Underestimated marine stratocumulus cloud feedback associated with overly active deep convection in models

N Hirota1,*, T Ogura2, H Shigogama2, P Caldwell3, M Watanabe2, Y Kamae4 and K Suzuki2

1 Earth System Division, National Institute for Environmental Studies, Tsukuba, Japan
2 Atmosphere and Ocean Research Institute, the University of Tokyo, Kashiwa, Japan
3 Lawrence Livermore National Laboratory, Livermore, CA, United States of America
4 Faculty of Life and Environmental Sciences, University of Tsukuba, Tsukuba, Japan

* Author to whom any correspondence should be addressed.
E-mail: hirota.nagio@nies.go.jp

Keywords: cloud feedback, climate sensitivity, CMIP5/6, convection

Supplementary material for this article is available online

Abstract
Cloud feedback remains the largest source of uncertainty in equilibrium climate sensitivity (ECS). Many studies have attempted to narrow uncertainties in cloud feedback and ECS by proposing observable metrics with high skill at predicting future climate, referred to as emergent constraints. These constraints are often associated with clouds, convection, and circulation, and are interrelated. However, physical explanations for these connections remain unclear. Here, we propose a new mechanism relating convection and clouds across multiple climate models. Some models show overly active deep convection on daily timescales in the subtropical low cloud regions, which contributes to weaker subsidence inversion and smaller amounts of low-level clouds. Such models predict smaller shortwave (SW) cloud feedback. Using precipitation frequency in these regions as an emergent constraint, encapsulating this mechanism, models with lower SW cloud feedback (<0.50 W m$^{-2}$ °C$^{-1}$) are found to exhibit erroneously frequent convection. Our results suggest that further improvements in understanding and better modeling of cloud and convective systems are necessary for accurate climate predictions.

1. Introduction
Large variations in cloud feedback across different climate models are by far the largest source of uncertainty in equilibrium climate sensitivity (ECS) (Bony and Dufresne 2005, Zelinka et al 2013, Ceppi et al 2017), the equilibrium global surface temperature response to atmospheric CO$_2$ doubling. In particular, the importance of low-level cloud responses to global warming over the subtropical oceans has been emphasized (Bony and Dufresne 2005). Because low-level clouds cover a large portion of tropical subsidence regions and effectively reflect shortwave (SW) solar radiation, their cloud radiative effects (CREs) exert significant influence on the global energy budget. Numerical experiments have suggested that representations of convection in climate models can significantly influence cloud feedback and ECS (Zhao 2014, Webb et al 2015). For example, when radiation, turbulence, convection, cloud, and surface scheme model parameters were perturbed within their uncertainty ranges, ECS values were most sensitive to convection scheme parameters (Stainforth et al 2005, Shigogama et al 2012). A possible explanation for the link between low-level clouds and convection is that convection mixes air between the cloud-topped boundary layer and the drier free troposphere, which disturbs inversion layers and disrupts low-level cloud formation (Brient and Bony 2012, Sherwood et al 2014). This hypothesis is consistent with previous research demonstrating that models with lower ECS values tend to overestimate convective precipitation over the southeastern Pacific (Hirota and Takayabu 2012, Tian 2015, Lutsko and Cronin 2018, Webb and Lock 2020). The precipitation bias over a low cloud region of the southeastern Pacific is known as ‘the double ITCZ bias’ and has long been recognized as one of the major deficiencies in climate models.
(e.g. Xie et al 2007, Fiedler et al 2020, Tian and Dong 2020).

2. Results

We first examine the SW cloud feedback, which is approximated by changes in SW CRE values (the difference in radiative flux between all sky and clear sky conditions) per 1 °C of global surface temperature warming in the climate models participating in phases 5 and 6 of the Coupled Model Intercomparison Project (CMIP5 and CMIP6). Figure E1 (available online at stacks.iop.org/ERL/16/074015/mmedia) shows the correlation between SW cloud feedback and ECS across the CMIP models. Consistent with previous studies, variations in the cloud feedback and ECS are shown to be correlated over the subtropical subsidence regions. In these regions, convective activities are limited, and a strong inversion layer in the lower troposphere (∼800 hPa) and associated low-level clouds are observed (Wood and Bretherton 2006). In this study, the subtropical low cloud regions are defined as corresponding to the tropical oceans (30° S–30° N) where the estimated inversion strength (EIS) (Wood and Bretherton 2006) on annual climatologies is larger than 3 °C (black contours in figure E1(a)) according to the European Center for Medium-Range Weather Forecasts Interim Re-Analysis (ERAI). EIS is calculated from the following formula:

\[
\text{EIS} = (\theta_{700} - \theta_{sfc}) - \Gamma_{m}^{850} (Z_{700} - Z_{lcl})
\]

where \(\theta_{700}\) and \(\theta_{sfc}\) are the potential temperatures at the 700 hPa and the surface, respectively, \(\Gamma_{m}\) is the moist adiabatic lapse rate at 850 hPa, \(Z_{700}\) is the height of the 700 hPa, and \(Z_{lcl}\) is the lifting condensation level. The correlation between SW cloud feedback averaged over the subtropical low cloud regions (hereafter referred to as dSW_{EIS<3 °C}) and ECS is 0.56 (figure E1(b)). Note that we used EIS of ERAI rather than that of models in defining the subtropical low cloud regions. We are investigating model’s performance in representing the subtropical low cloud regimes with a strong inversion layer and suppressed convection in the observation.

It should be noted that large correlations between SW cloud feedback and ECS are also found in the middle and high latitudes (figure E1(a)). When correlations for sub-model ensembles of CMIP5 and CMIP6 are calculated separately, we found that values in middle and high latitudes are mostly associated with variations in the CMIP6 models (figure E2). Recent studies showed that cloud feedback in the subtropics is the dominant source of ECS uncertainty in CMIP5; however, middle- and high-latitude processes also play important roles in CMIP6 (Zelinka et al 2020). The correlation between ECS and dSW_{EIS<3 °C} is reduced from 0.70 in CMIP5 to 0.48 in CMIP6 (figure E1(b)). Middle- and high-latitude processes are, however, beyond the scope of this study, in which we focus on understanding cloud feedback in the subtropical low cloud regions.

Next, we investigate how convection influences inversion strength in the subtropical low cloud regions. A typical temperature profile in these regions is close to a moist adiabat with a sharp temperature increase in the lower troposphere (∼800 hPa), which corresponds to the inversion layer (figure E3) (Wood and Bretherton 2006). A convective parcel ascending from the lifting condensation level into the free troposphere follows a moist adiabat. As a result, convection adjusts the temperature profile closer to a moist adiabat of the parcel, resulting in weaker inversion and fewer low-level clouds.

To determine the quantitative importance of convection in EIS variation across climate models, a scatter plot of EIS and a metric of convection frequency in the subtropical low cloud regions (hereafter referred to as \(\alpha\)) is shown in figure 1. The metric \(\alpha\) is defined as the percentage of days in which daily mean precipitation rate was greater than 5 mm d^{-1} in the subtropical low cloud regions (see definition above) and is shown for observations and models in figure E4. EIS and \(\alpha\) are closely related, having a correlation coefficient of \(-0.68\) (figure 1). When the correlation of precipitation frequency and EIS is examined at different precipitation intensities (figure E5), large negative values are found at intensities greater than 5 mm d^{-1}, suggesting that relatively
strong precipitation is responsible for the relationships between EIS and convection. Although we have emphasized that active convection reduces inversion strength, weaker inversion also results in more active convection. The causal relationship between convection and inversion should further be examined in future work.

We compare convection, inversion, and clouds in the present-day climate between model groups with the 30 highest and 30 lowest values of $\alpha$, which are named as active convection models (ACMs) and suppressed convection models (SCM), respectively (figure E4). Figures 2(a) and (b) shows probability distribution functions (PDFs) for precipitation rate and vertical pressure velocity at 500 hPa ($\omega_{500}$) in the subtropical low cloud regions (Bony et al 2004). These figures are based on daily average statistics on the T42 Gaussian ($\sim 2.8^\circ$) grid with a 1 mm d$^{-1}$ bin width for precipitation and a 20 hPa d$^{-1}$ bin width for $\omega_{500}$. The frequency of strong precipitation ($>5$ mm d$^{-1}$) and upward motions ($\omega_{500} < -70$ hPa d$^{-1}$), indicating the occurrence of deep convection, are smaller in SCM than in ACM. These differences are larger than the standard errors (shading in the figures) of ACM and SCM and are significant at the 95% level using a two-tailed t-test. The PDFs of observed precipitation from the Global Precipitation Measurement (GPM) mission and $\omega_{500}$ from ERAI are also shown. Although the PDFs of SCM are more realistic relative than those of ACM, SCM nevertheless still overestimates the occurrence of convection relative to observations. EIS and cloud water content are shown in figures 2(c) and (d). Consistent with the proposed mechanism described in figure E3, EIS and associated

Figure 2. Convection, inversion, and clouds in the present-day climate. (a) PDF of daily precipitation, (b) PDF of daily $\omega_{500}$, (c) EIS (°C) and (d) cloud water content ($10^{-6}$ kg kg$^{-1}$) for ACM, SCM and observations in the subtropical low cloud region. A, S, and E in (c) denote ACM, SCM, and ERAI, respectively. Shading in (a), (b) and (d) and tick marks in (c) indicate +/- one standard error for ACM and SCM.
low level cloud water contents are larger in SCM than in ACM. These differences are also significant at the 95% level using a two-tailed t-test.

The responses (feedback) of EIS, temperature, humidity, and clouds to global surface warming are examined in figure 3. Low-level cloud is shown to increase in ACM but decrease in SCM (figure 3(d)). This difference in cloud response is likely related to differences in the atmospheric temperature change. The warming in boundary layer is larger in SCM than ACM (figure 3(b)), which is consistent with the smaller increases of EIS (figure 3(a)). The warmer boundary layer with larger saturated water vapor also suggests smaller increase in relative humidity (figure 3(c)). Smaller changes in stability and boundary layer relative humidity in SCM are consistent with low-level cloud reduction in contrast to cloud increases in ACM. Moreover, changes in SCM are favorable for the development of convection, which may further reduce low-level clouds. Note that the causal relationship between boundary layer warming and changes in low clouds is still unclear.

Based on the association between deep convection in the present-day climate and cloud feedback in a changed climate, we use \( \alpha \) as a new emergent constraint. As shown in figure 4(a), correlation between our constraint and \( dS_{EIS,3} \) is \(-0.59\), explaining a significant part of inter-model spread in SW cloud feedback. The observed value of \( \alpha \) from GPM is 2.2\%, which is very small compared to its value in ACM. Using linear regression and standard deviation of \( dS_{EIS,3} \) in the CMIP models, the likely range (\( >66\% \) probability) of \( dS_{EIS,3} \) is estimated at 0.50–3.44 W m\(^{-2}\) C\(^{-1}\).

To examine important regions for the relationship between convection and SW cloud feedback, the spatial distributions of correlation of \( \alpha \) versus local SW cloud feedback and local precipitation frequency (>5 mm d\(^{-1}\)) are shown in figure E6. Interestingly, precipitation frequency in the subtropical low cloud regions seems to affect SW cloud feedback in the larger areas in low- and mid-latitude oceans.

We also examined an alternative metric defined as the 95th percentile of daily mean precipitation rate averaged over the subtropical low cloud regions. The correlation between this alternative metric and \( \alpha \) is 0.99 and very similar results are obtained (figure E7). This result support robustness of the relationship between relatively strong convection and \( dS_{EIS,3} \).

Our constraint of \( \alpha \) is significantly correlated with ECS in CMIP5 but not in CMIP6 (figure 4(b)). As discussed above (figure E2), ECS spread in CMIP6 is not dominated by SW cloud feedback in the subtropical low cloud regions (Zelinka et al. 2020).

Some CMIP6 models have very high ECS values larger than 4.5\(^\circ\)C, the upper bound of the likely range proposed in the 5th assessment report by the Inter-governmental Panel on Climate Change (Collins et al. 2013). This is an issue of great interest (Pendergrass et al. 2020, Sherwood et al. 2020, Zelinka et al. 2020) and is worth investigating using our proposed mechanism. We examined a group of five models with high climate sensitivity (ECS > 5\(^\circ\)C) and suppressed convection (\( \alpha < 4\%\) ) and a group of four models with high climate sensitivity (ECS > 4.3 \(^\circ\)C) and active convection (\( \alpha > 6\%\) ) named HSC and HAC, respectively (figure 4(b)). EIS and low-level cloud in the present climate are larger in HSC than in HAC, and cloud responses are negative in HSC but positive in HAC (figure E8). These results are qualitatively consistent with comparisons between SCM and ACM. However, even if low clouds in HSC and HAC are similar to those in SCM and ACM, respectively (figure E8(b)), ECS is very large in both HSC and HAC (figure 4(b)), indicating that our mechanism does not explain very high ECS values. Further exploration, including investigation of middle- and high-latitude processes, is needed to understand these very high ECS values (Zelinka et al. 2020).
Previous studies have proposed numerous emergent constraints associated with certain features of present-day climate, such as temperature variability (Cox et al. 2018), cloud characteristics (Volodin 2008, Qu et al. 2014, Zhai et al. 2015, Brient and Schneider 2016), and convection (Sherwood et al. 2014, Tian 2015). We calculated correlations between our constraint and 11 other constraints examined in Bretherton and Caldwell (2020) (figure E9). Interestingly, the correlations with constraints in Volodin (2008), Qu et al. (2014), Sherwood et al. (2014), Tian (2015), Zhai et al. (2015), and Brient and Schneider (2016) are significant at a 90% level using a two-tailed t-test. Tian’s constraint is defined as precipitation averaged over the southeastern Pacific (100°–150° E, 0°–30° S), which is a measure of the double ITCZ bias. Because model precipitation bias in this region is associated with the erroneously overactive convection, the significant correlation with our constraint is unsurprising. The constraints of Volodin, Qu, Zhai, and Brient are all associated with low cloud dependency on sea surface temperature (SST), thus their significant correlation with our constraint is consistent with our proposed mechanism, in which convection affects low-cloud formation and cloud response to surface warming. Our constraint is also correlated with Sherwood’s index, measuring the fraction of boundary layer air in ascending regions that leaves in the mid-troposphere rather than in the upper troposphere. When we examined these ascending regions, we found that convection in the SCM showed a shallower structure, potentially favorable for cloud reduction in a warming climate (Sherwood et al. 2014). Based on these results, we argue that the new constraint in this study is a refinement of previously proposed constraints with a clearer physical relationship between convection, clouds, and cloud feedback. Note that emergent constraints developed in CMIP5 generally have lower correlations in CMIP6 (Schlund et al. 2020).

Overly active deep convection is known to be a long-standing bias in climate models (Dai 2006, Lutsko and Cronin 2018, Fiedler et al. 2020). In particular, the bias over the southeastern Pacific corresponds to the double ITCZ bias (Tian and Dong 2020). It is often associated with a warm SST bias in the subtropics (Xie et al. 2007). Because warmer SST supplies energy and moisture for convection, the warm SST bias favors active convection. Meanwhile, overly active convection is also found in atmospheric models in which the observed SST is prescribed and attributed to convection-triggering conditions or the dilution of convective parcels with environmental air in convective schemes (Song and Zhang 2009, Hirota et al. 2014). This implies that the fewer low clouds could be a cause of the warm bias in the subtropics.

To discuss the relative importance of oceanic and atmospheric processes, scatter plots of dSW_{EIS-3 °C} versus SST and α in the Atmospheric Model Intercomparison Project (AMIP) experiment are shown in figure E10. Correlations between dSW_{EIS-3 °C} with SST and the AMIP α are −0.37 and −0.40, respectively. Therefore, both oceanic and atmospheric processes are likely to be contributing to the relationship between SW cloud feedback and overly active convection as shown in figure 4(a). Note that the
correlation between \(\text{dSW}_{EIS-3} \, ^\circ\text{C}\) and SST is not significant in CMIP6.

We should emphasize that the causal relationship between convection, EIS and SW cloud feedback is still unclear, and further exploration is needed. For example, the overly active convection may be resulted from the weaker inversion. Furthermore, SW cloud feedback is also affected by cloud-top radiative processes and surface fluxes (Vial et al 2016). Convective dehydration of the boundary layer strengthens the surface latent heat flux, which damps the reduction in low clouds. Low cloud reductions stabilize the lower troposphere by decreasing the cloud-top radiative cooling, which in turn decreases the surface latent heat flux and induces further low cloud reductions. The relative importance of low cloud mixing versus radiative cooling, and the resulting sign of the latent heat flux response, depends on the convective schemes in models.

3. Concluding remarks

Representing cloud and convection has been a significant challenge since the development of the first climate model (Arakawa 2004, Bony et al 2015).

\[
\frac{\int_{[\text{lat}<30]} H \left( \text{prcp} - 5 \, \text{mm d}^{-1} \right) H(\text{EIS} - 3 \, \circ\text{C}) \cos(\text{lat}) \, \text{dlon} \, \text{dlat}}{\int_{[\text{lat}<30]} H(\text{EIS} - 3 \, \circ\text{C}) \cos(\text{lat}) \, \text{dlon}} \times 100 \, (\%) 
\]

where \(H(z) = 1\) for \(z > 0\) and 0 otherwise. Daily data for all seasons of the analyzed periods (see below) are used. Precipitation, vertical velocity (circulation and convection), cloud cover, and inversion strength under present-day climate and changed climate were compared between model groups with the 30 highest and 30 lowest values of \(\alpha\), named the ACMs and SCMs, respectively. We confirmed that our results were not sensitive to the number of models selected. The significance of differences between model groups was tested at the 95% level using the two-tailed t-test. We also calculated inter-model correlation using all available models to examine the relationship across the CMIP models. Assuming samples of 65 models are independent, a correlation larger than 0.25 was considered significant at the 95% level using the two-tailed t-test.

For observational references of precipitation, this study used the version 06A product of the Dual-Frequency Precipitation Radar on the core GPM spacecraft (Hou et al 2014) (https://gportal.jaxa.jp/gpr; data for 2014–2020 are analyzed). We also analyzed the version 7 product of the precipitation radar on the Tropical Rainfall Measuring Mission (Kummerow et al 1998) (TRMM PR, https://gportal.jaxa.jp/gpr; 1998–2013) and the daily product of the Global Precipitation Climatology Project (Adler et al 2003, Huffman et al 2014) (GPCP1DD, https://climatedataguide.ucar.edu/climate-data/gpcp-daily-global-precipitation-climatology-project; 1997–2014). Values of \(\alpha\) are 2.15% for TRMM PR and 2.68% for GPCP1DD. Although TRMM PR has a known disadvantage when evaluating weak precipitation (Behrangi et al 2012), its value of \(\alpha\) is very similar to that of GPM with improved sensors for weak precipitation (2.17%; figure 4(a)), suggesting that daily precipitation rate greater than 5 mm d\(^{-1}\) is adequately captured by both GPM and TRMM. The value of GPCP1DD is slightly larger than that of GPM, but our conclusion that models with larger SW cloud feedback are more consistent with observation is unaffected. We considered that the value of the latest dataset of GPM is most reliable. We did not analyze precipitation retrieved from CloudSat because CloudSat observation is performed only around 1:30 and 13:30 local time, therefore estimating daily mean precipitation is difficult.

For other observational references, we used \(\omega\) and EIS based on ERAI (Dee et al 2011) (www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era-interim;...
1981–2020), SST compiled by the Hadley Centre (Rayner et al. 2003) (www.metoffice.gov.uk/hadobs/hadisst; 1981–2020), and cloud water contents from CloudSat 2B-CWC-RO.P1_R05 (Austin et al. 2009) (www.cloudsat.cira.colostate.edu; 2007–2016). CloudSat cloud water contents may be overestimated because they include precipitating particles (Jiang et al. 2012); therefore, we calibrated these values by multiplying the ratio of liquid water path from the Multisensor Advanced Climatology Mean Liquid Water Path (Elsaesser et al. 2017) (https://urs.earthdata.nasa.gov/; 2007–2016) with that from CloudSat. Although this study mainly used cloud water content, similar results are obtained even when cloud fraction is used (figure E11).

Present-day climate in the CMIP5 and CMIP6 models is defined as the 1981–2000 average of historical simulations. The feedback and ECS for the models were calculated following a standard regression procedure using difference in global surface temperatures between the abrupt-4xCO$_2$ procedure using difference in global surface temperatures were calculated following a standard regression models is defined as the 1981–2000 average of historical simulations. The feedback and ECS for the models were calculated following a standard regression procedure using difference in global surface temperatures between the abrupt-4xCO$_2$ and pre-industrial scenarios for 150 years (Gregory et al. 2004). All calculations were made after data are linearly interpolated onto the T42 Gaussian grid (∼2.8°); components with total (zonal + meridional) wave numbers larger than 42 were truncated because we are investigating convection and clouds on large-scale (∼1000 km) variabilities. Without the horizontal smoothing of the T42 truncation, some relationships discussed in this study are slightly weakened (figure E12) due to smaller scale variabilities resolved in high resolution models.

Data availability statement

The data that support the findings of this study are openly available at the following URL: https://esgf-node.llnl.gov.

Code availability

The codes used to calculate the precipitation frequency metric $\alpha$ are available on Zenodo at https://zenodo.org/record/4062782#.X32m_Wj7SUk, and the other codes are available on request from the corresponding authors.

Acknowledgments

We thank the anonymous reviewers for their careful reading of our manuscript and their many insightful comments and suggestions. This study was supported by the Integrated Research Program for Advancing Climate Models (TOUGOU) Grant Number JPMXD017935457 and KAKENHI (20K04067) from the Ministry of Education, Culture, Sports, Science, and Technology, Japan, and by the Environment Research and Technology Development Fund (JPMERF2019004) from the Environmental Restoration and Conservation Agency, Japan. We thank the climate modeling groups for producing and making available their model output, the Earth System Grid Federation for providing the data. The Earth Simulator at JAMSTEC and NEC SX-ACE at NIES were used to perform the model simulations, and the Grid Analysis and Display System was used to plot the figures.

Author contributions

N Hirota, T Ogura, and H Shiogama designed the research. N Hirota, P M Caldwell, and Y Kamae performed the analysis. N Hirota wrote the paper. All authors discussed the results and commented on the manuscript.

Conflict of interest

We have no conflicts of interest to disclose.

ORCID iDs

N Hirota https://orcid.org/0000-0002-7400-3365
T Ogura https://orcid.org/0000-0002-8441-0044
H Shiogama https://orcid.org/0000-0001-5476-2148
P Caldwell https://orcid.org/0000-0001-8604-0844
M Watanabe https://orcid.org/0000-0001-6500-2101
Y Kamae https://orcid.org/0000-0003-0461-5718
K Suzuki https://orcid.org/0000-0001-5315-2452

References

Adler R F et al. 2003 The version 2 global precipitation climatology project (GPCP) monthly precipitation analysis (1979–present) J. Hydrometeorol. 4 1147–67
Arakawa A 2004 The cumulus parameterization problem: past, present, and future J. Clim. 17 2493–525
Austin R T, Heymsfield A J and Stephens G L 2009 Retrieval of ice cloud microphysical parameters using the CloudSat millimeterwave radar and temperature J. Geophys. Res. 114 D00A23
Behrangi A, Lebock M, Wong S and Lambrigtsen B 2012 On the quantification of oceanic rainfall using spaceborne sensors J. Geophys. Res. 117 D20105
Bony S et al. 2015 Clouds, circulation and climate sensitivity Nat. Geosci. 8 261
Bony S and Dufresne J L 2005 Marine boundary layer clouds at the heart of tropical cloud feedback uncertainties in climate models Geophys. Res. Lett. 32 L20806
Bony S, Dufresne J L, Le Treut H, Morcrette J J and Senior C 2004 On dynamic and thermodynamic components of cloud changes Clim. Dyn. 22 71–86
Bretherton C S and Caldwell P M 2020 Combining emergent constraints for climate sensitivity J. Clim. 33 7413–30
Brient F and Bony S 2012 How may low-cloud radiative properties simulated in the current climate influence low-cloud feedbacks under global warming? Geophys. Res. Lett. 39 L20807
Brient F and Schneider T 2016 Constraints on climate sensitivity from space-based measurements of low-cloud reflection J. Clim. 29 5821–35
Ceppi P, Brient F, Zelinka M D and Hartmann D L 2017 Cloud feedback mechanisms and their representation in global climate models Wiley Interdiscip. Rev. Clim. Change 8 e465
Collins M et al 2013 Long-term climate change: projections, commitments and irreversibility Climate Change 2013: The Physical Science Basis ed T F Stocker et al (Cambridge: Cambridge University Press) pp 1029–136
Cox P M, Huntingford C and Williamson M S 2018 Emergent constraint on equilibrium climate sensitivity from global temperature variability Nature 553 319–22
Dai A 2006 Precipitation characteristics in eighteen coupled climate models J. Clim. 19 4605–30
Dee D et al 2011 The ERA-Interim reanalysis: configuration and performance of the data assimilation system Q. J. R. Meteorol. Soc. 137 553–97
Elsaesser G S, O’Dell C W, Lebsock M D, Bennartz R, Greenwald T J and Wentz F J 2017 The multisensor advanced climatology of liquid water path (mac-lwp) J. Clim. 30 10193–210
Fiedler S et al 2020 Simulated tropical precipitation assessed across three major phases of the coupled model intercomparison project (CMIP) Mon. Weather Rev. 148 3653–80
Gregory J et al 2004 A new method for diagnosing radiative forcing and climate sensitivity Geophys. Res. Lett. 31 L03205
Hirota N and Takayabu Y N 2012 Inter-model differences of future precipitation changes in CMIP3 and MIROC5 climate models J. Meteoro. Soc. Jpn 90 307–16
Hirota N, Takayabu Y N, Watanabe M, Kimito M and Chikira M 2014 Role of convective entrainment in spatial distributions of and temporal variations in precipitation over tropical oceans J. Clim. 27 8707–23
Hou A et al 2014 The global precipitation measurement mission Bull. Am. Meteor. Soc. 95 701–22
Huffman G, D et al 2014 Integrated multi-satellite retrievals for GPM (IMERG), version 4.4. NASA’s precipitation processing center (available at: ftp://arthurhou.pps.eosdis.nasa.gov/gpmdata/) (Accessed 15 August 2017)
Jiang J H et al 2012 Evaluation of cloud and water vapor simulations in CMIP5 climate models using NASA ‘A-Train’ satellite observations J. Geophys. Res. 117 D14105
Kummerow C, Barnes W, Kozu T, Shiue J and Simpson J 1998 The tropical rainfall measuring mission (trmm) sensor package J. Atmos. Ocean. Technol. 15 809–17
Lutsch N J and Cronin T W 2018 Increase in precipitation efficiency with surface warming in radiative-convective equilibrium J. Adv. Model. Earth Syst. 18 2992–3010
Pendegass A G 2020 The global-mean precipitation response to CO2-induced warming in CMIP6 models Geophys. Res. Lett. 47 e2020GL089964
Qu X, Hall A, Klein S A and Caldwell P M 2014 On the spread of changes in marine low cloud cover in climate model simulations of the 21st century Clim. Dyn. 42 2603–26
Rayner N et al 2003 Global analyses of sea surface temperature, sea ice, and near marine air temperature since the late nineteenth century J. Geophys. Res. 108 4407
Schlund M, Lauer A, Gentile P, Sherwood S C and Efring V 2020 Emergent constraints on equilibrium climate sensitivity in CMIP5: do they hold for CMIP6? Earth Syst. Dyn. 11 1233–58
Sherwood S C, Bony S and Dufresne J L 2014 Spread in model climate sensitivity traced to atmospheric convective mixing Nature 505 37
Sherwood S et al 2020 An assessment of earth’s climate sensitivity using multiple lines of evidence Rev. Geophys. 58 e2019RG000678
Shiogama H et al 2012 Perturbed physics ensemble using the MIROC5 coupled atmosphere–ocean GCM without flux corrections: experimental design and results Clim. Dyn. 39 3041–56
Stainforth D A et al 2005 Uncertainty in predictions of the climate response to rising levels of greenhouse gases Nature 433 403
Tian B 2015 Spread of model climate sensitivity linked to double-intertropical convergence zone bias Geophys. Res. Lett. 42 4153–41
Tian B and Dong X 2020 The double-ITCZ bias in CMIP3, CMIP5, and CMIP6 models based on annual mean precipitation Geophys. Res. Lett. 47 e2020GL087232
Vial J, Bony S, Dufresne J and Roehrig R 2016 Coupling between lower-tropospheric convective mixing and low-level clouds: Physical mechanisms and dependence on convection scheme J. Adv. Model. Earth Syst. 8 1892–911
Volodin E 2008 Relation between temperature sensitivity to doubled carbon dioxide and the distribution of clouds in current climate models Izv. Atmos. Ocean. Phys. 44 286–99
Webb M J et al 2015 The impact of parametrized convection on cloud feedback Phil. Trans. R. Soc. A 373 20140414
Webb M J and Lock A P 2020 Testing a physical hypothesis for the relationship between climate sensitivity and double-ITCZ bias in climate models J. Adv. Model. Earth Syst. 12 e2019MS001999
Wood R and Bretherton C S 2006 On the relationship between stratiform low cloud cover and lower-tropospheric stability J. Clim. 19 6425–32
Xie S P, Miyama T, Wang Y, Xu H, De Szoeke S P, Small R J O, Richards K J, Mochizuki T and Awaji T 2007 A regional ocean atmosphere model for eastern Pacific climate: towards reducing tropical biases J. Clim. 20 1504–22
Zelinka M D, Klein S A, Taylor K E, Andrews T, Webb M J, Gregory J M and Forster P M 2013 Contributions of different cloud types to feedbacks and rapid adjustments in CMIP5 J. Clim. 26 5007–27
Zelinka M D, Myers T A, McCoy D T, Po-Chedley S, Gelaro R, Xie S P, Miyama T, Wang Y, Xu H, De Szoeke S P, Small R J O, Richards K J, Mochizuki T and Awaji T 2007 A regional ocean atmosphere model for eastern Pacific climate: towards reducing tropical biases J. Clim. 20 1504–22
Zelinka M D, Klein S A, Taylor K E, Andrews T, Webb M J, Gregory J M and Forster P M 2013 Contributions of different cloud types to feedbacks and rapid adjustments in CMIP5 J. Clim. 26 5007–27
Zelinka M D, Myers T A, McCoy D T, Po-Chedley S, Gelaro R, Xie S P, Miyama T, Wang Y, Xu H, De Szoeke S P, Small R J O, Richards K J, Mochizuki T and Awaji T 2007 A regional ocean atmosphere model for eastern Pacific climate: towards reducing tropical biases J. Clim. 20 1504–22
Zelinka M D, Klein S A, Taylor K E, Andrews T, Webb M J, Gregory J M and Forster P M 2013 Contributions of different cloud types to feedbacks and rapid adjustments in CMIP5 J. Clim. 26 5007–27
Zelinka M D, Myers T A, McCoy D T, Po-Chedley S, Gelaro R, Xie S P, Miyama T, Wang Y, Xu H, De Szoeke S P, Small R J O, Richards K J, Mochizuki T and Awaji T 2007 A regional ocean atmosphere model for eastern Pacific climate: towards reducing tropical biases J. Clim. 20 1504–22
Zhao M 2014 An investigation of the connections among stratospheric low cloud cover and lower-tropospheric stability J. Geophys. Res. 119 28707–28723
Zhai C, Jiang J H and Su H 2015 Long-term cloud change from space-based measurements of low-cloud reflection J. Adv. Model. Earth Syst. 7 20140414
Zhao M 2014 An investigation of the connections among stratospheric low cloud cover and lower-tropospheric stability J. Geophys. Res. 119 28707–28723
