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On the Observational Determination of Climate Sensitivity and Its Implications

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Abstract: We estimate climate sensitivity from observations, using the deseasonalized fluctuations in sea surface temperatures (SSTs) and the concurrent fluctuations in the top-of-atmosphere (TOA) outgoing radiation from the ERBE (1985-1999) and CERES (2000-2008) satellite instruments. Distinct periods of warming and cooling in the SSTs were used to evaluate feedbacks. An earlier study (Lindzen and Choi, 2009) was subject to significant criticisms. The present paper is an expansion of the earlier paper where the various criticisms are taken into account. The present analysis accounts for the 72 day precession period for the ERBE satellite in a more appropriate manner than in the earlier paper. We develop a method to distinguish noise in the outgoing radiation as well as radiation changes that are forcing SST changes from those radiation changes that constitute feedbacks to changes in SST. We demonstrate that our new method does moderately well in distinguishing positive from negative feedbacks and in quantifying negative feedbacks. In contrast, we show that simple regression methods used by several existing papers generally exaggerate positive feedbacks and even show positive feedbacks when actual feedbacks are negative. We argue that feedbacks are largely concentrated in the tropics, and the tropical feedbacks can be adjusted to account for their impact on the globe as a whole. Indeed, we show that including all CERES data (not just from the tropics) leads to results similar to what are obtained for the tropics alone - though with more noise. We again find that the outgoing radiation resulting from SST fluctuations exceeds the zero-feedback response thus implying negative feedback. In contrast to this, the calculated TOA outgoing radiation fluxes from 11 atmospheric models forced by the observed SST are less than the zero-feedback response, consistent with the positive feedbacks that characterize these models. The results imply that the models are exaggerating climate sensitivity.

Key words: Climate sensitivity, climate feedback, cloud, radiation, satellite

1. Introduction

The heart of the global warming issue is so-called greenhouse warming. This refers to the fact that the earth balances the heat received from the sun (mostly in the visible spectrum) by radiating in the infrared portion of the spectrum back to space. Gases that are relatively transparent to visible light but strongly absorbent in the infrared (greenhouse gases) interfere with the cooling of the planet, forcing it to become warmer in order to emit sufficient infrared radiation to balance the net incoming sunlight (Lindzen, 1999). By net incoming sunlight, we mean that portion of the sun's radiation that is not reflected back to space by clouds, aerosols and the earth's surface. CO_2, a relatively minor greenhouse gas, has increased significantly since the beginning of the industrial age from about 280 ppmv to about 390 ppmv, presumably due mostly to man's emissions. This is the focus of current concerns. However, warming from a doubling of CO_2 would only be about 1°C (based on simple calculations where the radiation altitude and the Planck temperature depend on wavelength in accordance with the attenuation coefficients of well-mixed CO_2 molecules; a doubling of any concentration in ppmv produces the same warming because of the logarithmic dependence of CO_2's absorption on the amount of CO_2) (IPCC, 2007).

This modest warming is much less than current climate models suggest for a doubling of CO_2. Models predict warming of from 1.5°C to 5°C and even more for a doubling of CO_2. Model predictions depend on the 'feedback' within models from the more important greenhouse substances, water vapor and clouds. Within all current climate models, water vapor increases with increasing temperature so as to further inhibit infrared cooling. Clouds also change so that their visible reflectivity decreases, causing increased solar absorption and warming of the earth.

Cloud feedbacks are still considered to be highly uncertain (IPCC, 2007), but the fact that these feedbacks are strongly positive in most models is considered to be an indication that the result is basically correct. Methodologically, this is unsatisfactory. Ideally, one would seek an observational test of the issue. Here we suggest that it may be possible to test the issue with existing data from satellites.

Indeed, an earlier study by Forster and Gregory (2006) examined the anomaly of the annual mean temperature and radiative flux observed from a satellite. However, with the annual time scale, the signal of short-term feedback associated with water vapor and clouds can be contaminated by unknown time-varying radiative forcing in nature, and the feedbacks cannot be accurately diagnosed (Spencer, 2010). Moreover, as we will show later in this paper, the regression approach, itself, is an important source of bias. In a recent paper (Lindzen and Choi, 2009) we attempted to resolve these issues though, as has been noted in subsequent papers, the details of that paper were, in

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important ways, also incorrect (Chung *et al*., 2010; Murphy, 2010; Trenberth *et al*., 2010). There were four major criticisms to Lindzen and Choi (2009): (i) incorrect computation of climate sensitivity, (ii) statistical insignificance of the results, (iii) misinterpretation of air-sea interaction in the Tropics, (iv) misuse of uncoupled atmospheric models. The present paper responds to the criticism, and corrects the earlier approach where appropriate. The earlier results are not significantly altered, and we show why these results differ from what others like Trenberth *et al*. (2010), and Dessler (2010) obtain.

2. Feedback formalism

In the absence of feedbacks, the behavior of the climate system can be described by Fig. 1a. ΔQ is the radiative forcing, G_0 is the zero-feedback response function of the climate system, and ΔT_0 is the response of the climate system in the absence of feedbacks. The checkered circle is a node. Fig. 1a symbolically shows the temperature increment, ΔT_0, that a forcing increment, ΔQ, would produce with no feedback,

$$\Delta T_0 = G_0 \Delta Q \tag{1}$$

It is generally accepted that in the absence of feedback, a doubling of CO_2 will cause a forcing of $\Delta Q \approx 3.7$ Wm^{-2} and will increase the temperature by $\Delta T_0 \approx 1.1$ K (Hartmann, 1994; Schwartz, 2007). We therefore take the zero-feedback response function of Eq. (1) to be $G_0 \approx 0.3$ (= 1.1/3.7) K W^{-1} m^2 for the earth as a whole.

With feedback, Fig. 1a is modified to Fig. 1b. The response is now

$$\Delta T = G_0(\Delta Q + F\Delta T) \tag{2}$$

Here F is a feedback function that represents all changes in the climate system (for example, changes in cloud cover and humidity) that act to increase or decrease feedback-free effects. Thus, F should not include the zero-feedback (ZFB) response to ΔT that is already incorporated into G_0. The choice of ZFB response for the tropics in Lindzen and Choi (2009) is certainly incorrect in this respect (Chung *et al*., 2010; Trenberth *et al*., 2010). At

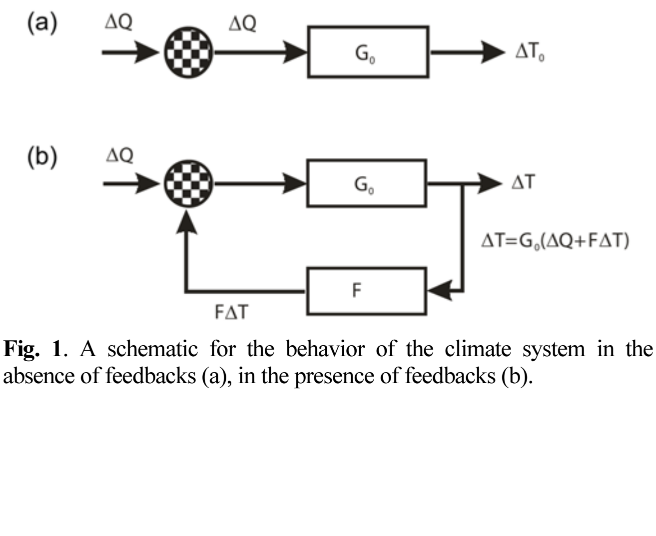

Fig. 1. A schematic for the behavior of the climate system in the absence of feedbacks (a), in the presence of feedbacks (b).

present, the best choice seems to remain $1/G_0$ (3.3 W m^{-2} K^{-1}) (Colman, 2003; Schwartz, 2007).

Solving Eq. (2) for the temperature increment ΔT and inserting Eq. (1) into Eq. (2) we find

$$\Delta T = \frac{\Delta T_0}{1-f} \tag{3}$$

The dimensionless feedback factor is $f = F\,G_0$. Also, dividing Eq. (2) by G_0, we obtain

$$-\frac{f}{G_0}\Delta T = \Delta Q - \frac{\Delta T}{G_0} \tag{4}$$

When looking at the observations, ΔQ and ΔT in Eq. (4) may be replaced by the change in outgoing net radiative flux, ΔFlux, and the change in sea surface temperature, ΔSST, respectively, leading to

$$-\frac{f}{G_0}\Delta \mathrm{SST} = \Delta \mathrm{Flux} - \mathrm{ZFB} \tag{5}$$

where ZFB indicates the zero-feedback response to ΔSST, i.e., $\Delta\mathrm{SST}/G_0$. The quantities on the right side of the equation indicate the amount by which feedbacks supplement ZFB response to ΔFlux. At this point, it is crucial to recognize that our equations are predicated on the assumption that the ΔSST to which the feedbacks are responding is produced by ΔFlux. Physically, however, we expect that any fluctuation in temperature should elicit the same flux regardless of the origin of temperature change. Note that the natural forcing, ΔSST, that can be observed, is actually not the same as the equilibrium response temperature ΔT in Eq. (4). The latter cannot be observed since, for the short intervals considered, the system cannot be in equilibrium, and over the longer periods needed for equilibration of the whole climate system, ΔFlux at the top of the atmosphere (TOA) is restored to zero. The choice of the short intervals may serve to remove some natural time-varying radiative forcing that contaminates the feedback signal (Spencer and Braswell, 2010). As explained in Lindzen and Choi (2009), it is essential, that the time intervals considered, be short compared to the time it takes for the system to equilibrate, while long compared to the time scale on which the feedback processes operate (which, in the tropics, are essentially the time scales associated with cumulonimbus convection). The latter is on the order of days, while the former depends on the climate sensitivity, and ranges from years for sensitivities on the order of 0.5°C for a doubling of CO_2 to many decades for higher sensitivities (Lindzen and Giannitsis, 1998).

The domain of the data is a major issue with critics. Recent papers (Murphy, 2010; Trenberth *et al.*, 2010) argued that quantification of global feedback based on Eq. (5) is inadequate with our tropical domain (20°S-20°N). The argument makes sense since there is the exchange of energy between the tropics and the extratropics. To resolve this issue, modification of Eq. (5) is necessary. Allowing the tropical domain to be an open system that exchanges energy with the rest of the earth, Eq. (5) must be replaced by

$$cf \approx -G_0\left(\frac{\Delta \mathrm{Flux} - \mathrm{ZFB}}{\Delta \mathrm{SST}}\right)_{tropics} \tag{6}$$

where the factor c results from the sharing of the tropical feedbacks over the globe, following the methodology of Lindzen, Chou and Hou (2001), (hereafter LCH01) and Lindzen, Hou and Farrell (1982), The methodology developed in LCH01 permits the easy evaluation of the contribution of tropical processes to the global value. As noted by LCH01, this does not preclude there being extratropical contributions as well. In fact, with the global data (available for a limited period only), the factor c is estimated to be close to unity, so that Eq. (6) is similar to Eq. (5); based on the independent analysis with the global data (Choi *et al.*, 2011, manuscript submitted to Meteorology and Atmospheric Physics) (results from which will be presented later in this paper), it is clear that the use of the global data essentially leads to similar results to that from the tropical data. This similarity is probably due to the concentration of water vapor in the tropics (more details are given in Section 6). With the tropical data in this study, the factor c is simply set to 2; that is to say that the contribution of the tropical feedback to the global feedback is only about half of the tropical feedback. However, we also tested various c values 1.5 to 3 (viz Section 6); as we will show, the precise choice of this factor c does not affect the major conclusions of this study.

From Eq. (6), the longwave (LW) and shortwave

$$f_{LW} = -\frac{G_0}{c}\left(\frac{\Delta \mathrm{OLR} - \mathrm{ZFB}}{\Delta \mathrm{SST}}\right)_{tropics} \tag{7a}$$

$$f_{SW} = -\frac{G_0}{c}\left(\frac{\Delta \mathrm{SWR}}{\Delta \mathrm{SST}}\right)_{tropics} \tag{7b}$$

Here we can identify ΔFlux as the change in outgoing longwave radiation (OLR) and shortwave radiation (SWR) measured by satellites associated with the measured ΔSST. Since we know the value of G_0, the experimentally determined slope (the quantity on the right side of Eq. (7)) allows us to evaluate the magnitude and sign of the feedback factor f provided that we also know the value of the ZFB response ($\Delta \mathrm{SST}/G_0$ in this study). For observed variations, the changes in radiation (associated for example with volcanoes or non-feedback changes in clouds) can cause changes in SST as well as respond to changes in SST, and there is a need to distinguish these two possibilities. This is less of an issue with model results from AMIP (Atmospheric Model Intercomparison Project) where observed variations in SST are specified. Of course, there is always the problem of noise arising from the fact that clouds depend on factors other than surface temperature, and this is true for AMIP as well as for nature. Note that the noise turns out to be generally greater for larger domains that include the extratropics as well as land. Note as well that this study deals with observed outgoing fluxes, but does not specifically identify the origin of the changes.

3. The data and their problems

SST is measured (Kanamitsu *et al.*, 2002), and is always fluctuating (viz. Fig. 2). To relate this SST to the flux in the entire tropics, the SST anomaly was scaled by a factor of 0.78 (the area fraction of the ocean to the tropics). High frequency fluctuations, however, make it difficult to objectively identify the beginning and end of warming and cooling intervals (Trenberth *et al.*, 2010). This ambiguity is eliminated with a 3 point centered smoother (A two point lagged smoother works too.). In addition, the net outgoing radiative flux from the earth has been monitored since 1985 by the ERBE (Earth Radiation Budget Experiment) instrument (Barkstrom, 1984) (nonscanner edition 3) aboard ERBS (Earth Radiation Budget Satellite) satellite, and since 2000 by the CERES (Clouds and the Earth's Radiant Energy System) instrument (ES4 FM1 edition 2) aboard the Terra satellite (Wielicki *et al*., 1998). The results for both LW radiation and SW radiation are shown in Fig. 3. The sum is the net outgoing flux.

With ERBE data, there is the problem of satellite precession with a period of 72 days, although in the deep tropics all clock hours are covered in 36 days. In Lindzen and Choi (2009) that used ERBE data, we attempted to avoid this problem (which is

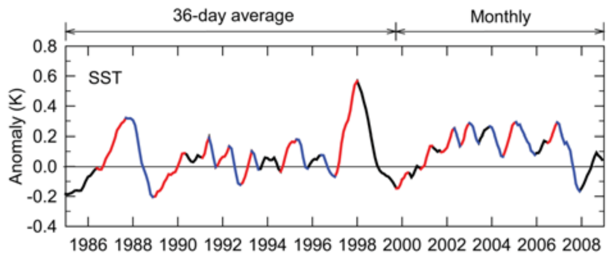

Fig. 2. Tropical mean (20°S to 20°N latitude) 36-day averaged and monthly sea surface temperature anomalies with the centered 3-point smoothing; the anomalies are referenced to the monthly (calendar months) means for the period of 1985 through 1989. Red and blue colors indicate the major temperature fluctuations exceeding 0.1°C used in this study. The cooling after 1998 El Niño is not included because of no flux data is available for this period (viz. Fig. 3).

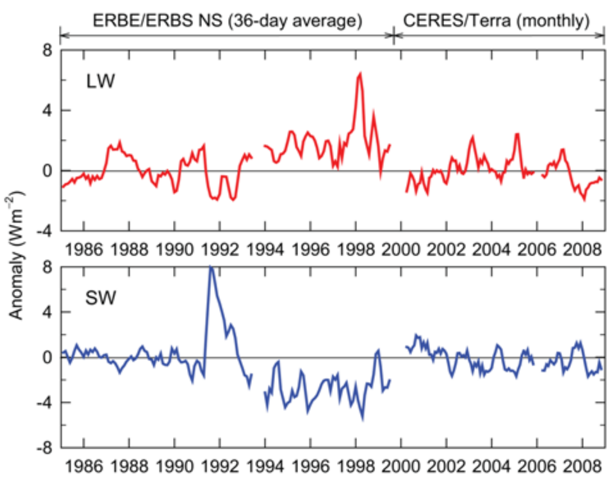

Fig. 3. The same as Fig. 2 but for outgoing longwave (red) and reflected shortwave (blue) radiation from ERBE and CERES satellite instruments. 36-day averages are used to compensate for the ERBE precession. The anomalies are referenced to the monthly means for the period of 1985 through 1989 for ERBE, and 2000 through 2004 for CERES. Missing periods are the same as reported in Wong *et al*. (2006).

primarily of concern for the short wave radiation) by smoothing data over 7 months. It has been suggested (Murphy, 2010) that this is excessive smoothing. In the present paper, we start by taking 36 day means rather than monthly means. The CERES instrument is flown on a sun-synchronous satellite for which there is no problem with precession. Thus for the CERES instrument we use the conventional months. However, here too, we take a 3 point smoothing in the flux data to minimize the effect of noise. This is also why we use the 36-day averaged SST for 1985-1999 and monthly SST for 2000-2008 in Fig. 2.

The discontinuity between the two datasets requires comment. There is the long-term discrepancy of the average which is believed to be due to the absolute calibration problem (up to 3 W m^{-2}) (Wong *et al.*, 2006). With CERES, we attempt to resolve the spectral darkening problem by multiplying SW flux by the scale factor (up to 1.011) from Matthews *et al.* (2005). However, this long-term stability should not matter for our analysis which only considers fluctuations over a few months for which the drift is insignificant. There is also the higher seasonal fluctuation in CERES SW radiation than in ERBE. The bias is up to 6.0 W m^{-2} as estimated by Young *et al.* (1998). This is attributed to different sampling patterns; i.e., ERBS observes all local times over a period of 72 days, while Terra observes the region only twice per day (around 10:30 AM and 10:30 PM). To avoid this problem, we reference the anomalies for radiative flux separately to the monthly means for the period of 1985 through 1989 for ERBE, and for the period of 2000 through 2004 for CERES. However, the issue of the reference period is also insignificant in this study since we use enough segments to effectively cancel out this seasonality.

The quality of ERBE and CERES data is best in the tropics for our feedback estimation. For latitudes 40^{o} to 60^{o}, 72 days are required instead of 36 days to reduce the precession effect (Wong *et al*., 2006). Both datasets have no or negligible shortwave radiation in winter hemispheric high latitudes. Also, the variations of solar irradiation that prevent distinguishing actual SW feedback always remain in the data partly including the extratropics. Moreover, our analysis involves relating changes in outgoing flux to changes in SST. This is appropriate to regions that are mostly ocean covered like the tropics or the southern hemisphere, but distinctly inappropriate to the northern extratropics. The effect of including extratropical data will, however, be discussed further in Sections 4-6.

Finally, there is the serious issue of distinguishing atmospheric phenomena involving changes in outgoing radiation that result from processes other than feedbacks (Pinatubo and non-feedback cloud variations for example) and which cause changes in SST, from those that are caused by changes in SST (namely the feedbacks we wish to evaluate) (Chung *et al*., 2010; Trenberth *et al*., 2010). Our crude approach to this is to examine the effect of fluxes with time lags and leads relative to temperature changes. The lags and leads examined are from one to five months. Our procedure will be to choose lags that maximize R (the correlation). This is discussed in our section on methodology (Section 4). To be sure, Fourier transform methods wherein one investigates phase leads and lags might normally be cleaner, but, given the gaps in the radiation data as well as the incompatibilities between ERBE and CERES, the present approach which focuses on individual warming and cooling events seems more appropriate.

Turning to the models, AMIP is responsible for intercomparing atmospheric models used by the IPCC (the Intergovernmental Panel on Climate Change); the AMIP models are forced by the same observed SSTs shown in Fig. 2. We have obtained the calculated changes in both SW and LW radiation from the AMIP models. These results are shown in Figs. 4 and 5 where the observed results are also superimposed for comparison. We can already see that there are significant differences. In addition, we will also consider results from CMIP (the Coupled Model Intercomparison Project), where coupled ocean-atmosphere models were intercompared.

4. Methodology

a. Feedback estimation method

As already noted, the data need to be smoothed first to eliminate the ambiguity in choosing segments. Then the procedure is simply to identify intervals of maximum change in ΔSST (red and blue in Fig. 2), and for each such interval, to find the change in flux. The reasoning for this is that, by definition, a temperature change is required to produce radiative feedback, and so the greatest signal (and least noise) in the estimation of feedback should be associated with the largest temperature changes. Thus, it is advisable, but not essential, to restrict oneself to changes greater than 0.1^{o}C; in fact, the impact of thresholds for ΔSST on the statistics of the results turns out, however, to be minor (Lindzen and Choi, 2009).

Let us define $t_1, t_2, \ldots, t_m$ as selected time steps that correspond to the starting and the ending points of intervals. Again, for stable estimation of ΔFlux/ΔSST, the time steps should be selected based on the maximum and minimum of the 'smoothed' SST. In addition, if the maximum and minimum of the smoothed SST appear at contiguous points or at points with no flux data (Fig. 3), we disregarded them (black in Fig. 2). Specifically, we disregarded the beginning of the time series since the start point of warming cannot be determined. Also, we disregarded the end of the time series since there was missing data in radiative flux. Note that these disregarded periods include some intervals (e.g., the cooling SST in 1998) used in Lindzen and Choi (2009) where they selected neighboring end points to avoid the missing flux data.

ΔFlux/ΔSST can be obtained by $\mathrm{Flux}(t_{i+1}) - \mathrm{Flux}(t_i)$ divided by $\mathrm{SST}(t_{i+1}) - \mathrm{SST}(t_i)$ where t_i is ith selected time steps ($i = 1, 2, \ldots, m - 1$). As there are many intervals, the final ΔFlux/ΔSST is a regression slope for the plots (ΔFlux, ΔSST) for a linear regression model. Here we use a zero y-intercept model ($y = ax$) because the presence of the y-intercept is related to noise other than feedbacks. Thus, a zero y-intercept model may be more appropriate for the purpose of our feedback analysis though the choice of regression model turns out to also be minor

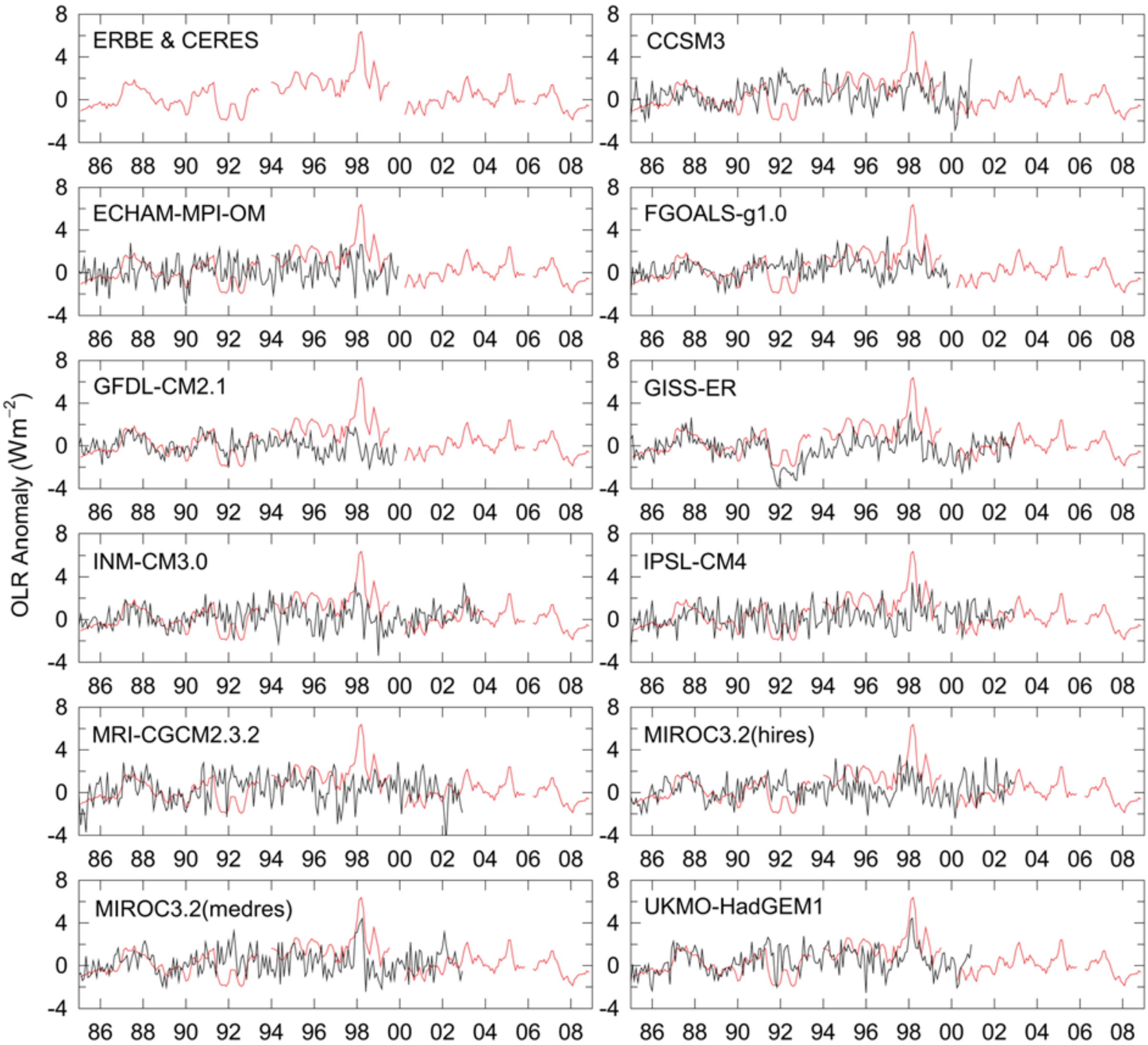

Fig. 4. Comparison of outgoing longwave radiation from AMIP models (black) and the observations (red) shown in Fig. 3.

in practice.

One must also distinguish ΔSST's that are forcing changes in ΔFlux, from responses to ΔFlux. Otherwise, ΔFlux/ΔSST can have fluctuations (as found by Dessler, 2010 and Trenberth *et al*., 2010, for example) that may not represent feedbacks that we wish to determine. The results from Trenberth *et al*. (2010) and Dessler (2010) were, in fact, ambiguous as well because of the very low correlation of their regression of ΔF on ΔSST. To avoid the causality problem, we use a lag-lead method (e.g., use of Flux(t + lag) and SST(t)) for ERBE 36-day and CERES monthly smoothed data). In general, the use of leads for flux will emphasize forcing by the fluxes, and the use of lags will emphasize responses by the fluxes to changes in SST.

The above procedures help to obtain a more accurate and objective climate feedback factor than the use of original monthly data. As we will show below, this was tested by a Monte-Carlo test of a simple feedback-forcing model.

b. Simple model analysis

Following Spencer and Braswell (2010), we assume an hypothetical climate system with uniform temperature and heat capacity, for which SST and forcing are time-varying. Then the model equation of the system is

$$C_P\left[\frac{d\Delta \mathrm{SST}}{dt}\right] = Q(t) - F\cdot\Delta\mathrm{SST}(t) \tag{8}$$

where C_p is the bulk heat capacity of the system (14 yr W m^{-2} K^{-1} in this study, from Schwartz, 2007); ΔSST is SST deviation away from an equilibrium state of energy balance; F is the feedback function that is the same as the definition in Eq. (2); Q is any forcing that changes SST (Forster and Gregory, 2006; Spencer and Braswell, 2010). Q consists in three components: (i) Q_1 = external radiative forcing (e.g., from anthropogenic greenhouse gas emission), (ii) Q_2 = internal non-radiative forcing (from

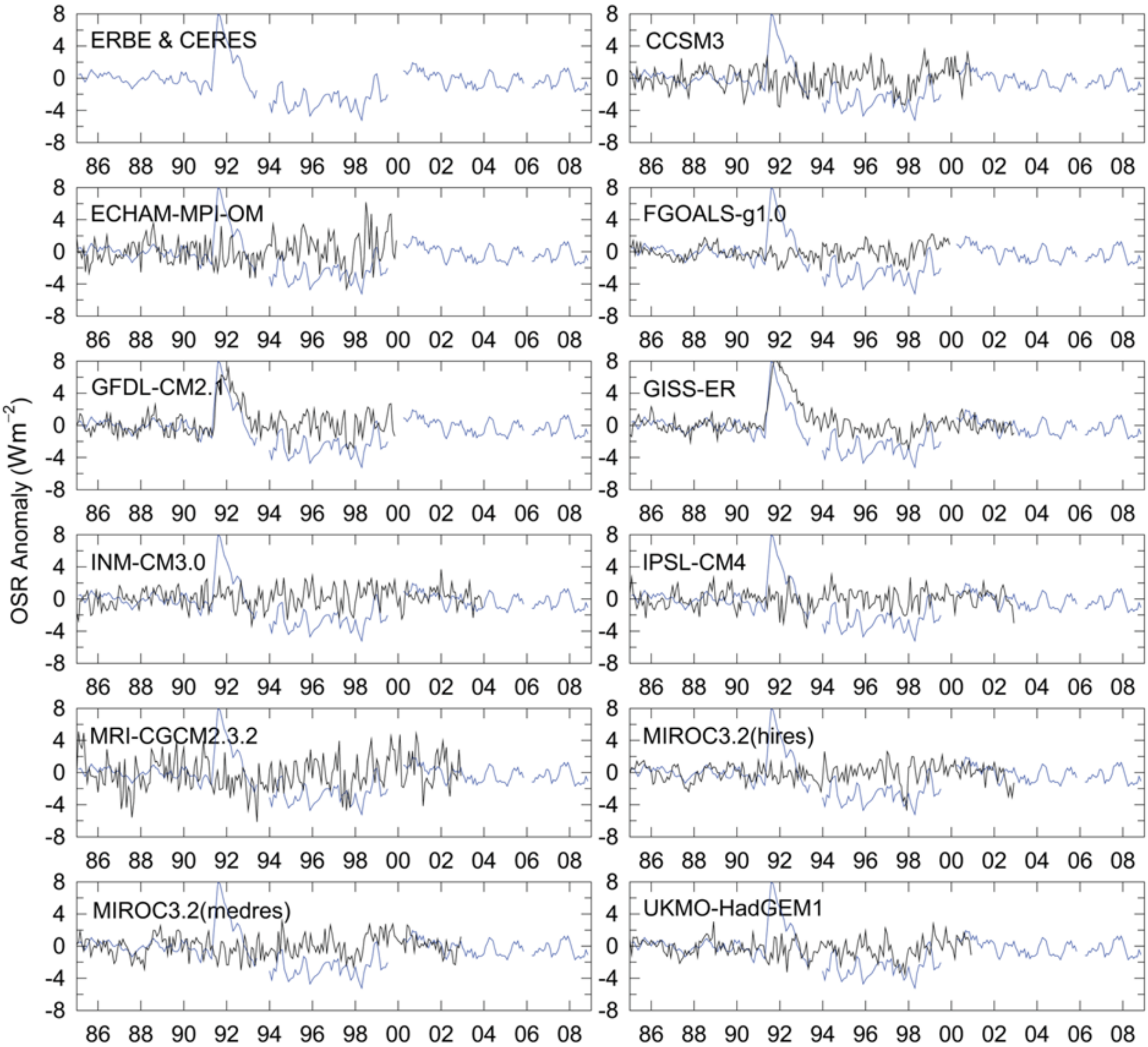

Fig. 5. Comparison of reflected shortwave radiation from AMIP models (black) and the observations (blue) shown in Fig. 3.

heat transfer from the ocean, for example), and (iii) Q_3 = internal radiative forcing (e.g., from water vapor or clouds.). Among the three forcings, the two external and internal 'radiative' forcings, and $F{\cdot}\Delta SST(t)$ constitute TOA net radiative flux anomaly; i.e., $\Delta Flux = F{\cdot}\Delta SST(t) - [Q_1(t) + Q_3(t)]$.

The model system was basically forced by random internal non-radiative forcing changing SST (ie, Q_2). The system was also forced by random internal radiative forcing (ie, Q_3). For this preliminary test, normally distributed random numbers with zero mean were inserted into Q_1 and Q_2; we anticipate using forcing with realistic atmospheric or oceanic spectra in future tests. Here the variance of internal non-radiative forcing is set to 5 and the variance of internal radiative forcing is set to 0.7. Hence, the ratio of variances of the two forcings is 14% (hereafter the noise level). These settings generally give simulated ΔSST and ΔFlux with similar variances to the observed, The simulated variances are, however, subject to model representation as well. Finally the system was additionally forced by transient external radiative forcing (0.4 W m^{-2} per decade due to increasing CO_2) (Spencer and Braswell, 2010). Integration is done at monthly time steps*. We used Runge-Kutta 4th order method for numerical solution of randomly forced system, Eq. (8) (Machiels and Deville, 1998). Figure 6 compares the simple regression method and our method for the feedback function $F = 6$ W m^{-2} K^{-1} (it indicates negative feedback as it is larger than Planck response 3.3 W m^{-2} K^{-1}). The maximum R occurs at small (zero or a month) lag and the corresponding ΔFlux/ΔSST (5.7 W m^{-2} K^{-1}) is close to the assumed F (6 W m^{-2} K^{-1}), whereas the simple regression method underestimates F (3.2 W m^{-2} K^{-1}).

The difference between the simple regression and our method

*It is also possible to integrate at daily time steps, and degrade the time series to the monthly averages without significantly changing the results - suggesting that the coarser time resolution is adequate for our purposes.

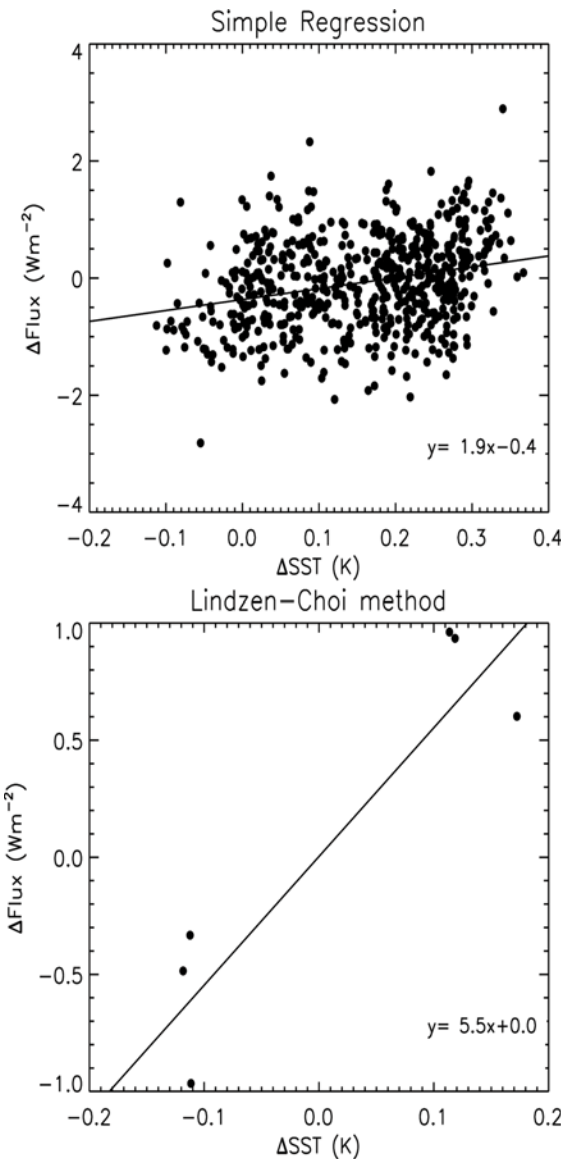

Fig. 6. Comparison between simple regression method and the method used in this study, based on simple model results for F = 6 Wm^{-2} K^{-1}.

is statistically significant by a Monte-Carlo test (10,000 repetitions). Figure 7 shows the probability density functions of the estimated ΔFlux/ΔSST, and compares with the three true F values (1, 3.3, and 6 W m^{-2} K^{-1}) that were specified for the model. We do not rule out the possibilities that both methods fail to estimate the actual feedback (the tail of the density functions), but we see clearly that the simple regression always underestimates negative feedbacks and exaggerates positive feedbacks. This is seen more clearly in Table 1 which shows the central values of gain and feedback factors for both the simple regressions and for the lag-lead approach (LC). The simple regression even finds fairly large positive feedbacks when the actual feedback is negative. This bias is, at least, partially because the simple regression includes time intervals that approach equilibration time, and at equilibrium, we would have a ΔSST with no ΔFlux.

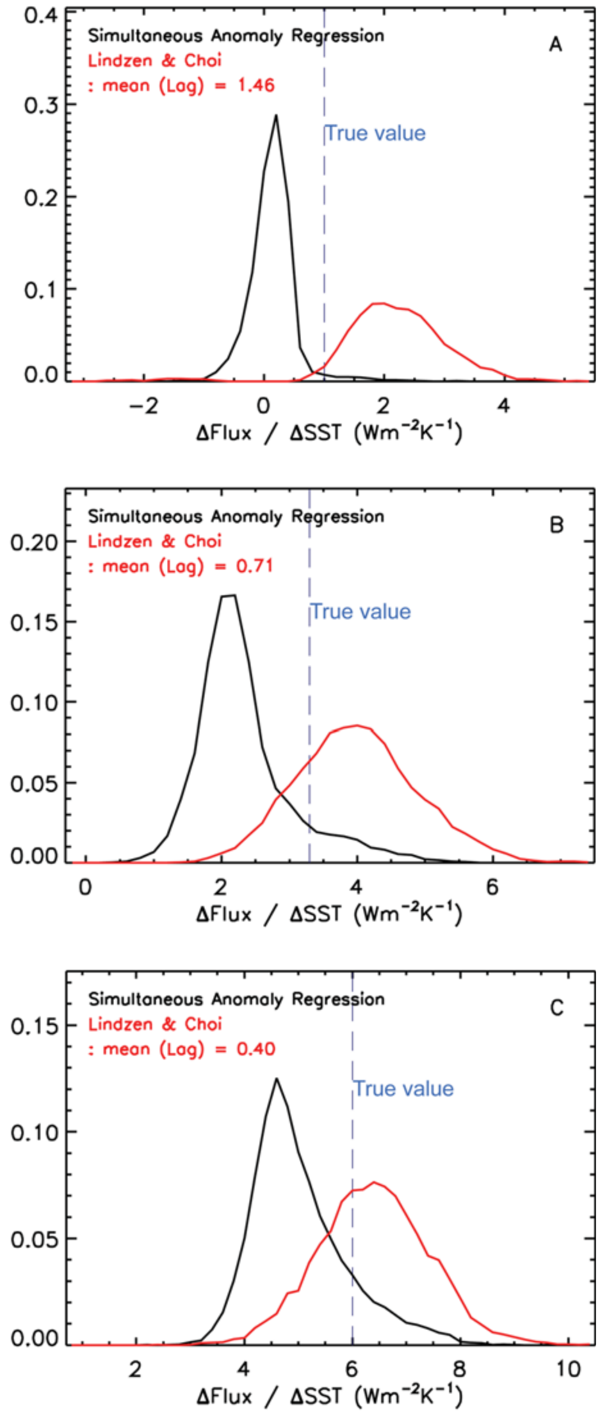

Fig. 7. Probability density function of simple model simulation results (10,000 repeats) for the feedback parameter F = 1, 3.3, and 6 Wm^{-2}K^{-1} (blue dotted line). The black line is from the simple regression, and the red line is from the methodology in this study. Note that, in the case of 'true' positive feedback, the LC method shows an insignificant indication of a negative feedback. The means of the lags with maximum R selected in our method are also noted.

By contrast, our method shows moderately good performance for estimating the feedback parameter especially for significant

Table 1. Summary of simple model simulation results shown in Fig. 7. The gain is $1/G_0$ divided by the averaged F. Note that the averaged F is larger than the value of the most frequent occurrence for the simple regression method.

True values		LC		Simple regression	
Gain	f	Gain	f	Gain	f
0.55	−0.80	0.52	−0.92	0.66	−0.51
1.00	0.00	0.83	−0.21	1.42	0.29
3.30	0.68	1.53	0.34	23.57	0.94

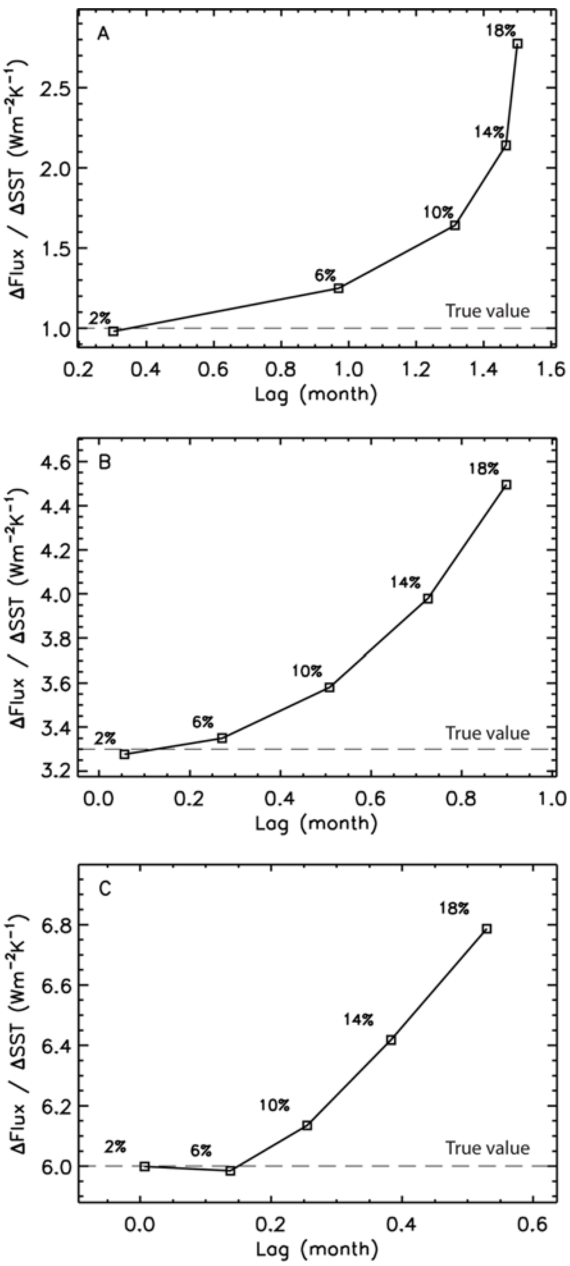

Fig. 8. The relationship between the estimated feedback parameter F, the lags with maximum R, and the noise level (in %).

negative feedbacks (comparable to what we observe in the data). The system with smaller F generates the sinusoidal shape of the

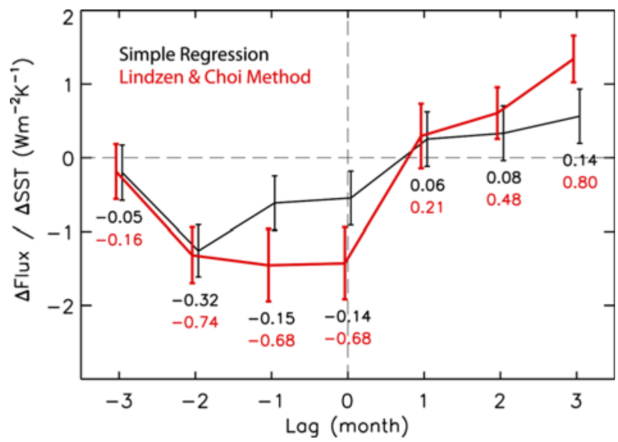

Fig. 9. The lagged regression slopes and their one-σ uncertainties of ΔFlux versus ΔSST from CERES and ECMWF interim data used in Dessler (2010). Note that here ΔFlux is 'global' radiative flux variation by clouds, and a positive ΔFlux/ΔSST means a negative cloud feedback. ΔFlux and ΔSST values are calculated by taking (black) original monthly anomaly data, and (red) the method in this study; the numbers indicate lagged linear correlation coefficients.

slopes with respect to lags, so that it turns out to have maximum R at larger lag. In this case, the estimated climate feedbacks are the lagged response though estimates are less reliable than when maximum R occurs at near-zero lag (Fig. 8). Therefore, for the system with smaller F our method is less efficient, and the true value is in between the simple regression and our method. This is also the case for the system with the same F with an increased noise level (Fig. 8). That is to say, the longer the lag needed to maximize R, the more our method overestimates F. This may be because the lagged response is attributed to both feedback and noise, and heavier noise at longer lag unduly raises the slope. Regardless of feedback strength, with either no internal (cloud-induced) radiative change or the prescribed temperature variation, ΔFlux/ΔSST at zero lag (with maximum R) is always identical to the assumed F. Thus AMIP systematically shows maximum R at zero lag, while CMIP does not; thus, the use of AMIP seems more appropriate in estimating model feedback than the use of CMIP.

An example of a comparison of simple regression with our lead-lag approach is taken from Choi *et al*. (2011, manuscript submitted to Meteorology and Atmospheric Physics) with slight modification. Here we compared the use of the simple regression approach with our approach for the complete CERES data set used by Dessler (2010). The results are shown in Fig. 9 where we show the impact of using segments (as opposed to the continuous record as was done by Dessler, 2010) and the use of lead-lag as opposed to simple regression. The former serves mainly to greatly increase the correlation (r^2) from the negligible value obtained by Dessler (2010); the latter leads to a significant negative feedback as opposed to the weak and insignificant positive feedback claimed by Dessler (2010). We will discuss these results later in connection with our emphasis on tropical data. Recall, that this example considers data from all latitudes covered by CERES. However, it should be emphasized that even Dessler's treatment of the data leads to negative feedback when lags are considered.

5. Results

a. Climate sensitivity from observations and comparison to AMIP models

Given the above, it is now possible to directly test the ability of models to adequately simulate the sensitivity of climate (see Methodology, Section 4). Figure 10 shows the impact of smoothing and leads and lags on the determination of the slope as well as on the correlation, R, of the linear regression. For LW radiation, the situation is fairly simple. Smoothing increases R somewhat, and for 3 point symmetric smoothing, R maximizes for slight lag or zero - consistent with the fact that feedbacks are expected to result from fast processes. Maximum slope is found for a lag of 1 'month', though it should be remembered that the relevant feedback processes may operate on a time scale shorter than we resolve. The situation for SW radiation is, not surprisingly, more complex since phenomena like the Pinatubo eruption and non-feedback cloud fluctuations lead to changes in SW reflection and associated fluctuations in surface temperature.

We see two extrema associated with changing lead/lag. There is a maximum negative slope associated with a brief lead, and a relatively large positive slope associated with a 3-4 month lag. The lags in SW that maximize R are rather long compared to what we get with the simple model. This is because the simple model is of total radiation with Planck response. Consistently, the summation of LW and SW radiations presents a shorter lag. It seems reasonable to suppose that the effect of anomalous forcing extends into the results at small lags because it takes time for the ocean surface to respond, and is only overcome for larger lags where the change in flux associated with feedback dominates. Indeed, excluding the case of the Pinatubo volcano for larger lags does little to change the results (less than 0.3 W m^{-2} K^{-1}). Under such circumstances, we expect the maximum slope for SW radiation in Fig. 10 to be an underestimate of the actual feedback (for reasons we discussed in Section 4b). We also consider the standard error of the slope to show data uncertainty.

The results for the lags associated with maximum R are shown in Table 2. We take LW and SW radiation for lag = 1 and lag = 3, respectively, and measure the slope ΔFlux/ΔSST for the sum of these fluxes. The standard error of the slope in total radiation for the appropriate lags comes from the regression for scatter plots of (ΔSST, Δ(OLR + SWR)). With the slope and its standard error, the feedback factors for LW, SW, and total radiation (f_{SW}, f_{LW}, and f_{Total}) are obtained via Eqs. (6) and (7). Finally, with f_{Total}, the equilibrium climate sensitivity for a doubling of CO_2 is obtained via Eq. (3). Here the statistical confidence intervals of the sensitivity estimate at 90%, 95%, and 99% levels are also calculated by the standard error of the feedback factor f_{Total}. This interval should prevent any problems arising from limited sampling. As a result, the climate sensitivity for a doubling of CO_2 is estimated to be 0.7K (with the confidence interval 0.5K - 1.3K at 99% levels). This observational result shows that model sensitivities indicated by the IPCC AR4 are likely greater than the possibilities estimated from the observations.

We next wish to see whether the outgoing fluxes from the AMIP models are consistent with the sensitivities in IPCC AR4. To the AMIP results, for which there was less ambiguity as to whether fluxes constituted a response (noise still exists due to autonomous cloud fluctuations), the same approach as that for

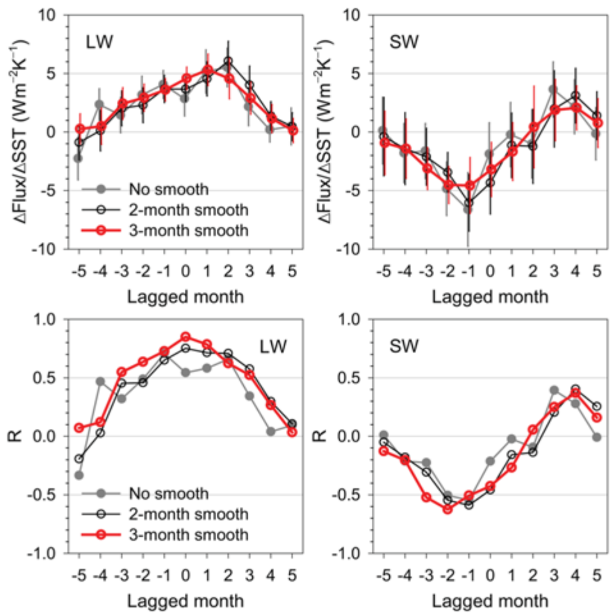

Fig. 10. The impact of smoothing and leads and lags on the determination of the slope (top) as well as on the correlation coefficient, R, of the linear regression (bottom).

Table 2. Mean ± standard error of the variables for the likely lag for the observations. The units for the slope are W m^{-2} K^{-1}. Also shown are the estimated mean and range of equilibrium climate sensitivity (in K) for a doubling of CO_2 for 90%, 95%, and 99% confidence levels. The numbers are basically calculated to the second decimal place, and then presented as the first decimal place in this table. The mean f_{Total} is actually −0.54.

	Variables		Comments
a	Slope, LW	5.3 ± 1.3	Lag = 1
b	Slope, SW	1.9 ± 2.6	Lag = 3
c	Slope, Total	6.9 ± 1.8	= a + b for the same SST interval
d	f_{LW}	−0.3 ± 0.2	Calculated from a
e	f_{SW}	−0.3 ± 0.4	Calculated from b
f	f_{Total}	−0.5 ± 0.3	Calculated from c
g	Sensitivity, mean	0.7	Calculated from f
h	Sensitivity, 90%	0.6-1.0	Calculated from f
i	Sensitivity, 95%	0.5-1.1	Calculated from f
j	Sensitivity, 99%	0.5-1.3	Calculated from f

the observations was applied. Maximum R occurs at zero lag in both LW and SW radiation, so we simply chose the AMIP fluxes without lag. The results are shown in Table 3. In contrast to the observed fluxes, the implied feedbacks in the models are all positive, and in one case, marginally unstable. Given the uncertainties, however, one should not take that too seriously.

Table 4 compares the climate sensitivities in degrees K for a doubling of CO_2 implied by feedback factors f in Table 3 with those in IPCC AR4. To indicate statistical significance of our results obtained from limited sampling, we also calculated the confidence intervals of the climate sensitivity using the standard errors of f in Table 3. All the sensitivities in IPCC AR4 are within the 90% confidence intervals of our sensitivity estimates. The agreement does not seem notable, but this is because, for positive feedbacks, sensitivity is strongly affected by small changes in f that are associated standard errors in Table 3. Consequently, the confidence intervals include "infinity". This is seen in Fig. 11 in the pink region. It has, in fact, been suggested by Roe and Baker (2007), that this sensitivity of the climate sensitivity to uncertainty in the feedback factor is why there has been no change in the range of climate sensitivities indicated by GCMs since the 1979 Charney Report (1979). By contrast, in the green region, which corresponds to the observed feedback factors, sensitivity is much better constrained.

While the present analysis is a direct test of feedback factors, it does not provide much insight into detailed mechanism. Nevertheless, separating the contributions to f from long wave and short wave fluxes provides some interesting insights. The results are shown in Tables 2 and 3. It should be noted that the consideration of the zero-feedback response, and the tropical feedback factor to be half of the global feedback factor is actually necessary for our measurements from the Tropics;

Table 3. Regression statistics between ΔFlux and ΔSST and the estimated feedback factors (f) for LW, SW, and total radiation in AMIP models; the slope is ΔFlux/ΔSST, N is the number of the points or intervals, R is the correlation coefficient, and SE is the standard error of ΔFlux/ΔSST.

		LW				SW				LW + SW			
	N	Slope	R	SE	f_{LW}	Slope	R	SE	f_{SW}	Slope	R	SE	f
CCSM3	17	1.2	0.4	2.0	0.3	−3.7	−0.9	1.0	0.6	−2.5	−0.5	2.2	0.9
ECHAM5/MPI-OM	16	1.1	0.4	1.6	0.3	−0.1	0.0	1.9	0.0	1.0	0.3	2.1	0.3
FGOALS-g1.0	16	0.4	0.2	1.2	0.4	−2.8	−0.8	1.0	0.4	−2.4	−0.6	1.4	0.9
GFDL-CM2.1	16	2.1	0.8	0.9	0.2	−2.1	−0.4	2.4	0.3	0.0	0.0	2.0	0.5
GISS-ER	21	3.2	0.8	1.1	0.0	−3.7	−0.6	1.8	0.6	−0.5	−0.1	1.3	0.6
INM-CM3.0	23	2.7	0.6	1.4	0.1	−3.4	−0.7	1.3	0.5	−0.7	−0.1	1.8	0.6
IPSL-CM4	21	−0.4	−0.1	1.1	0.6	−2.3	−0.5	1.6	0.3	−2.7	−0.5	1.7	0.9
MRI-CGCM2.3.2	21	−0.8	−0.3	1.3	0.6	−3.8	−0.6	2.5	0.6	−4.7	−0.7	2.5	1.2
MIROC3.2 (hires)	21	2.4	0.6	1.4	0.1	−2.4	−0.7	1.4	0.4	0.0	0.0	1.3	0.5
MIROC3.2 (medres)	21	3.4	0.8	1.0	0.0	−3.6	−0.7	2.0	0.5	−0.3	−0.1	1.6	0.5
UKMO-HadGEM1	17	4.4	0.8	2.2	−0.2	−3.6	−0.7	1.5	0.5	0.8	0.2	2.1	0.4

Table 4. Comparison of model equilibrium climate sensitivities (in K) for a doubling of CO_2 defined from IPCC AR4 and estimated from feedback factors in this study. The obvious difference between two columns labeled 'sensitivity' is discussed in more detail in the last paragraph of section 3.1. The estimated climate sensitivities for models as well as their confidence intervals are given for 90%, 95%, and 99% confidence levels.

Models	IPCC AR4	Estimate in this study			
	Sensitivity	Sensitivity	Confidence interval of sensitivity		
			90%	95%	99%
CCSM3	2.7	8.1	1.6 - Infinity	1.4 - Infinity	1.1 - Infinity
ECHAM5/MPI-OM	3.4	1.7	0.9 - 8.0	0.9 - 28.2	0.8 - Infinity
FGOALS-g1.0	2.3	7.9	2.2 - Infinity	2.0 - Infinity	1.6 - Infinity
GFDL-CM2.1	3.4	2.2	1.1 - 351.4	1.0 - Infinity	0.8 - Infinity
GISS-ER	2.7	2.5	1.5 - 8.7	1.4 - 16.4	1.2 - Infinity
INM-CM3.0	2.1	2.7	1.3 - Infinity	1.2 - Infinity	1.0 - Infinity
IPSL-CM4	4.4	10.4	2.1 - Infinity	1.8 - Infinity	1.4 - Infinity
MRI-CGCM2.3.2	3.2	Infinity	2.5 - Infinity	2.0 - Infinity	1.4 - Infinity
MIROC3.2 (hires)	4.3	2.2	1.3 - 6.4	1.2 - 10.0	1.1 - Infinity
MIROC3.2 (medres)	4	2.4	1.3 - 14.7	1.2 - Infinity	1.0 - Infinity
UKMO-HadGEM1	4.4	1.7	1.0 - 8.8	0.9 - 38.9	0.8 - Infinity

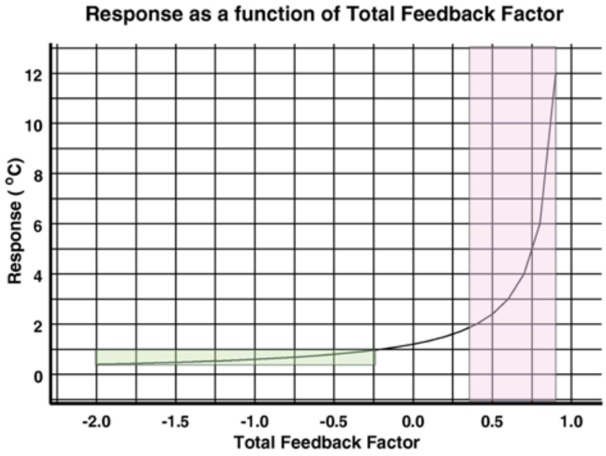

Fig. 11. Sensitivity vs. feedback factor.

however, these were not considered in Lindzen and Choi (2009). Accordingly, with respect to separating longwave and shortwave feedbacks, the interpretation by Lindzen and Choi (2009) needs to be corrected. These tables show recalculated feedback factors in the presence of the zero-feedback Planck response. The negative feedback from observations is from both longwave and shortwave radiation, while the positive feedback from models is usually but not always from longwave feedback.

As concerns the infrared, there is, indeed, independent evidence for a positive water vapor feedback (Soden *et al*., 2005), but, if this is true, this feedback is presumably cancelled by a negative infrared feedback such as that proposed by LCH01 on the iris effect. In the models, on the contrary, the long wave feedback appears to be positive (except for two models), but it is not as great as expected for the water vapor feedback (Colman, 2003; Soden *et al*., 2005). This is possibly because the so-called lapse rate feedback as well as negative longwave cloud feedback acting to cancel some of the TOA OLR feedback in current models. Table 3 implies that TOA longwave and shortwave contributions are coupled in models (the correlation coefficient between f_{LW} and f_{SW} from models is about −0.5.). This coupling most likely is associated with the primary clouds in models - optically thick high-top clouds (Webb *et al*., 2006). In most climate models, the feedbacks from these clouds are simulated to be negative in longwave and strongly positive in shortwave, and dominate the entire model cloud feedback (Webb *et al*., 2006). Therefore, the cloud feedbacks may also serve to contribute to the negative OLR feedback and the positive SWR feedback. New spaceborne data from the CALIPSO lidar (CALIOP; Winker *et al*., 2007) and the CloudSat radar (CPR; Im *et al*., 2005) should provide a breakdown of cloud behavior with altitude which may give some insight into what actually is contributing to the radiation.

b. Comparison to CMIP models and their limitations

It has been argued that CMIP models are more appropriate for the present purpose since the uncoupled AMIP models are prescribed with incomplete forcings of SST (Trenberth *et al*., 2010). However, it is precisely for this reason that AMIP models are preferred for feedback estimates. Note that we are considering atmospheric feedbacks to SST fluctuations. As already seen, in analyzing observed behavior, the presence of SST variations that are primarily caused by atmospheric changes (from volcanoes, non-feedback cloud variations, etc.) leads to difficulty in distinguishing SST variations that are primarily forcing atmospheric changes (i.e., feedbacks). This situation is much simpler with AMIP results since we can be sure that SST variations (which are forced to be the same as observed SST) cannot respond to atmospheric changes. The fact that CMIP SST variations are significantly different from observed SST variations further makes it unlikely that the model atmospheric processes are implicitly forcing the SST's used for AMIP. Note that important ocean phenomena such as El Niño-Southern Oscillation and Pacific Decadal Oscillation are generally misrepresented by CMIP models. As noted, AMIP results are still subject to noise since outgoing radiation includes changes associated with non-feedback cloud variations.

In applying our methodology to CMIP, we see that coupled models differ in the behavior of SST, and the intervals of SST must be selected differently for different models. Some models have much smaller variability of SST than nature and only a few intervals of SST could be selected. As we see in Fig. 12, the CMIP results (black dots) display behavior somewhat similar to ERBE and CERES results (red open circles) with respect to lags. However, when identifying each number, we found that the results are quantitatively ambiguous. The slope ΔOLR/ΔSST for lag = 1 is between 0.6 and 5.8 though it remains robust that LW feedbacks in most models are higher than nature. Not surprisingly, the inconsistent LW feedback was also shown in previous studies (Tsushima *et al.*, 2005; Forster and Gregory, 2006; Forster and Taylor, 2006). The slope ΔSWR/ΔSST for lag = 3 is between −3.4 and 3.9 so that one cannot meaningfully determine the feedback in the models. These values, moreover, do not correspond well to the independently known model climate sensitivities in IPCC AR4. Based on our simple model (viz Section 4b of Methodology), this ambiguity results mainly from non-feedback internal radiative (cloud-induced) change that changes SST. Also, such cloud-induced radiative change can generate the anomalous sinusoidal shape of the slopes ΔSWR/ΔSST with respect to lags as shown in Fig. 12. Therefore, previous studies that use the slopes ΔSWR/ΔSST at zero lag (Tsushima *et al.*, 2005; Forster and Gregory, 2006; Trenberth *et al*., 2010) may misinterpret SW feedback. This confirms that for more accurate estimation of 'model' feedbacks, AMIP models are more appropriate than CMIP models. Furthermore, nature is better than CMIP for SST simply because nature properly displays the real magnitude of SST forcing and the associated atmospheric changes.

6. Conclusions and discussions

We have corrected the approach of Lindzen and Choi (2009), based on all the criticisms made of the earlier work (Chung *et*

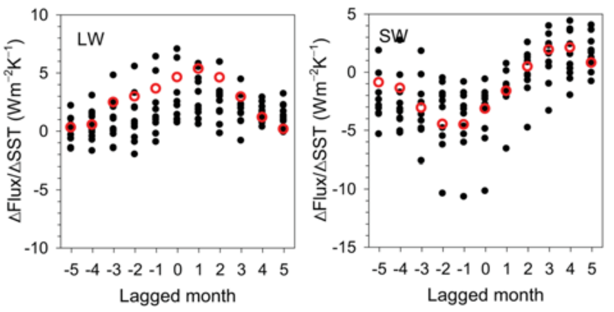

Fig. 12. Same as Fig. 4, but for the 10 CMIP models (black dots); GISS model was excluded because only few intervals of SST are obtained. The values for the 3-month smoothing in Fig. 4 are superimposed by red dots.

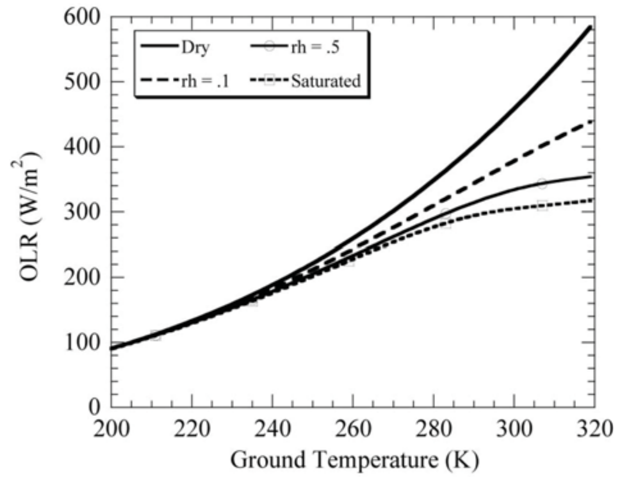

Fig. 13. OLR vs. surface temperature for water vapor in air, with relative humidity held fixed. The surface air pressure is 1 bar. The temperature profile in the model is the water/air moist adiabat. Calculations were carried out with the Community Climate Model radiation code (Pierrehumbert, 2009).

al., 2010; Murphy, 2010; Trenberth *et al*., 2010). First of all, to improve the statistical significance of the results, we supplemented ERBE data with CERES data, filtered out data noise with 3-month smoothing, objectively chose the intervals based on the smoothed data, and provided confidence intervals for all sensitivity estimates. These constraints helped us to more accurately obtain climate feedback factors than with the original use of monthly data. Next, our new formulas for climate feedback and sensitivity reflect sharing of tropical feedback with the globe, so that the tropical region is now properly identified as an open system. Last, the feedback factors inferred from the atmospheric models are more consistent with IPCC-defined climate sensitivity than those from the coupled models. This is because, in the presence of cloud-induced radiative changes altering SST, the climate feedback estimates by the present approach tends to be inaccurate. With all corrections, the conclusion still appears to be that all current models seem to exaggerate climate sensitivity (some greatly). Moreover, we have shown why studies using simple regressions of ΔFlux on ΔSST serve poorly to determine feedbacks.

To respond to the criticism of our emphasis on the tropical domain (Murphy, 2010; Trenberth *et al.*, 2010), we analyzed the complete record of CERES for the globe (Dessler, 2010) (Note that ERBE data is not available for the high latitudes since the field-of-view is between 60°S and 60°N). As seen in the previous section, the use of the global CERES record leads to a result that is basically similar to that from the tropical data in this study. The global CERES record, however, contains more noise than the tropical record.

This result lends support to the argument that the water vapor feedback is primarily restricted to the tropics, and there are reasons to suppose that this is also the case for cloud feedbacks. Although, in principle, climate feedbacks may arise from any latitude, there are substantive reasons for supposing that they are, indeed, concentrated mostly in the tropics. The most prominent model feedback is that due to water vapor, where it is commonly noted that models behave roughly as though relative humidity were fixed. Pierrehumbert (2009) examined outgoing radiation as a function of surface temperature theoretically for atmospheres with constant relative humidity. His results are shown in Fig. 13.

Specific humidity is low in the extratropics, while it is high in the tropics. We see that for extratropical conditions, outgoing radiation closely approximates the Planck black body radiation (leading to small feedback). However, for tropical conditions, increases in outgoing radiation are suppressed, implying substantial positive feedback. There are also reasons to suppose that cloud feedbacks are largely confined to the tropics. In the extratropics, clouds are mostly stratiform clouds that are associated with ascending air while descending regions are cloud-free. Ascent and descent are largely determined by the large scale wave motions that dominate the meteorology of the extratropics, and for these waves, we expect approximately 50% cloud cover regardless of temperature (though details may depend on temperature). On the other hand, in the tropics, upper level clouds, at least, are mostly determined by detrainment from cumulonimbus towers, and cloud coverage is observed to depend significantly on temperature (Rondanelli and Lindzen, 2008).

As noted by LCH01, with feedbacks restricted to the tropics, their contribution to global sensitivity results from sharing the feedback fluxes with the extratropics. This led to inclusion of the sharing factor c in Eq. (6). The choice of a larger factor c leads to a smaller contribution of tropical feedback to global sensitivity, but the effect on the climate sensitivity estimated from the observation is minor. For example, with $c = 3$, climate sensitivity from the observation and the models is 0.8 K and a higher value (between 1.3 K and 6.4 K), respectively. With $c = 1.5$, global equilibrium sensitivity from the observation and the models is 0.6 K and any value higher than 1.6 K, respectively. Note that, as in LCH01, we are not discounting the possibility of feedbacks in the extratropics, but rather we are focusing on the tropical contribution to global feedbacks. Note that, when the dynamical heat transports toward the extratropics are taken into account, the overestimation of tropical feedback by GCMs may lead to even greater overestimation of climate sensitivity (Bates, 2011). This emphasizes the importance of the tropical domain itself.

Our analysis of the data only demands relative instrumental stability over short periods, and is largely independent of long term drift. Concerning the different sampling from the ERBE and CERES instruments, Murphy *et al*. (2009) repeated the Forster and Gregory (2006) analysis for the CERES and found very different values than those from the ERBE. However, in this study, the addition of CERES data to the ERBE data does little to change the results for ΔFlux/ΔSST - except that its value is raised a little (as is also true when only CERES data is used.). This may be because these previous simple regression approaches include the distortion of feedback processes by equilibration. In distinguishing a precise feedback from the data, the simple regression method is dependent on the data period, while our method is not. The simple regression result in Fig. 7 is worse if the model integration time is longer (probably due to the greater impact of increasing radiative forcing).

Our study also suggests that, in current coupled atmosphere-ocean models, the atmosphere and ocean are too weakly coupled since thermal coupling is inversely proportional to sensitivity (Lindzen and Giannitsis, 1998). It has been noted by Newman *et al*. (2009) that coupling is crucial to the simulation of phenomena like El Niño. Thus, corrections of the sensitivity of current climate models might well improve the behavior of coupled models, and should be encouraged. It should be noted that there have been independent tests that also suggest sensitivities less than predicted by current models. These tests are based on the response to sequences of volcanic eruptions (Lindzen and Giannitsis, 1998), on the vertical structure of observed versus modeled temperature increase (Douglass, 2007; Lindzen, 2007), on ocean heating (Schwartz, 2007; Schwartz, 2008), and on satellite observations (Spencer and Braswell, 2010). Most claims of greater sensitivity are based on the models that we have just shown can be highly misleading on this matter. There have also been attempts to infer sensitivity from paleoclimate data (Hansen *et al*., 1993), but these are not really tests since the forcing is essentially unknown given major uncertainties in clouds, dust loading and other factors. Finally, we have shown that the attempts to obtain feedbacks from simple regressions of satellite measured outgoing radiation on SST are inappropriate.

One final point needs to be made. Low sensitivity of global mean temperature anomaly to global scale forcing does not imply that major climate change cannot occur. The earth has, of course, experienced major cool periods such as those associated with ice ages and warm periods such as the Eocene (Crowley and North, 1991). As noted, however, in Lindzen (1993), these episodes were primarily associated with changes in the equator-to-pole temperature difference and spatially heterogeneous forcing. Changes in global mean temperature were simply the residue of such changes and not the cause.

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