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Reducing the uncertainty in subtropical cloud feedback

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Key Points:
- The subtropical shortwave cloud feedback can be understood in a linear framework
- Observed interannual cloud sensitivity to meteorological changes constrains the feedback
- This constrained feedback is positive with less uncertainty than that produced by climate models

Supporting Information:
- Texts S1–S5, Figure S1–S6, and Table S1

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Abstract Large uncertainty remains on how subtropical clouds will respond to anthropogenic climate change and therefore whether they will act as a positive feedback that amplifies global warming or negative feedback that dampens global warming by altering Earth's energy budget. Here we reduce this uncertainty using an observationally constrained formulation of the response of subtropical clouds to greenhouse forcing. The observed interannual sensitivity of cloud solar reflection to varying meteorological conditions suggests that increasing sea surface temperature and atmospheric stability in the future climate will have largely canceling effects on subtropical cloudiness, overall leading to a weak positive shortwave cloud feedback ($0.4 \pm 0.9\ \mathrm{W\,m^{-2}\,K^{-1}}$). The uncertainty of this observationally based approximation of the cloud feedback is narrower than the intermodel spread of the feedback produced by climate models. Subtropical cloud changes will therefore complement positive cloud feedbacks identified by previous work, suggesting that future global cloud changes will amplify global warming.

1. Introduction

Horizontally extensive low-level clouds over the eastern subtropical oceans have a strong cooling effect on climate owing to their high albedo and weak greenhouse effect [*Hartmann et al.*, 1992]. Just a 3.5% to 5% absolute increase in their global coverage would exert a radiative forcing at the top of the atmosphere equal to that caused by a doubling of the atmospheric concentration of CO_2 [*Slingo*, 1980]. Global climate models disagree on how subtropical marine boundary layer (MBL) clouds will respond to anthropogenic climate change and therefore whether they will act to amplify or dampen global warming [*Bony and Dufresne*, 2005; *Qu et al.*, 2013]. Models that project an increase in subtropical low-level cloudiness in the future climate tend to simulate less global warming than models that project a decrease in cloudiness [*Myers and Norris*, 2015]. This uncertainty may arise because global models employ a wide variety of parameterizations of the physical processes underlying boundary layer clouds, which occur on spatial scales smaller than the models can represent explicitly. This study addresses this uncertainty by implementing linear regression to understand and observationally constrain the response of subtropical clouds to an increase in CO_2.

Subtropical MBL clouds exist under the descending branches of the Hadley Circulation, characterized by a relatively cool ocean surface, a temperature inversion separating the MBL from the overlying atmosphere, horizontal cold air advection near the surface, a relatively dry free troposphere, and subsidence [*Albrecht et al.*, 1995; *Norris*, 1998; *Myers and Norris*, 2015]. Such meteorological properties are known from first principles to be key in generating and sustaining subtropical clouds and can be considered as external cloud-controlling factors in both simple and complex models of the cloudy MBL [*Lilly*, 1968; *Blossey et al.*, 2013]. Given the importance of subtropical MBL clouds in global warming projections, determining their sensitivity to perturbations in cloud-controlling factors has been the focus of many studies [e.g., *Bretherton*, 2015, and references therein]. Recent research indicates that these large-scale meteorological factors are statistically predictive of observed decadal [*Seethala et al.*, 2015] and simulated anthropogenic [*Qu et al.*, 2013, 2015] changes in low-level cloud fraction.

Can observed relationships between clouds and their meteorological environment be similarly extrapolated to determine the cloud response to climate change? We address this question by employing multilinear regression to predict the subtropical cloud response to an instantaneous quadrupling of CO_2 ($4 \times CO_2$) in 19 global climate models participating in the Coupled Model Intercomparison Project phase 5 (CMIP5 [*Taylor et al.*, 2012]), using meteorological parameters as predictor variables (Text S1, Table S1, and Figure S1 in the supporting information). Such a method allows us to test the degree to which a linear model of subtropical

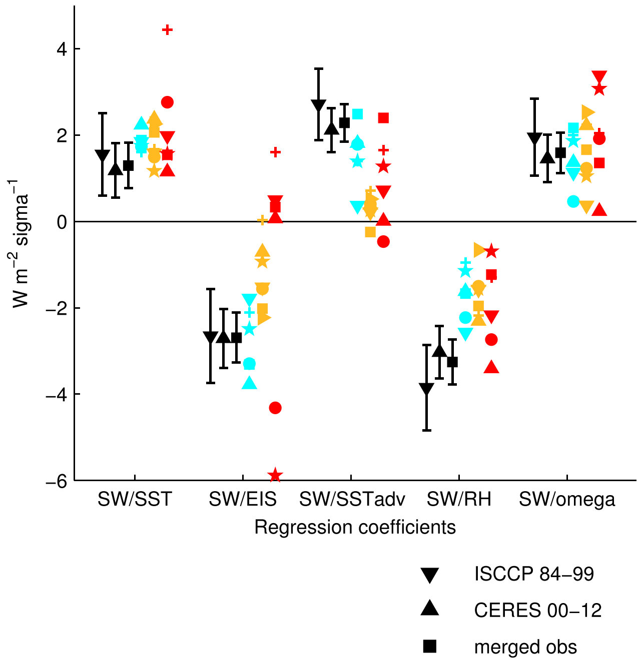

Figure 1. Regression coefficients of SW CRE as a linear function of SST, EIS, SSTadv, RH_{700}, and ω_{700} in observations and the control climate of CMIP5 models. For each coefficient, i.e., SW CRE sensitivity, we show two observational estimates computed using ISCCP and CERES paired with the ensemble mean of four atmospheric reanalyses, along with a weighted average of these two estimates. Error bars span 95% confidence intervals. Models are categorized into three levels of fidelity with respect to observations, denoted by cyan (best models), orange (second best models), and red (worst models). A model legend is provided in Figure S1. Units are in W m^{-2} per standard deviation of meteorological anomalies (sigma).

cloudiness is useful in projections of climate change and to determine what range of the cloud feedback is most plausible.

2. Regression Coefficients in Observations and CMIP5 Models

We linearly detrend and remove the monthly climatology from monthly values of shortwave cloud radiative effect (SW CRE, defined as all-sky minus clear-sky outgoing shortwave radiation at the top of the atmosphere) of all ocean grid boxes between 30°S and 30°N occurring under climatological subsidence. Then, SW CRE anomalies for all months and grid boxes are aggregated and regressed onto similarly aggregated anomalies of sea surface temperature (SST), estimated inversion strength (EIS), horizontal temperature advection over the SST gradient (SSTadv), relative humidity at 700 hPa (RH_{700}), and pressure vertical velocity at 700 hPa (ω_{700}). Negative values of SW CRE imply an energy loss of the climate system, while positive values of SW CRE imply a gain. We examine only those grid boxes experiencing climatological subsidence in the tropics for the models' preindustrial control and $4\times CO_2$ climates because clouds in these areas are governed by different dynamics compared to clouds that occur in regions of ascent (Text S2). Each of the resulting multilinear regression coefficients, shown in Figure 1, represents the interannual sensitivity of SW CRE to variations in each meteorological parameter (i.e., cloud-controlling factor) when all other factors are held fixed. Observed coefficients are similarly attained using data from the International Satellite Cloud Climatology Project (ISCCP), Clouds and Earth's Radiant Energy System (CERES) Energy Balanced and Filled data set, and the ensemble mean of four atmospheric reanalyses [*Rossow and Schiffer*, 1999; *Loeb et al.*, 2009; *Saha et al.*, 2010; *Dee et al.*, 2011; *Ebita et al.*, 2011; *Rienecker et al.*, 2011] (Text S2 and S3). For each SW CRE sensitivity, we compute a single "merged" observational coefficient as a weighted average of the two coefficients derived from ISCCP and CERES (Text S4). Figure 1 shows that in nature, anomalously strong subtropical cloud solar reflection (more negative SW CRE) is favored by anomalously cool SST, strong EIS, enhanced cold SSTadv, high RH_{700}, and weak ω_{700}, while anomalously weak subtropical cloud solar reflection (more positive SW CRE) is favored by the opposite meteorological conditions. This is consistent with the results of previous observational studies [*Klein and Hartmann*, 1993; *Norris and Leovy*, 1994; *Klein et al.*, 1995; *Myers and Norris*, 2013, 2015].

Climate models ought to simulate these relationships with reasonable accuracy if they are to be deemed reliable in the subtropical MBL cloud feedbacks they produce. Multilinear regression coefficients computed from 20 years of the preindustrial control simulation of each model are displayed in Figure 1 and vary widely from model to model, consistent with previous model evaluation studies [*Clement et al.*, 2009; *Webb et al.*, 2012; *Caldwell et al.*, 2013; *Myers and Norris*, 2015]. To highlight fundamental differences among models in the accuracy of their simulation of subtropical MBL cloud processes, it is useful to divide the CMIP5 ensemble into categories of performance according to a single metric. For each model we compute the root-mean-square error (RMSE) of the five coefficients with respect to a weighted mean of the ISCCP and CERES coefficients.

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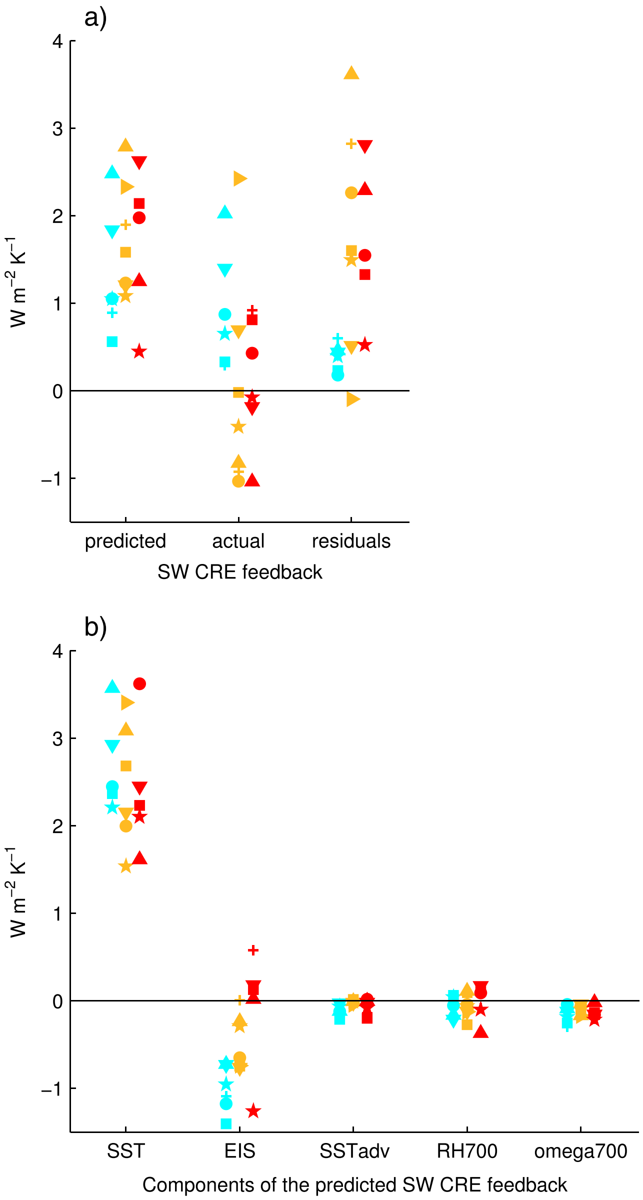

Figure 2. (a) The SW CRE feedback predicted via multilinear regression, the actual feedback produced by the CMIP5 ensemble, and the residuals between these two quantities and (b) components of the linear decomposition of the predicted SW CRE feedback. SST refers to the component of the feedback driven exclusively by the change in SST in the perturbed climate. The EIS, SSTadv, RH_{700}, and ω_{700} components are defined similarly. Note that the predicted feedback, residual, and SST component for one model (MIROC-ESM) are off the axes.

Models are color coded in Figure 1 and all subsequent figures into three levels of fidelity, including a subset with the six lowest (best), next seven lowest (second best), and six highest (worst) values of RMSE. A model legend is given in Figure S1. The worst models simulate the wrong sign or a very different magnitude of the relationships between SW CRE and both EIS and SSTadv, and several of these relationships are statistically indistinguishable from zero (Figure S2). The best models produce the correct sign and a reasonable magnitude of all relationships. The coefficients computed from the $4\times CO_2$ simulation of models are quantitatively similar, except for the SST coefficient simulated by the worst models (Figure S3).

3. Subtropical Cloud Feedback in CMIP5 Models

We predict the SW CRE global warming response produced by each model over the subtropical subsidence regime as the sum of the multilinear regression coefficients multiplied by the respective changes in meteorology that occur as a result of $4\times CO_2$ forcing. For each meteorological variable, we quantify its CO_2-forced change as its domain mean of years 121–140 of the $4\times CO_2$ run minus that of 20 years of the control run, divided by the increase in global mean surface temperature between the two time periods. We also apply this differencing method to compute the actual SW CRE change per degree global warming (the SW cloud or SW CRE feedback) produced by the CMIP5 ensemble.

All models predict a large increase in SST and moderate increase in EIS per degree global mean surface temperature warming (Figure S4). All models also predict a small decrease in both SSTadv and ω_{700}, meaning enhanced cold advection and weaker subsidence, while changes in RH_{700} are inconsistent and small across models. Figure 2 shows the actual SW cloud feedback simulated by the CMIP5 ensemble as well as the cloud feedback predicted via multilinear regression and its associated components. The most realistic models according to the RMSE metric produce an actual cloud feedback nearly the same as what the multilinear regression method predicts (Figure 2a). These models project a positive change in SW CRE per degree warming, i.e., a gain of energy of the climate system due to less solar reflection by MBL clouds. This positive cloud

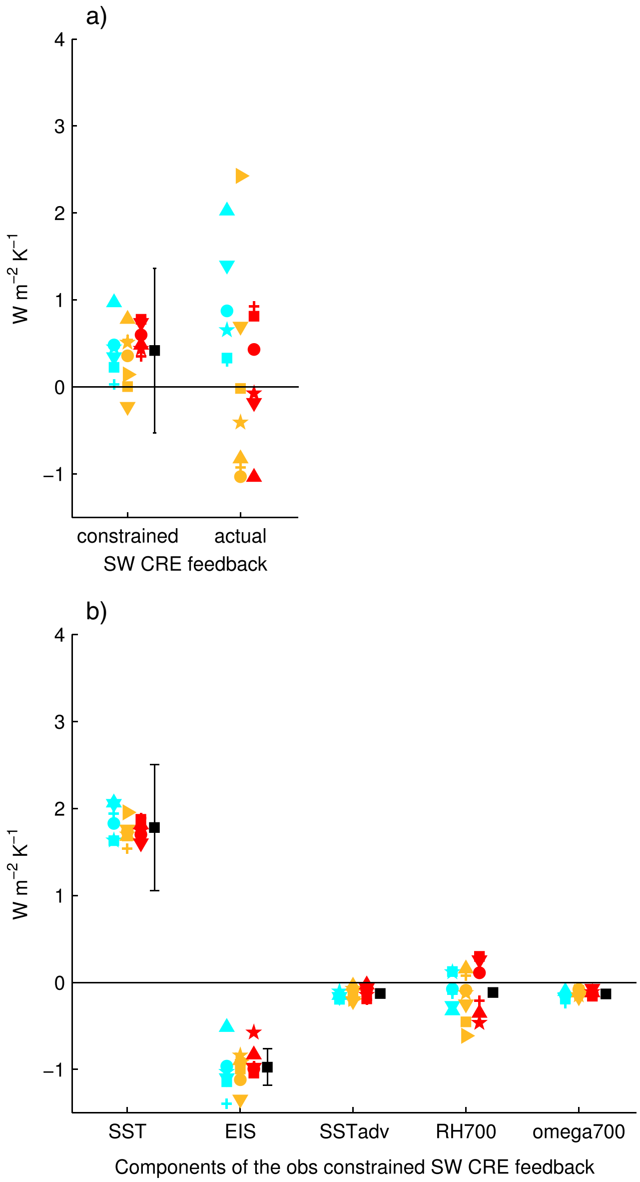

Figure 3. (a) The observationally constrained SW CRE feedback and the actual (unconstrained) feedback produced by the CMIP5 ensemble and (b) components of the linear decomposition of the observationally constrained feedback. The constrained feedback for each model is computed as the sum of the observed merged multilinear regression coefficients multiplied by the respective model-specific, CO_2-forced changes in meteorology. For the feedback computed using CMIP5 ensemble mean changes in meteorology (in black), error bars span 95% confidence intervals derived from observational uncertainty.

feedback arises mainly due to the combined effects of increasing SST, leading to more positive SW CRE, and increasing EIS, leading to more negative SW CRE (Figure 2b). Contrastingly, the poorest performing models produce an actual SW cloud feedback far from what the regression method predicts. In these models, some unknown cloud-controlling factors related to deficient subtropical MBL cloud physics produce a cloud feedback that is not captured by our physically based multilinear formulation and that is unlikely to occur in nature. In general, models with low RMSE have residuals between the actual SW CRE feedback and the feedback predicted via multilinear regression that are small in magnitude (Figure S5). Models with high RMSE have residuals that are large in magnitude. This suggests that we can formulate the SW CRE feedback for the real atmosphere in terms of our physically robust, multilinear framework—a finding corroborated by large-eddy simulations of subtropical MBL clouds [*Bretherton et al.*, 2013] and a new study that uses linear regression to explain observed decadal trends in subtropical low cloud fraction [*Seethala et al.*, 2015].

4. Observationally Constrained Cloud Feedback

Accordingly, we approximate the subtropical SW cloud feedback as the sum of the observed multilinear regression coefficients multiplied by the respective CO_2-forced changes in meteorology projected by the CMIP5 ensemble. Uncertainty of this approximation may result from imperfect knowledge of how the subtropical meteorological environment will change in the perturbed climate, the true values of the regression coefficients, or both. To compute a plausible range of the feedback, we therefore use two approaches. For the first method, we compute a feedback for each CMIP5 model as the sum of the observed multilinear regression coefficients ("merged obs" in Figure 1) multiplied by the respective CO_2-forced changes in meteorology. Considering intermodel differences in how the cloud-controlling factors change in the future climate and assuming perfect knowledge of the coefficients, this estimate of the subtropical SW CRE feedback yields an intermodel range of about −0.2 to 1 W m^{-2} K^{-1} (Figure 3a), substantially narrower than the range of −1 to 2.4 W m^{-2} K^{-1} actually produced by the ensemble. For the second method, we take the sum of the observed coefficients multiplied by the respective CMIP5 ensemble mean changes in meteorology. Considering observational uncertainty of the coefficients and assuming perfect knowledge of the meteorological changes, this estimate of the subtropical SW CRE feedback yields a 95% confidence interval of -0.5 to $1.4\ \mathrm{W\,m^{-2}\,K^{-1}}$ (Figure 3a and Text S4), also narrower than the range actually produced by the ensemble. Uncertainty of the observed relationship between SW CRE and SST is the dominant contributor to this range of the cloud feedback. Note that the mean feedback over all models that are observationally constrained in this way is identical to the feedback computed via the first method; only the uncertainty range differs. For either approach, the main contributions to the feedback are more positive SW CRE due to warmer SST in the perturbed climate and more negative SW CRE due to stronger EIS (Figure 3b). More negative SW CRE due to the combined effects of enhanced cold SSTadv and weaker ω_{700} acts as a small contribution to the feedback, and the effect of RH_{700} is also small and contributes to some uncertainty of the feedback computed via the first method (Figure 3b). These observationally constrained estimates of the SW cloud feedback are insensitive to the method used to compute cloud-induced SW radiative flux anomalies (Text S5 and Figure S6).

We conclude that boundary layer clouds over the eastern subtropical oceans likely act as a weak positive SW feedback to anthropogenic global warming rather than as a negative or strong positive feedback. Therefore, subtropical cloud changes will complement the robust positive cloud feedbacks produced by rising cloud tops and tropical expansion identified by previous work [*Boucher et al.*, 2013]. This suggests that cloud changes over the globe in a perturbed state of the climate will amplify and very likely not dampen anthropogenic warming.

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