Impacts of Precipitation Modeling on Cloud Feedback in MIROC6

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Abstract Uncertainties in cloud feedback remain stubbornly significant in global climate models, disrupting the credibility of climate projections. This study examined the impacts of the prognostic treatment of precipitation on cloud feedback using the Model for Interdisciplinary Research on Climate version 6 (MIROC6). In a prognostic precipitation scheme, precipitating hydrometers are explicitly predicted, allowing a more sophisticated representation of their microphysical and radiative effects than that of traditional diagnostic schemes. The introduction of the prognostic scheme in MIROC6 increases cloud feedback associated with the elevated altitude of clouds in warming climates. Moreover, the equilibrium climate sensitivity increases by about 20%. Because associated high-level clouds are better represented in the prognostic scheme, climate projections with larger altitude feedback are considered more credible. Additional analyses of Coupled Model Intercomparison Project models suggests that their altitude cloud feedback would be higher if their underestimation of high-level clouds were mitigated.

Plain Language Summary Uncertainties in global mean temperature projections are primarily associated with the spread in cloud feedback across models, which accelerate or decelerate global warming through cloud sunshade and/or greenhouse effects. A possible reason for the spread in cloud response is the overly simplified treatment of precipitation in models, where rain and snow particles immediately fall from the atmosphere down to the surface within a single model time interval of about 10 min. Here, we introduced a more sophisticated precipitation scheme that explicitly calculates the physical processes of falling rain and snow particles, thus preserving their “memory” in the atmosphere with their sunshade and greenhouse effects incorporated. As a result, the representation of clouds is significantly improved in this model, and greenhouse effects by clouds in warming climates are significantly enhanced. This study lends credence to higher cloud feedback and climate sensitivity if models incorporate the missing feedback processes in line with observational constraints.

1. Introduction

Accurate future climate projections are urgent issues for mitigations and adaptations to global warming. The sixth assessment report (AR6) of the Intergovernmental Panel on Climate Change reported that the uncertainty in the equilibrium climate sensitivity (ECS; the global equilibrium surface temperature response to CO₂ doubling) is largely reduced based on multiple lines of evidence (Sherwood et al., 2020). The likely ECS range (≥66% probability) is 2.5–4K in AR6 and 1.5–4.5 K in AR5 (Sherwood et al., 2020). However, the spread of ECS across global climate models (GCMs) in the Coupled Model Intercomparison Project phase 6 (CMIP6) even increased to 1.8–5.6 K compared with 2.1–4.7 K in CMIP5 (Zelinka et al., 2020), requiring a further understanding of ECS in GCMs. Particularly, cloud feedback (accelerations/decelerations of global warming associated with cloud response to the warming) varies broadly across GCMs, which remains the most crucial source of ECS uncertainties (Zelinka et al., 2020).

The spread in cloud feedback is often associated with clouds, precipitation, turbulence, and radiative processes that are parameterized in different ways in different GCMs (Shiogama et al., 2014). Among the parameterized physical processes, precipitation processes involving falling hydrometers (rain and snow) are particularly simplified in current GCMs. Most GCMs treat precipitation diagnostically, where precipitating hydrometers are removed from the atmosphere within a single time step (Ghan & Easter, 1992). This diagnostic approach has traditionally been convenient especially for GCMs with time steps of about 10 min or longer because processes of...
falling hydrometers (3–5 m s\(^{-1}\)) cannot be resolved in such large time intervals. However, in a diagnostic scheme, the microphysical and radiative effects of suspended and falling hydrometers in the atmosphere are poorly represented. This limitation is often considered one of the important causes for systematic biases commonly found in GCMs (Gettelman et al., 2015; Wang et al., 2012): too light and too frequent rain formation (Stephens et al., 2010) and too large cloud susceptibility to aerosol forcings (Bender et al., 2019; Quaas et al., 2009).

Recently, we introduced a prognostic precipitation scheme into a GCM called Model for Interdisciplinary Research on Climate version 6 (MIROC6; Michibata et al., 2019; Tatebe et al., 2019). In this prognostic scheme, physical processes of rain and snow particles are calculated explicitly using prognostic equations in a subtime step of 60 s, allowing more realistic treatment hydrometers in the atmosphere. This modification improved the representation of precipitation, clouds, and radiation processes (Michibata et al., 2020). Moreover, the prognostic scheme significantly mitigated the systematic biases of rain formation and cloud susceptibility to aerosols described above (Michibata & Suzuki, 2020).

Extending from the evaluations of microphysical and macrophysical processes in the present-day climate (Michibata & Suzuki, 2020; Michibata et al., 2019, 2020), this study examines how the prognostic treatments of precipitation affect cloud feedback in a warming climate. To the best of our knowledge, this is the third attempt to evaluate the impacts of prognostic precipitation on cloud feedback in GCMs after Gettelman et al. (2019), who used the Community Earth System Model Version 2 (CESM2), and Cesana et al. (2021), who used the Goddard Institute for Space Studies ModelE3 (GISS-E3). Given our very limited understanding of the link between cloud feedback and the precipitation process and its large model dependency, the present study intends to provide additional investigations on this issue using MIROC6, following previous studies. In particular, to facilitate the understanding of the link above, cloud feedback is decomposed into those associated with changes in cloud amount, altitude, and optical thickness. The methods used in this study are described in Section 2, the results are provided in Section 3, and the conclusions are presented in Section 4.

2. Methods

We compared MIROC6 simulations with the traditional diagnostic precipitation scheme (hereafter DIAG; Tatebe et al., 2019) and the prognostic precipitation scheme (hereafter PROG; Michibata et al., 2019). PROG prognosed precipitating hydrometers (rain and snow) for both mass mixing ratios and number concentrations, together with their radiative effects incorporated (for details, see Michibata et al., 2019). The model had 81 levels in the vertical direction, and the horizontal resolution was T85 spectral truncation (∼1.4°). The model time step was 10 min except for microphysical processes in PROG, where a 60-s subtime step was applied.

For observational references, we used the cloud area fraction from the International Satellite Cloud Climatology Project (ISCCP) in 1984–2008 (Zhang et al., 2004), cloud water and ice contents from CloudSat 2B-CWC-RO. P1_R05 in 2007–2016 (Austin et al., 2009), and sea surface temperature (SST) compiled by the Hadley Centre in 1979–2008 (Rayner et al., 2003). We also used 18 CMIP5/6 models in the last part of Section 3 to solidify the interpretation from the MIROC simulations.

Feedbacks and ECS for MIROC6 were estimated from three types of atmospheric experiments with prescribed SST (Shiogama et al., 2014): (A) control experiments forced by climatological SST and preindustrial CO\(_2\) concentration, (B) SST increased uniformly by 4K from the control, and (C) CO\(_2\) concentration quadrupled from the control. Using global averages of radiation at top of atmosphere \(R\) and surface air temperature \(T\) for experiments A, B, and C, ECS was calculated as

\[
\text{Total Feedback} = [R(B) - R(A)]/[T(B) - T(A)]
\]

\[
\text{Radiative Forcing} = \frac{[R(C) - R(A)]}{2}
\]

\[
\text{ECS} = -\text{Radiative Forcing}/\text{Total Feedback}.
\]

Each experiment was run for 11 years, and the last 10 years were used for the subsequent analysis. The cloud area fraction in the models was estimated using the Cloud Feedback Model Intercomparison Project Observation Simulator Package (COSP; Bodas-Salcedo et al., 2011; Swales et al., 2018) for consistent comparison with satellite observations. Cloud radiative effects (CREs) were diagnosed using the radiative kernels of Zelinka et al. (2012, 2013), which evaluate CRE changes associated with changes in ISCCP cloud area fraction. Moreover,
Zelinka et al.'s kernel decomposes the total CRE feedback into those associated with changes in cloud amount, cloud altitude, and cloud optical thickness. The statistical significance of the differences between DIAG and PROG was tested at the 95% level using a two-tailed $t$-test using their interannual variations.

### 3. Results

ECS increases by approximately 20% from 2.1 K in DIAG to 2.5 K in PROG, as shown in Figure 1a. The corresponding total feedback increases by 0.41 W m$^{-2}$ K$^{-1}$ ($-1.76$ to $-1.35$ W m$^{-2}$ K$^{-1}$), with radiative forcing decreasing by 0.34 W m$^{-2}$ (3.73–3.39 W m$^{-2}$). The increase in ECS and total feedback can mostly be explained by the 0.53-W m$^{-2}$ K$^{-1}$ increase in net CRE feedback, which resulted from the 0.58-W m$^{-2}$ K$^{-1}$ increase in the longwave (LW) CRE feedback ($d_{CRE_{LW}}$) and $-0.05$-W m$^{-2}$ K$^{-1}$ decrease in the shortwave (SW) component ($d_{CRE_{SW}}$), as shown in Figure 1b. The impacts of the prognostic precipitation are primarily dominated by $d_{CRE_{LW}}$.

Figure 2 shows the decomposition of $d_{CRE_{LW}}$ into those associated with responses in cloud amount, altitude, and optical depth to global surface warming. The change in $d_{CRE_{LW}}$ from DIAG to PROG is dominated by that associated with cloud altitude ($d_{CRE_{LW,Alt}}$), whereas the change in cloud amount and optical depth feedback has only minor impacts on $d_{CRE_{LW}}$. As the climate warmed, the tropopause height and thus the cloud top height are elevated. LW cooling is less effective for clouds at higher altitudes, resulting in the positive feedback of
The importance of dCRE$_{LW}$ Alt is well documented in previous studies (Hartmann & Larson, 2002; Yoshimori et al., 2020).

Figure 3 shows the vertical structure of atmospheric ice contents (including snow) in the present-day climate and in response to global surface warming (feedback) to understand the significant difference in the LW cloud feedback between the two models. High-level clouds in the present-day climate are largely underestimated in DIAG. In contrast, this underestimation is mitigated in PROG, as discussed in Michibata et al. (2019). The increase in higher clouds and the decrease in lower clouds in response to global warming indicates an elevated cloud altitude. The magnitude of the cloud altitude response is small in DIAG than that in PROG, consistent with the fact that DIAG has fewer high-level clouds in the present-day climate. Given that the representation of high-level clouds is more realistic in PROG, the DIAG model probably underestimates the inherent dCRE$_{LW}$ Alt in nature.

The changes in dCRE$_{SW}$ from DIAG to PROG have a smaller opposing effect compared with that in dCRE$_{LW}$. The $-0.05\text{ W m}^{-2}\text{ K}^{-1}$ change in dCRE$_{SW}$ from DIAG to PROG results from $-0.13\text{ W m}^{-2}\text{ K}^{-1}$ of cloud amount feedback, $-0.10\text{ W m}^{-2}\text{ K}^{-1}$ of altitude feedback, and $+0.18\text{ W m}^{-2}\text{ K}^{-1}$ of optical depth feedback (Figure 4).

Figure 3. Atmospheric ice hydrometeors in the present-day climate and their responses to global warming. (a–c) Total ice contents in the present-day climate (mg kg$^{-1}$) for the observation, DIAG, and PROG. (d, e) Responses of cloud ice contents to surface warming (mg kg$^{-1}$ K$^{-1}$) for DIAG and PROG.

Figure 4. The same as Figure 2 but for SW.
The negative change in the amount feedback is associated with increased high-level clouds reflecting more solar insolation (Figure S1 in Supporting Information S1). The negative change in SW altitude feedback corresponds to the more effective sunshade effects of higher altitude clouds (Figure 1b in Zelinka et al., 2012). The positive change in optical depth feedback is consistent with a smaller increase in liquid clouds, which is optically thicker than ice clouds (Figure S2 in Supporting Information S1). The change in the dCRE_{SW} from DIAG to PROG is positive in lower latitudes and negative in higher latitudes (Figure 4i). These are reminiscent of dCRE_{SW} changes associated with an increase in cloud lifetime resulting from a correction of overestimated warm rain occurrence suggested by a recent study (Figure 1 in Mülmensstädt et al., 2021). As Michibata and Suzuki (2020) described, the prognostic precipitation substantially alleviates biases of the too-short rain formation in MIROC6.

We examined the relationship between high-level clouds in the present-day climate and LW altitude feedback (dCRE_{LW-Alt}) across the CMIP5/6 models to solidify the proposed mechanisms from our two versions of MIROC. We analyzed 18 available models with ISCCP cloud area fraction (CanESM2, IPSL-CM5A-LR, IPSL-CM5A-MR, MIROC-ESM, MIROC5, MPI-ESM-LR, MRI-CGCM3, CESM2, CNRM-CM6-1, CNRM-ESM2-1, CanESM5, E3SM-1-0, GFDL-CM4, HadGEM3-GC31-LL, MIROC-ES2L, MIROC6, MRI-ESM2-0, and UKESM1-0-LL). Among the models analyzed here, only CESM2, E3SM-1-0, HadGEM3-GC31-LL, and UKESM1-0-LL include a prognostic treatment of both rain and snow particles (Golaz et al., 2019; Li et al., 2020).

The present-day climates for these models were defined as averages from 1981 to 2000 in historical experiments. Meanwhile, the feedback and ECS were calculated following a standard regression procedure using the difference in global surface temperatures between the abrupt-4×CO2 and preindustrial experiments for 150 years (Gregory et al., 2004). Note that we used amip and amip-p4K experiments to evaluate feedback for CESM2 because its ISCCP cloud is unavailable for abrupt-4×CO2. Previous studies have shown that cloud feedback from atmospheric (amip-p4K) and coupled experiments (abrupt-4×CO2) has a good consistency (e.g., Ringer et al., 2014; Webb et al., 2017).

Figure 5a shows the correlations between the high-level cloud fraction in the present-day climate and dCRE_{LW-Alt}. Positive correlations are found over the tropical Indian Ocean, the tropical Western Pacific, and the continents. Most of these areas correspond to regions where the high-level cloud fraction is large in the observation (contours in Figure 5a). The correlation between the high-level cloud amount and dCRE_{LW-Alt} averaged over the regions with high-level cloud fraction >30% in the observation is 0.54, explaining a significant part of the inter-model spread in dCRE_{LW-Alt}. The observed value of the high-level cloud fraction over those regions is 38.6%, indicating that many CMIP models underestimate high-level clouds. Using linear regression and the standard deviation of dCRE_{LW-Alt} in the CMIP models, the likely range (>66% probability) of dCRE_{LW-Alt} is estimated at 0.14–0.96 W m\(^{-2}\) K\(^{-1}\). This result implies that dCRE_{LW-Alt} would be stronger if the underestimation of high-level clouds were mitigated.

It should be noted that the regions of positive correlations are different from the regions where the high-level cloud fraction increased from DIAG to PROG in MIROC6 (Figure S1 in Supporting Information S1). Therefore, the origins of the link between the high-level cloud amount and dCRE_{LW-Alt} across the CMIP models may be different from that associated with the implementation of prognostic precipitation in MIROC6. Moreover, the high-level clouds in CESM2, E3SM-1-0, HadGEM3-GC31-LL, and UKESM1-0-LL with prognostic precipitation are underestimated compared with the observation. Further explorations are needed to understand the impacts of prognostic precipitation on cloud feedback when more models with prognostic precipitation are available in the future. Note that the high-level cloud fraction is not correlated with ECS (Figure 5c) because factors other than dCRE_{LW-Alt} are also important for ECS spreads in CMIP models (Zelinka et al., 2020).

Previous studies also reported larger cloud feedback in CESM2 (Gettelman et al., 2019) and GISS-E3 (Cesana et al., 2021), which had prognostic precipitation schemes. CESM2 shows larger amounts of supercooled liquid clouds in the extratropics than those of its previous version with diagnostic precipitation. The melting of ice clouds to liquid clouds in response to global warming increases the optical thickness, resulting in negative cloud feedback. Such negative feedback becomes less effective when supercooled liquid clouds increase in CESM2. To examine supercooled liquid clouds, we calculated the ratio of liquid condensate fraction (LCF) to total (liquid plus ice) water mass fraction following Zelinka et al. (2020). These ratios are then averaged into bins of atmospheric temperature as shown in Figure S3 in Supporting Information S1. The LCF in PROG is small compared with DIAG corresponding to the increase in cloud ice contents (Figures 3b and 3c). Therefore, in MIROC6, the change
in supercooled liquid clouds is not a reason for the larger positive cloud feedback. As for GISS-E3, the increase in cloud feedback by prognostic precipitation can be mostly explained by the weakening of the SW negative feedback over extratropics associated with snow decrease in response to global warming (Cesana et al., 2021). These mechanisms of increase in cloud feedback are not identified in MIROC6 with prognostic precipitation, where cloud ice increases under a warming climate (Figure S2b in Supporting Information). Thus, we suggest that the impacts of prognostic precipitation on cloud feedback can occur through different mechanisms across models, partly because this effect depends on how much cloud ice and snow water the models have. This deserves future studies when more models with prognostic precipitation schemes become available.

4. Conclusions

This study examined the impacts of the prognostic treatment of precipitation on the cloud feedback in MIROC6. Positive LW cloud feedback associated with higher altitude clouds in response to surface warming is largely increased from 0.12 to 0.70 W m\(^{-2}\) K\(^{-1}\). Accordingly, ECS increases by about 20%. Because the representation of high-level clouds is more realistic in PROG than in DIAG, climate projections with larger dCRE\(_{\text{LW Alt}}\) in PROG are considered more credible. Given that the current GCMs with simplified precipitation treatments omit the key feedback processes regarding ice hydrometeors, our results suggest higher climate sensitivity when models incorporate them in line with observational constraints. Although the mechanism behind the link between high-level

Figure 5. Relationship between high-level cloud amount and LW cloud altitude feedback across 18 CMIP models. (a) Correlations between the local high cloud area fraction in the present-day climate and local dCRE\(_{\text{LW Alt}}\) (W m\(^{-2}\) K\(^{-1}\)) across the CMIP models (color); the contours of the high cloud area fraction equals 30% in the observation. (b, c) Scatter plots of the high cloud area fraction versus dCRE\(_{\text{LW Alt}}\) (W m\(^{-2}\) K\(^{-1}\)) averaged over regions where the high cloud fraction in the observation is greater than 30% and versus ECS (K). DIAG and PROG are also shown in panels (b) and (c). The purple dots in panels (b) and (c) indicate CESM2, E3SM-1-0, HadGEM3-GC31-LL, UKESM1-0-LL, and PROG with prognostic precipitation.
clouds and dCRE1yr. Alt in MIROC6 is not observed across the CMIP5/6 models, it may play a role in the future generations of CMIP models where more models would adopt prognostic precipitation schemes.

Data Availability Statement

The simulation outputs of MIROC6 used in this study and codes for the analyses are available at https://doi.org/10.5281/zenodo.5555415. Other data can be obtained from the International Satellite Cloud Climatology Project (https://isccp.giss.nasa.gov/pub/data/D1), the CloudSat Data Processing Center (https://www.cloudsat.cira.colostate.edu/data-products/2b-cwc-ro), the Hadley Centre (https://www.metoffice.gov.uk/hadobs/hadiss), and the Earth System Grid Federation (https://esgf-node.llnl.gov). The Cloud Feedback Model Intercomparison Project (CFMIP) Observation Simulator Package and the radiative kernels of Zelinka et al. (2012, 2013) are available at https://github.com/CFMIP/CFMIPSv2.0 and https://markzdelinka.wordpress.com/kernels/, respectively.

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