Cloud variations and the Earth's energy budget

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Abstract: The question of whether clouds are the cause of surface temperature changes, rather than acting as a feedback in response to those temperature changes, is explored using data obtained between 2000 and 2010. An energy budget calculation shows that the energy trapped by clouds accounts for little of the observed climate variations. And observations of the lagged response of top-of-atmosphere (TOA) energy fluxes to surface temperature variations are not evidence that clouds are causing climate change.

Introduction

The usual way to think about clouds in the climate system is that they are a feedback — as the climate warms, clouds change in response and either amplify (positive cloud feedback) or ameliorate (negative cloud feedback) the initial change [e.g., Stephens, 2005]. In recent papers, Lindzen and Choi [2011, hereafter LC11] and Spencer and Braswell [2011, hereafter SB11] have argued that reality is reversed: clouds are the cause of, and not a feedback on, changes in surface temperature. If this claim is correct, then significant revisions to climate science may be required.

Energy budget calculation

LC11 (their Eq. 8) and SB11 (their Eq. 1) both write the Earth's energy budget as:

$$C\frac{dT_s}{dt} = \Delta R_{cloud} + \Delta F_{ocean} - \lambda \Delta T_s \quad (1)$$

C is the heat capacity of the ocean's mixed layer, ΔT_s is the surface temperature, and ΔF_{ocean} is the heating of the climate system by the ocean. The term $-\lambda\Delta T_S$ represents the enhanced emission of energy to space as the planet warms. λ is the climate sensitivity and it contains the Planck response as well as the climate feedbacks. ΔR_{cloud} is the change in TOA flux due to clouds. Note that ΔR_{cloud} is not a feedback in this formulation — it is a forcing and is independent of surface temperature (the cloud feedback is in the $-\lambda\Delta T_s$ term). All quantities are global monthly average anomalies (anomalies are calculated by subtracting the mean annual cycle.). Other terms, such as the change in radiative forcing by greenhouse gases, are small over the period examined, so they are ignored.

The formulation of Eq. 1 is potentially problematic because the climate system is defined to include the ocean, yet one of the heating terms is flow of energy to/from the ocean (ΔF_{ocean}). This leads to the contradictory situation where heating of their climate system by the ocean ($\Delta F_{ocean} > 0$) causes an increase of energy in the ocean ($C(dT_s/dt) > 0$), apparently violating energy conservation. While it may be possible to define the terms so that Eq. 1 conserves energy, LC11 and SB11 do not provide enough information to show that they have actually done so. However, to comprehensively evaluate the arguments of LC11 and SB11, I simply note this potential problem and assume in the rest of the paper that Eq. 1 is correct.

In their analyses, LC11 and SB11 test Eq. 1 by creating synthetic data for ΔF_{ocean} and ΔR_{cloud}, and this requires an assumption about the relative magnitudes of these terms. LC11 choose the ratios of the standard deviations of the time series $\sigma(\Delta F_{ocean})/\sigma(\Delta R_{cloud}) \approx 2$ while SB11 choose, for their most realistic case, $\sigma(\Delta F_{ocean})/\sigma(\Delta R_{cloud}) \approx 0.5$ (the time series are anomalies, so their means are zero by definition; thus, the standard deviation is a measure of the magnitude of the terms).

However, it is possible to use data to estimate the magnitude of $\sigma(\Delta F_{ocean})/\sigma(\Delta R_{cloud})$. I will focus on the period from March 2000 to February 2010, during which good data exist and the primary climate variations were caused by ENSO. This is the same period evaluated by SB11, and LC11's analysis also included this period.

To evaluate the magnitude of the first term, $C(dT_s/dt)$, I assume a heat capacity C of 168 W-month/m^2/K, the same value used by LC11 (as discussed below, SB11's heat capacity is too small). The time derivative is estimated by subtracting each month's global average ocean surface temperature from the previous month's value. Temperatures used in this calculation come from NASA's Modern Era Retrospective-analysis for Research and Application (MERRA) [Rienecker et al., 2011]. The standard deviation of the monthly anomaly time series, $\sigma(C(dT_s/dt))$, is 9 W/m^2.

This can be confirmed by looking at the Argo ocean heat content data covering 2003-2008. Using data reported in Douglass and Knox [2009], the month-to-month change in monthly interannual heat content anomalies can be calculated (σ = 1.2×10^{22} J/month). Assuming the ocean covers 70% of the planet, this corresponds to 13 W/m^2, in agreement with the previous estimate.

In Dessler [2010] (hereafter D10), the energy trapped by clouds each month over this period was computed (LC11 calculated similar values). If all of this energy is assumed to be a climate forcing — i.e., unrelated to surface temperature changes — then I can use these values for ΔR_{cloud}. This yields $\sigma(\Delta R_{cloud})$ = 0.5 W/m^2. Calculations for potential water vapor forcing are of a similar magnitude.

To calculate $\lambda\Delta T_S$, I assume that λ is between 1 and 6 W/m^2/K. Global and monthly averaged ΔT_S are from the MERRA reanalysis. I calculate that $\sigma(\lambda\Delta T_S) < 0.4$ W/m^2.

ΔF_{ocean} can be calculated as a residual using Eq. 1 and the terms calculated above. The result is that $\Delta F_{ocean} \approx C(dT_s/dt)$, and that $\sigma(\Delta F_{ocean}) \approx \sigma(C(dT_s/dt))$. Despite potential problems in Eq. 1, the conclusion here is robust: energy trapped by clouds can explain only a few percent of the surface temperature changes. This is consistent with previous work showing that heating of the surface and atmosphere during ENSO comes from ocean heat transport [e.g., Trenberth et al., 2002;

Trenberth et al., 2010] and it means that clouds were not causing significant climate change over this period.

A related point made by both LC11 and SB11 is that regressions of TOA flux or its components vs. ΔT_S will not yield an accurate estimate of the climate sensitivity λ or the cloud feedback. This conclusion, however, relies on their particular values for $\sigma(\Delta F_{ocean})$ and $\sigma(\Delta R_{cloud})$. Using a more realistic value of $\sigma(\Delta F_{ocean})/\sigma(\Delta R_{cloud})$ = 20, regression of TOA flux vs. ΔT_S yields a slope that is within 0.4% of λ, a result confirmed in Fig. 2b of Spencer and Braswell [2008]. This also applies to the individual components of the TOA flux, meaning that regression of ΔR_{cloud} vs. ΔT_s yields an accurate estimate of the magnitude of the cloud feedback, thereby confirming the results of D10.

As a side note, SB11 estimated their heat capacity by regressing ΔR_{cloud} vs. dT_s/dt and assuming that C is the slope. This is only correct, however, if $\Delta F_{ocean} = 0$. For the realistic case where $\sigma(\Delta F_{ocean}) >> \sigma(\Delta R_{cloud})$, the slope is much less than C, which explains why SB11's heat capacity is too small.

Comparison with models: LC11

LC11 base their conclusion that clouds are a forcing rather a feedback on a plot like the one in Fig. 1 (see their Fig. 9). The figure shows the slope of the correlation between ΔR_{cloud} and ΔT_s as a function of lag for the observations in D10.

The observations show that larger negative slopes exist when the cloud time series leads the surface temperature, with mostly positive slopes when the temperatures leads the cloud time series. Based on this correlation, LC11 conclude that clouds must be initiating the climate variations.

I've also plotted the results from nine models from the Atmospheric Model Intercomparison Project (AMIP) (CNRM CM3, INMCM 3.0, IPSL CM4, MIROC 3.2 MEDRES, MIROC 3.2 HIRES, MPI ECHAM 5, MRI CGCM 2.3.2a, NCAR CCSM, UKMO HADGEM1). While some disagreements between the observations and models exist, the models clearly simulate the key aspect of the data identified by LC11: larger negative slopes when ΔR_{cloud} leads ΔT_s.

This is an important result because the sea surface temperatures (SST) are specified in AMIP models. This means the interaction in these models is one-way: clouds respond to SST changes, but SST does not respond to cloud changes. In other words, realistic ΔR_{cloud} variations are generated in these models by specifying ΔT_s variations. The suggests that the observed lead-lag relation is a result of variations in atmospheric circulation driven by ΔT_s variations and is not evidence that clouds are initiating climate variations. This conclusion also agrees with the energy budget presented earlier that concluded that clouds are not trapping enough energy to explain the ΔT_s variations.

Calculations using fully coupled models yield similar lead-lag relations as the AMIP models. This means that closing the loop to allow clouds to affect SST does not change these conclusions.

Comparison with models: SB11

SB11's analysis is built on a plot like LC11's, but using TOA net flux instead of ΔR_{cloud}. Figure 2 shows my reconstruction of SB11's Fig. 3. Each line shows, for a single data set, the slope of the relation between TOA net flux and ΔT_s as a function of lag between them. The colored lines are observations: the blue line shows the data used by SB11 (CERES fluxes and HadCRUT3 temperature [Brohan et al., 2006]); the red lines use the same flux data, but different surface temperature data sets (MERRA, ERA-Interim, GISTEMP [Hansen et al., 2010]). The shaded regions show the 2σ uncertainties of the observations using GISTEMP and HadCRUT3. As done by SB11, all data have been 1-2-1 filtered.

The black lines are from pre-industrial control runs of 13 fully coupled climate models (CCCMA CGCM 3.1, CNRM CM3, GFDL CM 2.0, GFDL CM 2.1, GISS ER, FGOALS 1.0G, INMCM 3.0, IPSL CM4, MIROC 3.2 HIRES, MIROC 3.2 MEDRES, MPI ECHAM5, MRI CGCM 2.3.2A, NCAR CCSM 3.0) from the CMIP3 database [Meehl et al., 2007] (SB11 used de-trended 20th century runs; differences with my calculations appear minor). The models with the crosses '+' are 5 of the 6 models analyzed by SB11.

There are three notable points to be made. First, SB11 analyzed 14 models, but they plotted only six models and the particular observational data set that provided

maximum support for their hypothesis. Plotting all of the models and all of the data provide a much different conclusion. Second, some of the models (not plotted by SB11) agree with the observations, which means that the observations are not fundamentally inconsistent with mainstream climate models containing positive net feedbacks. Third, the models that do a good job simulating the observations (GFDL CM 2.1, MPI ECHAM5, and MRI CGCM 2.3.2A) are among those that have been identified as realistically reproducing ENSO [Lin, 2007]. And since most of the climate variations over this period were due to ENSO, this suggests that the ability to reproduce ENSO is what's being tested here, not anything directly related to equilibrium climate sensitivity.

ENSO coupling in the model

This leads us to a fundamental problem in their analysis of Eq. 1: LC11 and SB11 model ΔF_{ocean} as random time series, but this is incorrect. ΔF_{ocean} is actually a function of ΔT_s, with the coupling occurring via the ENSO dynamics: ΔT_s controls the atmospheric circulation, which drives ocean circulation, which determines ΔF_{ocean}, which controls ΔT_s.

Putting everything together, the evolution of ΔT_s during ENSO is due primarily to heat transport by the ocean. As the AMIP models show, these changes in ΔT_s also change clouds, but the impact of these cloud changes on ΔT_s is small. Thus, the lead-lag relation between TOA flux and ΔT_s tells us nothing about the physics driving ΔT_s.

Conclusions

These calculations show that clouds did not cause significant climate change over the last decade (over the decades or centuries relevant for long-term climate change, on the other hand, clouds can indeed cause significant warming). Rather, the evolution of the surface and atmosphere during ENSO variations are dominated by oceanic heat transport. This means in turn that regressions of TOA fluxes vs. ΔT_s can be used to accurately estimate climate sensitivity or the magnitude of climate feedbacks. In addition, observations presented by LC11 and SB11 are not in fundamental disagreement with mainstream climate models, nor do they provide evidence that clouds are causing climate change. Suggestions that significant revisions to mainstream climate science are required are therefore not supported.

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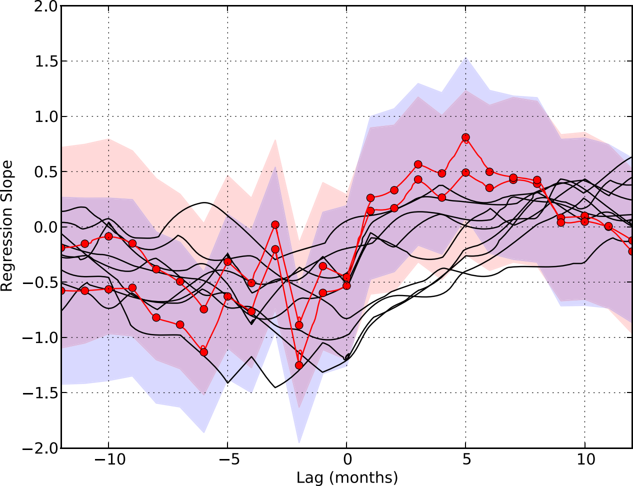
Figure 1. The slope of the regression (W/m^2/K) of energy trapped by clouds ΔR_{cloud} vs. surface temperature ΔT_s, as a function of the lag between the time series in months. Negative values of lag indicate that ΔR_{cloud} leads ΔT_s. The red lines are based on the observations in D10, using CERES flux data [Wielicki et al., 1996] and either ERA-Interim [Dee et al., 2011] or MERRA reanalyses [Rienecker et al., 2011]. The red and

blue shading indicates the 2σ uncertainty of the lines (purple shading is where the red and blue shading overlaps). The thin black lines are AMIP climate model runs.

Figure 2. Slope of the relation between TOA net flux and ΔT_s, in $W/m^2/K$ as a function of lag between the data sets (negative lags mean that the flux time series leads ΔT_s). The colored lines are from observations (covering 3/2000-2/2010 using the same TOA flux data, but different time series for ΔT_s); the shading represents the 2σ uncertainty of two of the data sets. The black lines are from 13 fully coupled pre-industrial control runs; lines with the crosses '+' are models used by SB11. Following SB11, all data are 1-2-1 filtered. See the text for more details about the plot.


2.0
1.5
1.0
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Regression Slope
−10
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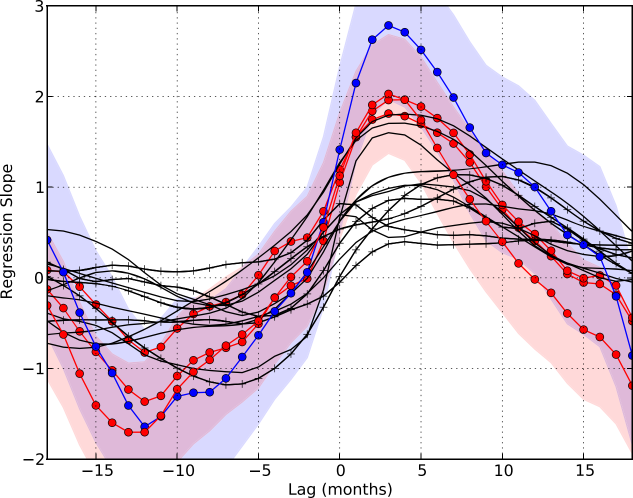
5
10
Lag (months)



Regression Slope
Lag (months)
3
2
1
0
−1
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−15
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