The 'too few, too bright' tropical low-cloud problem in CMIP5 models

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[1] Previous generations of climate models have been shown to under-estimate the occurrence of tropical low-level clouds and to over-estimate their radiative effects. This study analyzes outputs from multiple climate models participating in the Fifth phase of the Coupled Model Intercomparison Project (CMIP5) using the Cloud Feedback Model Intercomparison Project Observations Simulator Package (COSP), and compares them with different satellite data sets. Those include CALIPSO lidar observations, PARASOL mono-directional reflectances and CERES radiative fluxes at the top of the atmosphere. We show that current state-of-the-art climate models predict overly bright low-clouds, even for a correct low-cloud cover. The impact of these biases on the Earth' radiation budget, however, is reduced by compensating errors. Those include the tendency of models to under-estimate the low-cloud cover and to over-estimate the occurrence of mid- and high-clouds above low-clouds. Finally, we show that models poorly represent the dependence of the vertical structure of low-clouds on large-scale environmental conditions. The implications of this 'too few, too bright low-cloud problem' for climate sensitivity and model development are discussed. **Citation:** Nam, C., S. Bony, J.-L. Dufresne, and H. Chepfer (2012), The 'too few, too bright' tropical low-cloud problem in CMIP5 models, *Geophys. Res. Lett.*, *39*, L21801, doi:10.1029/2012GL053421.

1. Introduction

[2] Climate models exhibit a large range of climate sensitivity estimates, which primarily arises from differing cloud radiative feedbacks amongst models [*Randall et al.*, 2007; *Bony et al.*, 2006; *Andrews et al.*, 2012]. The response of low-level clouds has been identified as a key source of uncertainty for model cloud feedbacks under climate change [*Bony and Dufresne*, 2005; *Webb et al.*, 2006; *Wyant et al.*, 2006; *Medeiros et al.*, 2008]. In this context, the ability of climate models to simulate low-clouds and their radiative properties matters to assess our confidence in climate projections.

[3] Several studies have shown that previous generations of climate models tended to under-estimate the low-cloud cover, and to over-estimate its optical thickness [e.g., *Webb et al.*, 2001; *Weare*, 2004; *Zhang et al.*, 2005; *Karlsson et al.*, 2008], a problem commonly referred to as the 'too few, too bright' low-cloud problem. This study examines how much of this problem remains in the current generation of models participating in CMIP5.

[4] Comparing clouds simulated by models and derived from space observations is not straightforward because the definition of clouds depends on the sensitivity of space-borne instruments and on the vertical overlap of cloud layers. To make the comparison more consistent, some climate models now use COSP [*Bodas-Salcedo et al.*, 2011], a community software diagnosing what different satellites would observe if they were flying above an atmosphere similar to that simulated by the models. This study analyzes CMIP5 outputs from the CALIPSO [*Chepfer et al.*, 2008] and PARASOL (D. Konsta, personal communication, 2012) simulators embedded in COSP. These two simulators make it possible to evaluate simultaneously and consistently both the low-cloud fraction and the visible reflectance of cloudy scenes. In addition, we compare broadband radiative fluxes simulated by models at the top of the atmosphere (TOA) with those derived from CERES observations.

[5] The CMIP5 models, and the satellite simulators and observations used to evaluate them, are presented in Section 2. Section 3 assesses the 'too few, too bright' low-cloud problem in CMIP5 models. Section 4 reveals compensating errors in CMIP5 models and proposes some interpretations. Section 5 examines the vertical structure of low-clouds in different environmental conditions. Section 6 presents a conclusion and a discussion of the results.

2. Models and Observations

[6] This study analyses monthly-mean data of many CMIP5 general circulation models (GCMs) atmosphere-only experiments forced by observed sea surface temperatures (AMIP) [*Taylor et al.*, 2012] from June 2006 to December 2008 (Table 1). Of these models, eight are currently available with the CALIPSO lidar and PARASOL reflectance simulators. Satellite simulators take profiles of temperature, pressure, cloud water content and cloud fraction from each atmospheric column of a model, and divide the modeled profiles of liquid and ice water mixing ratio amongst subcolumns, to account for sub-grid scale variability, using a subcolumn generator (SCOPS) [*Klein and Jakob*, 1999]. After assuming the model's cloud overlap function, each instrument signal is mimicked and the instrument's diagnostic (cloud reflectance, lidar scattering ratio, cloud fraction) is derived for each subcolumn and averaged over the grid box. Satellite simulators thus account for intrinsic differences in the identification and definition of a cloud amongst observational data sets, and diagnoses clouds in a consistent manner between models and observations.

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Table 1. List of CMIP5 Models Used in This Study[a]

		Version	
Institute	Model Name	Amon	cfMon
IPSL, France	IPSL-CM5B-LR	2012.05.26	2012.05.26
CNRM-CERFACS, France	CNRM-CM5	2011.10.06	2011.10.06
MPI-M, Germany	MPI-ESM-LR	2011.10.05	2012.02.15
Hadley Centre, UK	HadGEM2-A	2011.08.03	2011.08.09
CCCma, Canada	CanAM4	2011.10.20	2011.10.20
MIROC, Japan	MIROC5	2012.07.10	2012.07.10
MRI, Japan	MRI-CGCM3	2012.07.01	2012.07.01
NCAR, USA	CCSM4	2012.07.18	2012.09.05
BCC, China	bcc-csm1-1	2012.05.19	
NOAA-GFDL, USA	GFDL-HIRAM-C180	2011.06.01	
NASA-GISS, USA	GISS-E2-R	2012.05.18	

[a]AMIP Experiment from 200606-200812. IPSL-CM5A-LR is excluded from our study due to an inconsistency in total cloud cover between the model and the satellite simulator.

[7] Lidar simulator outputs are compared with the GCM-Oriented CALIPSO Cloud Product (GOCCP) observational data set [*Chepfer et al.*, 2010], which is based on CALIOP Level 1B lidar Scattering Ratios (SR) instantaneous profiles. Mono-directional PARASOL reflectances associated with a single viewing angle, selected to be the most sensitive to the cloud optical depth and the least to other parameters (D. Konsta, personal communication, 2012) are compared with the simulated reflectances. The net TOA radiative fluxes of the Clouds and Earth's Radiant Energy System (CERES) data set used in this study is derived from Level 4 Energy Balance And Filled (EBAF) products. Global atmospheric reanalysis provided by the European Centre for Medium-Range Weather Forecasts (ERA-Interim) [*Dee et al.*, 2011] and from the National Center for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) [*Saha et al.*, 2010] are used to examine the large-scale atmospheric conditions associated with the cloud properties observed from June 2006 to December 2008. A more detailed description of the satellite observations and simulators provided in the auxiliary material.[1]

3. The 'Too Few, Too Bright' Low-Cloud Problem

[8] Figure 1 assesses the ability of CMIP5 models to reproduce observed statistics of TOA cloud radiative effects (CRE, defined as the difference between clear-sky and all-sky outgoing radiative fluxes) and cloud types in the tropics (30°S-30°N). Compared to CERES observations all models over-estimate both the strength of the ~27 Wm^{-2} longwave (LW) CRE and the ~−46 Wm^{-2} shortwave (SW) CRE, implying the LW CRE is too positive and the SW CRE is too negative (Figure 1a). Overall, modeled LW CRE shows better spatial variability and correlation with observations than SW CRE; the latter of which is oftentimes too variable. Compared to CALIPSO observations, all models over-estimate the ~34% high-cloud cover (Figure 1b), which certainly contributes to the over-estimate of LW CRE. Modeled mid-clouds vary around the observed ~13% cloud cover, and all but one model (MIROC5) under-estimates the observed ~30% low-cloud cover. The over-estimate of SW CRE is thus related to the over-estimated high-cloud cover or the simulation of overly bright clouds.

[9] To better isolate the relative contributions of cloud optical properties and cloud fraction in SW radiation biases, we examine the relationships between SW CRE or PARASOL reflectance and low-cloud cover, over the tropical oceans, in situations where low-clouds are non-overlapped by upper-level clouds (mid- and high-clouds smaller than 5%). Compared to observations, the probability density function of non-overlapped low-clouds in models is positively skewed in all but one model (CCCma) (Figure 2d). The occurrence of these situations can result from either an under-prediction of

[1]Auxiliary materials are available in the HTML. doi:10.1029/2012gl053421.

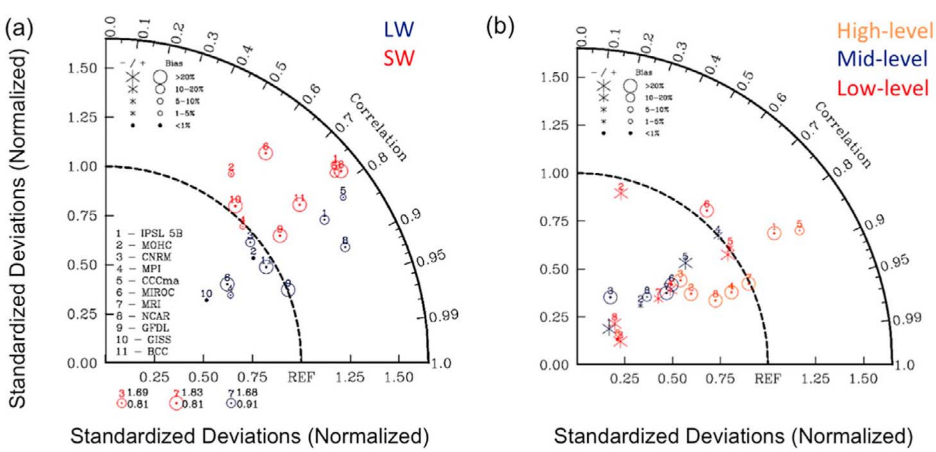

Figure 1. (a) Taylor diagrams [*Taylor*, 2001] present the variance, bias and correlation of the modeled shortwave (red) and longwave (blue) cloud radiative effects against CERES satellite observations in the Tropics (30°N to 30°S). Outliers with negative correlations and standard deviations greater than 1.65 presented below. (b) Similarly, the low-, mid-, and high-level clouds are compared with CALIPSO observations in red, blue and orange respectively.

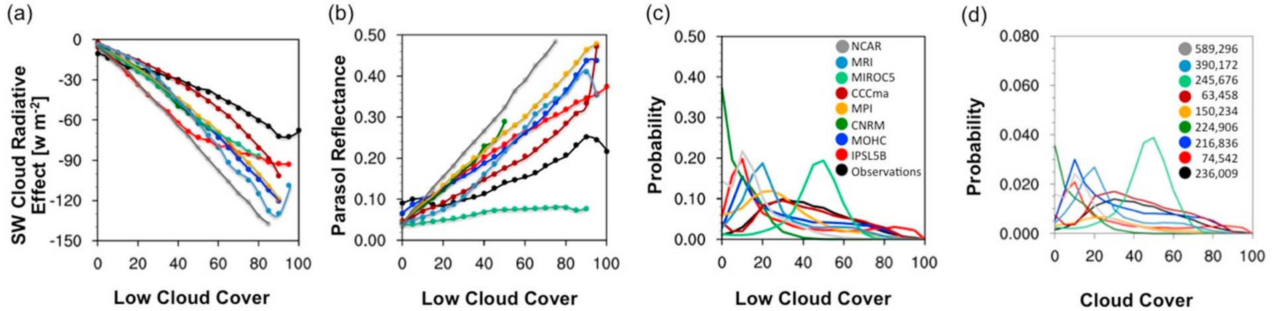

Figure 2. Mean relationship between non-overlapped low-cloud cover and (a) the shortwave Cloud Radiative Effect; and (b) the Parasol reflectance, derived for observations and for CMIP5 models over the Tropical oceans. (c) The probability density function of non-overlapped low-cloud covers alongside (d) the probability density function of non-overlapped low-cloud to total-cloud. The total number of points is presented in Figure 2d.

low-clouds, or from an over-prediction of high-clouds overlying low-clouds, or both. The distribution of non-overlapped low-clouds show the models generally over-estimate clouds with small cloud fractions (Figure 2c).

[10] As expected, the SW radiation reflected to space increases with the low-cloud cover (Figures 2a and 2b). The rate of increase, however, is over-estimated by the models, sometimes by up to a factor of two. For a given value of low-cloud cover, the SW CRE of all models and the PARASOL reflectances of all but one model consistently exceeds observed values. It demonstrates the optical thickness of low-clouds is systematically over-estimated. Therefore, the 'too few, too bright' low-cloud problem persists in CMIP5 models.

4. Compensating Errors in CMIP5 Models

[11] Coupled ocean-atmosphere models must have a nearly-balanced radiation budget at the TOA to avoid climate drifts. For this purpose, atmospheric model parameters may be adjusted (or 'tuned') to ensure the global LW and SW TOA radiative fluxes roughly match observations and balance each other on long time scales [e.g., *Mauritsen et al.*, 2012; *Hourdin et al.*, 2012]. This process can introduce error compensations in the simulation of radiative fluxes. For instance, models may partly compensate for the under-prediction of low-cloud cover with the over-estimate of SW cloud-radiative effects of low-clouds (Figure 2). By examining two regions of the globe predominantly covered by low-clouds, we investigate other sources of compensating errors.

[12] As proposed by *Webb et al.* [2001], we consider the oceanic Californian stratocumulus region (15°–35°N; 110°W–140°W) and Hawaiian Trade Cumulus regions (15°–35°N; 160°E - 140°W), examining the mean relationship between the NET (LW + SW) CRE and the total cloud cover or the non-overlapped low-cloud cover. As discussed in *Nam and Quaas* [2012], comparing both relationships allows identification of: (i) biases in the vertical distribution of high-, mid- and low-clouds, (ii) biases in the optical properties of modeled clouds, and (iii) compensating errors in the models. Note that the CRE associated with clear-sky conditions, over the Hawaiian region, is near -10 Wm^{-2}. This can be explained by differences in sampling times and time integration between CERES and CALIPSO. CERES fluxes are integrated over the diurnal cycle within its algorithms, as the instruments are onboard the Aqua and Terra platforms, whereas CALIPSO cloud fractions are based on instantaneous observations, which can lead to differences in CRE and cloud fraction.

[13] In the two regions, models produce too strong a radiative impact for a given value of the non-overlapped low-cloud cover (Figure 3). Discrepancies between modeled and observed CRE, and the spread amongst model estimates, are less pronounced for a given total cloud cover than for a given low-cloud cover. Examination of the relative frequencies of occurrence (not the cloud fraction) of different cloud types, as well as their combinations, above each region found the relative occurrence of high-cloud combinations over the Californian region are slightly over-estimated in the models, and the overlapping of low-clouds by high- and mid-clouds over the Hawaiian region are significantly over-estimated (Figure 3).

[14] As high-clouds exert a stronger LW CRE than low-clouds, these biases partly compensate for the overly bright low-clouds in these regions and reduce the discrepancy between observed and simulated net CRE. Biases in the relative frequency of occurrence of different cloud combinations thus constitutes another source of compensating errors in CMIP5 models. A study by *Kay et al.* [2012] found biases in optically intermediate and thick clouds reduced, in the CCSM4 (CAM4) to CAM5 model, compared to observations, due to a decrease in high-cloud amount and an increase in low-cloud amount.

5. Vertical Structure of Low-Level Clouds

[15] Figure 3 reveals another difference between observed and simulated radiation fields: the observed CRE associated with a given (non-overlapped) low-cloud fraction is more negative in regions predominantly covered by stratocumulus than by shallow cumulus clouds, while models simulate less contrasted values. This discrepancy is likely to reveal model difficulties in representing the contrasted properties of both cloud types.

[16] To examine this further, we identify shallow cumulus and stratocumulus cloud regimes over the Tropics following *Medeiros and Stevens* [2011]. Shallow cumulus and stratocumulus cloud regimes are distinguished in subsidence areas, characterized by $\omega_{500\ \text{hPa}} \geq 10$ hPa day^{-1} and $\omega_{700\ \text{hPa}} \geq 10$ hPa day^{-1}, where ω is large-scale vertical velocity, by the lower-tropospheric stability (LTS $\equiv \theta_{700\ \text{hPa}} - \theta_{sfc}$, where θ is potential temperature). Subsidence areas

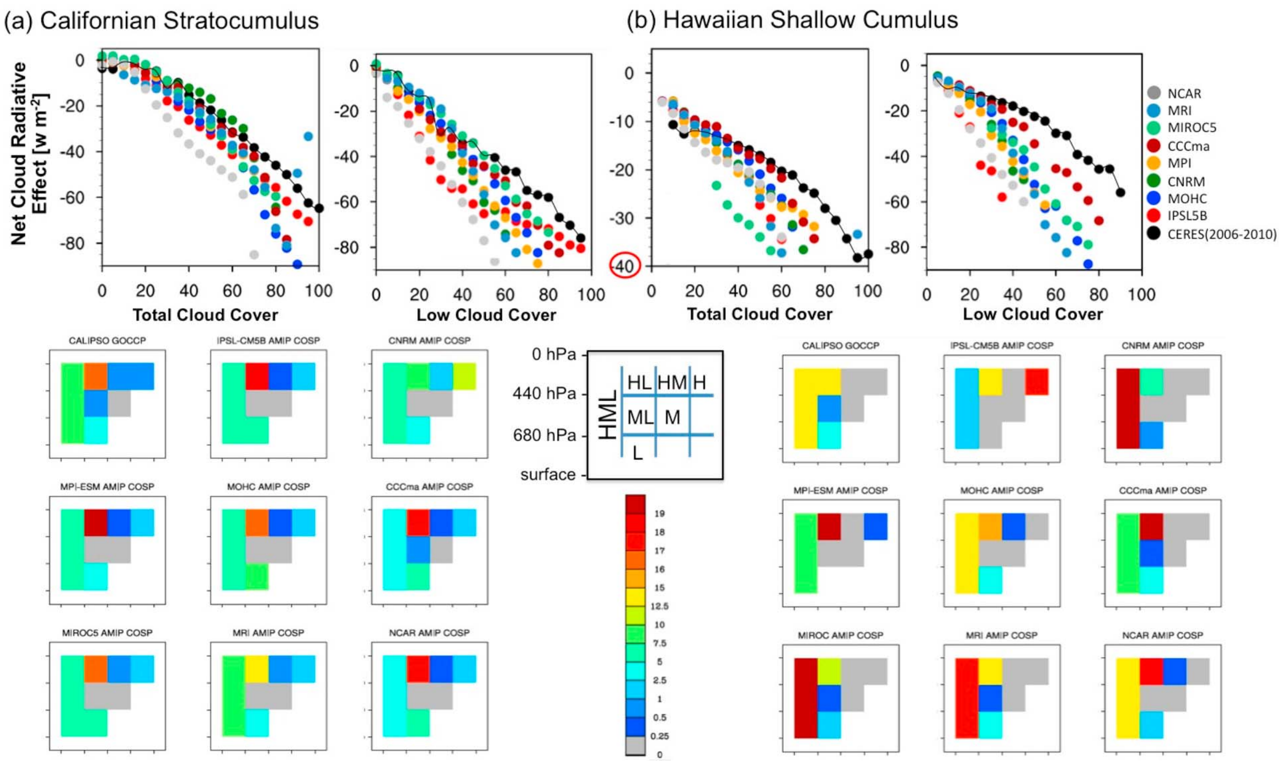

Figure 3. For (a) Californian stratocumulus and (b) Hawaiian Shallow Cumulus regions: top panels show the mean relationships between the NET cloud radiative effect and the total cloud cover or the non-overlapped low-cloud cover derived from observations and from CMIP5 models. Bottom panels show the relative frequency of occurrence of high-, mid- and low-level cloud cover combinations over each region. Non-overlapped low-level clouds are denoted by (*L*); Mid- overlying low-level clouds (*ML*); High- overlying low-level clouds (*HL*); Only mid-level clouds (*M*); High- overlying mid-level clouds (*HM*); Only high-level clouds (*H*); and combinations of high-, mid- and low-level clouds (*HML*).

covered by non-overlapped low-clouds are considered to be dominated by stratocumulus regimes if LTS $\geq$ 18.55 K, and by shallow cumulus regimes otherwise. Geographical distributions of the frequency of occurrence of both regimes are shown in Figure 4 using CALIPSO and ERA-Interim reanalysis (similar results are obtained using NCEP reanalysis, not shown).

[17] For each regime, we analyze the vertical distribution of cloud layers within the lowest 4 km of the atmosphere. In both the stratocumulus and shallow cumulus regimes, CALIPSO observations report cloud layers throughout the planetary boundary-layer, with a maximum frequency of cloud layers between 0.5 km and 1 km associated with cloud fractions lower then 20%. The main difference between the two regimes is that in the stratocumulus regime, clouds with fractions larger than 50% up to 2 km occur more often.

[18] Similar distributions are derived for the CMIP5 models using the model environmental conditions to conditionally sample the low-cloud regimes. In stratocumulus regimes, the IPSL-CM5B-LR, MPI-ESM-LR, CanAM4 and MRI models exhibit large discrepancies from observations: the occurrence of cloud layers is over-estimated below 1 km, while the occurrence of large cloud fractions is under-estimated above 1 km. The CNRM-CM5 model under-estimates the occurrence of large cloud fractions within the first 2 km. The HadGEM2-A, MIROC5 and to some extent CCSM4, are the only models of this ensemble to successfully reproduce the observed distribution of cloud layers in this regime. In the shallow cumulus regime, models successfully reproduce the occurrence of clouds layers above 1.5 km but four models out of eight strongly over-estimate the occurrence of large cloud fractions below 1 km. The HadGEM2-A, MIROC5, CCSM4, and CNRM-CM5 models reasonably reproduce observations.

[19] The comparison of models and observations for these two regimes shows: (i) models experience difficulties in reproducing the observed vertical structure of clouds in low-cloud regimes; and (ii) the vertical structure of clouds is insufficiently contrasted between shallow cumulus and stratocumulus regimes. In particular, some models (IPSL-CM5B-LR, MPI-ESM-LR, CanAM4, MRI) produce clouds of stratocumulus type in regimes that are expected to be predominantly covered by shallow cumulus clouds, while others (CNRM-CM5) produces clouds of shallow cumulus type in regimes that are expected to be covered by stratocumulus clouds. The inability of models to adequately represent the contrasted vertical structures of low-clouds in contrasted environmental conditions reveals shortcomings in the model parameterizations of boundary layer processes.

6. Conclusion and Discussion

[20] Comparing CMIP5 model outputs from satellite simulators with CALIPSO, Parasol and CERES observations, shows the current generation of climate models still experiences difficulties in predicting the low-cloud cover and its radiative effects. In particular, models are found to: (1) under-

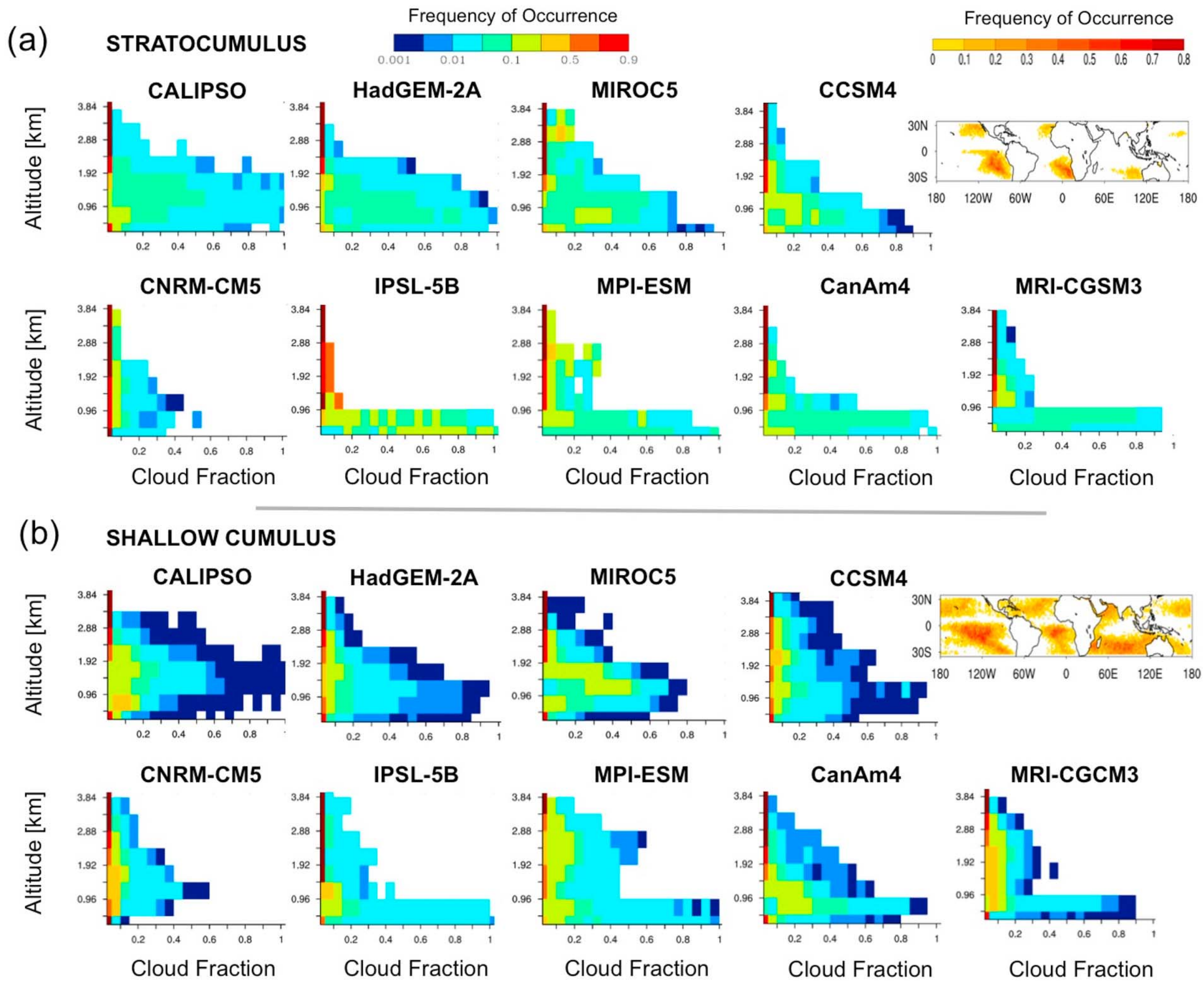

Figure 4. Comparison of the observed (from CALIPSO) and predicted (from CMIP5 models) frequency of occurrence of cloud layers of a given fraction at a given altitude in the lowest 4 km of atmosphere under non-overlapped low-level cloud conditions for (a) stratocumulus regime and (b) shallow cumulus regime. Maps show the frequency of occurrence of each regime derived from CALIPSO observations and ERA-Interim reanalysis.

estimate low-cloud cover in the tropics; (2) over-estimate optical thickness of low-clouds, particularly in shallow cumulus regimes; (3) partly compensate for the simulation of overly bright low-clouds by (i) under-estimating the low-cloud cover, and (ii) over-estimating the occurrence of high-clouds above low-clouds; (4) poorly represent the dependence of the low-cloud vertical structure on large-scale environmental conditions; and (5) predict stratocumulus-type of clouds in regimes where shallow cumulus cloud-types should prevail.

[21] What may be the consequences of over-estimated low-cloud radiative effects on the models' climate sensitivity? *Brient and Bony* [2012] suggest that the strength of cloud-radiative effects in the current climate may affect the strength of low-cloud feedbacks in climate change (a suggestion also made by *Karlsson et al.* [2008]) owing to a local positive feedback between cloud-radiative effects, boundary-layer relative humidity and low-cloud cover. The over-estimate of low-cloud radiative effects is likely to strengthen the climate change low-cloud feedback of climate models independently of their sign, and thus amplify the spread of cloud feedbacks amongst climate models.

[22] Several deficiencies may explain why models over-estimate low-cloud radiative effects, even for cloud fractions and large-scale environmental conditions comparable to those observed. One may be the mis-representation of the cloud structure, including the horizontal inhomogeneity of cloud optical properties and the vertical overlap of cloud layers. Several studies suggest assuming plane-parallel clouds with horizontally homogeneous distributions of optical properties reflects up to ~10% more shortwave radiation [e.g., *Barker et al.*, 2003; *Wu and Liang*, 2005; *Shonk et al.*, 2010]. In addition, most models assume adjacent cloud layers are maximally overlapped, which is also expected to strengthen the reflection of SW radiation by clouds by 10% as well [*Shonk et al.*, 2010]. In CMIP5 models, low-clouds tend to concentrate in the lowest 1 km of the troposphere instead of being spread out through the entire boundary layer. Cloud layers are thus more likely to be adjacent and to yield a maximum cloud overlap assumption, which may contribute

to the over-estimate in cloud optical thickness. Interestingly, the CanAM4 climate model, which includes state-of-the-art representations of the horizontal inhomogeneity of cloud optical properties and the cloud overlap [*Cole et al.*, 2011] is the model that minimizes the over-estimate of the low-cloud optical thickness.

[23] Models also had difficulty reproducing the observed vertical distribution of cloud layers dependent on the large-scale environment. It is likely related to deficiencies in the statistical cloud parameterizations used to predict the occurrence of clouds, and/or in their coupling with the parameterization of shallow convection. For instance, in shallow cumulus regimes the statistical cloud schemes that represent the subgrid-scale variability of total water through a single probability distribution function (PDF) are more likely to under-estimate the height of the cloud base and of the cloud top than the schemes that assume a double PDF and couple the statistical moments of these PDFs to the parameterizations of boundary-layer turbulence and shallow convection [*Golaz et al.*, 2002; *Perraud et al.*, 2011; *Jam et al.*, 2012]. Consistently, HadGEM2-A shows that a model including a cloud scheme which is sensitive to environmental conditions [*Lock*, 2009] can better represent the observed transition among different low-cloud types.

[24] Finally, one cannot exclude that the over-estimate of SW cloud-radiative effects may be caused by deficiencies in cloud microphysics. An under-estimate of the cloud effective radius, or an under-estimate of the precipitation efficiency might yield to an excessive cloud water content and optical thickness.

[25] To discriminate amongst different sources of potential bias, it is important large-scale evaluations of model clouds against satellite observations be completed by model evaluations of parameterizations in locally but more constrained frameworks such a parameterization test bed [*Neggers et al.*, 2012]. Soon analysis of high-frequency process outputs from CMIP5 models will offer opportunities to better unravel the origin of the overly bright low-clouds problem in climate models; distinguishing between the biases related to purely radiative problems or model parameterizations of the boundary layer.

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