How may low-cloud radiative properties simulated in the current climate influence low-cloud feedbacks under global warming?

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[1] The influence of cloud modelling uncertainties on the projection of the tropical low-cloud response to global warming is explored by perturbing model parameters of the IPSL-CM5A climate model in a range of configurations (realistic general circulation model, aqua-planet, single-column model). While the positive sign and the mechanism of the low-cloud response to climate warming predicted by the model are robust, the amplitude of the response can vary considerably depending on the model tuning parameters. Moreover, the strength of the low-cloud response to climate change exhibits a strong correlation with the strength of the low-cloud radiative effects simulated in the current climate. We show that this correlation primarily results from a local positive feedback (referred to as the "beta feedback") between boundary-layer cloud radiative cooling, relative humidity and low-cloud cover. Based on this correlation and observational constraints, it is suggested that the strength of the tropical low-cloud feedback predicted by the IPSL-CM5A model in climate projections might be overestimated by about fifty percent. **Citation:** Brient, F., and S. Bony (2012), How may low-cloud radiative properties simulated in the current climate influence low-cloud feedbacks under global warming?, *Geophys. Res. Lett.*, *39*, L20807, doi:10.1029/2012GL053265.

1. Introduction

[2] Cloud feedbacks remain the main source of spread in climate sensitivity estimates among climate models [*Soden and Held*, 2006; *Bony et al.*, 2006; *Andrews et al.*, 2012], with a key contribution from marine boundary layer clouds [*Bony and Dufresne*, 2005; *Webb et al.*, 2006]. While global observational constraints on cloud feedbacks have remained largely elusive, it is open to question whether some particular components of the feedbacks might be assessed using observations. Identifying simulated features or processes in models which exhibit some discriminating power for climate sensitivity and have some connection with the observed climate would help design such observational tests [*Hall and Qu*, 2006]. However, cloud feedbacks result from the interplay of a large number of processes and interactions within the climate system, and thus pointing out that such features may not be straightforward.

[3] To highlight the processes which primarily control the cloud feedback or climate sensitivity of a particular model, one approach consists in simplifying the modelling framework through a range of idealized configurations and in determining the minimum level of complexity necessary to reproduce the basic behavior of the most comprehensive model [e.g., *Medeiros et al.*, 2008; *Zhang and Bretherton*, 2008; *Wyant et al.*, 2009; *Medeiros and Stevens*, 2011; *Brient and Bony*, 2012; *Rieck et al.*, 2012]. Another approach consists in perturbing uncertain parameters of the model to point out the most critical ones with regard to climate feedbacks or sensitivity [e.g., *Murphy et al.*, 2004; *Webb et al.*, 2006; *Klocke et al.*, 2011; *Shiogama et al.*, 2012]. During the model development process, some uncertain parameters are used as "tuning" parameters, i.e., their value is adjusted to improve the agreement between observations and simulations and/or to ensure the global Earth's radiation balance at the top of the atmosphere. Although model tuning is done without examining climate projections [e.g., *Hourdin et al.*, 2012], assessing whether and how the tuning process may impact climate sensitivity constitutes a long-standing question [*Charney*, 1979; *Mauritsen et al.*, 2012] which needs to be addressed to evaluate the robustness of climate change projections from a particular model, to better understand the consequences of model uncertainties, and to suggest observational tests that may help assess our confidence in these projections.

[4] The IPSL-CM5A-LR general circulation model (GCM) predicts a high climate sensitivity compared to other climate models (4.4 K (J.-L. Dufresne et al., Climate change projections using the IPSL-CM5 Earth System Model: From CMIP3 to CMIP5, submitted to *Climate Dynamics*, 2012), i.e., close to the upper bound of CMIP5 estimates reported by *Andrews et al.* [2012]) which results from a strong positive cloud feedback. This feedback primarily stems from the decrease of tropical marine low-level clouds in a warming climate, which was interpreted energetically as the consequence of the enhanced import of low-entropy air into the boundary layer as temperature rises [*Brient and Bony*, 2012]. In section 2, we assess the robustness of this mechanism through a series of sensitivity experiments (both in single-column and three-dimensional frameworks) to uncertain parameters of the model, and we highlight a relationship between the strength of low-cloud radiative properties simulated by the model in the current climate and the change in low-clouds predicted in a warmer climate. In section 3, we show that the positive feedback between low-cloud radiative effects and boundary-layer relative humidity plays an active role in this relationship. In section 4, we discuss the implications of this relationship for constraining the

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Table 1. Table of Tuning Parameters Varied in Figure 1

	Weaker	Control	Higher
γ	0.0025	0.005	0.05
q_{crit} (10^{-4} kg/kg)	2.16	4.16	8.0
τ (s)	900	1800	3600
Re (μm)	6	12	18

strength of the model's cloud feedback to climate change by using observations.

2. Sensitivity Experiments

2.1. Perturbed Model Parameters

[5] To test the sensitivity of the model cloud feedback to uncertain parameters of the parameterizations, we perturb the values of four different quantities which belong to the larger set of parameters used to "tune" the IPSL model [*Hourdin et al.*, 2012] and which affect the simulation of low-level clouds.

[6] In the IPSL-CM5A model, clouds are parameterized through a statistical cloud scheme describing the subgrid-scale variability of total water within each gridbox through a generalized log-normal Probability Density Function (PDF) bounded by zero on the lower side [*Bony and Emanuel*, 2001]. In non-convective situations, the statistical moments of the PDF are diagnosed empirically, by assuming that the variance of total water fluctuations at each vertical level is proportional to the mean total water, with a proportionality coefficient γ that varies with pressure [*Hourdin et al.*, 2006]. In the standard version of the model, γ increases from 0.005 at the surface to 0.33 at 300 hPa. As sensitivity tests, we perturb the surface value of γ (Table 1). An increase of γ widens the PDF, favors the formation of clouds at low relative humidities and lowers the cloud fraction at higher relative humidities.

[7] Two other tuning parameters are related to the parameterization of the precipitation rate from warm clouds [*Sundqvist*, 1978]: one specifies the threshold value of condensed water (q_{crit}) above which precipitation starts to occur, and another (a time constant τ) controls the rate at which the condensed water is precipitated out. Decreasing (increasing) the value of either parameter results in an increased (decreased) precipitation efficiency and a lower (higher) cloud water content. An additional tuning parameter considered is the effective radius of warm cloud droplets (R_e), a decrease of R_e making clouds more reflective. Note that unlike γ which directly affects the formation of low-level clouds, the three other parameters are involved only in the parameterization of cloud radiative properties and their impact on the formation of clouds can only be indirect.

2.2. Tests in a Single Column Model (SCM)

[8] SCM simulations are performed by setting all parameters to their control value (Control), and then by perturbing the parameters one by one, by increasing or decreasing their value (Table 1).

[9] *Brient and Bony* [2012] show that the tropical cloud feedback of the IPSL-CM5A GCM arises primarily from low-cloud changes in regimes of weak subsidence. In addition, they show that the cloud fraction predicted by the GCM, both in the current climate and in a warmer climate, can be reproduced by a single-column version of the GCM driven by the large-scale forcings prepared for these regimes by the *CFMIP-GCSS Intercomparaison of Large-Eddy Models and Single Column Model* (CGILS) project (so-called S6 case (M. H. Zhang et al., CGILS: First results from an international project to understand the physical mechanisms of low cloud feedbacks in general circulation models, submitted to *Bulletin of the American Meteorological Society*, 2012)), provided that a stochastic forcing is added to the prescribed steady vertical velocity profile. We use the same single-column framework to test the influence of tuning parameters on the low-cloud fraction and its response to an idealized surface warming (a prescribed 2K warming of the ocean surface and reduced subsidence). Each sensitivity experiment is run for 200 days, and the results are analysed after 60 days of spin-up.

[10] In its standard version, the SCM predicts in regimes of weak subsidence (and low-level clouds) a SW Cloud Radiative Effect (CRE) of about -50 W/m^2 and a sensitivity to surface warming of about 6 W/m^2/K. Perturbing the tuning parameters γ, q_{crit}, τ and R_e greatly affects these values, with a factor-of-four difference between the lowest and highest values of the SW CRE in the current climate, and a factor-of-ten difference in the SW CRE sensitivity (Figure 1a). The perturbation of tuning parameters also affects the low-level cloud fraction and its response to climate warming by up to a factor-of-five (Figure 1d). However, although the *magnitude* of the cloud response to global warming predicted by our model greatly depends on tuning parameters, its *sign* does not, and thus appears to be robust.

[11] A striking outcome of this set of experiments is that the SW CRE of subsidence regimes predicted by the SCM in current climate conditions is very strongly correlated with its sensitivity to surface temperature rise (R^2 = 0.93 and R^2 = 0.73 for the SW CRE and the low-cloud fraction, respectively), a weaker CRE in the current climate being associated with a weaker sensitivity in climate change. However, a specificity of SCM experiments is that changes in the physical parameterizations do not affect the large-scale dynamics of the atmosphere. In a three-dimensional framework, the tuning parameters may also affect the large-scale circulation and hence the dynamical forcing of low-level clouds, leading potentially to a different relationship.

2.3. Tests Using General Circulation Models

[12] To examine whether the relationship shown in Figures 1a and 1d holds in a 3D framework, we repeat sensitivity experiments with the parent atmospheric GCM using identical physical parameterizations. This is done both in a realistic framework where GCM simulations are forced by observed sea-surface temperatures (referred to as AMIP [*Gates*, 1992]) and in an idealized framework by considering a water-covered planet ("aqua-planet") forced by a zonally-symmetric profile of sea surface temperatures (referred to as "QOBS" [*Neale and Hoskins*, 2000]). AGCM and aqua-planet simulations are run for 4 and 3 years, respectively, both for present-day sea surface temperatures (SSTs) and for SSTs uniformly warmer by 4 K (considering a larger surface warming than in SCM experiments allows us to enhance the signal to noise ratio). AGCM runs correspond to 1980–1983 period. Results from the first year are disregarded for spin-up.

[13] The tropical cloud feedback of the IPSL-CM5A-LR GCM primarily arising from the low-cloud response in regimes of weak subsidence, we focus our GCM analysis on

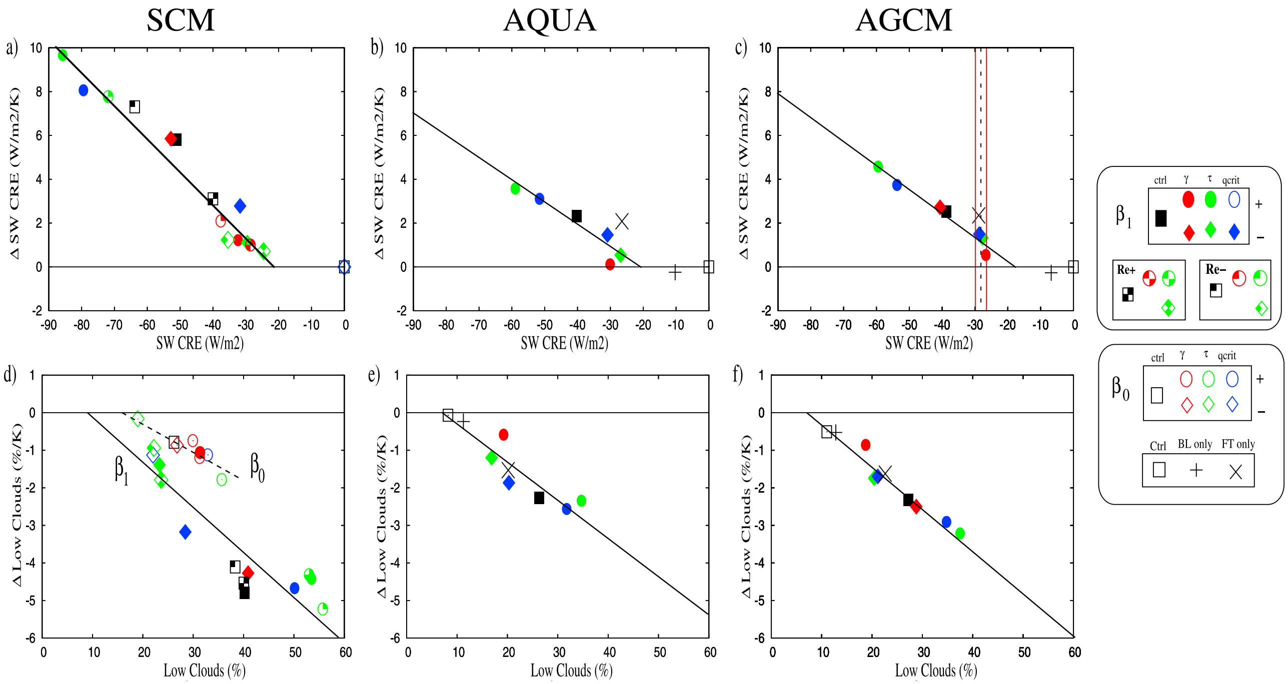

Figure 1. Relationship between (a, b, c) top-of-the-atmosphere SW cloud-radiative effect (in W/m^2) and (d, e, f) low-cloud cover below 800 hPa (in %) predicted by the IPSL model in regimes of weak subsidence over tropical oceans in the current climate (in abscissa) and their response to a prescribed sea surface temperature warming (normalized by the temperature change, in ordinate) derived from an ensemble of sensitivity experiments where the model parameters listed in Table 1 are perturbed one by one. Figures 1a and 1d show the results from single-column model experiments, and Figures 1b and 1e and Figures 1c and 1f show results from three-dimensional aquaplanet and AGCM experiments. β_1 and β_0 represent simulations with and without cloud radiative effects. Solid and dashed lines show least-squares regressions for β_1 and β_0 experiments respectively. The dashed vertical line denotes the multi-annual mean (with 5%–95% confidence interval) of SW cloud-radiative effects derived from observations in regimes of weak subsidence covered by non-overlapped low-clouds.

these regimes, that we define as the situations for which the monthly-mean large-scale vertical velocity at 500 hPa (ω_{500}) is close to 20 hPa/day ($\pm$5 hPa/day), and for which the mid and high-level cloudiness does not exceed 5%. Note that TOA imbalances of perturbed experiments are quite large, suggesting that this setup applied to a coupled ocean-atmosphere model could produce a drift.

[14] As in the SCM, perturbing the set of tuning parameters used in this study does not affect the sign of the SW CRE and low-cloud responses to global warming (Figures 1 b,c,e,f). *Brient and Bony* [2012] showed that in the IPSL-CM5A model, a warmer climate leads to enhanced surface fluxes, a deeper boundary-layer, a stronger clear-sky radiative cooling, an enhanced shallow convection, a decreased relative humidity in the bottom of the boundary-layer and a decreased low-cloud cover. Alternatively, they showed that the decrease of low-level clouds could also be interpreted through an energetic framework: owing to the Clausius-Clapeyron thermodynamic relationship, climate warming is associated with an increase of the vertical gradient of specific humidity and moist static energy (MSE) between the surface and the top of the boundary-layer, which enhances the vertical advection of low free-tropospheric MSE into the boundary layer. If in a warmer climate the increase of surface fluxes is not sufficient to counter the effect of this enhanced vertical advection, the PBL MSE budget requires a weakening of the cloud-radiative cooling and thus a decrease of low-level clouds.

[15] The analysis of the atmospheric MSE budget in the different experiments shows that changes in the vertical gradient of MSE and then in the vertically-integrated vertical advection of MSE depend very little (by about 10%) on tuning parameters (Figure 2), and that in a warmer climate the enhanced import of low-MSE air into the PBL always exceeds the enhanced input of high-MSE by surface fluxes. This is consistent with the robust decrease of the PBL cloud-radiative cooling as temperature rises (Figure 1).

[16] On the other hand, perturbing the tuning parameters does affect the strength of cloud-radiative effects in the current climate and the magnitude of the cloud response to global warming (Figures 1 b,c,e,f). As in the SCM, GCM results exhibits a strong correlation between the SW CRE or cloud fraction values predicted in current and warmer climates ($R^2 = 0.96/0.89$ for the SW CRE and $R^2 = 0.91/0.66$ for the cloud fraction in AGCM/aqua-planet configurations, respectively): stronger cloud-radiative effects in the current climate are associated with a larger sensitivity to global warming.

3. Interpretation

3.1. Cloud-Radiation-Relative Humidity Feedback

[17] How may the simulation of clouds in the current climate affect the cloud response to global warming? Owing to a larger infrared radiative cooling at cloud-top than cloud-base warming, low-level clouds exert a net radiative cooling

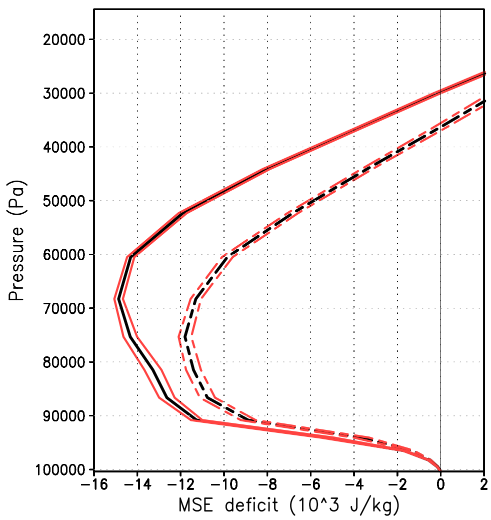

Figure 2. Vertical profile of the moist static energy deficit relative to the near-surface value in present-day (dashed line) and in +4K (solid line) experiments derived from AGCM simulations in regimes of weak subsidence. The mean of all sensitivity experiments is reported as a black line. Red lines show ± one standard deviation among experiments.

within the boundary-layer. By increasing relative humidity, this radiative cooling contributes to the self-maintenance of boundary-layer clouds. Consistently, a decrease of low-level clouds weakens the cloud-radiative cooling within the PBL, which tends to lower the PBL relative humidity and thus to amplify the decrease of low-level clouds. May this positive feedback between PBL cloud-radiative effects and cloud cover contribute to the relationship between the simulation of clouds in present-day and warmer climates?

[18] We explore this hypothesis numerically by making model clouds invisible to radiation: if $R(z)$ is the net radiative heating rate predicted by the model at altitude z, and $R_0(z)$ and $ACRF(z)$ its clear-sky and cloudy components, then $R(z)$ can be expressed as:

$$R(z) = R_0(z) + \beta \cdot ACRF(z) \qquad (1)$$

with $\beta = 1$. By setting β to zero, the impact of cloud-radiation interactions on the simulated atmosphere is removed. The comparison of SCM simulations of the subtropical atmosphere in regimes of weak subsidence using $\beta = 1$ (control) or $\beta = 0$ (clouds invisible to radiation) shows that cloud-radiative effects actually cool the boundary-layer, increase the relative humidity and increase the low-level cloud fraction by up to a factor of two (Figure 3). Similar results are obtained in AGCM experiments. This suggests that tuning parameters that strengthen the interaction between clouds and radiation (e.g., by increasing the cloud optical depth associated with a given cloud fraction) also tend to increase the low-level cloud cover. Could this local positive feedback (hereafter referred to as the "β feedback") contribute to the positive correlation between cloud-radiative properties in present and future climates?

3.2. Experiments With the β Feedback Switched Off

[19] To assess the role of the β feedback in the low-cloud response to climate warming, we repeat the SCM +4K experiments associated with different tuning parameters using $\beta = 0$. In that case, the SW CRE response is zero by definition. Compared to $\beta = 1$ experiments, the present-day low-cloud fraction is always smaller (Figure 1d). and the magnitude of the low-cloud response to climate warming is reduced by a factor-of-two (the fractional change in low-cloud fraction is $-12.4 \pm 1.9\%\cdot K^{-1}$ for $\beta = 1$ and $-6.4 \pm 1.5\%\cdot K^{-1}$ for $\beta = 0$). Consistently, three-dimensional experiments (AGCM or aqua-planet) performed with $\beta = 0$ show that the low-cloud decrease associated with climate warming is strongly reduced when cloud-radiative effects are switched off (Figure 1 e,f).

[20] As the radiative effects of deep convective clouds are known to affect the large-scale atmospheric circulation of the atmosphere and the stratification of the atmosphere [e.g., *Slingo and Slingo*, 1988; *Randall et al.*, 1989], one may not exclude that the reduced low-cloud response obtained for $\beta = 0$ be due to remote effects instead of a local radiative feedback. Additional experiments in which cloud-radiative effects are switched off only in the free troposphere (FT, at pressures lower than 700 hPa, Figure 1) or in the boundary layer (BL) confirm that the enhanced sensitivity of low-level clouds to global warming associated with the β feedback is primarily a local effect.

[21] Model parameters producing stronger low-cloud radiative effects make the β feedback more effective, which increases the present-day low-cloud fraction and amplifies the reduction of low-level clouds under global warming. The local β feedback thus contributes to the correlation between the current CRE and the CRE response to climate change shown in Figure 1.

3.3. On the Role of Surface Fluxes

[22] The vertically-integrated MSE budget of the atmosphere can be expressed as:

$$(LH + SH) + [ACRF] + [R_0] - \left[\omega \frac{\partial h}{\partial P}\right] - \left[\vec{V} \cdot \vec{\nabla} h\right] = 0 \qquad (2)$$

where LH and SH are surface latent and sensible heat fluxes, ACRF is the atmospheric cloud radiative effect,

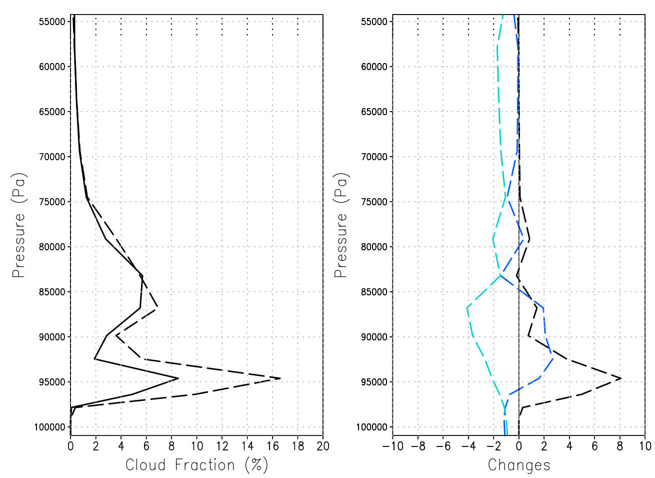

Figure 3. (left) Vertical profile of the cloud fraction (in %) predicted by the single-column model in the CGILS S6 case of weak subsidence for $\beta = 0$ (solid line) and $\beta = 1$ (control, dashed line). (right) Change in the vertical profiles of cloud fraction (in %, black), temperature ($\times 10$ in K, cyan) and relative humidity (in %, blue) when the β feedback is switched on (difference between $\beta = 1$ and $\beta = 0$ experiments).

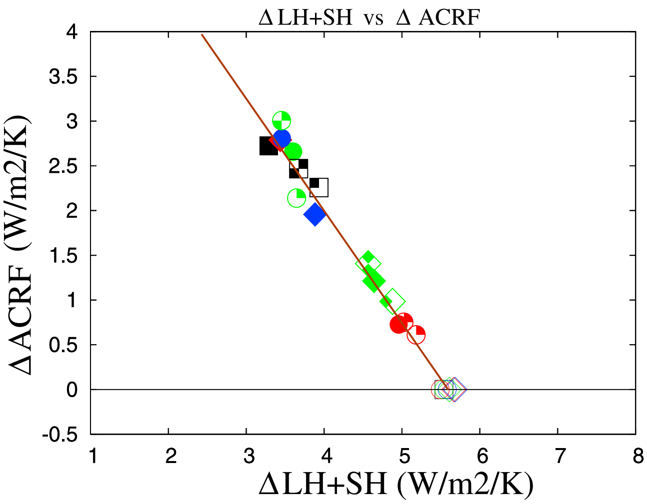

Figure 4. Relationship between changes in surface turbulent fluxes (the sum of latent and sensible heat fluxes) and in atmospheric cloud radiative forcing (ACRF) under climate warming derived from single-column model sensitivity experiments described in Table 1. Markers are described in Figure 1.

R_0 the clear-sky radiative heating rate, and the last two terms are the large-scale vertical and horizontal advections of MSE. Brackets denote vertical integrals over the atmosphere. The analysis of the MSE budget of sensitivity experiments tells us that for a prescribed surface temperature perturbation, the change in $[R_0]$ and in the vertically-averaged MSE advections do not depend much on tuning parameters (not shown). As horizontal advections are prescribed in SCM experiments, the sum $\Delta(LH + SH) + \Delta[ACRF]$ remains fairly constant (5.9 ± 0.3 W/m^2/K) whatever the model parameters are. It implies that changes in surface fluxes and in cloud-radiative effects are anti-correlated: for a given perturbation, the larger the increase of surface fluxes, the weaker the magnitude of the ACRF response (i.e., the weaker the low-clouds reduction) and vice-versa, the case $\beta = 0$ providing an upper bound to the change in surface fluxes (Figure 4). In AGCM experiments, the sum $\Delta(LH + SH) + \Delta[ACRF]$ also remains fairly invariant (6.2 ± 0.4 W/m^2/K) when parameters are perturbed. However, the anti-correlation between $\Delta(LH + SH)$ and $\Delta[ACRF]$ becomes noisier (R = −0.56) because of slight variations in the horizontal advection term.

[23] In any model, the response of surface fluxes to climate warming is likely to depend on parameterized features (e.g., the surface drag coefficient), and the strength of the β feedback on many model parameters used in cloud and radiative parameterizations. The magnitude of the cloud response to climate warming depending on both, we can easily understand why climate models exhibit such a large spread of cloud feedback magnitudes despite a better consensus on the sign [*Soden and Held*, 2006].

4. Towards Observationally-Constrained Cloud Feedbacks?

[24] The strong correlation between the simulation of low-cloud radiative properties in the current climate and the low-cloud response to climate warming exhibited by our model suggests that observations might be used to assess the credibility of the low-cloud feedback in climate change. For this purpose, we use monthly-mean observations of radiative fluxes at the top of the atmosphere (the CERES-EBAF data set [*Loeb et al.*, 2009]), ERA-Interim atmospheric reanalyses [*Dee et al.*, 2011] and CALIPSO GOCCP data [*Chepfer et al.*, 2010] over the period June 2006 to February 2010 to estimate the strength of cloud-radiative effects over tropical oceans (30°N-30°S) in regimes of weak subsidence (w_{500} = 20 ± 5hPa/day) when low-level clouds are non-overlapped by upper-level clouds (we select the situations for which the middle and high cloud fractions are less than 5%).

[25] In these regimes, the cooling effect of low-level clouds (SW CRE) predicted by the control version of the model is much stronger than that derived from observations (−42 W/m^2 vs −28 W/m^2) despite an underestimate of the low-cloud fraction (not shown), due to an overestimate of the cloud optical thickness (D. Konsta et al., Evaluation of clouds simulated by the LMDZ5 GCM using A-train satellite observations (CALIPSO-PARASOL-CERES), submitted to *Climate Dynamics*, 2012). Given the relationship shown in Figure 1c, the overestimate of the present-day cooling suggests that the magnitude of the SW CRE response to climate warming might also be overestimated by about 50%.

[26] The physical parameterizations of the IPSL-CM5A-LR GCM are very close to those of the IPSL-CM4 GCM participating in CMIP3, and cloud feedbacks in the IPSL-CM5A-LR and IPSL-CM4 models are very similar (Dufresne et al., submitted manuscript, 2012). *Soden and Held* [2006] report a global cloud feedback of 1.06 W/m^2/K in the IPSL model, which is about 50% higher than the multi-model mean cloud feedback value predicted by CMIP3 models in climate change (0.69 W/m^2/K [*Soden and Held*, 2006]). In a recent assessment of CMIP5 models diagnosing cloud feedbacks by taking the rapid cloud adjustments to CO_2 into account (J. Vial, personal communication, 2012), the IPSL-CM5A-LR tropical cloud feedback is also found to be 50% higher than the multi-model mean (0.78 W/m^2/K vs 0.53 W/m^2/K). Since the tropical cloud feedback of this model is primarily driven by the tropical low-cloud response to global warming [*Brient and Bony*, 2012], the observational constraint applied to this model suggests that a more plausible value of the tropical cloud feedback would be about 0.52 W/m^2/K, i.e., close to the multi-model mean tropical cloud feedback value predicted by 10 CMIP5 models.

[27] May this observational constraint be used to assess the credibility of cloud feedbacks from other models? Our study considered only a single GCM and a limited set of tuning parameters. Other studies considering a more extensive set of experiments and models [e.g., *Yokohata et al.*, 2010; *Klocke et al.*, 2011] pointed out that relationships between model fidelity and model sensitivity derived from single climate models may not carry into multi-model ensembles. Yet we believe that the β feedback, which has a simple and robust physical explanation, does operate in multiple models and hereby modulates the magnitude of the low-cloud feedback, irrespective of its sign. Consistently, analyses of perturbed parameters ensembles performed with two climate models (MIROC3.2 and HadSM3) show that model versions that predict a larger low-cloud albedo in the current climate also predict a stronger positive low-cloud feedback in climate change [*Yokohata et al.*, 2010]. On the other hand, the

analysis of ECHAM5 and MIROC5 ensembles suggests more contrasted behaviours [*Klocke et al.*, 2011; *Watanabe et al.*, 2012]. Comparing the low-cloud response to climate warming predicted by different models in experiments where the β feedback is deliberately removed (e.g., by making clouds invisible to radiation as done in this study) would allow us to assess the robustness of our conclusions regarding the role of the β feedback in amplifying the climate change cloud response. With such an assessment, we would then be able to evaluate the potential of observational constraints on low-cloud radiative effects in the current climate for constraining low-cloud feedbacks in climate change.

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