



HAL
open science

On the Dependence of Cloud Feedbacks on Physical Parameterizations in WRF Aquaplanet Simulations

Grégory Cesana, Kay Suselj, Florent Brient

► **To cite this version:**

Grégory Cesana, Kay Suselj, Florent Brient. On the Dependence of Cloud Feedbacks on Physical Parameterizations in WRF Aquaplanet Simulations. *Geophysical Research Letters*, 2017, 44 (20), pp.10,762-10,771. 10.1002/2017GL074820 . hal-03414012

HAL Id: hal-03414012

<https://hal.science/hal-03414012>

Submitted on 18 Nov 2021

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Copyright



RESEARCH LETTER

10.1002/2017GL074820

Key Points:

- WRF simulations with different combinations of parameterizations reproduce the range of uncertainty found in CMIP5 cloud feedback estimates
- Uncertainty in tropical low-level cloud feedbacks can be primarily attributed to microphysical and convective parameterizations in WRF
- WRF aquaplanet simulations represent a useful method for studying cloud feedback processes

Supporting Information:

- Supporting Information S1

Correspondence to:

G. Cesana,
gregory.cesana@columbia.edu

Citation:

Cesana, G., Suselj, K., & Briant, F. (2017). On the dependence of cloud feedbacks on physical parameterizations in WRF aquaplanet simulations. *Geophysical Research Letters*, 44, 10.762–10.771. <https://doi.org/10.1002/2017GL074820>

Received 6 JUL 2017

Accepted 4 OCT 2017

Accepted article online 9 OCT 2017

Published online 30 OCT 2017

On the Dependence of Cloud Feedbacks on Physical Parameterizations in WRF Aquaplanet Simulations

Grégory Cesana^{1,2,3} , Kay Suselj³, and Florent Briant⁴ 

¹Department of Applied Physics and Mathematics, Columbia University, New York, NY, USA, ²NASA Goddard Institute for Space Studies, New York, New York, USA, ³Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, USA, ⁴Centre National de Recherches Météorologiques, Toulouse, France

Abstract We investigate the effects of physical parameterizations on cloud feedback uncertainty in response to climate change. For this purpose, we construct an ensemble of eight aquaplanet simulations using the Weather Research and Forecasting (WRF) model. In each WRF-derived simulation, we replace only one parameterization at a time while all other parameters remain identical. By doing so, we aim to (i) reproduce cloud feedback uncertainty from state-of-the-art climate models and (ii) understand how parameterizations impact cloud feedbacks. Our results demonstrate that this ensemble of WRF simulations, which differ only in physical parameterizations, replicates the range of cloud feedback uncertainty found in state-of-the-art climate models. We show that microphysics and convective parameterizations govern the magnitude and sign of cloud feedbacks, mostly due to tropical low-level clouds in subsidence regimes. Finally, this study highlights the advantages of using WRF to analyze cloud feedback mechanisms owing to its plug-and-play parameterization capability.

1. Introduction

A fundamental goal of climate science is to characterize the equilibrium response of the global near-surface temperature to the change in radiative forcing at the top of the atmosphere as a result of anthropogenic activity. One way to address this question is to analyze equilibrium climate sensitivity, defined as a change in the equilibrium near-surface global average temperature per doubling of the CO₂ concentration with respect to the preindustrial levels (e.g., Gregory et al., 2004). Since the 1970s, general circulation models (GCMs) have been used as the primary tool in these analyses (e.g., Cess et al., 1990; Charney et al., 1979; Randall et al., 2007). Yet the uncertainty of climate sensitivity has not been reduced despite the tremendous development and increased complexity of GCMs since the early days (e.g., Flato et al., 2013; Knutti & Hegerl, 2008).

Ample evidence shows that cloud feedbacks, in particular that of tropical low-level clouds, dominate this uncertainty (e.g., Vial et al., 2013; Zelinka et al., 2013). The reason for this is most likely the difficulty to parameterize the subgrid variability of low-level clouds and consequently the inability of GCMs to properly simulate them (e.g., Bretherton et al., 2013). Because GCMs differ in many respects (e.g., subgrid-scale physical processes, dynamical core, numerical discretization, and resolution), the multimodel approach often used to analyze cloud feedbacks (e.g., Andrews et al., 2012) does not clearly identify key processes driving the cloud feedback uncertainty.

Other studies have attempted to shed light on this problem by perturbing cloud-related parameters (e.g., Briant & Bony, 2012; Tan et al., 2016), by interchanging parameterizations of cloud physical processes in a single GCM (e.g., Gettelman et al., 2012; Watanabe et al., 2012; Zhao et al., 2016), or a combination of both (Shiogama et al., 2014). While being very informative on the sensitivity of one particular GCM to specific parameters, results from the cloud-related parameters studies are often not relevant to explaining the intermodel diversity. The multiple-parameterization studies give a broader picture by investigating physical processes, which can be applied to all GCMs. In these studies, swapping physical schemes in a GCM produces significant variability in cloud feedbacks, as in classic multimodel studies. This makes it easier to identify the primary mechanisms driving the uncertainty in cloud feedbacks. However, such studies are challenging to conduct because of (i) the difficulty of implementing various physical parameterizations in a GCM, including the tuning process to achieve radiative balance, and (ii) the computational cost of running all Earth-like simulations for several decades.

In this work, we study how sensitive simulated cloud feedbacks are to physical parameterizations. For this, we use the Weather Research and Forecasting (WRF) model. WRF is built in a way that permits to select from many different parameterizations for each physical category, such as microphysics, convection, planetary boundary layer, and radiation. Therefore, several thousand combinations can be generated without the tedious work of implementing and testing new parameterizations contrary to conventional GCMs used in previous studies. To understand which physical category is most responsible for uncertainty of clouds and cloud feedback, we perform multiple WRF simulations with different sets of parameterizations.

We employ the framework of aquaplanet simulations, in which interactions with the land surface, oceans, and cryosphere are suppressed, thus removing their responses to global warming. This reduces the computational cost of simulations compared to Earth-like simulations and allows us to focus on the atmospheric component of the Earth's system and, in turn, to diminish the degree of complexity of the problem. Furthermore, running different WRF aquaplanet simulations is easier and faster than Earth-like configurations as no specific tuning is required and 1 year long runs are sufficient for cloud feedbacks analysis (Medeiros et al., 2015). The aquaplanet framework has proven to be useful for understanding behavior of clouds in GCMs (e.g., Levine & Schneider, 2011; Medeiros et al., 2015), as the cloud feedbacks are similar to that of their Earth-like counterparts (Medeiros et al., 2008).

The main goal of this paper is to highlight the usefulness of the WRF model for studying cloud feedbacks by leveraging its plug-and-play parameterization capability. To this end, we investigate whether changes in physical parameterizations are sufficient to reproduce Coupled Model Intercomparison Project Phase 5 (CMIP5) intermodel variability in cloud feedbacks. We then analyze the impact of these parameterizations on the sign and magnitude of cloud feedbacks. The paper is organized as follows. In section 2, we describe the experiments and the model ensembles. In section 3, we examine the variability of clouds and cloud feedbacks in WRF and CMIP5 simulations. We summarize the results in section 4.

2. Aquaplanet Experiment

Following the Aqua-Planet Experiment project (APE, Williamson et al., 2012), we perform two sets of eight simulations each, using WRF version 3.5.1 of the Advanced Research WRF core: a control experiment with zonally symmetric prescribed sea surface temperature (SST) referred to as Control, as in APE, and a warmer experiment with uniformly +4K increased SST simulations referred to as 4K. WRF model is run on $1^\circ \times 1^\circ$ regular latitude-longitude projection with a 40-level stretched vertical grid and a time step of 200 s. Our setup closely follows the one described in Bhattacharya et al. (2017). Orbital parameters are set to perpetual equinox conditions with a fixed solar constant, but the diurnal cycle is retained. Aerosol and ozone concentrations are zonally symmetric and close to the values found over the oceans in the current climate. The simulations are initialized with zonally symmetric initial conditions. We allow 4 months of spin-up before analyzing 1 year of monthly mean data, which appears sufficient for our purpose (Medeiros et al., 2016). More details about the experimental setup are given in the supporting information (SI; Text S1). Both Control and 4K experiments consist of a standard (St) and seven other WRF simulations using different parameterizations to represent the diversity of state-of-the-art GCM parameterizations as much as possible (see Table S1). Each member of a given experiment differs from St by only one parameterization. In the St simulation, microphysical processes are modeled with the WRF single moment microphysical scheme with six classes of hydrometeors (Hong & Lim, 2006). The convection scheme is based on the U.S. National Weather Service Global Forecasting (GFS) and essentially uses Arakawa and Schubert's (1974) framework, GFS(AS). The planetary boundary layer parameterization is based on the Mellor-Yamada-Nino-Nakanishi (Nakanishi & Niino, 2004) level 3 scheme. Finally, the radiative scheme follows the RRTMG model (Iacono et al., 2008). In addition, we employ the Xu and Randall (1996) cloud scheme to produce subgrid-scale cloud variability and to compute radiation fluxes and cloud diagnostics. Below are listed the other seven simulations, which differ from St by only one parameterization. The MPwdm and MPmor use different microphysics schemes: the WRF Double Moment-6 class scheme (MPwdm, Lim & Hong, 2010) and the Morrison scheme (Morrison et al., 2009), respectively. In COkf and COtie simulations, we change the convective schemes based on the modified Kain-Fritsch (Kain, 2004) and Tiedtke scheme (Tiedtke, 1989), respectively. In the PBLnn2 and PBLysu, we use the boundary layer parameterization from Mellor-Yamada-Nino-Nakanishi schemes level 2.5 (PBLnn2, Nakanishi & Niino, 2004) and from the Yonsei University (Hong et al., 2006). The last simulation, RAcam, uses the radiation scheme

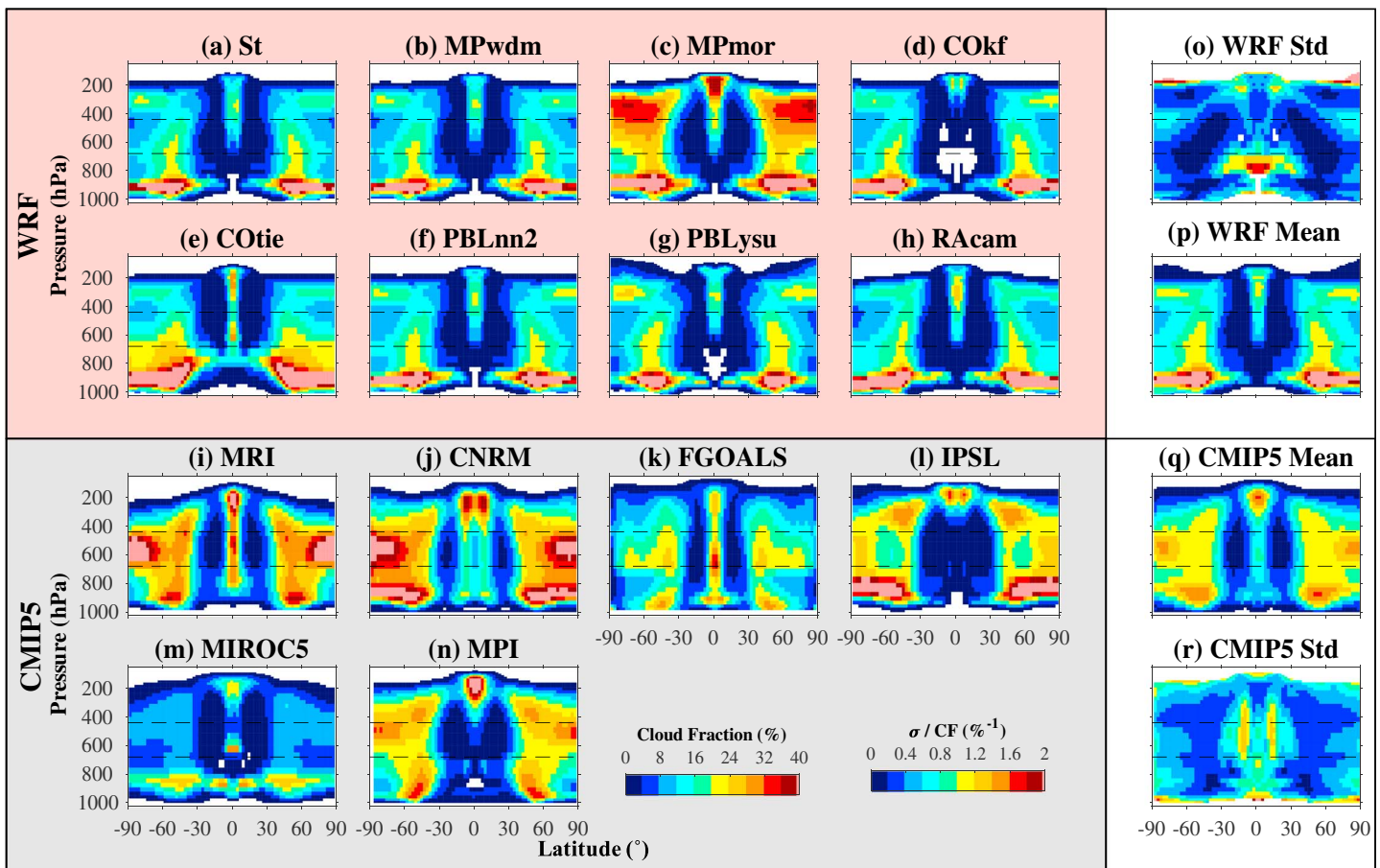


Figure 1. Zonal mean (x axis, °N) profiles (y axis, hPa) of CF (shading, %) simulated by (a–h) eight WRF configurations (pink box) and (i–n) six CMIP5 models (gray box) as well as their (p, q) multimodel mean and (o, r) standard deviation normalized by the mean (green box). Note that for Figure 1o and Figure 1r, we excluded grid cells where the mean was lower than 1% (white areas). The horizontal black dashed lines separate the low- and middle-level clouds (680 hPa) and middle- and high-level clouds (440 hPa).

based on the CAM model (Collins et al., 2004). Note that all three convection schemes represent shallow and deep convection.

We then compare the WRF Control and 4K experiments to six CMIP5 models: the Max Planck Institute-Earth System Model-Low Resolution (MPI-ESM-LR), the Institut Pierre Simon Laplace Coupled Model version 5A (IPSL-CM5A), the Model for Interdisciplinary Research on Climate version 5, the Flexible Global Ocean-Atmosphere-Land System model, grid point version 2, the Centre National de Recherches Météorologiques Coupled Model version 5 (CNRM-CM5), and the Meteorological Research Institute Coupled General Circulation Model version 3.

One of the key differences between the CMIP5 and WRF aquaplanet simulations is that the former are usually tuned to match observed fluxes at the top of the atmosphere (TOA) in Earth-like simulations (e.g., Hourdin et al., 2017), while no specific tuning is performed for WRF simulations. Nevertheless, the energy is conserved, and the steady state is reached in WRF simulations as described in supporting information (Text S2). Moreover, the WRF and CMIP5 ensembles show similar mean state dynamics and cloud fraction (Text S3 and Figures S3 and S4), zonal structure of TOA radiative fluxes, and global thermodynamic properties of the atmosphere (not shown). All WRF and CMIP5 simulations are projected onto the same $2.5^\circ \times 2.5^\circ$ spatial grid and the 40 WRF vertical levels to facilitate the comparison. CMIP5 simulations are 4 years long as compared to 1 year for WRF. Yet their interannual variation is negligible and using a specific year rather than all 4 years does not impact the results (e.g., Figure S5).

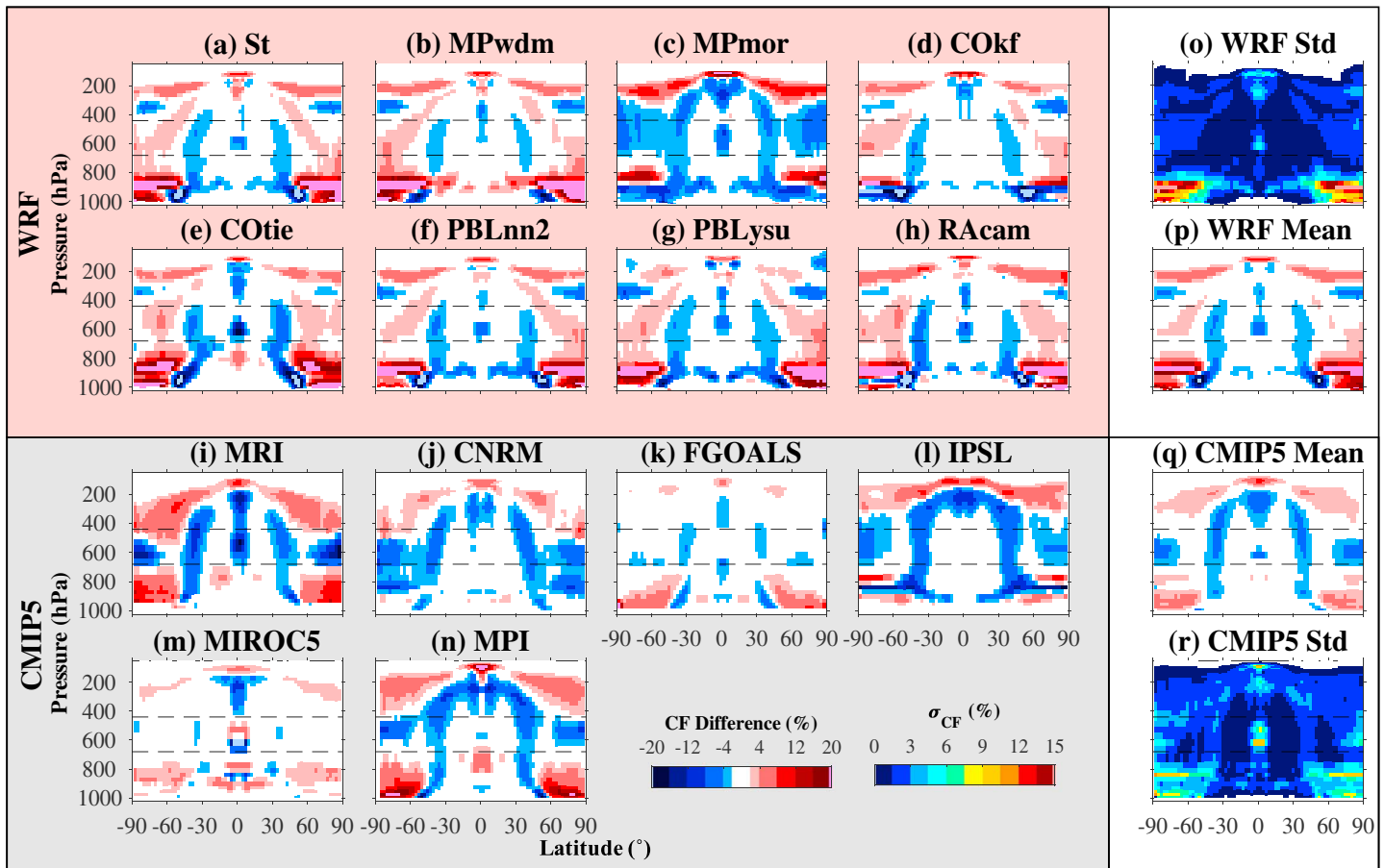


Figure 2. Same as Figure 1 for CF differences between 4K and Control experiments (STDs are not normalized).

3. Results

Throughout this analysis, we will often refer to three regions: the tropics, the midlatitudes, and the polar regions defined as being, respectively, equatorward of 30°, between 30° and 60°, and poleward of 60° and to three cloud layers: low-level ($P > 680$ hPa), middle-level ($680 \text{ hPa} > P > 440$ hPa), and high-level ($P < 440$ hPa) clouds.

3.1. Cloud Structure in the Control Experiment

We first investigate to what extent the zonal mean cloud fraction (CF) profiles in the WRF ensemble agree with the CMIP5 ensemble (Figure 1). In the tropics, substantial cloudiness extends across most of the troposphere in both ensembles except for IPSL and MPI models, which simulate very few low level clouds (Figures 1l and 1n). On the one hand, the pattern of tropical clouds is mostly modulated by convective schemes. For example, WRF simulations using GFS convective scheme produce a significant amount of clouds in the middle and high levels but very little below (Figures 1a–1c and 1f–1h). On the contrary, the COkf simulation (Figure 1d) shows clouds only in the high level while the COtie simulation (Figure 1e) also predicts significant low-level clouds compared to GFS scheme simulations. On the other hand, the amount of cloud seems sensitive to microphysics parameterizations, according to the larger CF found in the MPmor simulation (Figure 1b). At middle latitudes and in polar regions, CMIP5 models show slightly greater intermodel variability, likely because the standard microphysics parameterization limits the formation of ice clouds.

In conclusion, the amount of cloudiness may be slightly different between WRF and CMIP5 ensembles but their overall pattern is fairly similar (Figure 1p versus Figure 1q). Furthermore, they both show similar ranges of variability, particularly for tropical clouds (Figure 1o versus Figure 1r; also see Text S3 and Figure S4).

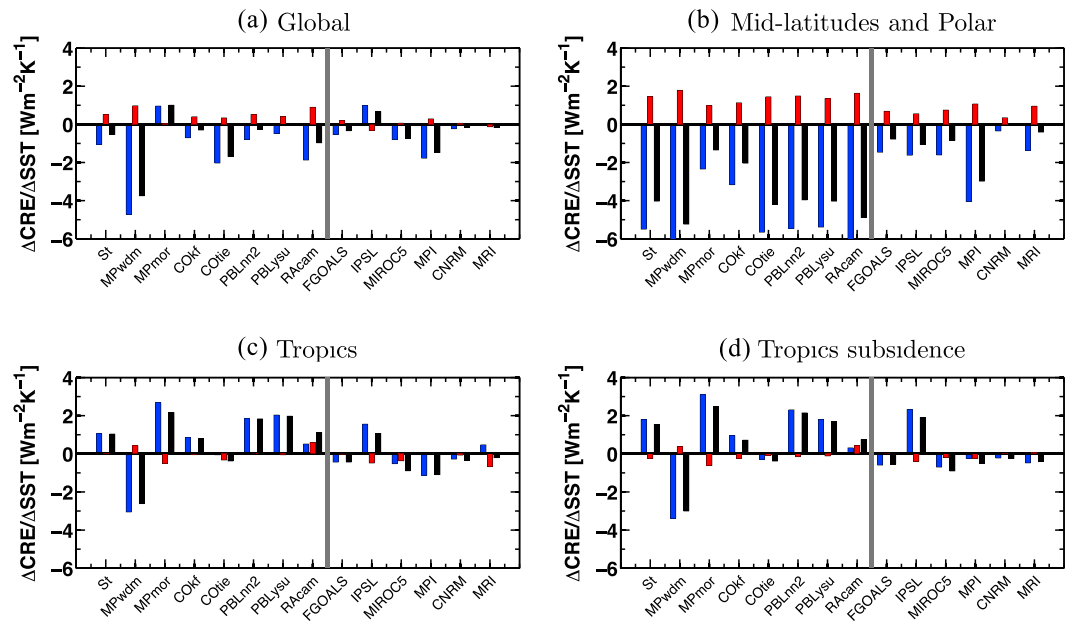


Figure 3. SW (blue), LW (red), and net (black bars) cloud feedbacks (y axis $W m^{-2} K^{-1}$) in WRF and CMIP5 simulations (x axis) for (a) the global domain, (b) the midlatitudes and polar regions, (c) the tropics, and (d) the subsidence regimes in the tropics.

3.2. Cloud Response to SST Increase

To understand how models respond to an idealized climate change, Figure 2 shows zonal profiles of cloud response to a uniform +4K SST increase for all WRF and CMIP5 simulations. In the tropics, most WRF and CMIP5 simulations show a substantial decrease in middle- and high-level clouds below ~ 200 hPa alongside an increase of very high level clouds above around 200 hPa generated by a deepening of the troposphere. The cloud top height increases, because the temperature of the tropopause must remain constant, following the fixed anvil temperature hypothesis (Hartmann & Larson, 2002). This implies that with the warmer atmosphere, the troposphere depth increases, and the high clouds therefore rise. In contrast, the models' behavior is more diverse in the low levels, where some models predict either a clear decrease of the CF (Figures 2a, 2c, 2d, 2f, 2g, 2h, and 2l), others predict an increase (Figures 2b, 2e, 2i, 2m, and 2n), and some predict both in different regions (Figures 2j and 2k). This diversity leads to a weak average low-cloud change in both CMIP5 and WRF ensembles (Figures 2p and 2q). It is worth mentioning that in the WRF simulations, whether the low-level tropical clouds increase or decrease depends mostly on microphysics and convective parameterizations.

At middle latitudes, the ensembles agree on a decrease of the CF in most of the column except around 60° . Poleward of 50° , while the response of middle-level clouds is more diverse, all models but CNRM simulate either an increase or an upward shift of the high- and low-level clouds. On average, the Hadley cell is widened, shifting clouds slightly toward the poles (blue versus red shading between 30 and $50^\circ S/N$ in Figure 2; e.g., Tsushima et al., 2006).

3.3. Cloud Radiative Feedbacks

Here we further study the impact of cloud changes on the radiative budget, via the use of the cloud radiative effect (CRE), defined as the difference between the all-sky flux minus the clear-sky flux at the TOA. Figure 3 shows the change in the short-wave, long-wave, and net CREs normalized by SST, hereafter called $\Delta CREs$. A positive ΔCRE indicates a warming effect due to the clouds when the SST increases; conversely, a negative ΔCRE indicates a cooling effect. This quantity may be used as a proxy to characterize cloud feedbacks, as in Medeiros et al. (2015). The magnitude and the sign of global net cloud feedbacks vary significantly among the models (black bars, Figure 3a). In most simulations, the cloud feedbacks are dominated by the SW component (blue bars, Figure 3), in agreement with previous literature (e.g., Zelinka et al., 2013). Twelve of the 14 CMIP5 and WRF simulations show negative net $\Delta CREs$ (Table S2). The range of WRF $\Delta CREs$ is more than 2

times as large as that of the CMIP5 simulations ($4.76 \text{ W m}^{-2} \text{ K}^{-1}$ versus $2.16 \text{ W m}^{-2} \text{ K}^{-1}$). It is worth mentioning that in the WRF simulations, the extremes, which have opposite sign, correspond to MPmor and MPwdm microphysical simulations. Furthermore, for almost the same cloud fraction mean state (Figure 1a versus Figure 1b), the MPwdm and St simulations have an opposite sign of the cloud feedback. This highlights the importance of microphysics schemes to determine low cloud feedbacks.

At middle latitudes and in the polar regions, all WRF and CMIP5 simulations agree on a negative cloud feedback driven by the short-wave component. However, because of a larger increase of low-level clouds, the WRF simulations show larger magnitudes of net ΔCRE than CMIP5 models (ensemble mean of $-3.72 \text{ W m}^{-2} \text{ K}^{-1}$ versus $-1.01 \text{ W m}^{-2} \text{ K}^{-1}$). As the atmosphere is warmer on average, more supercooled liquid clouds are formed with respect to ice clouds. Therefore, the liquid water content of these clouds is increased at the expense of ice, which means they reflect more short-wave radiation back to space resulting in a negative cloud feedback. This feature seems robust as it is represented in both WRF and CMIP ensembles, consistent with previous studies (Cesana & Storelvmo, 2017; McCoy et al., 2016).

Neither the WRF nor CMIP5 simulations agree on the sign of the tropical ΔCRE (Figure 3c and Table S2, column 3). This reflects the large variability of tropical low-cloud changes in both ensembles and confirms the determinant role of the tropical clouds in the global cloud feedback uncertainty. We then separate the tropical cloud feedbacks into cloud regimes defined by the vertical velocity at 500 hPa: subsidence regimes for $\omega_{500} > 15 \text{ hPa}$ and convective regimes for $\omega_{500} < -25 \text{ hPa}$. This confirms that cloud feedbacks in subsidence regimes, described in Figure 3d, are the main source of uncertainty of the tropical cloud feedbacks and hence global cloud feedbacks, as discussed by previous studies (Dufresne & Bony, 2008; Zelinka et al., 2013). The correlation between the net ΔCREs in subsidence regimes and over the whole tropics for both ensembles is 0.97, and it remains as high as 0.81 when compared to the global cloud feedbacks (Table S2).

3.4. Tropical Low-Level Cloud Feedbacks

As the global and tropical cloud feedbacks are dominated by feedbacks in the tropical subsidence regimes, we focus on this regime to better understand what is driving the spread of ΔCRE estimates across WRF simulations. Figure 4 shows the vertical profiles of CF in subsidence regimes, for the Control experiment and the difference between the CFs from 4K and Control experiments. In the Control experiment (Figure 4a), the WRF ensemble shows a single peak of low-level clouds around 900 hPa, larger and lower in height than that of CMIP5 ensemble, and very few high level clouds as opposed to CMIP5 ensemble. Note that convective schemes may significantly affect the height of the low-level CF peak and therefore the ensemble variability, such as in the COtie simulation (Figure 4c, orange dashed line). The WRF ensemble shows a range of variability similar to the CMIP5 ensemble although slightly smaller (Figure 4a, light red shading versus gray shading).

Interestingly, under a warmer climate such as the 4K experiment, the spread of cloud response is also very similar in both ensembles (Figure 4b). Six of the eight WRF simulations predict a clear decrease of low-level clouds (Figure 4d) as opposed to an increase in all CMIP5 models but IPSL (Figure S6). These increases or decreases of the low-level CF are similar with the two behaviors described by Brient et al. (2016) using CMIP5 models sorted as a function of their climate sensitivity. They argue that (i) for models with shallow low cloud in present-day climate, the convective drying in a warmer climate favors the deepening of the clouds and thus a decrease of the CF as in most WRF simulations and the IPSL model and (ii) for models with more extended low clouds in present-day climate, the turbulent moistening of the boundary layer favors a shallowing of the clouds and likely an increase of the CF as in the COtie simulation and all CMIP5 models but IPSL. This confirms that basic features of the low cloud response to a warmer climate can be captured using aquaplanet simulations and that the diversity of CMIP5 model behaviors can be reproduced by changing physical parameterizations in WRF. Finally, consistent with the FAT hypothesis, all simulations predict an elevation of high-level clouds (around 150 hPa). In addition, we found a reduction in the high cloud fraction in 10/14 simulations for the convective cases (Figure S7), in agreement with Bony et al. (2016).

The mean tropical net cloud feedback is positive for the simulations predicting a decrease in the low-level CF and negative for those predicting its increase (Table S2, column 3), which is driven by the choice of parameterization. For example, changing convection or microphysics schemes may result in a response of the low-level clouds opposite in sign to that of the Control simulation (Figure 4d, COtie, orange dashed line and MPwdm, blue dashed line). The Tiedtke convection scheme introduces cumuli that can extend above the

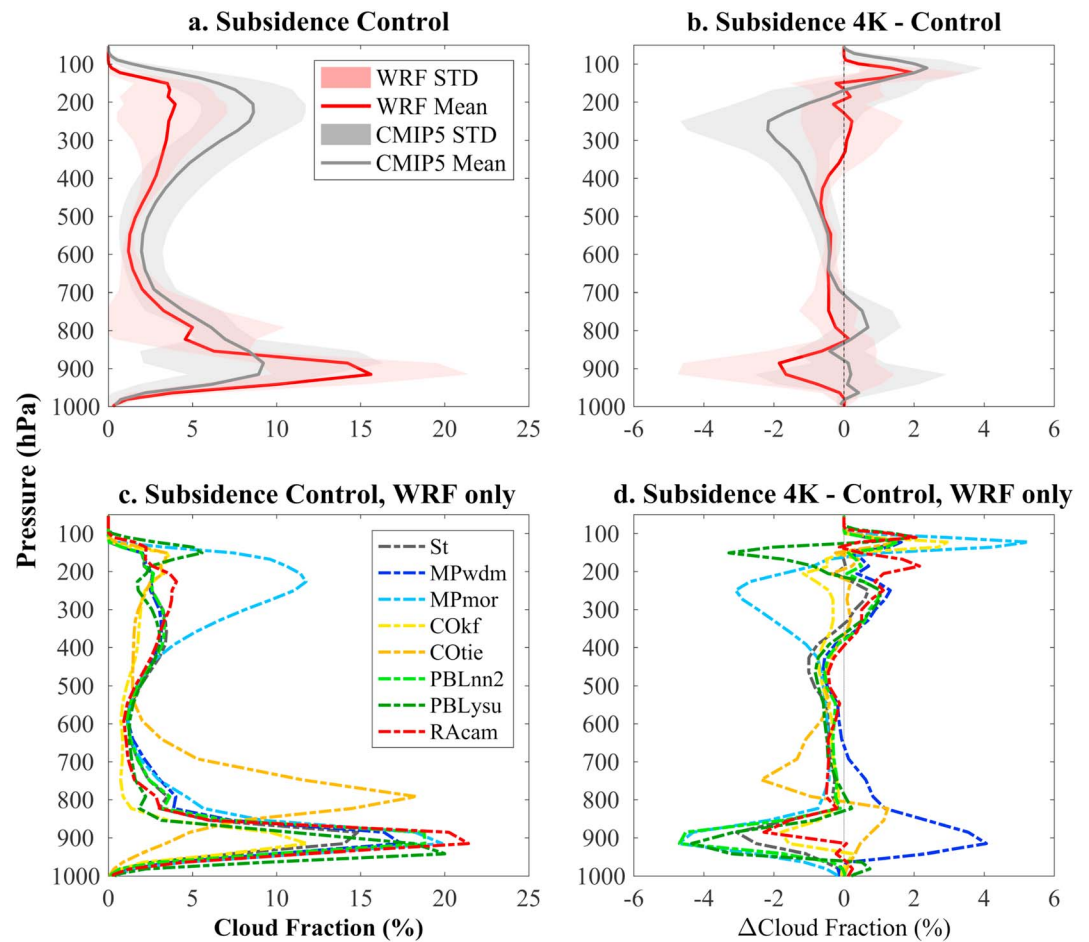


Figure 4. Vertical profiles (y axis, hPa) of multimodel mean cloud fraction (x axis, %) from (a, c) the Control experiment and (b, d) the difference between 4K and Control experiments for tropical subsidence regimes ($\omega_{500} > 15$ hPa/d). The colored dashed lines, the red line, and the light red area represent each WRF simulation, the WRF multimodel mean, and the WRF multimodel spread, respectively. The gray line and area correspond to the multimodel mean and spread for the CMIP5 models. The spread in WRF and CMIP5 models is defined as plus and minus one standard deviation.

inversion of the stable layer, referred to as “overshooting cumuli,” which explains why the clouds form from the low to the middle levels in the tropics (Tiedtke, 1989). In a warmer climate such as the 4K experiment, the inversion becomes stronger. These overshooting cumuli are therefore weakened, resulting in less clouds right above the stable layer (Figure 4d, orange dashed line). In the MPwdm simulation, the larger raindrop number concentration in the 4K compared to the Control experiment reduces the precipitation and results in excessive evaporation (Lim & Hong, 2010). In the 4K experiment, the turbulent moistening of the mixed layer may be enhanced in these two simulations, which explains why the low-level CF increases.

Finally, the cloud feedback variability is mostly due to local changes in the WRF ensemble, whereas local and large-scale changes contribute almost equally in the CMIP5 ensemble (Figure S8 and Text S4). On the one hand, changing physical parameterizations mostly affect cloud feedbacks locally. On the other hand, changing dynamical options in addition to the physical parameterization as in the CMIP5 ensemble generates additional variability in the cloud feedbacks due to large-scale circulation changes. Such result stresses the importance of the dynamical options on the cloud feedbacks, that is, horizontal and vertical resolutions and dynamical cores, not addressed in the present study.

4. Summary and Conclusions

Pin-pointing cloud feedback mechanisms to underlying physical processes remain very challenging, particularly with a multimodel approach. The present study investigates how physical categories of parametrizations

affect cloud feedbacks using an unprecedented approach based on the WRF model in aquaplanet mode. For this purpose, we constructed an ensemble of eight WRF simulations by substituting only one parameterization at a time with respect to the standard version. We then analyzed the cloud fraction and feedback differences between the standard and modified versions of WRF under climate change. Finally, we compared WRF results to CMIP5 simulations, aiming to determine how the WRF ensemble uncertainty in cloud feedbacks compares with that of conventional GCMs.

Our results show that modifying the parameterizations in WRF is sufficient to reproduce the spread of CMIP5 models in cloud fraction profiles (Figure 1) along with cloud changes (Figure 2) and cloud feedback estimates (Figure 3) in a warmer climate. Furthermore, the cloud feedbacks are mostly due to local changes rather than large-scale circulation changes. These results demonstrate that WRF is a relevant tool for understanding the diversity of cloud feedbacks in CMIP5 models.

In addition, our results confirm some key features already identified in conventional GCMs for Earth-like simulations, reinforcing our confidence in the WRF-aquaplanet-based approach: (i) most of the global uncertainty in cloud feedbacks comes from the tropical low-level clouds (e.g., Webb et al., 2006; Zelinka et al., 2013) and (ii) a change in the tropical low-level cloud fraction in response to a warmer SST dictates the sign of tropical cloud feedbacks (e.g., Brient et al., 2016). While some studies have shown that tropical low-level clouds are sensitive to PBL and convective parameterizations (e.g., Gettelman et al., 2012; Vial et al., 2016; Watanabe et al., 2012; Webb et al., 2015), little evidence this far has pointed toward a significant effect of microphysics in the tropics (e.g., Zhao et al., 2016). However, our findings suggest that microphysics parameterizations—as well as convective ones—are a primary contributor to cloud feedbacks in WRF by modulating the change of the low-level cloud fraction in a warmer climate (Figure 4). In particular, we found that for the same mean state, two different microphysical parameterizations can produce cloud feedbacks of opposite sign.

Overall, we confirm the relative importance of parameterizations in determining the sign and the amplitude of cloud feedbacks. This emphasizes the usefulness of the WRF model and its plug-and-play capability for improving our understanding of the physical mechanisms governing cloud feedbacks, and in turn, narrowing down their uncertainty in both regional and global climate projections.

Future work will include more thorough study of these physical mechanisms. For example, one could explore the effect of combined change of parameterizations, as the coupling between parameterizations was shown to be crucial in changing the magnitude and sign of cloud feedbacks (e.g., cloud and turbulence schemes; Watanabe et al., 2012). Finally, we will study sensitivity of clouds to the dynamical and numerical options in WRF, such as the horizontal and vertical resolution, and to the cloud fraction scheme, which is known to be a source of uncertainty in CMIP5 cloud feedback (Geoffroy et al., 2017).

Acknowledgments

G. C. was supported by a contract with the National Aeronautics and Space Administration, ROSES 2012; Earth Science Program; Modeling, Analysis, and Prediction Program at the Jet Propulsion Laboratory; and by a CloudSat-CALIPSO RTOP at the Goddard Institute for Space Studies. K. S. was supported by a contract with the National Aeronautics and Space Administration at the Jet Propulsion Laboratory, California Institute of Technology. The WRF simulations can be made available upon request, and the CMIP5 simulations were downloaded from the World Data Center for Climate (WDCC) website [<http://cera-www.dkrz.de/>]. We thank Bridget Samuels for proofreading the manuscript. All authors state that there is no conflict of interest. We would like to acknowledge the Editor and the two anonymous reviewers for their constructive and helpful comments that helped us improve the manuscript.

References

- Andrews, T., Gregory, J., Webb, M., & Taylor, K. (2012). Forcing, feedbacks and climate sensitivity in CMIP5 coupled atmosphere-ocean climate models. *Geophysical Research Letters*, *39*, L09712. <https://doi.org/10.1029/2012GL051607>
- Arakawa, A., & Schubert, W. H. (1974). Interaction of a cumulus cloud ensemble with the large-scale environment. Part I. *Journal of the Atmospheric Sciences*, *31*(3), 674–701. [https://doi.org/10.1175/1520-0469\(1974\)031%3C0674:IOACCE%3E2.0.CO;2](https://doi.org/10.1175/1520-0469(1974)031%3C0674:IOACCE%3E2.0.CO;2)
- Bhattacharya, R., Bordoni, S., & Teixeira, J. (2017). Tropical precipitation extremes: Response to SST-induced warming in aquaplanet simulations. *Geophysical Research Letters*, *44*(7), 3374–3383. <https://doi.org/10.1002/2017GL073121>
- Bony, S., Stevens, B., Coppin, D., Becker, T., Reed, K. A., Voigt, A., & Medeiros, B. (2016). Thermodynamic control of anvil cloud amount. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(32), 8927–8932. <https://doi.org/10.1073/pnas.1601472113>
- Bretherton, C. S., Blossey, P. N., & Jones, C. R. (2013). Mechanisms of marine low cloud sensitivity to idealized climate perturbations: A single-LES exploration extending the CGILS cases. *Journal of Advances in Modeling Earth Systems*, *5*(2), 316–337. <https://doi.org/10.1002/jame.20019>
- Brient, F., & Bony, S. (2012). How may low-cloud radiative properties simulated in the current climate influence low-cloud feedbacks under global warming? *Geophysical Research Letters*, *39*, L20807. <https://doi.org/10.1029/2012GL053265>
- Brient, F., Schneider, T., Brient, F., & Schneider, T. (2016). Constraints on climate sensitivity from space-based measurements of low-cloud reflection. *Journal of Climate*, *29*(16), 5821–5835. <https://doi.org/10.1175/JCLI-D-15-0897.1>
- Cesana, G., & Storelmo, T. (2017). Improving climate projections by understanding how cloud phase affects radiation. *Journal of Geophysical Research: Atmospheres*, *122*, 4594–4599. <https://doi.org/10.1002/2017JD026927>
- Cess, R. D., Potter, L., Blanchet, J. P., Boer, G. J., del Genio, A. D., Déqué, M., ... Zhang, M.-H. (1990). Intercomparison and interpretation of climate feedback processes in 19 atmospheric general circulation models. *Journal of Geophysical Research*, *95*, 16,601–16,615. <https://doi.org/10.1029/JD095iD10p16601>
- Charney, J. G., Arakawa, A., James Baker, D., Bolin, B., Dickinson, R. E., Goody, R. M., ... Wunsch, C. I. (1979). *Carbon dioxide and climate: A scientific assessment* (22 pp.). Washington, DC: National Academy of Sciences.
- Collins, W. D., Rasch, P. J., Boville, B. A., Hack, J. J., Mccaa, J. R., Williamson, D. L., ... Briegleb, B. (2004). Description of the NCAR Community Atmosphere Model (CAM 3.0). NCAR Tech. Note NCAR/TN-464+STR (214 pp.).

- Dufresne, J.-L., & Bony, S. (2008). An assessment of the primary sources of spread of global warming estimates from coupled atmosphere ocean models. *Journal of Climate*, 21(19), 5135–5144. <https://doi.org/10.1175/2008JCLI2239.1>
- Flato, G., Marotzke, J., Abiodun, B., Braconnot, P., Chou, S. C., Collins, W., ... Rummukainen, M. (2013). Evaluation of climate models. In T. F. Stocker, et al. (Eds.), *Climate change 2013: The physical science basis. Contribution of working group I to the fifth assessment report of the intergovernmental panel on climate change* (pp. 741–882). Cambridge, United Kingdom and New York: Cambridge University Press. <https://doi.org/10.1017/CBO9781107415324.020>
- Geoffroy, O., Sherwood, S. C., & Fuchs, D. (2017). On the role of the stratiform cloud scheme in the inter-model spread of cloud feedback. *Journal of Advances in Modeling Earth Systems*, 9(1), 423–437. <https://doi.org/10.1002/2016MS000846>
- Gettelman, A., Kay, J. E., & Shell, K. (2012). The evolution of climate sensitivity and climate feedbacks in the Community Atmosphere Model. *Journal of Climate*, 25(5), 1453–1469. <https://doi.org/10.1175/JCLI-D-11-00197.1>
- Gregory, J. M., Ingram, W. J., Palmer, M. A., Jones, G. S., Stott, P. A., Thorpe, R. B., ... Williams, K. D. (2004). A new method for diagnosing radiative forcing and climate sensitivity. *Geophysical Research Letters*, 31, L03205. <https://doi.org/10.1029/2003GL018747>
- Hartmann, D. L., & Larson, K. (2002). An important constraint on tropical cloud—Climate feedback. *Geophysical Research Letters*, 29(20), 1951. <https://doi.org/10.1029/2002GL015835>
- Hong, S., & Lim, J. (2006). The WRF Single-Moment 6-Class Microphysical Scheme (WSM6). *Journal of Korean Meteorological Society*, 42(2), 129–151.
- Hong, S. Y., Noh, Y., & Dudhia, J. (2006). A new vertical diffusion package with an explicit treatment of entrainment processes. *Monthly Weather Review*, 134(9), 2318–2341. <https://doi.org/10.1175/MWR3199.1>
- Hourdin, F., Mauritsen, T., Gettelman, A., Golaz, J.-C., Balaji, V., Duan, Q., ... Williamson, D. (2017). The art and science of climate model tuning. *Bulletin of the American Meteorological Society*, 98(3), 589–602. <https://doi.org/10.1175/BAMS-D-15-00135.1>
- Iacono, M. J., Delamere, J. S., Mlawer, E. J., Shephard, M. W., Clough, S. A., & Collins, W. D. (2008). Radiative forcing by long-lived greenhouse gases: Calculations with the AER radiative transfer models. *Journal of Geophysical Research*, 113, D13103. <https://doi.org/10.1029/2008JD009944>
- Kain, J. (2004). The Kain-Fritsch convective parameterization: An update. *Journal of Applied Meteorology*, 43(1), 170–181. [https://doi.org/10.1175/1520-0450\(2004\)043%3C0170:TKCPAU%3E2.0.CO;2](https://doi.org/10.1175/1520-0450(2004)043%3C0170:TKCPAU%3E2.0.CO;2)
- Knutti, R., & Hegerl, G. (2008). The equilibrium sensitivity of the Earth's temperature to radiation changes. *Nature Geoscience*, 1(11), 735–743. <https://doi.org/10.1038/ngeo337>
- Levine, X. J., & Schneider, T. (2011). Response of the Hadley circulation to climate change in an aquaplanet GCM coupled to a simple representation of ocean heat transport. *Journal of the Atmospheric Sciences*, 68(4), 769–783. <https://doi.org/10.1175/2010JAS3553.1>
- Lim, K.-S. S., & Hong, S.-Y. (2010). Development of an effective double-moment cloud microphysics scheme with prognostic cloud condensation nuclei (CCN) for weather and climate models. *Monthly Weather Review*, 138(5), 1587–1612. <https://doi.org/10.1175/2009MWR2968.1>
- McCoy, D. T., Tan, I., Hartmann, D. L., Zelinka, M. D., & Storelmo, T. (2016). On the relationships among cloud cover, mixed-phase partitioning, and planetary albedo in GCMs. *Journal of Advances in Modeling Earth Systems*, 8(2), 650–668. <https://doi.org/10.1002/2015MS000589>
- Medeiros, B., Stevens, B., Held, I. M., Zhao, M., Williamson, D. L., Olson, J. G., & Bretherton, C. S. (2008). Aquaplanets, climate sensitivity, and low clouds. *Journal of Climate*, 21(19), 4974–4991. <https://doi.org/10.1175/2008JCLI1995.1>
- Medeiros, B., Stevens, B., & Bony, S. (2015). Using aquaplanets to understand the robust responses of comprehensive climate models to forcing. *Climate Dynamics*, 44(7–8), 1957–1977. <https://doi.org/10.1007/s00382-014-2138-0>
- Medeiros, B., Williamson, D. L., & Olson, J. G. (2016). Reference aquaplanet climate in the Community Atmosphere Model Version 5. *Journal of Advances in Modeling Earth Systems*, 8(1), 406–424. <https://doi.org/10.1002/2015MS000593>
- Morrison, H., Thompson, G., & Tatarskii, V. (2009). Impact of cloud microphysics on the development of trailing Stratiform precipitation in a simulated squall line: Comparison of one- and two-moment schemes. *Monthly Weather Review*, 137(3), 991–1007. <https://doi.org/10.1175/2008MWR2556.1>
- Nakanishi, M., & Niino, H. (2004). An improved Mellor Yamada level-3 model with condensation physics: Its design and verification. *Boundary-Layer Meteorology*, 112(1), 1–31. <https://doi.org/10.1023/B:BOUN.0000020164.04146.98>
- Randall, D., Wood, R., Bony, S., Colman, R., Fichefet, T., Fyfe, J., ... Taylor, K. E. (2007). In *Climate change 2007: The physical science basis. Contribution of working group I to the fourth assessment report of the Intergovernmental Panel on Climate Change* (pp. 589–662). Cambridge, UK: Cambridge University Press.
- Shiogama, H., Watanabe, M., Ogura, T., Yokohata, T., & Kimoto, M. (2014). Multi-parameter multi-physics ensemble (MPMPE): A new approach exploring the uncertainties of climate sensitivity. *Atmospheric Science Letters*, 15(2), 97–102. <https://doi.org/10.1002/asl2.472>
- Skamarock, W., Klemp, J. B., Gill, D. O., Barker, D., Duda, M. G., Wang, W., & Powers, J. G. (2008). A description of the advanced research WRF version 3. Tech. Rep. June, NCAR, Technical Note NCAR/TN-475+STR. <https://doi.org/10.5065/D68S4MVH>
- Tan, I., Storelmo, T., & Zelinka, M. D. (2016). Observational constraints on mixed-phase clouds imply higher climate sensitivity. *Science*, 352(6282), 224–227. <https://doi.org/10.1126/science.aad5300>
- Tiedtke, M. (1989). A comprehensive mass flux scheme for cumulus parameterization in large-scale models. *Monthly Weather Review*, 117(8), 1779–1800. [https://doi.org/10.1175/1520-0493\(1989\)117%3C1779:ACMFSF%3E2.0.CO;2](https://doi.org/10.1175/1520-0493(1989)117%3C1779:ACMFSF%3E2.0.CO;2)
- Tsushima, Y., Emori, S., Ogura, T., Kimoto, M., Webb, M. J., Williams, K. D., ... Andronova, N. (2006). Importance of the mixed-phase cloud distribution in the control climate for assessing the response of clouds to carbon dioxide increase: A multi-model study. *Climate Dynamics*, 27(2–3), 113–126. <https://doi.org/10.1007/s00382-006-0127-7>
- Vial, J., Dufresne, J.-L., & Bony, S. (2013). On the interpretation of intermodal spread in CMIP5 climate sensitivity estimates. *Climate Dynamics*, 41(11–12), 3339–3362. <https://doi.org/10.1007/s00382-013-1725-9>
- Vial, J., Bony, S., Dufresne, J.-L., & Roehrig, R. (2016). Coupling between lower-tropospheric convective mixing and low-level clouds: Physical mechanisms and dependence on convection scheme. *Journal of Advances in Modeling Earth Systems*, 8(4), 1892–1911. <https://doi.org/10.1002/2016MS000740>
- Watanabe, M., Shiogama, H., Yokohata, T., Kamae, Y., Yoshimori, M., Ogura, T., ... Kimoto, M. (2012). Using a multiphysics ensemble for exploring diversity in cloud–shortwave feedback in GCMs. *Journal of Climate*, 25(15), 5416–5431. <https://doi.org/10.1175/JCLI-D-11-00564.1>
- Webb, M. J., Senior, C. A., Sexton, D. M. H., Ingram, W. J., Williams, K. D., Ringer, M. A., ... Taylor, K. E. (2006). On the contribution of local feedback mechanisms to the range of climate sensitivity in two GCM ensembles. *Climate Dynamics*, 27(1), 17–38. <https://doi.org/10.1007/s00382-006-0111-2>
- Webb, M. J., Lock, A. P., Bretherton, C. S., Bony, S., Cole, J. N. S., Idelkadi, A., ... Zhao, M. (2015). The impact of parametrized convection on cloud feedback. *Philosophical Transactions of the Royal Society A*, 373, 2054.

- Williamson, D., Blackburn, M., Hoskins, B. J., Nakajima, K., Ohfuchi, W., Takahashi, Y. O., ... Stratton, R. A. (2012). The APE Atlas. Technical report. National Center for Atmospheric Research. <https://doi.org/10.5065/D6FF3QBR>. Retrieved from <http://nldr.library.ucar.edu/repository/collections/TECH-NOTE-000-000-000-865>
- Xu, K.-M., & Randall, D. A. (1996). A semiempirical cloudiness parameterization for use in climate models. *Journal of Atmospheric Sciences*, *53*, 3084–3102.
- Zelinka, M. D., Klein, S. A., Taylor, K. E., Andrews, T., Webb, M. J., Gregory, J. M., & Forster, P. M. (2013). Contributions of different cloud types to feedbacks and rapid adjustments in CMIP5. *Journal of Climate*, *26*, 5007–5027. <https://doi.org/10.1175/JCLI-D-12-00555.1>
- Zhao, M., Golaz, J.-C., Held, I. M., Ramaswamy, V., Lin, S.-J., Ming, Y., ... Guo, H. (2016). Uncertainty in model climate sensitivity traced to representations of cumulus precipitation microphysics. *Journal of Climate*, *29*(2), 543–560. <https://doi.org/10.1175/JCLI-D-15-0191.1>