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Scott W. Feldman

Iowa State University

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Interannual Cloud Feedbacks: Observations vs. Climate Model Simulations

Scott W. Feldman
Department of Geological and Atmospheric Sciences, Iowa State University, Ames, Iowa

Dr. Mark D. Zelinka – Mentor
Cloud Processes Research Group, Lawrence Livermore National Laboratory, Livermore, California

Dr. Xiaoqing Wu – Co-Mentor
Department of Geological and Atmospheric Sciences, Iowa State University, Ames, Iowa

ABSTRACT

Global climate model predictions of future warming vary substantially due to uncertainties in how clouds respond, through their impact on Earth’s energy budget. Since it is not possible to evaluate how clouds changed as the planet warmed over the industrial era, it is useful to look at short-term cloud feedbacks operating on inter-annual timescales. Because cloud feedbacks on inter-annual timescales are highly correlated with those on climate change timescales, evaluating models’ cloud feedbacks on short timescales may help constrain climate sensitivity. Here, a novel cloud radiative kernel technique was used to detail the short-term cloud feedback in the Community Atmosphere Model version 5 (CAM5) and in a suite of satellite cloud observations. Whereas past studies indicated that models’ short-term tropical cloud feedbacks tend to be too positive, we found that the model closely matched observations. However, in agreement with previous work, we found that the tropical high cloud amount feedback is too large in models. We also found that the simulated total net high cloud feedback resembles the net high cloud amount feedback, but the observed net high cloud feedback more resembles the high cloud altitude and optical depth components. For low clouds, estimated inversion strength (EIS) was shown to be a strong indicator of the cloud amount feedback, and observations have a more positive optical depth feedback than the models. Finally, constraining meteorology using hindcast simulations improved regional and global aspects of the simulated feedbacks. Our results strongly suggest that high clouds in the model are too optically thick leading to biases in regional high cloud amount feedback, but future work is needed to quantify to what extent.
1. Introduction

Clouds have a strong impact on the Earth’s energy budget due to their ability to reflect incoming solar radiation and emit outgoing terrestrial radiation. The net impact of clouds on the planet’s radiation budget is quantified by adding together the longwave (LW) and shortwave (SW) cloud radiative effect (CRE), defined as the difference between clear-sky and all-sky radiative fluxes at the top of the atmosphere. Globally and annually averaged, LW CRE is roughly +30 W/m$^2$, indicating that clouds heat the planet relative to a cloud-free but otherwise identical Earth. LW CRE increases with increasing cloud cover, cloud top height, and cloud optical thickness (τ). Opposing the LW heating effect of clouds is an even stronger cooling effect in the SW. Globally and annually averaged, SW CRE is roughly -50 W/m$^2$, and its strength increases with increasing cloud cover and τ but is largely insensitive to cloud top height. Thus, overall, clouds have a strong net radiative cooling effect on the planet of roughly -20 Wm$^{-2}$ (Zelinka et al. 2017).

In response to a positive radiative forcing from increasing greenhouse gas emissions, the planet is warming, which is causing cloud properties to change. As these changes occur, the cooling effect of clouds may change, which feeds back on the initial warming. Cloud feedback quantifies how much this cooling effect changes per degree of global warming. If the cooling effect of clouds strengthens, the feedback is negative, resulting in a smaller temperature response to CO2 forcing. Positive cloud feedbacks would occur if, for example, 1.) Total cloud coverage decreases, which allows less shortwave (SW) radiation to be reflected to space 2.) Cloud top heights increase, which results in colder cloud tops, and thus less longwave (LW) radiation emitted to space 3.) Clouds become less optically thick, which causes less SW radiation to be reflected to space, or 4.) Clouds move poleward where there is less incident SW radiation, and thus less SW radiation reflected to space.

Cloud feedback is positive in most current global climate models (GCMs), which means that the temperature response to CO2 is amplified by cloud changes. This is because all models predict that the coverage of highly reflective low-level clouds will decrease and that high-level clouds will shift upwards. These two strong positive feedbacks are weakly opposed by a negative feedback from high latitude clouds becoming optically thicker and hence more reflective of sunlight (Zelinka et al. 2016).

However, there is substantial uncertainty in the magnitude of cloud feedbacks. Across models, the magnitude ranges from weakly negative to strongly positive (~0.13 to 1.24 Wm$^{-2}$ K$^{-1}$) (Ceppi et al. 2017). In fact, cloud feedback exhibits the largest inter-model spread of all the feedbacks, and thus, the spread of equilibrium climate sensitivity – the equilibrium response of global temperature to a doubling of carbon dioxide – is mostly due to the spread of cloud
feedbacks (Vial et al. 2013). Therefore, to constrain climate sensitivity, it is necessary to constrain the cloud feedback. Constraining climate sensitivity is important because it is a central focus in assessing the potential impacts of anthropogenic climate change.

Models are often compared to observations in the goal of improving their performance. In the case of cloud feedbacks, it would be ideal to evaluate which modeled cloud feedback is correct by seeing how clouds in nature changed as the planet warmed over the industrial era. However, this is not possible for three reasons: 1.) Observed climate change is an unknown combination of natural variability, greenhouse warming, and responses to aerosols, so it is difficult to extract the pure CO2-forced response to a high degree of confidence 2.) Satellite observational datasets are often too short to identify long-term changes and 3.) Longer cloud observations (~3 decades) have spurious trends that are difficult to separate from "true" climate change trends.

As an alternative, it is useful to look at short-term cloud feedbacks operating on the interannual timescale when comparing to observations. Rather than determining how clouds respond to the long-term global warming trend, short-term cloud feedbacks quantify how clouds respond to global temperature anomalies generated by natural climate variability on interannual timescales. These natural climate fluctuations arise primarily due to the El Niño–Southern Oscillation (ENSO) since that is the dominant mode of interannual climate variability. Importantly, interannual cloud feedbacks are highly correlated across GCMs with long-term cloud feedbacks (Zhou et al. 2015). Because modeled short-term cloud feedbacks can be evaluated against that derived from observations, this across-timescale correlation provides a potential avenue for constraining cloud feedbacks on the climate change timescales that are relevant to climate sensitivity.

Several recent studies have investigated the differences in short-term cloud feedbacks between models and observations. Dessler (2013) calculated cloud feedbacks in control runs of 13 fully coupled GCMs, where greenhouse gas amounts and other forcings were held constant at their pre-industrial concentrations. When compared to the observations, he found that the models on average overestimate the positive longwave cloud feedback and underestimate the negative shortwave cloud feedback in the tropics. Mauritsen and Stevens (2015) determined the change in the top of atmosphere (TOA) radiation per unit tropical warming for an ensemble of models and satellite observations. They found that models taking part in the 5th phase of the Coupled Model Intercomparison Project (CMIP5; Taylor et al. 2012) tend to underestimate the increase in longwave cooling compared to Cloud and the Earth's Radiant Energy System (CERES) observations, which is qualitatively consistent with Dessler's study. Lastly, Williams and Pierrehumbert (2017) calculated the change in tropical cloud radiative effect (CRE) per unit of tropical warming in bins of buoyancy in the
Community Atmosphere Model version 5 (CAM5). They found that CAM5 has anomalous net TOA heating in buoyant bins, but CERES observations show the opposite. Like previous studies, they also concluded this primarily seems to be a longwave bias.

It is evident from the studies mentioned above that models’ short-term tropical cloud feedbacks tend to be too positive, especially in the longwave, compared to observations. However, it is unclear from these studies which aspects of the cloud response are erroneous (e.g., cloud amount, altitude, and/or optical depth), and whether the errors are arising due to biases in large-scale meteorology (e.g., locations of anomalous ascent or descent) or from biases in how clouds are physically represented (e.g., sub-grid scale parameterizations). This leads to questions that we address in this study: 1) What are various contributors to the short-term cloud feedback in the observations and CAM5? 2) What aspects of the modeled and observed short-term cloud feedbacks are different? 3) Are model biases smaller when the meteorology is constrained in the model to remain close to reality?

In Sec. 2, we will discuss the details of the datasets we use, along with the methodologies used. In Sec. 3, we will apply this methodology to quantify short-term cloud feedbacks and break them into changes in cloud properties like amount, optical depth, and altitude for low and free tropospheric clouds, as well as the entire cloud distribution. Lastly, in Sec. 4 we will discuss the significance of our results, and the uncertainties that remain.

II. Data and Methods

a) Hindcast Simulations

The hindcast approach provides a unique opportunity to assess cloud feedbacks in a climate model in which the evolution of the large-scale atmosphere is forced to stay close to that which occurred in nature. This allows for more unambiguous attribution of model errors to model physics (e.g., how clouds are represented via sub-grid parameterizations) in the absence of confounding errors in the large-scale circulation. If controlling for meteorology leads to smaller errors in short-term cloud feedback, that means some portion of the model error is due to biases in the large-scale flow. On the other hand, if controlling for meteorology does not lead to smaller
errors in short-term cloud feedback then this is likely due to parameterization errors.

In this study, we use the output from a large ensemble of 3-day long hindcast experiments that were initialized at 00Z each day (Phillips et al. 2004, Ma et al. 2018) from 1997 to 2012. In these hindcast experiments, CAM5 is initialized like a weather forecast model with the analysis of the current state of the atmosphere (Fig.1). All the simulations use the finite volume dynamical core with a horizontal resolution of 0.9° × 1.25° latitude by longitude and 30 vertical levels. Atmospheric initial state variables (horizontal velocities, temperature, and specific humidity) are from the European Centre for Medium Range-Weather Forecasts Re-Analysis- Interim (ERA-Interim), which is a global atmospheric reanalysis from 1979, continuously updated in real time. Other atmospheric variables (e.g., aerosol, cloud) are from a UV nudging simulation (Ma et al. 2015), in which horizontal velocities are nudged towards the ERA-Interim. Land initial conditions are from the Community Land Model Version 4.0 (CLM4), which is an offline land simulation forced with atmospheric reanalysis and observations.

b) AMIP Simulations

We also used Atmospheric Model Intercomparison Project (AMIP) simulations, in which observed sea surface temperatures, sea ice concentrations, and radiative forcing is prescribed in the model, from 1997-2012 to evaluate the long-term hindcasts. These prescribed AMIP boundary conditions were previously specified such that the monthly means computed from the model output precisely agreed with observations (Taylor et al. 2015).

The AMIP model configuration enables us to focus on the atmospheric model without the added complexities of ocean-atmosphere feedbacks in the climate system. Thus, these simulations were not meant for climate change prediction, which requires a coupled-atmosphere ocean model. Unlike the hindcasts, for with both the boundary conditions (SST and sea ice) and initial state of the atmosphere and land are prescribed to match observations, these AMIP simulations are conducted with prescribed boundary conditions only. This means that the atmosphere can drift towards a more biased state as time goes on since the meteorology is not constrained like it is in the hindcasts.

c) Satellite Observations and Satellite Simulator Data

Clouds in hindcasts and AMIP simulations were compared to 4 independent satellite observations (Table 1). ISCCP, MODIS, and PATMOS-x datasets are provided as histograms of cloud fraction partitioned into seven cloud top pressure (CTP) bins and seven cloud optical depth (τ) bins (Rossow and Schiffer 1999). We also use high-, mid-, and low-level cloud cover derived from CALIPSO, a space-borne active cloud lidar.

We compare these observational products with cloud fractions provided by ISCCP, MODIS, and CALIPSO satellite simulators that are run in the CAM5 model. These
simulators apply the cloud retrieval algorithms and sampling features employed by their respective observational platforms to the model atmosphere, allowing for an apples-to-apples comparison between the observational cloud datasets and those produced by the model. For both models and observations, we consider only clouds with optical depths greater than 0.3 where both the model and observations provide data.

**TABLE 1:** Lists the observational datasets and their periods of coverage.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>International Satellite Cloud Climatology Project (ISCCP)</td>
<td>January 1984 to December 2009</td>
</tr>
<tr>
<td>Moderate Resolution Imaging Spectroradiometer (MODIS)</td>
<td>January 2003 to December 2016</td>
</tr>
<tr>
<td>Pathfinder Atmospheres-Extended (PATMOS-X)</td>
<td>January 1982 to December 2009</td>
</tr>
<tr>
<td>Cloud-Aerosol Lidar Infrared Pathfinder Satellite Observations (CALIPSO)</td>
<td>June 2006 to December 2015</td>
</tr>
</tbody>
</table>

**d) Cloud Radiative Feedback Calculation**

Interannual cloud feedbacks were quantified in hindcast simulations, AMIP simulations, and ISCCP, MODIS, and PATMOS satellite observations as follows. We computed anomalies in the cloud fraction histograms with respect to the climatological annual cycle for each dataset. We then regressed detrended cloud fraction histogram anomalies on detrended global mean surface temperature anomalies to compute the temperature-mediated changes in cloud fraction that induce feedbacks. The purpose of detrending these variables was to eliminate the long-term global warming trend and any spurious trends arising from satellite instrument artifacts since we are just concerned with calculating cloud feedbacks on interannual timescales. For consistency, we regressed both models and observations on the HadCRUT.4.6.0.0 surface temperature dataset (Fig. 2). These temperature-mediated cloud fraction responses were then multiplied by cloud radiative kernels (described below) to quantify their impact on TOA radiation. Summing these over desired portions of the histogram yields contributions of particular cloud types to the cloud feedback. This is encapsulated in the following equation:

\[
\frac{dR_C(x)}{dT_G} = \sum_{p=1}^{P} \sum_{\tau=1}^{T} K(p, \tau, x) \cdot \frac{dC(p, \tau, x)}{dT_G}
\]

Here, \( R_C \) is the TOA radiation anomaly due to cloud anomalies, \( T_G \) is the global mean surface air temperature anomaly, \( K \) is the cloud radiative kernel, \( C \) is the cloud fraction anomaly, \( p \) is cloud top pressure, \( \tau \) is cloud optical depth, and \( x \) represents a generalized position encompassing latitude, longitude, and month. Hence, the left-hand side (LHS) of the equation represents the cloud feedback (in units of W/m²/K), as it is the temperature-dependence of cloud-induced radiation anomalies. The right-hand side (RHS) represents the product of the cloud radiative kernel and the temperature-mediated change in cloud fraction
histogram, summed over the $P$ cloud top pressure and $T$ optical depth bins. Cloud radiative kernels quantify the sensitivity of TOA radiation to cloud fraction in each bin of the histogram (in units of $\text{W}/\text{m}^2/\%$):

$$K(p, \tau, x) = \frac{dR}{dC(p,\tau,x)}$$  \hspace{0.1cm} (2)

These are computed using a radiative transfer model and are described in detail in Zelinka et al. (2012a). They are a convenient way to quantify cloud-induced radiation anomalies and decompose cloud feedbacks into individual components.

These feedbacks were then broken down into changes in cloud properties like amount, optical depth, and altitude for both low (CTP>680 hPa) and free tropospheric (CTP<680 hPa) clouds, as well as for the entire cloud distribution following the procedures described in Zelinka et al. (2012b, 2013, and 2016). The sum of these three components would ideally equal the total cloud feedback. However, a small residual remains because the complete variations found in the cloud histogram are too complex to be expressed as just the sum of three terms (Zelinka et al. 2013).

FIG. 2: Dataset availability for the full duration and matched-in-time hindcasts and satellite observations (top). Surface temperature anomalies from the HADCRUT 4.6.0.0 dataset over the period of the model and observational datasets, in which interannual cloud feedbacks were regressed on (bottom). The black dotted line refers to the global mean surface temperature anomalies, and the grey dotted line refers to the tropical mean global surface temperature anomalies. Surface temperature anomalies are relative to the 1961-1990 reference period.
III. Results

In the following sections, we will focus on the short-term cloud feedback in the models and observations. Our goal is to understand how, and why these modeled and observed cloud responses differ. This will be determined by regressing various fields on interannual surface temperature anomalies. These analyses will be done both for available data in the various records, and for only the periods in which models and observations perfectly overlap (Fig.2).

a) Surface Temperature Responses

To orient the reader on the surface temperature pattern, to which the clouds and all other aspects of the meteorology are responding to, we show surface temperature responses in Figure 3. These responses refer to the pattern of surface temperature anomalies corresponding to a 1 K increase in the observed HadCRUT globally-averaged surface temperature anomaly. Because ENSO is the dominant mode of interannual variability on interannual timescales, the surface temperature anomaly pattern resembles the El Niño warm phase. Therefore, the full observational record, full model record, and the model and observations matched in time all have eastern equatorial Pacific warming. However, the strength and orientation of the El Niño signal differ based on the duration of each dataset. For example, the full MODIS observational record and the full model record have a broad region of warming stretching from the western Pacific to the western coast of North and South America. On the other hand, the ISCCP full observational record and MODIS overlap have a narrower region of warming over the equatorial Pacific. There are also differences in the surface temperature response outside the equatorial Pacific. For example, the full model record and the MODIS full observational record have lower negative temperature anomalies over the northern and southern Pacific than the ISCCP full observational record. The magnitude and sign of these temperature anomalies are important because it will drive the cloud anomalies shown hereafter.
b) Total Cloud Feedbacks

In this section, we show short-term LW, SW, and net total cloud feedbacks computed from the models and observations. For this section and all future sections, the model results derived using both the ISCCP and MODIS simulators are shown for Days 2 and 3 of the hindcasts and the AMIP simulations. Observational results are derived using ISCCP, PATMOS-x and MODIS cloud datasets. ISCCP simulator-derived model results are most comparable to results from ISCCP observations, and MODIS simulator-derived model results are most comparable to results from MODIS observations. Results from the PATMOS-x observations provide an independent observational dataset to assess the robustness of the observational results.

There is a large positive equatorial pacific feedback in the LW with no discernable differences in the orientation and the magnitude in the models and observations (Fig. 4). However, the hindcasts better capture the observed responses compared to AMIP in other regions. In the western Indian ocean, AMIP has a strong negative feedback, while the hindcasts and the observations have a strong positive feedback. In the North Pacific, the negative feedback in the AMIP simulation is smaller.
than the negative feedback in the hindcasts and observations. Lastly, off the western coast of Mexico, AMIP has a stronger and more broad negative feedback than the hindcasts and the observations.

In the SW, models and observations match closely for the equatorial pacific region, but instead, the feedback is negative (Fig. 5). Like the LW, some regions in the hindcasts better capture the observed response compared to AMIP. In the Western Indian ocean, AMIP has a strong positive feedback, while the hindcasts and the observations have a negative feedback. In the North Pacific, the positive feedback in the AMIP simulations are less than the positive feedback in the hindcasts and observations.

To better quantify the extent to which constraining for meteorology by performing hindcasts leads to feedbacks that more closely match those observed in nature, we generated Taylor diagrams (Taylor, 2001).
These diagrams show the correlation coefficient, the root mean square (RMS) difference of the model and observed fields, and the ratio of the standard deviation of the two patterns, all indicated by a single point.

Not only did the hindcasts better capture the observed response regionally compared to AMIP for the LW and SW total cloud feedback, it also did globally (Fig. 6). For the MODIS matching periods, AMIP had a much lower correlation for the LW and SW than the hindcasts. Thus, the hindcasts have a pattern that is more like the observations than AMIP. Both the hindcasts and AMIP in the LW and SW had a large RMS difference, but AMIP’s RMS difference was much larger than the hindcasts. This indicates that the hindcasts have LW and SW total net cloud feedbacks that are closer in value to the observations than to AMIP. Lastly, both AMIP and the hindcasts had a similar standard deviation to each other, but a larger standard deviation than the observations. Thus, both AMIP and the
hindcasts have too much spatial variability in the feedbacks.

The models and observations also match closely for the equatorial Pacific region for the net cloud feedback (Fig. 7). Unlike for the LW and SW, constraining for meteorology do not result in any noticeable improvements between the hindcasts and AMIP regionally. Thus, the model falls largely within the observational range. However, the observational range of the net feedback is quite large. At the equator, the net cloud feedback ranges from as low as approximately $-5 \text{ Wm}^{-2} \text{ K}^{-1}$ (MODIS) to as high as approximately $3 \text{ Wm}^{-2} \text{ K}^{-1}$ (PATMOS) (Fig. 8).

FIG. 6 Taylor diagram of the LW and SW total cloud feedback that gives the pattern correlation, the RMS difference (grey curved lines) and the standard deviation ($\text{Wm}^{-2} \text{ K}^{-1}$) for the MODIS simulator and observations with matching periods.
**FIG. 7** The net total cloud feedback with matching periods ($W m^{-2} K^{-1}$) for the ISCCP simulator, MODIS simulator and observations.

**FIG. 8** Zonal mean net total cloud feedback with matching periods ($W m^{-2} K^{-1}$) for the ISCCP simulator, MODIS simulator, and observations.
c) **High Cloud Feedbacks**

In this section, we will focus on the short-term high cloud feedback in the model and observations. In Figure 9, we show tropical mean net, SW, and LW high cloud amount feedbacks for the latitudes from 20S-20N and 30S-30N. These feedbacks were regressed on global mean temperature anomalies rather than tropical mean temperature anomalies as done in Mauritsen & Stevens (2015). We found that the tropical net high cloud amount feedback is less positive in the observations than it is in the model simulations, which lends some credence to Mauritsen & Stevens (2015) study. When the models are compared to MODIS and PATMOS observations, the bias comes from the LW component where the model has a feedback that is not negative enough. When the model is compared to ISCCP observations, the bias comes from the SW component where the model has a feedback that is too positive.

![Figure 9](image_url)

**FIG. 9** LW, SW, and Net tropical high cloud amount feedback in the models and observations at 20S-20N and 30S-30N. The orange labels represent Day 2, 3, and AMIP for the MODIS simulator, the blue labels represent the Day 2, 3, and AMIP for the ISCCP simulator, and the green labels represents PATMOS, MODIS, and ISCCP satellite observations.
The net high cloud amount feedback is negative in the equatorial Pacific and is positive in the subtropics (Fig. 10). However, the feedback is stronger in magnitude in the model compared to the observations. This can be due to local changes in high cloud fraction being larger in the models and/or the mean state high clouds in the model being too optically thick (i.e., where high clouds increase; the SW cooling is too large and vice versa). Changes in high cloud fraction were similar between the models and observations in most regions (Fig 11). However, the model slightly underestimated the high cloud increase in the central equatorial Pacific. Thus, the changes in high cloud fraction are the same as, or higher than the high cloud fraction in the models, which does not explain the high cloud amount feedback bias. This suggests that high clouds in the model are likely too optically thick, leading to biases in regional high cloud amount feedback.

**FIG. 10** High net cloud amount feedback with matching periods (W m$^{-2}$ K$^{-1}$) for the ISCCP simulator, the MODIS simulator, and the observations.
There is also some improvement in the hindcasts over AMIP when capturing the observed response of high cloud cover to interannual temperature anomalies. Despite noisy CALIPSO observations, the negative lobe over the West Pacific Warm Pool looks more realistic in the hindcasts (Fig. 12).

The high cloud amount feedback also has a notable impact on the total net cloud feedback. In the model, where high clouds increase (e.g., central Pacific), the high cloud amount feedback is positive in the longwave (Fig.13b) but is overwhelmed by a stronger negative SW component (Fig.13a). Therefore, the net cloud amount feedback is negative (Fig.13c), and thus resembles the SW. Similarly, where high clouds decrease (e.g., subtropical Pacific, equatorial Atlantic), the high cloud amount feedback is negative in the LW (Fig.13b) but is overwhelmed by a stronger positive SW component (Fig.13a). Therefore, the net cloud amount feedback is positive (Fig.13c), and thus resembles the SW. Because of this, the total net high cloud feedback (Fig.13g) resembles the net high cloud amount feedback. In contrast to the models, the LW and SW components of the observed high cloud amount feedback more closely cancel each other out (Fig. 14a,b). Hence, the observed total net high cloud feedback (Fig.14g) more closely resembles the high cloud altitude (Fig.14d) and optical depth components (Fig.14e).
Δ CALIPSO High Cloud Cover

**FIG. 12** CALIPSO full model and observational record for change in high cloud cover (%/K).

**Day 2 – ISCCP Simulator – High Cloud Feedbacks**

- a.) SW HI680 Cloud Amount Feedback
- b.) LW HI680 Cloud Amount Feedback
- c.) Net HI680 Cloud Amount Feedback
- d.) Net HI680 Cloud Altitude Feedback
- e.) Net HI680 Cloud Optical Depth Feedback
- f.) Net HI680 Cloud Residual Feedback
- g.) Net HI680 Cloud Feedback

**FIG. 13** Day 2 total high cloud feedbacks (W m\(^{-2}\) K\(^{-1}\)) for the ISCCP simulator full model record partitioned into SW, LW and net cloud amount, cloud altitude, cloud optical depth and cloud residual feedbacks.
In this section, we will compare the models and observations of short-term low cloud feedbacks. A higher estimated inversion strength (EIS), which estimates the strength of the planetary boundary layer (PBL) inversion given the temperatures at 700 hPa and the surface, has been shown to strongly correlate with a higher low cloud amount (Wood and Bretherton 2006). Thus, as we expected (and generally found) in our results, low cloud cover increases in regions where EIS increases and hence the low cloud amount feedback is negative. This is almost entirely a SW phenomenon since low clouds have little impact on LW radiation. So, increases in low clouds lead to more radiation reflected back to space, and vice versa. Thus, the EIS response and low cloud amount feedback have an inversely proportional relationship (Fig 15).

The hindcasts also perform better than AMIP in some regions for EIS and low cloud amount. In the North Pacific, the hindcasts and observations give an East-West dipole (positive to negative feedback, and negative to positive EIS), whereas the AMIP simulations have a uniformly positive feedback and negative EIS across the basin (Fig.15).

**FIG 14.** Day 2 total high cloud feedbacks (Wm$^{-2}$ K$^{-1}$) for the ISCCP observations full model record partitioned into SW, LW, and net cloud amount, cloud altitude, cloud optical depth and cloud residual feedbacks.
FIG 15. EIS responses with matching periods (K/K) for the ISCCP simulator, MODIS simulator, and observations (top). Low net cloud amount feedback with matching periods (Wm\(^{-2}\) K\(^{-1}\)) for the ISCCP simulator, MODIS simulator, and observations (bottom).
Like its regional performance, the hindcasts also perform better globally than AMIP for EIS (Fig. 16). For the MODIS matching periods, hindcasts have a higher pattern correlation than AMIP. Thus, the hindcasts have a pattern that is more like the observations than AMIP. The hindcasts also have a lower RMS difference than AMIP. This indicates that the hindcasts have an EIS closer in value to the observations than does AMIP. Lastly, the hindcasts have a standard deviation that is closer to the observations than AMIP, but both the hindcasts and AMIP have a higher standard deviation than the observations. Therefore, both the hindcasts and AMIP have too much spatial variability compared to the observations, but more so for AMIP.

**FIG. 16** Taylor diagram of the EIS Responses that gives the pattern correlation, the RMS difference (grey curved lines) and the standard deviation (K/K) for the MODIS simulator and observations with matching periods.
We also generated global low net cloud optical depth feedbacks (Fig. 17), in which the change in $\tau$ is the only contributor since cloud amount and CTP are held constant. We found that the short-term optical depth feedback is weakly negative globally, which is consistent with what most GCM’s show on climate change timescales. We also found that the observations have more positive low cloud optical depth feedbacks than the models. Lastly, there is also some suggestion that hindcasts do better than AMIP regionally. The hindcasts and observations have a small positive optical depth feedback off the coast of California and west of Australia, while AMIP has a feedback near zero.

**FIG. 17** The low net cloud optical depth feedback with matching periods (Wm$^{-2}$ K$^{-1}$) for the ISCCP simulator, MODIS simulator and observations.
IV. Discussion and Conclusion

In this paper, we used a novel cloud radiative kernel technique to calculate and detail short-term cloud feedbacks in hindcast simulations, AMIP simulations, and three independent satellite observations (ISCCP, MODIS, PATMOS). We also used a CALIPSO simulator and observations to look at cloud cover. Contrary to past studies, we found that the models matched closely to the observations for LW, SW, and total net cloud feedbacks in the equatorial pacific region. However, in agreement with previous work, we found that that the tropical high cloud amount feedback is too large in models. Lastly, constraining meteorology using hindcast simulations improved regional and global aspects of the simulated feedbacks.

We were not able to replicate the positive LW equatorial total cloud feedback bias found in Dessler (2013). In fact, we found that the model and observations matched each other very closely in the equatorial region for the SW, LW, and net total cloud feedback. A potential explanation for this is Dessler was looking at fully coupled simulations in a suite of preindustrial (Pi)Control simulations, including some that may be highly biased. We were looking at AMIP and hindcasts in a less biased model (CAM5.1). Another reason could be that there were methodological differences between Dessler’s (2013) study and ours. Dessler used the adjusted CRE method, which is based solely on TOA fluxes, while we used cloud radiative kernels. Future work could be done to see if going from fully coupled PiControl runs to AMIP simulations improve the realism of the interannual cloud feedbacks.

Our results lend some credence to Mauritsen and Steven’s (2015) study that showed that the tropical feedback is not negative enough in models compared to observations and that is due to their high cloud amount response. Similarly, we found that, despite a lot of inter-observational uncertainty, the tropical net high cloud amount feedback is less positive in the observations than the model in all cases. A possible reason for this could be due to the iris hypothesis first proposed in Lindzen et al. 2001. This hypothesis suggested that in a warmer climate, enhanced precipitation efficiency will lead to less detrainment of clouds into the troposphere from convection. With less cloud cover, more infrared radiation can escape to space, which leads to a strong stabilizing negative feedback. However, it is important to note that both this study and Mauritsen and Steven’s (2015) study does not generate a strong negative cloud feedback, despite cloud cover being reduced when the climate warms. This could be that even though reducing cloud cover lets more energy out it also lets more sunlight in. These effects act in opposite directions, and thus does not produce a strongly negative net high cloud amount feedback globally.

We ruled out that local changes in high cloud fraction resulted in the local high cloud amount feedback being stronger in the model than observations. Therefore, this strongly suggests that high clouds in the model are too optically thick, leading to
biases in regional high cloud amount feedback. We found that for the high cloud amount feedback, the LW component is overwhelmed by a stronger SW component in the model, but in the observations the LW and SW component more closely cancel each other out. Therefore, where the high cloud amount increases, the SW cooling is too large, which results in a negative feedback that is also too large. On the other hand, where the high cloud amount decreases, the SW cooling is too small, which results in a positive feedback that is also too large. Future work could be needed to better quantify the relationship between model cloud optical depth biases (i.e., too thick) and high cloud amount feedback biases.

We also found that there was significant inter-observational variation between PATMOS, MODIS, and ISCCP. For example, PATMOS, MODIS, and ISCCP had a global mean net total cloud feedback of 4.16 Wm$^{-2}$ K$^{-1}$, 0.37 Wm$^{-2}$ K$^{-1}$, and 0.02 Wm$^{-2}$ K$^{-1}$ respectively. A potential reason for this large difference is one or more of these observational datasets could have satellite artifacts that cause errors in cloud fraction data. Therefore, future work could be done to see if there are major artifacts in any of the satellite datasets that make one less reliable to use than another.

Lastly, model biases were shown to be smaller when the meteorology was constrained in the model to remain close to reality. For the total cloud feedback, this was more so regionally in the LW than the SW. For the low cloud amount feedback and EIS, which proved to be a strong indicator of low cloud response, the hindcasts performed better than the AMIP in the North Pacific. Lastly, the optical depth cloud feedbacks, which were more positive in the model than observations, performed better than AMIP off the coast of California and west of Australia. Future work may be needed for further quantification of the improvement in hindcast performance compared to AMIP.

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