Attributing Historical and Future Evolution of Radiative Feedbacks to Regional Warming Patterns using a Green’s Function Approach: The Preeminence of the Western Pacific

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Abstract

Global radiative feedbacks have been found to vary in global climate model (GCM) simulations. Atmospheric GCMs (AGCMs) driven with historical patterns of sea-surface temperatures (SST) and sea-ice concentrations produce radiative feedbacks that trend toward more negative values, implying low climate sensitivity, over recent decades. Freely-evolving coupled GCMs driven by increasing CO₂ produce radiative feedbacks that trend toward more positive values, implying increasing climate sensitivity, in the future. While this time-variation in feedbacks has been linked to evolving SST patterns, the role of particular regions has not been quantified. Here, a Green’s function is derived from a suite of simulations within an AGCM (NCAR’s CAM4), allowing an attribution of global feedback changes to surface warming in each region.

The results highlight the radiative response to surface warming in ascent regions of the western tropical Pacific as the dominant control on global radiative feedback changes. Historical warming from the 1950s to 2000s preferentially occurred in the western Pacific, yielding a strong global outgoing radiative response at the top of atmosphere (TOA) and thus a strongly negative global feedback. Long-term warming in coupled GCMs occurs preferentially in tropical descent regions and in high latitudes, where surface warming yields small global TOA radiation change but large global surface air temperature change, and thus a less-negative global feedback. These results illuminate the importance of determining mechanisms of warm pool warming for understanding how feedbacks have varied historically and will evolve in the future.
1. Introduction

In the traditional global energy budget framework (e.g., Gregory et al. 2004; Andrews et al. 2012), the net global top-of-atmosphere (TOA) radiation imbalance, \( \Delta Q \), is given by the sum of the radiative forcing \( \Delta F \), and the radiative response \( \lambda \Delta T \) to a change in global surface temperature:

\[
\Delta Q = \Delta F + \lambda \Delta T, \tag{1}
\]

where \( \Delta T \) is the change in global-mean near-surface air temperature; \( \lambda \) (units of Wm\(^{-2}\)K\(^{-1}\)) is the radiative feedback parameter, representing the efficiency with which the climate system can damp an energetic imbalance by emitting more radiation to space in proportion to surface warming. It is the sum of Planck response and feedbacks associated with changing atmospheric lapse rate, water vapor, clouds and surface albedo. The net global feedback parameter has to be negative in a stable climate; a more negative value implying that the Earth needs to warm less to balance an imposed radiative forcing. Quantifying the net radiative feedback is important because it determines the equilibrium climate sensitivity (ECS) – the steady-state \( \Delta Q = 0 \) global-mean near-surface air temperature change in response to a doubling of atmospheric CO\(_2\) concentration. That is, \( \text{ECS} = -\Delta F_{2x}/\lambda_{eq} \), where \( \Delta F_{2x} \) is the effective radiative forcing from CO\(_2\) doubling and \( \lambda_{eq} \) represents the net radiative feedback acting in that equilibrium state. Historical energy budget constraints are commonly used to estimate climate sensitivity (e.g., Otto et al. 2013; Knutti et al. 2017), producing an inferred climate sensitivity (ICS):

\[
\text{ICS} = -\frac{\Delta F_{2x}}{\lambda}, \tag{2}
\]

where \( \lambda \) represents the radiative feedbacks associated with transient warming. The use of ICS to estimate ECS depends crucially on the assumption that radiative feedbacks in the distant future will have the same value as those in operation today, i.e., that \( \lambda \) at any given time is equal to \( \lambda_{eq} \).
However, this assumption generally does not hold within simulations using state-of-the-art global climate models (GCMs). Fully-coupled GCMs driven by increased CO₂ forcing tend to show λ evolving toward less-negative values, implying a higher value of ICS (Murphy 1995; Senior and Mitchell 2000; Andrews et al. 2012; Williams et al. 2008; Winton et al. 2010; Armour et al. 2013; Andrews et al. 2015; Ceppi and Gregory 2017; Armour 2017; Proistosescu and Huybers 2017; Marvel et al. 2018). On the other hand, atmospheric GCMs (AGCMs) driven with observed historical sea-surface temperature (SST) and sea-ice concentration (SIC) patterns show that λ can vary substantially between decades and that it tends to evolve towards more-negative values over the course of the 20th century, corresponding to lower values of ICS, in the latter part of the historical record (Gregory and Andrews 2016; Zhou et al. 2016; Silvers et al. 2018; Andrews et al. 2018; Marvel et al. 2018). Consequentially, extrapolating feedback values from historical constraints leads to ICS estimates that are biased low compared to ECS values projected by fully coupled models (Andrews et al. 2018; Marvel et al. 2018).

We illustrate both historical and future feedback changes here (Fig. 1) from two prescribed-SST simulations within NCAR’s Community Atmosphere Model version 4.0 (CAM4; Neale et al. 2010), the atmospheric component of the Community Climate System Model version 4.0 (CCSM4). The historical simulation, hereafter referred to as the Historical run, shows the results of CAM4 forced by observed historical SST/SIC patterns (Hurrell et al. 2008, see Table 1). The future simulation, hereafter referred to as the 4xCO₂ run, shows the results of CAM4 driven by the
evolving SST/SIC anomaly patterns (relative to pre-industrial) produced by the freely-running
parent coupled GCM (CCSM4) under abrupt CO₂ quadrupling, performed as part of the Coupled
Model Intercomparison Project Phase 5 (CMIP5). In both experiments, all forcing agents (aerosols,
greenhouse gases, etc.) are fixed to a present-day (year 2000) level (i.e., ΔF = 0). This allows us
to diagnose radiative feedbacks directly from changes in global TOA radiation and near-surface
air temperature (TAS), and to attribute any feedback changes to evolving SST/SIC patterns. (See
Table 1 for additional details.)

Before moving to the results, we note that prescribed-SST simulations are useful for linearly
separating the effective radiative forcing from the radiative response to warming (i.e., the radiative
feedbacks). Previous studies indicate that prescribed-SST simulations within atmosphere-only
models can accurately capture the feedback changes in coupled versions of the same models
(Ringer et al. 2014; Andrews et al. 2015; Haugstad et al. 2017). Here we follow the Radiative
Forcing Model Intercomparison Project (RFMIP; Pincus et al. 2016) protocol by fixing SSTs at
pre-industrial values to calculate the effective forcing of CO₂ quadrupling (i.e., CMIP5’s
sstClim4xCO2 simulation), and the Cloud Feedback Model Intercomparison Project (CFMIP;
Webb et al. 2017) protocol by fixing CO₂ and other atmospheric constituents to evaluate the
radiative response to prescribed SST changes (our Historical and 4×CO₂ runs). We have validated
that the linear sum of the radiative forcing and the radiative response to warming (in the 4×CO₂
run) well approximates the net TOA radiation change produced by fully-coupled version of
CCSM4 in response to abrupt CO₂ quadrupling, with a global-mean error of 11% (not shown).
Fig. 1 shows that, in both *Historical* and $4\times CO_2$ simulations, net TOA radiation becomes increasingly negative with time as increasing TAS drives enhanced outgoing radiative fluxes (Fig. 1). However, the radiative feedback parameter, calculated as annual-global-mean net TOA flux change divided by annual-global-mean TAS change, becomes more negative with time in the *Historical* simulation, relative to mid-century (1950s) values, and becomes less negative with time in the $4\times CO_2$ run (Fig. 1 c, f). From Eq. (2), these feedback values give low ICS in recent decades in the *Historical* run, but higher ICS in the future in the $4\times CO_2$ run, consistent with aforementioned previous studies (e.g., Armour 2017, Proistosescu and Huybers 2017, Andrews et al. 2018, Marvel et al. 2018). Importantly, this different feedback behavior between historical and future warming occurs within the exact same AGCM and thus arises only from the different SST/SIC patterns in the two simulations. A key question is, what about the historical and future warming patterns drives these distinct feedback changes?

Recent studies have argued that feedbacks are sensitive to evolving spatial patterns of surface warming and have offered some interpretations on regional mechanisms, yet there exists no quantitative attribution of the importance of different regions and different mechanisms to this so-called *pattern effect* (Stevens et al. 2016). Armour et al. (2013) proposed a local feedback framework, wherein local TOA radiation change is assumed to be determined by only local surface warming. The net global feedback then varies as the evolving pattern of surface warming modifies the spatial weighting of constant local feedbacks. However, this local feedback framework has been challenged by recent studies pointing to the importance of remote warming on tropospheric stability and low cloud changes, particularly within the tropics (Rose et al. 2014; Rose and Rayborn 2016; Zhou et al. 2016; Mauritsen 2016; Ceppi and Gregory 2017; Andrews et al. 2015; Andrews...
and Webb 2018; Zhou et al. 2017; Silvers et al. 2018). For example, Zhou et al. (2016) linked the strength of the cloud feedback to the strength of the zonal SST gradient in the tropical Pacific Ocean. In this view, the increasingly negative cloud feedback in recent decades of the historical record can be linked to the cooling in the east Pacific relative to the west Pacific, which gives rise to increased lower tropospheric stability, thereby increasing low cloud amount and reflected shortwave (SW) radiation. The change in this east-west Pacific SST gradient also appears to be important for long-term feedback changes under CO₂ forcing, which favors east Pacific warming that would instead reduce low clouds and drive positive cloud feedback (Andrews et al. 2015; Ceppi and Gregory 2017; Andrews and Webb 2018; Zhou et al. 2017). In addition to the tropical Pacific, Silvers et al. (2018) suggested an important role for trade wind regions as a whole, including the tropical Atlantic. Yet other studies argued that it is the slow emergence of Southern Ocean warming (Armour et al. 2016) that gives rise to more positive feedbacks on centennial timescales (Senior and Mitchell 2000; Winton et al. 2010; Armour et al. 2013; Li et al. 2013; Rose et al. 2014; Rose and Rayborn 2016; Rugenstein et al. 2016).

In Fig. 2, we show the changes in SST patterns from the early period to the late period in our two AGCM simulations. That is, the SSTs averaged over the 2000s minus that over the 1950s in the Historical run, and the SSTs averaged over the last 20 years minus that over the first 20 years in the 4×CO₂ run. Both the zonal (east – west) Pacific SST gradient and meridional (extratropics – tropics) SST gradient are decreased in the 4×CO₂ run relative to the Historical run, with strong warming emerging at the east Pacific and high latitude at both poles under CO₂ forcing but not yet in the historical record. Some physical mechanisms of feedback changes associated with warming in these key regions have been discussed separately in earlier studies; however, still missing is a
comprehensive approach to quantify the relative contribution of each of the individual regions to the total change in global feedbacks.

Hence, the primary goals of this study are to attribute global feedback changes to specific regions of surface warming, and to understand the drivers of feedback changes both historically and in the future. To do that, we use a Green’s function approach to study the effect of regional SSTs on net TOA radiation, TAS, and feedbacks, respectively. The paper is organized as follows: section 2 proposes a global feedback framework and a Green’s function approach. Section 3 illustrate the structure of the Green’s function by showing the global response to localized warming. Section 4 validates the Green’s function approach within the above AGCM simulations. Section 5 attributes global feedback change to regional warming, for the Historical run and the 4×CO₂ run. Section 6 discusses the caveats and broader implications.

2. Formulating feedback dependence on warming patterns

The Green’s function approach assumes that the climate response to a prescribed large-scale SST/SIC pattern is a linear combination of the responses to prescribed SST/SIC changes at each location. This enables us to estimate TOA radiation response and TAS response to any specific global SST pattern, based on the sensitivity of the responses to regional SST change (section 2a). We derive the Green’s function by computing the dependence of TOA radiation and TAS on regional SST/SIC anomalies, from a suite of simulations within CAM4, each with a localized patch of SST and/or SIC anomalies (section 2b).

a. Global feedback framework
By convention, the net global radiative feedback is defined as the change in global-mean net TOA radiative response ($\mathbf{R}$) to warming divided by the change in global-mean TAS ($\mathbf{T}$):

$$\lambda(t) = \frac{\mathbf{R}}{\mathbf{T}}$$

(3)

where the overbar denotes the area-weighted global means; $\mathbf{R}$ represents a vector of changes in local net TOA flux ($\mathbf{R} = [\Delta R_1, ..., \Delta R_n]$); $\mathbf{T}$ represents a vector of changes in local TAS ($\mathbf{T} = [\Delta T_1, ..., \Delta T_n]$); $n$ denotes the total number of grid points in the global domain. We define all local responses as a function of time-dependent global SST changes ($\mathbf{SST}(t) = [\Delta SST_1, ..., \Delta SST_n]$).

That is, for any grid box $i$, the local radiation change ($\Delta R_i$) and the local TAS change ($\Delta T_i$) can be expressed by a first-order Taylor series with respect to SST change at all grid boxes $j$ over the ocean domain:

$$\Delta R_i = \sum_{j=1}^{n} \frac{\partial R_i}{\partial SST_j} \Delta SST_j + \varepsilon_R, \quad \Delta T_i = \sum_{j=1}^{n} \frac{\partial T_i}{\partial SST_j} \Delta SST_j + \varepsilon_T$$

(4)

where the error term $\varepsilon_R$ and $\varepsilon_T$ come from potential nonlinearities or residuals that are independent of SSTs. We can then rewrite the vector of TOA radiation change as

$$\mathbf{R} = \mathbf{J}_R \mathbf{SST}(t)$$

(5)

where $\mathbf{J}_R$ is a Jacobian matrix, representing the sensitivity of regional $\Delta R$ on regional $\Delta SST$:

$$\mathbf{J}_R = \begin{pmatrix} \frac{\partial R_1}{\partial SST_1} & \cdots & \frac{\partial R_1}{\partial SST_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial R_n}{\partial SST_1} & \cdots & \frac{\partial R_n}{\partial SST_n} \end{pmatrix}$$

(6)

Likewise, the vector of TAS change can also be reformulated as

$$\mathbf{T} = \mathbf{J}_T \mathbf{SST}(t)$$

(7)

where $\mathbf{J}_T$ is the Jacobian of regional $\Delta T$ with respect to regional $\Delta SST$. 

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Once we calculated each components of the Jacobians (see next section), substituting Eq. (5) and Eq. (7) into Eq. (3) gives us the final formulation of time-varying global feedback:

\[
\lambda(t) = \frac{J_R \text{SST}(t)}{J_T \text{SST}(t)}. \tag{9}
\]

In this framework, global radiative feedbacks are determined by (i) the sensitivity of local and remote TOA radiation and TAS responses to regional SST changes (i.e., the Jacobians \(J_R\) and \(J_T\), quantifying the “state dependence”), and (ii) time-varying global SST changes (i.e., \(T_{\text{SST}}(t)\), quantifying the “time dependence”). That is, the apparent time-variation of radiative feedbacks arises from their time-invariant dependence on the SST/SIC state which itself evolves over time (Armour et al. 2013; Stevens et al. 2016; Rose and Rayborn 2016; Proistosescu and Huybers 2017; Goosse et al., 2018). This framework enables us to systematically examine the change in feedback in response to the spatial and temporal evolution of SSTs.

b. The Green’s function and experiment design

We derive the sensitivity Jacobians \(J_R\) and \(J_T\) from a suite of AGCM simulations within CAM4, following the set-up in Zhou et al. (2017), who employed a Green’s function approach to study the dependence of cloud feedback on SSTs over global ice-free regions using CAM5.3 (Neale et al., 2012). Here, we extend the analysis to include sea-ice covered regions, examine the net feedback, and also decompose total feedback changes into individual components by use of radiative kernels (Shell et al. 2008).
Using CAM4 at 1.9° latitude × 2.5° longitude resolution, we performed 137 fixed-SST simulations, each with a localized patch of anomalous SST and/or SIC (Fig. 3). All simulations are run for 40 years, branched from the 5th year of a control simulation (noted as the Control run), which is run for 45 years (Table 1). The Control run uses monthly varying observed climatological SST/SIC at present-day level (averaged over years 1982-2001), and all forcing agents are held constant at year 2000 levels. For each experiment, we add a single patch of warm SST anomaly to the monthly climatology, following the form proposed by Barsugli and Sardeshmukh (2002) and used by Zhou et al. (2017) as:

$$\Delta \text{SST}(\text{lat}, \text{lon}) = A \cos^2 \left( \frac{\pi \text{lat} - \text{lat}_p}{\text{lat}_w} \right) \cos^2 \left( \frac{\pi \text{lon} - \text{lon}_p}{\text{lon}_w} \right),$$

(10)

where $A$ is the amplitude of the SST anomaly; subscript $p$ denotes the center point of the patch and subscript $w$ denotes the half-width of the patch. Each SST patch is confined within a rectangular area $(\text{lat}_p \pm \text{lon}_w, \text{lat}_p \pm \text{lon}_w)$. To cover the global ocean areas efficiently, we set $\text{lon}_w = 40°$ for all patches, and set different $\text{lat}_w$ as follows: $\text{lat}_w = 15°$ in tropical regions ($|\text{lat}_p| \leq 30°$) and $\text{lat}_w = 25°$ in polar regions ($50° \leq |\text{lat}_p| \leq 70°$); patches in mid-latitudes ($30° < |\text{lat}_p| < 50°$) are set to have $\text{lat}_w = 15°$ on the equatorial side and $\text{lat}_w = 25°$ on the polar side of the center point, to be consistent with adjacent patches. All patches are staggered to each other by half-width.

We set the amplitude of SST anomaly $A$ to 1.5 K for all patches except for polar patches, where we increase $A$ to 3 K, in order to increase the statistical significance of the response to high latitude warming. The amplitudes of our warming patches are smaller than those in Zhou et al. (2017) (where $A$ was +4K for warm anomaly and -4K for cold anomaly), but our simulations are carried
out with a longer period (40 years each instead of 6 years each). In addition, we perturb SIC along with SSTs within regions covered by sea ice: SIC anomalies within each individual patch follow the same cosine hump as Eq. (10), with the amplitude of SIC anomaly $A$ being -20% (SIC is set to be zero wherever the adjusted SIC falls below 0).

By analyzing the response from single-patch experiments, we are able to calculate each component of the sensitivity Jacobians ($J_{R_{ij}} = \frac{\partial R_{i}}{\partial SST_{j}}$ and $J_{T_{ij}} = \frac{\partial T_{i}}{\partial SST_{j}}$). The calculation is similar to that of Zhou et al. (2017), but we apply the Jacobian formulation to both net TOA radiation and TAS, while Zhou et al. (2017) only applied the Green’s function to TOA radiation from clouds. The net TOA radiation response and TAS response used to calculate the Jacobians are the anomalies relative to the Control run averaged over the last 39 years (excluding the first year to allow for atmospheric adjustment). In calculating the Jacobians, grid boxes whose anomalies are not statistically different from zero at 99% confidence level are set to zero. This is necessary because these insignificant responses are primarily noise due to the limited run time (40 years) of experiments. Removing these weak responses may introduce a small bias in the mean response, but it reduces noise and increases the accuracy of the Green’s function. We calculate the sensitivity of local radiative response to SST change within a certain patch $p$ as:

$$\left( \frac{\partial R_{i}}{\partial SST_{j}} \right)_{p} = \frac{\Delta R_{i}}{\Delta SST_{j}} \frac{a_{j}}{a_{p}},$$

where $\Delta R_{i}$ is net TOA flux anomaly in grid box $i$; $\Delta SST_{p}$ is the area-weighted averaged SST anomaly over the patch $p$; $a_{j}$ is the surface area of the grid box $j$ inside the patch $p$; and $a_{p}$ is the total ocean area of the patch $p$. The fact that grid $i$ and $j$ are two independent points enables this formulation to capture the remote effects of SST change. Given that one grid box is covered by up
to 8 patches staggered to each other, weighting all associated patches based on the value of SST anomaly leads to the final form of \( \frac{\partial R_i}{\partial SST_j} = \frac{\sum_p \Delta SST_j \left( \frac{\partial R_i}{\partial SST_j} \right)_p}{\sum_p \Delta SST_j} \),

where \( \Delta SST_j \) is the SST anomaly in the grid \( j \) within the patch \( p \), and the summation is over all patches that cover the grid \( j \). We can thus derive all components in the sensitivity Jacobians \( J_R \) and \( J_T \) (\( J_T \) follows the same procedures by replacing \( \Delta R \) with \( \Delta T \)), and then reconstruct the feedback response to any given SST patterns, assuming that the responses added linearly (we will verify this assumption in the following section).

Although not explicit, this approach includes the effect of sea-ice changes, since SIC anomalies are prescribed proportional to SST anomalies at the rate of -20% per 3K within sea-ice covered regions. This parameterized rate with respect to SST change, however, may not accurately capture the actual sea-ice changes in global surface warming patterns. Therefore, we add supplementary terms to Eq. (9) to calibrate responses to a given SST/SIC anomaly pattern, namely, \( R^* \) and \( T^* \), a vector of changes in local net TOA flux and a vector of changes in local TAS that both are associated with sea-ice underestimate. \( R^* \) and \( T^* \) are defined as:

\[
R^* = J_R^* SIC^*(t), \quad T^* = J_T^* SIC^*(t),
\]

where \( SIC^*(t) = [\Delta SIC^*_1, ..., \Delta SIC^*_n] \), is a vector representing local sea-ice changes in a particular warming pattern that are not captured by the Green’s function. That is, the offset between the SIC changes in the given anomaly pattern and the reconstructed SIC changes proportional to SST anomalies. \( J_{R^*} \) and \( J_{T^*} \) are the sensitivity Jacobians calculated with respect to SIC change:
Unlike the aforementioned full Jacobians, \( J_R^* \) and \( J_T^* \) contains only diagonal terms, i.e., \( \frac{\partial R_i}{\partial SIC_j} = 0 \) \( (i \neq j) \), representing local TOA radiation and local TAS responses to local SIC change. This is motivated by the fact that the response to SIC change is largely localized (see Fig. 4d). This formulation also allows us to keep track of the state dependence of feedback on global SST patterns. Finally, we reconstruct the global radiative feedback as

\[
\lambda(t) = \frac{J_R^{SST}(t) + \alpha J_R^{*SIC}(t)}{J_T^{SST}(t) + \alpha J_T^{*SIC}(t)},
\]

where \( \alpha \) is 0.1, a coefficient scaling up the response to SIC changes in order to compensate the underestimate of SIC in the Green’s function. Since we found that the global TOA radiation response is insensitive to \( \alpha \), the value of \( \alpha \) is tuned to maximize the Green’s function’s ability in reproducing surface warming response particularly at high latitude. The supplementary terms \( (\alpha J_R^{*SIC}(t), \alpha J_T^{*SIC}(t)) \) in Eq. (16) only serve to improve the accuracy of the Green’s function as in Eq. (9), considering potential SIC underestimates. The difference between the reconstructed responses using Eq. (9) versus that using Eq. (16) are not significant and only limited to regional TAS response in sea-ice covered regions.
To estimate the annual mean response using Eq. (16), we first calculate 3-month seasonal means and then average across the year. This is necessary because, although the SST/SIC anomalies imposed are constant over a year, the response to the SST/SIC forcing varies as the mean state changes over the seasonal cycle. For example, shortwave radiation change in response to SIC change is more significant in summer months. We found that using annual means without taking into account the seasonal cycle leads to bias both locally and globally; however, using monthly means also introduces errors as it does not capture the portion of the TOA radiation response that is lagged relative to the surface warming. Therefore, we average to four seasonal-mean Jacobians (DJF/MAM/JJA/SON) to produce all annual-averaged responses.

Finally, it should be noted that the radiative feedback parameter defined in this study does not include the direct response (e.g., land warming) to radiative forcing by CO₂ increase, as ΔF₂x in Eq. (2) is the effective radiative forcing (i.e., including rapid adjustments). The change in feedback arises only from the change in SST/SIC boundary forcing, which allows us to track the sensitivity of feedbacks to evolving spatial patterns of SSTs.

3. Global response to localized warming

We compare responses to four warming patches within several key regions highlighted in previous studies (e.g., Andrews and Webb 2018; Zhou et al. 2017): the west Pacific, the east Pacific, and high latitudes in the Northern Hemisphere (NH) and the Southern Hemisphere (SH) (Fig. 4). Importantly, SST warming in the western Pacific (a region of tropical ascent) drives strong remote responses on a global scale, while the responses to SST warming in the other three regions are more confined locally. For the west Pacific patch (Fig. 4a), warming is communicated to the upper
troposphere, which warms the whole troposphere across all latitudes (Fig. 4a, bottom panel), causing a large increase in outgoing radiation at the TOA. Furthermore, the patch of warming locally decreases tropospheric stability, measured here as estimated inversion strength (EIS), but increases EIS remotely over tropical marine low clouds regions, yielding an increase in global low cloud cover (LCC) which enhances the global SW reflection (Wood and Bretherton 2006). In contrast, surface warming in the east Pacific patch and high-latitude patches results in atmospheric warming that is trapped within the boundary layer and decreases local EIS and LCC, leading to a weakly positive TOA radiation change that is limited to local scale (Fig. 4 b, c, d). Overall, the global-mean TOA radiation and TAS responses to the west Pacific patch are about an order of magnitude greater than the responses to the three other patches.

The difference between NH and SH polar patches reveals another feature in net TOA radiation and LCC: the SH polar patch has a negative TOA radiation change and a positive LCC change (Fig. 4d), which is the result of local sea-ice change. The NH polar patch is applied to a region of open water, where surface warming decreases local EIS and local LCC, resulting in a positive TOA radiation change. However, the SH polar patch is located in the region partially covered by sea ice. When sea ice is forced to melt, new open water enhances heat and moisture transport in the boundary layer, and therefore generates positive LCC change, which reflects more TOA radiative flux (Wall et al. 2017; Goosse et al. 2018). However, this sea-ice effect has only a small impact on the global scale.

Next, we show the global-mean response to unit SST warming in each grid box (Fig. 5). The annual-global-mean net TOA radiation change and annual-global-mean TAS change to each grid
of SST warming (Fig. 5a and 5b, respectively) are calculated from seasonal Jacobians $J_R$ and $J_T$. Dividing the global TOA response by the global TAS response provides a qualitative sense of how the global feedback changes in response to a localized warming in each grid box (Fig. 5c). Consistent with Fig. 4, surface warming in tropical ascent regions has the strongest remote effect, driving large increases in outgoing TOA radiation and thus large negative feedbacks. Surface warming in tropical descent regions drives a relatively weaker increase in outgoing radiation, or even a decrease, thus producing more positive feedback values, consistent with previous studies (e.g., Andrews and Webb 2018; Ceppi and Gregory 2017; Zhou et al. 2017). High-latitude warming plays an important role in global TAS change, but contributes little to global TOA radiation change, leading to feedback values near zero.

We further partition the net TOA radiation response into individual components by use of radiative kernels (Shell et al. 2008) (Fig. 5d – i). The large net negative radiation response to warming in tropical ascent regions arises from Planck radiation, lapse rate (LR), and cloud SW radiation changes. The net positive radiation response to warming in descent regions is dominated by cloud SW radiation changes. The Planck response (Fig. 5d) largely mirrors the response of global TAS to local warming (Fig. 5b), as it must: it is negative in response to warming everywhere but the magnitude is larger in response to warming in the western Pacific as opposed to all other regions. The patterns of LR change (Fig. 5e) and water vapor change (Fig. 5f) are consistent with those proposed by Andrews and Webb (2018) and Ceppi and Gregory (2017). While radiation changes with LR and water vapor partially cancel when summed, the net value here is not zero and instead shows a pattern similar to the LR change (not shown), indicating a stronger radiative response associated with LR changes. The pattern of cloud SW changes (Fig. 5g), which dominates the net
TOA radiation pattern, suggests that LCC plays an important role in changing global TOA radiation. The global surface albedo change (Fig. 5i) is negligible everywhere, arising from the fact that sea-ice albedo changes result in localized TOA radiation changes.

4. Green’s function validation

Before moving to the final step of applying the Jacobians to attribute feedback changes to regional warming, we validate the Green’s function approach. First, we perform a linearity test by imposing two SST patches in a simulation simultaneously – one in the tropical west Pacific and one in the tropical east Pacific (noted as the Two-Patch run, Fig. 6a). The CAM4-produced output in this Two-Patch run is then compared to the linear sum of the response to two corresponding single patches (Fig. 6b). We find a remarkable similarity in spatial patterns for all responses of interests with spatial correlations higher than 90%, and nearly-identical global-mean responses (shown in Fig. 6). This test speaks to the strong linearity in the model’s responses, supporting the assumption that the response to a large-scale SST pattern can be estimated as the sum of responses to each of the SST forcing point. Additional two-patch tests performed within other regions also exhibit a strong linearity (not shown).

Next, we convolve the SST patterns from the Historical run and the 4×CO₂ run with the Green’s function, and compare the reconstructed response with the CAM4-produced response (Fig. 7). For both runs, the Green’s function reproduces the inter-annual variability and overall magnitude of global net TOA radiation, TAS, and radiative feedback. We note an offset in global-mean TOA radiation and radiative feedback in the 4×CO₂ run; we will discuss reasons of this potential nonlinearity in section 6b. Despite this relatively small offset for the 4×CO₂ simulation,
Green’s function reconstruction captures most of the feedback changes seen in both simulations. We interpret these results as a validation of the robustness of the Green’s function approach, allowing us to proceed with attributing feedback changes to regional warming patterns.

5. Attributing global feedback changes to regional warming

The selected patches in section 3 (Fig. 4) reveal an important property in the climate system: temperature and radiation changes depend on both local and remote surface warming. In this section, we identify where the changes in TOA radiation and TAS originate using the global-mean net TOA radiation change ($\Delta R_{\text{global}}$) and global-mean TAS change ($\Delta T_{\text{global}}$) that are associated with SST and SIC perturbations in any grid box $i$ in a particular warming pattern:

\[ \Delta R_{\text{global}} = \frac{\partial R_{\text{global}}}{\partial \text{SST}_i} \Delta \text{SST}_i + \alpha \frac{\partial R^*_{\text{global}}}{\partial \text{SIC}_i} \Delta \text{SIC}^*_i, \]

\[ \Delta T_{\text{global}} = \frac{\partial T_{\text{global}}}{\partial \text{SST}_i} \Delta \text{SST}_i + \alpha \frac{\partial T^*_{\text{global}}}{\partial \text{SIC}_i} \Delta \text{SIC}^*_i. \]

$\frac{\partial R_{\text{global}}}{\partial \text{SST}_i}$ and $\frac{\partial T_{\text{global}}}{\partial \text{SST}_i}$ are global-mean net TOA radiation change and global-mean TAS change to unit SST change in grid box $i$ (Fig. 5a and 5b), respectively. $\Delta \text{SST}_i$ is SST anomaly at grid box $i$ in a particular warming pattern; $\frac{\partial R^*_{\text{global}}}{\partial \text{SIC}_i}$ and $\frac{\partial T^*_{\text{global}}}{\partial \text{SIC}_i}$ are global-mean net TOA radiation change and global-mean TAS change to unit SIC change in grid box $i$ if $i$ is covered by sea ice. $\Delta \text{SIC}^*_i$ is residual SIC anomaly in this warming pattern that is not fully captured by the Green’s function. Eq. (17) and Eq. (18) are consistent with Eq. (16), but the second terms on the right-hand-side in these two equations are in fact close to zero, as the Jacobians with respect to SIC ($J_R^*$ and $J_T^*$) only represent local SIC effect and become negligible when averaged over the globe. Overall,
\( \Delta R_{global_i} \) and \( \Delta T_{global_i} \) represent the contribution from local SST change to global averaged change in TOA radiation and TAS, given a specific surface warming pattern.

We first show \( \Delta R_{global_i} \) and \( \Delta T_{global_i} \) for the Historical run (Fig. 8), using the SST and SIC change averaged over the 1950s and the 2000s, relative to the pre-industrial level (i.e., relative to the 1850-1890 average). The most striking finding is that the more negative TOA radiation in the 2000s is predominately due to SST change in tropical ascent regions (Fig. 8d). While many studies (e.g., Andrews and Webb 2018; Zhou et al. 2016) focus on the zonal SST gradient with preferential cooling in the eastern Pacific in this period, our result highlights the role of the western Pacific in driving most of the change in global TOA radiation. This arises for two reasons: (i) stronger surface warming in this region relative to the rest of the world oceans over the recent decades (Fig. 8b); (ii) stronger global radiative response to surface warming from this region driven by the deep convection (Fig. 5a). Overall, comparing the 1950s and the 2000s, the primary change in both global-mean TOA radiation and TAS from the early period to the late period is due to warming in tropical ascent regions.

Next, we show the same analysis for the 4\( \times \)CO\(_2\) run (Fig. 9), comparing the first 20 years in the simulation to the last 20 years. In this case, although global SSTs evolve toward a pattern with more warming in the eastern Pacific and high latitudes, the western Pacific is still the dominant contribution to the global TOA radiation change (Fig. 9, d), in both the early and late period. However, the evolution of the contribution to global TAS change shows a different behavior: SST warming outside of the deep convective regions, although contributing little in the early period, plays an ever-increasing role in global TAS change in the latter period (Fig. 9, e, f).
The attribution analysis for the two simulations can be summarized as follows: (i) in both runs, the change in global TOA radiation is dominated by the radiative response to warming in tropical ascent regions; (ii) this does not hold true for TAS, however, which has substantial contributions from all other regions. Based on these findings, we propose a guiding approximation:

\[ \lambda(t) \approx \frac{\Delta R_{global,WP}}{\Delta T_{global,WP} + \Delta T_{global,other}} , \]  

where \( \Delta R_{global,WP} \) and \( \Delta T_{global,WP} \) respectively denote global-mean net TOA radiation change and TAS change that are attributed to surface warming in the warm pool (WP) region, and \( \Delta T_{global,other} \) denotes global-mean TAS change that is attributed to surface warming in all other oceans outside of the WP. The WP region is defined here as broad deep convective areas in Indo-Pacific Ocean within 30°S - 30°N and 50°E - 160°W (shown as the grey box in Fig. 8 and Fig. 9) capturing the region with the most negative values of \( \Delta R_{global} \) (panels c and d in Figs. 8 and 9).

From this approximation, we can then reformulate the global radiative feedback as

\[ \lambda(t) = \frac{\lambda_{WP}}{1 + \gamma(t)} , \]  

where \( \lambda_{WP} = \Delta R_{global,WP}/\Delta T_{global,WP} \) denotes a nominal and constant value of feedback associated with the WP warming, and \( \gamma(t) \) is given by

\[ \gamma(t) = \frac{\Delta T_{global,other}}{\Delta T_{global,WP}} . \]  

\( \gamma(t) \) is the “warm pool (WP) warming ratio”, representing the ratio of the contribution to global TAS change from surface warming in all ocean areas outside of the WP relative to the contribution from surface warming within the WP region.
In this formulation (Eq. 19-21), we first approximate global-mean TOA radiation change to a response to SST change in the WP region alone (Eq. 19); the time-variation of feedback can then be explained solely by the evolution of $\gamma$ (Eq. 20), which compares how regional warming affects global TAS change (Eq. 21). When $\gamma$ decreases with time, meaning that the WP warming contributes more to global-mean TAS change, the strength of net global radiative feedback will be larger, i.e., a more negative value. This is because the surface warming in the WP is communicated to the free troposphere, driving more outgoing radiation to space that efficiently damps the heating, thus leading to a more negative feedback. In contrast, when $\gamma$ increases with time, meaning that warming outside of the WP features more in global-mean TAS change, then the feedback will be smaller in magnitude, i.e., a less negative value. This is because the local surface warming in tropical descent regions and high latitudes tends to be constrained near the surface, driving much smaller changes in global TOA radiation, and resulting in a less negative feedback (Zhou et al. 2017; Andrews and Webb 2018).

In Fig. 10, we show the evolution of $\gamma$ calculated using Eq. (21) for the Historical run and the 4x$CO_2$ run, and compare the evolution of the net feedbacks with the approximated feedbacks calculated by Eq. (19). In both the historical warming and future warming simulations, the evolution of $\gamma$ is responsible for the time-dependence in the strength of the global feedback, and the approximated feedback captures the main trend of the net feedback changes throughout the whole period. The radiation change induced by the east Pacific warming and all other oceans outside of the WP plays a minor role in feedback evolution. This is consistent with the assumption that surface warming in the WP region controls the change in global TOA radiation, and the evolution of global radiative feedbacks is thus due to the evolution of $\gamma$. 
In summary, applying the Green’s function approach we are able to isolate the effect of regional warming on global TOA radiation, TAS, and feedback changes, respectively, for different time periods. In contrast to previous studies that focus on the tropical east – west Pacific SST gradient or high-latitude – tropics SST gradient, our study pinpoints the relative importance of the western Pacific as the dominant driver of changes in global TOA radiation. We also propose that global feedback changes track the ratio of the contribution to global TAS change from regional surface warming in the WP region relative to the contribution from warming in all other regions. This is particularly useful for understanding the trend toward a less-negative global radiative feedback with high-latitude warming on long timescales as seen in our 4×CO$_2$ simulation and in previous studies (Winton et al. 2010; Li et al. 2013; Rose et al. 2013; Rose and Rayborn 2016; Rugenstein et al. 2016). While previous arguments have been focused on the radiation change coming from this warming pattern, our results offer the interpretation that the trend toward a less-negative radiative feedback can be attributed to the change in global surface temperature with little change in global TOA radiation (i.e., an increasing denominator in Eq. (19) associated with an increase in the WP warming ratio $\gamma$).

6. Discussion

There are two possible caveats to the results presented: the sensitivity of the results to the strength of cloud feedback in the AGCM we used, and the potential reasons for the noticeable nonlinearity in radiative response seen in the 4×CO$_2$ run (Fig. 7 d, f).

a. Comparison with CAM5
The model we used in this study (CAM4) to construct the Green’s function is known to lack an accurate representation of LCC sensitivity to local SST changes, and therefore potentially leads to less positive cloud feedback associated with warming in tropical descent regions (e.g., Gettelman et al. 2012; Park et al. 2014). We thus compare the CAM4 Green’s function to that of CAM5 (using output from the simulations of Zhou et al. 2017), which has an improved capacity to simulate LCC response to both local SST change and tropospheric stability change (Park et al. 2014). Fig. 11 shows the comparison of global-mean cloud radiative effect (CRE) and global-mean net TOA radiation to each grid of unit SST warming. (CRE is defined as the difference between net TOA radiation and clear-sky net TOA radiation). The patterns are consistent between the two models, although CAM4 has greater CRE and net TOA radiation response to SST warming in the warm pool region.

To test the robustness of our results concerning the processes responsible for the time-variation of global feedbacks, we repeat the calculations of Eq. (19) but using the CAM5 Green’s function. We find that feedback approximation, using only the global-mean TOA radiative response to SST change in the WP region, still captures most of the temporal variations in the net feedback in both the Historical run (Fig. 11e) and the $4\times CO_2$ run (Fig. 11f). This agreement between CAM4 and CAM5 suggest that the key result of this study – that warming in the western tropical Pacific dominates global feedback changes for historical and future warming – is robust across models with different cloud parameterizations.

b. Nonlinearity in the $4\times CO_2$ simulation
In section 4, we found that the global-mean TOA radiation, and thus radiative feedback, reconstructed from the Green’s function was offset from those in the $4\times CO_2$ run (Fig. 7 d, f). Note that these two predictions are both based on prescribed-SST simulations with the same mean state, therefore the disagreement here suggests a nonlinear behavior in climate response and a caveat for the use of the Green’s function approach. This offset appears in the first few decades, and then remains relatively constant over the rest of the simulation. We consider several hypotheses that could account for this nonlinearity.

The first hypothesis is that there may be a nonlinearity in global-mean TOA radiation change that is associated with global-mean temperature change (e.g., Bloch-Johnson et al. 2015). This would result in a residual between the Green’s function reconstruction and model output, hereafter noted as $\Delta R_{res}$, that should scale as a quadratic function of global-mean temperature: $b\Delta T^2$, where $b$ has unit of Wm$^{-2}$K$^{-2}$ (Bloch-Johnson et al. 2015). That is, the feedback ($\Delta R/\Delta T$), instead of being constant, may increase with global-mean temperature (Meraner et al. 2013; Block and Mauritsen 2013). If this holds, we would expect $\Delta R_{res} = b\Delta T^2$, or $\Delta R_{res}/\Delta T = b\Delta T$. Comparing $\Delta R_{res}$ from the $4\times CO_2$ simulation to that expected based on $b$ values found in other model simulations (Meraner et al. 2013; Roe and Armour, 2011) shows that this nonlinearity does not appear to explain the residual (Fig. 12). Instead, $\Delta R_{res}$ appears to show three separate regimes as time evolves: the first 1-2 years, the first few decades, and the longer time scale in the rest of 150 years. This seems more consistent with the three modes of evolving warming patterns proposed by Proistosescu and Huybers (2017). Only the second mode shows a nonlinear-like behavior, yet the best-fitting value of $b$ (approximately 0.17 Wm$^{-2}$K$^{-2}$) is well above the maximum value (0.06 Wm$^{-2}$K$^{-2}$).
\(2K^2\) found in previous studies (Roe and Armour 2011). Moreover, after the first few decades, \(\Delta R_{\text{res}}\) no longer fits the expected nonlinear relationship.

Moreover, after the first few decades, \(\Delta R_{\text{res}}\) no longer fits the expected nonlinear relationship. While the global-mean temperature nonlinearity does not explain the residual, it is possible that there could be a nonlinearity associated with local temperature change. That is, the error in global-mean TOA radiation estimate could arise from the local SST changes in the simulation being substantially larger than the SST anomalies we imposed to derive the Green’s function. To test this possibility, we perform an additional 30 year-long simulation, in which the SST/SIC anomalies have the same spatial pattern as in the last 30 years of the \(4\times CO_2\) run, but the magnitude of the anomalies is reduced by \(5/6\) at all locations such that the global-mean SSTs are comparable to that of the last 30 years of the Historical run (hereafter, the \textit{ReducedSST} run). In this simulation (see Fig. 7, blue lines), the offset between the CAM4-produced response (Fig. 7d, blue solid line) and Green’s function reconstructed response (Fig. 7d, blue dashed line) still remains, suggesting that the magnitude of local temperature is not the reason leading to the error.

A third possibility is that the nonlinearity in global-mean radiation arises from the spatial pattern of SST/SIC changes in the \(4\times CO_2\) simulation. For example, this relatively uniform warming pattern in the climate system may introduce spatially-smoothed response in convection and circulation, yet this smoothing effect is missing in the Green’s function since the global response is linearly summed from the responses to regional forcings that may, for instance, shift convection considerably within the tropics. Indeed, an offset in global TOA radiation of similar magnitude is found in an additional simulation within CAM4 where we impose a uniform warming pattern (1.5K SST perturbation globally). With the uniform warming, the Green’s function derived TOA
radiation changes have much more spatial variance and have a more negative global mean compared to the changes as simulated directly by the model. Yet this offset is much weaker in an additional simulation with regionally-uniform warming (1.5K SST perturbation over 160°W - 50°E, 45°S-45°N). Hence, we postulate that the smooth spatial pattern of surface warming predicted under CO$_2$ quadrupling may be responsible for the nonlinearity, suggesting an important caveat and a limitation for the use of Green’s function approaches to quantify future feedback changes.

7. Conclusion

Here we have examined the historical and future evolution of global radiative feedbacks within two AGCM simulations. Feedbacks trend toward more negative values over time for historical warming, yet trend toward more positive values over time under 4×CO$_2$. To quantify the impact of regional SST anomalies on global TOA radiation and TAS, we derived a Green’s function from a suit of patch simulations within CAM4, permitting the attribution of feedback changes to surface warming in each region.

The results first highlight the radiative response to surface warming in tropical ascent regions as the dominant control of global TOA radiation change both in the past and in the future. We propose that, to a good approximation, global radiative feedback changes track the “warm pool warming ratio” ($\gamma$), defined here as the ratio of contribution to global TAS change from surface warming in the regions outside of the WP relative to the contribution from warming in the WP region alone. We found that historical TAS changes from the 1950s to 2000s are preferentially attributed to SST changes in the warm pool, i.e., $\gamma$ is small over recent decades. This surface warming pattern yields
a strong global outgoing radiative response at TOA that can efficiently damp the surface heating, therefore producing a very negative global feedback. The projected future change in global TAS, on the other hand, features more warming in regions outside of deep convective regions, i.e., γ increases by time. Surface warming from these regions such as the eastern Pacific Ocean and Southern Ocean, yields locally amplified warming effects but limited global TOA radiation changes, thus leading to a less-negative global feedback in the projected (future) climate.

Comparing our results from CAM4 to those based on the CAM5 Green’s function of Zhou et al. (2017) shows that while the cloud radiative response is somewhat different between the two models, there is consistency between CAM4 and CAM5 regarding the regions of importance for the temporal change in global radiative feedbacks, in both the historical record and future projections of climate change. An expanded inter-model comparison using the Green’s function approach from multiple GCMs would be valuable. We also examined potential reasons for the nonlinearity seen in the 4×CO2 simulation. The specific mechanism is not clearly understood, but we propose that it might arise from the relatively uniform spatial pattern of SSTs in this simulation, which produces rather uniform radiative response that is not captured by the linearized Green’s function.

This study highlights the importance of warm pool warming relative to the rest of the world oceans for the evolution of global radiative feedbacks, both historically and in the future under CO2 forcing. A key question is thus whether the western Pacific will continue to warm quickly relative to the rest of the world oceans, as we have seen in observations to date, or whether it will warm by relatively less in the future, as GCMs predict. These results suggest that only in the case that
the western Pacific warming keeps warming at a greater place than the rest of the global oceans

can we expect ICS to remain as low as that derived from recent energy budget constraints (e.g.,
Otto et al. 2013; Lewis and Curry 2015; 2018; Armour 2017; Knutti et al. 2017). If GCMs are
accurate in their projection that the western Pacific warming will not keep pace with the eastern
Pacific and high latitude warming, then we can expect a less negative feedback, and a higher value
of ICS, in the future.

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Lagué, M.F. Stuecker, and C.M. Bitz, for assisting with the CAM4 simulations.

Reference

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Table 1. List of experiments performed in this study.

<table>
<thead>
<tr>
<th>Experiments</th>
<th>Run time</th>
<th>SST/SIC input</th>
<th>Description of anomaly defined in this study</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Control</strong></td>
<td>45 years</td>
<td>Monthly-varying observed climatology at the present-day level (averaged over years 1982-2001), from CAM4 model defaults (available at <a href="http://www.cesm.ucar.edu/models/cesm1.2/cam/docs/ug5_3/ch03.html">http://www.cesm.ucar.edu/models/cesm1.2/cam/docs/ug5_3/ch03.html</a>)</td>
<td>The model outputs averaged over the last 39 years relative to the Control run’s outputs averaged over the entire 45 years.</td>
</tr>
<tr>
<td><strong>Patch Simulations</strong></td>
<td>40 years</td>
<td>Each with a patch of warm SST anomaly and/or SIC anomaly added to the monthly-varying observed climatology used in the Control run</td>
<td></td>
</tr>
<tr>
<td><strong>Historical</strong></td>
<td>165 years (year 1850-2014)</td>
<td>Monthly-varying observed historical SST/SIC (Hurrell et al. 2008) (The CAM4 default time series data is available at <a href="http://www.cesm.ucar.edu/models/cesm1.2/cam/docs/ug5_3/ch03.html">http://www.cesm.ucar.edu/models/cesm1.2/cam/docs/ug5_3/ch03.html</a>)</td>
<td>The model outputs spanning over years 1900-2014 relative to the outputs averaged over years 1850-1890 in the same simulation</td>
</tr>
<tr>
<td><strong>4xCO₂</strong></td>
<td>150 years</td>
<td>Monthly SST/SIC anomalies from CCSM4 Abrupt4×CO₂ experiment relative to its piControl experiment in CMIP5, added to the monthly-varying observed climatology (used in the Control run)</td>
<td>The model outputs spanning over the entire 150 years relative to the Control run’s outputs averaged over the entire 45 years.</td>
</tr>
<tr>
<td><strong>ReducedSST</strong></td>
<td>30 years</td>
<td>As same as the last 30 years of the 4xCO₂ run, except the global-mean magnitude is reduced to be comparable to that of the last 30 years of the Historical run</td>
<td>The model outputs spanning over the entire 30 years relative to the Control run’s outputs averaged over the entire 45 years.</td>
</tr>
</tbody>
</table>
Figure 1: Evolution of global-mean response of (a, d) net TOA radiation (Wm$^{-2}$), (b, e) near-surface air temperature (K) and (c, f) global feedback (Wm$^{-2}$K$^{-1}$) from (left column) the *Historical* run and (right column) the 4×CO$_2$ run. The black lines denote annual mean values, and the blue lines denote 10-years running averages. The feedback parameter (c, f) is calculated as annual-global-mean net TOA flux change (a, d) divided by annual-global-mean TAS change (b, e).
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Historical run (SSTs averaged over the recent decade 1996-2005 minus those over the midcentury
1956-1965); and (b) in the $4\times CO_2$ run (SSTs averaged over last 20 years minus those over the first
20 years). Note the color scales in (a) and (b) are different.
Figure 3: Geographic location of SST patches. Black and red dots denote the center of all patches. The contour denoting the half-amplitude (i.e., 1.5 K for polar patches and 0.75 K for other patches) of each of the red patches is shown, demarking approximately half the size of the patch. The half-amplitude contour for the patches labeled by the black dots are not shown.
Figure 4: Response to selected SST patches. The patches are identified by the black contour (half-amplitude contour) in the panels in the top row, imposed in (a) the tropical west Pacific, (b) the tropical east Pacific, (c) the Northern Hemisphere high latitude, and (d) the Southern Hemisphere high latitude. From top to bottom: changes in near-surface air temperature $\Delta T$ (K), net TOA radiation $\Delta R$ (Wm$^{-2}$), estimated inversion strength $\Delta EIS$ (K), low cloud cover $\Delta LCC$ (%) and zonal-mean temperature $\Delta T_{zonal-mean}$ (K). Shown in each panel is the anomalies from each
experiment averaged over the last 39 years relative to the Control run. The area-weighted global
mean of each response is shown at the top of each plot, except for the zonal mean temperature
change ΔT_{zonal-mean} (bottom row). Note that the amplitude of SST anomalies imposed in polar
patches (c, d) is as twice as that imposed in the tropical patches (a, b).
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years relative to the *Control* run. From top to bottom: near-surface air temperature \( \Delta T \) (K), net TOA radiation \( \Delta R \) (Wm\(^{-2}\)), estimated inversion strength \( \Delta EIS \) (K), and low cloud cover \( \Delta LCC \) (%).
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Figure 8: Global-mean response to each grid box of actual SST change in the *Historical* warming pattern. The left column is the averaged response over the 1950s, the right column is the averaged response over the 2000s. (a) and (b) are the SST changes (K) relative to the pre-industrial level (i.e., values averaged over years 1850-1890). (c) and (d) denote the global-mean net TOA radiation response attributed to each grid of SST change ($\Delta R_{\text{global}_t}$, unit of W m$^{-2}$). (e) and (f) denote the
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Figure 9: Same as Fig. 8, expect for the 4×CO₂ run. The responses shown are taken as the anomalies relative to the Control run. The left column is averaged response over the first 20 years, the right column is averaged response over the last 20 years.
Figure 10: Evolution of radiative feedbacks estimated from the Green’s function (a, c) and WP warming ratio $\gamma$ (b, d), for the **Historical** run (left column) and for the **$4\times CO_2$** run. In panel (a) and (c), the black line (“Net”) denotes net feedback, the blue line (“WP only”) denotes the approximated feedback calculated by Eq. (19), i.e., the global-mean radiation change is approximated to the radiative response to the warm pool warming alone. The red line (“EP only”) shows the estimated feedback using the radiative response to surface warming in the east Pacific alone, i.e., $\frac{\Delta R_{global, EP}}{\Delta T_{global, WP} + \Delta T_{global, other}}$. The orange line (“Rest”) shows the estimated feedback using the radiative response to surface warming in the rest of the globe, i.e., $\frac{\Delta R_{global, other}}{\Delta T_{global, WP} + \Delta T_{global, other}}$. In panel (b) and (d), $\gamma$ is calculated as $\Delta T_{global, other}/\Delta T_{global, WP}$ (Eq. 21), both terms are 10-years running averages.
Feedback approximation

(a) CAM4

(b) CAM5 (Zhou et al. 2017)

(c) CAM4

(d) CAM5 (Zhou et al. 2017)

(e) Historical

(f) $4 \times \text{CO}_2$

- Black: Net
- Blue: WP only
- Red: EP only
- Orange: Rest
Figure 11: Comparison of results from this study with those from the CAM5 Green’s function in Zhou et al. (2017). Panel (a, b) shows global-mean cloud radiative effect (CRE) change to unit SST warming in each grid box (unit: Wm$^{-2}$/K). Panel (c, d) shows global-mean net TOA radiation change to a unit SST warming in each grid box (unit: Wm$^{-2}$/K). The left column shows results from CAM4 (this study), the right column shows results from CAM5 (Zhou et al. 2017). Note that panel (c) is identical to panel (a) in Fig. 5. Panel (e, f) show the evolution of feedbacks estimated from the CAM5 Green’s function, for (e) the Historical run and for (f) the 4$\times$CO$_2$ run, to be compared to in Fig 10 (a, c). The “Net” feedback is estimated using the Green’s function from Zhou et al. (2017). Note that CRE is slightly different to $R_{\text{cloud}}$ used in Zhou et al. (2017); it is defined as the difference between net TOA radiation and clearsky net TOA radiation, without removing the cloud masking effect.
Figure 12: Nonlinear TOA radiation residual ($\Delta R_{\text{res}}$) from the $4 \times CO_2$ simulation. $\Delta R_{\text{res}}$ is the difference in global-mean net TOA radiation produced by model and those produced by the Green’s function (unit: Wm$^{-2}$). Panel (a) shows the relationship of $\Delta R_{\text{res}}$ against global-mean TAS change ($\Delta T$, unit: K); panel (b) shows the relationship of $\Delta R_{\text{res}}/\Delta T$ (Wm$^{-2}$K$^{-1}$) against $\Delta T$. The black dots are running 10-years averages from the $4 \times CO_2$ simulation. The red lines in panel (a) and panel (b) denote quadratic relationship $\Delta R_{\text{res}} = b\Delta T^2$ and linear relationship $\Delta R_{\text{res}}/\Delta T = b\Delta T$, respectively, using $b$ of 0.03 Wm$^{-2}$K$^{-2}$ (from Meraner et al. 2013), 0.06 Wm$^{-2}$K$^{-2}$ (from Roe and Armour, 2011), and 0.17 Wm$^{-2}$K$^{-2}$ (best-fitting for the data points over the first few decades).