_{i,1} = R4i,1$. For each subsequent level $k = 2, \ldots, n_{\text{lev}}$,

$$y_{i,k} = \begin{cases} 
    y_{i,k-1}, & R5i,k \leq \rho_{k-1,k} \\
    R6i,k, & R5i,k > \rho_{k-1,k}
\end{cases}$$

With this, and an assumed probability distribution for condensate amount with probability density function $p_k(q)$ at level $k$, where $q$ is the condensate amount (specified as a mass mixing ratio), the condensate amount $q_{i,k}$ at each level is determined by finding $q_{i,k}$ such that

$$y_{i,k} = \int_0^{q_{i,k}} p_k(q') \, dq'$$

That is, $q_{i,k}$ is the mixing ratio at which the cumulative density function (CDF) of condensate mixing ratios is equal to $y_{i,k}$.

The problem of generating stochastic subcolumns of cloud condensate with generalized occurrence overlap and heterogeneous condensate distributions then reduces to specifying the parameters $\alpha_{k,k-1}$ and $\rho_{k,k-1}$ for each pair of adjacent layers within a gridbox, and specifying an appropriate probability distribution from which to sample condensate amount at each gridbox and time step.

Studies (based largely on cloud radar) have shown that the cloud occurrence overlap can be fit to an inverse exponential function of the separation between layers, such that

$$\alpha_{k1,k2} = \exp \left( -\frac{z_{k1} - z_{k2}}{z_0} \right)$$

(4.3)

where $z_{k1}$ and $z_{k2}$ are the heights of layers $k_1$ and $k_2$, and $z_0$ is the “decorrelation length” for cloud overlap that specifies how quickly the vertical correlation in cloud occurrence decays from maximal to random (Hogan and Illingworth, 2000; Mace and Benson-Troth, 2002; Räisänen et al., 2004; Pincus et al., 2005; Barker, 2008; Tompkins and Di Giuseppe, 2015). Räisänen et al. (2004) and Pincus et al. (2005) further suggest that the same exponential relationship can describe the rank correlation of condensate, but in general using a separate decorrelation length. These studies have suggested decorrelation lengths for cloud occurrence
overlap between 1.5 and 2.5 km, and somewhat smaller decorrelation lengths for condensate rank correlation (decorrelation lengths for rank correlation approximately half those for occurrence overlap). Overlap and decorrelation lengths will be parameterized in the following section for use with the SP-CAM output used in this study.

The R04 subcolumn generator as summarized above was designed specifically for generating stochastic subcolumns of cloud condensate. However, the treatment of subcolumn precipitation is critical to obtaining reasonable simulations of radar reflectivity factor from large scale model output (Chapter 3). The R04 generator is extended here to also generate stochastic subcolumns of precipitation condensate with horizontally heterogeneous condensate amount in order to also improve the treatment of unresolved precipitation for use with the simulators.

As an initial approach to extending this subcolumn scheme to handle precipitation, the subcolumn cloud occurrence $\tilde{c}_{i,k}$ is first generated using the subcolumn generator described above. The subcolumn precipitation occurrence $\tilde{p}_{i,k}$ is then generated using the PREC_SCOPS routine from COSP, with the precipitation adjustment described in the previous chapter to constrain the number of precipitating subcolumn elements by the precipitation fraction from the model. The subcolumn precipitation condensate amount is then prescribed in a similar manner to the subcolumn cloud condensate amount but with a separate rank correlation for precipitation, and in general a separate assumed probability distribution. Other approaches could certainly be designed to extend this to precipitation, but as demonstrated in the following sections this simple approach performs quite well (when the correct cloud occurrence overlap and variability are used).

This describes a complete subcolumn generator that can produce subcolumns with generalized cloud occurrence overlap, prescribed precipitation occurrence fraction, and horizontally heterogeneous cloud and precipitation condensate, given the occurrence overlap decorrelation length for cloud, the decorrelation lengths for condensate amount rank correlation, and assumed probability distributions for cloud and precipitation condensate amounts. In order to use this generator in a large-scale, however, these quantities must be parameterized, and
Section 4.2 and Section 4.3 describe parameterizing these quantities for use in the sensitivity study to follow. Because the goal of this study is to evaluate the sensitivity of the simulated satellite diagnostics to this new treatment of unresolved cloud and precipitation structure and variability, these quantities will be parameterized using a month of output from the SP-CAM. This approach is ideal for this study because it allows for direct comparison with diagnostics calculated from the unmodified SP-CAM model output in a similar manner as in Chapter 3, thus allowing quantification of the sensitivities to these parameters. However, it is important to recognize that the SP-CAM fields from which the parameterizations are developed here are model fields, not observations. As such, the parameterization developed here is subject to limitations of the model used, and may not be entirely consistent with observations of clouds in the physical atmosphere. Nonetheless, the analysis that follows offers a new perspective on overlap and variability that has not been fully explored in the literature, providing a global description of both overlap and variability statistics from a high resolution model. Previous efforts to quantify overlap have been limited in duration (Räisänen et al., 2004), limited to smaller domains using cloud resolving models (Pincus et al., 2005) or ground-based cloud radar (Hogan and Illingworth, 2000; Mace and Benson-Troth, 2002), or used satellite-based studies that come with their own limitations (Barker, 2008; Oreopoulos et al., 2012).

### 4.2 Parameterizing occurrence overlap and rank correlation from SP-CAM

Occurrence overlap and rank correlation are derived from the same SP-CAM model output used earlier to evaluate sensitivities in COSP diagnostics to overlap. With the high-resolution model output provided by the SP-CAM, the occurrence overlap can be directly calculated for each gridbox from the subcolumn cloud condensate amount by solving Equation 4.1 for $\alpha_{k_1,k_2}$ and assuming that the “true” combined cloud fraction between layers $k_1$ and $k_2$ can be described by generalized overlap, so that $\tilde{c}_{k_1,k_2}^{\text{true}} = \tilde{c}_{k_1,k_2}^{\text{gen}}$. This yields for the overlap parameter

$$\alpha_{k_1,k_2} = \frac{\tilde{c}_{k_1,k_2}^{\text{true}} - \tilde{c}_{k_1,k_2}^{\text{ran}}}{\tilde{c}_{k_1,k_2}^{\text{max}} - \tilde{c}_{k_1,k_2}^{\text{ran}}} \quad (4.4)$$
For each gridbox and for each pair of layers $k_1$ and $k_2$ then, $\alpha_{k_1,k_2}$ can be calculated by first calculating the true combined cloud fraction between the two layers $c_{\text{true}}^{k_1,k_2}$ and the theoretical maximally and randomly-overlapped cloud fractions $c_{\text{max}}^{k_1,k_2}$ and $c_{\text{ran}}^{k_1,k_2}$, and then using these in Equation 4.4. Using this, overlap is calculated for pairs of layers in each model gridbox and at each archived 3-hourly snapshot of the SP-CAM outputs used in the previous chapter. The overlap calculation is restricted to layers with partial cloud fractions between 5% and 95% cloud area. The dependence on the separation between layers is determined using 40 uniformly-spaced height bins from 0 to 5 km over the single month of output. The analysis is limited to separations of 5 km or less because layers separated by more than 5 km are essentially uncorrelated, and considering only those layers separated by 5 km or less tends to improve the quality of the fit to Equation 4.3 (Pincus et al., 2005). The monthly-averaged overlap as a function of separation is then calculated by summing the binned overlap and dividing by the number of valid counts in each bin. This is done for each latitude-longitude gridbox and separation bin. Rank correlation of total cloud and total precipitation condensate is similarly calculated at each gridbox and level for each 3-hourly snapshot, and binned using the same separation distance bins used to bin the overlap.

Figure 4.1 shows the globally averaged overlap and condensate rank correlation for total cloud condensate as a function of separation distance (the area-weighted average of the overlap and rank correlation calculated at each latitude-longitude gridbox and at all altitudes). Overlap and rank correlation are fit to Equation 4.3 using non-linear least squares, and the fit is plotted on Figure 4.1 as well. Two sets of points and fits are shown in the figure, corresponding to overlap statistics calculated using all layer pairs and statistics calculated for only adjacent layer pairs. The globally averaged overlap and rank correlation statistics shown in Figure 4.1 demonstrate the general tendency for both overlap and rank correlation to decrease as the separation between layers increases, and especially for distant layers the inverse exponential dependence on separation distance following Equation 4.3 seems reasonable. There is, however, generally larger spread in cloud overlap and rank correlation for small layer separations. This spread in statistics for small separations is not seen in previ-
Figure 4.1: Global (area-weighted) average cloud occurrence overlap parameter (left) and condensate rank correlation (right) as a function of separation distance between layers from a month of SP-CAM output. Also shown are fits to Equation 4.3, with values of decorrelation length scales from these fits shown in the upper right corner of each panel. Blue markers and curves correspond to statistics calculated using all layer pairs, while green markers and curves correspond to statistics calculated using only adjacent layer pairs.
ous analyses (e.g., Pincus et al., 2005), but those analyses have been primarily limited to much smaller domains, and presumably consist of a smaller subset of cloud regimes than the global, month-long simulation considered here. R04 show overlap decorrelation lengths for a single day of SP-CAM output as a function of latitude and vertical (pressure) level, and it is evident from that analysis that overlap statistics vary substantially with both location and height, with decorrelation lengths varying from less than 0.5 km near the surface up to 10 km in the upper troposphere (see Figure 3 in R04). Some amount of spread in Figure 4.1 can be expected then, due to grouping all profiles at all levels together. The good agreement for larger separations is nonetheless expected, however, since regardless of cloud type distant layers are expected to be uncorrelated and thus overlap and rank correlation should approach zero (random overlap and no correlation) as separations become large.

It is also possible that some of the spread in overlap statistics for small separations is partly due to the fact that these statistics are binned using separation in geometric height (altitude), while the model itself is formulated using a hybrid sigma-pressure grid (the CRM uses the lowest 24 levels of CAM; Marchand et al., 2009; Collins et al., 2004). Parameterizing overlap in terms of the geometric height separation makes sense for clouds in the physical atmosphere, but tighter constraints may be realized by binning overlap statistics on a grid more consistent with the native model grid. To examine this further, Figure 4.2 shows overlap and rank correlation calculated as in Figure 4.1 but for total cloud condensate binned by separation in pressure rather than by separation in height between layer pairs. It is clear that both overlap and rank correlation in total cloud condensate are fit better when binning by pressure separation rather than height (less spread in the averages). This is especially true at small separations and using only adjacent pairs, but binning by pressure separation seems to improve the quality of the fit to distant layers as well. However, parameterizing overlap by separation in pressure rather than by separation in height did not seem to significantly affect the simulation of COSP diagnostics (not shown), so overlap statistics will be parameterized by separation in height for consistency with the existing literature.

There appear to be two distinct groups of points in each panel in both Figure 4.1 and
Figure 4.2: Global (area-weighted) average cloud occurrence overlap parameter (left) and condensate rank correlation (right) as a function of separation in pressure between layers from a month of SP-CAM output. Also shown are fits to Equation 4.3, with values of decorrelation length scales from these fits indicated in the legend. Blue markers and curves correspond to statistics calculated using all layer pairs, while green markers and curves correspond to statistics calculated using only adjacent layer pairs.
Figure 4.2, with different overlap characteristics for separations greater than about 1.3 km (100 hPa) than below. These two groups correspond to distant layer pairs (layer pairs separated by one or more model layers) and adjacent layer pairs, respectively. A second set of points is plotted in each panel of Figure 4.1 and Figure 4.2, showing the overlap and rank correlation calculated using only adjacent layers (with a separate set of bins than used for all layer pairs in order to increase the resolution for adjacent pairs). These additional points show that indeed the two separate groups result from differences in the overlap characteristics for adjacent versus distant layer pairs. Fitting Equation 4.3 using only adjacent pairs results in larger decorrelation length scales for both cloud overlap and rank correlation than when fitting using all pairs.

The differences in overlap and rank correlation statistics for adjacent and non-adjacent layers mean that parameterizing overlap and rank correlation is a compromise between reproducing the correct relationships for adjacent layers versus reproducing the correct relationships for distant layers. Because the R04 subcolumn generator only considers relationships between adjacent layers, it might be possible to achieve better performance by parameterizing overlap and rank correlation using only adjacent layers as well. However, the distinction of adjacent and non-adjacent layers is not very meaningful outside the context of a model, so most efforts to parameterize these quantities by separation distance have considered all layer pairs. Furthermore, it might be argued that reproducing the correct overlap statistics for all layer pairs is more important than reproducing the correct overlap statistics for only adjacent pairs, if the former has a larger impact on the resulting vertically projected cloud area. This probably depends on the amount and nature of multi-layer cloud profiles. Fundamentally, the ability of the R04 subcolumn generator to faithfully reproduce both overlap and vertically projected cloud area rests on the assumption that considering only adjacent layers is sufficient to reproduce the overall statistics, including the relationships between distant layers. Thus, parameterizing using all layer pairs, rather than using only adjacent layer pairs, may help to reduce the impact of this assumption by explicitly building in the overall statistics.
In order to assess the spatial dependence of cloud occurrence overlap and condensate rank correlations, time-averaged overlap and rank correlations are fit to Equation 4.3 at each latitude-longitude gridbox. The decorrelation lengths from the cloud occurrence overlap fits at each point are shown in Figure 4.3 for overlap binned by separation in height. The subcolumn generator described here allows for generalized overlap of total cloud occurrence, using only the overlap parameter between adjacent layers for total cloud. The method of generating condensate distributions, however, in general allows for separate rank correlations to be specified for each hydrometeor type (cloud liquid, cloud ice, precipitating liquid, and precipitating ice). Thus, rank correlations are calculated separately for each hydrometeor type from the SP-CAM output, and are also fit to Equation 4.3 at each point. The decorrelation lengths from these fits are shown in Figure 4.4 for rank correlations binned by separation in height.

Decorrelation lengths for both cloud occurrence overlap and condensate rank correlations vary substantially with geographic location, which suggests that these overlap statistics are
Figure 4.4: Decorrelation lengths for condensate rank correlation binned by separation in height for cloud liquid (CRM_QC, upper left), cloud ice (CRM_QI, upper right), precipitating liquid (CRM_QPC, lower left), and precipitating ice (CRM_QPI, lower right). White areas on the map indicate where the fit failed to converge.
dependent on cloud type. Pincus et al. (2005) speculated that overlap and rank correlation are likely different for convective versus stratiform clouds, and showed that (for the month long simulation of convection over the ARM SGP site) convective clouds were more vertically coherent than stratiform clouds. Based on this argument, it might be expected that occurrence overlap decorrelation lengths would be systematically larger in more convectively-active regions. The maps shown in Figure 4.3 do not seem entirely consistent with this assumption, however, as occurrence overlap decorrelation lengths are generally lower throughout the deep tropics (where deep convective cloud systems are abundant), and systematically higher throughout the subtropics. These results are, however, consistent with the results shown by R04 using a single day of SP-CAM output; Figure 3 in R04 shows zonal-mean decorrelation lengths for both cloud occurrence and cloud condensate rank correlation as functions of height (calculated using adjacent layer pairs), and there are clear local maxima in decorrelation lengths near 30 N and 30 S throughout the middle troposphere. Oreopoulos et al. (2012) obtain a somewhat different result using CloudSat and CALIPSO-retrieved hydrometeor occurrences from the 2B-GEOPROF-LIDAR product; they find a clear zonal structure in decorrelation lengths for cloud overlap, with systematically higher decorrelation lengths in the tropics and lower decorrelation lengths in the extratropics (closely resembling a Gaussian). The Oreopoulos et al. (2012) result seems more consistent with a larger frequency of convective cloud systems throughout the tropics leading to generally larger decorrelation lengths, but is contradictory to the results shown here and in R04.

There are a number of caveats to note when trying to reconcile these different results. The Pincus et al. (2005) study composited statistics separately for columns deemed convective and for columns deemed stratiform, isolating the statistics of each. The results shown here (and in R04), however, contain contributions from a range of cloud types at each point, and comparing the statistics from different geographic regions is not sufficient to completely isolate the overlap statistics specific to certain cloud types. For example, while the tropics contain more convectively active cloud systems that are expected to have numerically higher overlap, they also contain a significant amount of cirrus cloud that may have completely
different (numerically lower) overlap. Cases with exceptionally large or exceptionally small values of overlap could tend to skew the results, even if the cloud types associated with those cases are less frequent.

Perhaps more importantly, the sources of cloud condensate information used for each of these studies are fundamentally different. The results represented here and those shown in R04 used SP-CAM model output, while the Oreopoulos et al. (2012) study used data retrieved from cloud radar and lidar. This distinction is crucial, because the model results are able to unambiguously discern between different hydrometeor types, while results obtained from radar reflectivity cannot reliably differentiate between clouds and precipitation because precipitation dominates the signal when present. Thus, the profiles used to derive cloud occurrence overlap in the Oreopoulos et al. (2012) study may very likely contain not only cloud, but also precipitation condensate. While they note that the presence of precipitation may influence the determination of condensate rank correlation, it is important to note here that this would also influence the determination of cloud occurrence overlap statistics, because precipitation is expected to be much more maximally overlapped than cloud. Such a contamination of “cloud” profiles by precipitation would explain the increase in occurrence overlap throughout the tropics, where precipitation occurrence is generally larger in association with deep convection. So, these results are likely different because the Oreopoulos et al. (2012) results show overlap for the combination of clouds and precipitation, while the results presented here show overlap for only cloud. The ability to confidently discriminate between cloud and precipitation statistics with a high resolution model like that used here should be viewed as a real strength in using this technique to derive overlap statistics, because it is straightforward to quantify statistics separately for different hydrometeor types. While the results obtained using such model results may be subject to additional questions regarding the fidelity of the model simulation itself, they do thus provide a complementary description of the overlap statistics not possible with available observations.

Regardless of these caveats, the spatially varying patterns in decorrelation lengths for both cloud occurrence overlap and condensate rank correlation suggest that assuming spa-
tially invariant decorrelation lengths will likely lead to spatially varying errors in cloud area. This is shown to be the case in the following sections. However, the goal of this study is to evaluate the sensitivity to these assumptions relative to using the maximum-random overlap assumption with horizontally homogeneous condensate, rather than to derive a comprehensive parameterization that can be immediately used by default in COSP. For simplicity then, spatially invariant decorrelation length scales for both cloud occurrence overlap and for condensate rank correlation are taken from the cosine-latitude-weighted global mean values, indicated above each panel in Figure 4.3 and Figure 4.4.

### 4.3 Parameterizing cloud and precipitation condensate variability

In order to use the R04 scheme to generate subcolumns of cloud and precipitation condensate with horizontally variable condensate, both the assumed distribution of condensate and the variance in subcolumn condensate must be specified. Because these details are not always specified in large-scale models, a simple parameterization is discussed here.

Various aspects of the statistical distribution of condensate have been quantified using a variety of data sources, including aircraft observations (Wood and Field, 2000; Larson et al., 2001), tethered balloon observations (Price, 2001), satellite retrievals using passive sensors (Barker et al., 1996) and more recently using CloudSat retrievals (Lee et al., 2010), and using high resolution model simulations from cloud resolving models and large eddy simulations (Lewellen and Yoh, 1993; Xu and Randall, 1996b,a). The primary motivation for these studies has been to parameterize the distribution of condensate for use in large-scale models. It is important that such a parameterization is consistent with clouds in the physical atmosphere so as to have a parameterization that is as realistic as possible. Thus, it is often desirable to use high-quality observations to derive these parameterizations. For this study, however, it is most important that the parameterization is consistent with clouds simulated by SP-CAM, rather than with observations of clouds, because the goal of this study is to test the ability of the subcolumn generator to reproduce subcolumn statistics from the SP-CAM. Because of this, the parameterization developed here is based entirely on output from the
SP-CAM. While caution should be exercised in trying to use this parameterization beyond the sensitivity studies presented here without further evaluation against observations, the use of SP-CAM output to derive such parameterizations provides distinct advantages over the approaches used previously, which will be discussed.

Cloud condensate distributions have been fit with a number of different statistical distributions. Larson et al. (2001) fit aircraft observations of the conserved quantity $s$ (related to the total specific humidity and saturation specific humidity and suitable for use in statistical cloud schemes) to various distributions, including single and double “delta” distributions (no variability), the generalized (3-parameter) gamma distribution, and various iterations of single and double gaussian distributions. They find that $s$ is fit well by the multi-parameter double gaussian distributions, but also find good agreement with the generalized gamma distribution. More recently, Lee et al. (2010) fit retrievals of cloud liquid water content from CloudSat to a selection of different distributions, including gamma, lognormal, exponential, gaussian, Weibull, beta, and uniform. They find that the CloudSat retrievals most closely follow either a lognormal or gamma distribution (depending on a number of conditions including geolocation, altitude, temperature, and the presence of precipitation). They also note that the data is reasonable well fit by the beta distribution, and Oreopoulos et al. (2012) subsequently use the beta distribution in their parameterization of subgrid-scale variability.

These studies suggest that the gamma distribution is a reasonable fit to observed distributions of cloud condensate, and in fact the most recent version of the NCAR Community Atmosphere Model (CAM5) microphysics scheme assumes subgrid-scale condensed cloud liquid follows a gamma distribution, although cloud ice and both precipitating liquid and ice condensate are still treated as homogeneous (Neale et al., 2010b). It is assumed here that the cloud liquid, cloud ice, precipitating liquid and precipitating ice condensate in the SP-CAM all follow gamma distributions.

The gamma distribution has probability density

$$p_{k,\theta}(q) = \frac{1}{\Gamma(k)\theta^k} q^{k-1} e^{-q/\theta}$$
where \( q \) is the condensate amount (mixing ratio), \( k \) and \( \theta \) are the shape and scale parameters of the gamma distribution, and \( \Gamma \) is the gamma function. The distribution has mean \( \mu = k\theta \) and variance \( \sigma^2 = k\theta^2 \). Using the method of moments (e.g., Wilks, 2011), the population mean and variance are equated with the sample mean \( \bar{q} \) and variance \( \sigma_q^2 \) and this system of two equations is easily solved to estimate the shape and scale parameters \( k = \mu^2/\sigma_q^2 \) and \( \theta = \sigma_q^2/\mu \). Using this formulation, the subgrid distribution of condensate within each grid-box is completely specified in terms of the grid-box mean and variance of condensate.

Cloud physics parameterizations in large-scale (global) models diagnose gridbox-mean cloud and precipitation condensate amounts, but traditionally have not diagnosed (or even implicitly assumed) the gridbox-variance. A variety of observations have been used to study the gridbox-scale variance (or “heterogeneity”), including aircraft observations, satellite retrievals, and ground-based retrievals from the CloudNet (Illingworth et al., 2007) and ARM (Ackerman and Stokes, 2003) sites. One way of quantifying heterogeneity is by calculating the coefficient of variation \( \sigma_x/\bar{x} \), where \( \sigma_x \) and \( \bar{x} \) are the standard deviation and the mean of a quantity \( x \) (such as cloud condensate amount). The coefficient of variation, often referred to as the fractional or relative standard deviation, has been used by other authors to quantify heterogeneity in cloud condensate (Hogan and Illingworth, 2003; Shonk et al., 2010; Hill et al., 2012; Boutle et al., 2014). Shonk et al. (2010) conclude that a fixed coefficient of variation is sufficient to specify the heterogeneity, with a value of \( 0.75 \pm 0.18 \). This would imply that the gridbox standard deviation in cloud condensate can be simply specified by scaling the gridbox mean. However, Hill et al. (2012) and Boutle et al. (2014) suggest that the coefficient of variation varies with cloud fraction. This suggests that the scaling between gridbox mean and standard deviation in cloud condensate might depend on the cloud fraction. Oreopoulos et al. (2012), in developing a simple parameterization to test the sensitivity of radiative fluxes to heterogeneity in a GCM, also state an observed dependence on cloud fraction using CloudSat retrievals, although those results were not shown explicitly in the manuscript. Hill et al. (2015) suggest that the coefficient of variation also has a regional dependence, with more heterogeneity in ice clouds in regions dominated by convection. Lebsock
et al. (2013) similarly show a regional dependence, with more heterogeneity in the tropics than in the extratropics. Ahlgrimm and Forbes (2016) further suggest a regime dependence on the heterogeneity.

While these studies have all been based on observations of clouds in the physical atmosphere, again for the purpose of this study it is most important that the parameterization is consistent with clouds simulated by SP-CAM. Thus, condensate variance will be parameterized based on output from the SP-CAM in this study. The results of many of these studies suggest that cloud condensate heterogeneity in the physical atmosphere may be better parameterized in terms of more than just the condensate mean, but the results of Shonk et al. (2010) suggest that a reasonable first attempt might be to represent the condensate standard deviation in terms of the gridbox mean alone (note that a constant coefficient of variation implies a linear dependence of standard deviation on the mean). The cloud microphysics scheme in CAM5 similarly assumes that standard deviation in condensed cloud water is directly proportional to the gridbox mean, and simplifies this relationship to $\sigma_q = \overline{q}$. Thus, this simple treatment of heterogeneity is consistent with what is being done in some current state of the art climate models.

Figure 4.5 shows the standard deviation in cloud liquid (upper left), cloud ice (upper right), precipitating liquid (lower left) and precipitating ice (lower right) condensate mixing ratios versus gridbox mean cloud and precipitation condensate, respectively, again for a single snapshot of SP-CAM output. The figure shows a kernel density estimate for the bivariate PDF of mean and standard deviation (shown by the contours). Because the distribution of the mean and standard deviation of condensate mixing ratios is strongly skewed, these are shown on a log-log scale. The figure shows that the standard deviation of condensate is strongly correlated with the mean, following an approximately linear relationship in log-log space. This suggests that the standard deviation $\sigma$ can be represented in terms of the mean $\mu$ for each condensate type by the relationship

$$\sigma = a \mu^b$$

(4.5)
where $a$ and $b$ are constants that need to be parameterized. Note that taking the logarithm of both sides shows that this leads to a linear relationship in log-log space:

$$\log \sigma = \log(a\mu^b) = \log a + b \log \mu$$

Note also that for $b = 1$, this relationship reduces to the definition for the coefficient of variation used in the studies discussed above, with $a = \sigma/\mu$.

Standard deviation is fit to $\sigma = a\mu^b$ by performing a linear regression of $\log \sigma$ versus $\log \mu$ to estimate the slope and intercept $a'$ and $b'$ in $\log \sigma = a' \log \mu + b'$, and then determining $a$ and $b$ such that $\sigma = a\mu^b$ by taking $a = 10^{a'}$ and $b = b'$. That is, the fit is performed in log-log space, and the fit parameters are then transformed back. The fit parameters $a$ and $b$, as well as the coefficient of determination $r^2$ (from the linear regression in log-log space) are indicated in each panel of Figure 4.5 for the example SP-CAM snapshot. This fit is repeated for each 3-hourly snapshot of SP-CAM output in the month of July 2000 (248 total snapshots), and the fit parameters for each snapshot are shown in Figure 4.6. The fit parameters are then averaged over all of the snapshots to provide a single parameterization of the scale and power parameters $a$ and $b$ for use in the sensitivity tests in this chapter, and are shown in Table 4.1.

The averages of the power parameters ($b$) are all around a value of $b = 1$. This suggests that variance might be nearly as well represented by simply parameterizing the coefficient of variation directly rather than including the additional parameter $b$, but including $b$ does improve the quality of the fit somewhat. Regardless, since the average power parameters are near unity, the values of the scale parameters can be assumed to approximate the coefficient of variation, since $\sigma = a\mu^b$ reduces to $a = \sigma/\mu$ for $b = 1$. The averages of the scale parameters $a$ for cloud liquid and cloud ice are 0.57 and 0.73, respectively. These values are within the range of values found by Shonk et al. (2010) for the coefficient of variability using a variety of observations, suggesting that the variability in the SP-CAM (and the parameterization developed here) is at least somewhat consistent with variability in the physical atmosphere.

The fits to Equation 4.5 shown in Table 4.1 provide a simple parameterization for con-
Figure 4.5: Kernel density estimate for the bivariate PDF of condensate standard deviation and mean for cloud liquid, cloud ice, precipitating liquid, and precipitating ice (contours) for a single global snapshot of SP-CAM CRM output. Shown in the upper left corner of each panel are the parameters for the fit to Equation 4.5, along with the coefficient of determination ($r^2$) of the fit.
Figure 4.6: Fits to Equation 4.5 for each of the 248 SP-CAM snapshots in July 2000.
densate standard deviation, so that given the gridbox mean values at each level, condensate standard deviation can be represented using the functional relationship Equation 4.5. Assuming constant values for the fit parameters is analogous to assuming a constant coefficient of variability for condensate, as suggested by Shonk et al. (2010). While more recent studies have shown that condensate variability likely depends on at least cloud fraction and cloud regime as well, assuming constant values for these fits provides a simple parameterization and is a natural starting point for testing the sensitivity of the COSP diagnostics to horizontal variability. The dependence of these fit parameters on cloud fraction was briefly explored, and preliminary results suggest that especially the scale parameter $a$ does vary with cloud fraction. However, no clear functional relationship emerged for use in the parameterization, so it is left for future work to explore this dependence using model output to compliment the observational studies.

Table 4.1: Averages of the fit parameters shown in Figure 4.6 over all 248 SP-CAM snapshots.

<table>
<thead>
<tr>
<th>Hydrometeor</th>
<th>Average $a$</th>
<th>Average $b$</th>
<th>Average $r^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cloud liquid</td>
<td>0.57</td>
<td>0.95</td>
<td>0.92</td>
</tr>
<tr>
<td>Cloud ice</td>
<td>0.73</td>
<td>1.03</td>
<td>0.91</td>
</tr>
<tr>
<td>Precip liquid</td>
<td>1.54</td>
<td>1.03</td>
<td>0.97</td>
</tr>
<tr>
<td>Precip ice</td>
<td>1.43</td>
<td>1.03</td>
<td>0.99</td>
</tr>
</tbody>
</table>

4.4 Quantifying improvements in COSP-simulated diagnostics

With the improved subcolumn generator and parameterizations described in the preceding sections, the sensitivity of the COSP diagnostics to the improvements can be quantified using the same framework presented in the previous chapter for quantifying the sensitivities to the maximum-random overlap and homogeneous condensate assumptions. Again, a set of modified cloud and precipitation condensate fields are created from a month-long SP-CAM
simulation, COSP is run on each set of modified fields, and the COSP outputs are compared with one another to quantify the sensitivity to different aspects of the improved subcolumn generator. These cases are described below, and illustrated for an example gridbox in Figure 4.7. The cases are also summarized in Table 4.2.

The first two cases are identical to those used in Chapter 3. The first is created by using the unmodified CRM fields from the SP-CAM, and is referred to as the “CRM” or “original” case. The COSP outputs from this case serve as the baseline against which the performance of the modified cases are assessed. This case is illustrated for the example gridbox in the top panels of Figure 4.7. The second case is created by homogenizing the cloud and precipitation condensate amounts: condensate amount for each hydrometeor type is replace with the (horizontal) gridbox-means (by level) everywhere that condensate type exists in the original CRM fields. Again, this case is referred to as the “CRM-HOM” (exact overlap from the CRM but homogenized condensate) or the “homogenized” case. This case is illustrated for the example gridbox in the second panel of Figure 4.7.

Table 4.2: Treatment of overlap and variance for each of the modified cases. See text for description of each case.

<table>
<thead>
<tr>
<th>Case</th>
<th>Overlap</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>CRM</td>
<td>Exact</td>
<td>Exact</td>
</tr>
<tr>
<td>CRM-HOM</td>
<td>Exact</td>
<td>Homogeneous</td>
</tr>
<tr>
<td>GEN-VAR-PARAM</td>
<td>Parameterized</td>
<td>Parameterized</td>
</tr>
<tr>
<td>GEN-HOM-PARAM</td>
<td>Parameterized</td>
<td>Homogeneous</td>
</tr>
<tr>
<td>GEN-VAR-CALC</td>
<td>Calculated</td>
<td>Calculated</td>
</tr>
<tr>
<td>GEN-HOM-CALC</td>
<td>Calculated</td>
<td>Homogeneous</td>
</tr>
</tbody>
</table>

The remaining cases are created in a similar manner as in Chapter 3: gridbox-mean profiles of cloud fraction, precipitation fraction, and condensate amount (mixing ratio) are
Figure 4.7: Total cloud (left) and precipitation (right) mixing ratios from the original CRM fields (top), homogenized CRM fields (CRM-HOM, second row), regenerated using the R04 scheme for cloud occurrence with generalized overlap but homogeneous condensate (GEN-HOM-PARAM, third row), and regenerated using the full R04 scheme with generalized overlap and heterogeneous condensate (GEN-VAR-PARAM, bottom row) for an example gridbox (00 UTC 01 July 2000, 10 N, 180 E).
calculated from the original CRM fields and then fed into various renditions of the improved subcolumn generator described here to regenerate subcolumn condensate fields. These cases are broadly referred to as the “regenerated” cases because they are attempts to regenerate the full distribution of condensate in the original CRM fields from the gridbox-means, but different cases are generated with varying degrees of parameterization of overlap, rank correlation, and heterogeneity in order to test the sensitivity to these parameterizations.

The first of these regenerated cases uses the full subcolumn generator described here, with the parameterization of overlap $\alpha$, rank correlation $\rho$, and gridbox standard deviation in condensate $\sigma_q$ discussed. This case is referred to as the “GEN-VAR-PARAM” case, because it uses the full generator with generalized overlap and horizontally variable condensate. This case is illustrated for the example gridbox in the bottom panel of Figure 4.7. Differences in the outputs between this case and the original CRM case quantify the total error inherent in using the full subcolumn generator with parameterized overlap, rank correlation, and variability.

In order to separate the errors due to the treatment of overlap from those that arise due to the treatment of variability, another regenerated case is created that uses the improved subcolumn generator to account for the occurrence overlap, but which uses horizontally homogeneous condensate instead of using the parameterization for horizontal variability. This case is referred to as the “GEN-HOM-PARAM” case because it uses generalized overlap but with horizontally homogeneous condensate amounts. This case is illustrated in the third panel of Figure 4.7. Because this case differs from the homogenized (CRM-HOM) case only in the treatment of occurrence overlap, differences between these two cases represent errors arising solely due to the parameterization of overlap.

The parameterization of horizontal variability is shown below to be somewhat less than ideal, so it is not expected that the regenerated (GEN-VAR-PARAM) case will perfectly reproduce the characteristics of the original CRM case. Rather, this case represents the performance that can be expected from the R04 generator with a very simple parameterization of overlap, rank correlation, and heterogeneity. In order to test the theoretical limit of per-
formance that can be expected using the R04 generator with ideal parameterization of these quantities, another case is created that uses the full generator, but with overlap, rank correlation, and condensate variance calculated at each gridbox and time step directly from the original CRM fields rather than parameterized. This case is referred to as the “GEN-VAR-CALC” case. Because this case uses the R04 scheme but with overlap, rank correlation, and variance calculated directly rather than parameterized, this cases represents the upper limit of the performance that can be expected from this subcolumn scheme, if these parameters could be perfectly prescribed. The distribution of subcolumn cloud and precipitation condensate looks qualitatively similar between the GEN-VAR-CALC and GEN-VAR-PARAM cases, so the GEN-VAR-CALC case is omitted from Figure 4.7. In order to separate the effect of the treatment of occurrence overlap from that of variability, another case is created using the subcolumn generator to account for occurrence overlap, with overlap $\alpha$ calculated directly from the original CRM fields but with homogeneous condensate. This case, referred to as the “GEN-HOM-CALC” case, is identical to the GEN-HOM-PARAM case but with calculated rather than parameterized overlap. Again, because this case is similar to the GEN-HOM-PARAM case already shown, it is omitted from Figure 4.7. Because this case differs from the homogenized (CRM-HOM) case only in the treatment of overlap, differences between these two cases represent errors that can be expected due to overlap alone, even with perfect parameterization of overlap.

Figure 4.8 shows the cumulative distribution of raw condensate amount $q$ (left panel) and of normalized condensate amount $q/\bar{q}$ where $\bar{q}$ is the gridbox-mean condensate amount (right panel) for each hydrometeor type from the regenerated GEN-VAR-PARAM (dotted curves) and GEN-VAR-CALC (dashed curves) cases for a single snapshot of SP-CAM output, compared with the CDFs from the original CRM fields (solid curves). The GEN-VAR-CALC and GEN-VAR-PARAM cases reproduce the general shape of the raw distribution, but fail to capture the distinct “kinks” in the distributions. This illustrates the limit of assuming that all cloud and precipitation condensate follows a gamma distribution, even when the mean and variance are known for each gridbox and at each level. The GEN-
Figure 4.8: Raw (left) and normalized (right) condensate empirical density functions from the CRM (solid curves), GEN-VAR-PARAM (dotted curves), and GEN-VAR-CALC (dashed curves) cases as described in the text for a single snapshot of SP-CAM output.
VAR-CALC case is able to reproduce the general shape of the distribution of normalized precipitating liquid and ice condensate, but fails to reproduce the the shape of the cloud liquid and ice condensate distributions, and the GEN-VAR-PARM case is unable to reproduce the shape of the distributions for any of the normalized condensate types. In general the parameterization tends to underestimate the number of hydrometeors with very small values relative to the mean, with larger values of condensate mixing ratios making up the majority of the distribution. The cause of the relatively poor performance of the parameterization is not yet known, but it should be noted that this parameterization is extremely simplified, and better performance may be had using a more sophisticated treatment (as suggested by the better agreement using the calculated variance). In particular, building in a dependence on hydrometeor occurrence fraction and either geolocation or cloud regime may improve the agreement with the CRM distributions. Regardless, it is clear that representing variance in terms of the mean using the (overly simple) parameterization described here will likely lead to remaining errors in COSP outputs. This is shown to be the case in the following sections. It should be emphasized again, however, that the primary goal of this study is to understand the sensitivity of the COSP outputs to parameterization of overlap and variability.

The sensitivity to both the overlap and the variability treatment can be quantified by taking appropriate differences between the outputs from these different cases. The CRM-HOM and GEN-HOM-PARAM (and GEN-HOM-CALC) cases differ primarily in the treatment of cloud (and precipitation) overlap, so the difference between the outputs from these cases quantifies the component of the error due to the generalized overlap treatment alone. This will be calculated for both the GEN-HOM-CALC case and for the GEN-HOM-PARAM case, showing both the generalized overlap errors that can be achieved with ideal overlap and with overlap specified only by a monthly and spatially invariant (averaged) decorrelation length. The component of the error due to the treatment of variability is quantified by calculating the residual between the total error in using the full subcolumn generator (GEN-VAR-CALC or GEN-VAR-PARAM minus CRM) and the component of the error due to the treatment of overlap (GEN-HOM-CALC or GEN-HOM-PARAM minus CRM-HOM). The total error
$E_{\text{total}}$ and the overlap and variability components $E_{\text{gen}}$ and $E_{\text{var}}$ are calculated for a simulated satellite diagnostic quantity $X$ then as

\begin{align*}
E_{\text{total}} &= X_{\text{GEN-VAR}} - X_{\text{CRM}} \\
E_{\text{gen}} &= X_{\text{GEN-HOM}} - X_{\text{CRM-HOM}} \\
E_{\text{var}} &= E_{\text{total}} - E_{\text{gen}}
\end{align*}

where GEN-VAR-CALC or GEN-VAR-PARAM can be used in place of GEN-VAR to evaluate separately the limits of the framework or the specific parameterization used. To specify whether calculated or parameterized overlap and variance are used, the “calc” or “param” suffix will be appended to $E_{\text{gen}}$ and $E_{\text{var}}$ (for example, $E_{\text{gen-calc}}$ indicates generalized overlap errors using calculated overlap). The sensitivity of the various simulated diagnostics to the modifications made in the new subcolumn generator are evaluated using this framework in the following sections. Note that, as in Chapter 3, the total error is equal to the sum of the components due to overlap and variability, such that $E_{\text{total}} = E_{\text{gen}} + E_{\text{var}}$.

\section*{4.5 Reduced errors in simulated passive remote sensing diagnostics}

Figure 4.9 and Figure 4.10 show the errors in MISR-simulated cloud area by cloud top height that arise due to using the R04 subcolumn generator to regenerate subcolumn cloud and precipitation condensate fields from gridbox-mean profiles. Figure 4.9 shows the errors in using the subcolumn generator with ideal or “best-case” overlap, rank correlation, and variance calculated directly from the original CRM fields (GEN-VAR-CALC), while Figure 4.10 shows the errors in using the new scheme with these quantities parameterized as discussed in Section 4.2 and Section 4.3. Comparing Figure 4.9 and Figure 3.3 it is clear that the new scheme (with ideal overlap and variability) is able to dramatically reduce the errors identified in Chapter 3 in regard to total error (left-most column), as well as due to both the treatment of variability (middle) and overlap (right-most column). The reduction in both variability and overlap errors means that the reduced error in the total is \textit{not} due to a cancellation of errors (in contrast to the errors shown in Chapter 3 that arise due to using
Figure 4.9: Errors in MISR-simulated cloud area by cloud top height arising due to using the improved subcolumn generator with calculated overlap and variability to regenerate subcolumns from gridbox-mean profiles (left), the component of the error due to the treatment of variability (middle), and the component of the error due to the treatment of overlap (right).
Figure 4.10: Errors in MISR-simulated cloud area by cloud top height arising due to using the improved subcolumn generator with parameterized overlap and variability to regenerate subcolumns from gridbox-mean profiles (left), the component of the error due to the treatment of variability (middle), and the component of the error due to the treatment of overlap (right).
homogeneous condensate with maximum-random overlap). Errors due to the treatment of variability (middle column) are everywhere less than 6% cloud area (and generally much smaller, between 0 and 2%) using the new scheme, compared with errors as large as 10% cloud area using homogeneous condensate (Figure 3.3). Errors due to the overlap treatment are similarly reduced, from regional errors as large as 10% using MRO down to less than 2% using the new scheme.

Using parameterized overlap, rank correlation, and variance results in larger errors than using the calculated values, as seen in Figure 4.10. The errors due to the treatment of variability are comparable to those that result from using homogeneous condensate (see Figure 3.3). High-topped cloud especially is overestimated throughout the tropical western Pacific. This is likely a consequence of the parameterization of the variance failing to capture the large spread of condensate values present in the original CRM fields. This is evident in the normalized CDFs shown in the right panel of Figure 4.8, which shows that using the parameterization results in an underestimation of condensate amounts with values much lower than the mean.

Errors due to using parameterized overlap show clear spatial patterns, with overestimation of cloud area especially in the Southern Ocean but also somewhat in the tropical western Pacific and over the continents, and an underestimation of cloud area elsewhere. The majority of these errors (especially in the Southern Ocean) appear to be in the low-topped cloud area. These errors, especially in the Southern Ocean low-topped cloud, have a similar spatial structure to the global map of decorrelation length shown in Figure 4.3. The errors due to using the parameterized overlap suggest that using a globally constant decorrelation length for cloud occurrence overlap is insufficient to characterize the overlap of clouds simulated by SP-CAM (and likely real clouds in the physical atmosphere).

One possible alternative is to use a spatially-dependent decorrelation scale for cloud overlap. (Oreopoulos et al., 2012) use a simple latitude-dependence to specify decorrelation lengths in their implementation in a GCM. Taking this one step further, a spatially-varying decorrelation length scale is tested here, using tabulated decorrelation lengths taken from
Figure 4.11: Errors in MISR-simulated cloud area due to the parameterization of overlap alone using a constant decorrelation length scale as described in Section 4.2 ($E_{\text{gen-param}}$, far-left column), using spatially-dependent decorrelation length scales derived from Figure 4.3 ($E_{\text{gen-tab}}$, middle column), and using overlap that depends instead on temperature rather than on separation distance, with a constant overlap (0.4) for warm clouds and a constant overlap (0.85) for cold clouds ($E_{\text{gen-temp}}$, far-right column).
Figure 4.3 at each latitude-longitude gridbox, and filling in with the global average where Figure 4.3 has missing data. The resulting errors in MISR-simulated cloud area are shown in the middle column of Figure 4.11. Unfortunately, these results show that even using a spatially-dependent decorrelation length scale is insufficient, and does not result in an appreciable reduction in errors relative to using the constant decorrelation length.

What each of these cases lack is any dependence on cloud type, and rather are combining the overlap effects of potentially different cloud types or regimes together. For example, it is expected that convective and stratiform clouds would have significantly different overlap characteristics (e.g., Pincus et al., 2005). It would be straightforward to implement separate overlap for convective and stratiform clouds in GCMs that separately parameterize cloud fraction for both of these categories, but how to do this for the SP-CAM is less clear because the embedded CRM (SAM) does not distinguish between convective and stratiform cloud. Instead, a simple temperature dependence is tested here, with a single constant overlap \( \alpha_{\text{cold}} = 0.85 \) (rather than a dependence on separation, as studied previously) selected for levels with temperature \( t < 273 \) K, and \( \alpha_{\text{warm}} = 0.40 \) for levels with temperature \( t \geq 273 \) K. The errors in MISR-simulated cloud area that result from this simple test are shown in the far right column of Figure 4.11. The errors in total cloud area are substantially reduced using this parameterization based on temperature, especially in the Southern Ocean. Regional errors in cloud area are still present with this parameterization, however, including an underestimate in high-topped cloud area throughout the tropical western Pacific (a reversal in sign from the errors in high-topped cloud from the other two parameterizations), and a remaining overestimation of low-topped cloud throughout the Southern Ocean. Errors may not be eliminated with this parameterization, but the sensitivity of the simulated MISR cloud area to changes in the parameterization of overlap demonstrated by the different columns in Figure 4.11 suggests that these errors can be reduced further by improving the parameterization of overlap.

While the results of Figure 4.10 suggest that more work needs to be done to characterize variability and overlap statistics in order to improve MISR-simulated cloud area by cloud top
Figure 4.12: Errors in CloudSat-simulated hydrometeor occurrence \((Z_e > -27.5 \text{ dBZ})\) arising due to using the improved subcolumn generator with calculated overlap and variability to regenerate subcolumns of cloud and precipitation (top), as well as components due to both the treatment of variability (middle) and the treatment of overlap (bottom).

height, the results of Figure 4.9 demonstrate the promise of using the improved subcolumn generator with COSP, and suggest that future research to improve the characterization of overlap statistics and horizontal variability in large-scale models would be a worthwhile endeavor.

### 4.6 Reduced errors in simulated CloudSat reflectivity and hydrometeor occurrence

Figure 4.12 and Figure 4.13 show the errors in the zonally-averaged CloudSat-simulated hydrometeor occurrence fraction. Comparing these errors to those shown in Figure 3.8 again shows a substantial reduction in errors of all types using the improved subcolumn generator relative to those errors that resulted from using SCOPS and PREC_SCOPS (when using the calculated overlap and variance). The total error that arises using the R04 scheme with calculated overlap and variance to regenerate subcolumns results in errors that are
Figure 4.13: Errors in CloudSat-simulated hydrometeor occurrence ($Z_e > -27.5$ dBZ) arising due to using the improved subcolumn generator with parameterized overlap and variability to regenerate subcolumns of cloud and precipitation (top), as well as components due to both the treatment of variability (middle) and the treatment of overlap (bottom).

Errors in CloudSat-simulated hydrometeor occurrence when using the parameterized treatment of overlap and variability are lower than when using the current COSP scheme (SCOPS and PREC,SCOPS), but are nonetheless much larger than when using the calculated overlap and variability. This suggests that considerable improvement can be realized with further efforts to parameterize variability. The errors due to the treatment of overlap remain small when using the parameterization, as one might expect given that the “cloud
Figure 4.14: Errors in CloudSat-simulated reflectivity with height histograms for the NH tropics (0 to 10 degrees north).

masking” effect discussed in the previous section for simulated MISR cloud area does not apply to CloudSat-simulated hydrometeor occurrence beyond than the effects of attenuation (which are likely a second order effect on hydrometeor occurrence shown here). Thus, overlap errors shown in Figure 4.12 and Figure 4.13 (bottom panels) are so low that they are barely visible on the color scale used.

Figure 4.14 and Figure 4.15 show errors in CloudSat-simulated reflectivity with height histograms for the northern hemisphere tropics (0 to 10 degrees north). The figures show a reduction in errors of all types (total error as well as components due to variability and overlap) using the new subcolumn scheme with either calculated or parameterized overlap
Figure 4.15: Errors in CloudSat-simulated reflectivity with height histograms for the NH tropics (0 to 10 degrees north).
and variability to regenerate subcolumns compared with the errors identified in Figure 3.10. Again, errors are somewhat larger using the parameterized variance treatment, while the error due to using the parameterized overlap treatment remains small. These errors are somewhat different in nature than identified in Chapter 3. While using homogeneous condensate primarily resulted in increased frequency of occurrence along the characteristic curve in reflectivity-height space, the errors shown in Figure 4.15 are not entirely on the characteristic curve. In particular, the errors at high-altitudes (where ice is present) are primarily at smaller reflectivity values, consistent with the issues identified above with representing the full distribution of cloud ice.

The errors shown in Figure 4.13 and Figure 4.15 that arise from using the simple parameterization of condensate variability presented here show that improvements to this parameterization are needed to accurately characterize the condensate heterogeneity, but these errors are still substantially smaller than arise when using homogeneous condensate, especially for the full reflectivity with height histograms. Figure 4.16 shows the total errors for the NH tropics from using each configuration of subcolumn generators, including SCOPS and PREC_SCOPS (MRO-HOM, far-left column), SCOPS and PREC_SCOPS with the precipitation adjustment (MRO-HOM-PADJ, second column), the new subcolumn generator with calculated overlap and variance (GEN-VAR-CALC, third column), and the new subcolumn generator with parameterized overlap and variance (GEN-VAR-PARAM, far-right column). Figure 4.17 shows the same cases but for the North Pacific region. It is obvious that although the errors using parameterized overlap and variance are larger than when using calculated overlap and variance, these errors are much smaller than when using SCOPS and PREC_SCOPS with homogeneous condensate, especially at lower-altitudes.

4.7 Discussion

In this chapter, a new cloud subcolumn generator using the algorithm of Räisänen et al. (2004) has been presented to potentially replace the current implementation of SCOPS in COSP. The new subcolumn generator allows for a more realistic representation of cloud
Figure 4.16: Errors in CloudSat-simulated reflectivity with height histograms for the NH tropics (0 to 10 degrees north) that result from using each of four configurations of the subcolumn generator, including, from left to right: the COSP implementation of SCOPS and PREC, SCOPS with homogeneous condensate and maximum-random overlap (MRO-HOM), SCOPS and PREC with adjusted precipitation fraction (MRO-HOM-PADJ), the improved subcolumn generator with calculated overlap and variance (GEN-VAR-CALC), and the improved subcolumn generator with parameterized overlap and variance (GEN-VAR-PARAM).
Figure 4.17: Errors in CloudSat-simulated reflectivity with height histograms for the North Pacific (35 to 60 degrees north latitude, 160 to 220 degrees east longitude) that result from using each of four configurations of the subcolumn generator, including, from left to right: the COSP implementation of SCOPS and PREC_SCOPS with homogeneous condensate and maximum-random overlap (MRO-HOM), SCOPS and PREC_SCOPS with adjusted precipitation fraction (MRO-HOM-PADJ), the improved subcolumn generator with calculated overlap and variance (GEN-VAR-CALC), and the improved subcolumn generator with parameterized overlap and variance (GEN-VAR-PARAM).
overlap by representing overlap as a linear combination of maximum and random overlap, as well as horizontally variable cloud and precipitation condensate amount sampled from gamma distributions. The impact of these changes on simulated satellite-observable cloud diagnostics from COSP has been evaluated by using the new subcolumn generator to regenerate subcolumns of cloud and precipitation condensate from CRM output from SP-CAM that has been averaged to mimic gridbox mean quantities as would be represented by a traditional GCM. These impacts have been tested both with idealized overlap and horizontal variability calculated directly from the original CRM fields and with overlap and horizontal variability parameterized.

The sensitivity test framework uses outputs from the SP-CAM to provide a plausible representation of cloud and precipitation structure and variability at scales similar to those at which the satellite retrievals are performed. While these outputs provide much higher resolution cloud fields than available in traditional GCMs, the fields simulated by the SP-CAM are in fact still model outputs, and may not perfectly simulate any observed cloud systems. Nonetheless, the overlap and condensate rank correlation statistics from SP-CAM are consistent with those found in observations from previous authors, and condensate variability is consistent with previous studies as well, following similar statistical distributions. Thus, since the goal of this study is to evaluate the sensitivity of COSP diagnostics to these properties, rather than to develop a perfect parameterization of subgrid-scale overlap and variability, the SP-CAM output is sufficient for this purpose. In order to run the individual simulators directly on output from the SP-CAM, it is important that the fields simulated by the SP-CAM are on a scale similar to that at which the satellite retrievals are performed. The SP-CAM output used in this study was run using 4 km grid spacing for the embedded cloud-resolving model. MISR cloud top height retrievals are performed at a spatial scale of 1.1 km (Moroney et al., 2002), and the CloudSat cloud radar has a horizontal resolution of 1.4 km cross-track and 1.7 km along-track (Tanelli et al., 2008). While these scales are somewhat smaller than the 4 km grid used by the SP-CAM CRM, the differences are small and are unlikely to affect the results of the sensitivity study performed with the 4 km fields
The ceiling of potential performance of the new subcolumn scheme is demonstrated by running COSP on subcolumns regenerated with overlap and variability calculated directly from the original CRM fields. It has been shown here that this leads to substantial improvements in satellite-simulated cloud properties. This suggests that implementing this framework can substantially reduce errors in simulated clouds that arise due to the currently used assumptions of maximum-random overlap and horizontally homogeneous cloud and precipitation (as shown in the previous chapter).

While results using the ideal (calculated) overlap and variability from the original CRM fields demonstrate the potential of the new subcolumn generator, results using the parameterized overlap and variability show that the performance of the subcolumn generator is somewhat dependent on how overlap and variability are parameterized within this framework. In particular, it appears that MISR-simulated cloud area by cloud top height is dependent on both the representation of variability and of overlap, while CloudSat-simulated radar reflectivity is primarily dependent on the representation of variability (and precipitation occurrence, as demonstrated in the previous chapter). Large errors arise when parameterizing overlap and rank correlation as functions of separation distance alone with constant decorrelation length scales, and assuming constant decorrelation length scales is insufficient for capturing the overlap characteristics of clouds simulated by SP-CAM (see Figure 4.3 and Figure 4.4). However, substantially better results are demonstrated when using overlap that depends instead on temperature, with separate (still spatially-invariant) values of the overlap parameter \( \alpha \) for warm and cold clouds, suggesting that further improvements can be made by parameterizing overlap as a function of not just separation but on additional aspects of the gridbox as well. Many questions about how best to represent overlap statistics remain, and this will be an interesting area of future research.

Errors arising due to the parameterization of variability presented here remain significant for both MISR-simulated cloud area by cloud top height and for CloudSat-simulated hydrometeor occurrence, demonstrating the need for continued efforts to improve parame-
terization of overlap and variability. Errors in CloudSat-simulated reflectivity with height are notably reduced even with the crude parameterization of variability presented here.

These issues are not unique to simulation of satellite-observable cloud diagnostics, and it has been recognized that subgrid-scale variability, including cloud and precipitation occurrence overlap and condensate amount, effect many important processes in large-scale models, and some researchers are trying to develop explicit subgrid treatments for GCMs. This includes so-called “statistical” or “assumed probability distribution” schemes, which predict the evolution of not only the mean, but also the probability distribution of total water (and to a degree the cloud and precipitation condensate) within each grid-box (e.g., Tompkins, 2002). There has been growing interest in using these schemes in GCMs. One such example of this is the Cloud Layers Unified By Binormals (CLUBB; Golaz et al., 2002) scheme, which is being implemented into the NCAR CAM and will be the standard scheme in CAM6 (A. Gettelman and R. Wood, personal communication). Because these schemes are formulated using a probability distribution for the subgrid variability of condensate, they are a natural fit to the stochastic treatment of subgrid clouds and precipitation used in COSP to simulate satellite retrievals (and also to radiation schemes that use stochastic treatments of subgrid clouds such as the McICA (Pincus et al., 2003), because the same distribution of condensate can be shared between these different components of the model. As shown here for simulated satellite diagnostics and by others for calculated radiative fluxes, these assumptions can have a large impact on diagnosed cloud effects, and thus consistency between cloud treatments in the different parts of the model is necessary in order to obtain a consistent picture of the performance of models in simulating clouds.
Chapter 5
SUMMARY AND IMPLICATIONS

Accurate representation of clouds in large-scale (global) climate models is of critical importance, but has remained elusive for model developers. An important test of the fidelity of models is the comparison of simulated climate against available observations of the physical climate. For cloud properties, this often means comparison with satellite-retrievals, but these types of comparisons have traditionally been challenging due to fundamental limitations in both the satellite retrieval process and in the model formulation of clouds. An increasingly common approach to dealing with these limitations is to use the simulator framework, whereby pseudo-retrievals are simulated from model cloud fields to account for some of the known features and limitations of specific satellite retrievals. While this approach has enabled more consistent comparisons between modeled and observed cloud properties, it is demonstrated here that limitations in both the retrievals and in the models themselves remain unaccounted for.

The simulation of satellite-retrieved cloud properties from the description of clouds provided by a large-scale model is a multi-step process, involving 1) downscaling model gridbox-mean quantities to scales approximating satellite pixels, 2) simulating the individual satellite retrievals, and 3) aggregating the pixel-scale pseudo-retrievals into statistical summary products analogous to those produced for the individual satellite instruments. In general there can be uncertainties associated with each of these steps, and the primary goal of this study has been to quantify (and reduce) uncertainties and biases related to both steps 1) and 2).

The performance of the MISR simulator is evaluated here by comparing pseudo-retrievals simulated from CloudSat and CALIPSO data with retrievals from MISR. The MISR simulator is able to correct for many of the features of the MISR retrieval and, in general,
cloud top heights retrieved from CloudSat and CALIPSO are in much better agreement with MISR after using the MISR-simulator to account for the features of the MISR retrieval. Mid and high-topped clouds are in particularly good agreement between MISR and CloudSat/CALIPSO retrievals when using the MISR simulator. Large differences remain in total and low-topped clouds, however, due to ambiguities in retrieving small (sub-pixel) scale clouds. The differences highlighted here between MISR and CloudSat/CALIPSO cloud area are discouraging because they represent a fundamental uncertainty in the quantification of low-topped and total cloud area, making robust comparisons of modeled cloud area with these satellite retrievals difficult. More importantly, these differences point to the fragility of cloud area as a measure of cloudiness. This has motivated the use of joint histograms of cloud top height and optical depth for model evaluation because comparisons can be limited to categories for which uncertainties are expected to be lower. For example, Pincus et al. (2012) suggest limiting comparisons of cloud area to only those pixels and gridboxes with cloud optical depth $\tau > 1.3$ in order to limit the uncertainties that arise due to sampling broken cloud scenes. While this does improve agreement among the different satellite retrievals of cloud area from MISR, ISCCP, and MODIS, errors arising in the simulated satellite retrievals due to homogenizing cloud condensate are shown here to affect not only total cloud area but also optically thick $(\tau > 23)$ cloud area. Thus, additional care must be taken to account for these inherent errors and uncertainties.

Because current global climate models do not explicitly resolve clouds at the scales at which satellite retrievals are performed, the additional step of downscaling cloud properties to pixel scales is needed before simulating the satellite retrievals. This process depends on additional assumptions about the unresolved cloud properties. In particular, cloud (and precipitation) condensate is nearly always assumed to be horizontally homogeneous on the scale of model gridboxes, and clouds are assumed to follow a simple “maximum-random” overlap. MISR-simulated cloud area is sensitive to both of these assumptions, while simulated CloudSat radar reflectivity is sensitive primarily to the treatment of precipitation and to the subgrid-scale variability in condensate. These errors can be quite large regionally, and
have significant consequences for the suitability of these simulators for model evaluation. The errors in CloudSat-simulated radar reflectivity that arise due to these assumptions are particularly large and, until these errors are corrected for, CloudSat radar reflectivity is probably not a suitable quantity for model evaluation.

The errors in simulated pseudo-retrievals that arise due to the generation of subcolumns from model gridbox-mean quantities can be significantly reduced with an improved subcolumn treatment that accounts for both horizontal variability in condensate amount and more realistic overlap of clouds and precipitation. The subcolumn scheme described by (Räisänen et al., 2004) is implemented here for use in COSP and the new scheme results in a significant reduction in errors due to generating subcolumns from gridbox means. The performance of this improved subcolumn generator depends, however, on the specification of cloud and precipitation overlap and rank correlation statistics, as well as on the subgrid-scale variance in condensate. These are all quantities which will need to be parameterized in order to use this improved subcolumn generator with traditional large-scale global models. Using overlap statistics and variance calculated directly from the high-resolution baseline simulation used in the sensitivity tests here results in a significant reduction in errors, but more modest results are obtained using a simple parameterization of these quantities. Nonetheless, the improvements demonstrated using the calculated quantities shows that this framework can significantly improve comparisons between models and satellite retrievals and that further work to better parameterize these quantities will be worthwhile.

It is important to note that the errors identified here are intrinsic to the model evaluation process itself and not directly connected to inherent errors in the formulation of a particular model. In other words, these errors arise on the diagnostic side, not on the model side. This is significant, because it means that if we fail to account for these errors we may draw incorrect conclusions about the models we evaluate. In particular, it is important that the assumptions used in generating these diagnostics are consistent with assumptions used elsewhere in the model in order to draw conclusions about models consistent with their internal formulation.

The importance of overlap and condensate heterogeneity extend beyond just the simu-
lation of pseudo-satellite retrievals. In particular, both of these characteristics of clouds are important in simulating radiative fluxes and in predicting microphysical process rates. This makes future work to improve the characterization of these quantities even more important. With the growing interest in statistical or PDF-based cloud schemes in large-scale models, it might ultimately make sense for subgrid-scale variance (and, perhaps, condensate probability distributions) to be specified by these schemes within the model, rather than by some external parameterization of the variance with an assumed distribution. Certainly, if such an assumption is made within the model, it makes sense for the same assumptions to be used on the diagnostic end. Regardless, it is clear that the representation (or implicit assumption) of cloud properties at scales below those resolved by global climate models is in dire need of improvement.

While the primary goal of this work has been to evaluate and reduce the errors in satellite diagnostics that arise due to unresolved cloud properties, this work also presents a step forward in the understanding and quantification of these unresolved cloud and precipitation properties. Traditionally, analysis of small-scale cloud statistics has been limited to direct in-situ observations of cloud properties using aircraft observations or tethered balloons, retrievals using a few select ground-based sites, retrievals using satellite observations, or limited area CRM or LES studies. Each of these sources of information carries with them specific strengths and limitations. The use of model output from the Multi-scale Modeling Framework presented here demonstrates a potentially new avenue for exploring the small (subgrid-scale) properties of cloud and precipitation condensate distributions. Using such model output for the study of cloud and precipitation condensate distributions has the advantage of providing resolved information about small-scale cloud and precipitation systems with global coverage, spanning a full range of atmospheric conditions and cloud regimes. This comprehensive spatial coverage is not possible using in-situ observations or ground-based retrievals and satellite-based retrievals of cloud properties are notoriously difficult to interpret and fraught with uncertainties and limitations. Of course, this approach is limited by the fidelity of the model itself, and the fact that simulated cloud systems may not be
consistent with clouds in the physical atmosphere. However, as global-scale high-resolution modeling frameworks like the MMF become more sophisticated and simulations improve (or as computational resources grow to accommodate true global cloud resolving models), the prospect of using such global simulations for the purpose of informing parameterizations for use in large-scale models becomes more reasonable.


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